A Window to the Emotions

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Abstract

Nowadays, psychologists classify the emotions into discrete categories in a common and universal language. The simplest category is composed of six basic emotions resulting from cross-cultural studies: happiness, sadness, fear, anger, disgust / displeasure and surprise. This work presents a new paint generator which uses facial feature extraction and analyzes most important face's contours to infer expressions with different degrades of intensity. These measurements conform the basis to create personalized (both in colour and design) generative paintings from the emotions detected earlier. Each emotion is reflected in a set of colours and shapes applied to a group of points drawn in a canvas using RGB colour palette. The resulting paint represents the user's facial emotion along a temporal axis. It is generated from a non-repeatable seed by means of complex transformations producing unique results. All of them have its own identity and are recognizable by the creative concept introduced in this work.

1. Introduction

A generative art algorithm could be divided in three parts:

The first one is the *generative seed* of the algorithm which could be random, pseudo-random or a natural observation. In this case, we will use the user's face expressions to feed the algorithm. The relation between vision and forms is introduced in section 2. Section 3 is devoted to the representation of emotions and expressions and the complete extraction process is detailed in section 4.

The second one is the *transformation engine* which makes complex changes over the initial values. In this case, we will use a set of rules which is described in section 5.

The last one is the *generative product* which could be paintings, music, sculptures, etc. Since our approach generates paintings, this is why section 6 contains some representative painting examples of canonical expressions.

One of the most important tasks for a generative algorithm is to maintain its identity, which could be generated in the main parts of the algorithm: the *generative seed* and the *transformation engine*. In the case of our algorithm, its identity comes from both parts.

In section 7 we describe the application created to test the algorithm. And in section 8 we can find the conclusions and the future work of this paper.

2. Vision and forms

Obtaining forms can be approached as a way to establish a relationship between an image in a 2D coordinate system and an object in a 3D system. To solve the problem computationally there are two directions: top-down, bottom-up [1].

The top-down strategy starts of a set of assumptions and expected properties based on expert knowledge [2], these properties are checked successively in each stage of processing up to the image data. Moreover, the bottom-up strategy is the proposal made by David Marr [2] [3]. Marr defined the process of object detection using a computational approach, in which the visual system is like a computer programmed to receive objects; their operation diagram is as follows:

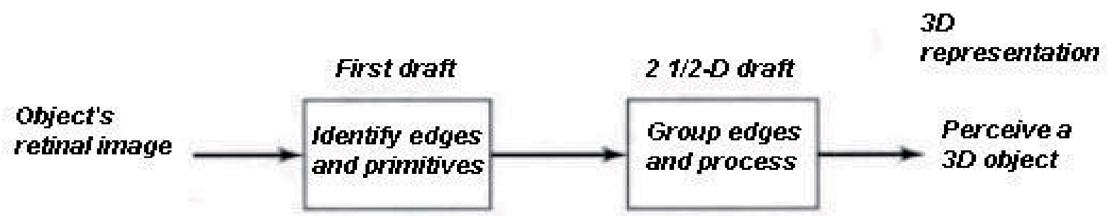


Figure 2.1: *David Marr's computational approach [2].*

In Figure 2.1, the starting point is the image of the object on the retina, the image is analyzed to identify areas of light and darkness and the parts that the intensity changes. The analysis result is a series of basic characteristics (closed areas, segments of lines, ends of lines and lines that define edges) called first draft. Then the contents of the first sketch is grouped according to size and features of similar guidelines, the result is processed again, and a new sketch - called 2½D - that ends in a three-dimensional perception is achieved.

3. Emotions and expressions

Information extracted from the facial features is regularly geometric character (associated with forms of eyes, nose, mouth, and location corners of the mouth or eyes) and related to the appearance or texture (wrinkles, furrows and protuberances). These are the bases of emotion recognition, which has grown particularly in the field of HCII (Intelligent Human Computer Interaction) [4] [5] [6] [7] [8], and it's focus of interest in the support of psychiatric and psychological diagnoses [9] [10] [11] [12].

