Emotions in Abstract Art: Does Texture Matter?

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Abstract. The classification of images based on the emotions they evoke is a recent approach in multimedia. With the abundance of digitized images from museum archives and the ever-growing digital production of user-generated images, there is a greater need for intelligent image retrieval algorithms. Categorization of images according to their emotional impact offers a useful addition to the state of the art in image search. In this work, we apply computer vision techniques on abstract paintings to automatically predict emotional valence based on texture. We also propose a method to derive a small set of features (Perlin parameters) from an image to represent its overall texture. Finally, we investigate the saliency distribution in these images, and show that computational models of bottom-up attention can be used to predict emotional valence in a parsimonious manner.

Keywords: Abstract paintings · Emotion recognition · Perlin images · Saliency · Eye-tracking

1 Introduction

During the centuries various art movements and artists used different tools and techniques to embed feelings in artworks. Art historians and artists have sought to describe this process via theories based on intuition, observation and experiments [1,7]. These rules incorporate the understanding of experts of the domain. It is also possible to look at this process from a reductionistic perspective and use visual perception models to understand it as a brain process [11]. Computer vision can be positioned between these approaches, as by virtue of descriptors of various levels of complexity, it can reveal new rules, or help us validate or change the existing ones. It may also be used to describe statistically what makes a painting to be perceived as emotional, or why certain parts of a painting command more attention.

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In this work we aim at assessing the contribution of texture to the emotional perception of abstract paintings. The latter choice is motivated by a need to reduce the effect of semantics (or top-down information) as much as possible. There is no doubt that the top-down information is more prominent in creating feelings. This is, however, difficult to analyse automatically, and the information obtained from such analysis would be at a different level. The information we extract from the bottom-up, or low level feature analysis can be useful in terms of assessing and using technique, rather than content. Yanulevskaya et al. [23] have previously assessed the informativeness of colour in estimating emotions induced by artworks, and made their database available. In this study, we look at the contribution of texture, and its relation to colour.

We determine the negative and/or positive feelings induced by the artwork with a user study, and make our annotations publicly available. We use two approaches for characterizing texture in artworks. The first approach is a classifier based on SIFT descriptors. The second approach is based on a study that evaluated textures for the perception of masculinity-femininity, heaviness-lightness, and hardness-softness perception [12]. In this work, we derive texture parameters for each artwork and use the psychophysical model proposed in [12]. To obtain this parametrization, we derive MR8 texture feature descriptors of [21], and train a classifier that maps these features to Perlin texture parameters [17].

We postulate that the contribution of colour to the feelings created by the artwork is more prominent than texture, but a combination of colour and texture may improve our models. To assess texture with respect to colour, we report a second user study that replicates the first, but this time with coloured images. We illustrate that the coloured and non-coloured versions of artworks have low, but visible correlation in the feelings they invoke in their viewers.

Finally, we look at image saliency to analyse qualitatively what features people associate with positive and negative feelings. We report an eye gaze study conducted with original and gray-scale artworks, and contrast it with predictions of a computational bottom-up saliency model. The high predictive power of the computational model establishes that the bottom-up estimation is reliable, and we are justified in our usage of abstract art for reducing the top-down effects. Furthermore, it suggests that by disabling the colour in the computational model, we can predict the eye gaze patterns in non-coloured images, and perform an analysis based on this.

Our main contributions are: (1) we study the role of texture and propose an inverse-Perlin parametrization to enable a psychophysical model on feelings induced by abstract paintings; (2) we apply a bottom-up saliency model to abstract paintings and analyse the relation between its predictions and the human fixations; (3) we implement a classifier that gives positive/negative feeling decisions for the study of abstract paintings, which can be useful for image retrieval, art historians, researchers and museum curators.

2 Related Work

Abstract artists were concerned about the basic elements of visual art and how these elements and their various compositions affect the viewer. They have extensively debated and written about these elements, and tested their theories via the use of their artworks. Hence, abstract art offers a good ground if one wants to study visual fundamentals and what emotions they generate in the viewer [15].

The visual texture is an intuitive part of the human sensory input and it can influence the human perception and emotions. Indeed, texture has been subject of study in many areas including psychophysics and computer science. Simmons and Russell [19], investigated the emotional effect of ten different visual textures on colours. They reported that, depending on a certain texture class, add texture to colours change significantly the humans raking of unpleasant colours. Kim et al. [8] extracted colour, texture and pattern features from textile images to predict humans emotions. The authors show that, their proposed textile indexing system was effective for predicting human emotions based on textile images. Thumfart et al. [20] used a layered prediction model to predict the human aesthetic judgments given a computational texture feature. These and others studies aim to simulate the human perception on texture in order to improve the computational representations for classification and segmentation.

