Hand Gesture Identification in Older Adults using Force-Myography

by

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Abstract

The projected increase in the proportion of seniors in society has prompted the growth of senior-technologies that support aging-in-place. The aim of this thesis to explore the suitability of Force Myography (FMG) for hand gesture identification in aging populations to complement other technologies that promote aging-in-place and to investigate the practical considerations for implementation.

Characteristics of using FMG with seniors (aged 60+ years old) was first determined with a protocol involving five seniors and five non-seniors. Participants were invited to don a custom FMG device and perform a series of stationary hand gestures while being guided by a virtual user interface. The interface provided online image instructions of the required gesture, as well as visual feedback of successful gesture identification. Participants also performed household activities based tasks in a self-selected manner. On average, seniors completed specified hand gestures within 1.4 seconds of online instruction, with inadvertent identification of control gestures during household tasks lasting at most 1.45 seconds. Although these times were comparable non-senior participants, seniors demonstrated increased variability. Lastly, online accuracies for gesture classification only reached 75% compared to the 91% of non-senior participants.

Considering the results of the first study, a follow up study was performed with a larger recruitment pool focusing on intrinsic user features that influence the variability in FMG acquisition and modelling. The results demonstrate that age and gender associated differences in band tightness, grip strength and ratio of skinfold thickness to forearm circumference account for at most 30% of the variability in FMG responsiveness, translating to 7% to 30% of the variability of model test accuracy. Intrinsic user features also influenced the severity that functional noise (the affect of unintended movements) had on classification. Results also revealed that variables independent of the user, such as band removal, contribute significantly to declines in testing accuracy, where declines ranged from 28% to 96%. Finally, results also showed that methods of FMG modelling typically encountered in the literature shows limited effectiveness during non-static activity.

Keywords: Activities of daily living; age-related rehabilitation; rehabilitative and assistive technology; biomedical devices; human factors; independent living; prosthetic control; sensors/sensor application; force myography

We weren't brought this far to stop now.

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List of Acronyms

Term	Initial components of the term
AAL	Ambient-Assisted Living
ADL	Activities of Daily Living
DOF	Degree of freedom
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
FMG	Force Myography
FSR	Force Sensitive Resistor
IADL	Instrumental Activities of Daily Living
IMU	Inertial Magnetic Units
MMG	Mechanomyography
OMG	Optical Myography
ROM	Range of Motion
sEMG	Surface Electromyography
SFU	Simon Fraser University
TFM	Topographic Force Map
UMG	Ultrasound Myography

Glossary

Term	Definition
Aging	process or group of processes occurring in living organisms that with the passage of time lead to a loss of adaptability, functional impairment, and eventually death […] with these processes being distinct from daily or seasonal biological rhythms and any other temporary change
Aging in place	the ability to live in one's own home safely and independently regardless of age, income, or ability level
Ambient Assisted Living	digital environments which are sensitive, adaptive, and responsive to human needs
Anatomical position	The body is standing erect, with the face and eyes looking straight ahead, feet together, arms by the sides with the palms facing forwards
Anterior	(body is in anatomical position) towards the front of the body
Chronic disease	A medical condition that is persistent or otherwise long-lasting in its effects, or a disease that comes with time.
Comorbidity	The simultaneous presence of two or more medical conditions
Deep	Away from or beneath the surface of the skin
Distal	Away from the torso
Infectious disease	A medical condition caused by a pathogenic microorganism
Inferior	(body is in anatomical position) towards the feet
Lateral	Away from the midline of the body
Medial	Towards the midline of the body
Morbidity	The condition of having a medical disease
Mortality	death
Myography	The measurement the force produced by a muscle when under contraction
Posterior	(body is in anatomical position) towards the back of the body
Proximal	Towards the torso
Successful Aging	[Rowe and Kahn definition] Having 1) a low probability of disease and disease related disability, 2) high cognitive and physical functional capacity, and 3) active engagement with life
Superficial	Towards or on the surface of the skin
Superior	(body is in anatomical position) towards the head

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Chapter 1.

Introduction

1.1. Chapter Overview

This chapter begins by outlining the background, motivation, and objectives for this thesis in ***Sections 1.2*** and ***1.3***. The scope of research and the contributions to the body of knowledge regarding FMG are also discussed in ***Sections 1.4*** and ***1.5*** respectively. Finally, the layout of the remaining chapters of this thesis is presented in ***Section 1.6***.

1.2. Background & motivations

Currently seniors, citizens aged 65 years old and above, make up about 16% percent of the population [1], and they are anticipated to become a larger portion of the population in upcoming decades [2], [3]. This is significant as seniors are one of the largest consumers of healthcare resources [4], [5], and the current availability of resources are ill-suited to meet these demands. Reasons for seniors absorbing so much of healthcare resources are associated with age-associated declines in physical and mental faculties [6]–[16], increased susceptibility to infectious diseases [17], and increased prevalence and severity of chronic diseases [18]. Given these challenges associated with aging, 'successful aging' [19] describes a state of having:

1) a low probability of disease and disease related disability,
2) high cognitive and physical functional capacity
3) active engagement with life.

There are many interventions that are utilized to meet the needs of seniors (regardless of whether they are aging successfully) and to promote successful aging where possible. These include financial services [20], social services [21], [22], residential service and care

[23], [24], home modifications [25], health services [26], transportation services [27]–[29], and preventative programs[16], [30]–[35]. However, high societal and personal financial burden[36], [37], more than half of seniors being home bound due to limited transportation resources [29], decreasing familial support [38], and a general shortage of health care professionals [39] will eventually cause these services to be insufficient. In response, stakeholders are advocating for more home-service based programs, as these programs are more cost effective [36], [37] and seniors prefer to age at home independently from others [40]–[43].

Generational attitudes towards technology are improving [44], and seniors are demonstrating increased technology/internet use [45]–[47]. Thus, technological interventions such as 'Assisted Ambient Living Tools' (AAL tools) [37], [48] and wearable technology are increasingly being explored. Technology to promote aging-in-place that have been developed include information and communication technology, robotics, telemedicine, sensor technology, medication management, and video games [48], [49]. Examples of ways in which these interventions address the needs of seniors are: movement and behaviour monitoring to track aberrant movements that indicate the onset of dementia or Alzheimer's [50], [51]; slip and fall detection [52]–[55]; control [54]; task prompting during activities of daily living (ADLs) [56]; biometrics and movement monitoring for telecare [57]–[60]; and emergency response [61].

Movement tracking of the upper extremities could be a significant method to address the functional independence of seniors at home. The hand is vital to the completion of activities of daily living (ADLs) and instrumental activities of daily living (IADLS). ADLs and IADLs refer to independently performed activities such as feeding, grooming, cleaning, transferring, and leisure. In adults, ADLs comprise about 9.5 hours of our day [62], with the hand being used for 60% to 75% of the time ADLs were being completed [63], [64]. The majority of object manipulation is achieved by less than 6 simple hand grasps [63], [64]. Unfortunately, there are several musculoskeletal and neurological barriers to arm and hand function such as bone fractures, sarcopenia, arthritis, and stroke, which are frequently present in aging populations [17] and in higher severity compared to non-senior groups [17].

Tracking arm and hand movements can be achieved by several sensing modalities, many of which are already being used in other assistive devices and AAL tools for seniors. Examples of these include ambient technology such as a vision systems [65], and wearable technologies incorporating inertial sensors (IMUs) [59], [66] and myography [67], [68]. The nature of ambient technology such as vision systems, unfortunately, suffers from limitations due to occlusion, the lack of direct movement data [48], and perceptions of privacy invasion [3], [69], [70]. In a similar manner, inertial sensing is limited by only being capable of monitoring gross upper limb movement behaviour, not necessarily hand grasp intention that could assist with ADLs. These limitations lead to myographic modalities, such as surface electromyography (sEMG) and force myography (FMG), to be the preferred method for identifying hand gestures during ADLs.

Amongst myographic sensing modalities, FMG presents many advantages including electrical robustness [71], not requiring specialized skin preparation [72], minimal signal processing [73], and being cost effective [74]. Indeed, FMG has shown to be very promising in areas of rehabilitation [75]–[77], device/prosthetic control [72], [78]–[83] , gait analysis [84], and grip strength analysis [85] – all fields applicable to addressing the needs of seniors. Despite this, there are areas of FMG implementation that require further research to support its effective implementation into AAL systems for seniors aging-in-place.

Firstly, FMG research presents a significant lack of senior targeted study design. Target populations tested (not just considered) thus far have been limited to stroke survivors [75]–[77], amputees [72], [80], [81], [86], and heathy young volunteers [68], [73], [75], [77], [79], [81], [84], [85], [87]–[103]. In fact, healthy young volunteers make up an overwhelming majority of test participants. This limited test pool is inconsiderate to the aspects of aging that make even successfully aging seniors distinct from young healthy populations or injured populations [6]. Secondly, there is a lack of research dedicated to understanding the impact of human factors on conclusions drawn from FMG recordings. Other myographic modalities such as electromyography (EMG), mechanomyography (MMG) have received direct research into the significant impacts of features such as skinfold thickness [104], [105] , hydration [106], and decreases in muscle cross sectional area [107]. With the nature of FMG being acquired at the surface of the skin and subject to the mechanical properties of the skin and underlying tissue, FMG should be afforded this same level of scrutiny. Thirdly, is that most research involving FMG has involved isolated hand gestures or one degree of freedom (DOF) movements. The forearm (a frequently used location for FMG acquisition [79], [88], [101]), houses musculature that realize wrist motions, forearm motions, AND hand/finger gestures – all of which can occur independently and simultaneously of each other. Together, the arm and hand are capable of many combinations of gestures/orientations. A final limitation considered, is that regression and/or classification machine learning algorithms encountered in FMG literature require retraining. The models developed rely on pre-labelled data [108], [109], which would have significant impacts on the deployability of a commercial FMG device, let alone a technology that targets seniors. Cost (mental, time, and monetary) and practicality are two factors that affect initial technology acceptance and adherence in seniors [69], [110]. And unfortunately, the need to retrain an FMG device would negatively impact seniors' adherence to FMG technology, and thus its long-term effectiveness. This could be addressed with translational learning or semi-supervised methods of training. However, further characterization of FMG variability and sources of variability would benefit further development.

1.3. Objectives

The main motivation and context for this thesis is to present Force Myography as a sensing method that would provide data measured directly from the user. The intention is that this data would be incorporated into home based systems that would allow seniors to access services from their home. Example services include telecommunication, remote monitoring of typical and a-typical activity, telerehabilitation applications, and remote interactions with health professionals. However, FMG as a method of movement tracking requires further development and characterization.

Considering the background presented in ***Section 1.2***, which is discussed in greater detail in ***Chapter 2***, this thesis seeks to explore the suitability of FMG for hand gesture identification in aging populations. This thesis consists of three main objectives.

- **Objective 1.** To characterize the use of FMG with aging populations

- **Objective 2.** To identify features intrinsic to the participant that significantly influence the variability of FMG measurements
- **Objective 3.** To quantify the impact of features intrinsic to the participant on performance of FMG modelling

The results of addressing **Objective 1** are obtained separately and provided the guidance for protocol design and analysis for **Objectives 2 & 3**. While senior participants were included in the recruitment pool for **Objectives 2 & 3**, the protocol performed with senior participants was limited to that which was achievable without triggering muscular and mental fatigue. Thus, **Objectives 2 & 3** included non-senior participants as well, to allow for a more extensive protocol and comprehensive analysis than would have been possible without.

1.4. Scope

The focus of this work is FMG acquired through force sensitive resistors (FSRs), and is referred to simply as FMG throughout this document for clarity. Given the number of variables involved with using FMG with seniors, the limitations and scope of this research is explicitly defined here to allow for a more focussed discussion in later chapters.

Hardware and Firmware. To date, FMG implementation demonstrates high variability of sensor choice, design, placement, electrical circuitry, approaches to data processing and machine learning. Although the variability in these areas are reviewed in greater depth in **Chapter 2**, no standardized approach to FMG implementation has been noted in the literature. In this regard, FMG would benefit from a comparative analysis on sensor types, placement, electrical implementation, and machine learning methods. However, this type of consideration is considered outside of the scope of this thesis.

Variability in physical and mental function in seniors. Although seniors are considered in a collective fashion, the author acknowledges the heterogeneity within aging populations. Demographics, morbidities/comorbidities, and differential aging of organ systems create a high degree of variability in aging seen amongst seniors. However, as an initial work into the use of FMG with seniors, participant recruitment was limited to those whom could follow instructions and self-identified as healthy. As FMG research matures, future study could be expanded to explore the effectiveness of FMG in the presence of debilitating morbidities. Along this vein, research could also better characterize which groups among seniors could benefit most from FMG, as well as the way that FMG could complement other sensing modalities in an integrated fashion in AAL research.

1.5. Contribution to body of knowledge

The results of this work contribute several things to body of knowledge surrounding aging-in-place and FMG. With respect to aging-in-place, this body of research presents an alternative sensing modality for movement and gesture tracking that could be used to complement other technologies being explored to promote aging-in-place. Also presented is the first documented targeted use FMG with community dwelling seniors. In addition, a detailed review of the needs of seniors and the current support network for seniors provides a sense for FMG can be implemented into the existing frameworks of geriatric technology research and development.

With respect to Force Myography, this work contributes knowledge that transcends the focused application of FMG to geriatric research. To date, FMG has been used with young healthy volunteers, stroke survivors, and amputees for device control, rehabilitation, and assistive systems. As mentioned in ***Section 1.2*** and discussed in detail in ***Chapter 2***, there are a number of areas of practical FMG implementation that are not explicitly addressed and/or quantified by the current state of FMG research. Explicit areas of force sensitive resistor (FSR) based FMG research lacking attention that this work addresses are: variability of sensors throughout the functional range of movement/effort, the effect of band removal, the effect of compound gestures/movement, and the validity of statically trained supervised models on non-stationary activity.

1.6. Document outline

The following chapters of this thesis document are organized as follows. ***Chapter 2*** provides a detailed review of the literature concerning aging, the needs of seniors, technologies that promote aging-in-place, and the state-of-the-art of FMG research. This is followed by ***Chapter 3*** which describes in detail the methodology, results, and analysis used to address **Objective 1**. ***Chapter 4*** describes in detail the methodology used to address **Objectives 2 & 3**, while the results are discussed in ***Chapter 5***. Concluding remarks are presented in ***Chapter 6***.

Chapter 2.

Literature Review

2.1. Chapter Overview

The following chapter provides context for the motivation and design choices of this thesis. Firstly, components of aging are considered in ***Section 2.2***, with attention to the needs of seniors. This provides the background for further discussion into the trends in technology development for seniors in ***Section 2.3***. An overview of arm/hand structure, function as well as the role of the arm/hand in daily living are presented in ***Section 2.4*** to facilitate the introduction of Myography, particularly Force Myography (FMG). Finally, Force Myography is introduced in ***Section 2.5*** with attention given to areas of FMG research that warrant further study and exploration. This chapter concludes in ***Section 2.6*** by summarizing the findings of the review.

2.2. Aging

Any discussion regarding assistive technology for aging should first seek to identify what is means 'to age'. Although the intuitive characterization of aging rests on the passage of time, many researchers and gerontologists seek other identifiable markers and milestones of aging. Spirduso et. al. defined aging as a "process or group of processes occurring in living organisms that with the passage of time lead to a loss of adaptability, functional impairment, and eventually death […] with these processes being distinct from daily or seasonal biological rhythms and any other temporary change" [6]. In this thesis, aging populations shall be referred to as 'seniors' consisting of persons aged 60 and above. This referral, however, does not adequately acknowledge the heterogeneity within aging groups. Heterogeneity results from differing lifestyles, geography, socioeconomic status, environment events, and variable accumulation of chronic illnesses. This section presents an overview of geriatric research and the characteristics of aging.

Section 2.2.1 begins with a presentation of the population demographics of seniors, and is followed by an overview of age-associated changes and milestones in ***Section 2.2.2***. Finally, ***Section 2.2.3*** concludes the discussion of aging by exploring the needs of seniors, both self-identified and those identified by stakeholders in successful aging.

2.2.1. Population demographics and dynamics

In Canada, the current life expectancy at birth is approximately 81.5 years old [111] - 77 years for males and 82 years for females [112]. Between 1920 to 1922, the life expectancy was only 59 and 61 years for males and females respectively [112]. This increase in life expectancy reflects the impacts of immunization, health promotion, illness prevention, community advocacy, broad social programs, and the use of legislation which reduce the mortality in earlier years [6], [111]. However, the total number of expected years past 65 years has remained relatively stable for almost the past century [111]. The significance of this trend is a compression of morbidity and mortality into later years of life [6], with a decline in functional health accelerating past 65 and more severe disability occurring on average around age 77 [111].

Data released by Statistics Canada indicates that in 2015, 16.1% of Canada's population were over 65 years old [1], and that the population of people over 65 years old is predicted to be 28% of all Canada's population by the year 2061 [2]. Seniors are one of the highest consumers of healthcare resources such as doctor's visits, care aids, hospital stays, prescriptions, and assistance with daily activities [4]. Thus, the increased proportion and growth of aging groups leaves less time to prepare for the impact on health systems compared to previous decades [3].

2.2.2. Age associated changes

Aging is associated with several changes, which are typically grouped around 4 major themes: functional, physiological, cognitive, social. While not an exhaustive list, **Table 2.1** below provides a more detailed overview of age associated changes across these realms.

2.1. Areas that typically decline with age amongst healthy seniors

Functional [6]	**Physiological** [6]–[12]	**Cognitive** [13]–[16]	**Social** [6], [16], [113], [114]
• writing • walking upstairs or shorts distances • shopping • laundry • bathing • grooming • preparing meals • eating • taking medications • light housework • dressing • transferring • toileting • help with incontinence	• weight • height • hearing • vision • renal function • glucose tolerance • systolic blood pressure • bone density • pulmonary function • immune function • sympathetic nervous system activity • skin thickness • skin elasticity	• rapid perception • rapid decision execution • working memory • verbal speed • episodic memory • semantic memory • vocabulary	• decrease in contact frequency • smaller social circles • less participation in activities due to fears of falling

In addition to these changes, seniors demonstrate an increased susceptibility to infectious diseases [17] and chronic conditions such as: osteoporosis, broken hips, hypertension, stroke, cancer, diabetes, heart disease, arthritis, obesity, weak or failing kidneys, asthma, and chronic obstructive pulmonary disease (COPD) [18]. Unfortunately, morbidity and mortality due to infectious diseases is higher among seniors [17]. Also, the accumulation of multiple chronic conditions is a strong predictor of upper- and lower- extremity limitations [115] which drive increased health system use [5] and functional dependence.

The changes and declines presented above in **Table 2.1** that mark the aging process are not necessarily inevitable, but they do beg the question, "What does it mean to age successfully?". There are approximately 26 separate definitions of successful aging [116], and the most frequent predictor of successful aging among researchers involving disability and/or physical function [116], [117]. Indeed, these definitions of successful aging form the basis of defining the term by well-cited researchers Rowe and Kahn [19], whom approach successful aging as having:

1) a low probability of disease and disease related disability
2) high cognitive and physical functional capacity

3) active engagement with life.

Surveys of community dwelling seniors indicate that seniors often define themselves as aging successfully despite chronic physical illness and disability [118]. In fact, a survey of community dwelling seniors demonstrated that independence, control, learning new things, and autonomy was more pervasive in personal ideas of successful aging than indicators related to physical health [117]. This shift in thinking about 'successful aging' and how to improve the quality of life for seniors in later years will prove beneficial when considering interventions to meet the needs of seniors.

2.2.3. Factors that affect aging and seniors' needs

Given the number of features associated with aging in general, there are several intrinsic and extrinsic factors that affect the aging process. These factors contribute to the high variability of aging encountered in society [6]. Intrinsic factors are considered inalterable, such as genetic predeterminants of health. Alternatively, extrinsic factors indirectly influence the aging process, and include income, demographics, socioeconomic status, culture, environment, world events, physical activity, diet, disease and disability level, education, living arrangement, and compensatory behaviours [6] .

Extrinsic factors of aging are particularly motivating, as they shape the interventions used to meet the needs of seniors. The literature identifies the needs of seniors as ranging from income, social services, long term care, housing and support for modifications, health needs and resources, to transportation needs. **Table 2.2** below provides some examples of interventions that address these needs.

2.2. Needs of seniors and example interventions

Need	Significance	Example Interventions
Financial Income [20]	• Often dictates the level of services that seniors can access in other realms	• Old age security (OAS) pension • Canada Pensions Plan (CPP) or Quebec Pension Plan (QPP) benefits • Registered retirement savings plan (RRSP) income • Annuity payments

		• Pooled registered pension plan (PRPP) payments • Retiring allowance, other pensions and superannuation, and other income • Employment
Social services [21], [23]	• Social workers help find solutions for older adults and families that address the personal, social, and environmental challenges that come with aging • Advocacy • Therapy for loneliness, depression, or anxiety • Act as a link to public and private programs, and sort out problems with delivery of resources	• Government agencies (HealthLink BC, Office of the Seniors Advocate) • Public agencies • Private agencies • Non-profit agencies
Residential Services & Care [23], [24]	• Provide monitoring and care support for aging groups • Aid in activities of daily living (ADLs) and instrumental activities of daily living (IADLs)	• Nursing homes • Retirement communities • Assisted living facilities • Nursing staff and care aids that make home visits • Live in caregivers
Housing (home modifications) [25]	• Aid in maintaining independence • Prevent accidents	• Wheelchair ramps • Increased lighting • Grab bars and rails • Stair lifts • Security systems • Software tools and SMART homes • Climate control • Walk in tubs
Health Service (public medical care) [26]	• Mitigating the effects of gradual physical and functional decline, infectious diseases, and chronic conditions	• Doctors' visits • Occupational therapy • Rehabilitation • Ambulatory Care • Emergency Care • Surgical visits
Transportation needs [27]–[29]	• Making it to doctors' appointments • Maintaining social engagement • Being able to reach services offered • Psychological benefits of independence • Ability to complete ADLs	• Driving personal vehicles • Time-tabled public transportation • Specialized door-to-door public transportation

		• Walking aids (canes, crutches, and walkers) • Mobility aids (wheelchairs) • Car share programs • Private drivers or car share programs • Walking clubs • Taxis
Preventative Programs	• Educate and engage seniors on lifestyle, diet, social engagement, and physical activity to help promote successful aging and independent living	• Cognitive training [30], [31] • Physical activity programs [32]–[34] • Social engagement [16] • Education about aging [35]

Many of these services are threatened by unmet transportation needs (causing many seniors to remain home-bound) [29], a predicted shortage of health professionals [39] and conflicting responsibilities of available family [38]. Fortunately, many of these services could potentially be provided at home. Examples include physical activity regimes implemented in the home [34], [119], socializing [120], and telecare/telerehabilitation [121]. In fact, home based services are increasingly being explored as a more cost effective option for both the government and the users [36], [37]. Also, a large number of elderly people prefer to age at home where it is a familiar environment for them and they can live independently from others [40]–[43]. The question remains - What can be done to encourage aging-in-place that also 1) adapts to or is considerate to the changes and declines that occur with aging, 2) meets the needs of seniors, and 3) addresses the shortage of resources and health care professionals, and 4) promotes the idea of successful aging as understood by both seniors and other stakeholders?

2.3. Technologies to promote 'Aging-in-Place'

2.3.1. Trends in seniors' technology use

Several key factors influence the preliminary acceptance of technology by seniors. These include perceived need and benefits, cost (monetary, time, effort, psychological), privacy, usability, effect on family members, obtrusiveness, stigmatization, inconvenience of false alarms, and fears of forgetting/losing the technologies [69], [110]. Many of these factors also influence the continued adherence to using the technology, in addition to other emergent issues with the practicality of using the device, such as not being able to use it outside of the home [69]. Despite this, review of the literature across various disciplines has shown that technological interventions are a viable option for addressing the challenge posed in the previous section [122], [123].

Seniors show the fastest rate of increasing computer and internet usage [45]–[47] and there have been noted generational improvements in attitudes towards technology [44]. Even though very old seniors (80+ years old) are least likely to adopt new technology [124], [125], a survey by Crabb, Raffie, and Weinhardt demonstrated that they use the internet and are open to do so for health purposes [124]. So far, it has been demonstrated that technology can replace or at least supplement personal assistance [126] and even decrease anxiety in those with dementia, their loved ones, and their care givers [127]–[129].

2.3.2. State of the art

'Aging-in-place' is a term coined to denote the ability to live in one's own home safely and independently regardless of age, income, or ability level [37]. This aptly describes the home-based care services that would be more cost affective and allow seniors to age at home where they are more comfortable. Designing technology to promote aging-in-place aims to be of a form that is readily accepted, but should also:

- accommodate age-related deterioration in physical and mental health [3]
- promote autonomy and social inclusiveness [3]
- be comprehensive and informative tool for the stakeholders in the well-being of aging populations [48]
- address family and care givers needs [44]

Examples of technology shown to be effective in promoting aging-in-place include information and communication technology, robotics, telemedicine, sensor technology, medication management, and video games [48], [49]. Aging-in-place technologies have also been incorporated as 'Ambient-Assisted Living' (AAL) tools [37], [48]. 'Ambient-Assisted Living' tools (or 'smart' homes) are digital environments which are sensitive, adaptive, and responsive to human needs [48]. This would be particularly imperative given the increased rate of physical and mental decline of older seniors in later years [111], which is correlated with diminished technology use [125].

There are several sensing modalities available, which are combined in various forms to meet the goals of aging-in-place. At this point, special attention is given to the sensing modalities used in aging-in-place technologies in two separate considerations: 1) ambient environments, and 2) wearable technological interventions. The purpose of the following sub-sections is to provide an overview of the current state of senior targeted technology research to create a picture of where any intervention developed as a part of this thesis would fit, if at all.

Sensing Modalities in Ambient Environments

For this discussion, sensing modalities used in ambient environments are not worn, but rather, are placed in the environment. One common feature monitored amongst these types of sensors are movement patterns from room to room. Monitoring the patterns of movement from room-to-room of seniors allows for tracking of aberrant behaviour indicative of declining cognitive faculties associated with dementia and Alzheimer's [130]. Examples of sensors which provide this information include magnetic sensors placed on doors to monitor entry and exit [54], [131]; radio frequency identification tags (RFIDs) to triangulate location [50], [51]; CO_2 gas to determine is someone is present in a room [131]; infrared sensors for location triangulation [54], [131]–[133], ultrasonic sensing for location triangulation [134], and pressure floor tiles [54], [135]. Pressure floor tiles have also extensively been incorporated into chairs, flooring, and bedding to provide information related to sleeping patterns, motion, transferring patterns, fall detection, and gait analysis [54], [134]–[136]. Other general features of smart environments have included RFID tags to help find easily lost items [54]; climate controlling using thermistors [54]; tracking the body temperature of user with thermistors for potential emergency response [54]; and monitoring the use of household appliances using magnetic switches [54], [131], wattmeters [131], and flame detectors [131].

Fall detection is particularly important in geriatric research. Accidental injuries are the 6th leadings cause of death in seniors [137], with slip and falls from standing constituting the most common mechanism of injury in the geriatric population [138]. Injuries due to falls include intracranial hemorrhage, hip fractures, vertebral fractures, pelvis fractures, leg and arm fractures, and kidney failure [139], [140], each with their own host of potentially debilitating secondary complications. In addition to increased risk for falls, seniors face a heavy economic burden due to associated costs [139], [140]. Complemented with extensive pattern recognition algorithms, sensors that have been used to track and predict slip and falls include infrared [52], [53], accelerometers [54], sound and vibration sensors [55].

Vision systems are particulary interesting due to the wide range of applications that use them, particularly for seniors. These include movement tracking, facial and object recognition [141]–[143], fall detections [144], smart-homes [145], emergency detection tools [146], exercise promotion [34], and device control [65]. One benefit of vision based systems, are their unobtrusiveness, which would combat concerns of stigmatization, and address challenges associated with deteriorating physical and mental capacities that affect technology viability [48], [56], [147]. Voice-based systems are also adopted as talking is a natural way of human communication, and voice and speech recognition for device control is a well establish field. Examples of voice activated systems include control of peripheral devices such as TV or radio, and even for control of emergency response protocols by calling for help [54], [61], [148]–[150]. The effectiveness of voice-based systems is maximized by state of the art recognition and noise reduction software, and high density of microphones in the living space [61], [151], [152].

These sensors demonstrate both application specific advantages and disadvantages. For example, RFIDs are cheap, but often lack the necessary accuracy for a proactive smart home [134]. They are also subject to loss of signal due to obstruction, false signals by reflections, and interference from high frequency sounds [134]. A review [153] of vision based technologies highlighted several limitations to overcome including illumination, occlusion, potential overhead costs for real-time, accurate, continuous, on-going monitoring. They have also been cited to potentially benefit from more comprehensive user information, such as grip strength, for rehabilitation purposes [48]. Privacy is the main concern for vision systems, and is the main source of resistance [3], [69], [70]. Silhouette-based systems, or a binary image system which only have two possible values [154], are often suggested to address concerns over privacy as they strip away identifying information [70]. They, however, lack the richness of comprehensive data for device control that RGB or Infrared vision system would have [70]. Although audio systems are particularly valuable when movement is not possible or is undetectable by vision systems, they are ill-suited to situations involving limited speech production capabilities and age related mental deterioration [48], [147], and ‘talking to a house’ is seen as awkward and deterring [148]. Audio systems also suffer from similar barriers to vision systems, such as privacy, confounding effects of ambient sounds and noises, and the lack of direct physical monitoring of the user.

Sensing Modalities in Wearable Interventions

Wearable technology provides an avenue to capture direct user data, which was shown to be lacking in previously discussed ambient systems. Wearable technology is characterized by small scale sensors that has enabled them to be implemented and commercialized into low-profile designs such as necklaces [155], belt clips, arm bands [156], and smart-watches [157]–[159]. Wearable/Portable sensors have already been shown to be effective in improving the independence of seniors in activities of daily living [49]. They also offer several benefits compared to hand-held devices, such as a reduced likelihood of being misplaced. Also, with self contained software for ambient monitoring, user interfaces are not a requirement. User interfaces can frustrate those with failing memories, eyesight, motor skills, and coordination in the aging community [67] and present a barrier to long term effectiveness [48]. Finally, wearable sensors provide an opportunity for anonymized data (addressing concerns over privacy) and direct user data to complement previously mentioned ambient systems. Examples of sensors used in wearable technology include:

- accelerometers and gyroscopes to promote/monitor physical activity[59], [66], [160] and fall detection [133]
- glucometers to measure blood glucose levels [57]
- pressure cuffs to measure blood pressure system [58]
- electroencephalography (EEG) to record brain activity [161]
- electrocardiography (ECG) to monitor the heart’s electrical activity and detect life threatening arrhythmias [59], [60]

- myography to measure muscle force production and send control commands for controlling devices, such as turning lights on and off or control a computer [67] be involved in rehab protocols of arm/hand movements [68]
- pulse oximetry to measure hemoglobin O_2 saturation levels, cardiorespiratory function and breathing rate [60].

Just as ambient sensors face their own challenges, so do sensors used in wearable technology. For example, the accelerometers, gyroscopes, and magnetometers in inertial magnetic units (IMUs) are typically characterized by heavy noisy signals, drift, and magnetic disturbances from household devices respectively [162], [163]. Additional examples include pulse oximetry which is affected by shivering or muscle twitching and intense bright lights [164], electromyography (EMG) which is affected by sweating [71] and subcutaneous adipose tissue [165].

With regards to tracking movement to promote the functional independence of seniors and to address the limited amount of user movement data from ambient sensors, myographic modalities show the most promise and development. For example, inertial magnetic units (IMUs) have been fused with electromyography (EMG) in [166] to provide comprehensive tracking of upper arm activity and hand gestures/object manipulation.

The state-of-the-art of myography research and development, will be discussed in further detail later sections. However, to facilitate the focussed discussion of FMG and its potential role in technologies that promote aging-in-place amongst seniors, the following section presents an overview of the forearm, wrist, and hand as the upper extremity plays a significant role in maintaining functional independence [63].

2.4. Arm and Hand

The arm and hand are one of the more complex and intrinsic structures of the human body. This section begins with a description of the role of the hand in daily living and the impacts of its dysfunction in ***Section 2.4.1***. Next, metrics of hand function are considered in ***Section 2.4.2***. Finally, an overview of forearm, wrist, hand structure and function in ***Section 2.4.3*** concludes this section.

2.4.1. Role in ADLs and dysfunction

In a typical case, the upper extremities enable us to communicate and complete activities of daily living (ADLs). A survey of working individuals indicated that approximately 9.5 hours of each day was spent doing activities other than working or sleeping [62]. Of this time, video surveillance demonstrates that one or both hands are used 61% to 73% of the time on activities such as food preparation, feeding, personal care, housekeeping, shopping, driving and transport, leisure, and others (like talking on the phone) [63], [64]. The hand is largely significant due to its ability to form different gestures, grasp, and manipulate objects. A widely-utilized hand taxonomy developed by Cutkosky identified 16 dominate hand gestures [167]. However, Vergara et. al. found that 9 grasps covered most of activities performed, with as little as 5 different grasps being used: pinch, lateral pinch, cylindrical grasp, lumbrical grasp, and non-prehensile grasps [63]. These grasps are described below in **Table 2.3**.

2.3. Five most common grasps utilized during activities of daily living (ADLs)

Name	Description
Pinch	Thumb and finger tips (one or more) are used
Lateral Pinch	The lateral part of the fingers (one or more) are used, and usually the thumb as well
Cylindrical Grasp	The palm is involved. The thumb is in direct opposition to the fingers (in abduction or neutral)
Lumbrical Grasp	Thumb and proximal part of the fingers are involved, but the palm is not involved*
Non-Prehensile Grasp	Objects are manipulated without grasping them

Note (*): interphalangeal joints are extended and metacarpophalangeal joints are flexed

Zheng et. al. [64] and Bullock et. al. [168], found that some of the same gestures listed in **Table 2.3** (pinch, lateral pinch, and cylindrical grasp) and others such as power sphere and tripod accounted for approximately 80% of the gestures used during activity. With such a small collection of hand gestures/movements that impact our ability to interact with our environment and complete activities of daily living, the inability to complete even one of them would have far reaching consequences. These few gestures are deemed to be even more important to task completion than even rotation and flexion of the moving arm [169]. However, range-of-motion of proximal joints still plays a role in independent living.

