

The Painting Fool Sees! New Projects with the Automated Painter

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Abstract

We report the most recent advances in The Painting Fool project, where we have integrated machine vision capabilities from the DARCI system into the automated painter, to enhance its abilities before, during and after the painting process. This has enabled new art projects, including a commission from an Artificial Intelligence company, and we report on this collaboration, which is one of the first instances in Computational Creativity research where creative software has been commissioned directly. The new projects have advanced The Painting Fool as an independent artist able to produce more diverse styles which break away from simulating natural media. The projects have also raised a philosophical question about whether software artists need to see in the same way as people, which we discuss briefly.

Introduction

The Painting Fool (thepaintingfool.com) is software that we hope will be taken seriously as a creative artist in its own right, one day. It is a well established project, with an emphasis on implementing processes which could be described as artistic and/or creative, rather than merely producing images which look like they may have been painted by a person, as with many graphics packages, as per (Strothotte and Schlechtweg 2002). Many technical details of the project and discussions of the outreach activities performed with The Painting Fool are given in (Colton 2012b). Progress in the project is usually both technical and/or societal, and the work presented here addresses both aspects.

On the technical side, we have enabled The Painting Fool to use machine vision techniques before, during and after painting, to take on more creative responsibility, produce more interesting pieces and provide better framing information. This has involved integrating aspects of the machine vision abilities of the DARCI system (Norton, Heath, and Ventura 2013; Heath, Norton, and Ventura 2014). In addition to being used in art generation itself (Norton, Heath, and Ventura 2011), DARCI has been used as an artificial art critic (Norton, Heath, and Ventura 2010), which makes it the perfect complement to The Painting Fool. Implementing such synergies is rare in Computational Creativity research, with a few notable exceptions, such as the combination of parts of the MEXICA, Curveship and GRIOT programs into the Slant storytelling system (Montfort et al. 2013).

On the societal side, to get The Painting Fool accepted as an artist, we engage the public, journalists and members of the art world (artists, art students, art educators, critics, curators, gallery owners, etc.), as natural stakeholders in the question of whether software can be creative or not. Exploration of some of the stakeholders issues in Computational Creativity is given in (Colton et al. 2015), where The Painting Fool is a case study. This, along with a philosophical underpinning given in (Colton et al. 2014) provide a general grounding for the design decisions presented here, in terms of why they represent significant progress towards the long-term aim of public acceptance of The Painting Fool as a creative artist. In this context, we describe here three new art projects where The Painting Fool has used its new visual capabilities with increasing sophistication, to produce interesting art and experiences for audiences via more autonomous behaviours in the software. These projects include a mood-based portraiture demonstration, where the visual processing was used to express intent; The Painting Fool's first art commission for a third party; and a private art project.

The collaborative projects with DARCI have progressed The Painting Fool project along a number of axes. With machine vision abilities, it can now analyse its output, albeit simplistically: new functionality with potential to make it more appreciative in motivating and assessing projects, and via analysis during sketching activities. Also, choosing rendering styles can now be done by the software itself, rather than a person. This adds much autonomy, increases impressions of creative responsibility in the software, and has led to surprising results, as the paintings no longer only resemble those produced in traditional ways by people. The Painting Fool uses the digital medium more fully in interesting new styles difficult for people to achieve, which again increases the impression of independence and creative responsibility.

This paper is organised as follows. In the next section, we describe aspects of The Painting Fool and DARCI used in the collaboration, followed by a discussion of how association networks from DARCI were used by The Painting Fool in increasing levels of sophistication. We then present the three new art projects enabled by this collaboration, and put these into the context of related work. We conclude with a discussion of the advances made in The Painting Fool project, and we briefly question whether software artists need to see in the same way as people.

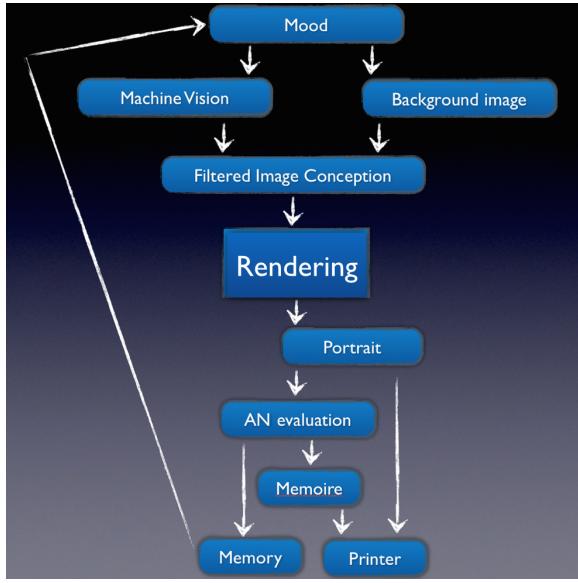


Figure 1: A workflow representation of The Painting Fool’s processing for the *You Can’t Know My Mind* exhibit.

