July 25th, 2021

Dr. W. Craig Scratchley
School of Engineering Science
Simon Fraser University
Burnaby, BC
V5A 1S6

Re: ENSC 405W/440 Funding Proposal for Smart Swim by Smart Swim Analytics

Dear Dr. Scratchley,

Attached to this letter is a funding proposal for the Smart Swim as requested for ENSC 405W. The Smart Swim relies upon machine learning models to detect and track a swimmer using swimming competition footage or in real-time using a tilt-pan camera, and to provide an estimation of the swimmer's stroke rate. It provides valuable data for competitive swimmers and trainers.

The attached proposal will present a overview of the Smart Swim Product including an introduction and background as well as an outline of the project scope. The proposal will move on to provide a risk and benefit analysis of the project as well as a market and competition analysis. Furthermore, the proposal will include a project plan showing the main milestones and cost considerations of Smart Swim.

Smart Swim Analytics is a team of 6 senior Computer Engineering students, Tim Woinoski, Kiran Brar, Kuro Chen, Ethan Cai, and Ray Kim, and Systems Engineering student Kudus Elbo-Iswadi. Together, we aim to utilize our combined knowledge to make the concept of Smart Swim a reality.

Thank you for taking the time to read the Smart Swim funding proposal. For any questions or concerns, please feel free to contact Tim Woinoski at tim_woinoski@sfu.ca.

Kind Regards,

TimW

Tim Woinoski
Project Lead
Smart Swim Analytics

Project Proposal

for

Smart Swim Analytics System

Version 1.0

Prepared by

Kudus Elbo-Iswadi, Gurkiran Brar, Ethan Cai, Kuro Chen, Ray Kim, Tim Woinoski

Smart Swim Analytics

July 25, 2021

Acknowledgements

We would like to thank Taha B. Esmael for his excellent design of the Smart Swim Analytics logo.

1. Executive Summary

Smart Swim Analytics aims to help Canadian swimmers improve their performance in a more cost effective and inclusive manner than presently available. Thus we have designed Smart Swim, inspired by research completed by Tim Woinoski. This system will determine a swimmer's stroke length and stroke rate, which are essential metrics for measuring performance. Not only will the system be quicker than the current method of measuring these metrics by hand, it will also be cheaper than such methods.

The product will consist of an annotation tool that lets users easily annotate videos to train swimmer models. Such models are vital for the completion of the proposed tasks. The annotation will only need to be performed once at a given pool, after which the models will be ready to use with the Real-time Swimmer Tracking System and Swimmer Positioning System, which detects the swimmers in real-time and determines their position in the pool.

Team Canada is very competitive on the world stage in swimming and produces Olympic medalists every Olympic quad. Since swimming is such a competitive sport, swimmers look for ways to improve their performance and keep track of their progression. The current method of measuring swimming metrics is by hand, which is both expensive and time-consuming. However, those tasks have the potential to be automated by computers. Therefore, there is a demand among swimmers and analysts for a better measurement system.

Our prototype, the Smart Swim System, is an automated system that determines a swimmer's stroke length and stroke rate. Our system will automate swimming analysis as well as get more accurate measurements of swimmers. Thus, it saves time and reduces cost. Additionally, swimmers can benefit from getting real-time swimming footage, which is more effective as the race is fresh in their minds at that point. Lastly, an automated system can save coaches' and analysts' time from post-race analysis by analyzing videos. They can then adapt future workouts according to such results.

Our company is excited to provide the Smart Swim System as an accurate and cheap solution to monitor swimmers' performance. We are an enthusiastic team of skilled and diligent senior engineering students with experience in software development, system engineering and machine learning models. We will continue to improve our product, do experiments and make it a reality within the upcoming months. Our Smart Swim System will help track swimmers performance easier and better!

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2. Introduction

2.1. Document Overview

This document outlines a proposal for creating the Smart Swim System, a complete Automated Swimming Analytics System. As such, this document gives a general summary of Smart Swim. The following sections are described in this document.

- Section 3 - Which gives a high level overview of Smart Swim functionality and architecture.
- Section 4 - Which details both potential risks involved in the creation of Smart Swim and the potential benefits.
- Section 5 - Which describes the need for the Smart Swim system while detailing current solutions.
- Section 6 - In which the Smart Swim team presents the company name, product name, and logo; in addition it gives outlines of relevant skills and expertise of all team members.
- Section 7 - In which major details, processes and milestones of the project are given and includes a Gantt chart.
- Section 8 - Which includes a realistic estimate of project costs, potential funding sources and contingencies of such costs/fundings.
- Section 9 - Which summarizes Smart Swim and the topics covered in this document.

2.2. Project Scope

The Smart Swim system allows for the collection of swimmer analytics from general non-static footage of swimmers, also known as general overhead race video (ORV), as seen in Figure 2.1. This system makes almost no assumptions about how the footage is or was collected. In other words, it is very robust. Many analytics can be collected by humans utilizing ORV; however, only two will be collected with this system. Such metrics will be Strokes Per Minute (SPM) and Distance Per Stroke (DPS), defined in Appendix A. There are five main sub-systems to this system, and more detail is given in Section 3.1. Each part works together to allow the analytics system to be utilized in any swim competition setting while maintaining robust analytics results quickly and efficiently.

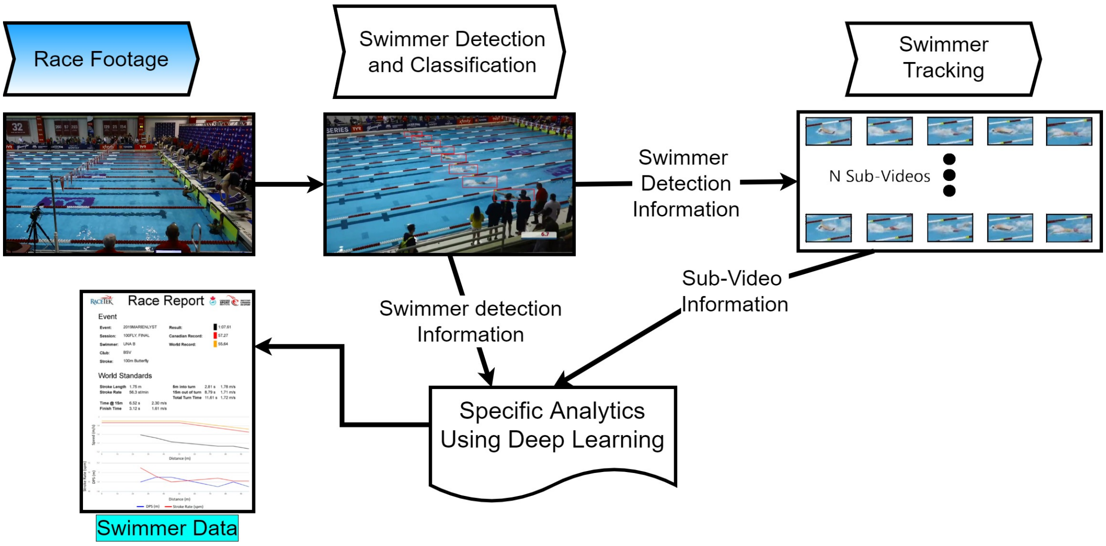

Figure 2.1.: A pictorial representation of the Smart Swim System

3. System Overview

This section gives a high-level overview of the proposed Smart Swim system and how it will be implemented.

