Painterly Rendered Portraits from Photographs using a Knowledge-Based Approach

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1. ABSTRACT

Portrait artists using oils, acrylics or pastels use a specific but open human vision methodology to create a painterly portrait of a live sitter. When they must use a photograph as source, artists augment their process, since photographs have: different focusing - everything is in focus or focused in vertical planes; value clumping - the camera darkens the shadows and lightens the bright areas; as well as color and perspective distortion. In general, artistic methodology attempts the following: from the photograph, the painting must 'simplify, compose and leave out what's irrelevant, emphasizing what's important'. While seemingly a qualitative goal, artists use known techniques such as relying on source tone over color to indirect into a semantic color temperature model, use brush and tonal "sharpness" to create a center of interest, lost and found edges to move the viewers gaze through the image towards the center of interest as well as other techniques to filter and emphasize. Our work attempts to create a knowledge domain of the portrait painter process and incorporate this knowledge into a multi-space parameterized system that can create an array of NPR painterly rendering output by analyzing the photographic-based input which informs the semantic knowledge rules.

Keywords: Non Photorealistic Rendering, Stroke based Rendering, Painterly Rendering, Human Vision

2. INTRODUCTION

Non Photorealistic Rendering (NPR) is a computer graphics technique which creates imagery with a wide variety of expressive styles inspired by painting, drawing, technical illustration, and cartoons. This is in contrast to typical computer graphics which focuses on photorealism. Within 3D and 2D NPR techniques, stroke based or painterly rendering typically uses a 2D source such as a photograph and creates a list of strokes to be rendered on a new canvas. NPR already has applications in video games, movies, architectural and technical illustration, animation and rising fields such as computational photography. NPR also has applications in learning and medicine (e.g. communication systems for autistic children) where filtering out un-needed detail is important, as is true in technical illustration.

Since computer systems cannot typically hold a semantic representation of the object to be rendered (e.g. a face for a portrait, or an emotional emphasis), many current NPR techniques rely on computer imaging approaches (e.g. edge detection, image segmentation) that model at the physical level such as blobs, strokes and lines. We propose a novel approach to painterly rendering which relies on parameterizing a knowledge space of how a human painter paints - that is their open methodology to the process. In general, artistic methodology attempts the following: from the photograph or live sitter, the painting must 'simplify, compose and leave out what's irrelevant, emphasizing what's important'. Since human painters have knowledge of the source imagery, we are limiting this approach to portraiture and therefore take advantage of portrait and facial knowledge in the NPR process. We believe this portrait painting knowledge approach when fully realized has two intertwining and interdisciplinary benefits. The first benefit is creating a novel type of NPR system that within its domain (portraiture but with benefits to still life and figurative work) may produce both a wider range of results and improved results compared to current techniques. The second possible benefit, which is more speculative, is that portrait artists over 1000's of years have somewhat unconsciously evolved a 'painting methodology' which exploits specific human vision and cognitive functions, and, therefore, if presented in a quantitative way, can shed light on psychological research in human vision and perception or at least validate them via another method. In this paper detailing early results we mainly describe the general system approach and preliminary acquired data (through artist interviews and reference material) of the human portrait painter process. We also describe how we have begun, using hierarchical parameterized language techniques, to quantify this soft knowledge space, starting with lower level constructs and building them up to higher level parameterized components into a working system that achieves painterly rendering results from consumer level photographs of people.

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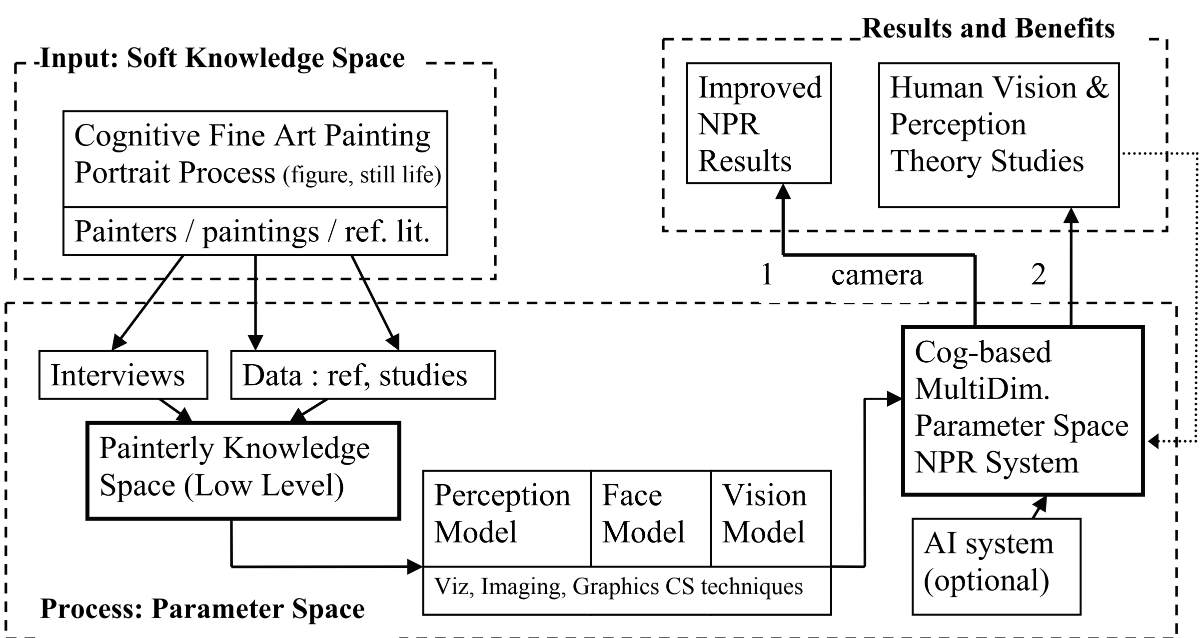
3. RELATED WORK