Background

The Painting Fool: Workflows

There is no single way in which The Painting Fool produces artworks, but rather a set of tasks it can achieve through performing certain behaviours, and workflows which combine these into art-producing processes. The behaviours make use of various AI techniques including natural language processing (Krzeczkowska et al. 2010), constraint solving (Colton 2008b), evolutionary search (Colton 2008a), design grammars (Colton and Pérez-Ferrer 2012) and machine learning (Colton 2012a). The workflows are constructed through a teaching interface currently consisting of 24 screens. An example workflow, for the *You Can’t Know My Mind* exhibit (described below) is given in figure 1. This highlights that the vision system is used both at the start of the process and towards the end (the ‘AN evaluation’ node).

Before the work described here, The Painting Fool had a very rudimentary visual analysis system that was able to evaluate features of an image such as texture, colour variance and symmetry. It is also able to segment a given digital photograph into a set of *colour regions*, using a threshold-based neighbourhood construction method, path-finding for edge rationalisation and edge abstraction methods. A waypoint in every workflow is the construction of such a set of colour regions, which can be achieved using this segmentation process, via design grammars, variation of hand-drawn scenes and/or a constraint solver placing rectangles onto the canvas. The colour regions direct the rendering process, whereby each region is either filled-in or outlined via the simulation of natural media such as paints and implements such as paintbrushes. The rendering of each region can include multiple fill/outline passes, and the rendering of the entire segmentation of colour regions can be done repeatedly, building up a layered image.

The segmentation and rendering methods are highly parameterised, requiring 14 and 57 parameters to be set respectively, as described in (Colton 2012b). Choosing from the space of possible segmentation and rendering methods constitutes a large part of the creative responsibility taken on in an art project, along with choosing and arranging subject matter, etc. We show below how the software now takes on the responsibility of choosing the rendering settings.

DARCI: Association Networks

One way for The Painting Fool to have an increased appreciation of the artefacts it produces and some level of intentionality (both desirable qualities), is for it to employ a perceptually grounded cognitive model that can associate visual stimuli with linguistic concepts. That ability was realized by borrowing a piece of the DARCI system, a visuo-linguistic association approach, which consists of a set of neural networks that perform a mapping from low-level computer vision features to adjectival linguistic concepts, learned from a corpus of human-labeled images.

These images come from a continuously growing dataset obtained via a public facing website (darci.cs.byu.edu) that solicits volunteer labeling of random images. Volunteers are allowed to label images with any and all adjectives they think describe the image, and as a result, images can be described by their emotional effects, most of their aesthetic qualities, many of their possible associations and meanings, and even, to some extent, by their subject. Furthermore, through additional labeling exercises, volunteers can specify labels that explicitly *do not* describe the image, allowing the collection of explicit negative labels as well as positive ones. The result is a rich, challenging, dynamic dataset. A recent snapshot of the data reveals 17,004 positive labels and 16,125 negative labels using 2,463 unique adjectives associated with 2,562 unique images, an average of approximately 12 unique labels per image, and 110 adjectives with at least 30 positive and 30 negative image associations.

Images are perceived by the system as a vector of 102 low-level computer vision features extracted from the image using the DISCOVIR system¹. This level of image perception does not admit significant semantic understanding, but it does allow appreciation of concepts that can be adequately expressed with global, abstract features dealing with characteristics of the image’s color, lighting, texture, and shape. Given training data in the form of (image feature vector, adjectival label) pairs, a mapping is learned using a set of artificial neural networks that we call *association networks*. Since learning image-to-concept associations is a multi-label classification problem, and we cannot assume implicit negativity, the only appreciation networks trained for a particular image are those explicitly labeled with (positive or negative examples of) the associated concept. Each adjectival concept is learned by a unique association network, which is trained using standard backpropagation and outputs a single real value, between 0 and 1, indicating the degree to which an input image can be described by the network’s associated adjectival concept.