Nowadays, psychologists classify the emotions into discrete categories in a common and universal language. As we can see in Figure 3.1, the simplest category is composed of six basic emotions resulting from crosscultural studies [14] [13]: happiness, sadness, fear, anger, disgust/displeasure and surprise.

To quantify and classify these basic emotions FACS model - proposed by Ekman and Friesen (1978) [15] - attempts to address the lack of metrics for classification of basic emotions with a series of points to note in the face. It is almost a standard when it comes to classification of facial expression and is present in the research area of psychology and in the area of 3D animation [16] [17].

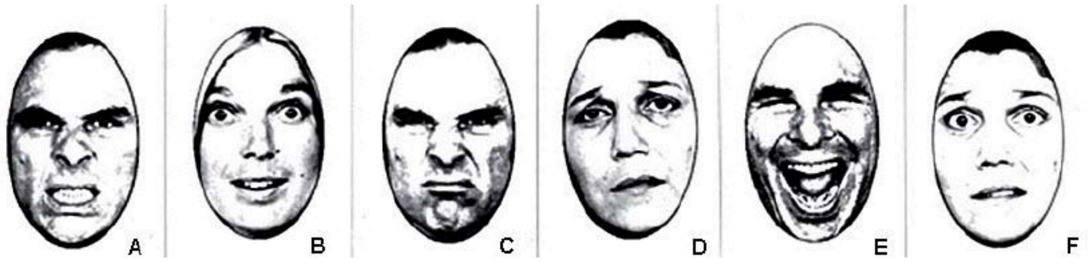


Figure 3.1: *Faces expressive of the emotions anger (A), surprise (B), disgust (C), sadness (D), happiness (E) and fear (F) from the collection made by Ekman and Friesen [Ekman00].*

FACS describes all visual activities based on only 46 action units (AUs), moreover several categories of head and eye positions and movements. Importantly, although FACS arises in anatomy there is no 1:1 correspondence between muscle groups and the AUs, this is due to the fact that a muscle can act in different ways - or contract in different regions - to produce different visible actions. A clear example of this are the frontal muscles, the contraction of the middle of them only raises the inner corners of eyebrows (producing AU1) while contraction of the lateral frontal raises the eyebrows from their side outer (producing AU2).

4. Extracting features

Our algorithm to extract the characteristics of a facial expression is based on contour extraction and morphological operators. This approach was presented in a Master Thesis Project [18] and is defined - in general - on the following stages:

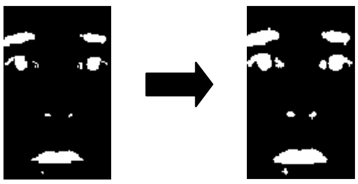
• Capture a frame from a video or camera.

• Locate and remove a sub image from the frame and get only the face to be analyzed[1].

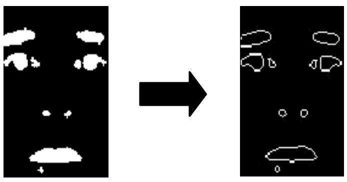
• Convert the facial image to greyscale.

• Binarize the sub image by setting a threshold over which the pixels grey level exceeded X are all black and all white under the threshold.

• Apply the morphological filter dilate on the binarized image. Then, we get an image with accentuates eyebrows, eyes and mouth.



• Apply *Canny edge detection algorithm* [19].



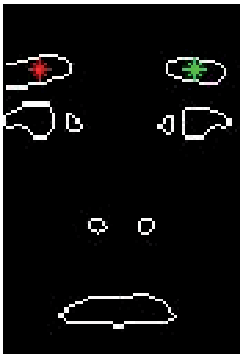
[1] This task is performed by the AdaBoost classifier over Haar features. This is part of the public distribution OpenCV libraries and a compiled version for use in Matlab. http://www.mathworks.com/matlabcentral/fileexchange/19912

• Delete smaller objects that do not exceed a threshold number of pixels that may define the objects.

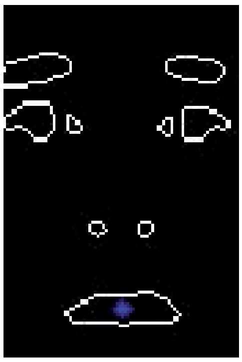
• Joining line segments broken by bridge operator.