Within NPR research, a number of painterly rendering techniques were developed in the early 1990s, starting with Haeberli's pioneering work[1] which introduced painting with an ordered collection of strokes described by size, shape, color and orientation. Litwinowicz [2], created a fully automated algorithm based on Haeberli's earlier work producing paintings by using short linear paint strokes tangent to Sobel edge gradients. Relying on Haeberli's work as a base, many approaches appeared that used local image processing techniques in an attempt to achieve relevant high level content semantics to better control stroke/placement/color choices. Hertzmann[3-4] advanced the field by using a multi-pass system of coarse-to-fine curved b-spline strokes aligned to a layered course-to-fine image difference grid with multiple styles. This was inspired by his observation that artists begin a painting with large broad strokes and then refine the process with smaller strokes to create detail. Our system is inspired by his work and the general procedure of using artist knowledge to dictate parameters. For instance, we have moved away from a multi-pass course-to-fine grid for stroke placement choices and toward tonal masses based on lighting and drawing types. We also are developing a color system that moves away from color sampling with perturbations to a system which uses source tone to indirect into a semantic color temperature model.

More global oriented computer vision techniques to model scene semantics began to appear in an attempt to both automate the higher level process and improve aesthetics. Gooch and others[7-8] first proposed segmenting the image into homogeneous grayscale regions leading to a significant reduction in the number of brush strokes. Segmentation was also used by Santella and Decarlo[10-11] who presented a salience extension of guiding the painting process by eye movement, emphasizing which area the user thinks is important. An automatic system for salience adaptive painting, driven by machine learning, was presented by Collomosse and Hall[12-13]. Hertzmann[5] summarized and categorized many stroke-based rendering (SBR) techniques. Hertzmann and later Hays and Essa[15] used the variation of low level parameters such as stroke length to create different painterly styles. Our system relies heavily on hierarchical parameters which build up higher constructs from low level components based on portrait painter methodology. Collomoose and others[14] formed a mapping onto parameters using a high level emotional parameterization derived from a facial tracking system. And Setlur and Gooch[9] use a technique to create rendered faces by exploring facial emotions using low and high spatial frequency details based on human vision knowledge. Gooch[7-8] as well as Collomosse and Hall[12-13] relied on several human vision techniques. Rodrigues, du Buf and others[17-18] used human vision techniques to better tie visual perception theories to NPR and painterly rendering. Kang and others[16] introduce several techniques to adaptively generate stroke and other artistic parameters or attributes to tailor to a wide variety of SBR styles.

4. PROCESS PLAN

Table 1. Proposed process chart.



Our research system uses a parameterized approach to approximate a knowledge domain for painterly rendering of portraits. The knowledge domain uses fuzzy knowledge rules gained from interviews with oil portrait painters, data from the traditional 'portrait painter process' combined with human vision techniques and semantic models of the face and upper torso. By knowledge domain we mean that the system attempts to act on the semantic level a human painter might function at, such as: human vision techniques, facial planes and expression, tonal masses, and color temperature control. It also relies on an historical, open methodology that artists have created and passed down to each other. This qualitative knowledge data is parameterized into an n-dimensional space of low level rules which can be accessed at different semantic levels. Non-professional photographic imagery of people's heads is used as input. Table 1 shows the proposed process starting at the top left, which can be summarized as collecting a knowledge space of the painterly process (qualitative at this point – lower left) from artists interviews, reference materials and user studies, then using known computer science and cognitive science models and methods, parameterize the knowledge (bottom middle) into the NPR system (lower left) which can be used for 1) better/wider NPR results as well as 2) clues/data into human vision/perception theory which can be mapped back into the system. In this paper detailing early results we describe a first pass through the system but mainly concentrate on the left and middle portions of the table.