¹appsrv.cse.cuhk.edu.hk/~miplab/discovir

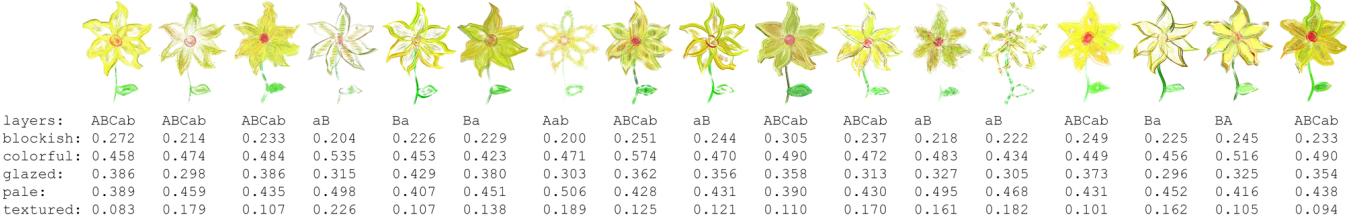


Figure 2: Seventeen painting styles along with layering scheme and partial visual profile.

Implementing Vision-Enhanced Painting

From the DARCI system, The Painting Fool inherited a set of 236 association networks (ANs), and a method of turning a given image I into the numerical inputs to the ANs. Each AN corresponds to a particular adjective, i.e., the higher the output from the AN for adjective A when given input values for I , the more likely (the AN predicts) that a viewer will use A to describe I . We first determined which of the adjectival ANs were suitable for dealing with The Painting Fool’s output. To do this, we ran each AN over hundreds of painterly images from The Painting Fool and recorded the range of the numerical outputs. We found that for the majority of the ANs, the output range was so low that we couldn’t meaningfully claim that it was differentiating between images based on visual properties. We selected all ANs where the range of outputs was 0.05 or greater, and then performed a sanity check on those remaining, removing any which described images in a particularly counter-intuitive way, e.g., the AN for ‘red’ outputting a higher score for a patently green image than for a patently red image.

This left a selection of 65 usable ANs, to which we implemented an interface in The Painting Fool. For each selected AN, we recorded the highest and lowest outputs over the hundreds of images mentioned above, and when output from a new image is calculated, it is normalised between these extremes. As described below, the ANs have been used in a number of new workflow behaviours for The Painting Fool. The simplest of these is to allow the software to frame its output (Charnley, Pease, and Colton 2012) by describing it visually. It can also compare and contrast images in terms of a particular adjective, or in terms of a profile of multiple adjectives. It can also employ the ANs during the painting process, as described in the following subsections.

A Space of Simulated Visual Art Implements/Styles

Given an image segmentation of colour regions as described above, The Painting Fool produces a non-photorealistic rendering of it in a series of whole-segmentation layers, during which each region itself is rendered in multiple layers. During the rendering of each layer, which can either be filled in, or outlined, the software simulates natural media such as paints, and the usage of implements such as brushes in outline/fill styles such as hatching, as described in (Colton 2012b). The rendering of a layer is determined by a set of 57 parameters, which cover the simulation of the media itself (e.g., wetness of paint), the implement (e.g., brush size) the support (e.g., canvas roughness) and the style (e.g., number of times to draw an outline).

We defined a space of painting styles by fixing the rendering to a single whole-segmentation layer during which a scheme of up to five rendering layers per region was allowed. The region layering scheme was represented as a string with letters A, B, C, a, b or c . Upper case letters represent a fill layer with lower case letters representing outline layers. Where upper and lower case letters correspond (e.g., $A = a$), all the other settings are the same, hence they represent the simulation of the same natural media in roughly the same way, but one produces an outline, the other produces a fill. For instance, $ABCab$ represents three fill layers and two outline layers, with all the settings of the first two fill layers exactly as for the two outline layers. We found that it increased visual coherence if the fill layers corresponded to the outline layers in this way. After initial experimentation, we constrained the space to include five layering schemes: aB , Ba , $Abab$, Aab and $ABCab$, which we found produced a suitably large variety of visual styles.

We generated 1,200 painting styles by randomly sampling the space of rendering styles with each of the 57 parameters set randomly to an appropriate value in its range, and then mapping a set of these styles onto one of the five layering styles above, also chosen randomly. For each style, we used The Painting Fool to render a given segmentation of an abstract flower. Then, for each of the 65 selected ANs described above, we calculated the normalised output for each of the 1,200 flower paintings, thus creating a visual profile for each style. Example painting styles, along with the layering scheme and part of their visual profile are given in figure 2. The seventeen pictures demonstrate somewhat the diversity in the painting styles within this space. The partial profiles indicate that while the AN outputs have a relatively small range, it is sufficient for a choice of painting style based on these values to be meaningful.