At least 70% of wrist function is necessary to complete household tasks [170]. Studies report as little as 30° wrist extension, 5° wrist flexion, 15° ulnar deviation , and 10° radial deviation is required for upper extremity functionality during ADLs [171]. Decreases in the range of motion (ROM) in proximal joints (like the elbow and the forearm) and distal joints (like the wrist and in the hand) are also correlated with decreased hand function [172].

With aging, there is a natural decline in range-of-motion [173] as well as a decline in hand function and dexterity due to increasing arthritic severity [18]. Along with arthritis, there are several other barriers to full hand/arm function that are associated with aging and/or affect seniors more severely [17]. These are presented below in **Table 2.4**.

2.4. Neurological and Musculoskeletal which impeded forearm, wrist, and hand function

Neurological Barriers	**Musculoskeletal Barriers** [139], [140]
• High level spinal cord injury [174] • Multiple Sclerosis (demyelination of the neurons of the CNS) [175] • Physical brain injury (blunt or penetrating) • Cerebral palsy (abnormal development or damage to developing brain) • Stroke • Carpal Tunnel	• Muscular dystrophy (genetic mutation that results in deficient muscular proteins which results in wasting and weakness) • Sarcopenia (degenerative muscle loss associated with aging) • Amputation • Bone fractures • Repetitive Stress Injury • Sprains (Stretching or tearing of ligament) • Strains (Stretching or tearing of muscle of ligament) • Inflammation (muscles, tendons, bursae) • Arthritis (pain and stiffness of the joints, such as osteoarthritis and rheumatoid arthritis) • Joint dislocations

As was seen in ***Section 2.2.2***, due to the high risk of falls amongst seniors [139], [140], and associated medical costs, resultant bone fractures and other acute disruptions to hand and wrist function are a frequent barrier. This suggests that addressing arm and hand function in senior-targeted technological interventions could also play a significant role in addressing seniors' ability to perform activities of daily living, thus influencing independent living and aging-in-place.

2.4.2. Metrics of function

Metrics of upper extremity function are relevant, as they provide a guide of clinically relevant methods to quantify forearm, wrist, and hand movement and function. There are a multitude of assessments and diagnostics to quantify upper extremity function across various healthy and non-healthy populations, including but not limited to [176]: Box Block (BB) Test [177], Fugl-Meyer (FM) Assessment of Motor Function [178], Action Research Arm Test (ARAT) [179], Wolf-Motor (WM) Test [180], 9 Hole-Peg (9HPT) Test, Jebsen Hand Function (JB) Test [181], Chedoke-McMaster test (CM), Chedoke Arm and Hand Activity Inventory (CAHAI), Manual Muscle Testing (MMT), Arthritis Hand Function Test (AHFT) [181], Grip Ability Test (GAT) [181], Rheumatoid Hand Functional Disability Scale (The Duroz Hand Index [DHI]) [181], Across these various diagnostics and monitoring techniques are some common themes related to upper extremity function. These include:

- grip strength [176], [178], [180], [181]
- dexterity [176], [177]
- range of motion [178], [179]
- hand grasp formation [178], [179]
- functional task completion [180], [181]
- ability to complete activities of daily living [176], [181]
- sensations [176], [178]
- agility [178], [180]

These metrics are not only used to quantify differences between healthy and non-healthy groups, but also quantify the physical and functional changes that occur within cohorts which are grouped by age, and track of the success of physical interventions. For example, features of arm/arm diagnostics applicable to seniors in health services include: grip strength as a predictor of functional, psychological, and social health [182], movement repetition in stroke rehabilitation [183], and gesture/grasp frequency as indicative of functional independence [77].

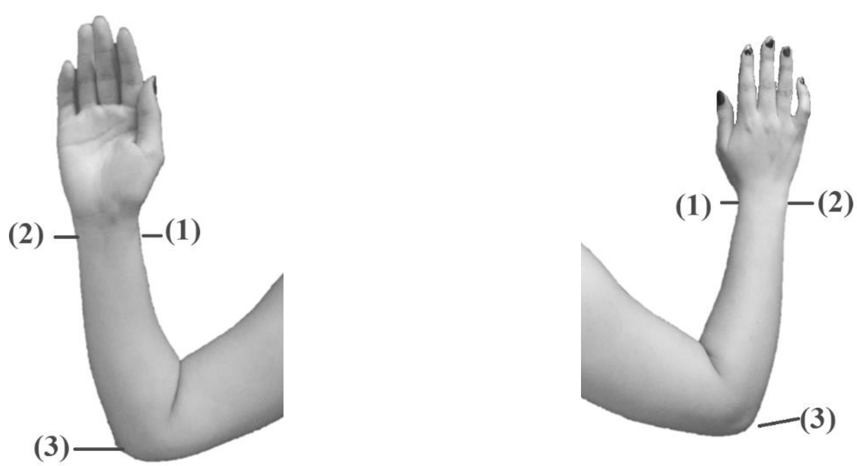
2.4.3. Structure and movements

The purpose of this final section, and the anatomical/directional terms listed in the ***Glossary*** are to provide consistent descriptions of the forearm, wrist, and hand for discussion in later sections. Directional terms for the arm are referenced to anatomical position. The following has been summarized from [184].

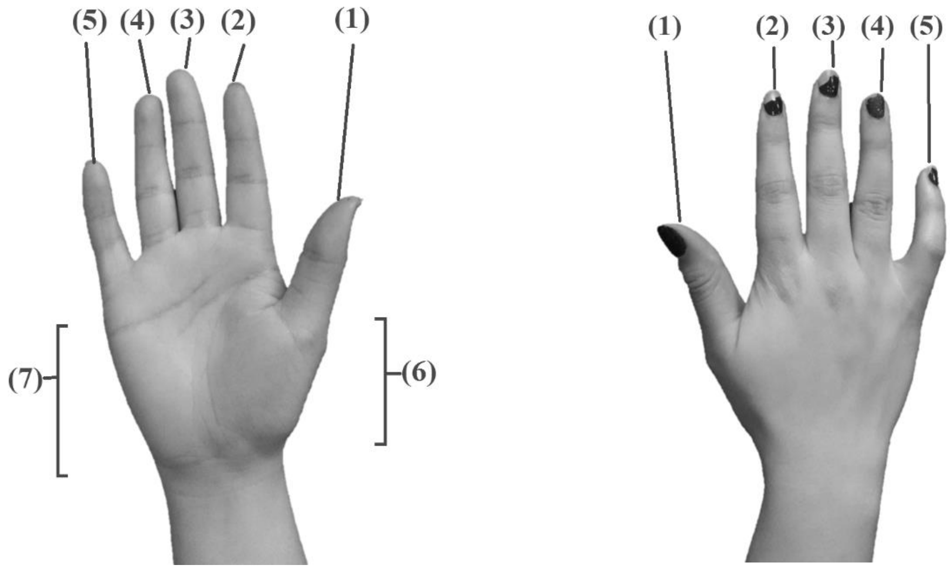
Surface Landmarks

Surface landmarks allow for the non-invasive identification of major regions of interest of underlying muscle, bone, and tissue. In this work, the forearm of the upper limb is identified as the region between the wrist and elbow. In this case, the wrist is identified by two prominences, the radial and ulnar styloid processes, which also mark the distal end of the long bones of the forearm. At the other end, the olecranon process (the bony prominence at the back of the arm) marks the elbow and the 'beginning' of the forearm. The part of the forearm that faces the front of the body in anatomical position is the 'anterior' side, while the part that faces the back of the body is the 'posterior' side.

Distal to the forearm are the hand and fingers, capable of grasping and providing the rich tactile feedback. Major surfaces of the hand are the dorsal and palmar surfaces. Two additional surface landmarks, located on the palmar aspect of the hand are the thenar and hypothenar eminences, which are muscle groups located at the base of the thumb and the little finger respectively. Finally, are the five fingers, digits I-V, starting with the thumb as digit I. **Figures 2.1** and **2.2** below summarizes the landmarks of the forearm and hand as discussed in this section.



2.1. Forearm surface landmarks.
Note. Anterior (left) and posterior (right) aspects are shown. Significant features shown are the 1) radial and 2) styloid processes which mark the wrist, and 3) the olecranon process which marks the elbow



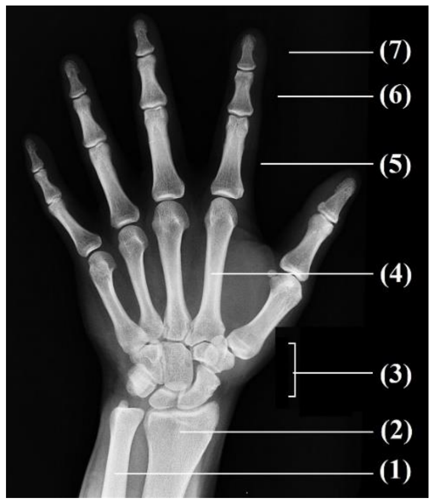
2.2. Hand surface landmarks.
Note. Anterior (left) and posterior (right) aspects are shown. Significant features shown are the 1)-5) digits I to V, 6) the thenar prominence, 7) the hypothenar prominence.

Bones and Joints

The bones of the hand provide structural support and points of attachment for functional muscle groups, while their articulation (points of contact) allow for movement. There are two major bones in the forearm, the radius and the ulnar, which form the long axis of the forearm. The ulna is particularly marked by the olecranon process, which marks the proximal end of the forearm and the elbow. The radius and ulnar articulate each other at the proximal and distal radioulnar joints, located at the wrist and elbow respectively. Twisting of the radius and ulnar bones realize forearm pronation and supination. The radius and ulna are also in contact with humerus (of the upper arm) via the humeroradial and humeroulnar joints to form the elbow joint, a 1 DOF hinge joint. The humeroulnar joint plays the most significant role in realizing elbow function by allowing elbow flexion. Finally, the last major point of contact for the radius and ulna is with the bones of the wrist, the carpals. The principal articulation in the wrist is the radiocarpal joint, a 2 DOF, allowing flexion, extension, radial deviation, ulnar deviation, and circumduction.

The carpals mark the beginning the hand. The carpals are 8 irregularly shaped bones that form the wrist and are in contact with the base of the thumb and the long bones of the palm of the hand. Running along the length of the hand and at the base of the thumb are

5 bones referred to as the metacarpals, which terminate at metacarpophalangeal joints (the knuckles), 1 DOF hinge joints. Finally, each of digits II to V are made up of the 3 bones: the proximal, intermediate, and distal phalanges. Digit I (the thumb) has only 2 phalanges, the proximal and distal. The articulations between the phalanges are referred to as the interphalangeal joints, 1 DOF hinge joints**. Figure 2.3** below summarize the bones of the forearm, hand, wrist as discussed in this section.

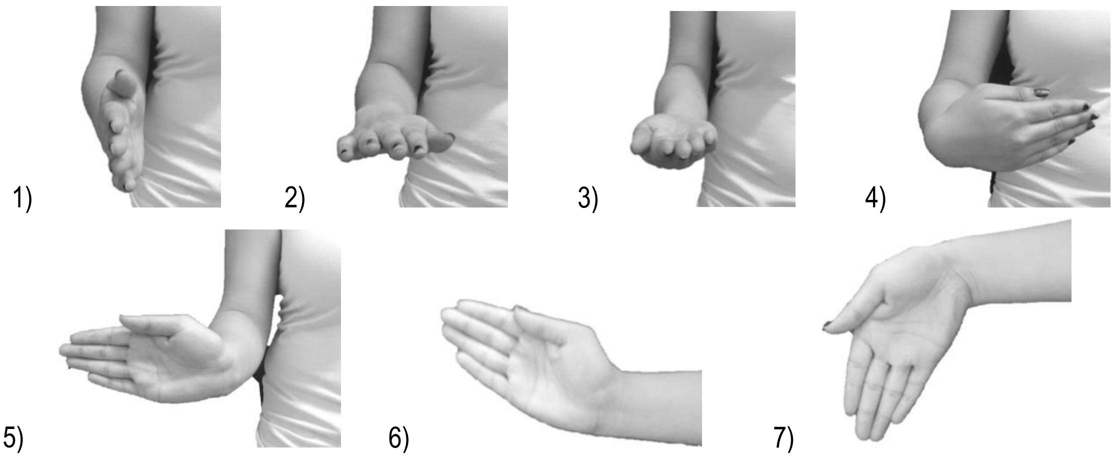


2.3. Bones of the forearm, wrist, and hand.
Note. Significant structures shown are the 1) ulna, 2) radius, 3) the carpals, 4) the metacarpals, 5)-7) the proximal, intermediate, and distal phalanges. By com329329 (Own work) [CC0 Public Domain (https://pixabay.com/en/x-ray-health-arm-doctors-medicine-1704855/)] via Pixabay

Muscles and Movements

There are 20 muscles in the forearm alone. Rather than provide an exhaustive list of muscles in the forearm and hand, a general overview of forearm and hand musculature organization as it relates to forearm/hand function is presented.

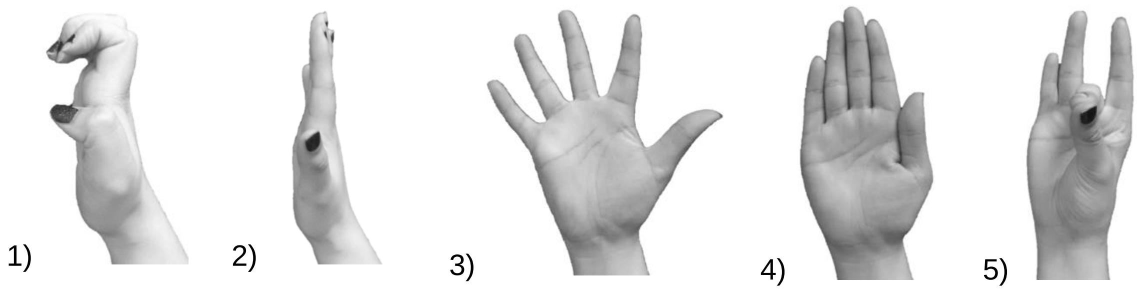
The underlying musculature of the forearm has 3 major categorical distinctions, which facilitate the discussion of the hand and forearm's various movements and functions. Firstly, 'intrinsic' or 'extrinsic' categorical labels identify whether the muscles of the forearm act on the bones of the forearm (intrinsic) or cross the wrist joint to act on the bones of the hand (extrinsic). The hand also has intrinsic musculature that originates and terminates within the hand structure itself. Secondly, 'superficial' and 'deep' categorical labels identify whether the muscles of the forearm are closer or farther to the surface of the skin respectively. Finally, the ‘anterior’ and ‘posterior’ categorical labels identify whether the muscles of the forearm are in the anterior or posterior compartments of the forearm (defined in ***Surface Landmarks***). The main movements of the forearm are pronation and supination, while the main movements of the wrist are flexion, extension, radial deviation, ulnar deviation, and circumduction. **Figure 2.4** below presents these motions for further discussion.



2.4. Motions of the forearm and wrist.
Note. Motions shown from left to right are 1) neutral wrist and forearm, 2) forearm pronation, 3) forearm supination, 4) wrist flexion, 5) wrist extension, 6) wrist radial deviation, 7) ulnar deviation

Anterior and posterior categorical distinctions of forearm musculature bear a functional significance due to movement synergies of their constituents. For example, forearm pronation and wrist flexion are primarily achieved via anterior compartment forearm muscles, while forearm supination and wrist extension are achieved primarily by posterior compartment muscles. In addition, these muscles (which control gross forearm and wrist movement) are typically superficial to the extrinsic forearm muscles that act on the hand/digits.

The main gross motions seen in the digits are flexion, extension, abduction, and adduction, and opposition. **Figure 2.5** below presents these movements for further discussion.



2.5. Movement of the hand/digits.
Note. Motions shown are 1) digit flexion, 2) digit extension, 3) digit abduction, 4) digit adduction, and 5) opposition, which involves touching the thumb (digit I) to the tips of the other fingers (digits II to V)

With regards to the hand, extrinsic muscles of the forearm act on the digits to generate digit extension and flexion. Similar to the wrist flexors and extensors located in the anterior and posterior compartments of the forearm respectively, so are digit flexors and extensors analogously located. Complementing the function of extrinsic forearm muscle are intrinsic hand muscles. Grouped by function, they include the thenar group, hypothenar, and the interosseous and lumbrical muscles. The muscles in the thenar and hypothenar group, which act on the thumb and little finger respectively, act to flex, abduct, and oppose their respective digits. The interosseous on the dorsal and palmar aspects of the hand abduct and adduct the fingers respectively, while the lumbrical muscles simultaneously flexes the metacarpophalangeal joints (knuckles) and extend the digits.

2.5. Myography & Force Myography (FMG)

The review of literature thus far has provided an overview of aging, 'successful aging', and technologies that promote aging-in-place. Special attention was given to the wearable technologies and the significance of the arm/hand to ADLs, setting the stage for the potential role of myography, which measures the force produced by muscle due to contraction. An in-depth overview of Myography and FMG theory and development is now presented in ***Sections 2.5.1*** and ***2.5.2*** below.

2.5.1. Myography

Myography in general refers to a method of data collection that characterizes the force produced by a muscle during contraction. For the arm and hand, there are various methods that have been used to track hand patterns and gestures, some of which were discussed in ***Section '2.3 Technologies to promote 'Aging-in-Place''***. Myographic technologies have been implemented as watch-like bands, marker attachments at points of interest, and data gloves [162]. The focus of this section shall be on markers or devices worn on at the wrist and/or arm, as gloves are associated with reduction of haptic feedback and interfere with natural movement [185].

Mechanomyography (MMG)

Mechanomyography is also referred to as Acoustic Myography (AMG) [186]. MMG uses inertial sensors [187]–[191], microphones [191], lasers [192], [193], or piezoelectric crystals [194] to measures the vibration of underlying muscle tissue oscillating at their resonant frequencies during voluntary movement. MMG has been used to monitor muscle fatigue [195], control prosthesis [191], track balance [187], and classify hand gestures [188]–[190]. With respect to classifying hand gestures, the literature demonstrates that at most 8 classes (finger movements, hand gestures, and wrist movements) can be classified using 2 to 4 sensors. Unfortunately, MMG typically requires a significant amount of signal processing [196] and there are not any successful attempts to fashion MMG into a wearable and portable device, possibly due to the sensitivity to muscle artifacts [186]. Features related to anthropometry that influence the MMG amplitude are muscle stiffness, tension, length, mass, intra-muscular pressure, viscosity of the surrounding medium, and motor unit firing frequency [197].

Ultrasound Myography (UMG)

Ultrasound Myography is also referred to as Sonomyography [198]. Captured at the skin's surface, UMG uses Doppler ultrasound to measure muscle movement velocity, which is directly related to muscle force production [199]. As an ultrasound based technique, UMG can detect muscle morphology and architecture. One of the advantages of UMG is that it can track the activity of deeper muscles [198], a feature other myographic methods lack. The main uses for UMG have been diagnosis and therapy [199], with a few applications in control [198]. Although even a single sensor can be used to control a 1 DOF robot [198], Chen et. al. [198] and Castellani [200] have acknowledged that most ultrasound technologies are too expensive and that the ultrasound probe is too large for practical use. Lastly, the acoustic fields created by ultrasound have been known to give rise to heating [199], [201] are suggested to only be used by trained professionals. Thus, further sensor development would need to occur before any practical application of UMG can occur.

Optical Myography (OMG)

Optical Myography (OMG) is relies on optically tracking the skin undulations that occur with gesture formation [143], which is distinct from MMG that tracks vibrations at the skins surface. An example implementation of OMG have utilizes *AprilTags* [202], a 2D barcode style tag which are attached to the skin. Average normalized root mean square error (NRMSE) for OMG is within the same range as sEMG and FMG, ranging between 0.05 to 0.22 on average [142], [143]. The benefits of this type of system range are the same as ambient vision systems described in ***Section 2.3***. Primary amongst these are unobtrusiveness. However, as a vision system, OMG also shares challenges due to occlusion. Unfortunately, OMG studies thus far have been limited to having the arm in fixed positions and require further development [142], [143], [202].

Electromyography (EMG)

Electromyography (EMG) measures the electrical activity that occurs with muscle activation, and can be achieved with either intramuscular electrodes or surface electrodes [203], [204]. EMG is distinguished by its far reaching applications, and is the preferred method for rehabilitation and human interface purposes [204]. Applications of EMG [204] range between ergonomics, exercise physiology, rehabilitation medicine, biofeedback, control of exoskeletons and prostheses. EMG has a demonstrated ability to track upper extremity movements and hand gestures [205] and has been commercialized into products for the general populations [206]. There are several challenges associated with using surface electromyography (sEMG) due to various sources of noise. These sources include inherent noise in the electrode, movement artifacts, electromagnetic noise, cross talk, ECG artifacts, skin formation, blood flow velocity, measured skin temperatures, the tissue structure (muscle, fat, etc.), and the measuring site [105]. However, many of these challenges can be addressed through machine learning and data preprocessing [105].

Force Myography (FMG)

Force Myography is also referred to as Pressure Myography (PMG) [80], Topographic Force Mapping (TFM) [72], Residual Kinetic Imaging (RKI) [86], and Surface Muscle Pressure (SMP) [84]. The theoretical principle of FMG are volumetric changes in the limb that occur with functional movement. With concentric muscle contraction, the cross-sectional area of the muscle fibres increases. FMG measures the patterns in surface pressure caused by volumetric changes in the limb. FMG has been used in multiple fashions across exoskeleton control [72], [78]–[83], gait analysis [84], gesture identification [68], [73], [79], [87]–[94], and rehabilitation [75]–[77].

The inclusion of FMG has gained momentum in innovative and novel device design, typically dominated by EMG [207]. This is because it:

1) is robust to external electrical interference and sweating [71]
2) does not require precise sensor placement or extensive skin preparation [72]
3) does not require the same level of signal processing required in EMG datasets [73]
4) can be a cost effective method of tactile sensing, with off-the-shelf discrete FSRs sensors costing less than $10 [74]
5) FMG signals are more stable over time during static gestures [79]

In addition, the nature of the sensors used in FMG acquisition are not associated with increasing tissue heat, as ultrasound is.

2.5.2. Force Myography (FMG): current state of research & recommendations for further study

Force Myography was briefly introduced in Section 2.5.1. within a general overview of myographic sensing methods. Towards developing senior-targeted tools for seniors, FMG was selected outright as the sensing method of choice for several reasons. Significant reasons are that FMG does not require extensive skin preparation, it does not require specific sensor placement, and it does not require expert experience for optimal implementation. These were considered ideal characteristics for a deployable device into the general community. Further research comparing FMG to gold standards of myographic sensing methods (i.e. sEMG) would contribute to the verification and validation of FMG's effectiveness. However, this would build on the scope of this current project, which is to establish the characteristics of using FMG with seniors.

The application of FMG ranges from rehabilitation, assistive device design, prosthetic control, and gait analysis. A survey on FMG related research is tabulated and summarized in **Tables A.1. to A.7**. in ***Appendix A***. Areas of focus for this survey were:

- Type of participants included in FMG studies
- Areas of research where FMG has successfully been utilized
- Types of sensors used in FMG acquisition
- Areas of placement of an FMG sensing device
- Methods of data processing, data representation, and feature extraction used in FMG research
- Machine Learning Algorithms used in FMG research
- Number of classes used in FMG classification

Based on the results of this survey, several areas for further study have been noted which would support the practical implementation of FMG into senior targeted technology to support aging-in-place.

Senior targeted research

Firstly, FMG research presents a significant lack in senior targeted study design. As can be seen in **Table A.1. 'Types of participants included in FMG studies'**, participant recruitment has been limited to stroke survivors, amputees, and healthy individuals. In fact, not only is an overwhelming majority of the participants considered 'healthy', but the average age of recruited participants did not exceed 30 years old. This is significant as the 'successfully aging' senior is distinct from young healthy population, due to naturally occurring physical changes. Even in the face of healthy and successful aging, age-associated changes in mental and physical function can could impede the effectiveness of healthcare technologies [69]. Motivated to develop a senior targeted tool to promote aging-in-place, recruitment of seniors in the early stages of FMG development would be beneficial.

Machine Learning Methods & Feature Extraction

Table A.6. 'Machine Learning Algorithms used in FMG research' provides an overview of the machine learning methods utilized in FMG research. The merits of each algorithm aside, there is a noted dominance of supervised training methods in current research. In supervised machine learning methods, each discrete input is assigned a category/label for future prediction [108], [109]. However, this can be a labor intensive and time-consuming process which requires expertise in the task at hand. This is also a process which could render a publicly deployed device impractical. An alternative would be an unsupervised FMG model of hand/arm function, which is task dependent and relies on naturally appearing distinguishing features of the data [109]. Semi-supervised methods provide an additional alternative, utilizing both labelled and unlabelled data [108].

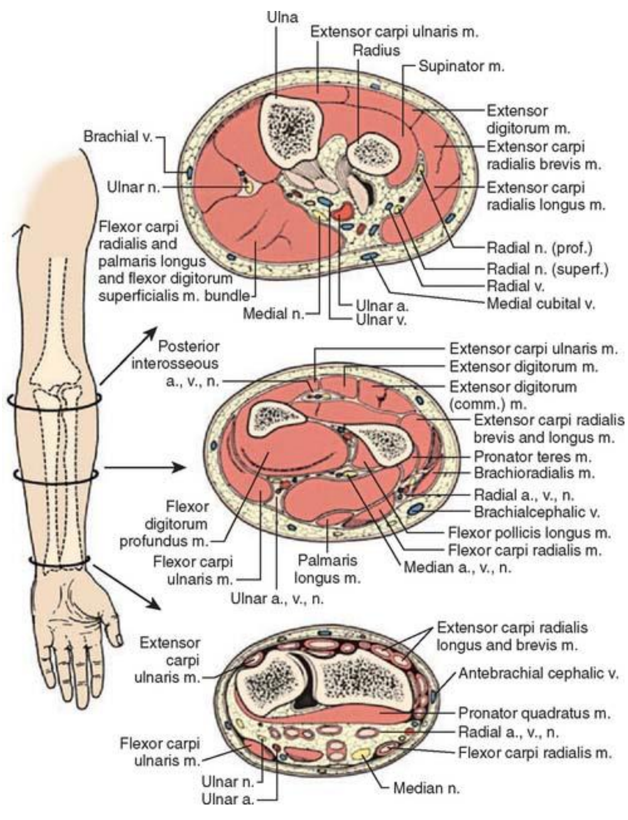
In addition, feature extraction methods used with FMG were surveyed and tabulated in **Table A.5. 'Methods of data processing, data representation, and feature extraction used in FMG research'**. FMG is frequently compared to sEMG, thus, feature extract and data preprocessing for FMG has been guided by standards set for sEMG. However, FMG presents as a different type of signal profile from sEMG [79]. A beneficial avenue for FMG research would be to explore feature extraction methods uniquely beneficial to FMG.

Need for retraining

The current state of FMG research has yet to address or acknowledge the need for machine learning algorithm retraining. From the overview provided in **Table A.6. 'Machine Learning Algorithms used in FMG research'** supervised learning models make up the majority of method used to predict hand and arm gestures from FMG. However, once an FMG band is removed and donned again, the respective machine learning algorithm needs to be trained again with pre-labelled data. This can be a time-consuming process, especially given that the number of reported classes in FMG studies ranged from 2 to 48 classes. This would have significant and negative impacts on the acceptance and long-term effectiveness of a commercial FMG device, let alone a technology that targets seniors [69], [110]. This is unfortunate given the potential to incorporate FMG into technology and systems that promote aging-place. A suggested avenue for further study could focus on FMG specific feature extraction methods that could either 1) improve the success of a pre-train model across multiple sessions or 2) reduce the amount of input needed to retrain a model after each donning. An additional avenue for further study would be developing a generalized model of FMG for translational learning.

Human Factors

So far, FMG has demonstrated that it does not require precise sensor placement [72], but that measurements taken at the wrist are more accurate [73]. Gesture classification also appears to be affected by grasp force when considering an object [92]. For FMG collected on the arm, the underlying tissue is quite variable. Forearm cross sectional area is composed of muscle, bone, connective tissue, adipose tissue, and skin. In addition, the relative contribution of these different tissues types changes along the length of the forearm, where muscle tissue is more prominent closer to the elbow [208]. The is visually represented in the schematic below in **Figure 2.6**.



2.6. Forearm compartments: transverse sections through the left forearm at various levels.

Note. Taken from [208]

Volumetric changes due to muscle contraction are transmitted through these tissues. However, studies thus far have not explored if anthropometry also has an affect on FMG acquisition and modelling.

It is hypothesized that age-associated changes in the mechanical properties of underlying tissues contribute to the variability of FMG acquisition and modelling. With aging, there is a decrease in muscle mass and muscular strength [6], which intuitively might affect the generalizability of FMG as there is a positive correlation between muscle cross sectional area and strength [209]. In addition, the amount of subcutaneous adipose tissue decreases with age [210], and connective tissue and skin tissue become thinner and less elastic [211] influencing how muscular forces are transmitted. With other myographic modalities [104]–[107] these effects are considered and accounted for in via feature extraction and machine learning [105]. The same level of consideration and understanding for FMG related work would be beneficial.

Lack of multiple DOF movement characterisation

Most research involving FMG has involved classification of grasps and/or wrist/forearm movements, which have also been applied to the control of peripheral devices. The number of classes for these classifications has ranged from 2 to 48. However, for all the studies encountered, these gestures/grasps were considered as separate classes without an consideration for compound actions.

The human forearm (a frequently used location for FMG acquisition [79], [88], [101]), houses musculature that realize wrist motions, forearm motions, AND hand/finger gestures – all of which can occur independently and simultaneously of each other. Thus, since elbow position affects the accuracy of FMG modelling [87], [212], the effects of wrist and forearm position should also be considered. Hand gesture recognition in FMG research focussed on mitigating the effects of wrist and forearm position (if any) would be beneficial.

2.6. Chapter Summary

As the highest consumers of healthcare resources, our rapidly growing senior population poses a significant challenge for stakeholders in successful aging. High costs and a predicted shortage of healthcare professionals have prompted the exploration of alternatives methods to meet the needs of seniors. This has led to increasing consideration of technological interventions that allow aging-in-place, particularly in the home.

Technology that supports the completion of activities of daily would contribute a great deal to the functional independence that would allow seniors to age more successfully in the home. As the arm and hand are an integral part of completing activities of daily living, technologies that track or monitor arm/hand activity could be particularly beneficial to promoting functional independence. One of the technologies capable of this is Force Myography (FMG), which tracks the volumetric changes that occur in an arm resulting from muscle contraction. FMG is an attractive choice for further development as it offers many advantages to other myographic modalities, including being electrically robust against sweating, not requiring specialized skin preparation, utilizing minimal signal processing, and being cost effective.

By providing a thorough review of the declines associated with aging, needs of seniors, and nature of services provided, we have built a comprehensive framework with which to answer, "Where would FMG fit within the grand scheme of senior targeted services?" The literature demonstrates that FMG has been successful in device control, movement tracking, gesture identification and classification, grip strength, and gait analysis – all areas that are applicable to promoting seniors aging in place. However, there are still several areas that have not been adequately covered within FMG research to support its practical implementation into aging-in-place technology/systems. These include a lack of:

1) standardization in FMG acquisition and sensor placement
2) semi-supervised or unsupervised methods of FMG analysis
3) Translation learning of FMG models to reduce training costs
4) senior targeted research
5) Considerations of the effect of human factors

6) Consideration of functional noise

Addressing all these questions is beyond the scope of the research, as outlined in **Section 1.4**. However, addressing the objectives of this thesis will offer insights into 1) the characteristics of using FMG with aging populations, 2) the intrinsic user features that significantly influence the variability in FMG acquisition and 3) how user variability translates to the variability in FMG model performance.

Chapter 3.

Feasibility of using an Force Myography (FMG) system with Seniors

3.1. Chapter Overview

The work described in this chapter is intended to address **Objective 1** of this work, which is to characterize the use of an FMG based system with seniors. ***Section 3.2*** opens with an overview of the study, and is followed by an in-depth description of the methodology in ***Section 3.3***. ***Section 3.4*** follows with a presentation of the results, which are discussed in ***Section 3.5***. Finally, the implications of this pilot study on further sections of this thesis are considered and presented on ***Section 3.6***.

3.2. Study Overview

The purpose of this study was to characterize the use of FMG with seniors to promote aging-in-place. The protocol consisted of a control scenario in a constrained environment, whereby participants were taught a set of pre-selected grasps and used them to control a custom designed graphical user interface. In addition, participants performed a set of tasks that were modelled after activities of daily living. It was predicted that seniors could successfully control and FMG system and would demonstrate similar performances to that of non-senior participants. Characteristics considered that were related to this prediction were 1) how long it took the senior and system to respond to gesture instruction, 2) cumulative accuracy while gestures were held, and 3) the frequency of unintended activation of the 'virtual control scheme'.