5. PAINTERLY KNOWLEDGE DOMAIN

Our first task has been to collect and quantify human painterly knowledge. With this knowledge we can begin to create both low level components that match known portrait painter techniques as well as build initial higher level, more adaptive semantic techniques which are built up from the lower level parameters. Multidimensional and hierarchical parameter spaces using knowledge domains have been used successfully in several areas including generative systems and facial animation. Our portrait painter research comes out of the work we have done with multidimensional parameter spaces for virtual facial systems[19-20] as well as with animal simulation systems using artificial intelligence techniques[21]. The basis of this approach is to create a low level set of parameters that are object oriented, encapsulated and mathematically rigorous. They become low level dimensions (e.g. axes) in a large knowledge space which can be accessed through higher level constructs which are solely comprised of the lower level parameters often with logical, spatial and temporal attributes. As an example in facial animation, low level muscle parameters can be built up into a more semantic 'smile' parameter (corner mouth pull, nostril flare all by differing amounts) and 'smile' with other parameters and temporal considerations could be built up into 'joyousness'. To begin this process we first need to parameterize a soft knowledge space of portrait painter methodology which we outline in this section and then with this knowledge space begin to build low level constructs which we discuss in the following section. Deriving portrait methodology knowledge from interviews and reference materials with working artists on their artistic process (as well as art experts) is obviously fraught with ambiguities, seemingly ad hoc methods, differing opinions, and techniques that have no current software based analog. With this challenge in mind, the goal is to create a toolkit research system that can be iteratively updated and refined based on information and user studies from the NPR, art criticism and cognitive science sectors. Many in the art world are somewhat uncomfortable overly dissecting an aesthetic pursuit like portrait painting. We hope a system that attempts to quantify the process in a parameterized way can serve as a tool in both science and art (both separate and interdisciplinary) discussions. Following is our preliminary data from artist reference materials and artist interviews.

5.1 Tonal

The artist Max Meldrum[22] in his 1919 essay "The invariable truths of depictive art" argued that painting was 'the science of optical analysis by means of which the artist, in carefully perceiving and analyzing tone and tonal relationships, could produce an exact appearance of the thing seen'. Tone was the most important component of the art of painting, next came proportion, 'the superficial area occupied by one tone', and then color, the least important component.

The tonal value (tone) is the relative likeness or darkness of an object. It is a gray scale and void of color. Artists squint when they look at the portrait sitter to see more in tones than colors. They also adaptively squint to see more in general masses, allowing artists to decide the size of mass they are interested in tone sampling at the moment. At the fine or stroke level, final color is generally derived from a 'sampled' tonal value. First an artist decides the correct tone for a given fine area, and then, with that tonal value, chooses a color by the rules of color temperature, as well as other rules in the color section. It is often said that if you get the tone right in a stroke, you can pick almost any color within that tonal space. Hence 'the tone first approach' allows an artist to be more creative in their color choice without sacrificing the portrait integrity.

Too many values in a painting can cause the viewer's eye to jump around, thereby failing to find the painting's center of interest. So an artist tries to limit the overall number of values in painting. In portraiture (and other styles including still life and figurative) values can be categorized into particular "types" where the first 3 are the most important:

1. Body tone (or light) – in line with the light source; in direct light (usually warm colors).
2. Halftone – where the light begins to turn – in between light and shadow.
3. Body shadow – turned away from the light source. – the darkest area (usually cool colors).
4. Cast shadows – dark tones that are caused by subjects standing in the path of the light source.
5. Reflections – tones by light striking surrounding areas and bouncing back onto the subject.
6. Highlights - Body tone that is directly hit by the light.

One commonly used approach in portrait painting is to first paint the gross head masses in 3 divisions of value – body tone, halftone and shadow. Within these gross areas fit degrees of finer tonal gradation (light to dark) which benefit from the semantic information of what gross tone area they are in. A value scale of around 9 total values is common. Even in a 9 value system, not all paintings have all 9 degrees. It depends if it is a high-key, low key or middle key painting. Some painting systems use much less than 6 types and 9 values. It is said of light areas (body tone) and dark (shadow areas), "neither one should borrow values from the other". As the face curves from the light, in general, the shadow side is about 40% darker than the sunlit side.