Employing Vision During Painting

To recap, we supplied The Painting Fool with 1,200 different painting styles, each with a visual profile derived from applying association networks. As described above, there are various workflows for producing images with The Painting Fool. When the workflow starts with a digital photograph, images are segmented into a certain number of colour regions, with more regions usually leading to more photorealism in the final paintings. Each colour region corresponds, therefore, to a region of the original photograph, and this photo-region can be interrogated in order to choose an appropriate painting style. To do this, The Painting Fool extracts the photo region onto a transparent image, then applies

all 65 adjectival ANs to the extract, to compile a profile. The Euclidean distance of this photo-extract profile from the visual profile of the 1,200 painting styles is used to order the styles in increasing distance. The distance can be interpreted as an *appropriateness* of the painting style to the underlying photo extract. That is, the style with least distance will render the region in a way that is most similar in nature to the original photograph (according to the ANs).

The new workflow for The Painting Fool uses machine vision during painting as follows: it takes a photograph and segments it into colour regions. For each colour region, a photo-extract profile is produced using the ANs, and this is used to order the painting styles in The Painting Fool's database, in terms of how appropriate they are to the photo extract. From the top ten most appropriate styles, one is chosen randomly to paint the region in question. Choosing from the top ten in this fashion means that each time the same photograph is painted, it produces a different image, yet each time, each painting style is appropriate to the region it is used to paint. We have enhanced this workflow by enabling a sketching mechanism. That is, The Painting Fool tries all of the ten most appropriate sketching styles in situ, then produces a visual profile of the resulting region of the painting, and chooses the one where this profile is closest to the photo-region profile. This reduces the reliance on the initial flower experiments somewhat, as The Painting Fool can see what each style looks like actually in the painting, before committing to one in particular. It also opens up the potential for The Painting Fool to produce a sketchbook to accompany each painting, as framing information.

Cultural Applications

In the subsections below, we describe new cultural application projects with The Painting Fool which have been enabled by its access to a vision system. These span the kinds of public, private and commissioned art projects that an artist might expect to undertake as part of their general activities.

The ‘You Can’t Know My Mind’ Exhibition

For the *You Can’t Know My Mind* exhibit reported in (Colton and Ventura 2014), we focused on the question of intentionality in creative software. As software is programmed directly, it is fair criticism to highlight that in most Computational Creativity projects, the intention for the production of artefacts comes from the software’s author and/or user. For the *You Can’t Know My Mind* project, we raised our intentions to the meta-level, i.e., we intended for the software to produce portraits and entertain sitters in order to learn about its own painting styles. However, the aim of each artefact production session was determined by The Painting Fool itself, in order for it to exhibit behaviours that unbiased observers might project the word ‘intentionality’ onto.

An 8-point description of how The Painting Fool operated in this project is given in (Colton and Ventura 2014). Of note here, we used the machine vision system from DARCI offline, to prepare the software for portraiture sessions. That is, for each of 1,000 abstract art images produced by the Elvira sub-module (Colton, Cook, and Raad 2011), and for

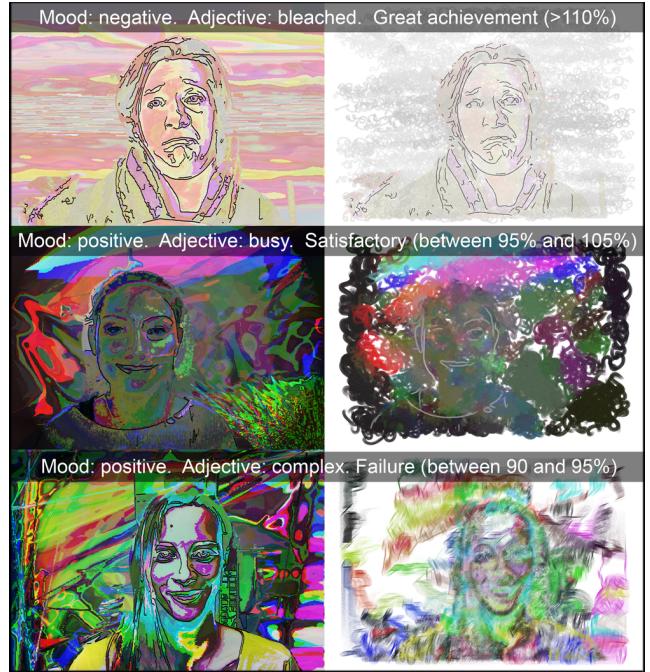


Figure 3: Example comparisons of sketch conceptions (left) and associated portraits (right). The percentages portray the range of the output from the adjective AN for the second image in terms of the AN output value for the first image.