3.3. Methods

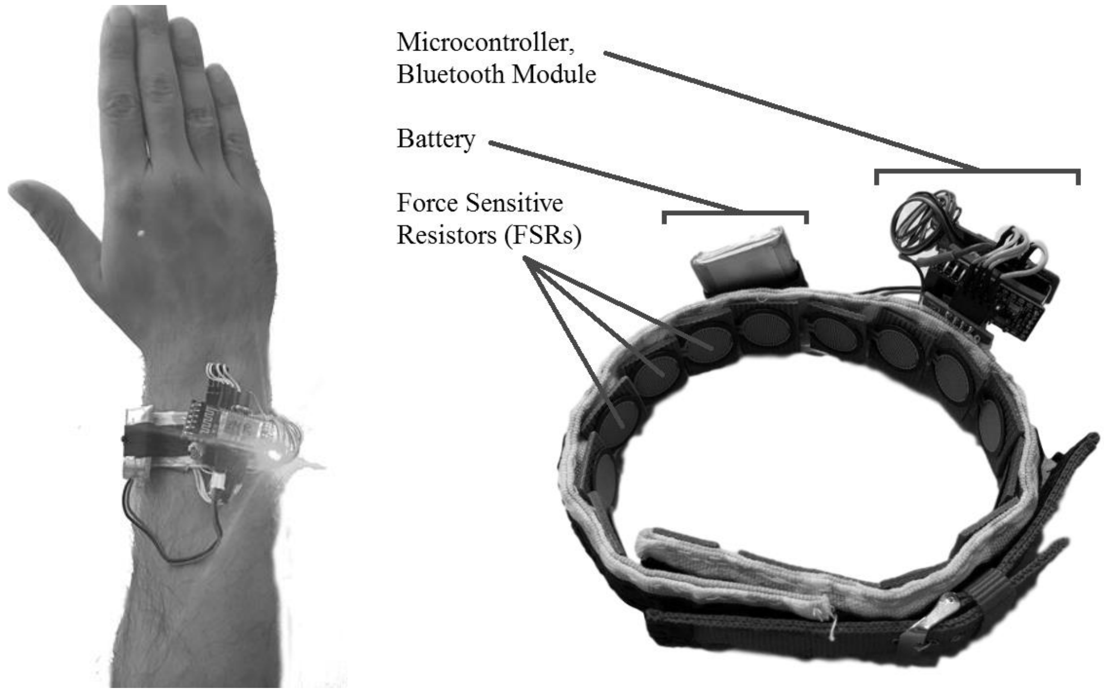
3.3.1. Participants

Participants were recruited from the students, faculty, and staff of Simon Fraser University. Inclusion criteria for participation required that participants can follow instructions of the experimental protocol and perform the required gestures/tasks to completion. Exclusion criteria were limited to self-identified neurological or musculoskeletal barriers to functional movements of the upper extremities. All participants provided informed and written consent. Save for muscle fatigue, there was little to no risk to participants.

3.3.2. Data collection devices

A custom FMG band was designed in-house for this protocol. FMG relies on tracking patterns of skin deformation caused by volumetric changes in underlying musculature during movement. The band used in this study utilizes 16 Force Sensitive Resistors (Model 402, Interlink Technologies) in series, spaced 2 cm apart in a row. Force Sensitive Resistors (FSRs) consists of a polymer thick film (PTF) circuitry printed on a flexible substrate, which demonstrates a variable force resistance relationship. FSRs were selected for FMG acquisition due to their low-profile dimensions, flexibility, cost-effectiveness, wide-spread availability, and the ease of implementation into a portable and wireless design.

FSRs were implemented in a series with a 4.6 kΩ resistor and supplied with a voltage of 3.7 V. An ATMega328 microprocessor was used to facilitate data collection and transmission. Each FSR was sampled at approximately 10 Hz, with raw analog values converted to a digital signal ranging from 0 to 1023 (0.00361 V/bit). Digital values were time stamped and transmitted to an on-site computer via serial connection and saved onto a .txt file for offline processing. Participants donned the FMG band on the wrist, 1 to 1.5 inches proximal to the radial and ulnar styloid process surface landmarks. The placement of the band is shown in **Figure 3.1**. As seen in **Figure 3.1**, the FSR sensors were positioned to be in contact with the participants' skin, and the band was designed to be portable and wireless.

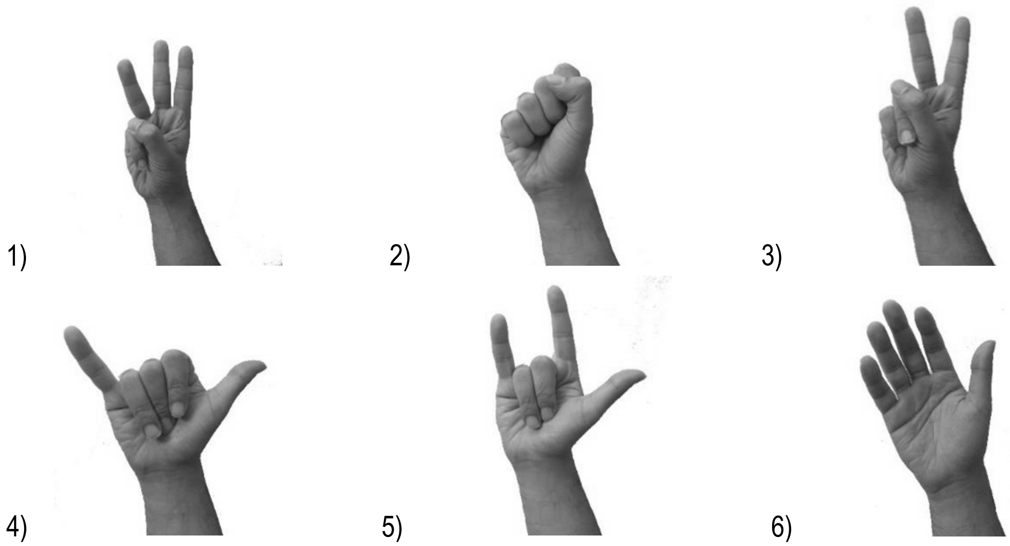


3.1. (Left) View of the positioning of the FMG band on participants' wrist. (Right) View of the Force Sensitive Resistor (FSR) band used to gather Force Myography (FMG) data.

Note. The green light emitted from the Bluetooth module indicates the module is powered and transmitting. Shown are: the battery, the Microcontroller Module, and the series of FSRs that line the inside of the band which are in contact with the skin

3.3.3. Experimental protocol

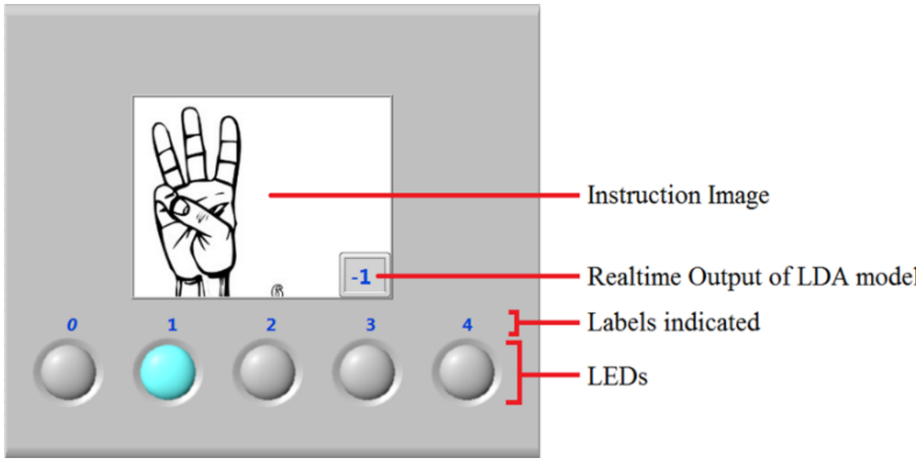
All participants performed 3 repetitions of a test sequence that had 3 phases: (1) training, (2) online testing, and (3) household tasks. During training, raw FMG signals were recorded from the participant while they performed a set of pre-defined control hand gestures, which would eventually be used to train a Linear Discriminant Analysis (LDA) classifier for online classification. These gestures were used to control the user interface, and were experimentally selected based on their distinguishability from gestures most commonly used in object grasping and manipulation in activities of daily living. The selected gestures based on American Sign Language, and are shown below in **Figure 3.2**.



3.2. The control gestures used and classified in the experimental protocol: 1) '6', 2) close, 3) '2', 4) 'Y', 5) 'I Love You', 6) relax

Our classification model included a 'relaxed' class/condition to account for a relax hand and other erroneous hand movements. Each gesture was repeated 4 times, with each repetition lasting 5 seconds. FMG recordings were saved as .csv files for further training of our online classification model. For each repetition of the test sequence, a new LDA model was trained if the FMG band was removed.

During the online testing phase, participants were instructed with an image shown in **Figure 3.3**. Participants were also provided real-time feedback, by way of a visual indicator on the user interface, which lit up when the gesture was correctly identified by LDA model. Each gesture was presented for ten seconds in a random sequence in continuous succession. Overall, each gesture was presented 4 times during online testing. Digital FMG signals were recorded and recorded in a .csv file for offline analysis. The gesture completed by the participant was confirmed via direct observation.



3.3. User interface during online testing
Note. The four main components include: the instruction image which gave a visual reminder of the desired gesture; the real-time output of the LDA model and threshold filter algorithm; the LEDs which provided the user with positive feedback when the gesture formed and identified by the LDA model coincided with the gesture shown in the instruction image (based on the trained LDA model); and the LED labels.

Lastly, during the household tasks phase, participants performed a select number of 'household tasks'. These tasks were based on upper extremity diagnostic measures that incorporate functional ability measures, such as the 'Rating of Everyday Arm-use in the Community and Home (REACH)' [213]. These tasks also served as a reference for how the FMG implementation would perform in an unconstrained setting separate and apart from the intentional control of the virtual interface. Household tasks were performed in a self-selected manner using the objects shown below in **Figure 3.4**. The tasks were as follows: buttoning and unbuttoning a shirt; wiping a table; picking up a cup; opening and closing a jar; and sorting a set of pens. Digital FMG signals were recorded during the household task phase, and the predicted gesture was recorded in a .csv for offline analysis.

1) 

3.4. Objects used to complete household tasks. 1) shirt buttoning/unbuttoning, 2) table wiping, 3) picking up a cup, 4) opening and closing a jar, 5) sorting a set of pens

3.3.4. Data analysis

A custom program was designed in LabVIEW (© 2014) to facilitate data collection and recording for offline analysis. This custom program allowed for a user interface (**Figure 3.3**) that presented the image instruction of the gesture to be performed, as well as LED feedback to the participant to indicate when the control gesture was correctly identified by the LDA model. Digital FMG signals were normalized using the global minimum and maximum of FMG training data, and served as a sample-by-sample input to a multi-output LDA model. Our LDA model was developed using built-in MATLAB R2016a machine learning functions. Linear Discriminant Analysis was chosen for this study due to its experimentally comparable performance to Support Vector Machine (SVM), and the added benefit of a decreased demand on processing and computational resources. This is ideal when considering a system where data collection and processing might be entirely self-contained within a deployable device such as a watch.

The multiclass LDA online control scheme constituted a 6-class problem, with 5 of the classes being identified as one of the predefined control gestures shown in **Figure 3.2** (gestures 1-5). The sixth class identified included all other erroneous movements and the relaxed hand gestures ('non-control gesture'). The likelihood output for the multiclass LDA model ranged from 0 to 1, and a 0.95 threshold indicated a 'successfully' identified gesture. In the case where no single class achieved a likelihood greater than or equal to 0.95, the output for that sample identified the gesture as 'relax/erroneous'.

In offline processing, three main outcome measures were considered for analysis and further discussion:

- **Cumulative Accuracy.** The cumulative was the primary outcome measure, and was considered with an increasing window size from the first instance a control gesture was correctly identified to the duration that a specific gesture instruction was displayed. This outcome provided an indication of our gesture identification model to correctly identify a sustained gesture.
- **Reaction Time.** Secondly, during online testing, the reaction time of the system was considered. The reaction time was determined to be the time between when the instruction image was first displayed and the first instance when the control gesture was correctly identified. This provided an indication of how complicated the gesture was, the smoothness of control, and the sensitivity of identification. The reasoning behind this measure is that longer reaction times would translate to feelings of lack of control and frustration with

the control strategy. This would in turn hinder its continued use. Reaction time was also constituted one limitation of FMG with seniors.

- **Inadvertent Activation.** This feature was identified as the amount of time a control gesture was inadvertently identified during household activities. This measure provides an indication of the likelihood of unintended triggering of paired devices, which would also contribute to feelings of lack of control and frustration. Inadvertent activation also constituted and additional of an FMG based system used with seniors.

Non-senior participants were considered separately for comparison. Descriptive statistics were collected and further analyzed.

3.4. Results

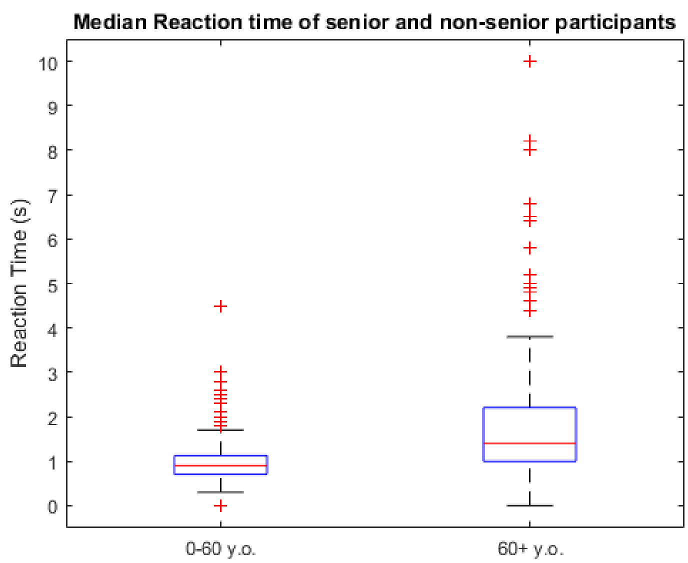
There were 10 participants in total, whom were divided into two groups based on their age. Participants aged between 0 and 60 years old were identified as ‘non-senior’, whilst participants aged 60+ years old were identified as ‘senior’. In the non-senior group, there 2 females (mean 24 years old) and 3 males (mean 26.33 years old). In the senior group, there was 1 female (aged 73) and 4 four males (mean 65.5 years of age). Senior and non-senior participants achieved a mean LDA training accuracy of 91.6% and 97.57%, respectively.

During online testing of control gestures, senior participants successfully performed the gesture within 1.4 (2.34) seconds of the instruction. For the control gestures selected for these tasks, shown in **Figure 3.2**,the time to successfully complete the ‘6’ gesture took the most time at 1.1 seconds, followed by ‘I love you’,’2’,’Y’, and ‘close’ at 0.9, 0.8, 0.8 and 0.7 seconds, respectively. Non-senior participants demonstrated an average reaction time of 0.9 (0.54) seconds. Gesture specific timings during household tasks were 1.9, 1.6, 1.4, 1.3, 0.8, and 0.3 for ‘relax’, ’I love you’, ’2’, ’close’, ’Y’, and ‘6’.Gesture specific data for non-senior and senior participant reactions time are shown in **Table 3.1**, and summarized in **Figure 3.5**.

3.1. Summary of system reaction time (median ± standard deviation) to complete a gesture when prompted with an image

	Reaction Times (seconds)					
	'6'	close	'2'	'Y'	'I Love You'	Average
Non-senior	1.1 (0.56)	0.7 (0.2)	0.8 (0.4)	0.8 (0.83)	0.9 (0.25)	0.9 (0.54)
Senior	1.8 (2.66)	1 (2.57)	1.3 (2.61)	1.6 (2.03)	1.9 (1.74)	1.4 (2.34)

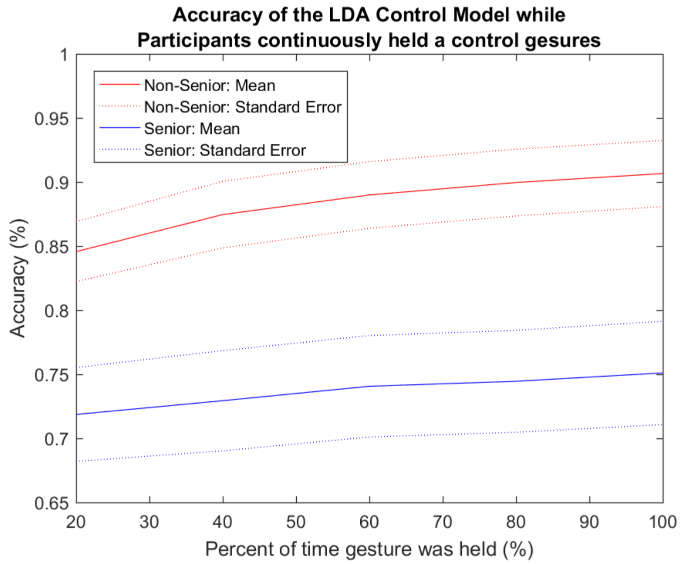
Note. Values (for age, weight, height, BMI) are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.



3.5. Boxplot of absolute reaction times (s) over all gestures for senior and non-senior participant during online testing.

Note. These reaction times indicate how long the participant took to correctly form a control gestures (as monitored by a trained LDA model) after an initial instruction

Once the gesture was successfully identified by the trained identification algorithm, seniors achieved a cumulative accuracy of 75.11% (15.61%). On the other hand, non-senior participants achieved a cumulative accuracy of 90.66% (9.99%). **Figure 3.6** below summarizes the changes that occur in accuracy over the progression of a gestures.



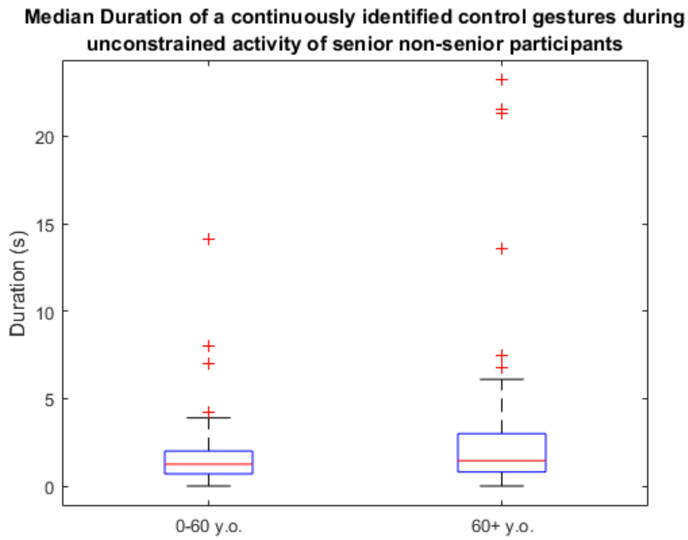
3.6. Cumulative accuracy of system expressed as a percentage of the duration a control gesture was held

Finally, during household tasks, when a control gestures was mistakenly identified, continuous identification of the gesture lasted at most 1.45 (1.86) seconds for seniors over all gestures. For non-seniors, this was 1.25 (1.86) seconds over all gestures. Gesture specific timings are tabulated below in **Table 3.2**, and summarized in **Figure 3.7**.

3.2. Summary of participant maximum duration (median ± standard deviation) a control gesture is continuously identified when performing unconstrained activities of daily living

	Continuous identification of control gestures (seconds)					
	'6'	close	'2'	'Y'	'I Love You'	Erroneous Gestures/ 'Relax'
Non-Senior	0.3 (1.76)	1.3 (0.98)	1.4 (0.98)	0.8 (0.54)	1.6 (0.95)	1.9 (3.48)
Senior	0.9 (0.96)	3.6 (6.49)	0.9 (2.07)	1.2 (0.96)	1.3 (0.63)	3.3 (6.89)

Note. Values (for age, weight, height, BMI) are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.



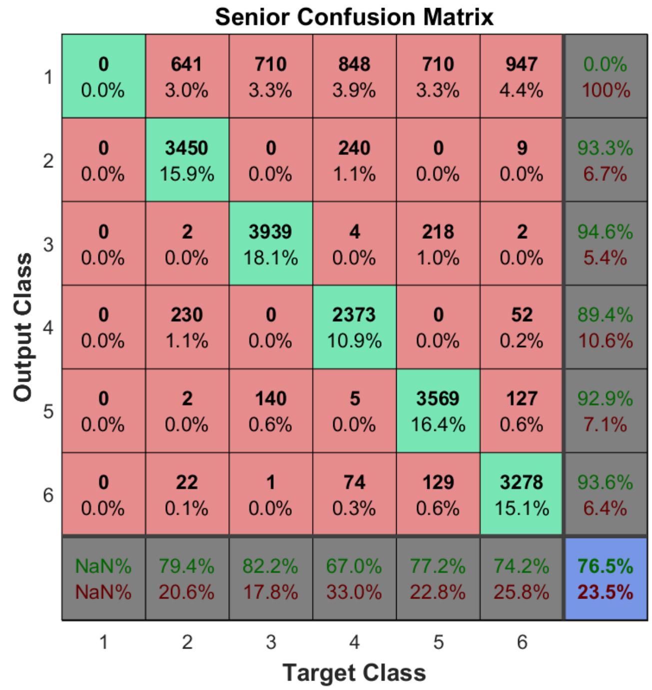
3.7. Boxplot of maximum durations of a continuously identified signal for all gestures for senior and non-senior participants during household tasks.

Note. These times indicate the typical duration a control gesture is continuously identified by the participants trained LDA model whilst completing activities of daily living

3.5. Discussion

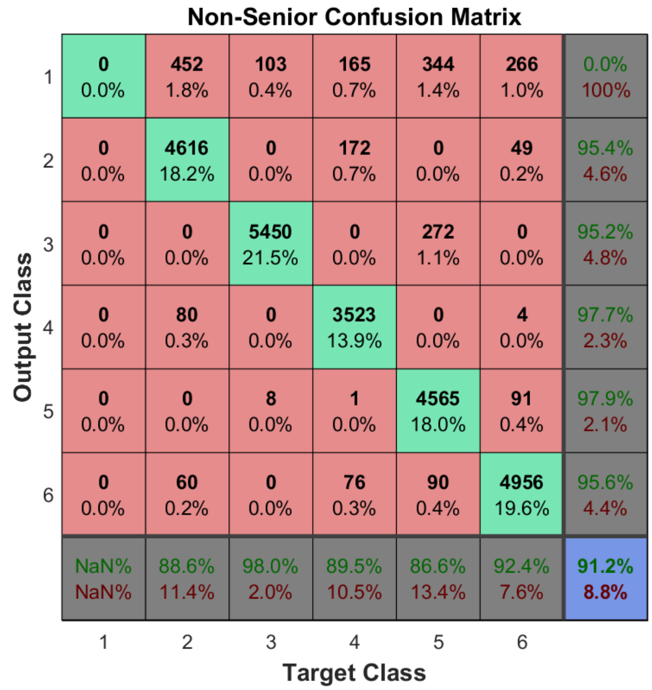
During the 'Testing Phase' where participants performed the specified control gestures with image instruction and LED feedback, senior participants demonstrated longer reaction times. **Table 3.1** and **Figure 3.5**. presents the distribution of reaction times of each group across all three repetitions of the experimental protocol performed. Although this suggests that seniors are slower in successfully performing a control gesture on command, this would not necessarily translate to a direct measure of increased difficultly or frustration. Reasons for this increased time may be related to the intuitive nature of the control gesture, the amount of additional practice that seniors may required to perform comparably to non-senior participants, or the sensitivity of FMG to intended gestures. In addition, senior participants also demonstrated a larger variability in reaction time. This variability is a feature of using FMG amongst seniors that would need to be addressed in future research.

Once a control gesture was correctly identified, non-senior participants demonstrated increased accuracy for the duration the gesture was held. This appeared to be consistent throughout the duration that a gesture was held, which has been graphically represented in **Figure 3.6**. Taken at face value, a 75% accuracy amongst seniors would have implications on the real-world usage of FMG in aging-in-place technology. An inaccurate system would lead to false activations, potential frustrations, and subsequently, device abandonment. It was previously mentioned that the intuitiveness of the gesture as well as age-related differences in learning may have had an impact on the difference in performance between the two groups, as both groups of participants were given identical training sessions. It is also noted that with aging, new information in internalized differently [214]. Future work on comprehensive systems utilizing FMG should take into account these age-associated differences and incorporate effective learning strategies that are better suited for aging populations. In addition to age-associated cognitive changes, there are also age associated changes to skin, muscle, and adipose tissue that could impact the transmission of forces to overlying FMG sensors [6], [11], [12]. This may also explain the variability in performance observed. The confusion matrices shown in **Figures 3.8** and **3.9** present a more comprehensive perspective of the control schema's performance presented in **Figure 3.6.**



3.8. Confusion Matrix for control gestures for senior participants during online testing.

Note. Classes 1-6 indicated the following gestures (in order): 'Erroneous', '6', 'close','2','Y', and 'I Love You' respectively. Red and Green squares indicate the number/percentage of incorrect and correct classifications, respectively. The grey row and column show the gesture specific accuracy, whilst the blue box shows the overall accuracy.



3.9. Confusion Matrix for control gestures for non-senior participants during online testing.

Note. Classes 1-6 indicated the following gestures (in order): 'Erroneous', '6', 'close','2','Y', and 'I Love You' respectively. Red and Green squares indicate the number/percentage of incorrect and correct classifications, respectively. The grey row and column show the gesture specific accuracy, whilst the blue box shows the overall accuracy

As previously mentioned, 5 gestures were used to control our virtual environment (turning on the LEDs). Our LDA scheme also had an additional ‘relaxed’ condition to capture unintentional movements and movements not specific to the control scheme. The confusion matrix for seniors in **Figure 3.8** indicates that most of the false positives in classification, when compared to non-senior participants, where due to poor differentiation of control gestures from relaxed or erroneous movements. For seniors, the 5 control gestures were mislabeled as relax/erroneous 17.9% of the time, compared to only 5% for non-senior participants. Reasons for this may lie in the sensitivity of the FMG to small movements, or perhaps the 0.95 probability threshold used with the LDA models. This variability may also be explained by differences in the amount of force exerted by seniors as each gesture was repeated. Gesture force and effort would have changed because of fatigue, joint stiffness, or perhaps diminishing awareness of the effort they were exerting. Moving forward, an unsupervised learning model addressing differences in sensitivity and increase variability of FMG sensors would prove beneficial for ongoing use of FMG technology [48].

Finally, considered was unintended triggering. In a practical sense, unintended triggering provides some insight into the design choices to that would distinguish ambient activity from control specific movements. These distributions are graphical shown and tabulated presented in **Table 3.2** and **Figure 3.7**. The similarity in times is encouraging as it shows that the system demonstrates similar usability between senior and non-senior users.

3.6. Limitations and future directions

The similarity in timing between ‘seniors’ and ‘non-seniors’ for unintentional system triggering during activities of daily living is promising. This suggests that an appropriately chosen method of differentiating between erroneous movements and intentional gesture control could be stable, to a degree, throughout progressive aging. However, despite its potential strengths, the commercial implementation of FMG into healthcare systems/technologies is limited by lack of characterization of inter- and intra- patient inconsistencies which require FMG retraining before each use. The temporal and mental effort to retrain and recalibrate a system is an additional factor that could affect the system’s acceptance and adherence. Further study of FMG within the senior population should seek to quantify the effect of age associated changes to motor ability and underlying musculoskeletal tissue for use in a predictive and self-correcting model [48]. Ideally, future work should also consider an application specific and generalizable model of FMG patterns that could be extended across users. This would support unsupervised learning models of hand/arm activity, and in effect, minimal effort to recalibrate the system.

The strengths of this work would be improved by adjustments that increase the sample size of the study, as well as incorporate concrete measures of satisfaction and usability. As our protocol was constrained to limited set of control methods and learning strategies, this work would also benefit from increased evaluation of FMG in unconstrained settings. Finally, given the review of geriatric research in ***Chapter 2***, FMG would be better suited as a complement to senior target devices by providing direct user data. This would involve a. The most effective method of technological intervention delivery has been shown to (1) involve multiple modalities of communications (such as SMS messages or websites AND kinematics/tactile sensors) and to (2) incorporate environmental cues to guide notification delivery [48], [215].

The conclusion of this study is that seniors can successfully use an FMG based system, however with increased variability and decreased accuracy when compared to non-senior counterparts. Further work is needed to incorporate FMG into a comprehensive system for effective healthcare intervention in the aging population.

3.7. Follow Up Study Considerations

Despite the high training accuracies, the results of this study suggest that using FMG with seniors would be unreliable. This is indicated by seniors achieving 75.11% accuracy during online testing. When compared to non-senior participants, whom achieved an average training accuracy of 90.66%, that the cause of this discrepancy was age related. Thus, a follow-up study was developed to determine age related differences between participants that would result in low FMG performance.

A review of the protocol highlighted two areas that would be adjusted for this follow up study. One is the intuitiveness of the gestures, which was previously mentioned to be a probable cause of longer reaction times of seniors compared to non-seniors. As such, gestures in the follow up study were selected to involved more gross hand/arm manipulation rather than fine finger tasks. The second is the difference in the amount of training/learning participants would require to perform motions naturally. In this current study, instruction images were presented serially without pause. However, the follow-up study would be executed so that gestures would be completed individually and the observing experiment facilitator would correct participants in correct gesture formation.

Finally, the results of this study also suggest that one of the reasons for lower accuracies is poor discernibility of control gestures from erroneous gestures. This is indicated by the confusion matrix in **Figure 3.8**, which shows that many false-positives occurred with the relax/erroneous condition. Thus, if age-related differences were assumed to a significant factor in FMG performance, anthropology was deemed to be one of the main causes. The justification for this is that the age-associated changes that occur in underlying musculoskeletal tissue would change how FMG is transmitted to sensors during functional movement.

Further details of this follow-up study are presented in ***Chapter 4 Factors that influence an FMG model: Methodology*** and in ***Chapter 5 Factors that influence an FMG model: Results and Analysis.***

Chapter 4.

Factors that influence an FMG model: Methodology

4.1. Chapter Overview

The work described in this chapter addresses **Objectives 2 & 3** of this thesis. The first study presented in ***Chapter 3*** sought to characterize the use of an FMG based system with seniors. The aim of this study addressing **Objectives 2 & 3** is to identify measurable features intrinsic to the participant that can influence the variability of FMG acquisition and modelling. This chapter opens with a study overview in ***Section 4.2***. Participants inclusion and exclusion criteria are presented in ***Section 4.3***. ***Section 4.4*** presents a detailed overview of the instrumentation used, and is followed by a review of the experimental protocol in ***Section 4.5***. Data processing and analysis methods are then discussed in ***Section 4.6*****.** The chapter concludes with a discussion of internal and external validity of the experimental design in ***Section 4.7***. Results obtained using the methodology discussed in this chapter are reviewed and analyzed later in ***Chapter 5***.

4.2. Study Overview

The purpose of this study is to identify features intrinsic to FMG users that are related to FMG acquisition variability and gesture classification success. As discussed in **Chapter 2**, aging is associated with various physical and functional changes such as reduced strength, reduced muscle cross sectional area, and changing mechanical properties non-muscle tissue. It is believed that these changes are related to variability in FMG acquisition, and indirectly influence machine learning testing accuracy. Participants are invited to complete a set of predefined hand gestures through various degrees of stationary and non-stationary wrist/forearm orientation. Hand gestures are composed of gross hand movements as well as fine finger movements based on those most likely utilized during activities of daily living. In addition, anthropometric features (limb lengths, limb circumferences, skinfold measurements, active ROM, and grip strength) are measured. Various simple machine learning models are generated to illustrate the effect intrinsic user properties. Correlations within descriptive statistics are taken, and student's t-tests are used to established statistically significant differences in gesture classification.

4.3. Participants

Testing took place across three locations: 1) MENRVA Laboratory, School of Engineering Science in the Faculty of Applied Science, Simon Fraser University, 8888 University Drive, Burnaby, British Columbia, CANADA; 2) MENRVA Laboratory School of Mechatronic Systems Engineering in the Faculty of Applied Science, Simon Fraser University, 250-13450 102nd Avenue, Surrey, British Columbia, CANADA; and 3) Confederation Seniors Centre, 4585 Albert Street, Burnaby, British Columbia, CANADA.

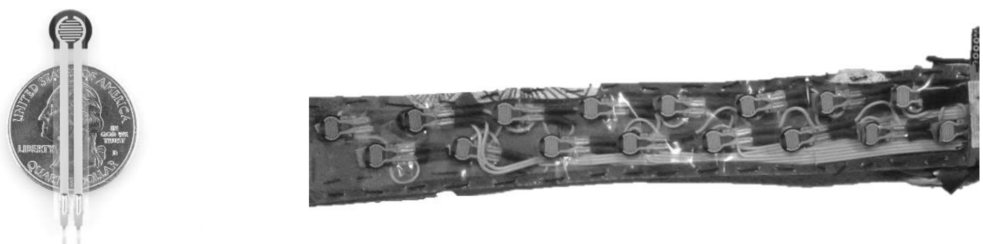
Participants were recruited from Simon Fraser University students, faculty, and staff, and the general population. Inclusion criteria for participation required that participants can follow instructions of the experimental protocol and perform the required gestures/tasks to completion. Exclusion criteria were limited to self-identified neurological and musculoskeletal barriers to functional movements. All participants provided informed and written consent. Save for muscle fatigue, there was little to no risk to participants.

4.4. Instrumentation

4.4.1. Force Myography band

The primary instrumentation for this work is a custom design FMG sensing device, similar to that described in ***Section 3.3.2***, but with an adjusted design. Adjustments to the design involved using Interlink polymer thick film FSRs with smaller active areas (25.5 mm^2 vs 126.7 mm^2) in a staggered design. Smaller FSRs (Interlink Technologies, model: 400) were used to allow for placing the FSRs in closer proximity to each other, without overlapping the active areas. These adjustments were made to increase the number of FSRs in direct contact with the skin.

The FSRs were backed with Flex foam and fastened onto the interior of the band. The interior of the band was formed from cellulose acetate, a flexible and non-elastic material commonly used in overhead projector film transparencies. The data sheet for FSRs recommends more rigid backing in implementation [216] , the backing was used to facilitate better contact between the FSR and the skin while allowing the band to conform to the shape of the wrist. ***Figure 4.1*** below shows the new band design.



4.1. (Left) Smaller FSRs used in the adjusted designed of the FMG band (Right) Staggered placement of the FSRs on a flexible non-elastic backing

Note. Interlink FRS400 is shown in reference to a quarter for sizing information.

4.4.2. Peripheral instrumentation

The following itemized list summarizes the additional instrumentation utilized to address the **Objective 2 & 3** of this thesis project.