A painting must have a domain value, either it's light, or its medium, or it's dark. For example, a small sketch might be dominated by a light value, an impressionist landscape is dominated by a medium value and a Rembrandt portrait is dominated by a dark value. The more you veer from this principle the weaker the painting. With 3 values: dark, mid and light, one should be dominant, the other two together typically make up less than half of the first; none being of equal amount of the others. This 'rule' is often referred to as Unequal Dominate Value. Artists have lectured that if you can't easily discern a paintings dominant value - dark, medium or light - then it fails that category. If a painting has great design than dominant value recedes to a second level of importance.

5.2 Color

The tonal value points to what color to pick within the other rules of portrait color, the most important of which is color temperature. Temperature refers to the relative warmth or coolness of any given color. Warm colors and cool colors work harmoniously both globally and within regions of a painting. Warm light appears more yellow, orange or red, while cooler light has a blue, green or violet in it. Foremost concern when picking a color is getting the value correct. Many artist exploit color temperature rules do not simply darken a color but add its complement to grey it down. By placing a warm color next to its cool version, it is said that a painter sets up a beautiful visual vibration. A typical process would be to determine the color of the light on the area of your subject, say the body tone area. Light gives its temperature to what it touches. Everything left in shadow takes the opposite temperature. When the light areas are going to be warmed tones, generally speaking the shadows will be cool. Most portraits have warm light (skin) and cool shadows but there are many exceptions. So warm lights produce cool shadows and cool lights produce warm shadows.

The rule of unequal balance dictates that both light and cool temperatures can not be shown equally. Usually within a portrait the warm light is dominate over the cool in shadows. Inversely, subjects lit by cool, indirect sun or artificial light have warm shadows. So once the color of the light area (body tones) has been determined, it is easy to deduce the color of the shadows. Besides a dominant value most successful paintings have a dominant color. An overly cool canvas can be helped with a couple of spots of warmth, and a hot canvas can be relieved by a small area of cool. Placing equal amounts of warm and cool in a painting can make a painting look weak and indecisive.

Most painters use the classic 3 primary color system around a color wheel. More recently many artists have adopted the Munsell Color Notation system's 5 "principal" colors (red, yellow, green, blue and purple) which are spaced equally around a color wheel. Artists typically make a decision about palette or color harmony for a given painting before they start. With the standard 3 primary systems there are many color harmonies[23], here are two examples:

- Analogous Color Harmony includes adjacent wedges of color on the color wheel, including grayed-down neutrals and light and darker version of the colors themselves. A yellow-green example wedge is: orange - yellow - green. With this system an artist would pick the dominant color and then the wedge. Discords can be added at five and seven o'clock from the dominant (at 12). Used very sparingly, discords give energy and capture the eye's attention.
- Complementary Color Harmony is the most versatile for portrait use. Complementary means color directly across the color wheel. Since all skin has some aspects of red and yellow in it, it can easily adapt to a red-green, yellow-violet or blue orange schemes, keeping in mind the principle of unequal balance.

Munsell's five "principal" colors shift the complements, so red's complement to blue-green instead of green, yellow is purple-blue rather than blue. Here is a summary of how an artist can use this system: 1) a painting should have a dominant color that is readily evident, 2) complementary color (from across the color wheel) may be introduced, occupying much smaller space at full intensity, or greater area if grayed, 3) discord colors (equidistant on the color wheel from the dominant hue and from each other) should be added sparingly in approximately equal amounts. Discords bridge and add visual excitement. Graying down a complement will allow you to use more of it. On the color wheel the closer a color moves towards the center the more the complement is introduced to it, graying and reducing its intensity. A color and its complement cancel each others identity and form a version of grey. A color finds its identity and actually is intensified if it is put in juxtaposition to its complement.

Highlights need color too. The very last strokes painted on a surface are the highlights reflecting the light source itself. The most effective device to convey the intensity of this is to change the temperature of the light source, i.e. warm light sources yielding cool highlights and visa versa. Highlights can be overused - they should have a location shape and color and should not be painted if they are not there. Highlights are the one thing that will move with the viewer's gaze, so they give away the cameras or viewers eye point.

5.3 Shadows and halftone 'core'

There are no textures/details or strong colors in the shadows. The more gradually an objects turns away from the light the softer and wider its shadow edge will be. So a forehead or cheek turns gradually, making a soft shadow edge while a nose would be sharper. Hard edges are found in cast shadows, closest to the object casting the shadow. Soft edges are fuzzy such as in form shadow.

The color of skin in shadows (and lesser so in light) is influenced by the color of the background or clothing, in the turning down or away planes (underside of chin and nose). Since shadow side is darker then the light side, the flow of color and value is broken up by the facial features. Artist generally: avoid strong color in the shadow (grayed down hues and lower intensity), avoid hard edges in the shadows (softer than those in the light) and avoid strong contrast in shadows (narrower range of values that in the light areas). Areas where two objects (say palm and cheek) touch in shadows have reflected light (light bouncing back and forth). These make an effect that causes a slight change in color and value, making the area of reflected light a tiny amount lighter that the rest of the shadow. It can be often overstated (because it looks so nice). One artist stated that reflected light is always darker than you think.