3.1. Product Functions

The motivation for this project is to develop a system that will automate the collection of swimming analytics in swim competition videos using image-based processing methods and tracking algorithms. Specifically, those analytics will be the SPM and DPS, as defined in appendix A, of a particular swimmer selected before the commencement of a race. In addition to collecting these metrics, the analytics system must work for a general competition setting. To solve these problems, we propose the following subsystems, which support each other in the following order.

1. A data collection system: Which allows for the collection of training and test data for creating and augmenting swimmer models.
2. A model training and testing system: Which utilizes collected swimmer data to train, augment and test swimmer models.
3. A real-time swimmer tracking system: Which utilizes the swimmer models to direct a camera to track a swimmer of interest.
4. A swimmer stroke analysis system: Which utilizes the swimmer models to collect the stroke count data required as the first part of one of the required product functions.
5. A swimmer positioning system: Which takes the real-time swimmer tracking results and estimates the positions of the swimmers in the pool; the second part of the required product function.

3.2. Intended Use of System

With the functions of the system defined, the intended use of each of the system's functionalities can be given. When given a competition venue for data collection utilizing the Smart Swim system, the following procedures are followed, which can also be seen in Figure 3.1. If the competition venue of interest is new or if the viewpoint at which the competition will be analyzed is different, then the Data Collection System is utilized by

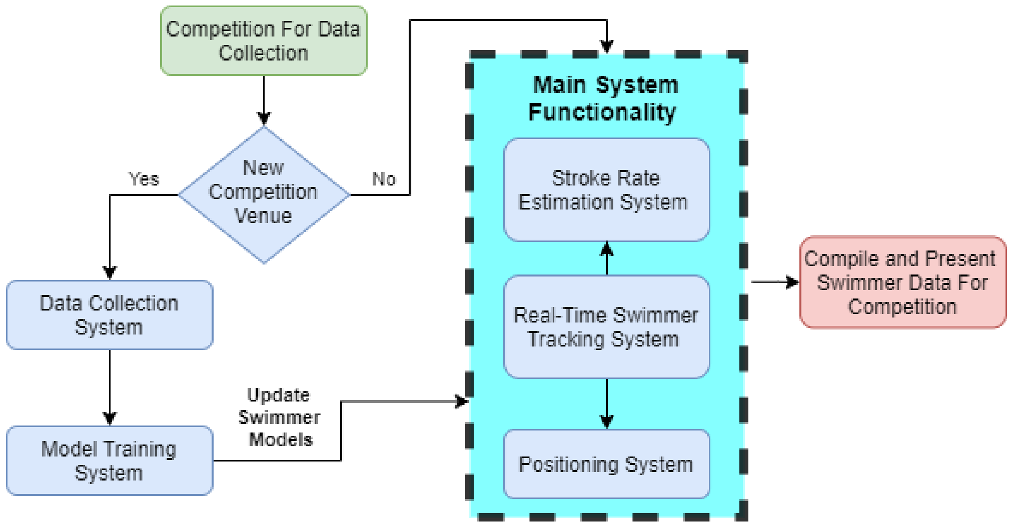

Figure 3.1.: A summary of the expected use of system functions

the Data Collection Specialist to create training data in the competition of interest. This data will be used for updating or creating models utilizing the Model Training System, facilitated by the Sports Analyst, so that Smart Swim will work in a general setting. The Main System Functionality is monitored and overseen by Footage Collectors. The output of the main functionality is received by the Sports Analyst, interrupted and possibly modified such that it can be utilized most effectively by the Athletes and Coaches.

3.3. System Architecture

Figure 3.2 details how all the sub-systems are implemented with software, hardware, and a database. It also depicts how all parts of the system work together to implement the mentioned sub-systems, which collects the required data in the database, that being analytics files, annotated footage and model weights. Lines with arrows depict the flow of information or data to and from the user, hardware and database.

The blue boxes denote all hardware required in running the proposed functionality. The following is a summary of the hardware utilized in this project.

- Embedded GPU and Processor
- Tilt-Pan Hardware and Camera
  - Micro Controller
  - Image Sensor
  - Micro Controller Controlled Motor
- Linux OS Computer

- High Powered GPUs
- General Computer (Linux OS, Windows OS, Mac OS)

The green boxes denote software implementations, which run on the hardware they are connected to by a line with a circle attached.

- Data Collection Software
- Swimmer Positioning Software
- Swimmer Tracking Software
- Tilt-Pan Firmware (Implemented in the Tilt-Pan Hardware)
- Swimmer Analytics Software
- Model Training Software

Lastly, the database is represented by the purple circle.