- **Hand Grip and Pinch Grip** were measured with a digital hand dynamometer (Vernier Software & Technology, model: HD-BTA), via Vernier Go!Link Connector (Vernier Software & Technology, model: GO-LINK). Offline maximum voluntary grip strength and recorded via Logger Lite software (Vernier Software & Technology, version: 1.9). Grip and pinch strength, measured concurrently with FMG activity was recorded via the Vernier LabVIEW Virtual Instrument plug-in (Vernier Software & Technology, version 1.16.00)
- **Skinfold thickness** was measured with an analog Slim Guide Skinfold Caliper (Creative Health Products).
- **Upper extremity segment circumferences and lengths** were measured with a standard tape measure
- **Baseline active range of motion** of the forearm and wrist were captured using an analog goniometer (Jamar Plus+ Digital 8" Goniometer by Patterson Medical, serial: 081660133).
- **Band tightness**, represented as skin surface contact pressure, was estimated using a separate Force Sensitive Resistor (Interlink Technologies, type 400)

experimentally calibrated to measure skin surface contact pressure. Further details of implementation and calibration are described below.

- **Angle of forearm pronation/supination** measured concurrently with FMG activity was measured by two Inertial Magnetic Units (SparkFun 9DoF IMU Breakout - LSM9DS1) placed on the wrist and the upper arm. Further details of implementation and calibration are described below.
- **Angle of wrist flexion/extension** measured concurrently with FMG activity was measured by an analog rotary potentiometer (TT Electronics/BI, model: P160), with a range of 300 degrees. Further details of the implementation are described below.

Estimating Band Tightness with a force sensitive resistor (FSR)

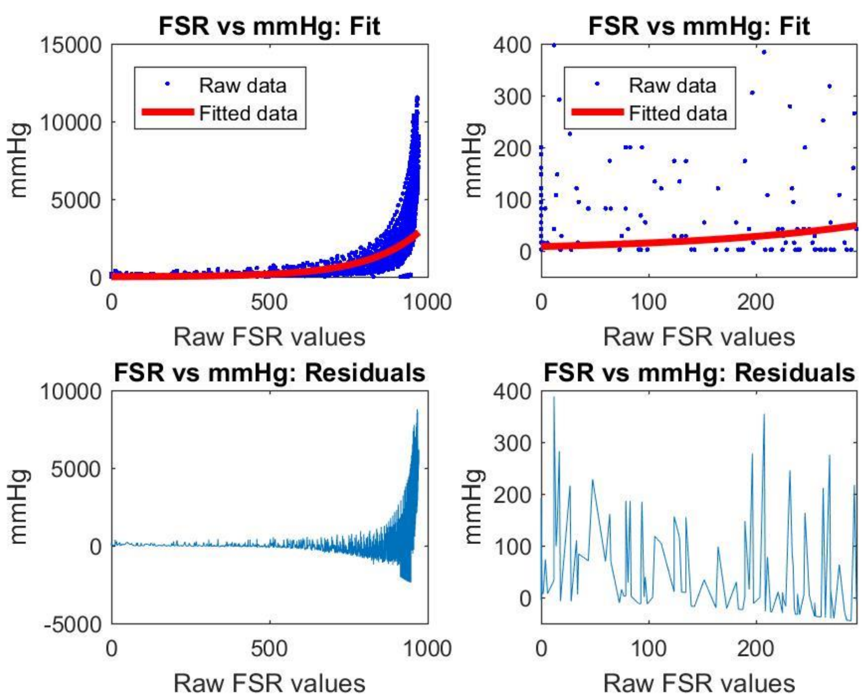
To evaluate FMG band tightness, the literature was reviewed for devices or medically related tools where compression of the limb is a significant factor. Compression stockings represented these features. Compression socks are rated according to the amount of pressure they exert onto the surface of the lower leg. Typically, they are calibrated using a pneumatic bladder based system such as Kikuhime or PicoPress [217], [218] with the rating expressed in millimeters mercury (mmHg). FSRs have been used to evaluate commercially available compression socks [219], and have also been used as an alternative form of measuring skin contact pressure [218]. This served as a motivation for the proposed methodology to measure the tightness of the FMG band.

Band tightness was represented as skin contact pressure, and was estimated using an experimentally calibrated FSR. To do this, data was simultaneously collected from the FSR and a digital pinch force dynamometer. While the FSR was attached to the pinch dynamometer, as shown below in **Figure 4.2**, light touch to maximum pressure was applied to the FSR with the thumb. The thumb was used to relate the calibration technique to the mode of implementation more closely in later testing.

4.2. Placement of FSR on pinch on dynamometer

Values from the hand dynamometer, expressed in in Newton's (N), were divided by the active area of the FSR (126.68 mm^2), to obtained a representation of pressure in Pascals (Pa) later expressed in millimeters of mercury (mmHg). Measured pressure (mmHg) was regressed with raw FSR values in a 1st order exponential relationship (**Equation 4.1** below) and graphically represented below in **Figure 4.3**.

$$mmHg = 8.0433e^{0.006FSR} \qquad (4.1)$$



4.3. Band Tightness sensor calibration.

Note. Shown are (Left) the FSR-mmHg regression and residuals for the full range of values obtained during calibration, and (Right) the FSR-mmHg regression and residuals for the range of values encountered during testing with participants.

As seen in **Figure 4.3**, there is a pronounced increase in residual values at higher applications of force (larger FSR values). Although hysteresis effects of forces application are more pronounced at higher forces [216], the functional range of this sensor during testing was within the advised limit prescribed by the datasheet (0.2 to 20 N) [216], corresponding to lower ranges of the raw FSR digital output (less than 300). The median residual within the range of values recording during testing was 85.97 mmHg, while the root-mean-square error (RMSE) was 20.69 mmHg.

Estimating forearm pronation/supination by inertial magnetic unit (IMU)

IMUs placed on the arm and the wrist were used to measure elbow and forearm angle. A representative example of the IMUs location on the forearm and upper arm is shown below in **Figure 4.4**. The IMU used in this project employed an integrated chip (ST Microelectronics iNEMO inertial module, model: LSM9DS1), which houses a tri-axial magnetometer, a tri-axial accelerometer, and a tri-axial gyroscope. Prior to use, the magnetometer scale and offset were calibrated using a method described in [220] while the accelerometer scale and offset were calibrated using a method described in [221] and adapted to accelerometers. The gyroscope was calibrated by removing baseline values recorded whilst the gyroscope was stationary. The mean centered variability of the sensors' signals is tabulated below in **Table 4.1**.

4.1. Inertial Magnetic Unit (IMU) signal variability

Sensor	Units	Location	
		Wrist	Arm
Magnetometer	Gauss (G)	1.35×10^{-5}	1.06×10^{-5}
Accelerometer	Gravity (g)	7.27×10^{-6}	9.83×10^{-6}
Gyroscope	Degrees/second (°/s)	0.063	0.24

During offline post-processing, IMU axes were rotated so that the positive Z axis was pointed superiorly, and the positive X axis was pointed anteriorly. Movements were either slow or stationary, thus the accelerometer was deemed sufficient to estimate angle of forearm pronation/supination. Roll (angle of tilt of the Y axis) and pitch (angle of tilt of the X axis) euler angles were calculated using **Equations 4.1** and **4.2** below:

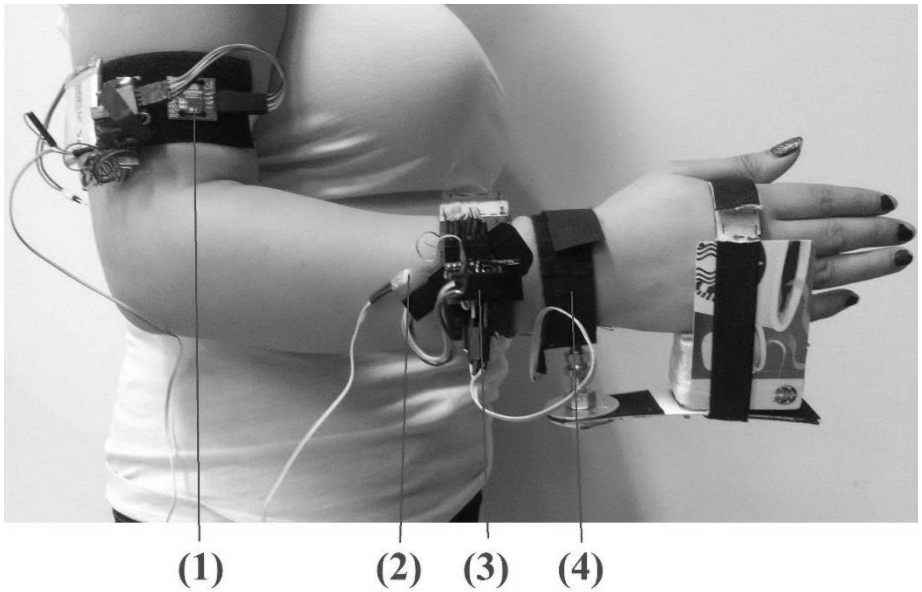
$$roll = \text{atan}\left(\frac{\vec{a}_y}{\sqrt{\vec{a}_x^2 + \vec{a}_z^2}}\right) \tag{4.2}$$

$$pitch = \text{atan}\left(\frac{\vec{a}_x}{\sqrt{\vec{a}_y^2 + \vec{a}_z^2}}\right) \tag{4.3}$$

Baseline values were recorded while the participant was at 90° elbow flexion and neutral wrist, and subsequently subtracted from later measurements to obtain degrees of forearm pronation and supination. Forearm pronation/supination was taken as the roll angle of the IMU placed at the wrist. Elbow was taken as the relative pitch between the IMU at the wrist and the arm.

Estimating wrist flexion/extension by rotary potentiometer

An analog rotatory potentiometer was used to track wrist flexion/extension angles. The relationship between the degree of rotation of rotary shaft and the analog output value is linear, and the analog-to-digital resolution of the potentiometer during testing was 0.293 °/bit. The potentiometer was incorporated into a Velcro strap, and the rotary shaft was attached to a lightweight and semi-rigid moving arm. A Styrofoam spacer was used to maintain contact and position between the hand and moving arm. On the participant, the potentiometer was positioned at the ulnar styloid process, while the moving arm was positioned along the hypothenar side of the hand. A representative example of placement on the participant is shown below in **Figure 4.4** below. Baseline values were recorded while the participant was at 90° elbow flexion and neutral wrist. Baseline values were subsequently subtracted from later measurements to obtain degrees of wrist flexion and extension.



4.4. Full instrumentation
Note. Shown are the (1) the IMUs used to measure forearm orientation on the upper arm, (2) the FSR used to measure band tightness, (3) the FMG band, and (4) the rotary potentiometer used to track angle of wrist flexion/extension.

4.5. Experimental Protocol

Table 4.2 below summarizes the full procedure employed with each participant, while the following subsections detail the experimental methods employed. Age, weight, height, and hand dominance were obtained via the participant's consent form. Wrist circumference, forearm circumference, forearm length, and upper arm length were recorded separately. While participants completed the set of predefined tasks and wore the FMG band, wrist orientation, forearm orientation, and grip strength were simultaneously recorded using the instruments described in ***Section 4.4***. Instruments were sampled at approximately 10 Hz, timestamped, and finally transmitted to an on-site computer via serial connection for further processing. Participants performed the required tasks once, removed the band completely and then re-donned the band for a second session. Maximal voluntary grip strength was assessed prior to testing and after each session.

For this work, neutral shoulder was defined as (approximately) 0° abduction/adduction, 0° internal/external rotation, and 0° flexion/extension. Neutral forearm orientation was defined as 0° pronation/supination, and was identified by the palm of the hand pointing towards the midline of the body. Neutral wrist was approximately defined as 0° wrist flexion/extension, and finally, relaxed hand, was defined as not actively engaging the fingers. All testing was performed on the right side.

4.2. Full experimental procedure employed with each participant

	Item	Description
0	Informed Consent	Review of study consent form
1	Protocol Instruction	Verbal instruction and demonstration of hand gestures and wrist/forearm orientations required in the participant tasks
2	Anthropometric measurements	Measurement of forearm length, upper arm length, wrist circumference, forearm circumference, and forearm skinfold
3	Maximum Voluntary Grip Strength	Average of 3 attempts at maximum voluntary contraction
		*****Band is donned*****
4	Calibration	Participant holds the shoulder in neutral, elbow flexed to 90°, forearm in neutral, wrist in neutral, and hand relaxed
5	Participant Tasks	Dynamic Motions, Static Singleton Gestures, Static Compound Gestures
		*****Band is removed*****
6	Maximum Voluntary Grip Strength	Average of 3 attempts at maximum voluntary contraction
		*****Band is donned*****
7	Calibration	Participant holds the shoulder in neutral, elbow flexed to 90°, forearm in neutral, wrist in neutral, and hand relaxed
8	Participant Tasks	Dynamic Motions, Static Singleton Gestures, Static Compound Gestures
		*****Band is removed*****
9	Maximum Voluntary Grip Strength	Average of 3 attempts at maximum voluntary contraction

4.5.1. Segment length and circumference

Standard positioning for limb length and circumference measurements was a neutral shoulder, 90° elbow flexion, neutral forearm, neutral wrist orientation, and relaxed hand. Forearm circumference was measured at the muscle belly, approximated by the widest part of the forearm. Wrist circumference was measured within 1 inch proximal to the wrist. When measuring segment circumference, standard protocols were used. Forearm length, was measured from the olecranon process to the ulnar styloid process. Lastly, the upper arm length was measured from the acromial process to the olecranon process. Measurements were taken to the nearest millimeter.

4.5.2. Skinfold thickness

Skinfold thickness was measured from the anterior aspect of the forearm, approximately at the widest part of the forearm. Methods for taking skinfolds were taken from [222]. In brief, the skin is firmly grasped between the first three digits. The jaws of the calipers are then placed approximately 1 cm from where the skin is grasped, and the skin is released for measurement. Measurements were taken to the nearest millimeter.

4.5.3. Baseline wrist and forearm ROM

Wrist range-of-motion (ROM) for flexion and extension were performed while the shoulder was in neutral position, 90° elbow flexion, and neutral forearm orientation. The participant was instructed to actively flex or extend their wrist to the fullest capabilities, and the measurement for each motion was taken as the smallest relative angle between the 2nd meta-carpal and the central axis radius. Measurements were recorded to the nearest degree.

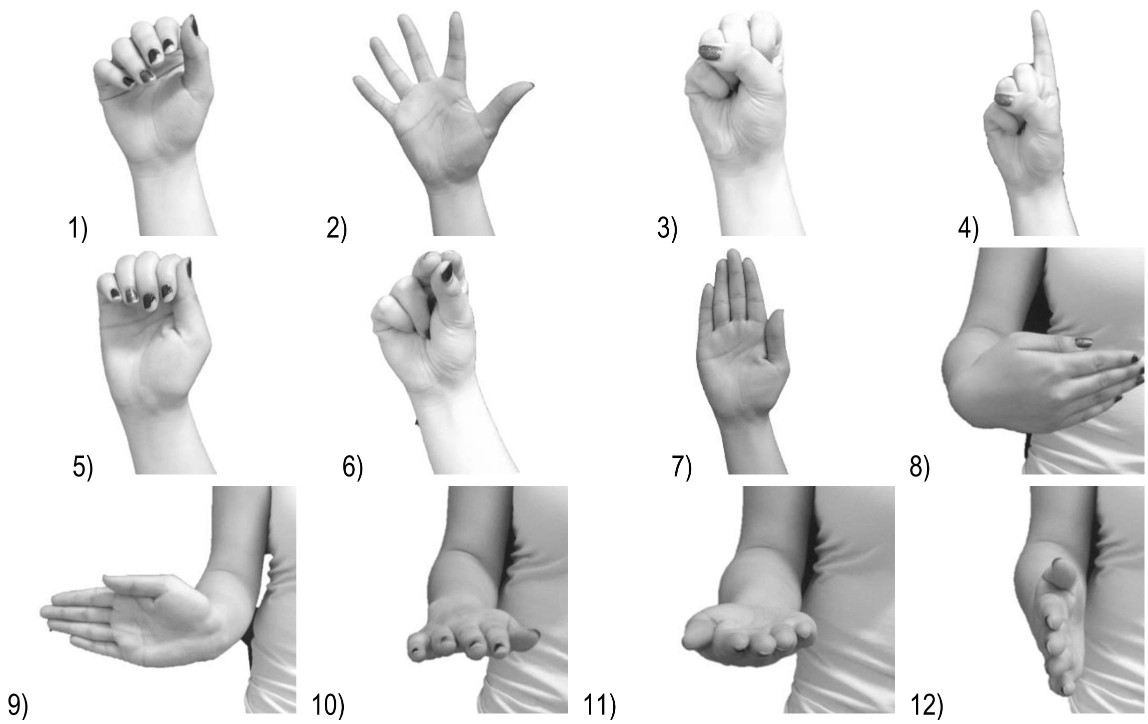
Forearm ROM for pronation and supination were performed while the shoulder was in neutral position 90° elbow flexion, and neutral wrist position. The participant was instructed to hold a pencil in a closed fist, and to actively pronate or supination to the fullest capabilities. The measurement for each motion was taken as the smallest relative angle between the starting and ending position of the length of the pencil. Measurements were recorded to the nearest degree.

4.5.4. Grip strength

Grip strength tests were performed while the shoulder was in neutral position 90° elbow flexion, and neutral wrist position. Participants were instructed to the hold the hand dynamometer in a closed fist, and to squeeze the dynamometer with maximum effort (maximum voluntary contraction) for approximately 3 seconds. This was repeated 3 times, with the average value being reported to the nearest 0.01 kilogram. [223]

4.5.5. Hand gesture and wrist/forearm orientation

Force Myography (FMG) was recorded from a custom FMG sensing device described in ***Section 4.4.1***. All tests were based on a set of 6 different hand gestures (based on those most commonly used in activities of daily living [169]): relaxed, open, close, point, key, tripod; and 5 wrist/forearm orientations: neutral, flexion, extension, supination, and pronation. These are shown below in **Figure 4.5**.



4.5. Hand gestures and wrist motions used in testing.
Note. Shown is 1) relaxed, 2) open, 3) close, 4) point, 5) lateral pinch (key), 6) pinch (tripod), 7) straight, 8) wrist flexion, 9) wrist extension, 10) forearm pronation, 11) forearm supination, 12) straight hand gesture and neutral wrist/forearm

For uniformity, participants were given specific instructions and demonstrations for each gesture. For each of the wrist orientations (flexion, extension, neutral, pronation, and supination), unless otherwise indicated, participants were instructed to keep the fingers and thumb fully extended and adducted. For hand gestures:

- **Relax**. fingers and thumb are not engaged are actively flexed/extended
- **Open**. fingers and thumb are fully extended AND fully abducted
- **Close.** a fist with the buttressing of the distal tips of the phalanges against the central palm and buttressing of the thenar eminence and thumb against the dorsal surfaces of digits 2 and 3 [224] or the lateral aspect of the 2nd digit.
- **Point.** only the 2nd digit (index finger) is fully extended, with the pad of the thumb resting on the lateral aspect of the 3rd digit
- **Tripod.** the pads of the thumb, 2nd, and 3rd digits are in contact
- **Key.** the pad of the thumb is in contact with the proximal interphalangeal joint of the 2nd digit

Participants performed three groups of tasks based on the hand gestures and wrist/forearm orientations shown above in **Figure 4.5**: 1) Dynamic Motions, 2) Static Singleton Gestures, and 3) Static Compound Gestures.

- **Dynamic Motions. P**articipants were instructed to either move between two extremes of range-of-motion or produce a grip with minimal to maximal effort. Participants performed 1 repetition of each dynamic motion for 60 seconds.
- **Static Singleton Gestures.** Participants were instructed to perform each of the hand gestures and wrist/forearm orientations individually, for a total of 11 different classes. Participants performed 5 randomized repetitions of each static gesture for approximately 7 seconds each.
- **Static Compound Gestures.** Participants were instructed to simultaneously perform a hand gesture AND a wrist/forearm orientation. For example, for ‘point_supination’ the participant was instructed to simultaneously point the hand AND supinate the forearm. All possible combinations of the 6 hand gestures and the 5 wrist/forearm orientations were considered, for a total of 30 different classes. Participants performed 5 randomized repetitions of each possible combination for approximately 7 seconds each.

In consideration of greater potential for fatigue in senior adults and mental overload, an abridged version of these tasks was implemented with senior participants. In effect, the ‘Static Compound Gestures’ tasks only required combinations between 3 of the hand gestures (relax, open, close) with all wrist positions rather than the full set of hand gestures (relax, open, close, point, key, tripod). **Table 4.3** below provides an overview of the specific gestures that constitute each group of tasks.

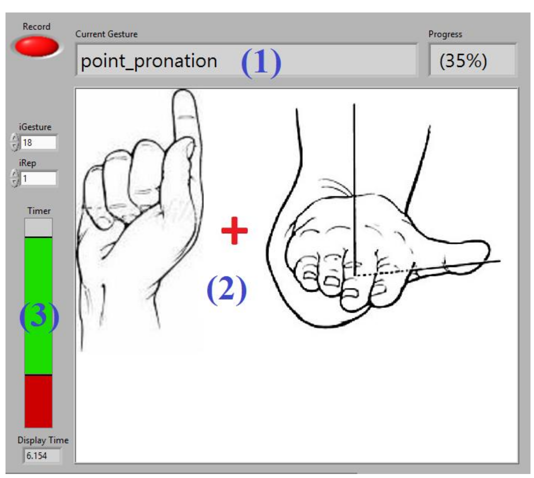
4.3. Tasks completed by participants in experimental protocol

Dynamic Motions	Static Singleton Gestures	Static Compound Gestures	
• Flexion <-> Extension • Pronation <-> Supination • Cylindrical Grip, Squeeze and Relax • Pinch Grip, Squeeze and Relax • Lateral Pinch Grip, Squeeze and Relax	• relax • open • close • point • tripod • key • neutral • flexion • extension • pronation • supination	All possible combinations of hand gestures and wrist orientations	
		Hands Gestures	**Wrist Orientations**
		• relax* • open* • close* • point • key • tripod	• neutral • flexion • extension • pronation • supination

Note. Seniors performed an abridged version of the protocol. In static compound gestures, seniors performed only the starred (*) hand gestures.

4.5.6. Environment

Measurements and testing was performed while sitting at a chair of standard height and depth. Instructions were given as images via a visual interface, shown below in **Figure 4.6**, and displayed in real time on a monitor positioned between eye level and desk level. When necessary, the investigator demonstrated the hand gesture desired at the time and/or corrected the participants' hand gesture to match the standards set for all participants.



4.6. User Interface.

Note. Features shown are the 1) Tasks Title, 2) Instruction Image, 3) Progress Timer

4.6. Data processing & analysis

The dependent variable considered for this protocol is the FMG recording obtained during movement, while the independent variables considered for this research are as follows: 1) age, 2) weight, 3) height, 4) hand dominance, 5) segment length and circumference, 6) skinfold thickness, 7) band tightness, 8) wrist/forearm orientation, 9) grip strength, 10) maximum wrist/forearm range-of-motion, 11) maximum voluntary grip strength, and 12) true class labels for statically held gestures. The following sections describe in further detail the data processing, feature extraction, and transformations utilized in this study.

4.6.1. Processing, feature extraction, & transformations

The following feature extraction methods and transformations were used.

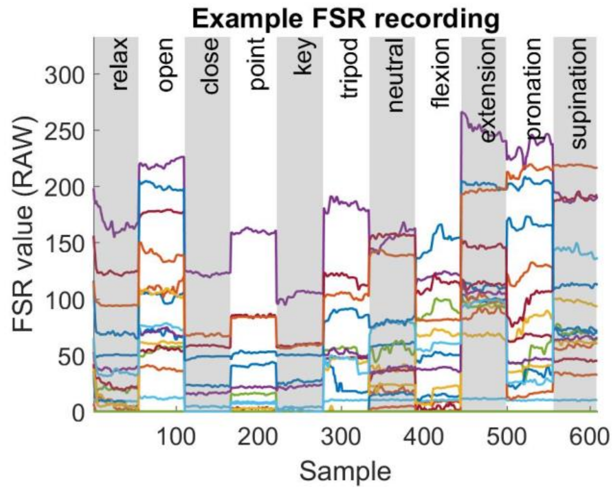
Calculation of new variables

Upon collection, all FSR, grip strength, and angle/orientation values were filtered using a moving average filter of the data point immediately prior and following each sample. In addition, some of the variables measured were recombined to create new variables of interest. These include:

- Ratio of skinfold thickness to forearm circumference, on range of [0,1]
- Ratio of wrist circumference to forearm circumference, on a range of [0,1]
- Percent drop in maximum voluntary grip strength after completing the required tasks
- Online grip strength, pinch strength, lateral pinch strength as a ratio of maximum voluntary grip strength, on range of [0,1]
- Online wrist flexion/extension, and forearm pronation and supination as a ratio of the full range of motion, on range of [0,1]

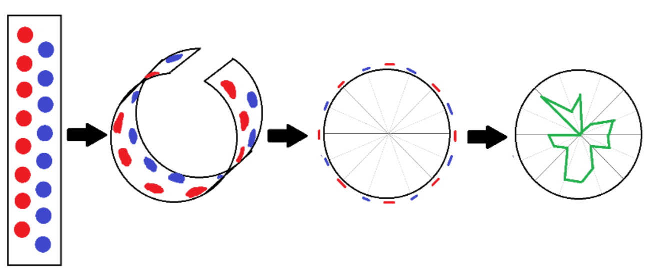
Spatial Representation of FMG

With respect to the FMG data, FMG was considered in two respects: 1) 1D samples consisting of 16 features, where each feature corresponds to a single FSR sensor in the FMG band, and 2) as a 2D transverse radial profile. The first form is trivial, and is shown graphically below in **Figure 4.7**.

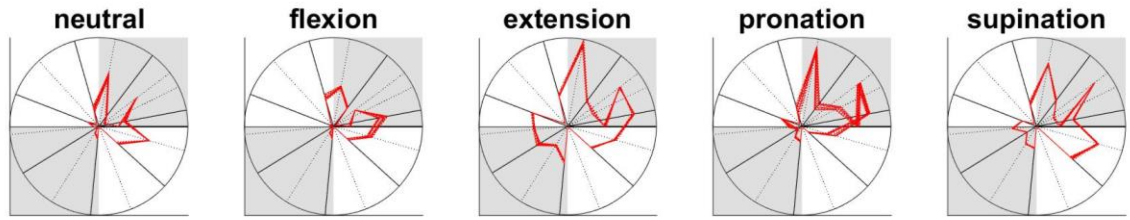


4.7. Example of 1D FSR data.
Note. Shown are the FSR signals from each of the FSR used in the FMG band (colored) and the delineations between each of the 6 hand gestures and the 5 wrist/forearm orientations (white/grey areas). The labels for each of these gestures are indicated in each area. Only a single repetition is shown.

The second form of representing FMG data, which retained spatial information, is essentially a radial representation of the FMG data centered about the central axis of the wrist. In this form, the value for a FSR sensor after applying a given force is indicated by the distance from the center of the plot, which approximates the center of the wrist. The process is demonstrated using the info graphic below in **Figure 4.8**, with an example visualized in **Figure 4.9** below.



4.8. Example of 1D FSR data that retains spatial information.
Note. In the first image, the FMG band is shown laid out flat, with the FSRs indicated in red and blue. Red and blue color identifiers are used to visualize the relative position of each sensor in a 2D transverse radial plane in the third section. Finally, the last section shows how the instantaneous value of the FSR is mapped as a distance from the center of the figure.



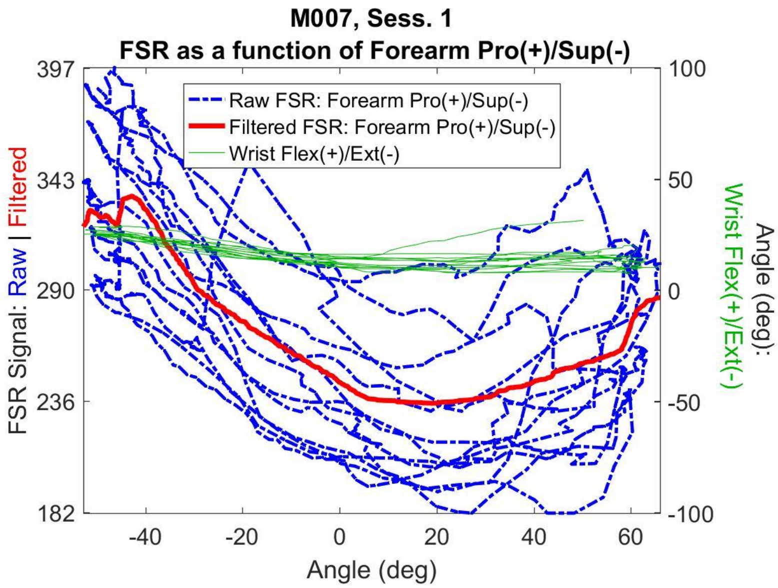
4.9. Example of 2D FSR data.

Note. This view is a trans-radial view of FSR activation (red) for wrist/forearm orientation. FSRs were approximately 1.25 cm apart (identified by the black solid and dotted lines radiating from the center to the perimeter of the plot). Grey/white delineations identify areas of FSR activation that were approximately 0% to 25%, 25% to 50%, 50% to 75%, and 75% to 100% of the wrist circumference. Only a single repetition is shown.

For 1D representations, in addition to considering raw data, data was normalized using the global maximum and minimum. This representation was trivial in the 2D representation as the relative distances/positioning between each FSR remain unchanged in the visual profile, and was not considered. Non-supervised feature extraction methods were considered to reduce the dimensionality of the data. In this work, singular value decomposition was used to perform principal value analysis on FMG data.

FMG Sensor Variability

The variability of an FMG reading was calculated for tasks that involved repetitive and continuous motions. An example of this is shown below in **Figure 4.10**.



4.10. Example of variability in a sensor through repetitive movements
Note. Shown above are the raw FSR readings (blue), the filtered signal (red). The readings pertain to forearm pronation/supination, so wrist flexion/extension is shown (green). The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination.

As can be seen in the above figure, throughout the same degree of motion of wrist flexion/extension, FMG demonstrated variable readings. The variability observed was quantified as the root mean square (RMS) residual between the digital FMG signal (shown in blue in **Figure 4.10**) and the filtered signal (shown in red).

Separability of gesture/orientation class clusters

A Separability Index was calculated to quantify the linear separateness of the class data clusters used in classification. Consider the following, where:

- ω_i, class label
- m_i, mean of class ω_i
- K_i, number of samples in class ω_i
- m, overall mean
- K, overall number of samples
- P_i, the *a priori* probability of class $\omega_i = {}^{K_i}/_{K}$
- S_i, scatter (covariance) matrix for class ω_i

- S_W, within class scatter matrix, $\sum_{i=1}^{nClasses} P_i\, S_i$
- S_B, between class scatter matrix, $\sum_{i=1}^{nClasses} P_i (m_i - m)\,(m_i - m)^T$

Then the Separability Index was calculated as:

$$J_{B/W} = trace(S_W^{-1} S_B)$$

Intuitively, the optimal separability is achieved by maximizing the between-class variance and minimizing the within-class variance, correlating to larger values of $J_{B/W}$. It is assumed that larger values of $J_{B/W}$ would correlate to better predictive capabilities.

Magnitude of Change and Derivative of FMG

Quantifying the magnitude of change and derivative of FMG was also utilized, however this was only applied to dynamic tasksn listed in **Table 4.3.** The following steps were taken to procress FMG in order to quantify the changes that occur in an FMG over a range of motion/effort. Let FMG be an n dimensional random vector, made up of samples X_i for i = 1,2,3….n and $X_i \in R^{16}$, the steps to determine the derivative were:

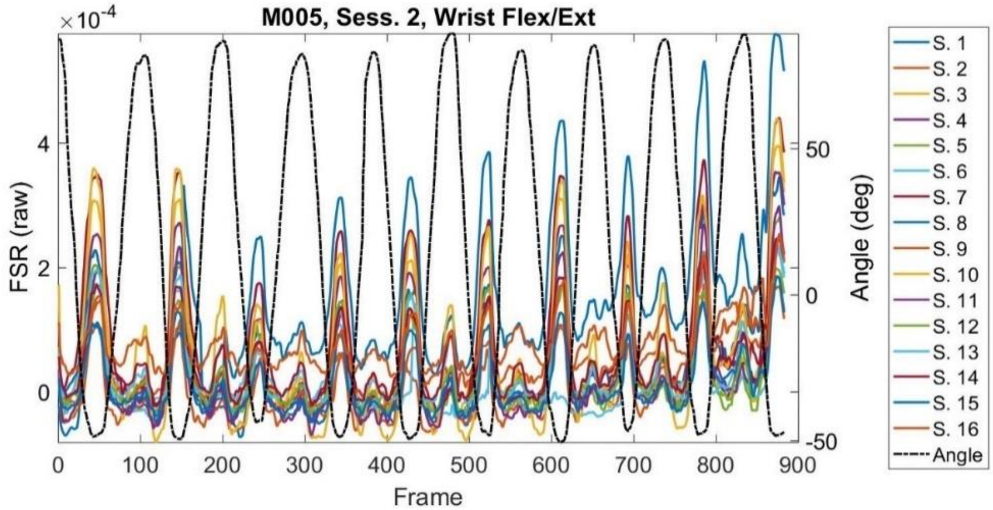
1. **Linearize data.** In a series circuit implementation of FSRs, the relationship between the applied force and resultant voltage was non-linear. An approximate linearization was was achieved by taking the elemental inverse of each X_i.
2. **Remove baseline signal.** Initial (linearized) sensor values taken during calibration were subtracted from the dynamic session.
3. **Sort.** FMG, $\{X_1, X_2, ... X_n\}$, was sorted based on the range of motion (degrees) of amount of effort (kg) at the time.
4. **Fliter.** To filter the sorted signal, a low pass 1st order Butterworth fulter with ah normalized cutoff freqeuncy of 0.01 was used.
5. **Calculate successive differences between X_i and X_{i-1}.**

$$diff_i = X_i - X_{i-1}, \text{ for I = 1,2,…n}$$

6. **Represent filtered magnitude $(X_{RMS,i})$ and successive differences $(diff_{RMS,i})$ of the filtered signal as an RMS over the dimensions of X_i.**

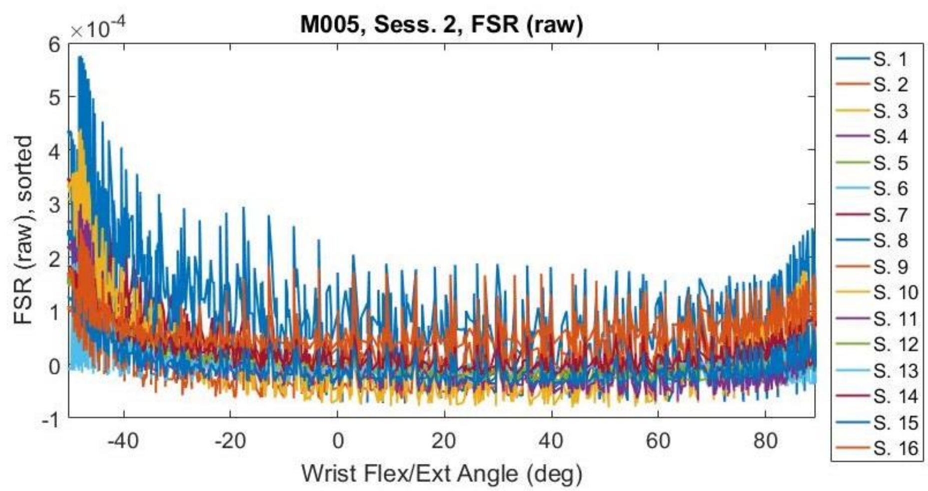
$$X_{RMS,i} = \sqrt{\sum_{j=1}^{16} X_{i,j}^2} \text{ and } diff_{RMS,i} = \sqrt{\sum_{j=1}^{16} diff_{i,j}^2}$$

This process is visually represented in **Figures 4.11** to **4.14** below. The resultant derivative, shown in **Figure 4.14**, was incoporated into further analysis.