The soft transition edge that is created where the form turns and light meets the shadow is called 'the core' of the shadow. The core is where the color and value are the truest - neither obscured by shadow nor bleached by light. So the core is where the artist's hit their color most strongly. Artists also widen the core area for aesthetic effect.

5.4 Shapes, Edges and 'Lost and Found Edges'

Shapes and composition can be more important than subject. Artists link shapes to create pattern and thereby composition. Lines (edges) and shapes moving vertically or horizontally convey formality and solidity. Diagonals convey movement and excitement. Every subject has some diagonals. A painter strengthens those elements and perhaps downplays the more static lines. Shapes are related to edges.

Edges occur wherever shapes meet. By softening or hardening edges or making them disappear entirely, the artist strengthens the illusion of form and gives a painting dramatic flow - this is know as Lost and Found Edges. In losing an edge we allow it to merge with an adjacent shadow, creating a link between objects, which is a powerful tool for design. For instance a subject can emerge from a strongly textured background, yet remain one with it, with the help of edges softened or entirely lost and shadow cores. Edges accomplish:

1. Control of the viewers eye movement over the canvas – eyes always move to sharp edges and coast softly over soft edges. On a lost edge the viewer finds comfort in seeking out the place where it is found again.
2. Sharp edges are at or in the center of interest.

Edges have four types: hard, soft, lost and found. Edges are lost when the shapes value is equal to the value of the shape next to it. They are found again when one of the values change. Due to the way a camera focuses, photos will give you false edge readings making edges too sharp. An edge plan can create a story for the painting. For a viewer to find the center of interest, artists place sharp edges at or near this interest. Sharp edges that have strong value shifts work even better. Differentiating between the harder edge of a shadow cast by the nose on the upper lip and the softer edge of the form across the bridge of a nose or curve of the cheek will create energy.

5.5 Photography

The three main problems with portrait painting from photography are: depth of field (everything is in focus or the camera focus in unnatural vertical planes - no center of interest focus), value clumping (the camera darkens the shadows and lightens the bright areas) and color distortion (as well as perspective distortions). From the photograph to the painting an artist attempts to simplify, compose and leave out what's irrelevant, emphasizing what's important. An artist must create the center of interest, for the photograph will almost always have none. A camera will focus on everything.

Photographs distort the tonal range, known as value clumping, making values on either end of the scale compressed, showing less differential than actually exists in nature. So when painting from a source photograph, artists attempt to extend the middle value by extend out (making lighter) areas that look dark in value, as well as extending lighter areas to range to darker in value. Dark areas are filled with more subtle color and detail than appear in the photograph because of this value compression, however artists are careful not to put detail in both shadow and light areas. The same is true for overexposed areas.

5.6 Center of Interest

A chosen center of interest in a portrait, say a mouth smirk or intense eye gaze, can draw the viewer to the desired personality of the sitter. An artist creates and draws the viewer toward the paintings center of interest by how they establish edge quality or detail in the portrait. The sharpest edges are at the center of interest, less sharp edges move the viewer's eyes across the canvas toward the center of interest and softest edges are where they want the viewer's eye to glide over. Sharp edges that have strong value shifts can intensify the perception of the center of interest. Outside of what will become the center of interest, an artist softens edges and reduces contrast, brightness and detail. Artists leave out intense color elsewhere in the painting that will abruptly lead the eye away from the center of interest.

5.7 Brush Strokes

The conditions that dictate the placement, size, shape and direction of a particular brush stroke is less verbalized by artists than other painting techniques. There are however many sometimes conflicting rules artists pick from. When making brushstrokes, artists often think about the way the facial surface or plane is orientated and paint in color and strokes to suggest the surface itself -- they let the form guide their brushstrokes. The right kind of brush stroke can create depth and dimension. Often they stroke the paint on in the same direction as the plane. If they want the lower lip to protrude, they pull the stroke out. If they want the front plane of the cheek come forward and the side plane of the cheek to go down, they apply the paint in that fashion. There are shapes that follow vertical planes and those that follow horizontal. But the planes from front to back give the dimensional effect. One artist suggested the following advise: Pull or push the stroke in the direction of the plane. Strokes put down in the same direction become monotonous. They have to be broken with strokes in opposing directions. One stroke in one direction butted up against the next stroke in a somewhat opposite direction brings energy to a painting. It is possible to use a choppy aggressive technique for the clothing and background contrasted with the painterly look of the face. For the lost edge, pull the brush away from the canvas. Start your stroke with pressure where you want a found line. You need found "sharp" and lost "fuzzy" lines to make the planes of the entire periphery project and recede.