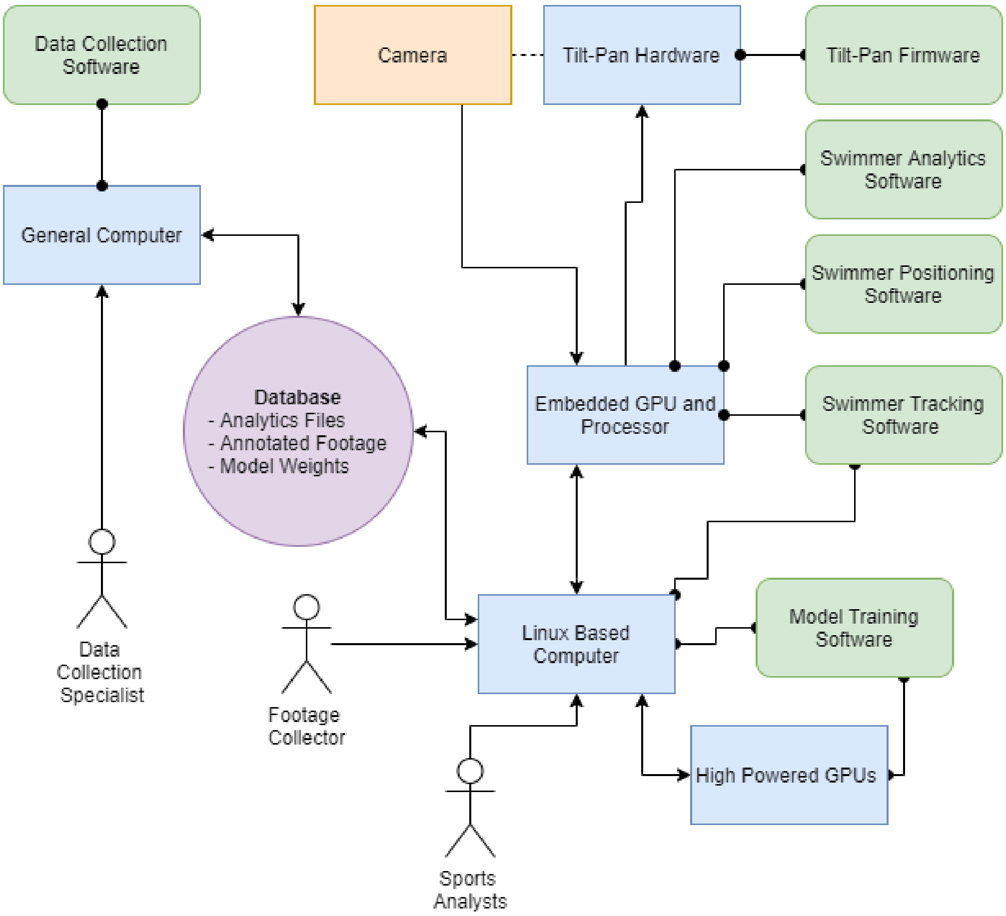

Figure 3.2.: The main system functions and how they work together

4. Risks and Benefits Analysis

This section details both potential risks involved in the creation of Smart Swim and the potential benefits. These benefits were gathered and created in conjunction with Swim Canada's Data Analyst and Manager of High Performance Pathways, Aaron Maszko.

4.1. Benefits

The following benefits are split into three sections: Real-time Analytics, Athlete Performance History, and Cost Reduction. The following benefits apply to the creation of a system that has the functions outlined in Section 3.

4.1.1. Real-time Analytics

Athlete analytics from videos of swimming events have a wide variety of critical impacts. Primarily, fast analytical comparisons are made between athletes within the same field or events, providing quantitative and meaningful measures to coaches prior to, during, and post major championships. World Championships and Olympic Games competitive swimming portions take place over 10 or 11 days. Athletes in multiple events or relays will likely swim against the same individuals multiple times, and each will be looking to fine-tune and improve with every race. Having the ability to compare to one's previous performances is an essential analysis to prepare to make minor adjustments and set goals for the next race, and one that every nation provides to their athletes. However, understanding how others swim their races and identifying critical tactical points where Canadian athletes can gain an edge is an enormous task. Furthermore, such a task is unlikely to be reliably performed by a single analyst between sessions. With computer vision analysis, this becomes possible.

As a secondary consideration, this project's innovation would bring to Swimming Canada a vast increase in efficiency for championship race preparation. For instance, if a group performing race simulations done an hour apart would require analytics, it simply would not be possible for a single analyst to gather race analytics from 8 or more athletes racing just 100 or 200-metre races in that time, not to mention prepare detailed analytical comparisons for the athletes between swims. Even in this simple illustration, the benefits of analysing the athlete's performances are apparent. It removes the time consuming task of collecting data, and provides more time to the analyst, coach, and athlete to review the materials and make the necessary changes for improvement. This dramatically impacts the peak competition environment, as described in the previous section, and has the potential for a profound impact on the daily training environment and Swimming Canada's domestic program.

4.1.2. Athlete Performance History

Understanding an athlete's performance history and their benchmarks is a huge advantage when taking teams away into preparation camps and major championships. Not all athletes get to travel with their home coach, and so much work must be done in advance to share and prepare the new coach-athlete tandem adequately. For example, 2019 World Championship Gold Medalist Maggie MacNeil had neither her home club coach nor her varsity team coach at the competition. An entire competitive workup of what an athlete has done and how they have progressed, both in terms of raw performance times and specific race metrics, provide the "new" coach with the tools they need to communicate effectively and prepare the athlete for the competition ahead. While there is little that can be changed in the final weeks heading into a competition, simply understanding where an athlete's peak performance baseline is (e.g. stroke counts, stroke rates, splits, etc.) gives the coach and athlete an idea of what is happening and what needs to be adjusted, if anything, in time for racing.

Lastly, the knowledge gained from analyzing all the world's top performers can be applied to the next cycle's Gold Medal Profile and all Senior carded athletes. Many of Canada's top athletes only take a few weeks off between a major championship and the start of the next competitive season, and much of this time is used by the athlete's coach to review and plan around where the following improvements can be made. Being able to provide invaluable benchmarks and data-driven recommendations to coaches at the start of their planning cycle is critical in ensuring that targets are set as early as possible for technical and tactical interventions. Due to the time-consuming nature of our current methods to capture race analytics, it is difficult to synthesize enough race video data, both past and present, to make these recommendations and discuss how different events or competitive fields are changing in time.

4.1.3. Cost Reduction

With the capability of automated computer vision analytics capturing, analysis that has been primarily limited by time and expertise and only made available to Canada's elite athletes and coaches can now be provided on a grand scale. Provided there is a quality video of each race of competition at any domestic competition, analysis can be made available to all participants and allow for the same type of gap analysis typically available to Canada's top athletes. Coaches and athletes would then be exposed to tactical gap analysis and race analysis earlier in their careers, preparing them for the processes expected at the international level. Race comparisons can easily be made to the aforementioned tactical benchmarks, clearly defining where the most significant performance gaps lie between the current performance and those competing internationally. Both coaches and athletes may then address tactical gaps at a junior level before poor tactics and race skills become so ingrained that they are challenging to undo.

4.2. Risks

Given the vast quantity of benefits of Smart Swim for competitive swimming, the main risk is that the product is not developed further beyond the research and development phase and is not productionized and managed. In addition to productionization, resources to maintain the system are needed. It would require support from the swimming association and funding from investors to prevent the risk. Once the product is ready to be commercialized, there could be challenges to deploy and distribute the product because the real-time camera components of the product need to be installed at the swimming pool sites. Another risk is that funding to pay people to manage such a system is not given, and the system is forced to be shut down. Other more technical risks involve the proposed system not working as expected or unforeseen issues occurring that make a solution to the problem infeasible. If the solution turns out to be just as expensive or less accurate as current alternatives, it is unlikely that this work will be of use. Lastly, it is possible that other groups could be exploring such topics and, as such, produce the same work first.