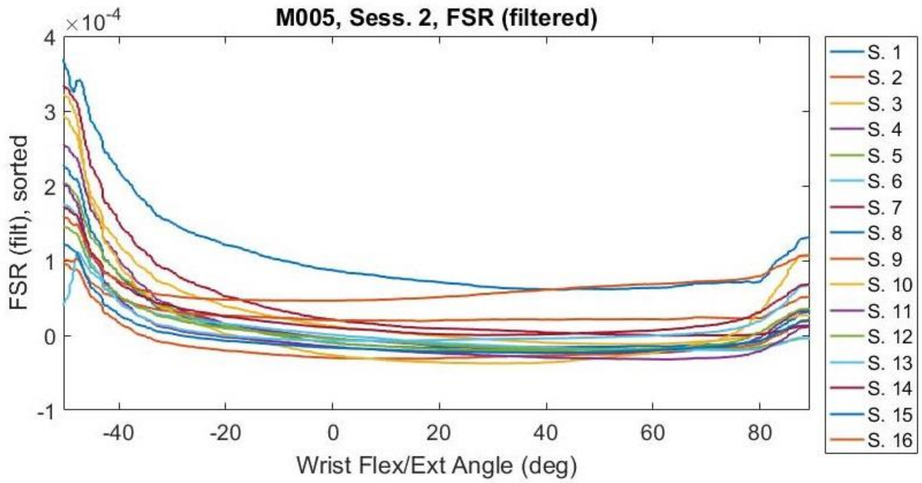
4.11. Example linearized FSR recording (coloured lines) during a dynamic task with corresponding joint position (black dotted line).

Note. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Only one trial is shown, with each FSR signal labelled as S. X, where X is a number from 1 to 16.



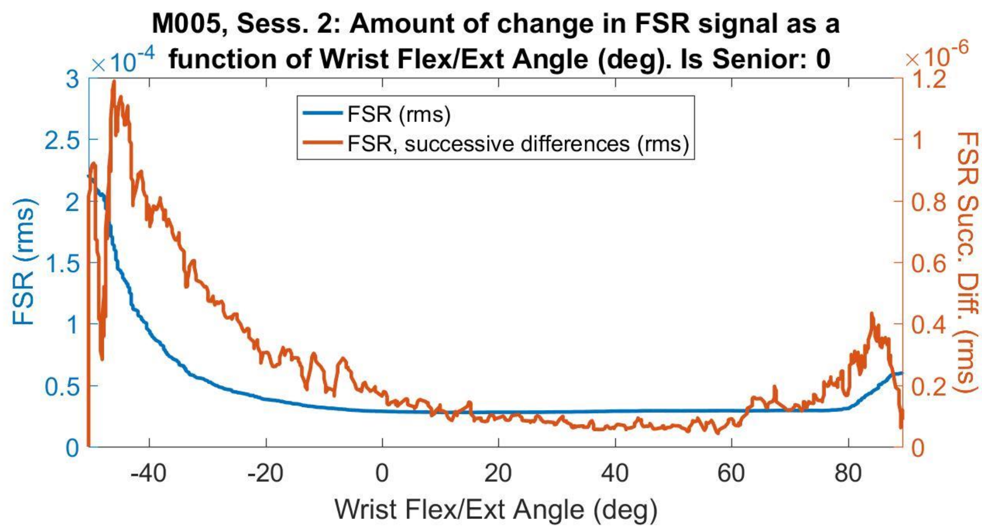
4.12. Example sorted linearized FMG signal.

Note. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Only one trial is shown.



4.13. Example filtered sorted linearized FMG signal.

Note. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Only one trial is shown.

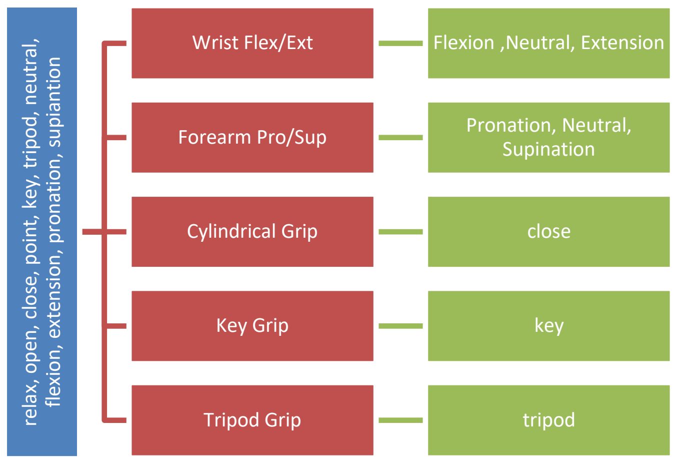


4.14. Example RMS of (linearized, sorted, filtered) FMG magnitude (blue) and FMG differential (orange) signal.

Note. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Only one trial is shown.

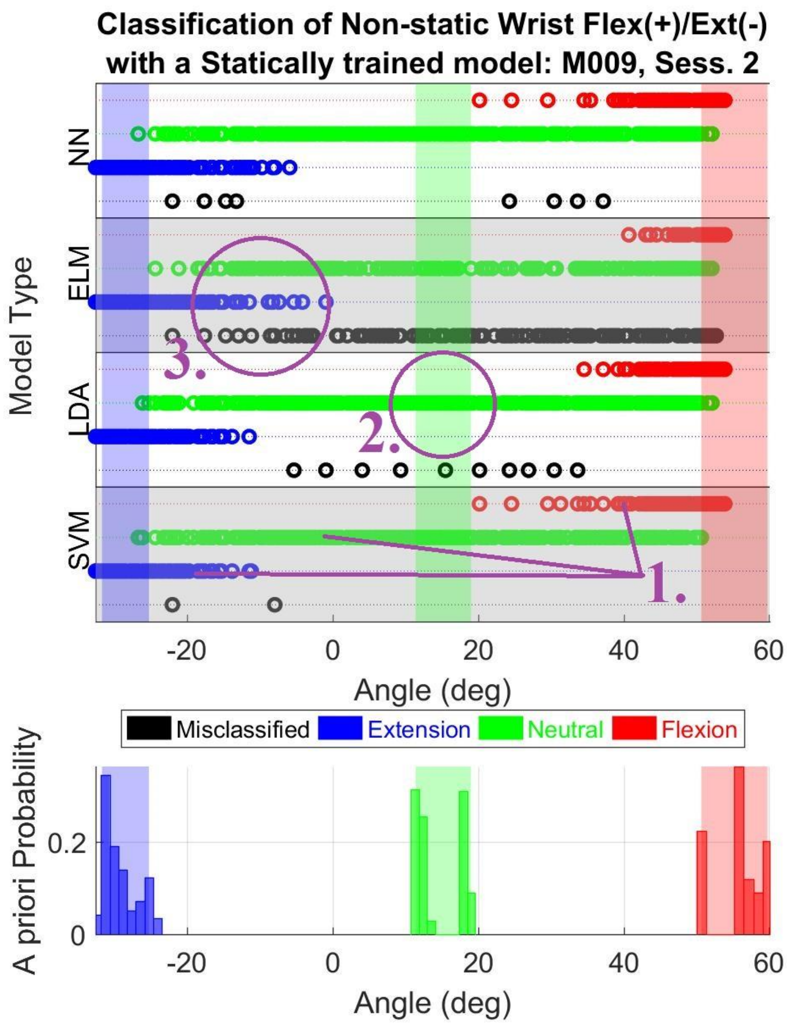
Characteristics of a statically trained model during non-static activity

The effectiveness of an FMG model (trained in static conditions) in non-static conditions was also considered. The method of processing for this analysis is shown below in **Figure 4.15.**



4.15. Schema for exploring gesture identification during non-static activity
Note. Shown above are (blue) the static gestures used to train models, (red) non-static tasks onto which models were applied, and (green) the expected classification outputs

As shown in **Figure 4.15**, models developed from static conditions using 11 standard gestures were implemented on non-static data from the dynamic tasks: wrist flexion/extension, forearm pronation/supination, cylindrical grip squeeze and release, key grip squeeze and release, and tripod squeeze and release. The expected output was based on the gestures of the task. For the example output shown below in **Figure 4.16**, there were three expected outputs for the Wrist Flexion/Extension task: flexion, neutral, and extension.



4.16. Example of (top) statically trained model performance on non-static degree of motion, and (bottom) degree of motion measured during statically held gestures

Note. The colored regions are (black) misclassified areas, (blue) wrist extension, (green) neutral wrist, and (red) wrist flexion. Circular markers indicate the output of the specific model type. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination.

Figure 4.16 above shows an example output of this process, highlighting 3 features used for further analysis:

- **Number of Clusters.** The number of clusters of classes identified during the task. The correct number of classes for wrist flexion/extension is three (3): extension, neutral, and flexion. For forearm pronation/supination is three (3): supination, neutral, and pronation. For cylindrical grip is one (1): close. For key grip, is one (1): key. For tripod grip is one (1): tripod. In the example shown in

Figure 4.16, three classes are identified for each of the model types during wrist flexion/extension.

- **Overlap with training region.** Whether of not the class cluster overlapped with the training region for that static class. In the example shown in **Figure 4.16**, each of the three expected class clusters (extension, neutral, and pronation) overlapped with the corresponding training region (shaded area).
- **Variability within class clusters.** In the example shown in **Figure 4.16**, for the ELM model, the degree of motion occupied by the 'Extension' class cluster is also occupied by 'Neutral' and 'Misclassified' class clusters. Thus, demonstrating a higher amount of variability than if that region was only occupied by the 'Extension' class cluster. This was expressed as a proportion of a class cluster that was correctly identified.

4.6.2. Analysis

In this, work, to illustrate the influence of user features on FMG modelling, several simple machine learning models were simultaneously generated from the FMG data. In this work, the choice of simple machine learning model types was motivated by those encountered in the literature, and include: Artificial Neural Network (ANN), Extreme Machine Learning (ELM), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM). While acknowledging the strengths and merits of each type of supervised method, the purpose of generating multiple types of models was to establish trends of FMG behaviour that were persistent despite model parameter selection and optimization.

Lastly, Student's t-Test, ANOVA, and Spearman's correlation coefficient (R), Coefficient of Determination (R^2) were used to evaluate the interaction between variables of interest. Significance tests were based on a significance level of $\alpha = 0.05$.

4.7. Internal and external validity

Validity is the criteria for how effective the design is in employing methods of measurement that will capture the data to address the research questions. There are two types of validity: internal and external validity. In a quantitative study, such as this, internal validity is the ability to determine cause and affect. On the other hand, external validity describes the extent to which the results of the study can reflect similar outcomes elsewhere, and can be generalized to other populations or situations.

Steps to maximize the external validity of this study involved recruiting both senior and non-senior males and females, with a range of anthropometric differences. In addition, participants from both SFU and community dwelling adults were recruited. Steps to maximize the internal validity of this study involved:

- Taking FMG and range of force/motion measures simultaneously
- Placing the band in the same position/orientation each time
- Direct observation of the participant during tasks, and correcting the gesture performed if incorrect
- Using the same protocol and instrumentation for each participant
- Restricting recruitment to self-identified healthy individuals so that pathological differences in musculoskeletal morphology would not be a factor

Chapter 5.

Factors that influence an FMG model: Results and Analysis

5.1. Chapter Overview

The motivations for this thesis are to explore the suitability of FMG as a potential tool for seniors aging in place. The results of the first study addressing **Objective 1**, demonstrated that seniors could successfully use an FMG based system, but with more variability and decreased accuracy. Further age-related characterization of FMG is required for long-term and practical implementation. This chapters continues the presentation of the study introduced in ***Chapter 4***, which seeks to address **Objectives 2 & 3** of this thesis. **Objectives 2 & 3** of this thesis seeks to reveal user dependent variability in FMG data, as well as to quantify the effect on FMG modelling. As discussed in **Chapter 2**, aging is associated with various physical and functional changes such as reduced strength, reduced muscle cross sectional area, and changing mechanical properties non-muscle tissue. It is believed that these changes are related to variability in FMG acquisition, and indirectly influence machine learning testing accuracy. This chapter begins with an overview of non-FMG related participant statistics in ***Section 5.2***, including comparisons with general populations norms for the values presented. Next, in ***Section 5.3***, is an overview of the influence of intrinsic participant variables on the effectiveness of FMG processing. This chapter concludes with a chapter summary in ***Section 5.5***.

5.2. Descriptive Statistics: Non-FMG variables

There were 21 participants recruited overall for this study. **Tables 5.1** to **5.9** summarize the age group and gender specific data related to: participant demographics, anthropometric measures, band tightness, grip strength, and online and offline range-of-motion. The purpose of this section is to convey how representative the recruitment pool was, and to allow for further discussion of where restricted sampling may or may not have influenced the statistical significance of the relationships observed. Where present, significant differences between groups or variations from national/literature norms are noted and elaborated upon further.

5.1. Demographics

	Non-senior		Senior	
	Female	Male	Female	Male
Number	6	9	4	2
Age (years)	26.25 (2.44)	27.11 (3.55)	74.75 (5.44)	64.50 (4.95)
Weight (kg)	65.40 (14.71)	87.11 (9.25)	74.50 (15.51)	82.41 (3.41)
Canadian Averages for Weight (kg) [225]	70.94 (45.55, 112.14)	87.06 (61.96, 126.79)	71.82 (51.47, 98.24)	85.15 (61.49, 107.07)
Height (m)	1.61 (0.04)	1.83 (0.08)	1.59 (0.07)	1.65 (0.07)
Canadian Averages for Height (m) [225]	1.63 (1.55, 1.73)	1.78 (1.68, 1.87)	1.59 (1.49, 1.71)	1.73 (1.61, 1.85)
BMI (kg/m^2)	25.01 (4.74)	26.12 (3.17)	29.31 (5.57)	30.30 (1.34)
Canadian Averages for BMI (kg/m^2) [225]	26.57 (18.72, 40.05)	27.37 (20.26,39.42)	28.12 (20.56, 37.60)	28.39 (21.82, 35.98)

Note. Values (for age, weight, height, BMI) are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation. Canadian national averages (for weight, height, and BMI) are presented as 50th percentile (5th percentile, 95th percentile).

5.2. Anthropometric Measures (cm)

	Non-Senior		Senior	
	Female	Male	Female	Male
Wrist Circumference (cm)	15.92 (1.88)	17.72 (0.97)	16.88 (1.80)	19.25 (0.35)
Recommended American design norms for Wrist Circumference (cm) [226]	15.5 (14.5, 16.3)	16.8 (15.5, 18.5)	See Note.	See Note
Forearm Circumference (cm)	24.33 (2.82)	27.50 (3.82)	25.00 (1.78)	27.25 (0.35)
Recommended American design norms for Forearm Circumference (cm) [226]	26.3 (24.4, 27.7)	29.2 (26.7, 32)	See Note.	See Note
Forearm Length	25.17 (1.57)	27.89 (1.54)	25.63 (1.80)	28.50 (0.71)
Recommended American design norms for Forearm Length (cm) [226]	23.4 (21.8, 25.4)	25.4 (23.4, 26.9)	See Note.	See Note

Skinfold Thickness (cm)	0.99 (0.23)	0.66 (0.25)	1.25 (0.51)	1.30 (0.42)
Ratio: Skinfold Thickness to Forearm Circumference (unitless)	0.04 (0.01)	0.02 (0.01)	0.05 (0.02)	0.05 (0.02)
Ratio: Wrist Circumference to Forearm Circumference (unitless)	0.65 (0.04)	0.66 (0.10)	0.68 (0.05)	0.71 (0.02)

Note. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation. American national reference norms (for wrist circumference, forearm circumference, and forearm length) are presented as 50th percentile (2.5th percentile, 97.5th percentile) for non-seniors only.

All measurements were performed on the right side, and all participants were right hand dominant – with the exception of 3 left-hand dominant participants (2 senior females, and 1 non-senior male). The measurements for wrist circumference, forearm circumference, and forearm length (shown above in **Table 5.2**) fall within in the 2.5th and 97.5th percentiles of age and gender matched norms [226].

For forearm skinfold thickness, up to date age and gender group data is limited. However, based on a study utilizing forearm skinfold thickness, the mean (standard deviation) for women aged 40 to 64 years is 0.84 (3.4) cm to .9 (3.8) cm, and for men aged 40 to 64 years is 0.58 (0.2) to 0.6 (.23) cm [227]. Seniors were expected to demonstrate increased fat distribution compared to non-senior groups [6] as well as increased skin compressibility [10], [11]. However, the forearm is not a skinfold site traditionally shown to have high correlations with obesity measurements and was not expected to yield significant differences in such a small sample size.

For the samples obtained, ANOVA showed significant (p = 0.0001, 0.0148, 0) gender associated differences in wrist circumference, forearm circumference, and forearm length. In contrast, skinfold thickness demonstrated a significant (p = 0.0002) age-associated difference, with larger skin fold thickness measurements occurring with seniors. Finally, the ratio of skinfold thickness to forearm circumference, related to the amount of muscle vs. muscle-free tissue, demonstrated both a significant age (p = 0.0002) and gender (p = 0.0244) based difference.

5.3. FMG Band Tightness (mmHg)

	Non-Senior		Senior	
	Female	**Male**	**Female**	**Male**
Band Tightness	24.79 (5.74)	26.12 (5.50)	13.18 (5.78)	17.89 (1.83)
Difference in Band Tightness between Session 1 & 2	5.55 (2.42)	3.88 (3.31)	5.18 (5.16)	3.16 (0.26)

Note. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

Band tightness, as tabulated above in **Table 5.3** above, has never been considered in FMG research before, and as such, there are no norms for comparison. However, it is of note that the skin surface pressure observed is within range of that observed in commercially available light to moderate compression socks [219], which would feel tighter than an everyday athletic sock. Attempts were made to maintain the positioning and tightness of the FMG band across sessions, however there was a significant difference in band tightness ($p < 0.01$) between sessions 1 & 2 across subjects. As seen from the table above, the band tightness for seniors was lower ($p = 0.000$), but did not demonstrate any relationship to gender ($p = 0.5434$). The FMG band was adjusted for comfort, but it was the indentation in the skin caused by tightening the band and the number of initially activated sensors served as an indication of sufficient tightness for testing. However, despite these qualitative criteria, seniors demonstrated lower band tightness no matter how tightly the band was donned. This is attributed to age-associated changes in the mechanical properties of the skin and underlying tissues. Other qualitative observations made during measurements that support this were that the skin of seniors was less firm and more compressible upon taking skinfold measurements.

5.4. Offline Grip Strength (kg, % of max)

	Non-Senior		Senior	
	Female	**Male**	**Female**	**Male**
Maximum Grip Strength (kg)	16.11 (4.43)	29.83 (7.55)	10.54 (2.72)	20.24 (4.45)
Canadian Averages for Maximum Grip Strength [228] (kg)	27.65 (21.25, 34.78)	45.725 (34.775, 57.58)	23.65 (16.075, 29.75)	39.08 (26.6, 50.03)
Grip Strength after Session 1 (% of Max)	96.68 (23.11)	88.46 (10.53)	102.23 (27.96)	96.15 (8.32)

Grip Strength after Session 2 (% of Max)	74.32 (20.93)	92.62 (26.19)	106.26 (28.38)	100.01 (5.09)

Note. Offline refers to measurements taken while the FMG band was not donned. The grip used for this measure was a cylindrical grip. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation. Canadian national averages (for maximum grip strength) are presented as 50th percentile (5th percentile, 95th percentile).

From the grip strengths tabulated above in **Table 5.4**, males demonstrate larger grip strength values than females ($p = 0.0005$), both of which appear to decline with age ($p = 0$). Although, this trend is shared by both the reference data AND the experimental data, the grip strengths of the recruitment pool is markedly lower (less than the 5th percentile) than that of age and gender matched national averages. This is attributed to the difference in instrumentation. In this study, a non-deformable hand dynamometer was utilized, however, the protocol conducted by the Canadian Health Measures Survey used a deformable hand dynamometer (Smedley III handgrip dynamometer). An additional explanation for the lower grip strengths is that the shape of the hand dynamometer used does not allow for customizable or optimal hand/finger joint angles in maximum grip strength testing. Fine finger motions have been shown to result in discernable differences in FMG patterns [97]. A non-deformable hand dynamometer was utilized to create a more stable signal and so that any variability in FMG could be attributed to variations in grip strength, as opposed to variable grip strength AND variable finger joint position. Unfortunately, there is no normative data available for grip strength tests performed with the Vernier Hand Dynamometer (model HD-BTA).

Also tabulated above in **Table 5.4**, are the reductions that occurred in maximum grip strength that occurred after completing the protocol. Fatigue is defined as achieving less than 50% of maximum voluntary grip strength [6]. Although, none of the participants demonstrated textbook fatigue after the protocol, there was a marked decline in maximum voluntary grip strength, particularly for female participants. Seniors did not show this same decline; however, this is attributed to seniors being provided an abridged version of the protocol. **Table 5.5** below provides an overview of online grip strengths for three different types of grasps (cylinder grip, key grip, and tripod grip) achieved whilst wearing the FMG band.

5.5. Online Grip Strength (kg, % of max)

		Female		Male	
		kg	%	kg	%
Non-senior	Grip	14.01 (3.87)	87.19 (7.12)	18.91 (7.68)	63.65 (21.00)
	Key	6.28 (0.67)	40.72 (8.62)	7.47 (2.14)	26.57 (10.44)
	Tripod	4.38 (0.62)	28.68 (7.98)	5.87 (2.19)	20.57 (8.26)
Senior	Grip	10.66 (2.27)	104.66 (25.62)	13.01 (5.00)	63.06 (10.82)
	Key	4.72 (0.47)	46.86 (11.61)	9.85 (1.01)	49.29 (5.85)
	Tripod	3.86 (0.83)	38.93 (15.55)	7.64 (1.06)	38.08 (3.15)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for the absolute grip strength reading (kg) as well as a percentage of the maximum grip strength (%) recorded offline. 'Grip', 'key', and 'tripod' refer to the participant using a cylindrical grip, a lateral pinch grip, or a pinch grip to squeeze the dynamometer. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

5.6. Offline Active Range of Motion (degrees)

	Non-Senior		Senior	
	Female	Male	Female	Male
Wrist Flexion	75.83 (11.69)	64.89 (15.03)	58.25 (12.61)	70.00 (7.07)
Population Norms for Wrist Flexion [173], [229]	72.4 (55.46, 101.53)	67.4 (54.40, 97.40)	59.30 (36.93, 74.35)	56.9 (38.67, 74.73)
Wrist Extension	-70.83 (-.70)	-66.89 (8.22)	-58.50 (7.51)	56.00 (15.56)
Population Norms for Wrist Extension [173], [226]	-79.1 (-116.81, -66.27)	-72.8 (-105.25,-58.82)	-49.72 (-55.82, -24.67)	-43.3 (-55.93, -28.53)
Forearm Pronation	91.17 (13.79)	88.44 (5.15)	93.00 (5.60)	86.00 (1.41)
Population Norms for Forearm Pronation [230]	82 (72.46, 125)	76.9 (65.39,114.56)	80.8 (70.44,122.17)	77.7 (67.83, 117.58)
Forearm Supination	-98.33 (6.89)	-98.22 (13.20)	-93.50 (6.03)	95.50 (10.61)
Population Norms for Forearm Supination [230]	-90.6 (-134.54, -76.62)	-85 (-128.57, -74.14)	-87.2 (-131.67, -75.65)	-82.4 (-122.75, -70.06)
Wrist (full range)	146.67 (10.76)	131.78 (20.41)	116.75 (15.11)	126.00 (8.49)
Forearm (full range)	189.50 (18.88)	186.67 (13.46)	186.50 (7.72)	181.50 (9.19)

Note. Offline refers to measurements taken while the FMG band was not donned. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation. Population norms for forearm pronation/supination are presented as 50th percentile (5th percentile, 95th percentile).

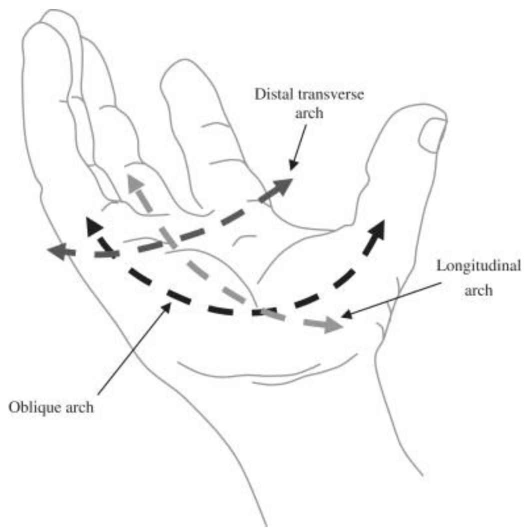
There are no remarkable differences between measured values and those reported for age and gender matched data for wrist and forearm range of motion. It is noteworthy, that the data of recruited participants demonstrates similar age related declines in wrist flexion/extension angle as the predicted in the literature ($p < 0.1$). **Table 5.7** below provides an overview of the maximum range-of-motion achieved during online testing.

5.7. Online range-of-motion (ROM) across all tasks

		Female		Male	
		degrees	%	degrees	%
Non-Senior	Wrist Flexion	96.00 (12.68)	129.85 (29.13)	72.49 (11.16)	118.67 (41.01)
	Wrist Extension	-55.42 (5.90)	-79.39 (12.58)	-55.40 (11.95)	-83.31 (16.74)
	Forearm Pronation	59.68 (22.74)	65.22 (23.42)	70.00 (13.80)	78.87 (12.63)
	Forearm Supination	-64.62 (5.66)	-65.87 (6.26)	-67.84 (13.37)	-69.36 (12.74)
	Wrist Full Range	151.42 (10.80)	104.00 (13.63)	127.90 (16.62)	98.66 (17.76)
	Forearm Full Range	124.30 (20.02)	65.92 (11.47)	137.84 (18.65)	74.03 (10.15)
Senior	Wrist Flexion	86.79 (10.36)	158.60 (60.99)	89.21 (13.05)	129.04 (31.68)
	Wrist Extension	-54.93 (4.59)	-95.76 (19.65)	-51.12 (9.32)	-97.36 (43.69)
	Forearm Pronation	82.21 (14.18)	89.10 (19.08)	72.51 (10.69)	84.43 (13.82)
	Forearm Supination	-60.20 (14.15)	-65.18 (19.14)	-56.83 (23.84)	-61.27 (31.76)
	Wrist Full Range	141.72 (14.66)	124.36 (30.81)	140.33 (3.73)	111.53 (4.55)
	Forearm Full Range	142.41 (16.14)	76.67 (11.03)	129.34 (13.15)	71.54 (10.87)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for absolute range of movements (degrees) as well as a percentage of the maximum ROM (%) recorded offline. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

From the **Table 5.7** above, it appears that the participants frequently went beyond the full range of wrist flexion, achieving 119% to 158% of full wrist flexion during online testing. However, because the full range of wrist flexion/extension remained approximately to 100% (relatively), this appears to be a systematic error between the offline and online methods of method measuring wrist flexion/extension angle. This could be attributed to the location of the measurements. Offline, wrist flexion and extension was measured as the smallest angle between radius and 3rd metacarpal (ring finger). However, during online measurements, placement of the moving arm of the rotary potentiometer was placed on the 5th metacarpal. Thus, flexion of the distal transverse arch (shown below in **Figure 5.1**) while completing hand gesture or wrist/forearm movements would contribute to a systematic difference between the two modes. With the location of the moving arm of the rotary potentiometer, that radial and ulnar deviation motions of the wrist also contributed to the systematic measurement error. Despite this, it is believed that the relative differences in wrist flexion/extension within-subjects and between-age/gender groups, and its influence on FMG, would still be informative as the error would be systematic across all participants.



5.1. Arches of the hand.
Note. Image reproduced from [231]

Shown below in **Table 5.8** is additional information regarding actual wrist flexion/extension and forearm pronation/supination angles measured when the participant was instructed to performed movements that required wrist flexion/extension or forearm pronation/supination. Finally, as wrist flexion/extension and forearm pronation/supination are not mutually exclusive movements, the degree of interaction between these two groups were also considered and tabulated below in **Table 5.9**.

5.8. True online wrist position (degrees of flexion/extension) and forearm position (degrees of pronation/supination) when participants were instructed to actively flex/extend their wrist OR pronate/supinate their forearm

		Female		Male	
		degrees	%	degrees	%
Non-senio	Wrist Flexion	82.21 (11.12)	111.71 (28.37)	55.01 (10.36)	91.40 (38.01)
	Wrist Extension	-39.62 (10.25)	-55.70 (12.54)	-39.09 (10.11)	-58.74 (14.54)

	Forearm Pronation	39.35 (23.74)	42.10 (25.19)	43.56 (7.77)	49.27 (8.56)
	Forearm Supination	-54.48 (4.56)	-55.49 (4.21)	-53.66 (12.82)	-54.91 (12.83)
Senior	Wrist Flexion	66.19 (8.82)	120.05 (41.82)	63.94 (4.34)	92.13 (15.51)
	Wrist Extension	-39.37 (5.13)	-68.31 (14.23)	-30.38 (8.82)	-58.70 (32.07)
	Forearm Pronation	53.52 (11.25)	58.13 (15.29)	50.89 (22.16)	59.39 (26.74)
	Forearm Supination	-42.92 (4.63)	-46.15 (6.85)	-43.14 (28.67)	-47.13 (35.26)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for absolute range of movements (degrees) as well as a percentage of the maximum ROM (%) recorded offline. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

5.9. Degree of online isolation between each individual wrist motion (flexion/extension) and forearm orientation (pronation/supination)

		Female		Male	
		degrees	**%**	**degrees**	**%**
Non-Senior	During Pronation, Angle of the Wrist	13.38 (9.92)	19.41 (15.60)	7.32 (10.82)	13.69 (20.73)
	During Supination, Angle of the Wrist	21.78 (8.19)	30.42 (14.93)	4.59 (12.88)	10.72 (24.29)
	During Flexion, Angle of the Forearm	-10.73 (5.87)	-10.97 (6.14)	-13.49 (6.49)	-13.71 (6.23)
	During Extension, Angle of the Forearm	-5.96 (4.66)	-6.11 (4.74)	-6.71 (4.32)	-6.81 (4.48)
Senior	During Pronation, Angle of the Wrist	12.70 (4.61)	23.82 (13.95)	2.18 (21.19)	-1.02 (38.79)
	During Supination, Angle of the Wrist	10.02 (14.83)	21.06 (30.72)	5.64 (10.22)	8.14 (16.49)
	During Flexion, Angle of the Forearm	-7.85 (4.06)	-8.38 (4.40)	-17.12 (6.09)	-18.39 (8.41)
	During Extension, Angle of the Forearm	-4.83 (2.56)	-5.16 (2.82)	-1.83 (1.73)	-2.03 (2.03)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for absolute range of movements (degrees) as well as a percentage of the maximum ROM (%) recorded offline. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

The results in **Table 5.9** suggest a frequent coupling between wrist flexion and forearm supination when completing the required gestures. Finally, online wrist and forearm orientation was tabulated below in **Tables 5.10** and **5.11** to provide an indication of true wrist and forearm angle when the participant was instructed to hold a neutral wrist and forearm.