So in summary balance and variety seem to be the key. Stroke to match the shape, then complement it with a stroke in the opposite direction to it. Never completely finish edges. Always overlap rather than putting objects in a row. Use stroke direction with edges to move views to the center of interest.

5.8 Background

The background affects the overall relationships and should be painted first or at the same time. The background is most unique to portrait artists although is sometimes used in still life and figurative work. The main rule of backgrounds is that they recede compared to foregrounds. There are four main types of portrait backgrounds: 1) The plain solid colored background, 2) The imaginary background made-up of shapes & colors, 3) A representational background of what is really there, 4) An abstract of what is really there.

For a plain solid colored background, usually an artist will use a color in your portrait to maintain color harmony. The inverted background is one of the most common. Typically the same kinds of brushstrokes are used in the background as in the portrait but the background the edges are softer than on the model. Busy backgrounds confuse the image unless they use an unrelated color to the subject. Warm backgrounds bring out warm flesh tones while cool backgrounds emphasize cooler tones. A light background shows up the shape of a dark figure, while a darker one blends with dark tones on the subject.

6. KNOWLEDGE BASED IMPLEMENTATION

Our early research methodology, as shown in table 1, is to gather and systematically convert qualitative painterly portrait knowledge into a quantitative parameterized software toolkit. These low level parameters than can be iteratively built-up into more semantic high level components which exploit computer vision, recognition and imaging techniques as well portrait painting theories. This paper is reporting on the first phase of our work. This parameterized software toolkit approach, allows us to test assumptions with scripting before implementing higher level automatic components. At this stage, scripting is often used in place of full vision and recognition subsystems, allowing us to test scenarios and benefits rapidly. A current example of such is creating the source input image in Fig. 1D which shows center of interest, and object map (segmenting face, cloths, background) by hand using an image processing program before implementing a recognition system to produce similar input.

6.1 Implementation Details

To exploit tone and color portrait knowledge, the system uses a multi-layer stroke analyzer/renderer which perceives and lays strokes down in large masses first, progressively using smaller stokes and more detailed analysis. This approximates how painters squint at first to read large tonal masses and progressively add greater levels of detail over exposed paint from the layer before. Rather than use progressive difference grid techniques to move through a source image, the system progressively iterates over tonal masses, beginning with major tonal areas of the face: body tone, half-tone and shadow by calculating a 'gross tone map' (Fig. 1B). Then exploits working in limited tonal spaces via a 'fine tone map'(Fig. 1C). These maps are recalculated per level of detail and are affected by other value plan parameters. A value plan is used which can rescale and re-center the tonal space of source masses. Unequal dominate and sub-dominate value parameters also can rescale how the system analyzes/uses the source image. This is an example where painterly knowledge rules can supersede the information from the source sitter image (the sitter photograph) by filtering, emphasizing/deemphasizing, and scaling input information as well as by other rule based means.

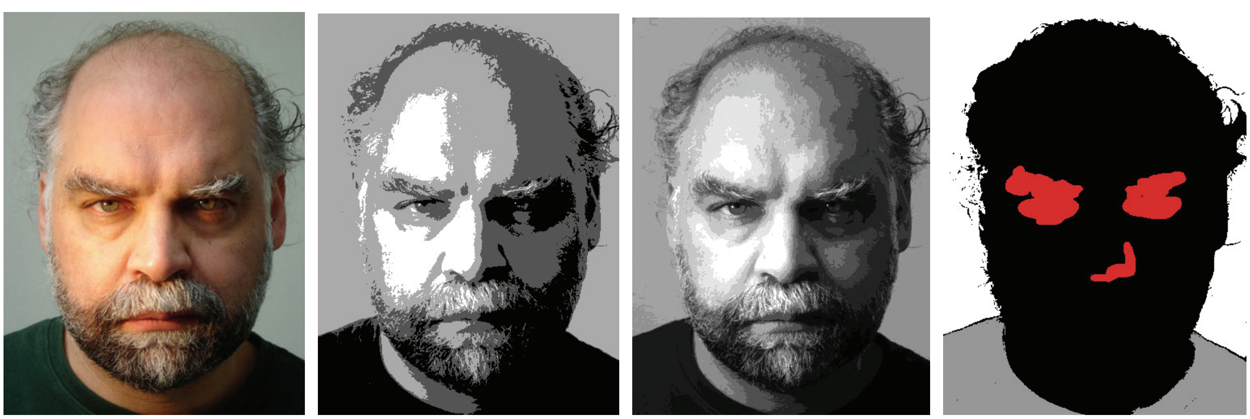


Fig. 1.Intial Image (A), 3 tone Gross Tone Map (B), Fine Tone Map (C), Object/Center of Interest Map (D).