5. Research Rationale

This section describes the need for the Smart Swim system while detailing current solutions. As mentioned in Section 4 the benefits of having swimmer analytics are substantial. As such, this section assumes that the benefits are greater than the risks. This section argues that Smart Swim is an effective method for obtaining the benefits noted, so much so that it is the best option and should be pursued as a research subject.

5.1. Current Swimming Analytics Methods

Currently, in swimming, data is collected for swimmers at competitions utilizing ORV of swimmers by various people. Of particular note, RaceTek [1] provides Canadian swimmers with racing data, as seen in Figure 5.1, for every major and some minor competitions. The basic services provided by RaceTek include; Swimmer velocity (meters per Second), stroke rate analysis (Strokes Per Minute), and stroke distance analysis (Distance Per Stroke in Meters) collected from videos recorded at swim competitions. All calculations are done by hand using video footage to analyze swimming. RaceTek has been analyzing swimmers for many years now, but unfortunately, their services are costly, and data can not be released to the public.

Other groups provide similar services in practice environments, such as Form Swim goggles and TritonWare [2, 3]. However, these projects can not be used in a race setting, as FINA rules [4] of swimming do not allow such devices, and most data is stored in video form to be analyzed.

In addition, automated swimming analytics has been attempted by a few organizations [5, 6] however these organizations are yet to put anything on the market. In contrast to what is proposed in Smart Swim, the assumptions made in [5, 6] are much more stringent. For example, they assume collected video captures the entirety of a given pool. As such, if Smart Swim is completed, it will have the upper hand as it will be easier and cheaper to collect footage for analysis.

5.2. Need for Smart Swim

The final goal is to create a system that will automate accurate measurements of swimmer analytics utilizing resources already created (footage of swimmers). An organization completes the proposed tasks but at a very high cost and low speed since it is not automated [1]. The systems created by Form Swim and Tritonwear [2, 3] only work when attached to a swimmer. This means every swimmer would need one. It also means that it can not use race footage to extract swimming analytics. Lastly, [5, 6]

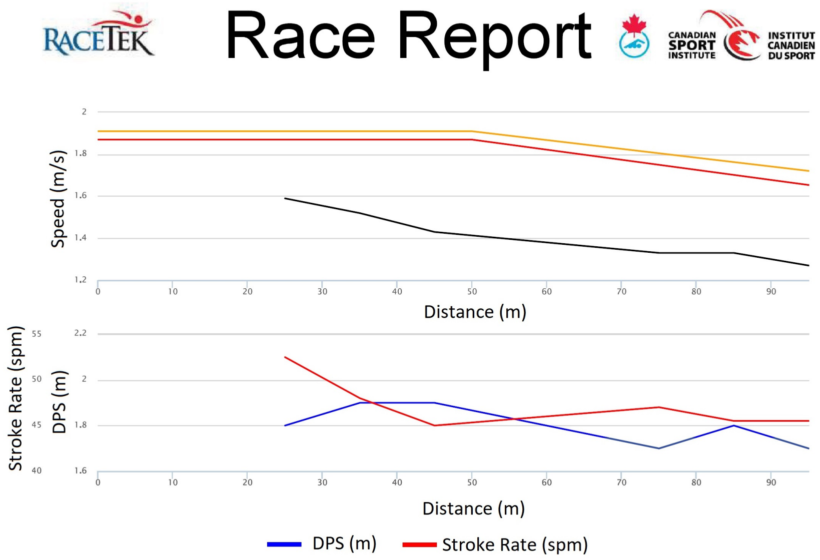

Figure 5.1.: A modified example report from RaceTek [1], found under Video Race Analysis (VRA). Source: Adapted from [1]

propose similar systems but have more stringent assumptions and are not available to the public. At this point there are no available systems that achieve the goal of automated swimming analytics; as such, Smart Swim seems to be an excellent solution to automatically collecting swimming data.

6. Company Details

This section presents the Smart Swim team, product name, and logo as shown in Figure 6.1; in addition, it gives outlines of relevant skills and expertise of all team members.

Figure 6.1.: The Smart Swim Logo

6.1. About Smart Swim Analytics

Smart Swim Analytics is a company founded in May, 2021 by Tim Woinoski, Ethan Cai, Kuro Chen, Gurkiran Brar, Ray Kim, and Kudus Elbo-Iswadi. The product, Smart Swim, was aptly named to describe its function: analyzing swimmers using artificial intelligence technology and providing valuable data that will assist swimmers and swimming trainers in achieving better and more efficient results. Graphic designer Taha B. Esmael designed the company logo, and it is composed of the abbreviation SSA (Smart Swim Analytics) in the shape of a fish.

6.2. Tim Woinoski - Project Lead

Tim is a seventh-year Computer Engineering student with an interest in sports, sports analytics, deep learning, and swimming. He has published multiple works in the subject of automated swimming analytics [7, 8] at workshops such as AAAI and ICME. He is an active member of Dr. Ivan Bajić's research group, which is part of the SFU Multimedia

Lab. He has completed a thesis in swimming analytics and passed with distinction. He has completed his co-op terms at Transoft Solutions Inc. and WWEST (spearheaded by Dr. Lesley Shannon). He has experience in computer vision and tracking methods utilizing deep learning. He has knowledge of multimedia research such as tensor completion, analytics of deep learning models through estimation of mutual information, effects of image compression on tracking, collaborative intelligence and many more subjects. Lastly, he competed for the SFU men's swim team from 2014 to 2018. In which time he had competed internationally and nationally in swimming competitions in three different countries at various championship competitions. He is the Project Lead at Smart Swim Analytics and he is responsible for directing Smart Swim so that it can be best utilized for swimming and in particular by Swimming Canada.

6.3. Ethan Cai - Positioning Systems Specialist

Ethan Cai is currently a fifth-year Computer Engineering student. He is passionate about the development and application of artificial intelligence image recognition. He has interned at Vancouver local Virtual reality platform development company and is well experienced with 3D panorama tour making and immersive virtual reality platform development. Ethan is the Positioning System Specialist at Smart Swim and he is responsible for panorama image-stitching and positioning the swimmer in the panorama frame.

6.4. Kuro Chen - RT Systems Specialist

Kuro is a fifth-year Computer Engineering Student at Simon Fraser University. His interests include FPGA design and optimization, various abstract data type (ADT) project implementation, and product firmware design. He has completed co-op terms at Algo Communication Product Ltd., given duties on trouble shooting and fixing on PCB products, product firmware QA and product testing. He is experienced with SQL database supported and web-based software project design in back-end, multi-threaded programming, and AI algorithm implementation. He is a Real-Time Systems Specialist at Smart Swim Analytics and he is involved in firmware connection between the tilt-pan sensor system and embedded GPU processor, hardware communications between electronic controllers, and real-time detection and tracking software design.