• Label the remaining objects individually and calculate their centroids.

• Locate the two less distant objects to the X-axis (according to coordinates of the picture) and identify them as eyebrows. The coordinate axis will always have its origin at the upper-left pixel of the image.



• Locate the object with the largest area in the bottom of the picture and identify it as the object that represents the mouth.



To measure the expressions we focus the attention on AU1, AU4, AU26 and AU27 of FACS, as we can see in Figure 4.1

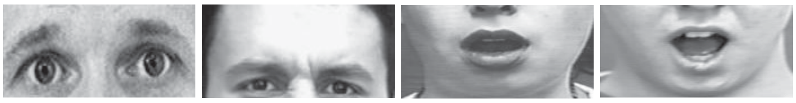


Figure 4.1: *AU1, AU4, AU26 and U27 respectively.*

And we classified the expression using this criterion:

	>=4 objects	2 objects	Opened mouth	Closed mouth	Center of eyebrows up	Center of eyebrows down
Anger			X			X
Surprise	X		X			
Disgust		X		X		
Sadness				X	X	
Happiness		X	X			
Fear	X			X		

Table 4.2: *The image has divide in two equal parts, upper and bottom.*

In order to measure the intensity of the expression we analyze degrees of inclination on eyebrows, mouth aperture and number of objects detected in the face.

5. The painting process

The system makes use of existing associations made between groups of colours and expressions [20] using the Colour Image Scale, developed by Shigenobu Kobayashi in 1981 [21]. In figure XXX we can see some representative examples of colour combinations which will be used by the algorithm to paint the user's emotions

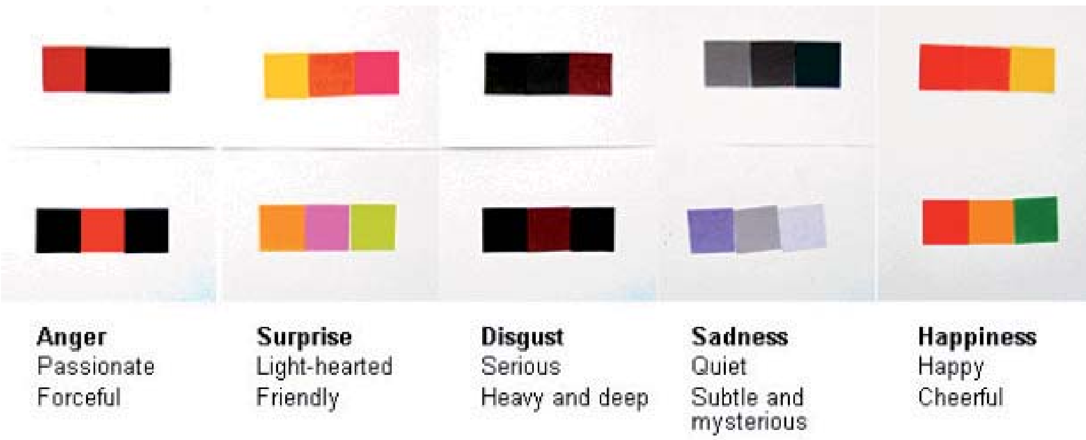


Figure 5.1: *Representative examples of the three-colour combinations for emotions with the images associated with similar colour co*mbinations in Kobayashi's Colour Image Scale

The painting process is inspired by the so called *Blind Paintbrush* [22], using a group of points which move along a 2D canvas changing its colour and position depending mostly on face measures obtained from the user as explained earlier. The intensity of the colours will change linearly during the process, starting from dark and finishing with light colours. These changes create cloud-like results recognizable in all paintings generated by this algorithm.

Those points change it position by means of jumps. Intense emotions, such as anger and disgust, make small jumps and smooth ones, such as happiness and sadness, make greater changes in their position. After a number of iterations, this will lead to sparse results for smooth emotions, and dense paintings for intense ones.

The direction of each point will be determined by the input too, allowing free changes of direction when negative emotions, and minimizing it with positive ones. It will produce more cloud-like forms in the first case, and sharpened forms in the second case.