5.10. True online wrist position (degrees of flexion/extension) while participants were instructed to hold a neutral wrist

			Female		Male	
			degrees	%	degrees	%
Non-Senior	Overall		13.04 (7.12)	18.59 (11.58)	2.70 (9.15)	6.16 (16.77)
	Gesture Specific	relax	5.84 (6.40)	8.03 (9.18)	2.14 (8.55)	4.63 (15.15)
		open	20.58 (10.24)	29.27 (18.87)	3.03 (9.22)	6.34 (16.25)
		close	15.99 (7.43)	22.28 (11.54)	6.48 (8.77)	12.24 (16.70)
		point	16.74 (7.66)	23.75 (13.73)	1.41 (11.11)	4.89 (19.89)
		key	10.70 (14.57)	15.54 (21.53)	1.93 (10.47)	5.07 (18.21)
		tripod	9.40 (8.62)	12.82 (12.36)	4.71 (11.30)	9.38 (21.64)
		straight	11.13 (7.65)	16.29 (12.98)	-0.89 (10.13)	0.50 (16.90)
Senior	Overall		3.83 (4.86)	8.31 (11.51)	-2.06 (13.44)	-7.12 (26.27)
	Gesture Specific	relax	4.75 (2.74)	9.40 (8.25)	-9.19 (11.83)	-20.13 (26.72)
		open	23.36 (4.38)	42.17 (13.90)	2.81 (13.85)	1.93 (24.69)
		close	4.39 (6.19)	7.80 (11.41)	9.39 (11.57)	14.33 (17.98)
		point	0.98 (9.83)	1.91 (17.21)	-6.43 (21.65)	-17.32 (43.81)
		key	-6.08 (11.86)	-9.31 (25.58)	0.07 (14.41)	-3.34 (27.05)
		tripod	-10.43 (4.40)	-17.31 (5.34)	-4.48 (8.74)	-10.54 (18.61)
		straight	9.47 (13.75)	20.13 (29.88)	-6.98 (11.84)	-15.99 (25.63)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for absolute range of movements (degrees) as well as a percentage of the maximum ROM (%) recorded offline. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

5.11. True online forearm position (degrees of pronation/supination) while participants were instructed to hold a neutral forearm

			Female		Male	
			degrees	%	degrees	%
Non-Senior	Overall		-4.70 (4.73)	-4.73 (4.71)	-4.20 (2.79)	-4.30 (2.88)
	Gesture Specific	relax	-5.52 (3.69)	-5.59 (3.67)	-4.04 (2.30)	-4.15 (2.36)
		open	-3.90 (5.37)	-3.94 (5.36)	-1.86 (3.89)	-1.81 (3.92)
		close	-3.40 (4.63)	-3.44 (4.61)	-4.08 (3.42)	-4.16 (3.61)
		point	-4.61 (6.17)	-4.60 (6.26)	-4.43 (4.10)	-4.51 (4.29)
		key	-6.87 (5.18)	-6.86 (5.02)	-5.37 (2.86)	-5.46 (2.80)
		tripod	-4.64 (5.84)	-4.71 (5.96)	-6.61 (3.85)	-6.76 (4.05)
		straight	-3.34 (4.23)	-3.25 (4.20)	-2.89 (2.63)	-2.97 (2.82)
Senior	Overall		-2.42 (2.85)	-2.68 (3.30)	-4.16 (10.79)	-4.66 (12.36)
	Gesture Specific	relax	-3.94 (1.77)	-4.29 (2.19)	-6.61 (11.39)	-7.49 (12.99)
		open	0.34 (4.22)	0.43 (4.72)	-1.65 (6.36)	-1.82 (7.30)
		close	-4.45 (4.77)	-4.93 (5.56)	-1.73 (10.85)	-1.85 (12.50)
		point	0.37 (1.92)	0.46 (2.23)	-1.46 (11.99)	-1.52 (13.83)
		key	-7.03 (6.93)	-7.89 (8.04)	-8.24 (13.78)	-9.33 (15.71)
		tripod	-0.46 (1.26)	-0.44 (1.28)	-5.84 (16.95)	-6.52 (19.44)
		straight	-1.56 (3.14)	-1.74 (3.64)	-3.66 (4.33)	-4.10 (4.99)

Note. Online refers to measurements taken while the FMG band was donned. Shown are age and gender divided data for absolute range of movements (degrees) as well as a percentage of the maximum ROM (%) recorded offline. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination. Values are presented as μ (σ^2), where μ is the mean and σ^2 is the standard deviation.

Initial observations of the data presented in **Tables 5.10** and **5.11** demonstrate that during online use, the repetition of a movement is quite variable, and that defining neutral as 0 degrees is not a true reflection of the functional range for gesture identification. For evaluating online data, defining a range of values for identification of a ‘neutral’ would be more practical.

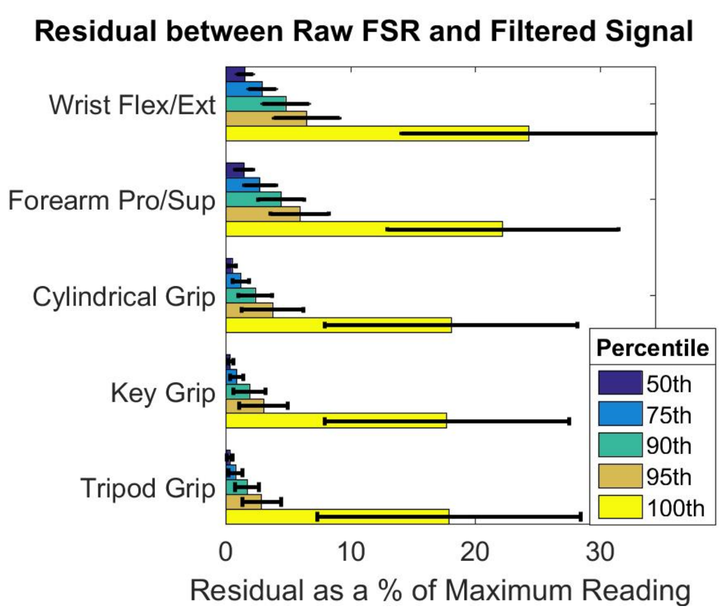
5.3. Variables influencing FMG

Objectives 2 and **3** of this thesis are to identify intrinsic user features that contribute to variability in FMG acquisition and modelling. Five features of FMG processing and analysis were considered to illustrate the affect of user variability. The selection of these features was motivated in part by the limitations in FMG research presented by the literature review in ***Chapter 2***, as well as, practical considerations for day-to-day use of FMG in the community. These features discussed in this section are:

- variability of FMG sensors throughout non-static repetitive motions, addressed in ***Section 5.3.1***
- magnitude of FMG response to incremental activity, addressed in ***Section 5.3.2***
- presence of compound movements/actions, addressed in ***Section 5.3.3***
- effect of non-static conditions on the performance of statically trained models, addressed in ***Section 5.3.4***
- effect of FMG band removal, addressed in ***Section 5.3.5***

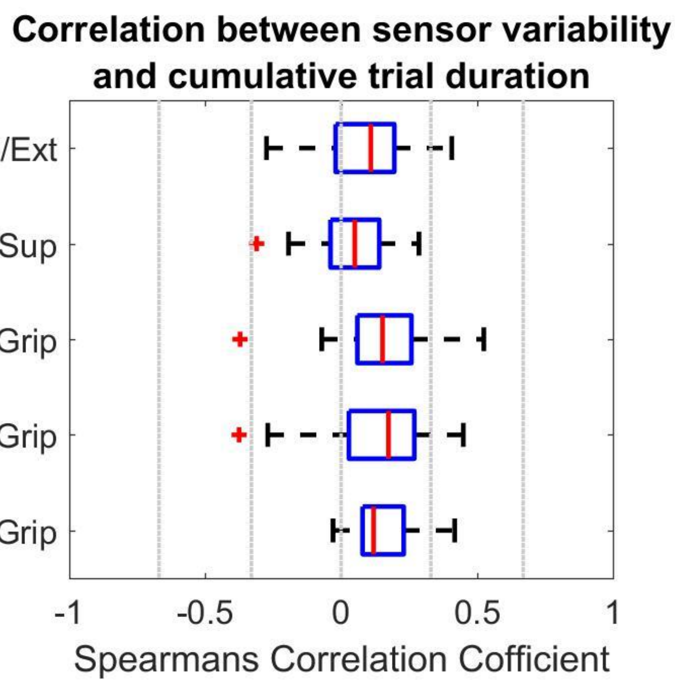
5.3.1. FMG variability during non-static and repetitive activity

There were 5 dynamic tasks used in this section: wrist flexion/extension, forearm pronation/supination, cylindrical grip, key grip, and tripod grip. Variability was quantified using the method described in ***Section 4.6.1***. The root mean square (RMS) residuals across all subjects for these dynamic tasks are summarized in **Figure 5.2** below.



5.2. Bar graph of RMS Residual (50th, 75th, 90th, 95th, 100th) expressed as a percentage of the maximum reading for dynamic tasks

From **Figure 5.2** above, approximately 95% of residuals calculated only represent between 2.85% to 6.47% of the range of readings. It is surmised that sources for this variability include: 1) Relaxation of the skin around the FMG sensor, 2) Variations in joint angle during movement, 3) underlying musculoskeletal structure. Firstly, regarding the role of skin relaxing around the FMG sensors, there was low (|R| < 0.3) correlation between residual magnitude and ongoing trial duration. These results are summarized below in **Figure 5.3**. Secondly, regarding variations in joints angles during movement, the wrist and forearm were considered. For example, during the Wrist Flexion/Extension task, participants were instructed to keep a neutral forearm. Deviation from this instruction could contribute to variability in the signal. Unfortunately, no data is available for intrinsic hand joint angles. However, as tabulated in **Table 5.12**, the wrist and forearm angle were stable through dynamic tasks, with standard deviations ranging from 2° and 5°. Finally, regarding the role of underlying musculature in signal variability, there are only low correlations (|R| < 0.3) between sensor variability and anthropometric variables. These results are summarized in **Figure 5.4**, with significant correlations tabulated in **Table 5.13**.

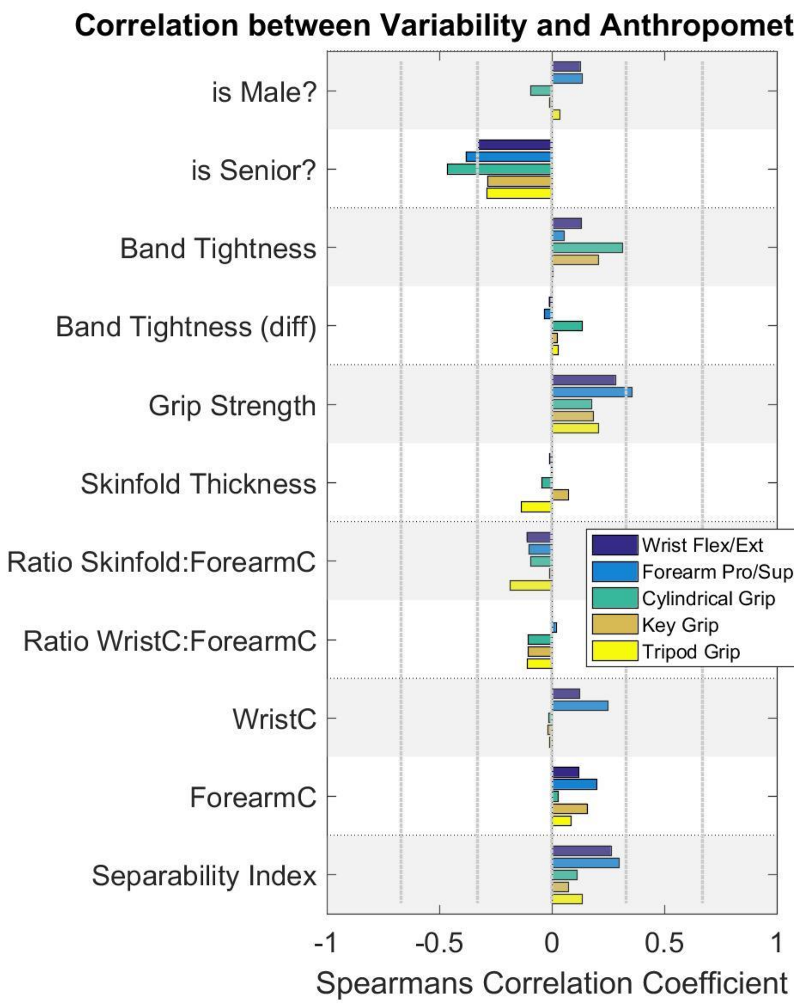


5.3. Boxplot of correlations between sensor residual and ongoing trial duration
Note. Vertical grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 < |R|).

5.12. Mean standard deviation of Wrist and Forearm angles (degrees) during dynamic tasks

		Task				
		Dynamic Wrist Flex/Ext	Dynamic Forearm Pro/Sup	Cylindrical, squeeze & relax	Key, squeeze & relax	Tripod, squeeze & relax
Joint	Wrist Flex/Ext	--	4.95 (1.81)	3.00 (0.89)	3.14 (1.92)	3.16 (1.51)
	Forearm Pro/Sup	4.22 (2.02)	--	2.46 (0.94)	2.06 (0.88)	2.47 (1.42)

Note. Values are presented as μ (σ2), where μ is the mean and σ2 is the standard deviation.



5.4. Bar graph of correlations between FMG variability and anthropometry

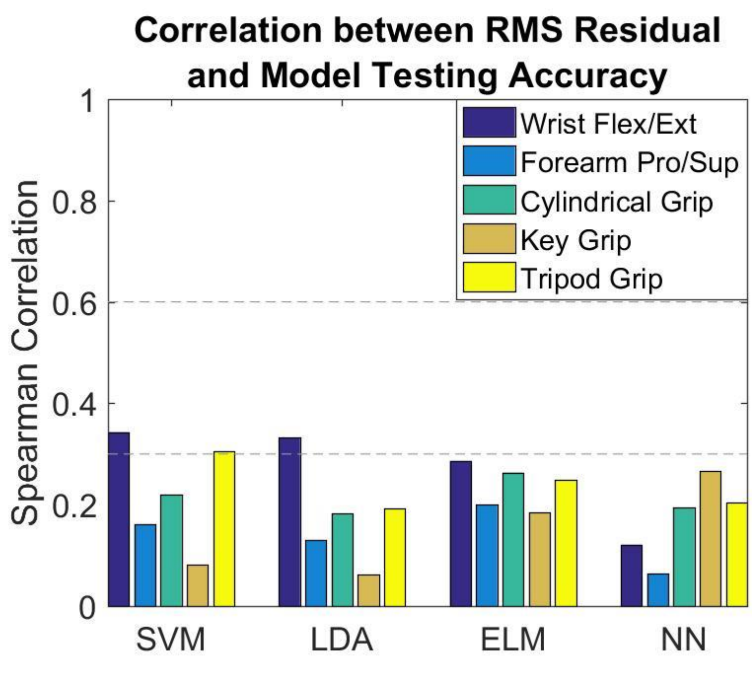
Note. Vertical grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 ≤ |R|).

5.13. p-values of Correlations between anthropometry and task specific signal variability which were significant

Anthropometry	Task	p-value
Is Senior?	Wrist Flex/Ext	0.037
Is Senior?	Forearm Pro/Sup	0.012
Is Senior?	Cylindrical Grip	0.002
Band Tightness	Cylindrical Grip	0.045
Grip Strength	Forearm Pro/Sup	0.0211

Although, generally there was only low and insignificant correlations (|R| < 0.3) between FMG variability and user properties, **Figure 5.4** above indicates the strongest relationship between FMG variability and age.

Finally, as shown in **Figure 5.2**, mean RMS residual represented less than 1% of the range of FSR values. Not only were mean RMS residuals small in range, but they also demonstrated a low relationship to model testing accuracy as shown below in **Figure 5.5**. Unfortunately, these correlations were not significant (as p > 0.05).

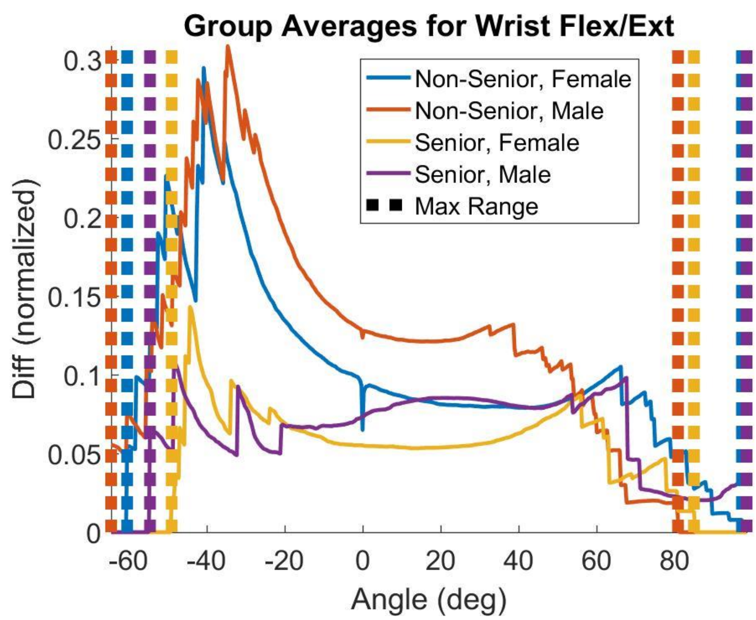


5.5. Summary of correlations between mean RMS residual and testing accuracy
Note. Horizontal grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 ≤ |R|).

What these results demonstrate is that FMG stable throughout repetitive dynamic motions, as well as static conditions which was shown in [79].

5.3.2. Responsiveness of FMG

The dynamic tasks involved in this study incorporated gross wrist and forearm movements (wrist flexion, wrist extension, forearm pronation, and forearm supination), gross hand gestures (cylindrical grip), fine finger movements (tripod grip) and isolated thumb actions (key grip). Sensitivity of FMG to changes during each task was calculated as per the method described in ***Section 4.6.1***. In this context, sensitivity serves as a measure of responsiveness of FMG to incremental changes in range of motion or effort expended. Participants were also grouped and averaged based on age and gender, and an example summary of the results for Wrist Flexion/Extension is presented below in **Figure 5.6**.



5.6. Example normalized derivative FMG throughout range of wrist flexion/extension.

Note. Data has been separated into non-senior females (blue), non-senior males (orange), senior females (yellow), and senior males (purple). The dotted lines show the minimum and maximum ranges for each respective group. The convention used in this work use positive (+) values for Wrist Flexion and Forearm Pronation, while using (-) values for Wrist Extension and Forearm Supination.

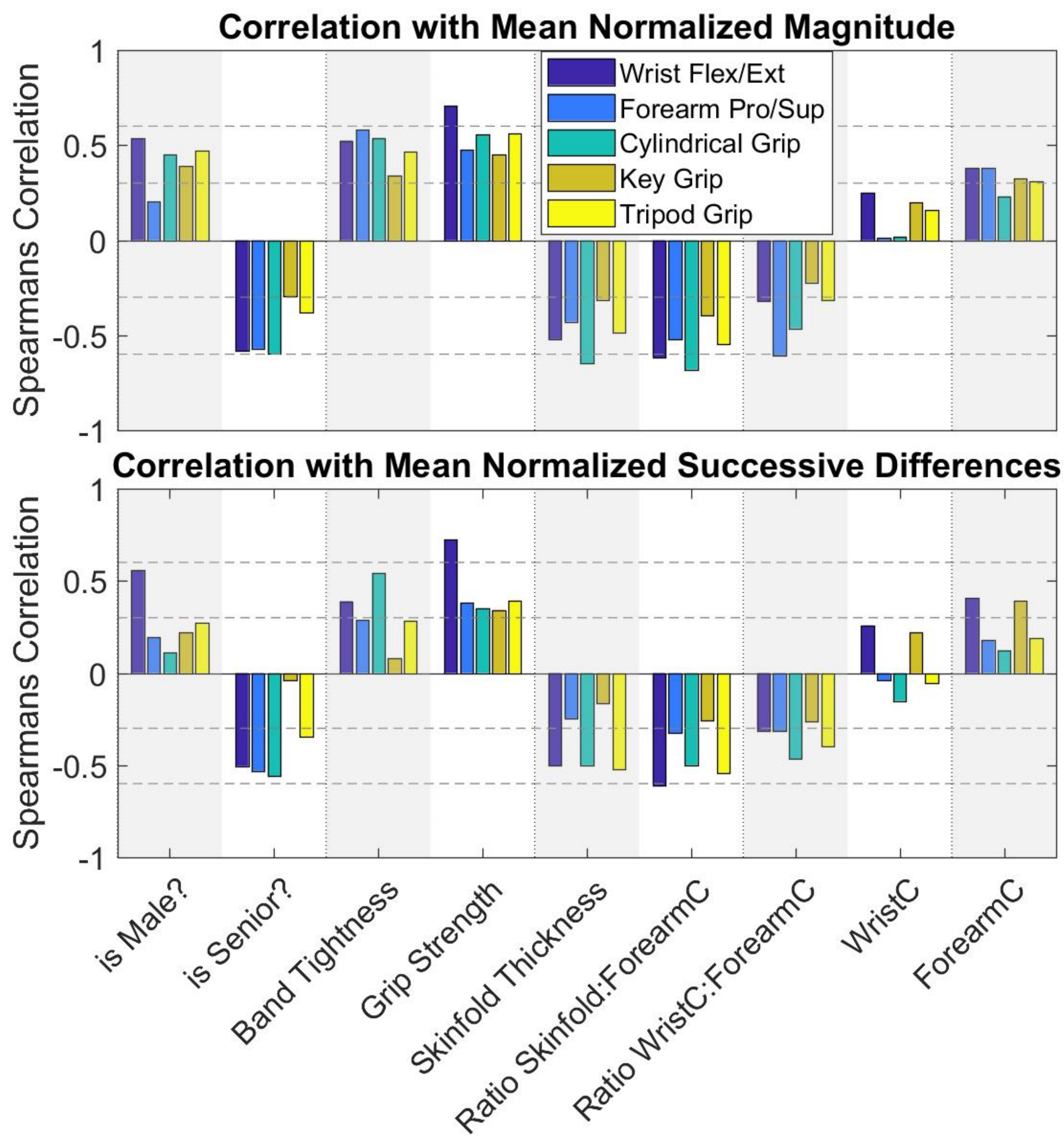
Sensitivity was explored as 1) the RMS magnitude of change from baseline values, and 2) as RMS slope (successive differences of sorted values). ANOVA demonstrated significant age AND gender based differences in FMG magnitude ($0 \leq p \leq 0.1097$) except for forearm pronation/supination, which only showed age based differences. With respect to sensitivity as defined as successive difference between sorted values, significant gender based differences were only observed during wrist flexion/extension, key grip, and tripod. Significant age based differences were observed during wrist flexion/extension, forearm pronation/supination, and cylindrical grip. These results indicate that being young and being male is correlated to having an FMG profile that is more responsive to changes in range of motion or effort. Gender and age accounted for approximately 17% and 24% of the variability in FMG magnitude. These results are tabulated in **Table 5.14** below, and shown in greater detail in **Figure** Error! Reference source not found..

5.14. Mean correlation between anthropometry and 1) magnitude of response, and 2) peak derivative of response

Variable	Magnitude		Successive Differences	
	Mean Correlation	% contribution to variability	Mean Correlation	% contribution to variability
is Male?	0.41	16.86	0.27	7.32
is Senior?	-0.49	23.55	-0.40	15.73
Band Tightness	0.49	24.00	0.32	10.07
Band Tightness (difference)	-0.08	0.71	-0.06	0.34
Grip Strength	0.55	30.31	0.44	19.20
Skinfold Thickness	-0.48	22.90	-0.39	14.94
Ratio of Skinfold Thickness to Forearm Circumference	-0.55	30.56	-0.45	19.95
Ratio of Wrist Circumference to Forearm Circumference	-0.39	14.91	-0.35	12.31
Wrist Circumference	0.13	1.62	0.05	0.22
Forearm Circumference	0.33	10.58	0.26	6.62

Also, shown in **Table 5.14** above are correlations with some of the independent measures of anthropometry considered in this study. Grip strength and ratio of skinfold thickness to forearm circumference (two features that demonstrate age and gender based differences) demonstrated the greatest relationship with FMG responsiveness, accounting for approximately 30% of the variability in magnitude and 19% to 20% of the of the variability in slope. Greater details of this relationship for each dynamic task are shown below in

Figure Error! Reference source not found., with p-values for the correlations tabulated in **Tables 5.15** and **5.16**.



5.7. Correlation of Mean Normalized Derivative with variables of anthropometry
Note. Horizontal grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 ≤ |R|).

5.15. p-values for correlations between anthropometry and magnitude of FMG response

	Wrist Flex/Ext	Forearm Pro/Sup	Cylindrical Grip	Key Grip	Tripod
is Male?	0.000	0.194	0.003	0.011	0.002
is Senior?	0.000	0.000	0.000	0.057	0.012
Band Tightness	0.000	0.000	0.000	0.027	0.002
Band Tightness (diff)	0.513	0.904	0.437	0.399	0.621
Grip Strength	0.000	0.001	0.000	0.003	0.000
Skinfold Thickness	0.000	0.005	0.000	0.044	0.001
Ratio Skinfold:ForearmC	0.000	0.000	0.000	0.009	0.000
Ratio WristC:ForearmC	0.038	0.000	0.002	0.158	0.041
WristC	0.110	0.949	0.904	0.211	0.314
ForearmC	0.013	0.013	0.140	0.035	0.047
Separability Index	0.000	0.002	0.000	0.072	0.005

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow.

5.16. p-values for correlations between anthropometry and derivative of FMG response

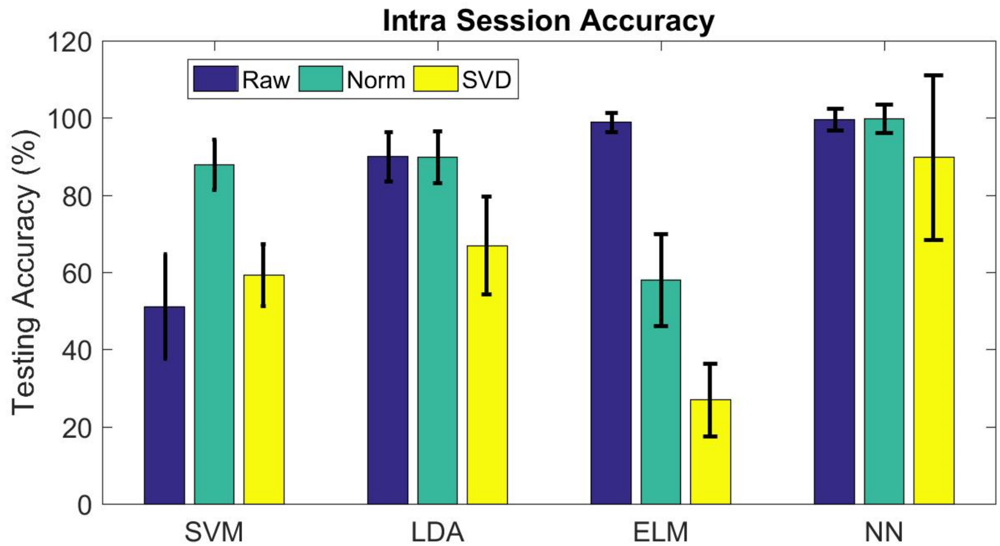
	Wrist Flex/Ext	Forearm Pro/Sup	Cylindrical Grip	Key Grip	Tripod
is Male?	0.000	0.221	0.488	0.161	0.082
is Senior?	0.001	0.000	0.000	0.806	0.024
Band Tightness	0.011	0.064	0.000	0.614	0.067
Band Tightness (diff)	0.520	0.454	0.680	0.767	0.566
Grip Strength	0.000	0.013	0.022	0.027	0.010
Skinfold Thickness	0.001	0.117	0.001	0.306	0.000
Ratio Skinfold:ForearmC	0.000	0.036	0.001	0.100	0.000
Ratio WristC:ForearmC	0.044	0.043	0.002	0.094	0.009
WristC	0.098	0.795	0.341	0.159	0.736
ForearmC	0.007	0.258	0.435	0.011	0.235
Separability Index	0.002	0.000	0.003	0.915	0.107

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow.s

The correlations observed in **Figure** Error! Reference source not found. suggest that having a greater grip strength is associated with greater responsiveness of FMG, whilst greater skinfold thickness relative to muscle and bone tissue are correlated to decreased responsiveness. The influence of grip strength is explained via the increase in muscle fibre cross sectional area that is associated with greater grip strength [232]. Similarly, the influence of skinfold thickness is explained as a dampening affect on the transmission of volumetric changes through underlying tissues. This variability is significant to FMG implementation, particularly for AAL tools for seniors, due to the age-associated changes that occur with grip strength and skin compressibility. As discussed in ***Section 2.2.2***, non-pathological age-associated changes include decreased grip strength, increased distribution of subcutaneous adipose tissue, and decreased skin elasticity. As such, these variables would need to be accounted for in FMG implementations.

Initial band tightness also demonstrated strong relationships with FMG responsiveness, accounting for 24% of the variability in magnitude of response. In this aspect of FSR based FMG, magnitude of response is related to the sensitivity of the FSRs which could be addressed via circuitry [216]. Band tightness has never been addressed in FMG research, and further research into optimal band tightness would benefit future study.

On average, FMG responsiveness showed a moderate correlation with linear separability of static hand gestures and wrist positions data clusters (0.4496 for magnitude and 0.2913 for slope). This affect on the separability of static clusters also translated to affects on the testing accuracy of machine learning models. **Figure 5.8** presents an overview of testing accuracies achieved with raw, normalized, and singular value decomposed FSR data.



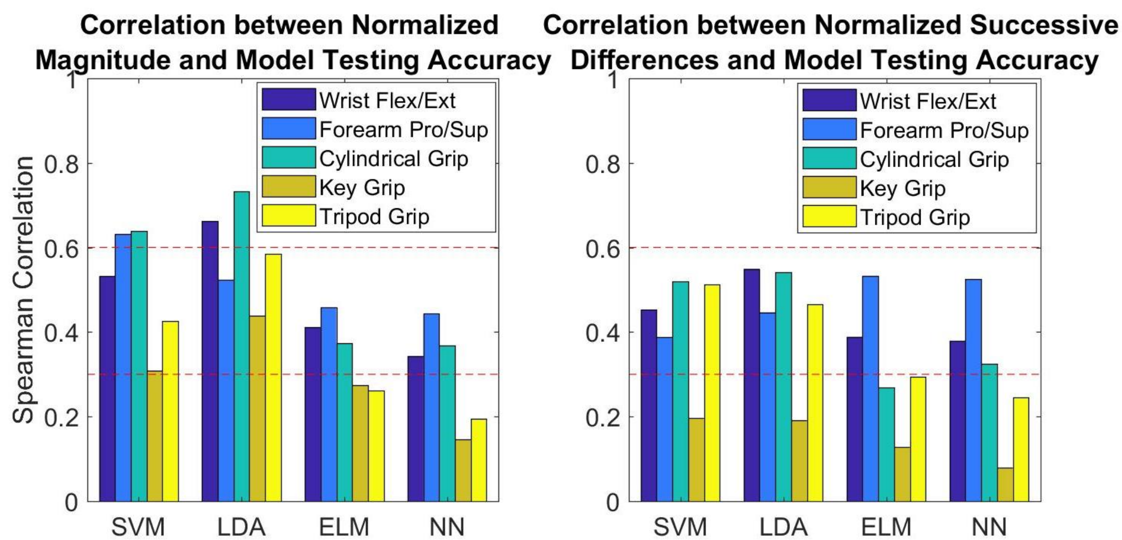
5.8. Overview of testing accuracies across all participants
Note. The standard deviation in accuracy for each test and data type are presented with the error bar at the top of each bar, while the training accuracy is printed in text above each bar. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

In this work, the raw, global min-max normalized, and singular value decomposed FSR were used to train four types of machines learning models: Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Extreme Learning Machine (ELM), and Neural Network (NN). While it is acknowledged that models such as SVM, ELM, and NN benefit from parameter optimization, the purpose of training various models was to illustrate trends independent of parameter optimization. Selecting the best data-model pairs, FMG responsiveness demonstrates moderate correlations with the testing accuracies of machine learning models, accounting for 25%, 35%, and 13% of the variability in SVM, LDA, and ELM testing accuracy. These results are tabulated and shown in greater detail in **Table 5.17** and **Figure 5.9** below. The relationship with the testing accuracy of the NN testing model was quite low with no significant relationships ($p > 0.05$). It is hypothesized that this is due low variability of testing accuracies – a restricted a range of data which is documented to have a negative affect on calculations of correlation [233].

5.17. Summary of influence of FMG responsiveness on model testing accuracy

	Training Accuracy (%)	Testing Accuracy (%)		Magnitude		Successive Differences	
		min	max	Mean Correlation	% contribution to variability	Mean Correlation	% contribution to variability
SVM	86.94	69.72	96.48	0.51	25.76	0.41	17.11
LDA	89.21	69.05	98.51	0.59	34.63	0.44	19.26
ELM	98.23	88.07	100.00	0.36	12.65	0.32	10.39
NN	98.72	83.95	100.00	0.30	8.95	0.31	9.64

Note. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.



5.9. Influence of FMG responsiveness on model testing accuracy
Note. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively. Horizontal red lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 ≤ |R|).

The last item of note are the differences observed when considering the magnitude and slope (successive sequential differences). For example, it can be observed from **Table 5.17** and **Figure 5.9** that the relationships with FMG magnitude were much stronger (had higher correlations) than with successive differences. An explanation for this is [TODO].

5.3.3. Sensitivity to compound movements/manipulations

As described ***Section 4.5.5***, participants were asked to perform a series of compound movements, which involved a hand gestures and a simultaneous wrist/forearm orientation. This was motivated by the dominance of singleton tasks in FMG research and the little regard for combinations of hand gestures, wrist movements, and forearm orientations possible. All possible combinations were subsequently reorganized to explore the influence of hand manipulation on the discriminability of wrist/forearm orientations, and visa versa.

Classes for hand classification were: relax, open, close, point, tripod, key, and straight. The baseline performance was calculated for hand gestures completed only with a 'neutral' wrist and forearm. Noise was introduced by performing the hand gestures with varying wrist and forearm orientations (wrist flexion/extension and forearm pronation/supination). Classes for wrist/forearm orientation were: neutral, wrist flexion, wrist extension, forearm pronation, and forearm supination. The baseline performance was calculated for wrist/forearm orientations completed only with a 'straight' hand gesture. Noise was introduced by completing the wrist/forearm orientation tasks with varying hand gestures (relax, open, close, point, tripod, key, and straight).

