Aesthetic Visual Quality Assessment of Paintings

Congcong Li, *Student Member, IEEE*, and Tsuhan Chen, *Fellow, IEEE*

***Abstract*— This paper aims to evaluate the aesthetic visual quality of a special type of visual media: digital images of paintings. Assessing the aesthetic visual quality of paintings can be considered a highly subjective task. However, to some extent, certain paintings are believed, by consensus, to have higher aesthetic quality than others. In this paper, we treat this challenge as a machine learning problem, in order to evaluate the aesthetic quality of paintings based on their visual content. We design a group of methods to extract features to represent both the global characteristics and local characteristics of a painting. Inspiration for these features comes from our prior knowledge in art and a questionnaire survey we conducted to study factors that affect human's judgments. We collect painting images and ask human subjects to score them. These paintings are then used for both training and testing in our experiments. Experiment results show that the proposed work can classify high-quality and low-quality paintings with performance comparable to humans. This work provides a machine learning scheme for the research of exploring the relationship between aesthetic perceptions of human and the computational visual features extracted from paintings.**

***Index Terms*— Visual Quality Assessment, Aesthetics, Feature Extraction, Classification**

I. Introduction

The booming development of digital media has changed the modern life a lot. It not only introduces more approaches for human to see and feel about the world, but also changes the ways that computer "sees" and "feels". It raises a group of interesting topics about allowing a computer to see and feel as human beings. For example, in the field of compression, lots of metrics have been proposed to allow a computer to evaluate the visual quality of the compressed images/videos and come to conclusions in accordance with human's subjective evaluations. We can see that these metrics are all aiming to measure the visual quality degradation caused by compression artifacts, which is mainly dependent on the compression techniques. However, this is only one aspect of visual quality. Visual quality as a whole can be more complex, which not only includes the visual effect that is due to techniques used in digitalization, but also include other aspects that are relevant with the content of the visual object itself. In this paper, we focus on the visual quality on the aspect of aesthetics. As known to us, judging the aesthetic quality is always an important part of human's opinion towards what they see. The visual objects to be evaluated in this paper are paintings, more exactly, digital images of paintings.

The motivation for evaluating the aesthetic visual quality on paintings is not only to build a bridge between computer vision and human perception, but also to build a bridge between computer vision and art works.

A. Aesthetic Visual Quality Assessment of Paintings

1) Definition

Aesthetic visual quality assessment of painting is to evaluate a painting in the sense of visual aesthetics. That is, we would like to allow the computer to judge whether a painting is beautiful or not in human's eyes. Therefore, different from the visual quality related to the degradation due to compression artifacts, the aesthetic quality is mainly related to the visual content itself – in this paper, the visual content of a painting.

2) Motivations

In the past, to evaluate the visual quality related to the content can only be done on-site because digital media were not available. However, with the trend of information digitalization, digital images of paintings can be easily found on the internet. This makes it possible for computers to do the evaluation. At the same time, common people now have more opportunities to appreciate art works casually without going to museums since online art libraries or galleries are emerging. Inside these systems, knowing the favorable degree of each painting will be very helpful for painting image management, painting search and painting recommendation. However, as we can imagine, it is impossible to ask people to evaluate a gallery of thousands of paintings. Instead, efficient evaluation by a computer will help in solving these problems.

Another motivation for evaluating aesthetic quality on paintings is to help popular-style artists and designers to know about the potential opinions of viewers or users more easily. Since art is no longer luxurious enjoyment for a charmed circle, it has pervaded common people's life and different areas. What's more, in recent years, favorable styles or patterns of paintings are widely introduced into the appearance design of architecture, product, and clothes etc. The spread of the post-impressionist Piet Mondrian's painting style into architecture and furniture is one typical example. Therefore, with automatic aesthetic quality analysis, designers and popular-art artists will have one more guidelines to evaluate their ideas in the designing course.

In addition to the above motivations towards applications, another motivation for this research is to get a better understanding of human vision in the aspect of aesthetics – to find out whether there is any pattern that can represent human

Congcong Li is with Electrical and Computer Engineering Department, Carnegie Mellon University, Pittsburgh, PA 15213 USA (e-mail: congcong@andrew.cmu.edu; Phone: 412-268-7115).

Tsuhan Chen is with the school of Electrical and Computer Engineering, Cornell University, Ithaca, NY 14853 USA. (e-mail: tsuhan@ece.cornell.edu; Phone: 607-255-5728).

vision well. Art itself can be considered to a representation of human vision because it is created by human and highly related to its author's vision towards real objects. Therefore, the viewer's visual feeling on art works is in fact the second-order human vision. To study computational patterns related to such a special course can be also helpful for biological and psychological research in human vision.