Several works in computer vision that focuses on emotion recognition has used texture as one of the features to recognize emotions in images and artworks. Yanulevskaya et al. [22] proposed an emotion categorization system, trained on the International Affective Picture System (IAPS) [9], which is based on the assessment of local image statistics followed by supervised learning of emotion categories using Support Vector Machines. In [13], low-level features were combined with concepts from psychology and art theory for categorization of emotion in affective images and artworks. They obtained better accuracy in affective categorization of semantically rich images in comparison with abstract paintings that were relatively free of semantics. In [23] a Bag-of-Visual-Words model was trained to classify abstract paintings in positive or negative emotions. With the Backprojection technique they determined which parts of the paintings evoke which emotions. Recently, [24] applied multiple kernel learning framework for affective classification of digital abstract art images. These and the other studies extensively rely on colour in predicting affective content. There are scarcely any studies that investigate texture independent of colour for this problem.

3 Texture Analysis

Texture can give the beholder a 'visual sense' of the artwork composition, which is almost multimodal, in that it can invoke tactile associations. In abstract art, feelings of hardness, softness, smoothness, etc. can be created via texture, and we postulate that texture is an integral element of the feeling induced by the artwork (regardless of the artist intentions). To analyse how texture affects feelings in abstract paintings, we have conducted a user-study of positive and negative feelings invoked by abstract paintings with no hue value.

3.1 MART Dataset: A Dataset of Abstract Paintings

We conduct our analyses on the publicly available set of 500 abstract paintings from the electronic archive of the Museum of Modern and Contemporary Art of Trento and Rovereto (MART), collected by [23]. The paintings chosen for the dataset are from 78 artists, including Wassily Kandinsky, Luigi Veronesi, and Carlo Belli. These artists are particularly distinct by their studies of abstract art and its characteristics, in terms of colour, shapes and texture. For studying texture only, we have prepared a gray-scale version of this dataset.

3.2 User Study for Assessing Feelings Induced by Abstract Paintings

To collect the ground truth of gray-scale version of MART dataset, we use the relative score method from our previous work [18] by asking people to choose the more positive painting in a pair. Our assumption is that judging between two images, placed side by side, is a relatively straightforward setting. The following instruction was provided: "Which painting in the pair looks more positive to you? Let your instinct guide you and follow your first impression of the paintings."

The method to annotate the paintings in positive and negative feeling and the scoring procedure is based on the TrueSkill ranking system [5,16]. The TrueSkill ranking system, developed by Microsoft Research for Xbox Live, identifies and ranks the skills of the players of a game and matches players with similar skills for a new game. With this method, the annotation task is more manageable, as it gives a representative annotation with only 3,750 pairs of paintings, instead of 124,750 comparisons $(500 * (500 - 1) * 0.5)$ in case each painting is compared with all the remaining paintings in the dataset.

During the annotation process, we consider that all paintings initially have the same 'skills' and the painting which is chosen as more positive in a single trial wins a 'game'. Then, the rankings of the compared paintings are updated. Afterwards, the paintings with similar rankings are compared, until each painting is compared with at least 15 other paintings. The results are considered as feeling scores of the paintings, which lower values correspond to negative feelings and the higher values to positive feelings. 55 subjects participated in the annotation task, 22 females and 33 males, respectively. Each subject annotated from 5 to 334 pairs of paintings, 67 paintings on average. The subjects participated voluntarily and were free to annotate at any time they wanted.[1]

We have no overlapping annotations, as the rating system determines the annotation sampling online, and never presents the same pair of images to two different annotators. This makes the computation of an inter-annotator agreement impossible. We have, however, matched the TrueSkill ratings obtained at the end of the user study to the individual annotations of the pairs, presented to all the annotators. The results show about 79% agreement, which is effectively

[1] The dataset with its respective ground truth is publicly available at: http://disi.unitn.it/∼sartori/datasets/

Table 1. Texture emotion scales based on Perlin parameters (from [12]). Emotion scales are MF: masculinity-femininity, HS: hardness-softness, HL: heaviness-lightness, given as a function of mean intensity (L) and parameters of Perlin noise texture (oct: octaves, freq: frequency, pers: persistence, lac: lacunarity).