each of 1,000 image filters produced by the Filter Feast sub-module (Torres, Colton, and Rueger 2008), the output of all of the adjective ANs were calculated. Hence the software could choose from the most appropriate abstract backdrops and the most appropriate filters for an adjective, A , chosen to fit a mood, to produce a *sketch conception* to aim for with each portrait. The ‘background image’ and ‘filtered image conception’ nodes in figure 1 correspond to these.

Under the assumption that the sketch will invoke people to project certain adjectives onto the image upon viewing, the sketch conception has aspects which The Painting Fool aspires to achieve in its painting. The conception image is segmented into colour regions, and a simulation of various painting media (paints, pastels and pencils) are used in one of eight styles, to produce a portrait. At the end of each portraiture session, The Painting Fool uses the vision system to compare the level of adjective projection in the portrait to that of the sketch. To do this (indicated by the ‘AN evaluation’ node in figure 1), it applies the adjectival AN for A to the sketch conception and to the final portrait, and compares the output. If the AN output for the portrait, O_p , is within 95% to 105% of the AN output for the conception, O_c , i.e., $0.95 \times O_c \leq O_p \leq 1.05 \times O_c$, this is recorded as satisfactory. If it is higher than 105% , this is recorded as a success, and if it is higher than 110% , this is recorded as a great achievement, with failures similarly recorded. Three examples comparisons of conception and portrait are given in figure 3. The level of achievement/failure is used to update a probability distribution that The Painting Fool can use to choose painting styles later to (attempt to) achieve an image with maximal output respect to a given adjectival AN.



Figure 4: Front page and excerpt from the Japanese version of the essay for the ‘I Can See Unclearly Now’ commission. Third image: an early photograph of artwork hung in the Behaviour Informatics Laboratories of UBIC.

The ‘I Can See Unclearly Now’ Commission

UBIC² is a behavioural information data analysis company based in Tokyo. In early August of 2014, UBIC’s CTO, Mr. Hideki Takeda came across The Painting Fool’s website while exploring recent advances in Artificial Intelligence research on the web. At that time, UBIC’s Behavior Informatics Laboratories (BIL) in Shinagawa, Tokyo, was implementing a complete office renovation scheme reflecting the company’s reorientation from eDiscovery vendor to supplier of in-house Big Data Analytics solutions powered by an AI engine called the Virtual Data Scientist. The new office concept of the BIL can be summed up as: “Shaking the boundaries between the virtual and the real so as to stimulate the senses and promote intelligence and creativity”. For example, the new office features both real bamboo and bamboo imprinted on a glass wall. The choice of bamboo is not arbitrary, but motivated by the fact that this plant plays a prominent role in traditional Japanese culture. It is highly symbolic and associated with, for example, Noh theatre³ in which the protagonists are often ghosts from another plane of existence but appearing in the real world.

Mr. Takeda decided to commission artworks from The Painting Fool, as this would fit very well with the blurring of virtual and real spaces in the BIL. The first author of this paper – who is the lead researcher in The Painting Fool project – was contacted by the second author acting on behalf of UBIC, and ultimately three series of images were commissioned, along with an essay highlighting how the machine vision system was used in increasingly sophisticated ways from the first to the third series. Constraints were put on the commission: (i) to include a portrait from a live sitting, and (ii) to include a piece involving Alan Turing, as an AI pioneer. Moreover, it was agreed that the commission would involve an element of research and implementation, driving The Painting Fool project forward. Example images (with details) from the three series are given in figure 6, and details from the essay, along with an early photograph of one of the pieces hung in the BIL are given in figure 4. The title of the commission was chosen to highlight The Painting Fool’s new usage of machine vision techniques, while indicating that the system is far from perfect.