Since photographs "value-clump" compared to human vision, our system approximates High Dynamic Range input by using three bracketed exposures of the same content (a feature available on most commercial digital cameras) to insure a wide sampling range of tone, color and texture detail in the darks and lights of the photographs.

The system has several low level color parameter routines that indirect into a color temperature system via tonal value information at stroke time. We are still evaluating and researching the best solutions for which type of high level color components to build up in the system. Since many artists work in known palette space, one of our first high level color components creates a pre-constructed palette by sampling the source photograph(s) as a pre-process along with other image analysis. This determines input attributes like dominate value and dominate color, both overall and locally for the body tone, half tone and shadow areas as well as a color temperature plan and a lost edges (i.e. tonal contrast) plan. These input attributes are used at stroke analysis time by the knowledge system to indirect into a unique but constructed palette for the specific final painting. The system also uses an initial configuration file that affects and informs the knowledge rules allowing for a range of painterly styles such as expressionistic, impressionistic and others. These initial configuration values effect the relationship between the image, the knowledge rules and low level attributes like brush size/length/orientation.

Facial recognition techniques are proposed to populate the knowledge domain with semantic data of facial areas which mimics the painter process of orienting brush strokes in the direction of the surface planes (i.e. the plane of a nose, or the circular muscle around an eye). The recognition system could also determine center of interest which will affect brush detail and tonal detail in the final rendering. Currently we are using XML scripting techniques to define initial conditions and photo manipulation program created input data for center of interest and facial recognition objects (see fig. 1D) to understand and evaluate our low level process before we feel ready to bring in a specific high level system. All parameters and configuration attributes are pixel resolution independent, allowing all global and local scaling to be rescaled by a few scale parameters. This allows us to render test output fast at small sizes without the need to change all but the scale parameters to render larger final paintings.

Here is a general algorithm which demonstrates the current painting process (note that with our toolkit and scripting language, the process is highly configurable):

Initial configuration attributes and parameters:

- Pre distortion / pre crop source image (config. file)
- Create object matte - OBJmap (segments objects: background, hair, cloths, non-face skin)
- currently hand created
- Create center of interest matte - COImap
- currently hand created: can be a point, full matte or importance(grayscale) matted area
- Dominant Value & Value Plan
- via analysis of source, and initial configuration
- Dominate Color & Color Temp Plan & Palette
- via analysis of source, and initial color system configuration (e.g. Analogous, Complementary, Munsell)
- Edge plan
- currently edge plan are parameters that scale other low level edge parameters
- Brush Style
- brush types, plan, overlap/plane-based percentage, and many other attributes