The binary information contained in the contour matrix obtained in the extraction process will be used as a mask (adding or subtracting a small constant to both colour and jump size values) in order to add some extra user identity to the painting.

Mouth aperture determines de number of points which will draw during the painting process, and the main initial position and direction will be determined by the information obtained from the eyebrows inclination.

Small random values are added to all parameters in order to increment the number of iterations for the whole process (initially fixed).

The identity of the generative algorithm comes from three sources: first of all, the contour binary matrix. Second, the colours and shapes generated by means of the user emotions. Lastly, the linear colour intensity change (from dark to light).

6. Some examples

This section contains some representative painting examples of canonical expressions. Figure 6.1 shows the resulting painting from a happiness face, in which we can see green colour (one of its representatives), and big jumps with small changes of directions in some points. Figure 6.2 shows sadness expression by means of sparse structure with grey-blue colours. Figure 6.3 shows the resulting painting from a surprise face, in which we can see pink colour and big jumps with small changes of directions in some points.

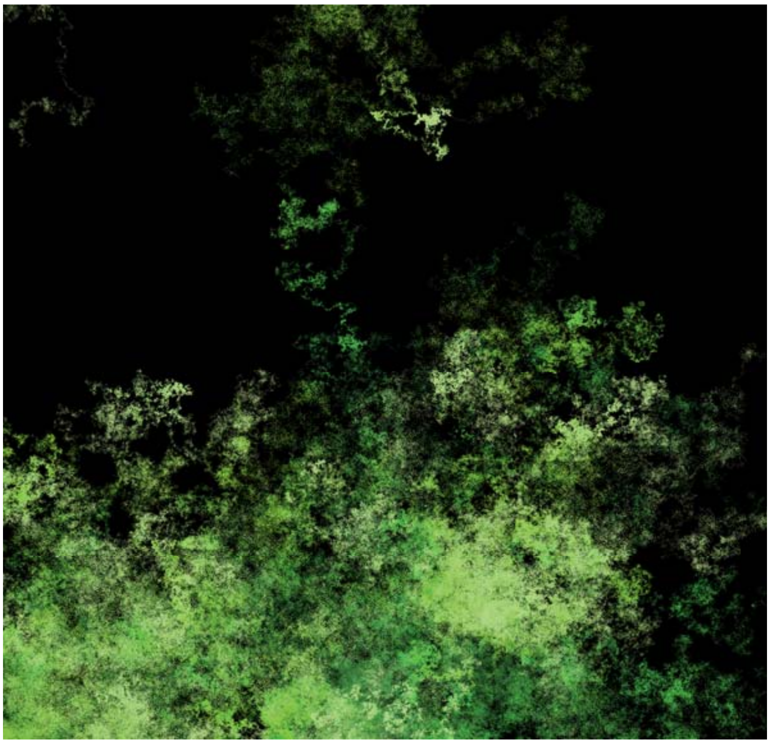


Figure 6.1: *Example of a painting generated by a happiness expression.*

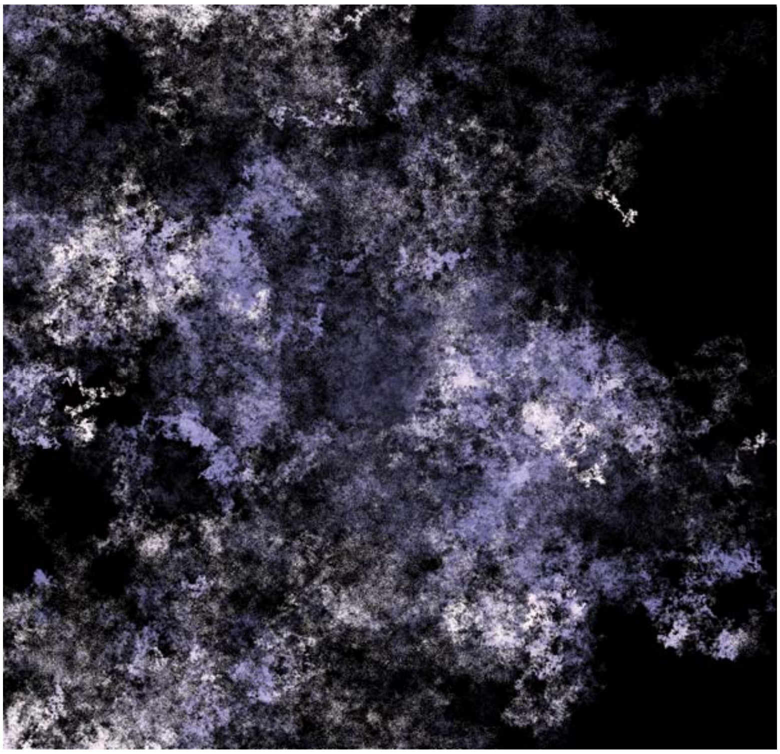


Figure 6.2: *Example of a painting generated by a sadness expression.*

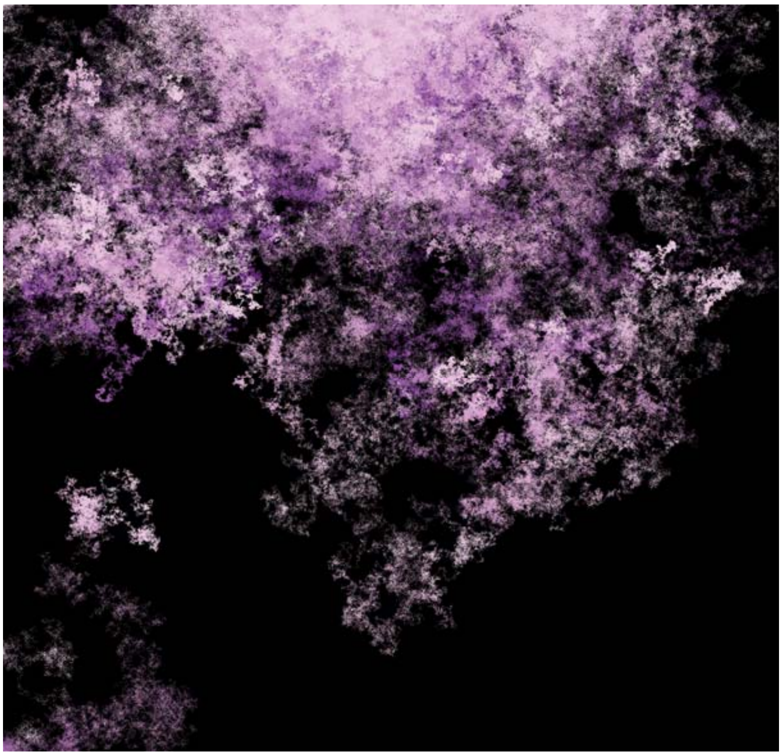


Figure 6.3: *Example of a painting generated by a surprise expression.*

7. The application