To tie the three series of images together, the same style of

backdrop was used, consisting of 10,000 adjectives rendered in a handwritten way in varying shades of greyscale pencil, onto dark backgrounds. In all the pieces, the mass of adjectives open up in multiple places into which red handwritten adjectives are strategically placed. For the first series, *StarFlowers*, paintings of the abstract flowers used for assessing painting styles were placed using a constraint solver to avoid overlap, as per (Colton 2008b), with slightly differing sizes. Before placement, each flower image was assessed by the 65 adjective ANs, and from the top ten highest scoring adjectives, two were chosen to appear alongside the flower in the piece, in red handwriting. The pairs were automatically chosen so that no flower had the same two adjectives next to it. For instance, in the detail of figure 6, the first flower is annotated with ‘peaceful’ and ‘warm’.

In the second series, *Good Day, Bad Day*, two photographs of the second author seated, posing firstly in a good mood, and secondly in a bad mood were used. The 65 adjectives were split into positive, neutral and negative valence categories, e.g., happy, glazed, bleary respectively. The painting style with the highest average AN output over the positive adjectives was chosen to paint the first pose, and the most negative style was similarly chosen to paint the second pose. Each portrait was annotated at its edges with red handwritten adjectives appropriate to the painting at that edge point. In the third series, *Dynamic Portraits: Alan Turing*, a photograph of Turing was hand annotated with lines to pick out his features. We then used the method of arbitrarily choosing from the top ten most appropriate painting styles for each colour region described above, to produce a number of portraits, with the annotated lines being painted on at the end, to gain a likeness. The rendered painting was analysed with the 65 ANs and the 17 most appropriate adjectives were scattered around the backdrop of the image, in a non-overlapping way, as usual in red handwriting.

Dozens of images from the three series were sent to UBIC to choose from for the BIL, with very little curation from the first author. UBIC representatives confirmed that the commission achieved the brief of producing pieces which blur the line between the real (i.e., painted by a person) and the virtual (i.e., painted by a computer), and were very happy with the commission. They produced a translated version of the essay for visitors to the lab, and hung an example from each series in the BIL.

²www.ubicna.com

³en.wikipedia.org/wiki/Noh

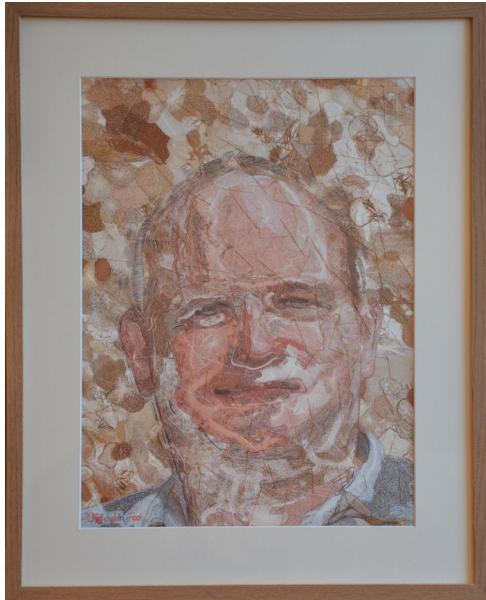


Figure 5: Portrait of Geraint Wiggins.

The Portrait of Geraint Wiggins

In (rather belated) celebration of a milestone birthday, we used the vision-based sketching approach described above, to produce a portrait. Given an original image, hand-annotated with lines picking out facial features, The Painting Fool segmented it into 150 colour regions/lines, and for each, chose the top ten most appropriate painting styles, as described above. For each of the ten, it painted the region, calculated the visual profile of the region of the painting that resulted, and finally chose the style with minimal distance between its visual profile and that of the original photo-extract. In this way, the painting process was deterministic, but not predictable, and produced a striking portrait with painterly and distinctly non-painterly effects. To add a physical uniqueness, the image was printed onto 300 4cm by 4cm squares which were composed into the final piece in an overlapping formation, as per the Dancing Salesman Problem piece described in (Colton and Pérez-Ferrer 2012). The portrait is shown in figure 5.

Related Work

It is commonplace for an artist to be commissioned to work with a bespoke piece of software, or even to develop new code, to produce artwork, with the person using the software as a tool, and this tool may be generative. However, it is much less common for a commission to be made specifically because the software will take on some of the creative, not merely generative, responsibilities.