6.5. Kudus Elbo-Iswadi - RT Systems Specialist

Kudus is a fifth-year Systems Engineering student at Simon Fraser University. He is passionate about digital signal processing, biomedical technology, and feedback control application. He has completed two co-op terms at Mazdis Innovations Inc and Vancouver Shipping LLC. His experience includes working with back-end development and quality testing, as well as control design. He is a Real-Time Systems Specialist at Smart Swim

Analytics and his role involves designing and building the tilt-pan camera sensor system and creating an interface that will allow for detection and tracking in real-time.

6.6. Gurkiran Brar - Data Scientist

Gurkiran (Kiran) Brar is currently a sixth-year Computer Engineering student at Simon Fraser University. Her interests include learning more about testing for quality assurance (QA), as well as learning more about database systems. She has completed her co-op terms at Gatekeeper Systems Inc and Appnovation. Her co-op experience has been in QA with a focus on helping writing test cases for and testing web-based services. She will apply the experience gained to help make data collection and use as easy for the end user of Smart Swim as possible. She is a Data Scientist at Smart Swim Analytics and she is responsible for the data collection system and helping with model training/augmentation.

6.7. Ray Kim - Data Scientist

Ray Kim is a fifth-year Computer Engineering student at Simon Fraser University. Ray's interests are in data and learning new technologies. He has been working as a Data Engineer at Insurance Corporation of British Columbia for 4 years implementing development frameworks and analytics solutions. He is well-experienced in SQL, Hadoop, Spark, and Scala. He is a Data Scientist at Smart Swim Analytics, and his role involves researching and developing data collection and deep learning solutions.

7. Project Planning

Smart Swim will be designed over three phases, where each builds upon the previous.

Initially we have the Proof of Concept (POC), or alpha stage, which will be completed by the end of the summer 2021 semester (end of ENSC 405W). The purpose behind this stage is to build the crucial aspects of the product. As such, the POC will ideally incorporate the following:

- Use the existing API provided by Tim for annotation [9], as well as adding on the functionality for position annotations
- Ability to train and augment a deep learning model [10]
- Ability to do basic tracking of a single swimmer for the real-time swimmer tracking system (detection in real-time resulting in basic output data representing the detections)
- Ability to estimate a single swimmer's position in the pool in real-time from a non-static video with tracking data, outputting the one-dimensional position of the swimmer as a function of time

Following the alpha stage is the beta stage, which will be completed half way through the fall 2021 semester (halfway through ENSC 440). The purpose behind this stage is to build upon the POC to a more refined look and with more efficiency. As such, this stage will result in a prototype that ideally incorporates the following:

- GUI for the existing API provided by Tim for annotation [9]
- Ability to test and augment the trained deep learning model
- An evaluation method to determine how accurate the positioning system is
- The positioning system will operate in a reasonable time frame and generate data before the following race

Lastly we have the production stage, which will be completed by the end of the fall 2021 semester (end of ENSC 440). The purpose behind this stage is to finish the product with the final tweaks that give it a more professional feel when using it. As such, this stage will result in a final product that ideally incorporates the following:

- Clean user experience when using the API for annotation [9]
- The deep learning model is integrated with the real-time system

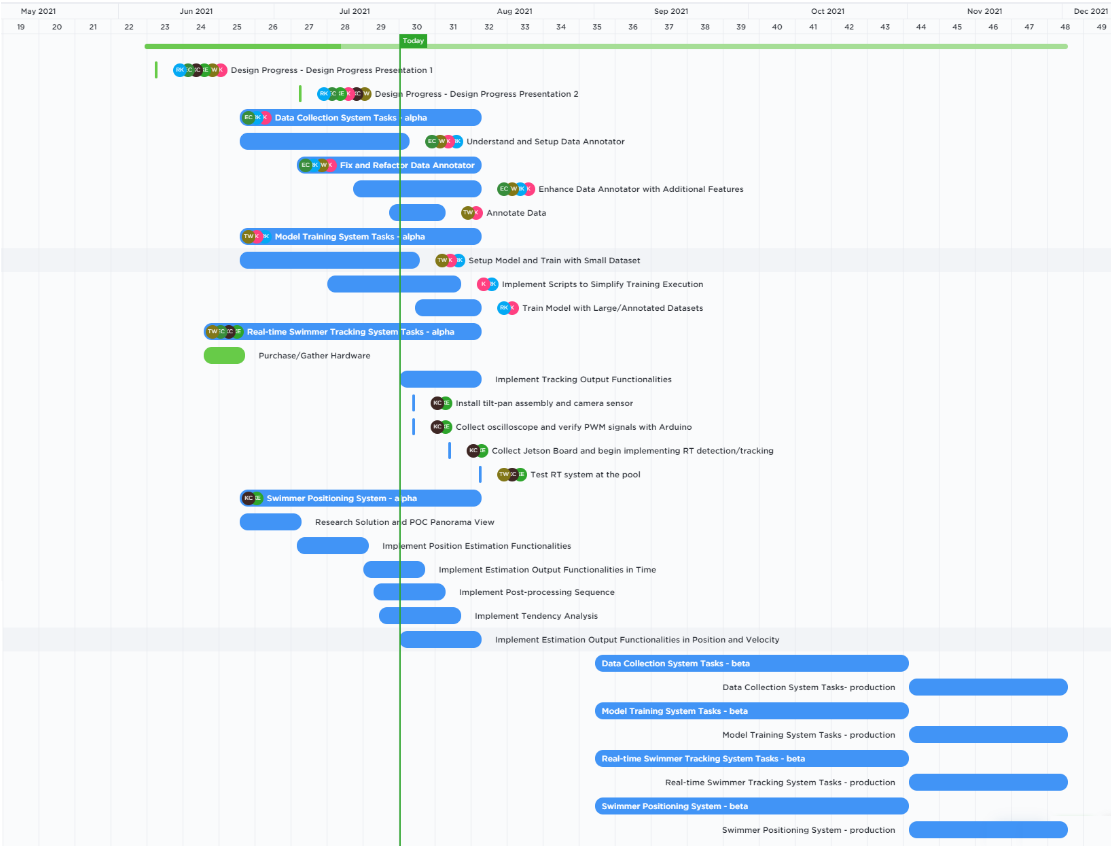

Figure 7.1.: Gantt chart for Smart Swim project planning

- A real-time tracking system that produces output files shortly after the race is over, before the next race begins
- The output file of the positioning software is clear and human-readable
- Proper documentation to ensure the user can use the product as intended

In Figure 7.1 is a Gantt chart (created with use of [11]) to detail the various tasks to be completed in the stages that were discussed. We have four major tasks (Data Collection System, Model Training System, Real-time Swimmer Tracking System, Swimmer Positioning System) as well as a variety of sub tasks to break these components down into manageable portions with deadlines.