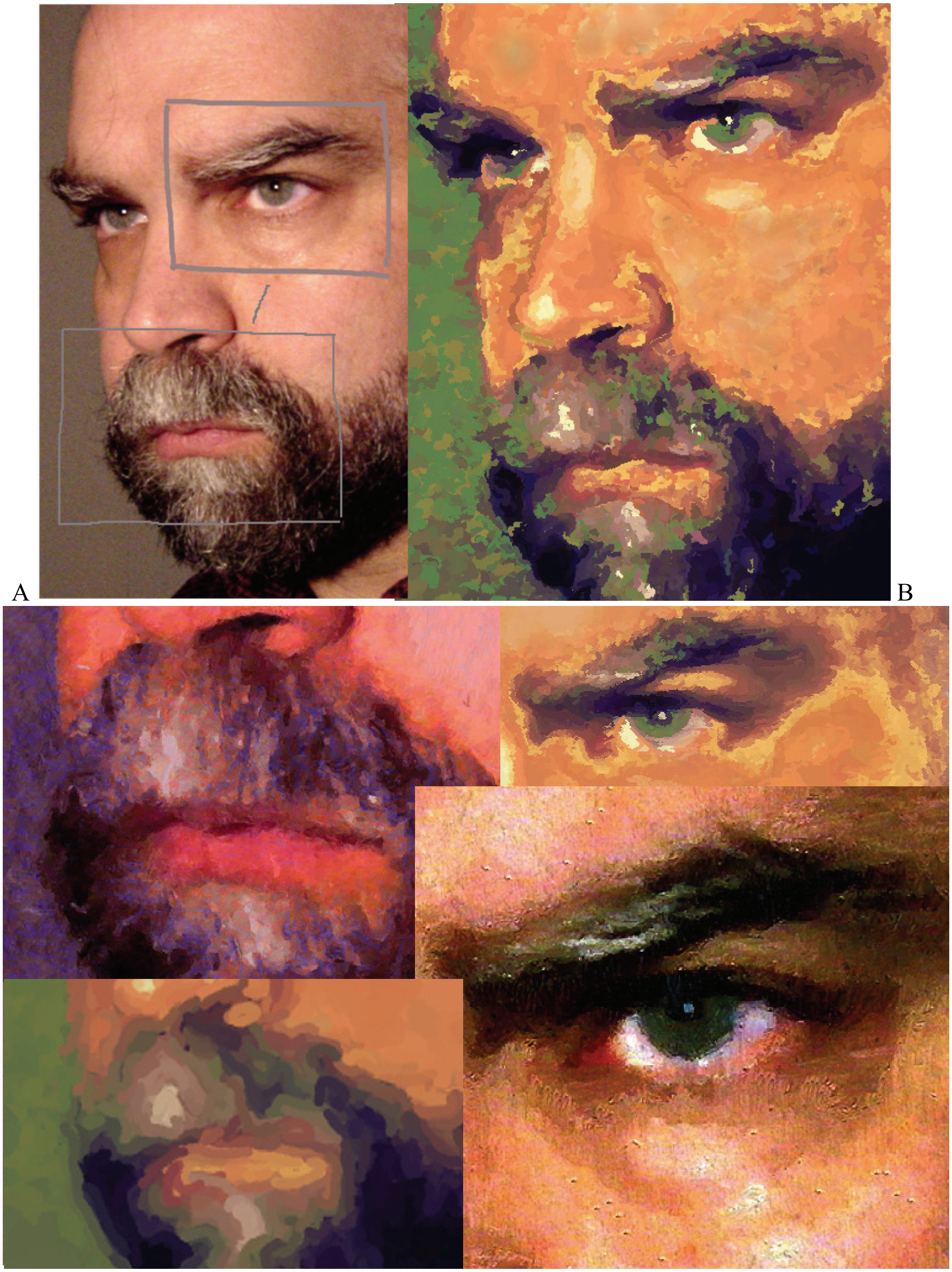
System flowchart:

Create 3 tone GrossToneMap (GTMap) (fig 1b) - based on Source Image, Value Plan params and OBJmap
Create 9 tone FineToneMap (FTmap) (fig 1c) - from Source Image, GTmap, Value Plan params
Upgrade tonal maps to take into account shadow core/clumping and other photography issues
Use GTmap to iterate brush size levels (main loop)
Use OBJmap + COImap + FTmap to dictate 'sharpness' at different levels
Use above + ValuePlan + Color Plan to dictate palette choice for stroke color at different levels
- currently the color palette is precomputed, then indirected into by value: OBJmap, GTmap, FTmap
Use above + Brush Style to dictate brush path/size/type at different levels
Recompute GTmap for next level (back to main loop)

The current system is a Java based toolkit that accepts as input XML configuration files, and input image files then works automatically to render brush stroke based images using OpenGL. The system can also output a rendered XML based brush stroke list file with full details of stroke styles, positions and curvature nodes including temporal and comment data. We have used this stroke script output to render images using Corel Painter; a natural media brush stroke renderer with very sophisticated natural brush stroke capabilities via its (automatic) scripting facility. The eye/eyebrow output image in the lower right of Fig. 2c shows output sent through this renderer. While Corel Painter is typically used interactively as a paint program, we are using it as an automatic brush stroke renderer, which interprets our high level brush stroke commands including stroke speed and pressure.

7. EARLY RESULTS

These early results use the non-professional photograph in figure 2a, an XML configuration and input image files as input (as described in section 5), automatically producing output in figure 2b. By changing some of the input variables, a wide range of styles are possible as demonstrated by the output detail in figure 2c (all cropped to show detail).



A B C

Fig. 2 Output (B) is computationally derived from source image (A). Additional close-up examples of varied output (C) from same input (A). Only ~10% of the painterly rules have been implemented in these early results.

8. CONCLUSION

We have described our initial work on a novel and customizable painterly rendering system which uses a portrait painter knowledge base and present early results. The parameterized knowledge system uses fuzzy knowledge rules gained from interviews with oil portrait painters, and gather reference data from the traditional 'portrait painter process'. The knowledge data is parameterized into an n-dimensional space of low level rules which can be accessed at different semantic levels. Non-professional photographic imagery of people's heads is used as input. We have described how this parameterized toolkit can be scripted using XML, allowing for experimentation and the creation of high level parameters constructs. Our on going goal is build up high level constructs using additional vision and perception techniques that support the portrait painter knowledge, allowing for an interdisciplinary system which has research benefits for NPR as well as art theory and cognitive science.

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