The ANGELINA system (Cook and Colton 2014) has been commissioned to produce games for the New Scientist, Wired and PC Gamer Magazines. In the former, ANGELINA designed a game as normal, but its designer provided custom visual theming, drawing new sprites and creating sound effects for *Space Station Invaders*, since ANGELINA was not capable of this. The commissions for

Wired and PC Gamer came much later, when ANGELINA had more independence and could produce full games, given just an initial theme of a short phrase, proposed by the journalist. For the PC Gamer game, *NBA Mesquite Volume 2*, ANGELINA used a database of labelled textures compiled from social media mining, for the first time in a released game. This happened because the theme chosen, ‘avocado’, matched a label in the database for the first time since the database had been added. This created an additional talking point for the article, and in general the games were well received and drove up online viewing figures.

The *Paul* drawing robot by Patrick Tresset (Tresset and Fol Leymarie 2012) has much in common with The Painting Fool, in that it uses a camera and machine vision techniques to capture an image, then automatically draws a portrait: in this case, physically, using a robotic arm and a pen. It also simulates looking while it draws, but this is only for entertainment purposes, i.e., after the initial photograph is taken, the vision system is not used again. Paul has been commissioned on a number of occasions, most notably for a week-long workshop at the Centre Pompidou in late 2013. Tresset has also found success in selling versions of the robot painter to art museums. Another robotic painter, which does use machine vision during painting and has also been commissioned for art is the eDavid system, as described by (Lindemeier, Pirk, and Deussen 2013). Here, a camera is used to photograph the canvas after a series of paint strokes have been applied, with a vision system employed to optimise the placement of future strokes based on the visual feedback.

It is beyond the scope of this paper to perform a survey of commissions where software creators rather than artists controlling software have produced artworks. However, we can tentatively introduce some metrics for comparing projects/software/programmers to begin to characterise such commissions. For instance, one could compare the domain specific training of the programmer, e.g., comparing the commissions of artist Harold Cohen (who represented the UK in the Venice Biennale) and his AARON system (McCorduck 1991) with Oliver Deussen (who has no artistic training) and his eDavid system mentioned above, as this may indicate more autonomy in the software (but doesn’t necessarily). Other measures could include how much curation takes place, i.e., how much of the software’s output is usable; what amount of hand-finishing of output takes place; and how much extra coding is required for each project.

Conclusions and Future Work

Through the above projects, The Painting Fool has advanced as an artist in three major ways. Firstly, the creative responsibility of choosing a painting style has been handed to the software. With the *You Can’t Know My Mind* project, it learned a probability distribution which can choose between one of eight painterly rendering styles, to produce an image which people will probably describe using an adjective, chosen intentionally to express a mood. With the *I Can See Unclearly Now* project, the software gained the ability to choose between 1,200 painting styles for each colour region dynamically during painting. With the *Portrait of Geraint Wiggins* project, it went further: performing *in situ* sketches

to test painting styles in the context of the painting at hand. Hence, the decision making involved in determining rendering styles is now undertaken by the software, which is a major advance in autonomy, and potentially towards its acceptance as an artist in its own right.

Secondly, on close inspection of the pieces in figures 5 and 6, while the images produced retain a painterly style somewhat, there are aspects which couldn't be produced with natural media simulation. This is because the painting styles in its database include ones which simulate the ground in-between natural media such as paints and pastels, and others which have no analogue in the physical world. This means that – for the first time – The Painting Fool can produce images using a much broader range of pixel manipulations, producing styles which have little grounding in traditional painting. We also see this as a major advance, as it extends the variety of images the software can produce, and potentially increases perceptions of autonomy.

The third advance will be expressed more in future work than in the projects presented here. Through the mapping of visual stimuli to linguistic concepts, The Painting Fool is able to project adjectives onto images, and we plan to enhance this with the ability to similarly project nouns. This will increase its capacity to appreciate its own work and that of others, enabling it to provide more sophisticated commentaries about what it has produced, and we touched on this with the output in the *You Can't Know My Mind* project, where the conceived and rendered images are compared visually. We plan to take this framing further, with The Painting Fool keeping a sketchbook for each project, adding value, and helping audiences to understand its processes.

It is clear from figure 2 that the visio-linguistic system does not yet match that of people perfectly. Moreover, we acknowledge that – as pointed out by a reviewer – we have not provided data to verify that our strategy to match the visual profile of an image with appropriate painting styles for regions is a good strategy, nor have we yet compared and contrasted alternatives or tested people's reactions to the artworks produced. We aim to experiment with this approach and explore alternatives in future work. However, before undertaking much further work, we wish to raise, discuss and be guided by responses to a philosophical question for the Computational Creativity community: is it important that an automated artist has a visual system similar to that of people? For communication/framing value, it might be preferable for the software's visual judgements to match ours closely. However, as illustrated by a recent internet storm about colours in a dress (Rogers 2015), we all have different visual perception systems, and notions of beauty differ from generation to generation and person to person. As art is driven forward by such differences, it may be more interesting and important artistically for us to learn The Painting Fool's visual system, rather than it learning ours.