The application to test the algorithm consists of a window with two panels, as we can see in Figure 7.1. The upper one shows the video capture during the recording process. And the lower panel is used to show the resulting painting when the generative algorithm ends. It needs an initial recording to capture a neutral expression in order to compute measure differences during the process using those base values. It's a two step algorithm: firstly it extracts the expressions, and later it generates the final painting.

8. Conclusions and future work

This paper proposes a generative algorithm to generate paintings starting from facial feature values representing degrades of expressions intensity by means of contours matrices. These measurements conform the basis to create personalized generative paintings from the detected emotions, each one reflected in a set of colours and shapes applied to a group of points drawn in a canvas using RGB colour palette. The resulting painting represents the user's facial emotion along a temporal axis. It is generated from a personal and non-repeatable seed by means of complex transformations producing unique results, but with an identity.

Figure 7.1: *Example of a painting generated by an anger expression.*

One possible future work is to incorporate the identification of micro-expressions which bring us closer to the detail of the expression by monitoring muscle movement. In this case it could apply an AAM (Active Appearance Model) or an ASM (Active Shape Model) to obtain more detail of what the eyes, eyebrows, cheeks, mouth and forehead are expressing. Thus the parameters and the paint generated from the face would be more accurate.

The painting process could be improved too creating a more complex set of transformation rules and changing the way of obtaining the identity of the algorithm. Other *generative products* could be investigated, such as music or text.

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