3) Challenges

First of all, the subjective characteristics of the problem bring great challenges. Aesthetic visual quality is always considered to be subjective. Especially when evaluating this subjective quality on paintings, the problem comes to a further subjective task. There are no absolute standards for measuring the aesthetic quality for a painting. Different persons can have very different ideas towards the same painting.

Secondly, it is also hard to totally separate the aesthetic aspect with other aspects within human's feelings when people make a decision on the visual quality. For example, the interestingness, or the inherent meaning of the painting can also affect people's opinion towards the visual quality.

Furthermore, as described above, the problem in front of us is not to measure the visual quality produced by certain computer processing techniques. Instead, what we try to measure is the aesthetic quality that is mainly related to the appearance of the image. Hence the previous quality evaluation metrics for compressed images may not solve this problem well. As examples, we perform some experiments by using the metrics proposed in [8][9] to compute the visual quality. The output results from these metrics are not well consistent with the aesthetic judgments from participants in our survey. This is understandable because these metrics aim to measure the quality degradation caused by compression artifacts, while the survey participants are required by us to focus on the aesthetic aspect of the visual quality.

B. Related Works

Aesthetic visual quality assessment is still a new research area. Limited works in this field have been published. Especially for assessing paintings, we did not find any previous work on it to our best knowledge.

The closest related works are the visual quality assessment of photographs, e.g. [1][2][3][4][5]. We mainly refer to two representative works here: the work by Ke et al. where the authors try to classify photographs as professional or snapshots [1] and the work by Datta et al. where the authors assess the aesthetic quality of photographs [2]. These two works both extract certain visual features based on the intuition or common criteria that can discriminate between aesthetically pleasing and displeasing images. However, both works are based on photographs. Photographs and paintings can have different criteria for quality assessment. For example, in [1], features are selected to measure the three characteristics: simplicity, realism and basic photographic techniques. For paintings, intuitively, these may not be the most important factors. Therefore, specific criteria and features should be considered for paintings. Further more, there are so many different styles in paintings that paintings can not be simply put together for assessment as what has been done to photographs in the previous works.

There are also some works [20]-[28] that are not related with visual quality assessment, but are building a bridge between art and computer vision. Four research groups tried different methods of texture analysis in order to identify the paintings of Vincent Van Gogh in the First International Workshop on Image Processing for Artist Identification [20]-[23]. Earlier in [24], the authors built a statistical model for authenticating works of art, which are from high resolution digital scans of the original works. Some other researchers are also making great efforts on introducing computer vision techniques to justify the possible artifices that have been used by the artists [25]-[28]. Although these works seem not directly related with our study here, they do inspire us a lot on how to extract art-specific features in the visual computing way.

C. Overview of Our Work

The subjective characteristic of the problem does not mean it is not tractable. A natural intuition is that a majority of people with similar background may have similar feelings towards certain paintings, just as many people may feel more comfortable with certain rhythms in music. Therefore, one way around this is to ignore philosophical/psychological aspects, and instead treat the problem as one of data-driven statistical inferencing, similar to user preference modeling in recommender systems [11].

Therefore, the goal of this paper is to allow the computer learn to make a similar decision on the aesthetic visual quality of a painting as that made by the majority of people. The key point is to find out what characteristics are related with the aesthetic visual quality.

Three important issues need to be concerned about in solving our problem:

1. The variance can be large among human ratings on painting. Therefore, instead of training the computer to "rate" a painting, we simplify the problem into training the computer to classify a painting, discriminating it with "high-quality" or "low-quality" in the aesthetic sense.
2. Since there are no obvious standards for assessing the visual quality of a painting, it is not easy to relate the quality with their visual features. In our work, we try to overcome this problem by combining our knowledge in art, intuition in vision and feedback from the surveys we conducted.
3. As mentioned above, it is hard to totally separate the aesthetic feelings from other feelings in people towards the visual quality. So in our work we try to diminish all the other effects as much as possible by carefully selecting paintings and survey participants. We also consulted with psychology researchers for the survey design.

Briefly speaking, in this paper, we present a framework for extracting specific features for this aesthetic visual quality assessment of paintings. The inspiration for selecting features comes from our prior knowledge in art and a study we conducted about human's criteria in judging the beauty degree of a painting. To measure global characteristics of a painting we apply classic models; to measure local characteristics we develop specific metrics based on segments. Our resulting system can classify high quality paintings and low quality paintings. Informally, "high quality" and "low quality" are defined in relative sense instead of absolute sense. We conducted a painting-rating survey in which 42 subjects gave scores to 100 paintings in impressionistic style with landscape content. Based on the scores, we separate the paintings into two classes: the relative high-score class and the relative low-score class. Hence our ground truth are based on human consensus, which means that the assessment is only to assess the aesthetic visual quality in the eyes of common people instead of specialists who may also consider the background, the historic meanings or more technical factors of the paintings. The features extracted here may not be the way that human perceive directly towards a painting, but aim to more or less represent those perceptions of human.