Emotion Scale	Function Predicting Absolute Scale Values
MF	$101.36 + 9.27L^{0.1} - 30.06oct^{0.05} - 6.06freq^{0.3} - 53.38pers^{0.1} - 25.15lac^{0.1}$
HS	$116.12 + 6.10L^{0.1} - 32.30oct^{0.05} - 13.13freq^{0.1} - 48.81pers^{0.1} - 29.33lac^{0.1}$
HL	$42.67 + 0.064L - 12.46oct^{0.05} - 11.35freq^{0.1} - 5.84pers^{0.5} - 17.23lac^{0.05}$

the mean human performance for the valence classification task, and represents an upper bound for the automatic algorithm.

The distribution of gray-scale paintings from the most negative to the most positive annotation scores is illustrated in Fig. 1 (a). To better visualize the results, we arrange the paintings in a matrix 50×10, where the paintings are sorted in reading order from the most negative to the most positive. From the annotation results, we observe that lightness is a determinant factor of positive and negative feelings. Paintings with low value of overall intensity (nearly black) are considered as more negative. Itten [7] postulates that neutral gray is a characterless, mute, indifferent, achromatic colour, and the number of distinguishable shades of gray depends on the sensitivity of the eye. This may be the reason of the mixed distribution. Another factor effecting the ranking from negative to positive seems to be in the structural qualities of the paintings, i.e. some very dark paintings with light spots are considered positive, probably due to their composition and the way they use light colors. We also note that the ordering of the paintings is quite different compared to the ordering induced by coloured images. Compared to the distribution of coloured images, one can say that gray-scale ranking is more dependent on the composition of the paintings, whereas in coloured images colour itself plays a much more important role in determining the overall positive/negativeness of the painting.

3.3 Inverse Perlin Parametrization

A psychophysical experiment assessing the effect of texture on color emotion was conducted by Lucassen et al. [12] using Perlin images. They presented the subjects with textured image patches in varying colours and asked subjects to place those images on four emotion[2] scales: warmness-coolness, masculinity-femininity, hardness-softness and heaviness-lightness. As a result of their experiment, the authors performed a regression analysis and established parametric relations between the Perlin images and the subject classifications (Table 1).

[2] We use the word ‘emotion’ following the terminology of [12], but in general ‘emotion’ may be a strong word for what we are assessing, and ‘feeling’ is more appropriate in this context.

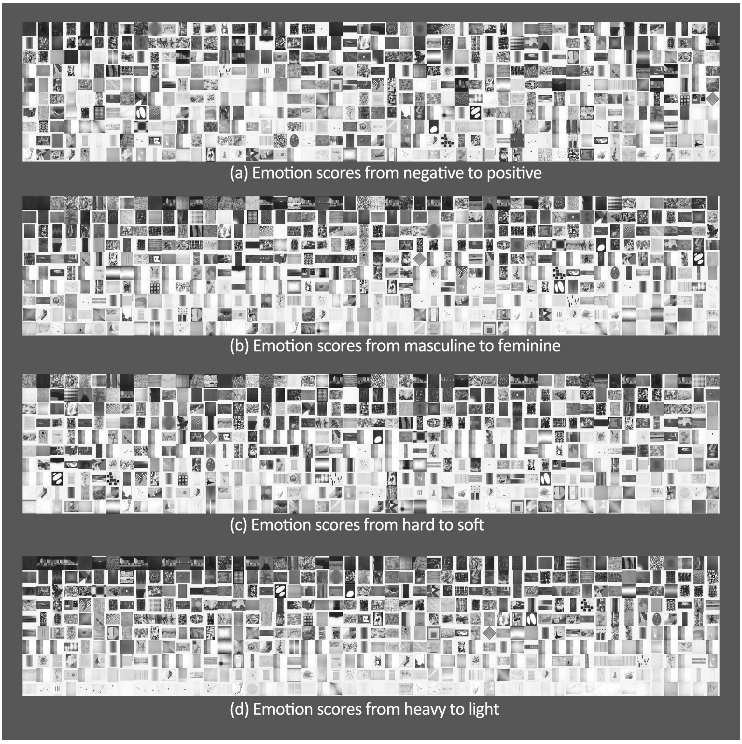

Fig. 1. MART dataset depicted as thumbnails. The paintings in (a) are ordered by TrueSkill scores from the most negative to the most positive. The paintings in (b), (c) and (d) are ordered by computing Perlin parameters and using the psychophysical model. High resolutions of these images are available at: http://disi.unitn.it/∼sartori/datasets/

Perlin images are textures created using Perlin noise, which is a method to create a parameterized, pseudo-random noise [17]. We used the same library [2] used by [12] to generate those images. They have four parameters: octave, frequency, persistence and lacunarity. The computation of these parameters for a given image can provide us with a parsimonious and informative representation of the texture features.