As described in ***Section 4.5.5***, senior participants completed an abridged protocol with only the (relax, open, close) hand gestures. Non-senior participants performed the full sequence of tasks for more comprehensive analysis.

Abridged Protocol

At a neutral wrist, the mean (standard deviation) separability of FMG clusters across the 3 hand gestures was 124.79 (96.35). In the presence of noise (variable wrist/forearm orientation), separability of clusters significantly decreases to 8.94 (5.58) ($p = 4.5481e\text{-}10$). With a straight hand gesture, the mean separability of FMG clusters across 5 wrist/forearm positions (neutral, wrist flexion, wrist extension, forearm pronation, forearm supination) was 76.21 (41.28). In the presence of noise (variable hand gestures), separability significantly decreases to 17.96 (8.12) ($p = 9.6784e\text{-}14$). Even with this decrease in separability, FMG clusters of wrist position are statistically still more separable than FMG clusters of hand gestures ($p = 2.8332e\text{-}07$).

Without noise, ANOVA revealed only age associated differences in the separability of hand gestures and wrist gestures. With the introduction of noise, ANOVA revealed both age and gender associated differences in the decline of class separability. These ANOVA results are summarized in **Table 5.18**.

5.18. ANOVA p-value results: Gender and Age associated in differences in 1) Separability of classes and 2) Decline in Separability after introducing noise

	Gender	Age
Separability of Hand gestures (without noise)	0.6831	0.0001
Decline of Separability of Hand gestures after introducing noise	0.0436	0.0004
Separability of Wrist/Forearm orientation (without noise)	0.7168	0.0001
Decline of Separability of Wrist/Forearm orientation after introducing noise	0.0449	0.0004

Closer inspection of anthropometric and band placement variables indicated that these results are moderately correlated to grip strength, ratio of skinfold thickness to forearm circumference, and band tightness. These results are summarized in **Figure 5.10**. Grip strength, ratio of skinfold thickness to forearm circumference, and band tightness were three anthropometric variables that also demonstrated age and gender related differences as seen in ***Section 5.2***. In addition, **Figure 5.10** indicates that anthropometric variables demonstrated stronger relationships with the discriminability of hand gestures and declines after introducing noise. This indicates that wrist positions are less susceptible to the introduction of noise and anthropometric differences. Knowing the wrist position regardless of hand gesture reduces the classification scheme from a 30 class problem (6 hand gestures and 5 wrist/forearm orientations) to a 6 class problem (6 hand gestures). This potentially supports the idea of a 2 stage-classifier which first identifies the wrist/forearm positions and adjusts the parameters of a subsequent hand classifier. An advantage of this proposed schema is the reduction of the amount of required training input.

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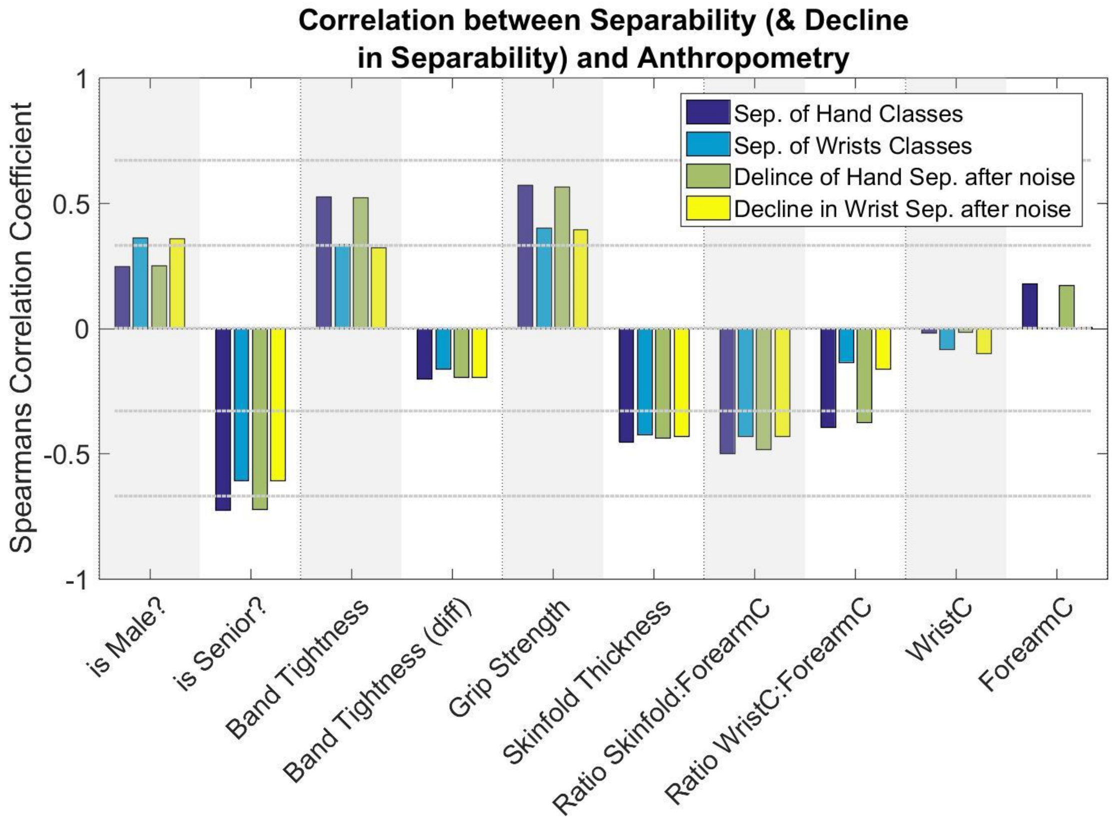


5.10. Correlation between anthropometric variables and 1) Separability of classes and 2) Decline in Separability after introducing noise

Note. Horizontal grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 < |R|).

Table 5.19 below provides tasks specific p-values for the correlations shown above in Figure 5.10. Significant relationships (p < 0.05) are highlighted in yellow.

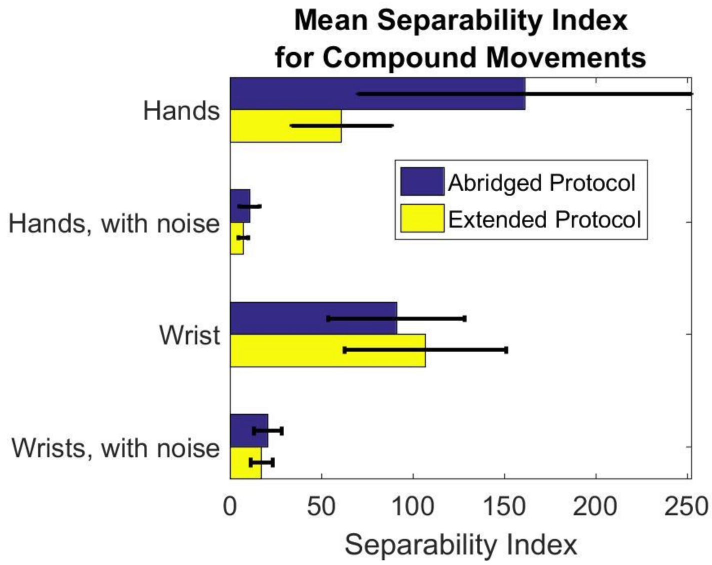
5.19. p-values of correlations between anthropometry and separability

	Sep. of Hand Classes	Sep. of Wrists Classes	Decline of Hand Sep. after noise	Decline in Wrist Sep. after noise
is Male?	0.114	0.019	0.108	0.020
is Senior?	0.000	0.000	0.000	0.000
Band Tightness	0.000	0.029	0.000	0.038
Band Tightness (diff)	0.200	0.307	0.214	0.218
Grip Strength	0.000	0.009	0.000	0.010
Skinfold Thickness	0.003	0.005	0.004	0.004
Ratio Skinfold:ForearmC	0.001	0.005	0.001	0.004
Ratio WristC:ForearmC	0.010	0.396	0.015	0.301
WristC	0.910	0.603	0.928	0.531
ForearmC	0.259	0.985	0.277	0.971

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow.

Extended Protocol

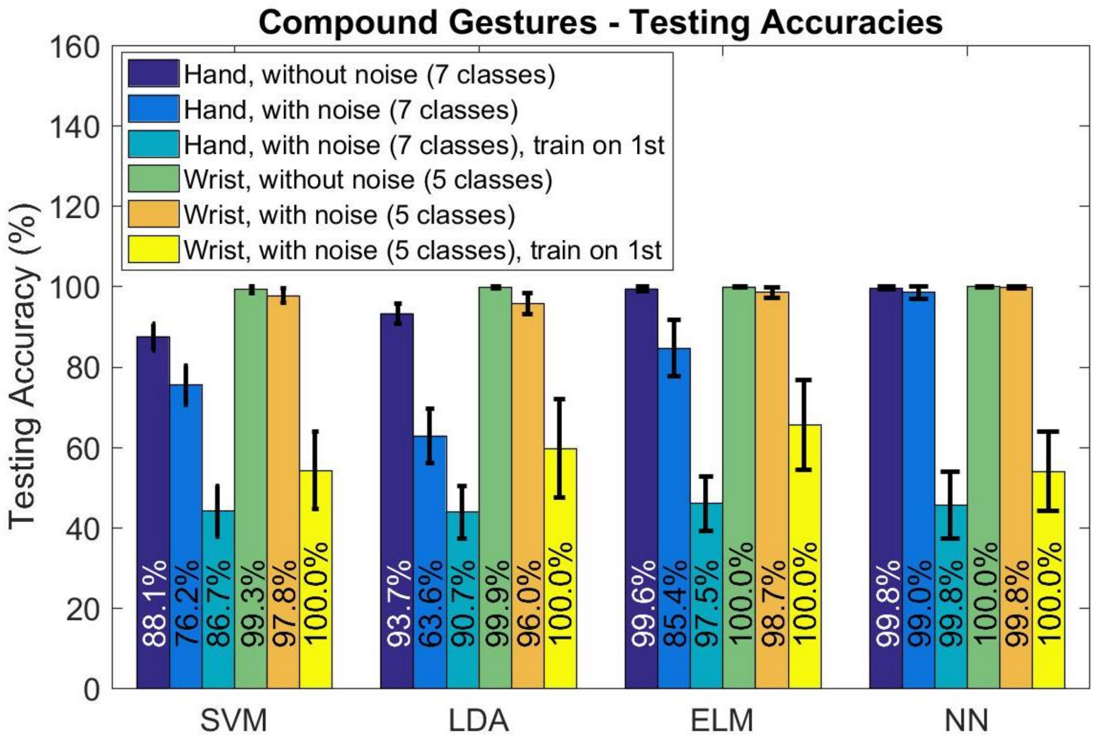
With the introduction of additional hand gestures for classification with non-senior participants, the separability of hand gestures decreased and the separability of wrist/forearm positions increased. This is demonstrated via **Figure 5.11** below.



5.11. Mean separability of Hand and Wrist/Forearm class (non-senior participants)
Note. Error bars indicate the standard deviation of the data.

At a neutral wrist, the mean (standard deviation) separability of FMG clusters across 7 hand gestures (relax, open, close, point, key, tripod, straight) was 160.86 (91.16). In the presence of noise (variable wrist/forearm orientation), separability of clusters significantly decreases to 10.62 (5.58) (p = 7.7374e-12). With a straight hand gesture, the mean separability of FMG clusters across 5 wrist/forearm positions (neutral, wrist flexion, wrist extension, forearm pronation, forearm supination) was 90.80 (37.20). In the presence of noise (variable hand gestures), separability significantly decreases to 20.38 (7.53) (p = 3.8230e-13). Even with this decrease in separability, FMG clusters of wrist position are statistically still more discernable than FMG clusters of hand gestures (p = 2.4371e-08).

This suggests that classification of hand gestures is more susceptible to variations in wrist/forearm orientation than the alternative (classification of wrist/forearm orientation being more susceptible to variations in hand gestures). Indeed, this pattern seen in separability indices also manifests itself in the testing accuracies of SVM, LDA, ELM, and NN models. **Figure 5.12** presents the testing accuracy results of models using the best model-data pairs. For SVM, LDA, ELM, and NN, this was normalized data, normalized data, raw data, and normalized data respectively.



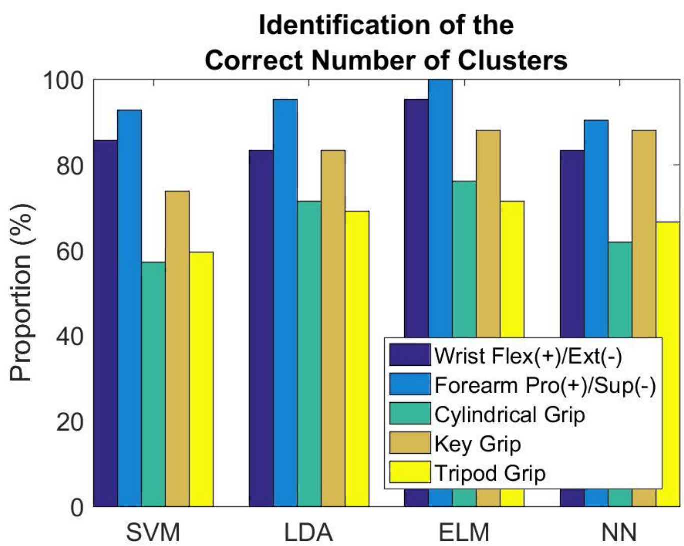
5.12. Testing accuracies, as a function of introduced noise, of machine learning models trained on normalized FMG data

Note. The standard deviation in accuracy for each test and data type are presented with the error bar at the top of each bar, while the training accuracy is printed within each bar. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively. For Hand, 'train on 1st' indicates that the model was trained on data only at neutral wrist/forearm. For Wrist, this indicates that the model was trained on data with a straight hand gesture only.

Shown in greater detail in **Figure 5.12** above, with the introduction of noise the accuracy of identifying hand gestures decreases by a mean (standard deviation) of 13.83% (4.12), 32.71% (6.12), 4.87% (6.72), and 1.06% (1.35) for SVM, LDA, ELM, and NN model respectively. However, for wrist/forearm orientations, the decline in accuracy only ranged between 0.18% (0.30) and 4.0% (2.52) across all model types introduced. When the training data is reduced, the effect of noise is more pronounced. Reducing the training data for hand gesture identification to a single wrist orientation causes accuracy to decline between 50% and 54% across all models. Similarly, reducing the training data for wrist/forearm orientation identification to a single hand gesture caused accuracy to decline between 34% and 46% across all models. As suggested by these results, the identification of wrist/forearm identification is less susceptible to noise, indicated by significantly lower declines in testing accuracy ($2.3571e-08 \leq p \leq 0.0475$) when training data is reduced. It is hypothesized that these results would be exacerbated with increasing age, due to the variability and low sensitivity related to decreased grip strength, increased skinfold, and diminishing mechanical properties of underlying tissues.

5.3.4. Gesture identification during non-static activity

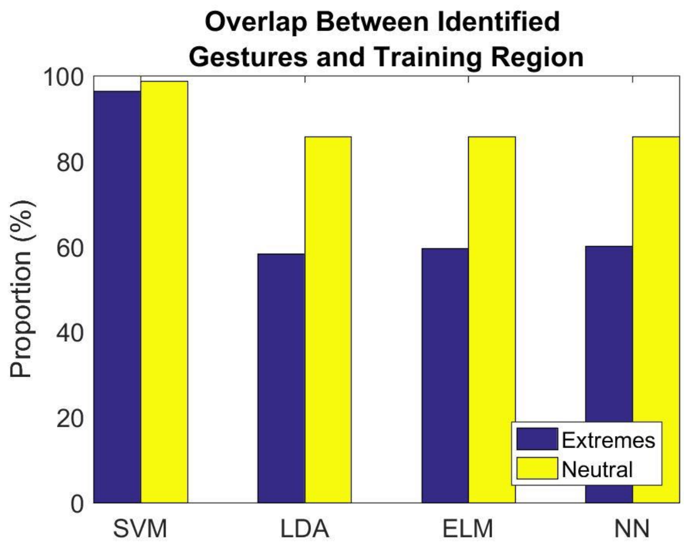
As discussed on the literature review in ***Section 2.5.2***, all the of the FMG studies to date have utilized supervised learning methods only. In addition, for classification of hand gestures and wrist/forearm orientations, models are trained on statically held gestures. The practicality of this scheme of implementation is explored in this section using the processing and feature extraction methods explained in ***Section 4.6.1.*** The results of this analysis across all participants are summarized in in **Figures 5.13** to **5.16** below.



5.13. Proportion of times when the correct number of classes was correctly identified by statically trained model tested on non-static activity

Note. The correct number of classes for wrist flexion/extension is three (3): extension, neutral, and flexion. For forearm pronation/supination is three (3): supination, neutral, and pronation. For cylindrical grip is one (1): close. For key grip, is one (1): key. For tripod grip is one (1): tripod. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Shown in **Figure 5.13**, the proportion of trials where the correct number of classes were identified ranged from 57% to 100%. The dynamic wrist and forearm motions were more likely to produce the correct number of classes, as the more closely resembled the static training position. For cylindrical, key, and tripod grips, the static models were trained without the hand dynamometer, explaining the decreased likelihood of correctly identifying the gesture.



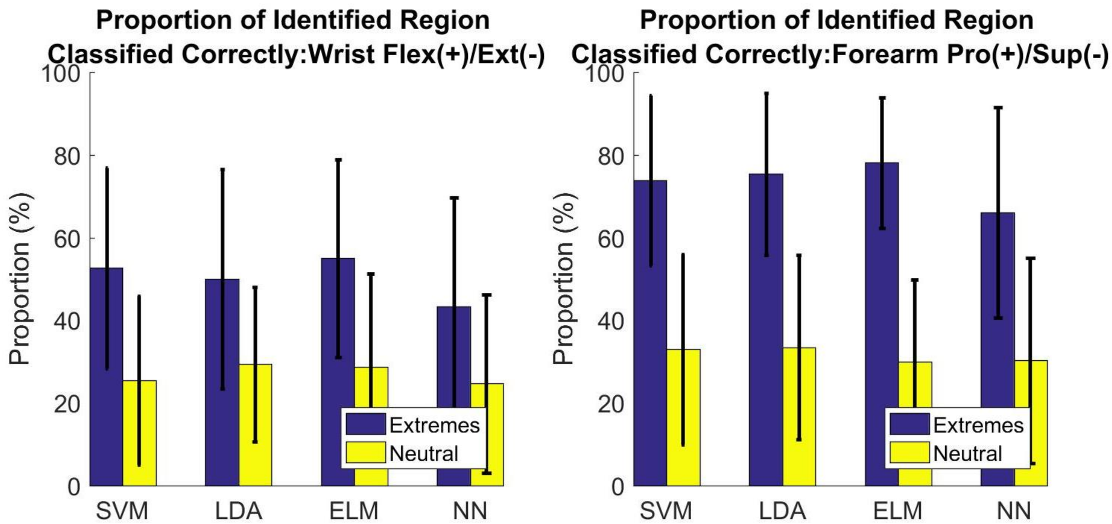
5.14. Proportion of times when the classes identified by the statically trained model overlapped with the training region

Note. Only data for wrist flexion/extension and forearm pronation/supination is shown. 'Extremes' refers to flexion/extension and pronation/supination for the wrist and forearm respectively. 'Neutral' refers to neutral wrist and neutral forearm. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Shown in **Figure 5.14**, there was a high degree of overlap between the training region for wrist/forearm movements and their associated class clusters, ranging between 58% and 96% of trials. LDA, ELM, and NN models demonstrated a significantly lower proportion of trials whose class clusters in the extremes of range-of-motion overlapped with training regions.

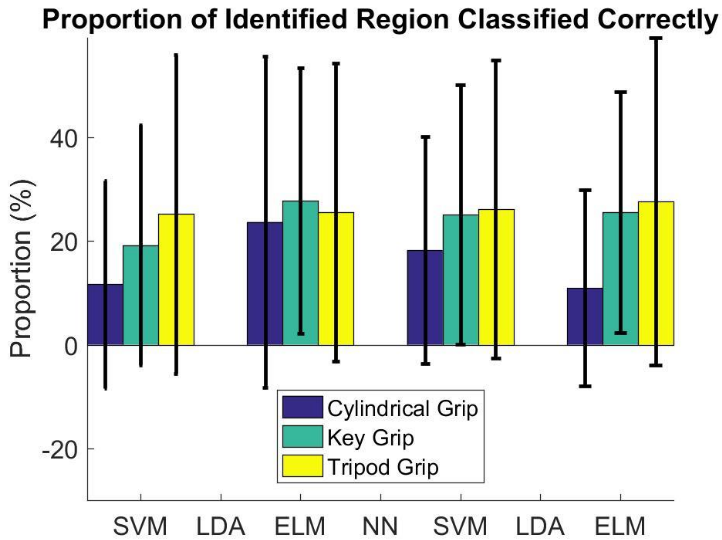
Shown in **Figure 5.15**, FMG at the extremes of range of motion (for the wrist and forearm) demonstrates the least amount of variability, indicated by higher proportions of correct classifications. In contrast, neutral wrist and forearm demonstrated the higher variability. It is believed that this behaviour is related to the differences in separability of hands gestures and wrist/forearm orientations in the presence of noise (as discussed in ***Section***

5.3.3). hand dynamometer) and the resultant effect of the difference in hand/finger joints angles.



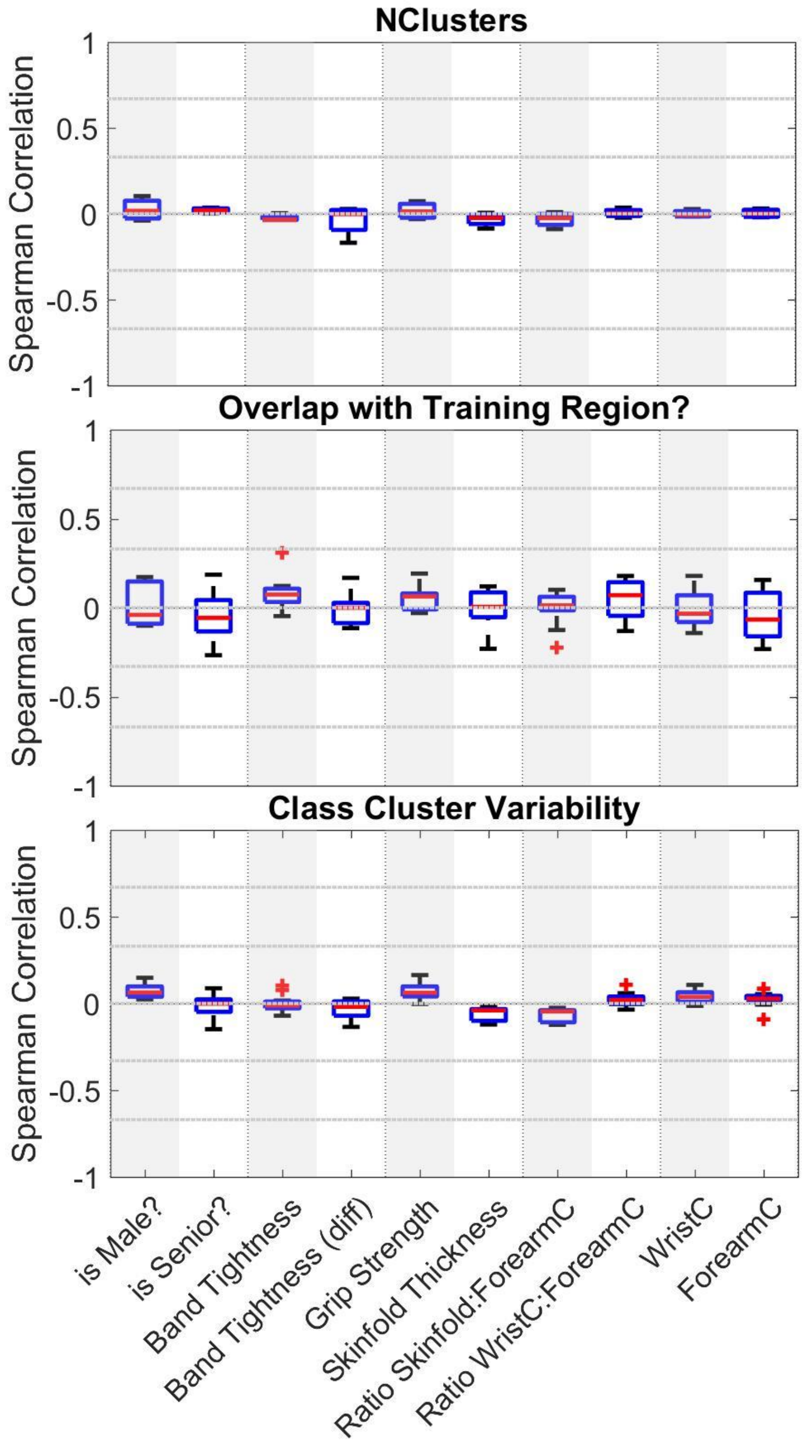
5.15. Dominance of correct class within identified clusters of motions
Note. Only data for wrist flexion/extension and forearm pronation/supination is shown. Standard deviations are shown via error bars. ‘Extremes’ refers to flexion/extension and pronation/supination for the wrist and forearm respectively. ‘Neutral’ refers to neutral wrist and neutral forearm. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Finally, **Figure 5.16** shows that continuous identification of close, key, and tripod grips during dynamic cylindrical grip, key grip, and tripod grip tasks quite poor. This is indicated by low proportions of trials being correctly identified, ranging between 11% and 28%. However, as previously mentioned, this is attributed to presence of an object (the



5.16. Dominance of correct class within identified clusters of motions
Note. Only data for hand grips are shown. Standard deviations are shown via error bars. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Sources of variability in these three features were also considered. ANOVA revealed little to no age or gender based differences, which was further supported by low ($|R| < 0.3$) correlation with anthropometric variables (shown below in **Figure 5.17**).



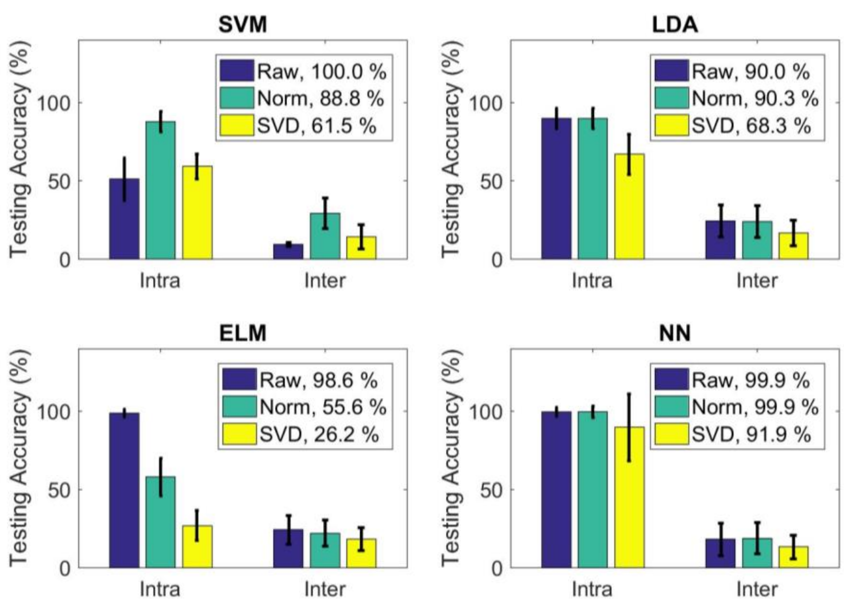
5.17. Correlation between features of performance during non-static activity with variables of anthropometry

Note. Horizontal grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 < |R|).

These results indicate that the performance of statically trained models in non-static environments are more related to the nature of the models trained, feature selection, and the nature of implementation, rather than the variability between participants.

5.3.5. Sensitivity to band removal

A key and final part of the protocol considered the effect of removing and donning the FMG band on the effectiveness of a pre-trained model. As outlined in ***Section 4.5***, the protocol for each participant involved repeating the entire set of dynamic and static gesture tasks twice, having removed and redonned the FMG band prior to the second session. For this section of analysis, an 11-class problem was considered, consisting of 6 hand gestures (relax, open, close, point, key, tripod) and 5 wrist/forearm orientations (neutral, wrist flexion, wrist extension, forearm pronation, and forearm supination). For all models considered, there was a marked and significant decrease in testing accuracy by 28% to 96% when a model was trained on using the entire data of one session and tested on the other. **Figure 5.18** provides an overview of the impact of band removal prediction performance.



5.18. Influence of band removal on testing accuracy
Note. The standard deviation in accuracy for each test and data type are presented with the error bar at the top of each bar, while the training accuracy is printed in text in the legend. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Using the optimal performing model-data type pairings, ANOVA indicated several age-gender based differences in the preliminary testing accuracy and subsequent decline. Optimal data input types for SVM, LDA, ELM, and NN were normalized data, normalized data, raw data, and normalized data respectively. ANOVA P-value results are tabulated below in **Table 5.20.**

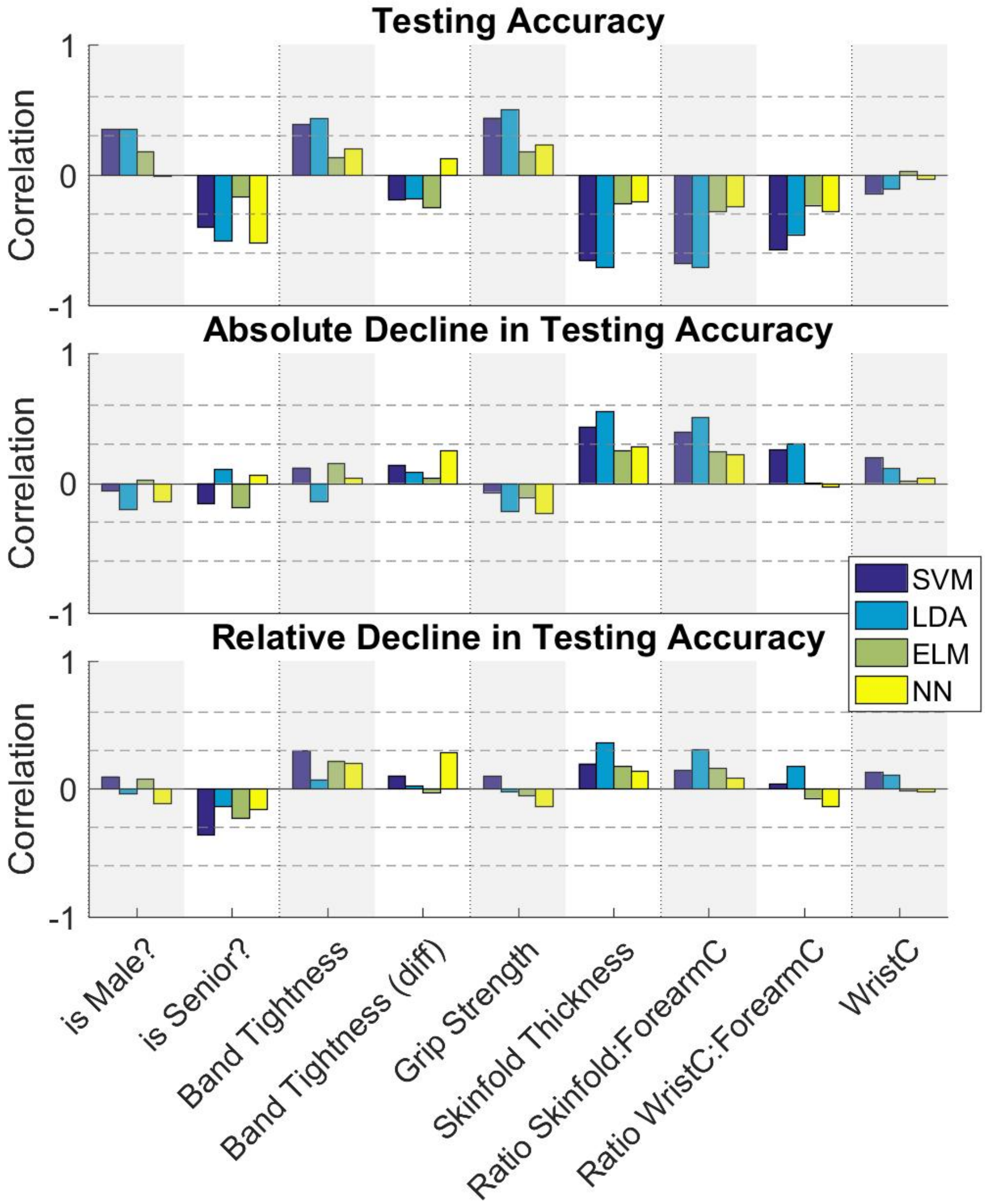
5.20. ANOVA results: Gender and Age associated in differences in 1) Original Testing Accuracy, 2) Absolute decline in testing accuracy, 3) Proportional decline testing accuracy

		p-value			
		SVM	**LDA**	**ELM**	**NN**
Testing Accuracy achieved without taking the band off	gender	0.0961	0.1956	0.2172	0.8613
	age	0.0088	0.0001	0.2301	0.0001
Absolute Decline in Testing Accuracy after band removal	gender	0.4366	0.1978	0.6537	0.1099
	age	0.3797	0.7956	0.2176	0.6473
Proportional Decline in Testing Accuracy after band removal	gender	0.8280	0.2956	0.8546	0.0982
	age	0.0253	0.1863	0.1332	0.1203

As can be seen in **Table 5.20** above, the variability in testing accuracy before the band was removed demonstrated significant age based differences, only for the SVM, LDA, and NN data types. Age are gender did not have an influence on the absolute decline in percentage or the proportional decline. Proportional decline is a ratio of absolute decline in testing accuracy ($acc_{after} - acc_{before}$) and the preliminary testing accuracy prior to removing the band (acc_{before}). This was calculated using the expression below:

$$acc_{proportional} = \frac{acc_{after} - acc_{before}}{acc_{before}}$$

Closer inspection of the correlations between anthropometric variables and the testing accuracies of optimal model-data type pairs, shown below in **Figure 5.19**, only partially supported the results in **Table 5.20**.