The rest of the paper is organized as follows: Section II describes the proposed method for extracting visual features, including global features and local features. Section III describes the painting-rating survey from which scores given by human subjects are used to generate "ground-truth" for the paintings used in our experiments. Section IV evaluates the classification performance of the proposed approach and analyzes different roles of features for classification. Section V concludes the proposed approach and discusses about future directions for this challenging research.

II. Feature Extraction

Extracting features to measure the aesthetic quality efficiently is a crucial part of this work. With knowledge and experiences in art, we believe some factors can be especially helpful to assess the aesthetic visual quality. While looking for efficient features, we first lead a questionnaire to study what factors can affect human's judgment on the aesthetic quality of a painting. Inspired by the results in the questionnaire and also based some well-known rules in art or based on intuition, we extract a number of features and then evaluate whether the extracted features are useful or not.

In the questionnaire (details in Section III and Appendix), we asked participants to list important factors that they are concerned with when judging the beauty of a painting in everyday life. The top four frequently-mentioned factors are "Color", "Composition", "Meaning / Content" and "Texture / Brushstrokes". Other factors mentioned by people include "Shape", "Perspective", "Feeling of Motion", "Balance", "Style", "Mood", "Originality", "Unity", etc.

We discuss the rationality for the top 4 factors in the following. "Color", which represents the palette of the artist, is obviously important. The sense of "Composition" includes both the characteristics of separate parts and the organization manner for combining these parts as a whole. "Meaning" equals to the human's understanding on the content of the painting, i.e. what the painting depicts and what emotion it expresses. It is natural for people to have this concern, which is related to the inherent knowledge and experience of human. For example, recognizing that it is a flower often leads the feeling towards the beauty side, while recognizing a wasteland may lead in the opposite direction. This indicates semantic analysis will be helpful to the assessment problem. Although in this work, we do not work in a perfect semantic way, we keep our efforts on relating the semantics with color or composition characteristics by extracting high-level features. "Texture", referred to "Brushstrokes" here, variant due to the touches between the brush and the paper with different strength, direction, touching time, mark thickness, etc., are also considered to be important signs of a particular style. However, in this work, the digital images for the paintings are not in high-resolution so that it is inaccurate to evaluate the brushstroke details, though human may still make their judgment based on some visible brushstrokes.

Therefore, our feature extraction focuses on the first two factors: color and composition. Color features are mainly based on HSL space. Composition features are analyzed through analysis on shapes and spatial relationship of different parts inside the image. These two factors are not totally separable. For example, different composition can be reflected through different modes of color mixture, while color can be analyzed globally and locally according to the painting's composition.

In general, this paper proposes 40 features which together construct the feature set $\Phi = \left\{ f_i \,|\, 1 \le i \le 40 \right\}$. The features selected in this paper can be divided into two categories: global features and local features, which mainly represent the color, brightness and composition characteristics of the whole painting or of a certain region. These features are not randomly selected or simply gathered; instead, they are proposed with analysis on art and human perception. Compared with the previous works on aesthetic visual quality, our work has these advantages:

1. The choice of features and the choice of models used for feature extraction are illuminated by analysis in art, which will be introduced in detail in the following sections;
2. Features are extracted both globally and locally, while only global features based on every pixel are extracted in [1][3][5];
3. Both our work and [2][4] consider local features, but in [2][4] local features are only extracted within regions. Our work develops metrics to measure characteristics within and also between regions.

A. *Global Features*

A feature that is computed statistically over all the pixels of the images is defined as a global feature in our work. In art and our everyday life, it turns out that when cognizing something, people first get a holistic impression of it and then go into segments and details [7]. Therefore global features may affect the first impression of people towards a painting. Global features that are considered in this paper include: color distribution, brightness effect, blurring effect, and edge detection.

1) *Color Distribution*

Color probably is the first part of information that we can catch from a painting, even when we are still standing at a certain distance from it. Mixing different pigments to create more appealing color is important artifice used by artists.

We analyze color based on Munsell color system, which separates hue, value, and chroma into perceptually uniform and independent dimensions. Fig.1 illustrates the Munsell color space by separating it into the hue wheel and the chroma-value coordinates. In implementation, we use the HSL (hue, saturation,

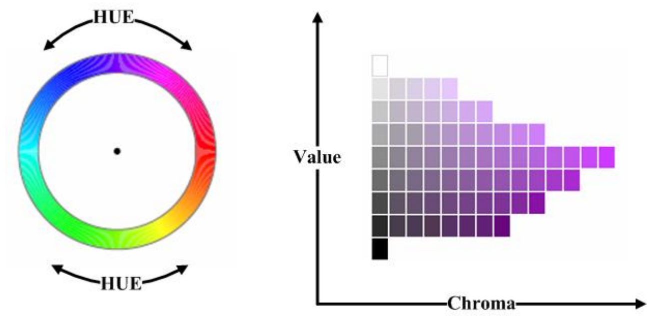


Fig. 1. The hue wheel and chroma-value distribution coordinates separated from the Munsell hue–value–chroma (HVC) color system. The HVC color space can be approximated with HSL color space. L (Lightness) corresponds to the Value in Munsell system and S (Saturation) corresponds to the Chroma by ignoring the characteristic of no upper limit for the chroma.