To determine the Perlin parameters for any given image, we developed an inverse Perlin method, which consists of extraction of texture features of Perlin images and machine learning to give us Perlin parameters from those features. To extract texture features from the raw images, we used the MR8 texture descriptors of [21]. These features are low dimensional, include rotational invariance properties, and allow us to perform parameter interpolation from a single image.

To create the MR8 texture descriptors and train our classifier, we create a gallery of Perlin images with different appearances for each parameter set used by [12], and take the convolution of the these images with the designated filter bank. The responses, called textons, are clustered using k-Means clustering algorithm, following the procedure of [21]. From a given image, the textons are extracted and their histograms are formed, then used as feature vectors in the classifiers. We used Extreme Learning Machines (ELM), a single-hidden layer feedforward network implementation for classifying the Perlin parameters [6]. Essentially, what we propose is to create a rich training set of Perlin images (i.e. the gallery), and derive the texton histograms for each such image. Then for a given probe image, we extract its texton histogram, and use it as an input to a classifier that outputs the corresponding Perlin parameters. An overview of the method is presented in Fig. 2. Using those parameters and the formulae of Table 1, we calculated the predicted emotion scores for each image.

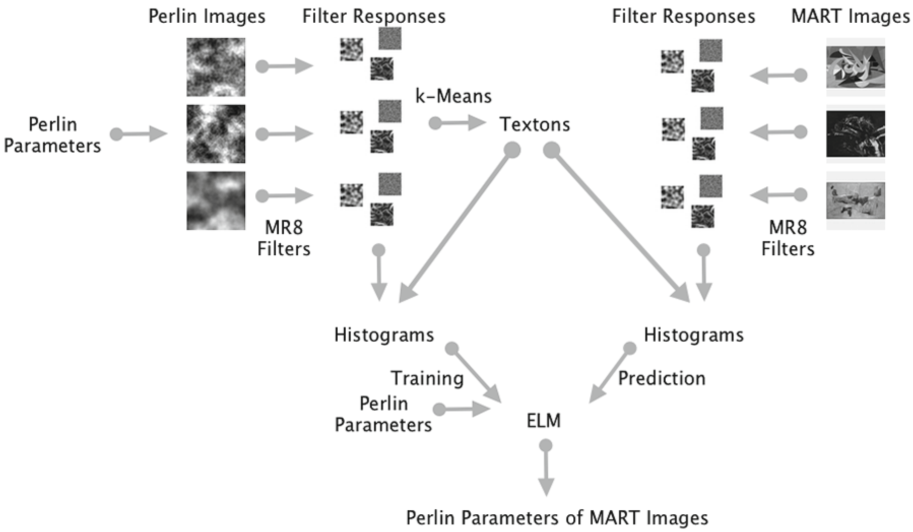

Fig. 2. Schema of the Inverse Perlin Method

Fig. 1 shows MART paintings sorted by emotion scores. The paintings sorted from heavy to light (Fig. 1(d)) follow a luminosity pattern. The distribution of hard to soft (Fig. 1(c)) has a similar pattern: in general, the darker a painting, the harder it is scored. However, 'texture' itself plays a great importance in the distribution of images from 'hard' to 'soft'. This observation is in agreement with the results of [12] which reports the hard-soft scales independency of colour and its dominance by texture. Hence the parameters that bring texture to the fore, such as brushstrokes, complexity, composition become essential elements. Paintings with chaotic structure and granular patterns are ranked as hard, whereas paintings with geometrical structure, neat lines and a look of 'matte' finish are ranked as soft. We observe a similar pattern in the distribution of masculine-feminine (Fig. 1(b)): dark and chaotic paintings seem to be more masculine, whereas light and simple designs are feminine. This observation again supports the findings of [12], when they report the effect of texture as being most influential in the hard-soft scale, followed by masculine-feminine, and then heavy-light.