8. Cost Considerations

The following table (Table 8.1) summarizes the specific spending details and we will add extra components if needed to complete the project. We will prepare an additional 20 percentage of the funds to be used as a reserve fund in case there are some other changes made in the project.

8.1. Estimated Project Costs

Since the actual amount we spend is not much different from the estimated cost we originally planned, we only list one table (Table 8.1) to list out each item's cost in detail and calculate the amount of the total consumption. If we need to purchase additional components, we will use the backup fund as we mentioned before.

8.2. Funding Sources

8.2.1. Engineering Science Student Endowment Fund

The Engineering Science Student Endowment Fund (ESSEF) is a fund that is managed by the School of Engineering Science Student Association. The fund is used for encouraging and supporting engineering students to complete novel and creative projects. The ESSEF fund falls under four different categories: Category A – Competition, Category B – Entrepreneurial, Category C – Class and Category D – Miscellaneous. The categories we are interested in are Category B - Entrepreneurial and Category C -Class. We know that our project is relatively cheap and low cost from the previous cost calculation, so there is no need for Engineering Science Student Endowment Fund to provide too much capital.

8.2.2. Undergraduate Student Research Awards

Undergraduate Student Research Awards is a fund managed by the Natural Sciences and Engineering Research Council of Canada. USRAs aims to cultivate your interest and give full play to your potential for research in the fields of natural science and engineering. If the funds from ESSEF are insufficient, USRAs will be a realistic funding source of additional funding.

Table 8.1.: Estimated cost for Smart Swim.

Estimated Cost List		
Item Name	Description	Estimated Cost
Nvidia Jetson Tx2 Development Kit	A type of development kit that gives a fast, easy way to develop hardware and software	CAD 1170
Raspberry Pi 2 Model B board	A single-board computer that can be used for many things such as spreadsheets, word-processing and games	CAD 350
2x HS-422 Standard Servo	The power distribution and supporting solution to the whole system	CAD 35
FLIR Firefly DL camera	The camera can be used to capture and track the specific swimmer	CAD 500
All the connection wires and electronic elements overhead	The wires and other electronic elements used in building the system	CAD 20
Total Amount		CAD 2075

9. Conclusion

Our company hopes to optimize the cost and time of analyzing swimmers' performance by providing a new automated analytics system. Smart Swim analytics system is such a system intended to accomplish this goal by using machine learning models.

This proposal has outlined Smart Swim Analytics as a whole and provided a background of needs in the swimmer market. We have researched and evaluated the current market, seeing that there are no existing competitive products. This proposal also shows the benefits and risks of commercializing the system. We will continue working on this product to examine both safety risk and funding risk.

Our team hopes to devote our skills and knowledge to create a robust automated analytics system aimed to be both an accurate and cheap solution that could benefit all users involved in swimmer tracking.

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A. Background on Swimming

This background is based off the work in [12]. Understanding this subject matter will prove to be useful when considering the issues being solved in this work. Understanding how a race occurs, or how a swimmer swims, allows one to understand the challenges being faced. This section will continuously be referred to throughout this work when exploring challenges and solutions.

This section is broken down into the following sections.

- Section A.1: In which the Strokes Per Minute (SPM) and Distance Per Stroke (DPS) metrics are defined.
- Section A.2: In which a background on pools is given which is important for understanding the swimmer detection, tracking and positioning problems.
- Section A.3: In which an introduction to swimming races is given, which is important for swimmer tracking and positioning.
- Section A.4: In which the styles of swimming are more adequately defined, which is required for defining SPM.

For the purpose of this work, the aspect of swimming we are concerned with is speed and the strokes the swimmers take. The swimmer who can legally swim the specified race distance in the least time possible is the winner of the race. Swimming races are very controlled and thus a competition can take place where many races of the same event can occur in sequence. In order to compare two athletes, the time taken to complete the event is all that is required to rank the two swimmers. In fact swimming is so controlled that swimmers may be ranked across all occurring races at any given time and at any pool around the world and in some cases even when the pool is not the same length. This is in contrast to other sports like marathon events or ski jumping in which the ability of two athletes can only be quantified in a consistent manner when the athletes are at the same competition. Due to the very controlled environment swimming competitions require, many assumptions can be made in terms of pool size and swimmer position.

A.1. Swimmer Velocity Model

This section details the swimmer metrics that will be automatically obtained by the Smart Swim system. The following signals and values will be defined.

- L the length of the pool.

Figure A.1.: Common watch used by swim coaches to estimate swimmer SPM

- f the frame rate in frames per second (FPS) of the video footage of swimmers.
- n is a frame number in a video sequence sampled at a constant frame rate f.
- $x[n]$ is a signal which defines the position of the swimmer in meters relative to the starting blocks at frame n, as such $L \geq d[n] \geq 0, \forall n$.
- $x'[n]$ is a signal which defines the velocity of the swimmer relative to the starting blocks at frame in meters per second.
- $s[n]$ is a signal which defines the position of the top of a stroke (top of a stroke is defined in section A.4). When a frame n contains a swimmer at the top of their stroke, the function takes a value of 1, if not, it takes a value of 0. In other words $s[n] \in \{0, 1\}$.
- $s_r[n]$ which is the strokes per minute (SPM) of the swimmer as a function of n. This value stays the same between the top of each stroke the swimmer takes and changes after the end of a new stroke, that is $s_r[n] \geq 0$ and only changes values when $s[n] = 1$.
- $d[n]$ is a signal which defines the distance per stroke (DPS), in meters per stroke, of a swimmer as a function of n. This value stays the same between the top of each stroke the swimmer takes and changes after the end of a new stroke, that is, $d[n] \geq 0$ and changes when $s[n] = 1$.