lightness) color space to approximate the Munsell color space. The hue and value in Munsell system can be equal to the hue and lightness in the HSL color space. Both chroma and saturation represents the purity of the color. The difference is that chroma doesn't have an intrinsic upper limit and the maxima of chroma for different hues can be different. However, it is difficult to have physical objects in colors of very high chroma. So it does not harm to have an upper limit for the chroma. Therefore saturation is used in the following analysis.

To measure the rough statistic color characteristics of a painting is to calculate the average hue and saturation for the whole painting. In artistic sense, the average hue and saturation more or less represents the colorful keynote of that painting, relative the "Mood" factor mentioned by people in the survey. The saturation of color present on the paintings is often related to opaque or transparency characteristics, which may depend on the quantity of water or white pigment the artist adds to tune the pigment color. The average hue feature and average saturation feature can be respectively expressed as:

$$f_1 = \frac{1}{MN}\sum_n \sum_m I_H(m,n), \tag{1}$$

$$f_2 = \frac{1}{MN}\sum_n \sum_m I_S(m,n), \tag{2}$$

where M and N are the number of rows and columns of the image, $I_H(m,n)$ and $I_S(m,n)$ are the hue value and saturation value at the pixel (m,n).

Another kind of features of interest is to measure the colorfulness of the paintings. Some artists prefer the color of the painting to be more united by using fewer different hues while others prefer polychrome by using many different colors. Intuitively, a painting with too few colors may seem to be flat while one with too many different colors may appear jumbled and confusing. Here we use three features to measure this characteristic: 1. the number of unique hues included in an image; 2. the number of pixels that belong to the most frequent hue; 3. hue contrast – the largest hue distance among all the unique hues.

The hue count of an image is calculated as follows. The hue count for grayscale images is 1. Color images are converted to its HSL representation. We only consider pixels with saturation I_S > 0.2 and with lightness 0.95 > I_L > 0.15 because outside

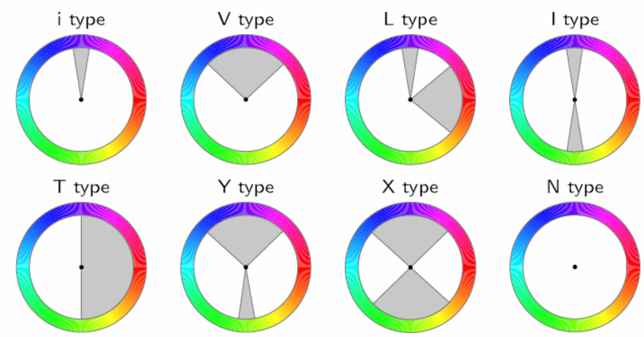


Fig. 2. Hue distribution models. The gray color indicates the efficient regions of a model.

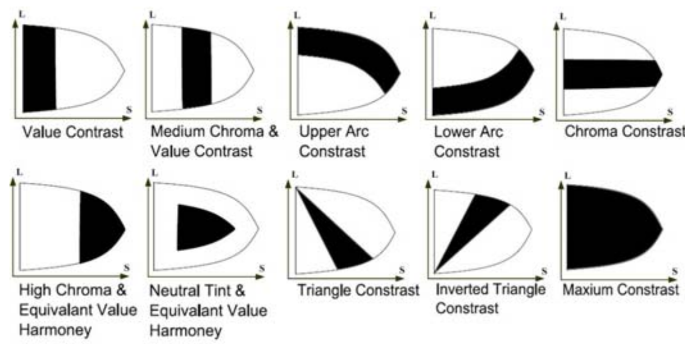


Fig. 3. Saturation-Lightness distribution models. The horizontal axis indicates "Saturation" and the vertical axis indicates "Lightness". Pixels of an image whose (S, L) fall in the black region of a model are counted as the portion of the image that fits the model.

this ranges the color tend to be white, gray or black to human eyes, no matter what the hue is like. A 20-bin histogram $h_{I_H}(i)$ is computed on the hue values of effective pixels. The reason for choosing 20 bins is that in Munsell system the hue is divided into five principal hues: Red, Yellow, Green, Blue, and Purple, based on which we can uniformly subdivide the hue into $5 \cdot k$ bins, where k is a positive integer. We choose k = 4 here.