3.4 Coloured vs. Gray-Scale Images

The user study we conducted produced valence ratings of paintings viewed in gray-scale. We compare these ratings with the results of our previous work [18] obtained by using the coloured version of the paintings. In [18] 25 subjects (11 females, 14 males) participated in the annotation. Each person annotated from 145 paintings on average. Even though the annotation approach is essentially the same in both studies (but with different sets of subjects performing the evaluation), we could observe that there was a low correlation between the preferences of subjects (linear correlation coefficient: 0.3674).

Fig.3 displays the relation between the results of these two sets of annotations. We sort the paintings by the annotated valence in gray-scale, and show these values in a black line that monotonically increases from 4 to 47. The scattered points are the valence annotations for the same images, but made on coloured paintings. The regression line, shown in red, shows the small but positive correlation between the two annotations. These results suggest that texture by itself has a smaller contribution for the positive and negative emotional valence of coloured paintings compared to the contribution of colour. The emotional valence of gray-scale images (including black and white photographs) should be assessed independently.

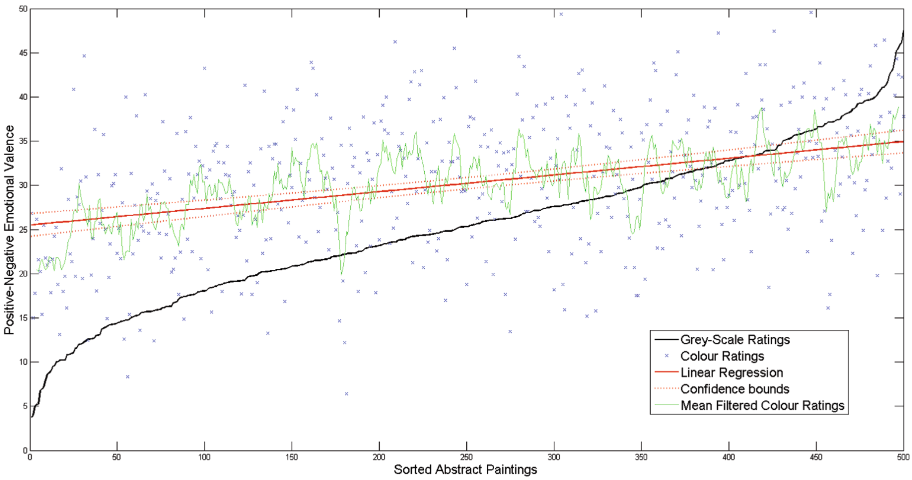

Fig. 3. Correlation between annotations of gray-scale and coloured paintings. The x axis shows the paintings index sorted by valence. The black line indicates the valence ranking on gray-scale dataset. The blue crosses are the rankings for these images on coloured dataset. The green line illustrates the mean filtered results on the coloured set, and the red line shows the linear regression fit to the ratings on the coloured set. The small positive correlation manifests itself in the slope of the red line.

4 Visual Attention and Emotional Content

When making a valence judgment, different parts of a painting may influence a subject in different ways. One way of analysing which parts are most influential in the evaluation is to track the subject's gaze while he or she looks at the painting. Another way is to use a computational model that can simulate the gaze behaviour of a subject. We have used abstract artworks in this study to minimize the effect of semantics in the attribution of positive and negative feelings. It is postulated that attention is driven by a combination of bottom-up and top-down components, the former being data-driven, and the latter depending on higher level cognitive factors like intentions, context, knowledge, and such [4]. Most computational models of attention are bottom-up, as the top-down part is extremely complex and very difficult to model. If our premises hold, we expect that the visual attention while viewing abstract paintings will mostly be a bottom-up process, especially in the absence of narratives that may direct the subject to look at an image in a particular way.

To validate this, we compare the predictions of a successful computational saliency model, implemented by Dirk and Koch [3], with the eye-tracking results we had previously obtained on the MART dataset [23]. In [23] we analysed whether people prefer to look at positive or negative parts of paintings. Guided by a user study that established ground truth of valence for coloured paintings, we have trained a valence classifier based on the Bag-of-Visual-Words approach. We used colour features described by LAB and SIFT descriptors. We have then labelled parts of images using the valence classifier. By comparing averaged pixel-wise contributions from fixated and non-fixated locations with the classifier outputs, we concluded that there is a positive attention bias when people look at abstract paintings, meaning that positive visual words have more important contribution in fixated locations, compared to non-fixated locations.