Acknowledgements

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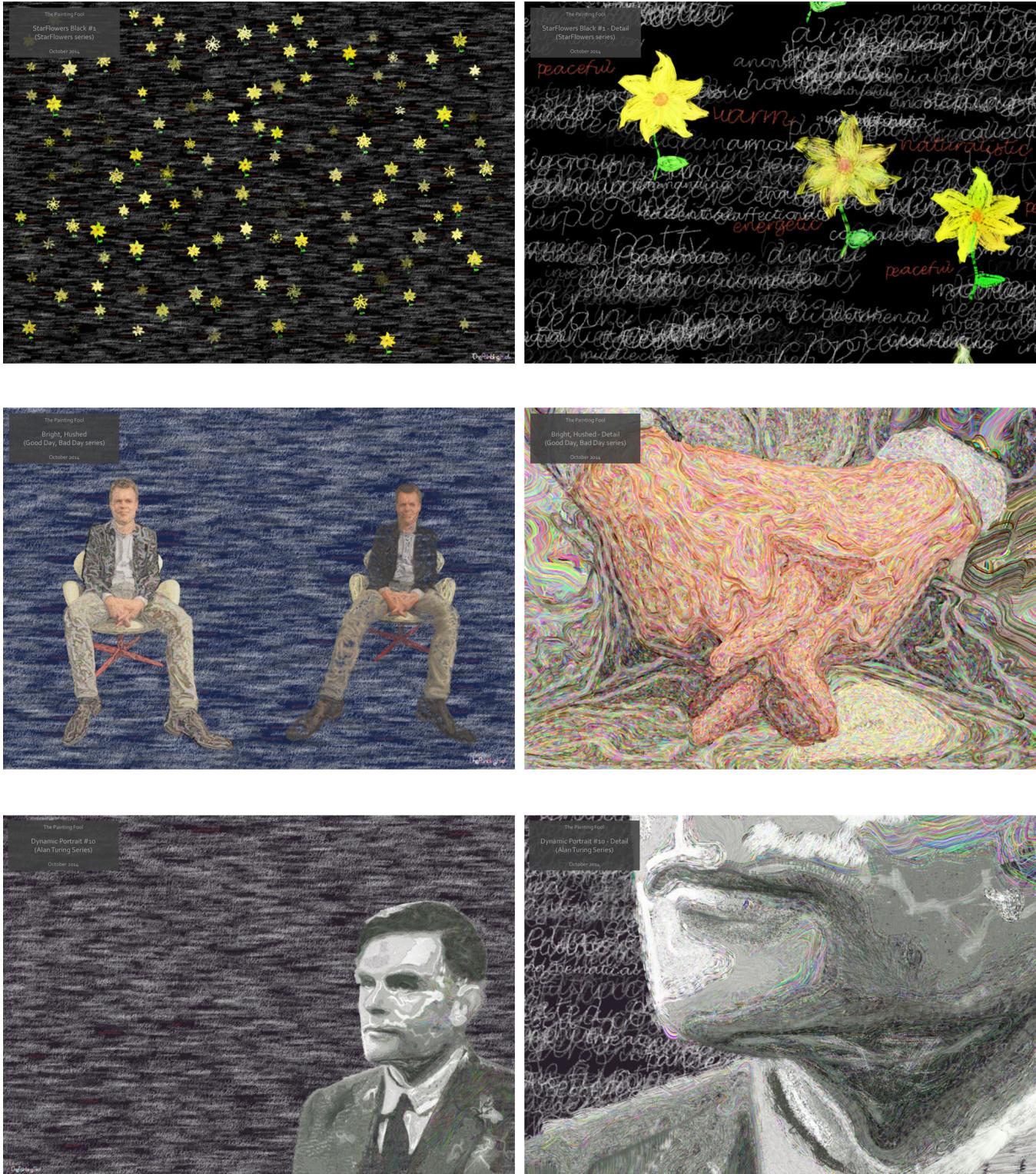


Figure 6: Example images, each with detail, from the ‘I Can See Unclearly Now’ commission. First pair: from the *Star Flowers* series. Second pair: from the *Good Day, Bad Day* series. Third pair: from the *Dynamic Portraits: Alan Turing* series.