Suppose Q is the maximum value of the histogram. Let the hue count be the number of bins with values greater than $c \cdot Q$, where c is manually selected. c is set to be 0.1 to produce good results on our training set. So the hue count feature can be expressed as:

$$f_3 = \#of\ \{i \mid h_{I_H}(i) > c \cdot Q\} \tag{3}$$

The number of pixels that belong to the most frequent hue is calculated as:

$$f_4 = \max\{h_{I_H}(i)\} \tag{4}$$

The hue contrast can be calculated as :

$$f_5 = Hcontrast = \max(\|\bar{I}_H(i) - \bar{I}_H(j)\|), \quad i, j \in \{k \mid h_{I_H}(k) > c \cdot Q\} \tag{5}$$

where $\bar{I}_H(i)$ is the center hue of the i^{th} bin in the hue histogram. The distance metric $\| \bullet \|$ refers to the arc-length distance on the hue wheel.

In addition to the hue count and average computation on hue and saturation, we also consider whether the distributions of the color have specific preference by fitting the models shown in Fig.2 and Fig.3. The group of models in Fig.2 is to measure the hue distribution, while the group in Fig.3 is to measure the saturation-lightness distribution.

These models come from Matsuda's Color Coordination [11]. Matsuda executed investigation of color schemes which are adopted as print clothes and dresses for girl students by questionnaire for 9 years, and classified them into some groups in two categories of hue distribution and tone distribution, including 8 hue types and 10 tone types. These models are based on Munsell color system. Here we use HSL space color to approximate the Munsell color representation. The sets of models have been introduced in some work to evaluate the degree of color harmony in an image or provide a scheme for re-coloring [12] [13]. However, in these previous works the models are used either in a fuzzy way or used not for evaluation. Here we utilize them for evaluation. Instead of measuring how well the color of a painting fits every model, we examine which type of model the color distribution of a painting fits best.

Using these models instead of directly using histograms has an obvious advantage: the models measure the relative relationship of the colors in the painting while the histograms can only measure the specific color distribution.

The model-fitting method can be described as below:

a) Fitting the Hue Models:

In Fig.2, the type-N model corresponds to gray-scale images while the other seven models, each of which consists of one or two sectors, are related with color images. All the models can be rotated by an arbitrary angle α in order to be fitted at proper position. Given an image, we fit the hue histogram of the image into each of these models and find out the best fitting model. We utilize the method proposed in [13] for modeling fitting. To set up a metric to measure the distance between the hue histogram and a certain model, it associates the hue of each pixel, $I_H(m,n)$ with the closest hue on the model, that is, the closest hue in the gray region of that model in Fig. 2. In this work, we look for the model that fits best with the image.

First we define $T_k(\alpha)$ as the k^{th} hue model rotated by an angle α and $E_{T_k(\alpha)}(m,n)$ as the hue of model $T_k(\alpha)$ that is closest to the hue of pixel (m,n), defined as below:

$$E_{T_k(\alpha)}(m,n) = \begin{cases} I_H(m,n) & \text{if } I_H(m,n) \in G_k \\ H_{nearsest\_border} & \text{if } I_H(m,n) \notin G_k \end{cases}, \tag{6}$$

where G_k is the gray region of model $T_k(\alpha)$ and $H_{nearsest\_border}$ is the hue of the sector border in model $T_k(\alpha)$ that is closest to the hue of pixel (m,n).

The distance between the hue histogram and a model can be defined in a function:

$$\mathrm{F}_{k,\alpha} = \sum_n \sum_m \left\| I_H(m,n) - E_{T_k(\alpha)}(m,n) \right\| \cdot I_S(m,n), \tag{7}$$

where $\| \bullet \|$ refers to the arc-length distance on the hue wheel. $I_S(m,n)$ appears here as a weight since distances between colors with low saturation are perceptually less noticeable.

Now the problem becomes to look for the parameters (k,α) that minimize the function $\mathrm{F}_{k,\alpha}$. The solution can be separated into two steps: For each model T_k, look for $\alpha(k)$ that satisfies:

$$\alpha(k) = \arg\min_{\alpha}(\mathrm{F}_{k,\alpha}) \tag{8}$$

Then to compare all the models, look for k_0 that satisfies:

$$k_0 = \arg\min_{k}(\mathrm{F}_{k,\alpha(k)}),\ \ k_0 \in \{1,2,\cdots,7\} \tag{9}$$

k_0 represents the model fitted by the image best. Note there may be multiple solutions for k_0. It is because some model is included in another model. e.g. if an image fits the type-i model, it can also fit the other models. In such case, we choose the strictest solution among the multiple solutions. That is, to choose type-i in the above example. We set a descending strict-degree ordering for these models: i-type, I-type, V-type, Y-type, L-type, X-type, T-type, i.e. St(i) > St(I) > St(V) > St(Y) > St(L) > St(X) > St(T), where St(·) is the strict degree of the model. Since it is very hard for an image to totally fit with those highly strict models, we try to modify equation (9) into equation (10), to define the hue distribution feature.