A.1.1. Strokes Per Minute

Strokes Per Minute (or SPM) is a measurement of the rate at which a swimmer takes strokes. The units are more generally in **stroke cycles per minute**. This is due to the fact that the four swimmer strokes contain two strokes with so called "half strokes"; see Section A.4 for more details. When calculating SPM coaches often take a three stroke (cycle) average where they utilize a watch as seen in Figure A.1. Beyond this, there seem to be no standard SPM collection method for all swim coaches. For the purposes of our work SPM is the output of the function $s_r[n]$ divided by two when SPM is required for asymmetric strokes. For the symmetric strokes it is simply the output of $s_r[n]$. Calculating $s_r[n]$ is completed in the following manner. Firstly, the difference in frames Δf_k for stroke k in frame n is found by taking the difference in l and m of frames such that $s[l] = 1$, $s[m] = 1$, $l < n < m$ and $\nexists p$ such that $s[p] = 1$ and $l < p < m$. The reciprocal of this value is taken and multiplied by 60 (as there is 60 seconds in a minute) and divided by the reciprocal of f, the frame rate of the footage in question. This is summarized in Equation A.1. If there exists n, such that there is no value l where $s[l] = 1$ and $l < n < m$ then $s_r[n] = 0$. Conversely, if there exists n, such that there is no value m where $s[m] = 1$ and $l < n < m$ then $s_r[n] = 0$. Note this equation does not account for different strokes and thus if there are half strokes or not.

$$s'[n] = \frac{60}{f^{-1}\Delta f_k} \tag{A.1}$$

A.1.2. Distance Per Stroke

Distance Per Stroke or DPS is a measurement of the distance a swimmer moves given a single stroke, rather than stroke cycle (reference Section A.4 for more details on the difference between stroke and stroke cycle). DPS is generally measured in meters as most pools are measured in meters, however this is not a standard as it is common in the United States to have pools that are measured in yards. **In this work, all DPS will be given in meters**. For the purposes of our work DPS is the output of the function $d[n]$. $d[n]$ is calculated in a similar manner to SPM, values l and m for frame n are found such that $s[l] = 1$, $s[m] = 1$, $l < n < m$ and $\nexists p$ such that $s[p] = 1$ and $l < p < m$. The absolute difference between $x[l]$ and $x[m]$ is the value of $d[n]$. Again, if there exists n, such that there is no value l where $s[l] = 1$ and $l < n < m$ then $d[n] = 0$. Conversely, if there exists n, such that there is no value m where $s[m] = 1$ and $l < n < m$ then $d[n] = 0$. As such, this is summarized in Equation A.2.

$$d[n] = |x[m] - x[l]| \tag{A.2}$$

A.1.3. Swimmer Velocity

Swimmer velocity is the time rate of change of the position of a swimmer, also known as the derivative of their position. As such a simple manner for solving for a swimmers velocity is to differentiate, in time, the position of a swimmer. This can be approximated for each n by the well known difference equations A.3 - A.5. However, this method can become unstable if $x[n+1] - x[n]$ takes a value of zero due to a lack of precision of measurement. If this is the case, then more advance methods must be taken to find the velocity of a swimmer.

$$x'[n] = \frac{x[n+1] - x[n-1]}{2f^{-1}} \tag{A.3}$$

$$x'[n] = \frac{x[n+1] - x[n]}{f^{-1}} \tag{A.4}$$

$$x'[n] = \frac{x[n] - x[n-1]}{f^{-1}} \tag{A.5}$$

Another method to finding a swimmers velocity is to use the swimmer model [13]. This model says that a swimmer velocity is equal to SPM multiplied by distance per stroke to obtain meters per minute. To change to meters per second the result is divided by 60. This formula allows us to estimate $x'[n]$ by multiplying $d[n]$ by $s_r[n]$ for each n and divide by 60, this is summarized by Equation A.6.

$$x'[n] = \frac{d[n]s'[n]}{60} \tag{A.6}$$

A.2. Pools

Swim competitions happen in many different pools and environments. The course of a pool refers to the distance the swimmers must travel in order to complete one pool length. For example, in a long course meter (LCM) pool, swimmers must complete fifty meters before they encounter a wall. Around the world, there are three main competition pool lengths in swimming: long course meters (LCM), short course meters (SCM) and short course yards (SCY). LCM pools are 50 meters long, SCM pools are 25 meters long and SCY pools are 25 yards long. Furthermore, pools can have different numbers of lanes. In each race every lane does not always contain a swimmers. More about pools can found in [14].

Different pools can have different numbers of lanes. Typically, there is an even number of lanes, ranging from six to ten. However, in some situations, competitions can be held in LCM pools but raced as SCY or SCM. This can result in up to a twenty-lane race. Causing even more confusion, some competitions have swimmers racing in one half of the pool, but warming up in the other half. An example would be having lanes 0 to 9 with swimmers racing while having lanes 10 through 19 open to swimmers who are not racing.

Lane ropes are the division between lanes. They run parallel to the pool edges and stop a swimmer from getting too close to another swimmer while also dampening waves. On the world stage there are very strict rules on how lane ropes may look and what color pattern they must adhere to. In general competition however, pools will use whatever lanes ropes are available and thus their detailed structures are of little use for swimmer detection. They are useful in a broad sense as they are fairly straight and define areas where swimmers can and cannot be. In a training set, it would be desirable to have a wide variety of examples of pools with different styles of lane ropes.

A.3. Races

Swim racing has four strokes: butterfly (fly), backstroke (back), breaststroke (breast), and freestyle (free). These strokes all fall under the category of swimming. They are relatively easy to distinguish on a camera and can easily be identified by a human.

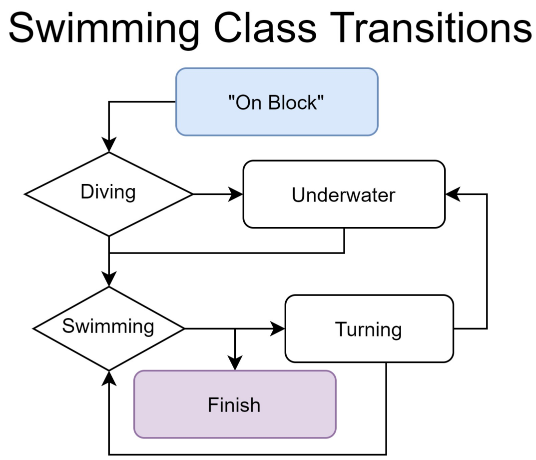


Figure A.2.: Order of swimming operations in a race

Each race starts with a dive. This is when the swimmer is positioned on an elevated starting block and then jumps through the air to enter the pool. This section is generally a very small fraction of a race as it only happens once and takes very little time. This action can be troublesome for automation as the swimmers position on the blocks (bent over) is very different than when they are in the water (stretched out) and due to the high speed of the swimmer.

The next part of a race is the underwater sections. In the early 1980s it was shown that swimmers can be much faster underwater than on the surface, especially when pushing off the wall during a turn and after the dive. A considerable portion of a swimming race involves the swimmer underwater. This part of a race is problematic for automated swimming analytics. When swimmers are underwater they can be very difficult to see from an above-water camera. This is due do to the phenomenon of refraction, where light is bent because of the difference in densities between two substrates. This phenomenon can make a swimmer invisible for periods of time, creating what is known as occlusion. Another occluder of swimmers underwater is lane rope – the plastic floating ropes separating swimmers in a race.