We replicate the eye-tracking study of [23] on the gray-scale version of the abstract paintings with 12 participants (8 male and 4 female). To present the stimuli we used the ASL Eye-Trac 6 software in a full-size 19 inch screen (ASUS VW192T+, 1680x1050 resolution). To collect the data we follow the same procedure of [23]. The results show positive attention bias (63%) when people look at the paintings with no colour. Only 4 paintings present neutral attention bias.

Subsequently, we believe that inspecting the distribution of saliency over the images in our study can be potentially informative. The saliency algorithm of [3] is partly a reimplementation of the iNVT toolkit, in which the colour features, intensity, edges, etc. are evaluated over the visual scene independently before being integrated into a saliency master map that shows what part of the visual scene is interesting.

We first establish whether computational models do a good job in predicting the gaze patterns of subjects on abstract paintings. We use the Fixation Analysis Software of Le Meur [10] to compare predictions of the computational model of attention (i.e. using Dirk and Koch's software) with the eye fixation ground truth data that was made available with the MART dataset for coloured paintings and the ground truth results collected for gray-scale paintings.

The Area Under the Curve (AUC), computed from the ROC curve, is the suggested method of assessing similarity of these streams. An AUC value of 0.50 indicates random performance, where 1.00 denotes a perfect match. The average AUC between eye-fixation ground truth and simulations of the computational model of attention was 0.93 for colored paintings and 0.94 for gray-scale. These results indicate that 1) the bottom-up computational approach is a good substitute for the eye-tracking study, and can be used to find the salient locations of abstract paintings; 2) there is little difference in salient locations for coloured and gray-scale paintings. While colour is the dominant modality for inducing feelings, texture dominates in guiding the attention of the subject.

5 Classifying Positive and Negative Images

In this section we describe a classification approach to automatically estimate the emotional valence of a given painting. Our approach is a standard bag-of-words paradigm based on SIFT descriptors, extracted from either a dense grid over the image, or just from salient locations. We train a Support Vector Machine with a histogram intersection kernel for supervised learning, using the fast approximation of [14]. The TrueSkill ratings are used as ground truth labels.

For testing the approach, a 5×2 cross validation setup is used, where the images are assigned to folds randomly. Table 2 shows the classification results. We have obtained a 73.0% correct classification rate when the entire images were used, which is close to the 79.0% human classification rate reported in Sect. 3.2. Using the computational saliency model described in the previous section, and extracting SIFT features from only the top 2.5% most salient locations in the image with the same experimental setup gives a classification rate of 73.9%. The difference is not significant (as established by a t-test), but a much smaller portion of the painting is evaluated for reaching this accuracy. Using the inverse Perlin coefficients, and the emotional scales of Lucassen et al. that are derived from these coefficients with a Support Vector Machine classifier directly results in an accuracy of 62.0%. The primary reason is that the latter set of descriptors are very parsimonious, compared to the SIFT-based descriptors, and while useful in qualitative evaluation, do not contain enough discriminatory power for automatic classification.

Table 2. Classification Results.

Type	Correct Classification Rate
Entire image	73.0%
Only top 2.5% most salient parts	73.9%
Emotions derived from Perlin parameters	62.0%
Human classification rate (upper bound)	79.0%

6 Conclusions

In this work we studied how texture affects the positive and negative feelings evoked by abstract paintings. To this effect, we conducted a user study to establish a ground truth of emotional valence for 500 abstract paintings with no hue value. The analysis of annotations revealed that people reacted differently to gray-scale versions of paintings when annotating the emotional content. Our experiments confirmed that colour played a greater role than texture in emotional assessment, yet the effect of texture was visible. We proposed an inverse-Perlin parametrization method to map a given image to a four-dimensional representation of its overall texture content. We have used this parametrization in a psychophysical model to depict the paintings in several emotional scales. A quantitative analysis showed that texture was especially influential in giving an impression of hardness and softness.

Existing computational models of attention use colour and texture jointly to predict where the bottom-up attention of a subject will be directed, and as we have observed via eye tracking studies, they make a good job of predicting attention in abstract paintings. It is quite interesting that these models, when used on gray-scale versions of the paintings, predict very similar saliency maps. This may be partly due to the abstract nature of the images, and partly due the prominence of texture-based channels over colour-based channels in the computational approach. However, the user study we report in this paper established that the feelings induced by gray-scale images are quite different than the feelings induced by their coloured counterparts.

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