$$f_6 = \begin{cases} \arg\max\limits_{k\in\{j|\mathrm{F}_{j,\alpha(j)}<TH_F\}} (\mathrm{St}(k)), & \text{if } \exists k \in \{1,2,\cdots,7\}, \mathrm{F}_{k,\alpha(k)} < TH_F \\ \arg\min\limits_{k\in\{1,2,\cdots,7\}}(\mathrm{F}_{k,\alpha(k)}), & \text{if } \forall k \in \{1,2,\cdots,7\}, \mathrm{F}_{k,\alpha(k)} \ge TH_F \end{cases}, \tag{10}$$

where TH_F is a threshold. When $\mathrm{F}_{k,\alpha(k)} < TH_F$, we consider the image fits with the k^{th} model and choose the strictest model among all the models being fitted by the image.

b) Fitting the Saturation-Lightness Models:

There are 10 models for saturation-lightness distribution in Fig. 3, each of which contains a black region. Pixels that fall in the black region of a model are considered to be fitted with that model. How much an image fits with a model depends on the proportion of pixels that fall in the black region of that model. In our work we consider 9 of these S-L models, except the Maximum Contrast Type model. It is because the Maximum Contrast Type contains all tones so that all pixels in any image will fall into its black region.

The black region of each model is defined as R_{T_k}, where T_k represents the k^{th} model S-L model. Then the distance between the image and any S-L model can be defined in a function:

$$G_k = 1 - \frac{\#of\left\{(m,n)\,|\,[I_S(m,n), I_L(m,n)] \in R_{T_k}\right\}}{MN} \tag{11}$$

To determine the best S-L model for the image equals to look for k_0', that satisfies:

$$k_0' = \arg\min_{k}(G_k),\ \ k_0' \in \{1,2,\cdots,9\} \tag{12}$$

So the saturation-value distribution feature is expressed as:

$$f_7 = k_0' = \arg\min_{k}(G_k) \tag{13}$$

2) Brightness Features

Artist use a series of artifices to represent light condition of a scene. Sunshine in art can be expressed in many ways, e.g. using warm color which contains a large portion of red and orange. So the previous part about color distribution may already contain some information about light condition of the painting to some extent. In this section, we will measure three features that represent light conditions more directly. The three features are arithmetic average brightness, logarithmic average brightness and brightness contrast.

The arithmetic average brightness of a painting can be calculated as:

$$f_8 = \frac{1}{MN}\sum_n \sum_m L(m,n), \tag{14}$$

where $L(m,n) = (I_R(m,n) + I_G(m,n) + I_B(m,n))/3$, I_R, I_G, I_B are the R, G, B channels of the image.

The logarithmic average brightness also represents the light condition across the whole image as the arithmetic average brightness. The logarithmic average brightness is calculated as:

$$f_9 = \frac{255}{MN}\exp\left(\sum_n \sum_m \log(\varepsilon + \frac{L(m,n)}{255})\right), \tag{15}$$

where ε is a small number to prevent from computing log(0). The difference between the two average brightness features is: the logarithmic average brightness is the conjunct representation for brightness and dynamic range of the brightness. For example, two images with the same arithmetic average brightness can have different logarithmic average brightness, due to the different dynamic range.

Another feature to be introduced is the brightness contrast. Human vision towards color can be explained in the two systems: WHAT system and WHERE system [6]. Without hue contrast, it would be difficult for human eyes to recognize different objects; without brightness contrast, it would be difficult for human eyes to decide the exact place for something. Looking at a painting with flat brightness over it, human eyes can not easily find a proper point to focus on. That means the painting may not be attractive enough to people. On the other hand, low contrast is not definitely bad. "One of the most novel accomplishments of the impressionist artists is the shimmering, alive quality they achieve in many of their painting … Some of the color combinations these artists used have such a low luminance contrast – and are in effect equiluminant – that they create an illusion of vision."[6] As mentioned previously, although we selected the features by intuition or rules, we did not manually set any rules to assert a relationship between the visual quality and a certain distribution of features. The relationship is learned in the training stage through classification algorithms.

Based on the above analysis, we add the brightness contrast feature and define it as the following. Let h_L be the histogram for the brightness $L(m,n)$ .The brightness contrast is defined as:

$$f_{10} = b - a, \tag{16}$$

where (a,b) satisfies that the region $[a,b]$ *centralizes* 98% energy of the brightness histogram. Let d be the index of the bin with the maximal volume, i.e. $h_L(d) = \max(h_L)$. Starting from the d^{th} bin, the histogram is searched step by step alternately towards the two sides until the summation reaches 98% of the total energy.