5.19. Correlation between Anthropometry model accuracy and decline (absolute and proportional) in model accuracy after FMG band removal

Note. Horizontal grey lines identify margins for low correlations (|R| < 0.33), moderation correlations (|R| < 0.67), and high correlations (0.67 < |R|). SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

Figure 5.19 shows that the testing accuracies of only SVM and LDA appeared to have moderate or strong relationships (0.3 <|R|) with the variability in testing accuracy. Of the participant variable considered, grip strength, ratio of skinfold thickness to forearm circumference, and band tightness demonstrated the strongest influence on model testing accuracy. Band tightness, grip strength, and ratio of skinfold thickness to forearm circumference accounted for (on average) 17%, 22%, and 48% of the variability in tasting accuracies in SVM and LDA models. As mentioned in previous sections, these three variables were also variables shown to have strong age and gender based differences, however it appears ages based differences have a stronger impact on model performance.

With respect to the absolute decline in model testing accuracy that occurred after taking the FMG band off, only skinfold thickness related variables demonstrated moderate relationships to the absolute decline in testing accuracy. Despite this relationship (observed in **Figure 5.19**), variability in skinfold thickness did not result in any age or gender based differences in testing accuracy declines (indicated by the lack of significant group based differences in **Table 5.20**). Thus, it can be concluded that the absolute decline in testing accuracy was unrelated to difference in anthropometry.

Lastly, with respect to proportional declines in testing accuracies, the results of ANOVA were inconsistent with the relationships (or lack thereof) observed in **Figure 5.19**. Thus, it can be concluded that the proportional decline in testing accuracy was unrelated to difference in anthropometry.

Regarding band placement, band tightness only demonstrated moderate relationships with the testing accuracy prior to band removal. After removing the band, band tightness only demonstrated low relationships (|R| < 0.3) to the variability observed in the absolute decline in testing accuracies. Also, although the difference in band tightness (4.68 $\pm$ 3.40 mmHg) between sessions 1 and 2 was significant, there was only low correlation with testing accuracy decline due to band removal. The difference in band tightness between sessions 1 & 2 only accounted for less than 2% of the variability of absolute or proportional decline in SVM, LDA, and ELM models. In NN, the difference in band tightness between session 1 & 2 only explained less than 8% of the variability. The only remaining variable to be considered that would result in this reduction would be minute differences in sensor positioning that occurred even though the FMG was placed in the same location for each session. The p-values for the correlations shown above in **Figure 5.19** are tabulated below in **Tables 5.21 to 5.23.** Significant p-values are highlighted in yellow.

5.21. p-values for correlations between anthropometry and testing accuracy

	SVM	LDA	ELM	NN
is Male?	0.023	0.021	0.246	0.980
is Senior?	0.009	0.001	0.302	0.000
Band Tightness	0.011	0.004	0.382	0.196
Band Tightness (diff)	0.236	0.247	0.113	0.418
Grip Strength	0.004	0.001	0.262	0.132
Skinfold Thickness	0.000	0.000	0.161	0.195
Ratio Skinfold:ForearmC	0.000	0.000	0.077	0.123
Ratio WristC:ForearmC	0.000	0.002	0.144	0.077
WristC	0.374	0.501	0.840	0.866
ForearmC	0.141	0.406	0.286	0.436
Separability Index	0.000	0.000	0.000	0.003

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

5.22. p-values for correlations between anthropometry and the absolute decline in testing accuracy

	SVM	LDA	ELM	NN
is Male?	0.711	0.203	0.882	0.385
is Senior?	0.322	0.493	0.247	0.702
Band Tightness	0.447	0.374	0.326	0.798
Band Tightness (diff)	0.372	0.600	0.797	0.108
Grip Strength	0.668	0.165	0.505	0.138
Skinfold Thickness	0.004	0.000	0.108	0.073
Ratio Skinfold:ForearmC	0.009	0.001	0.116	0.156
Ratio WristC:ForearmC	0.097	0.049	0.981	0.860
WristC	0.210	0.469	0.922	0.797
ForearmC	0.811	0.989	0.578	0.370

Separability Index	0.476	0.136	0.724	0.386

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

5.23. p-values for correlations between anthropometry and the relative decline in testing accuracy

	SVM	LDA	ELM	NN
is Male?	0.536	0.824	0.620	0.472
is Senior?	0.020	0.395	0.150	0.309
Band Tightness	0.051	0.632	0.157	0.193
Band Tightness (diff)	0.505	0.885	0.883	0.066
Grip Strength	0.516	0.888	0.749	0.405
Skinfold Thickness	0.206	0.018	0.250	0.381
Ratio Skinfold:ForearmC	0.342	0.046	0.294	0.591
Ratio WristC:ForearmC	0.795	0.252	0.664	0.396
WristC	0.397	0.484	0.952	0.891
ForearmC	0.383	0.659	0.429	0.391
Separability Index	0.535	0.726	0.746	0.763

Note. Significance based on $p < 0.05$. Significant correlations are highlighted in yellow. SVM, LDA, ELM, and NN stand for Support Vector Machine, Linear Discriminant Analysis, Extreme Learning Machine, and Neural Network respectively.

5.4. Discussion

Five features were used to illustrate the impact of user anthropometry on FMG acquisition, modelling, and day-to-day use. These were:

- variability of FMG sensors throughout non-static repetitive motions
- magnitude of FMG response to incremental activity
- presence of compound movements/actions
- effect of non-static conditions on the performance of statically trained models
- effect of FMG band removal

Overall, age-associated differences in FMG performance were observed in two of the five features selected for experimentation. These were 1) the responsiveness of FMG to range of movement/effort, and 2) in the severity of impact of functional noise in gesture identification. Based on ANOVA and Spearman's correlation results, specific anthropometric variables resulting in these relationships were:

- grip strength
- band tightness
- ratio of skinfold thickness to forearm circumference (as an indicator of muscle cross sectional area)

Grip Strength

Grip strength is an anthropometric measurement that is directly related to muscle fibre cross-sectional area. The motor unit of a muscle fibre is the sarcomere, which interact with each through mechanical cross bridges. A larger number of sarcomeres in the cross section of a muscle fibre, means greater volume as well as greater strength. A visual metaphor would be having one person pulling a large object with a rope vs having many individuals pulling on the same object with separate ropes. As FMG measures the volumetric changes that occur with activity, an understandable conclusion is that the lower grip strengths observed in seniors would result in lower magnitude of changes.

Band Tightness

With respect to band tightness and FSR implementations of FMG, it is assumed that there is surface contact pressure which optimizes the range of readings observed. With too much pressure, sensors would be too saturated to register any significant changes, whilst with too little pressure, there wouldn't be enough contact force on the FSRs to register changes in underlying muscular tissue. As a non-rigid structure, the skin acts as a dampener of the forces produced by muscle fibres as they are transmitted to the FSR sensors.

Although the band were fitted based on comfort and minimal activation of FMG sensor, the band tightness observed in seniors were significantly lower than non-seniors. It is believed that the age-related differences in band tightness observed are related to age-related differences in mechanical properties of the skin. This is supported by documented changes in skin mechanical properties that occur with ages, such as a decline in the amount of connective tissue. This is also supported by qualitative observations of mechanical skin properties during skinfold measurements. Seniors' skin tended to be less elastic and more compressible than that of non-seniors. In effect, it's hypothesized that the increased dampening from the skin, related to declining elasticity, helps explain why FMG was less responsive with seniors and why the effect functional noise was more severe.

Ratio of Skinfold Thickness to Forearm Circumference

A skinfold consists of 4 layers - 2 layers of skin and 2 layers of subcutaneous adipose tissue (SAT). It was previously mentioned that skin had a dampening effect on the transmission of forces from the volumetric expansion of the muscle fibre to the FMG sensors. As a nonrigid structure capable of energy dissipation, it is believed that SAT also plays a similar role. With this reasoning, increase adipose tissue would cause increased dampening, and thus decreased discernibility between gestures and decreased responsiveness to range of movement/effort. Ratio of skinfold thickness to forearm circumference went a step further by relating the among of skin and adipose tissue to underlying muscular tissue. The assumption in this regards is that the cross section area of bone was similar between participants.

5.5. Limitations and future directions

The conclusions drawn from this work and future research would benefit from addressing the limitations observed in the protocol. One limitation observed was the physical history of the participants. The nature of participant consent was limited to: hand dominance, weight, gender, age, damage/disease/surgeries to the upper extremity, self assessment of functionality (as a percentage), and any therapy they might be participating. Additional history that would have benefit the comprehensive use of FMG with seniors would have been cognitive assessments (to confirm that participants could follow instruction), hand assessments (to identify the possible confounding affect of arthritis), level of physical activity. An additional limitation is that all participant donned the FMG band on the right hand, regardless of hand dominance. This study would be strengthened by increased recruitment of left handed individuals (as only 3 of the participant were left handed) or perhaps performing the same protocol on both the dominant and the non-dominant hand for comparison. As mentioned in ***Section 2.5.2***, FMG was specifically chosen as it doesn't require extensive skin preparation, sensor placement, or technical expertise. However, further work related to the effect of anthropometry would include gold standard methods of myography (i.e. sEMG) for comparison and cost-benefit analyses of prototype devices. Along this vein, further work into using FMG for senior targeted tools would be to characterize the performance of FMG during long term wear (days, weeks) and in unconstrained environments. Finally, this work would benefit increased recruitment of seniors for improved statistical significance.

5.6. Chapter Summary

The aim of this study was to two-fold: 1) identify user features that contributed to the variability of FMG acquisition, and 2) to quantify the effect on FMG modelling. Five features of FMG processing were utilized to demonstrate the effect of these variables, motivated in part by the limitations in FMG research presented by the literature review in **Chapter 2**, as well as, practical considerations for day-to-day use of FMG in the community:

- Signal variability during repetitive motions
- Responsiveness to amount of motion/effort
- Multi-DOF movements
- The use of statically trained models on non-static activity
- Band removal

Twenty-one participants were invited to performance stationary and non-stationary orientations and movements of the hand, wrist, and forearm significant to the completion of the activities of daily living. FMG was collected at the wrist using a custom designed FMG device, as well as several intrinsic variables: grip strength, band tightness, skinfold thickness, and range-of-motion. Multiple simple machine learning models were developed, and outcomes measures were based on ANOVA, Student's t-test, and

Spearman's Correlation Coefficient which identified significant differences and patterns. The main outcomes of the results were as follows:

Variability. That FSR-based FMG was quite stable (< 6% variability) and demonstrated no significant relationships with anthropometry or influence on testing accuracy.

Responsiveness. That there were age and gender based differences in the responsiveness of FMG to movement/effort which were explained in part by band tightness, grip strength, and ratio of skinfold thickness to forearm circumference. Differences in FMG responsiveness explained between 7% and 27% of the variability model testing accuracy.

Presence of 'functional' noise. That FMG was strongly influenced by the presence of noise. Given the multi-DOF nature of the hand, wrist, and forearm, noise was described as the influence of unintended compound movements/gestures. This effect was more pronounced in seniors and was related to differences in grip strength, band tightness, and skinfold thickness. Noise resulted in a 1% to 14% decline in accuracy, which increased to a 35% to 50% decline when the amount of input training data was reduced. Overall it appears that identifying wrist position was less susceptible to noise (variable hand positioning) than identifying hand gestures in the presence of noise (i.e. variable wrist/forearm positioning).

Performance during non-static activity. At the bare minimum, using a statically trained model to identify classes expected during non-static activity presented moderate to high success. Between 60-80% for cylindrical grip and tripod grip, and at least 80% for wrist flexion/extension, forearm pronation/supination, and key grip. However, this performance was not consistent through the full range of motion or effort, and was not necessarily related to the training conditions. Clusters of correctly identified activity were more consistent at the extremes of movement, but were least likely to overlap with the training region for that intended gesture. At neutral wrist/forearm, there was a high degree of variability and misclassification, however it is surmised that this is due to the inherently low separability of hand gestures. When the participants trained hand gestures without objects, there was a low probability of correctly identifying that gesture in the presence of an object (<27%). The performance of static models during non-static activity had little to no relationship with anthropometry and band placement, and is more likely related to the nature of the machine learning paradigm itself.

Band removal. Decline in testing accuracy after band removal ranged from 28% to 96%. Although the variabilities in testing accuracy is partially explained by anthropometry (grip strength, ratio of skinfold thickness to forearm circumference, and band tightness), there was little to no relationship between anthropometry and band placement and the absolute or relative decline in testing accuracy. This suggests that that this decline is more likely related to the nature of the machine learning paradigm itself rather than variables intrinsic to the participant.

Chapter 6.

Concluding Remarks

6.1. Chapter Overview

The purpose of this chapter provides a summary of the findings of this thesis. Firstly, the objectives of this work are recalled and discussed in **Section 6.2**. Finally, future work considering the results of this thesis are considered in **Section 6.3**.

6.2. Summary of Objectives and Findings

The aim of this thesis is to explore the use of FMG as an additional tool to complement home-based senior-targeted technologies and to promote aging-in-place. Given the changes that occur with aging, increasing demands on healthcare resources and decreased availability of healthcare professionals pose a significant challenge to addressing the needs of seniors. Increasing use of technological interventions by seniors and the significance of the arm in hand in functional independence supports the exploration of FMG. FMG that provides direct user-movement data could complement Ambient Assisted Living environments which lack this information, and provide an alternative and potentially more advantageous sensing modality for tele rehab, communication, device control, and social applications. However, the literature review in ***Chapter 2*** indicated areas of FMG research that required further development to support the practical implementation of FMG into aging-in-place technologies for seniors. Based on the results of ***Chapter 2***, three objectives for this thesis were identified.

Objective 1 of this thesis was to characterize the use of FMG with senior populations. To meet this objective, a study was designed and executed to recruit senior participants to perform 3 repetitions of donning an FMG device for gesture identification and control of a virtual user interface. The experimental protocol consisted of training an LDA classifier on 5 select hand gestures for interface control, and subsequently performing an online identification routine. For online identification, four repetitions of each gesture were performed in a randomized manner. The trained LDA model was then tested on erroneous data (created by performing household activities) to track unintended activation of the system. Outcomes measures for characterization were comparisons with non-senior participants on the following variables: 1) the time to complete a gesture effectively after instruction, 2) cumulative accuracy while a control is held, and 3) the incidence of inadvertent classification during household tasks. Experimental data was collected for 5 senior participants and 5 non-senior participants. When compared to non-senior participants, seniors were able to the utilize the FMG system, but with increased error and variability. This was indicated by lower online testing accuracies (75% vs 91%), increased amount of time for the system to identify the gesture (1.4 s vs 0.9 s), and increased misidentification of erroneous movements as control gestures (1.45 s vs 1.28 s). These results suggest that on average, using FMG with seniors was feasible but more prone to misclassification. Reasons for the noted differences in performances were attributed to the intuitiveness of the gestures, learning differences between the two groups of participants, variability in the mechanical properties of underlying tissue, initial grip strength, fatigue, and joint stiffness. Unsupervised feature extraction guided by age and gender based differences in FMG sensitivity and increased variability were recommended.

Objective 2 of this thesis was to identify intrinsic participant features that account for the variability in FMG measurements. **Objective 3** of this thesis was to quantify the impact of intrinsic participant features on the accuracy of FMG modelling. To meet these objectives, a study was designed and executed to recruit senior and non-senior participants to perform 2 repetitions of donning an FMG device for hand gesture and wrist/forearm orientation identification in a constrained setting. Several types of simple machine learning models were developed to identify consistent behavior and five features of FMG processing and analysis were considered to illustrate the impact of intrinsic participant variables:

- Signal variability during repetitive motions
- Responsiveness to amount of motion/effort
- Multi-DOF movements
- The use of statically trained models on non-static activity
- Band removal

The experimental protocol consisted of holding static gestures, holding combinations of static hand gestures and wrist/forearm orientations, and moving through extremes of movements/effort. Experimental data was collected for 21 participants, 6 non-senior females, 9 non-senior males, 4 senior females, and 2 senior males. Outcomes measures of this study were age/gender group differences in select anthropometric variables, and ANOVA, Spearman's correlations, and Students' t-test to identify significant differences in model performance or FMG variability. **Firstly,** the experimental results indicate that FMG is quite stable with low variability (<6%) throughout repetitive movements/efforts, and was influenced very little by user variability. **Secondly,** there were demonstrated age and gender associated differences in band tightness, grip strength, and ratio of skinfold thickness to forearm circumference, which explained 24%, 30%, and 30% of the variability in FMG responsiveness to change. Differences in FMG responsiveness explained between 7% and 27% of the variability model testing accuracy. **Thirdly,** examining compound gestures highlighted age related relationships to the separability of class clusters as well as the decline in separability that occurred with the addition of functional noise. Gender based differences only demonstrated significance influence on the decline in separability with the introduction of noise. Noise resulted in a 1% to 14% decline in accuracy, which increased to a 35% to 50% decline when the amount of input training data was reduced. This effect was more pronounced when considering the identification of hand gestures than when identifying wrist/forearm orientations. **Lastly,** although there were noted declines in FMG model performance after band removal (28% to 96% decline) and unreliable performance during non-static activity – these behaviours were unrelated to user variability. This last result suggests that FMG performance in this regard was more related to the nature of model and feature selection.

The results of this thesis provide preliminary confirmation of the suitability of using FMG for hand gesture and wrist/forearm orientation identification with seniors. In addition, this work has also identified intrinsic participant variables (grip strength, band placement, and ratio of skinfold thickness to forearm circumferences) which demonstrated age and gender based differences and explained a portion of the variability of FMG data and modelling performance. Finally, this work also quantified the impact of practical FMG use on the effectiveness of FMG modelling from methods encountered in the literature. This work lays the ground work for investigating FMG and its implementation into senior-targeted technology to promote aging in place.

6.3. Future Work

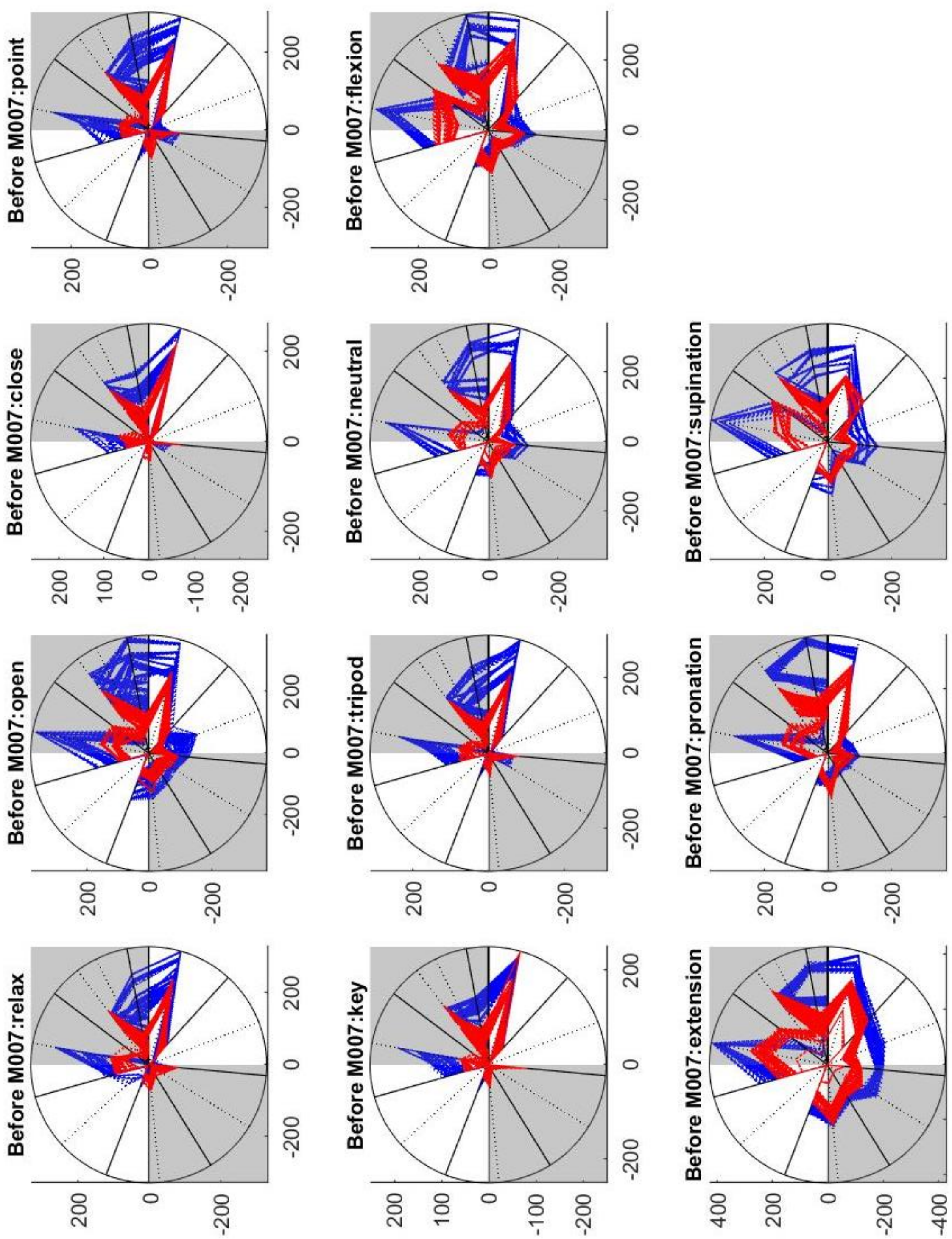
Despite the results of this thesis, there are further areas of FMG implementation that require further consideration and research. Although not an exhaustive list, a selection of areas is summarized below.

6.3.1. Calibrating for Differences in Anthropometry

The results of the second study discussed in ***Chapter 4*** and ***Chapter 5*** demonstrated that several intrinsic user variables influenced the effectiveness of FMG based modelling. These variables (which also demonstrated age related decline) were: grip strength, ratio of skinfold thickness to forearm circumference, and band tightness. Although the recruitment pool was limited to healthy participants, these variables also demonstrate variability in the face of pathological declines in motor ability. This would be particularly significant to the practical implementation of FMG with seniors, as seniors are marked by increased co-morbidities that reduce motor function. Further development of FMG would benefit from settings or scaling factors of raw FMG data that could mitigate the decline in accuracy and increase in variability that occurs because of these variables. This could be implemented as a calibration setting, a method currently being used in many commercial activity trackers.

6.3.2. Image processing

In this work, visualize inspection of 2D FMG data revealed spatial characteristics which inspired the use of image-processing techniques in FMG analysis. An example of this is the similarity between sessions 1 and 2 of the 2D FMG profiles of statically held gestures. The sample data shown in **Figure 6.1** demonstrates this qualitative similarity. Exploration of image processing techniques in FMG processing and analysis would be beneficial. The end goal of this type of research would be a pretrained model or database of activity that would allow the user to just don an FMG band and immediately use without training.



6.1. Example spatial profile of statically held hand gestures and wrist/forearm orientations during sessions 1 (blue) and 2 (red)

6.3.3. Further Evaluation with Seniors

As introduced in ***Section 1.4***, this is an initial work on the use of FMG for hand gestures and wrist/forearm orientation identification with seniors. As such, participant recruitment was limited to seniors whom identified as healthy. However, as seen via a more detailed discussion in ***Chapter 2***, demographics, morbidities/comorbidities, and differential aging of organ systems create a high degree of variability in aging seen amongst seniors. As FMG research matures, future study could be expanded to explore the effectiveness of FMG in the presence of debilitating morbidities. Along this vein, research could also better characterize which groups among seniors could benefit most from FMG, as well as, the way that FMG could complement other sensing modalities in an integrated fashion in AAL research.

6.3.4. Methods to reduce the amount of training input required

In the hand alone there are 27 degrees-of-freedom, capable of forming a plethora of gestures. Compounded with the 3 degrees-of-freedom the wrist and forearm are capable of, training a supervised learning algorithm for all gestures possible would prove to be an enormous task. As mentioned in **Section 2.3.1**, the time and effort to train such a classifier would deter acceptance and adherence of a technology in community dwelling seniors, and reduce it's long term effectiveness. Further work should seek to consolidate methods to reduce the amount of training required into a cohesive algorithm to improve accuracy after band removal and/or reduce the amount of required training data. This could potentially be realized through the development of a generalized model of FMG which utilizes specialized age and gender based setting to account for differences in grip strength, band tightness, and ratio of skinfold difference to forearm circumference.

6.3.5. Machine Learning in Non-Stationary Environments

The survey of FMG research showed that most FMG research has utilized static and supervised training regimes. The application of this method in non-static scenarios was explored as a part of this thesis in **Section 5.3.4**, and demonstrates poor consistency in non-static scenarios. This also demonstrated sensitivity to the presence of objects held in the grasp, which reduce FMG identification accuracy. Continued developed development of FMG would benefit from machine learning algorithms dedicated to non-stationary environments.

6.3.6. Bench to Bedside Considerations

As stated in **Section1.3**, the main motivation and context for this thesis is to present Force Myography as a sensing method that would provide data measured directly from the user. The intention is that this data would be incorporated into home based systems that would allow seniors to access services from their home. In working towards this goal, the strength of this thesis is that is explores and analyses signal characteristics of FMG unique to seniors which could be used in future software development and hardware design. By investigating the unique characteristics of using FMG with seniors, this work is a stepping stone towards deploying a a reliable and convenient FMG system in the general community.

The minimum required deliverable, as implied with this work and outline in **Section 3.3.2**, are tactile sensors placed on a flexible non-elastic backing which would allow the device to conform to the shape of the wrist. Considerations for comfort, convenience, and aesthetics would require that an FMG device be wireless, have a lower profile than what is proposed in **Section 3.3.2** with the exposed wires and circuitry encased and hidden from the preview of the wearer. Thus a recommended avenue for further consideration is further prototype development of a standalone FSR based FMG device, or perhaps a sensing strip that could be incorporated into an existing watchband.

A second milestone in bench to bedside translation of this work is the fusion of FMG with other sensing systems. Recommends include fusion with camera and audio systems, to facilitate remote health check ups with physicians, therapists, or other health professionals. Additional recommendations include integration with actuators systems to open doors and cabinets, with robotics for assistive and rehabilitative technology, and with proximity sensors for peripheral control of devices and household items.

Chapter 7.

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Appendix A.

Current state of FMG research

A.1. Types of participants included in FMG studies

Study Participants	Reference
Young healthy	[68], [73], [75], [77], [79], [81], [84], [85], [87]–[103]
Stroke survivors	[75]–[77]
Amputees	[72], [80], [81], [86]

A.2. Areas of research where FMG has successfully been utilized

Area	References
Control of hand prostheses, exoskeletons, and orthoses	[72], [78]–[83]
Tracking of intra-socket pressure in prostheses	[234]
Classification of grasps and/or hand/wrist/forearm gestures	[68], [75], [79], [87], [88], [90]–[92], [235]
Detection of a grasp	[77]
Regression of grasp force	[85]
Regression of 6DOF wrist torques	[236]
Regression of finger forces	[81], [95], [96], [207]
Regression of finger position/displacement	[97]
Classification of ankle position	[75], [98]
Analysis of gait	[84]

A.3. Types of sensors used in FMG acquisition

Sensor	Mode of Operation	Reference
Accelerometer	Measures acceleration and used to measure the vibration of muscles during contraction in MMG.	[104], [107]

Force Sensitive Resistor	Is a low power sensor, housing variable resistor whose resistance is inversely proportional to the amount of compression pressure/force applied to the active area of the sensor. Implemented as off-the-self discrete sensors as well as custom made high density arrays.	[68], [73], [75], [77], [79], [80], [82]–[85], [87]–[89], [91]–[98], [234], [236]
Open-cell Polymeric Foam Pneumatic Sensors	A custom design foam sensor and electrical interface, whose output is directly related to the amount of pressure applied. Has a considerable high fabrication cost.	[81], [86]
Optical Fiber Specklegram Sensor	A fiber optic sensor placed in between two ridged deformer plates, whereby the laser intensity in the fiber is modulated by the displacement of the two deformer plates.	[100], [102]
Piezo-resistive Fabric Material	A fabric material which displays variable resistivity under mechanical stress.	[90], [101]
Space-charged Piezo-electrets	An 'electret' is a permanently polarized piece of dielectric material, analogous to a permanent magnet. These materials have voids, which helps decrease the mass. These voids can be charged to create dipole moments, whereby the dipole moment can change due to mechanical, thermal, or electrical stress. [237]	[99]
Strain Gauge Sensors	A low power sensor, which demonstrate variable output based on the amount of tensile forces applied	[94], [235]

A.4. Areas of Placement of FMG device

Area of Placement	Reference
Thigh	[84], [99], [104], [107], [238]
Ankle	[98]
Calf	[75]
Forearm - cuff	[85], [86], [90], [91], [93], [100], [234]
Forearm - distal, wrist	[68], [73], [88], [92], [94]
Forearm - mid	[79], [88], [101]
Forearm - proximal	[73], [77], [80], [82], [83], [87], [96], [97], [102], [236]
Forearm - ventral side only	[95]

A.5. Methods of data processing, data representation, and feature extraction used in FMG research

Data Processing	Description	Reference
Base line removal	Subtracting the minimum-most value from the entire data set	[84], [85]
Full-wave rectification	Taking the absolute value of all data points	[84]
Kurtosis coefficient	Skewness of the data distribution (a method typically applied to EMG that was utilized with FMG)	[99]
Log Detector	A non-linear detector used to estimate muscle contraction force. (a method typically applied to EMG that was utilized with FMG) $$LOG = e^{\frac{1}{N}\sum_{i=1}^{N}\log(\lvert x_i \rvert)}$$	[99]
Mean Absolute Value (MAV)	For FMG devices that have more than value, a single value is reported by combing the n sensors in the following manner: $$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i \rvert$$ (a method typically applied to EMG that was utilized with FMG)	[99]
Median filter	Each point is expressed as the median of a fixed number of points preceding and following the point of interest. Where m is the window size $$x_i = \frac{1}{2m+1}\sum_{j=i-m}^{i+m} x_j$$	[92]
Moving average filter	Each point is expressed as the mean of a fixed number of points preceding and following the point of interest.	[84]
Normalized	Scaling the data set so that the minimum-most and maximum-most values correspond to the range [0 1].	[88], [94]
Principle Component Analysis	A statistical procedure that uses orthogonal transformation to convert a set of observations to linearly uncorrelated variables called principal components. The principal components are ordered based on how much they account for the variability in the data.	[78], [79], [90], [95]
Raw	Raw un processed FMG signals.	[96]
Root Mean Square Rectification	Multi channeled data are represented using the square root of the mean of the squared values.	[84]

	$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$	
Separability of clusters	Theory is that the more separable the clusters are, the better classification will be in general [239]. Expressed using Fisher's Separateness Index, which is the global maximum of J(w) given that $$J(w) = \frac{w^T S_B w}{w^T S_W w}$$ Where S_B is the between class scatter matrix and S_W is the within class scatter matrix	[79]
Simple Square Integral (SSI)	Summation of square values of FMG sensor amplitudes. Also considered an energy index. $$SSI = \sum_{i=1}^{N} x_i^2$$ (a method typically applied to EMG that was utilized with FMG)	[99]
Third Temporal Moments (TM3)	A statistical method employed with EMG. $$TM3 = \left\lvert \frac{1}{N}\sum_{i=1}^{N} x_i^3 \right\rvert$$ (a method typically applied to EMG that was utilized with FMG)	[99]
t-Stochastic Neighbor Embedding	a non-parametric unsupervised approach that maps high-dimensional data to a low-dimensional space for visualization while preserving the significant structure of the original representation	[101]
Wavelet extraction	Time-frequency transformation of optical based-FMG	[100]

A.6. Machine Learning Algorithms used in FMG research

Machine Learning Algorithm	Description	Reference
Artificial Neural Network (ANN)	Implemented as a supervised method in the literature. A multilayer network, whereby each successive layer is a linear combination of the outputs of the previous layer. Layer weights are optimized for optimal separability [240].	[77], [83], [90], [99], [100], [102]
Extreme Learning Machine (ELM)	A feedforward neural network for classification or regression with a single layer of hidden nodes, where the weights connecting inputs to hidden nodes are randomly assigned and never updated [241]. Has been shown to have equal or superior performance to SVM and ANN, with faster learning speed [242].	[82], [87], [101]

Incremental Ridge Regression with Random Fourier Features (RR-RFF)	Ridge Regression builds a linear model f(x) = wTx, where x denotes the sensor values, w is a weighting vector and f(x) is the predicted output; Random Fourier Features further employ a non-linear mapping from the input space to a higher-, finite-dimensional feature space, where the linear regression is more likely to succeed [243]. A non-linear extension of Ridge Regression.	[78], [79], [96]
K-nearest neighbor (KNN)	Implemented as a supervised method in the literature. A non-parametric classification, with the object being assigned to the class most common among its k nearest neighbors.	[99]
Linear Discriminant Analysis (LDA)	A supervised method of classification, which constructs a linear combination of the data which results in the highest amount of separability	[73], [80], [88], [91], [92], [94], [98], [100]
Random Fourier Features Regularized Least Squares	It can be seen as a non-linear, finite-dimensional extension to RR	[96]
Support Vector Machine (SVM)	A supervised method which maps the input data into a higher dimension, and constructs a hyperplane or set of hyperplanes in a high- or infinite dimensional space where data separability is optimized for classification or regression [244]. Deemed more accurate than Ridge Regression.	[68], [89], [93]–[96]
Support Vector Regression (SVR)		[92], [97], [236]

A.7. Number of classes used in FMG classification

Number of Classes	Reference
2	[82], [83]
4	[95], [99]
5	[80], [101]
6	[68], [87]
8	[88], [90], [91], [94]
9	[100], [102]
11	[80]
16	[92]
17	[93]
48	[73]