The next portion of the race is the turn action. The goal of a turn is to transition back to swimming when the swimmer reaches the end of a length. Turns can take many forms based on the event being preformed. After a turn, a swimmer usually ducks underwater and starts a new underwater section. The turn is problematic as the white water produced by the swimmers causes occlusions of the boundaries of the swimmer. This can make it difficult to localize the swimmer's position.

Between the underwater portion and turning portions of the race is the swimming. As mentioned before, there are four strokes that can occur, but only once per length. Possibly one of the easiest parts of the race to identify a swimmer is when they are swimming; it is also the most prevalent. There are a few reasons why a swimmer would be hard to recognize in this portion, but it is mainly due to occlusions. People or the sets of ropes hanging over the pool designed to warn a swimmer of an approaching wall caused these.

Finally, a race ends with a finish. This simple action transitions the swimmer from swimming to finish and is easy to identify. Once the swimmer is finished they generally stay in the same place until the rest of the swimmers finish, marking the end of a race.

In general, the order of operation in a race is as follows: on-blocks, dive, underwater, swim, turn, underwater, swim and finish. However, there are varying numbers of swim, turn, underwater and finishes depending on the race category (event) – see Figure A.2 for a complete state transition diagram.

In addition to the technicalities of swimming, events can have different distances and styles. Such distances range from lengths of 50 meters to lengths of 1,500 meters. Some styles have swimmers preform all four strokes in one race, such as the individual medley (IM), or only one stroke at a time. Swimming has 18 different styles of individual events and another 5 team events known as relays. All the different positions, transitions, actions, pool lengths, pool environments and pool lane numbers for each event must be taken into account when creating a fully functioning automated swimming analytics system.

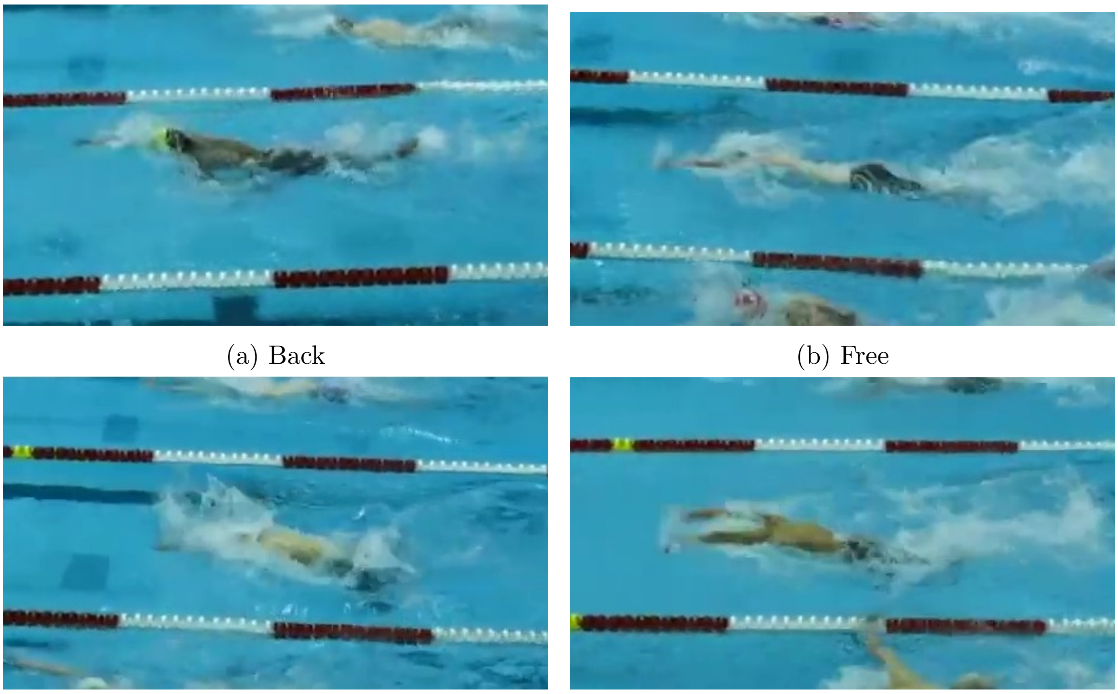
A.4. Stroke Styles Definitions

As mentioned in Section A.3 there are four strokes: fly, back, breast, and free. Each of the four strokes produce propulsion, which moves the swimmer though the water. Both the arms and the legs of the swimmer cause the propulsion. While the legs produce considerable power and increase the buoyancy of a swimmer in the water, swimming analytics, at this point, is mainly concerned with the arms of a swimmer. This is because arms are more straightforward to correlate to faster swimming and also because the arms are generally responsible for approximately 80% of a strokes propulsion. Furthermore, for each of the four strokes, a stroke is counted as a stroke cycle. Because each stroke has its own definition of a stroke cycle, we shall briefly go over stroke cycle definitions.

A.4.1. Stroke Cycle Definitions

In terms of stroke cycles, the four strokes can be split into two categories for the purposes of stroke recognition. The first category is asymmetric strokes, seen in Figure A.3, which are the back A.3a and free A.3b styles of swimming. They are denoted as asymmetric as the stroke is not symmetric through the human sagittal plane. In terms of a stroke cycle, one arm pulls past the body while the other is recovering above the water allowing for strokes to be taken by each arm individually in quick succession. Thus, stroke cycles for free and back are completed when one of each arm is pulled and recovered past the body.

The second category of strokes is symmetric, seen in Figure A.3, which consists of the fly A.3d and breast A.3c styles of swimming. This is because these strokes are symmetric across the human sagittal plane. Stroke cycles are more straightforward in this category



(a) Back (b) Free

(c) Breast (d) Fly

Figure A.3.: An example of the top of each of the four strokes

because in each stroke, both arms are pulled past the body and recovered in unison. So, stroke cycles for fly and breast are counted for each stroke pull and recovery.

A.4.2. Top of Stroke

It was noted that an when $s[n] = 1$ the “top of a stroke” was occurring. In this section the definition of the “top of a stroke” for each of the four strokes will be given. Unfortunately each stroke has a unique definition for its top. Figure A.3 gives pictorial examples for each of the strokes “top of a stroke”. For the asymmetrical strokes, free A.3b and back A.3a, in order to remove confusion the “top of a stroke” occurs twice per stroke cycle. This happens when either the left or right hand enters the water from the stroke’s recovery. For the symmetrical strokes, Fly A.3d and breast A.3c. The top of the stroke is counted when both hands enter the water in the stroke recovery. As such, for fly and back, the “top of the stroke” occurs only once per cycle.