3) Blurring Effect

Blurring is considered to be a degraded effect when the visual quality of a compressed image is measured to evaluate compression techniques. However, for measuring the aesthetic quality of a painting, it is not necessarily an unfavorable effect. Instead, blurring artifice helps to create plenty of magic effects on paintings, such as motion illusion, shadow illusion and depth indication and so on.

To estimate the blurring effect in a painting, we applies Ke et al.'s method [1] to model the blurred image I^b as the result of Gaussian smoothing filter G_σ applied on a hypothetic sharp image I^s , i.e. $I^b = G_\sigma * I^s$. The symbol $*$ here means convolution. Here the parameter σ of Gaussian filter and the sharp image I^s are both unknown. Assuming that the frequency distribution for I^s is approximately the same, we have the parameter σ of Gaussian filter to represent the degree of blurring. By taking Fourier-Transform on I^b , this method looks for the highest frequency whose power is greater than a certain threshold and assumed it inverse-proportioned to the smoothing parameter σ . If the highest frequency is small, it can be considered to be blurred by a large σ . So the blurring feature is measured as:

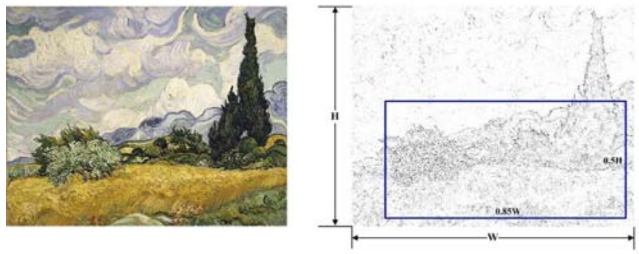
$$f_{11} = \max\left(\frac{2(m - \lfloor \frac{M}{2} \rfloor)}{M}, \frac{2(n - \lfloor \frac{N}{2} \rfloor)}{N}\right) \propto \frac{1}{\sigma}, \tag{17}$$

where (m,n) satisfies $|\zeta(m,n)| = |FFT(I^b)| > \varepsilon$ and ε is set to be 4 in our experiments.

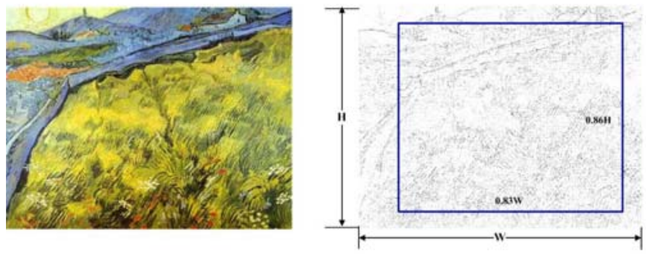
4) Edge Distribution

Edge distribution is selected as a feature due to the intuition that objects being emphasized by the artists often appear with more edges in the painting in most cases. Therefore distribution of edges reflects the artist's idea on the composition of the painting. Concentrated distribution can help create a clearer foreground-background separation, while uniform distribution tends to express a united scene. To measure the spatial distribution of edges, we apply the following method to calculate the ratio of area that the edges occupy which is similar to Ke's method on analyzing photographs.

Different from the method used to analyze photographs, our method first preprocesses the painting image by applying Gaussian smoothing filtering on it. This step is for eliminating nuance only due to the discontinuity of brushstrokes. Then the method applies a 3×3 "Laplacian" filter with $\alpha = 0.2$ to the smoothed image and takes its absolute value to ignore the direction of the gradients. For color images, we apply the filter each of the RGB channels separately and then take the mean across the channels. Then on the output image, we calculate the area of the smallest bounding box that encloses a certain ratio of the edge energy. Through trials on the training set, the ratio is selected to be 81% (90% in each direction). So the feature for edge distribution is to calculate the area ratio of the bounding



(a)



(b)

Fig. 4. Edge distribution analysis. For (a), the proportion of the bounding box area is 0.425 and the average rating score for this painting is 3.93; For (b), the proportion of the bounding box area is 0.714 and the average rating score is 3.07. The average bounding area ratios for the "high-quality" labeled paintings and for the "low-quality" labeled paintings are respectively 0.47 and 0.68.

box over the area of the whole image, i.e.

$$f_{12} = \frac{H_b W_b}{H W} \tag{18}$$

where H_b and W_b are the height and width of the bounding box, and H and W are height and width of the image.

Fig. 4 gives two examples of the corresponding Laplacian-filtered images and bounding boxes for two paintings with different edge distributions.

From the examples, we can see that edge-concentrated painting like Fig. 4(a) is highly likely to produce a smaller bounding box, while the edge-uniform painting like Fig. 4(b) is more likely to produce a larger bounding box. For Fig. 4 (a) and (b), the bounding box area is 0.425 and 0.714, respectively. The average bounding area ratios for the "high-quality" labeled paintings and for the "low-quality" labeled paintings are respectively 0.47 and 0.68.

B. *Local Features*

While global features represent the holistic visual characteristics of a painting that may be highly related with human's first impression on the painting, local features can help to represent some prominent parts inside the painting which can catch human's attention more easily. To analyze different parts of a painting, the painting needs to be segmented into different parts. Two methods are used to separate out different parts of a painting: one is the image-adaptive segmentation method and another is rule-based region-cutting method.

1) *Shape of Segments*

To analyze local characteristics of a painting, we try to see into different parts that represent different contents. An image-adaptive method called Graph Cut [15][16][17][18] is used to segment the painting image into multi-regions. The segmentation is based on both color in RGB space and geometrics. *K*-means method is utilized to initialize color clusters. The number of clusters is set to 8 in this work. Fig. 5 shows an example of a painting and its segmentation result. The above method only provides a rough segmentation result. Other characteristics like texture and edge can be considered in the segmentation method to earn higher accuracy. Take the painting in Fig. 5 for example. With consideration on texture, the two parts that both indicate "sky" may be given the same label.

Fig. 5. Segmentation on a painting with Graph Cut method.

However, even with the simple color-based only segmentation result, we can extract much information about the local characteristics of the image. Shapes of the major segments are considered here. It can be understood that human vision is sensitive to shape of the components on an image. It is common that we consider something unfavorable by feeling a malformed shape. So we apply some metrics to measure the shape of different segments.

For each painting, we calculate the following shape features for the segments with top 3 largest areas: center of mass (first-order moment), variance (second-order centered moment) and skewness (third-order centered moment). So totally 12 features are added to the feature set, calculated by the following equations:

$$f_{13+i} = \frac{\sum_{k \in Region_i} x_k}{area\ of\ Region_i} \tag{19}$$

$$f_{16+i} = \frac{\sum_{k \in Region_i} y_k}{area\ of\ Region_i} \tag{20}$$

$$f_{19+i} = \frac{\sum_{k \in Region_i} [(x_k - \overline{x})^2 + (y_k - \overline{y})^2]}{area\ of\ Region_i} \tag{21}$$

$$f_{22+i} = \frac{\sum_{k \in Region_i} [(x_k - \overline{x})^3 + (y_k - \overline{y})^3]}{area\ of\ Region_i} \tag{22}$$

where i ($i = 0, 1, 2$) is the index of the largest three regions and (x_k, y_k) is the normalized coordinates (normalized by the width and height of the image) of a pixel and $(\overline{x}, \overline{y})$ is the normalized coordinates of the center of mass in the corresponding region. The height and width are both normalized to 1 so that the moment computation for images with different sizes is fair.

Note that all these features are only related with the region shape and are not contain any color or brightness features.

2) *Color Features of Segments*

Previously in the global feature extraction section, both the statistic variables and the form of histogram distribution have been studied to represent the general color characteristics across the whole image. Color features are important not only to measure the global characteristics, but also for the local analysis. For local segments, we choose a simple way to represent their color characteristics, that is, to calculate the average hue, saturation and lightness for the top three largest segments. Totally 9 features will be added in this part, expressed as below.

$$f_{25+i} = \frac{1}{area\ of\ Region_i} \sum_{(m,n)\in Region_i} I_H(m,n),\ i = 0,1,2 \tag{23}$$

$$f_{28+i} = \frac{1}{area\ of\ Region_i} \sum_{(m,n)\in Region_i} I_S(m,n),\ i = 0,1,2 \tag{24}$$

$$f_{31+i} = \frac{1}{area\ of\ Region_i} \sum_{(m,n)\in Region_i} I_L(m,n),\ i = 0,1,2 \tag{25}$$

where i is the index of the largest three regions.

3) *Contrast Features between Segments*

In the previous two parts, we consider the shape and color features for the top largest segments individually. In this part, we will consider the relationship between different segments. We start to study the relationship by raising such a question: “Which case would lead to more aesthetic effect: being more united or more contrastive between the major parts of a painting or a compromise between the two?” As mentioned at the beginning, we treat this problem as a data-driven learning problem instead of manually setting any rule for judgment.

With the question, we try to measure contrast on different aspects among the segments. For the segments with top five largest areas, the following features are first calculated:

1. The average hue and saturation for the i^{th} region: $H_R(i)$, $S_R(i)$, i.e.

$$H_R(i) = \frac{\sum_{(m,n)\in Region_i} I_H(m,n)}{area\ of\ Region_i} \tag{26}$$

$$S_R(i) = \frac{\sum_{(m,n)\in Region_i} I_S(m,n)}{area\ of\ Region_i} \tag{27}$$

2. The average brightness for the i^{th} region: $L_R(i)$; The average brightness is computed as arithmetic average here. Method for calculating this feature can be referred to “Brightness Features” part in the previous “Global Features” section.

$$L_R(i) = \frac{\sum_{(m,n)\in Region_i} L(m,n)}{area\ of\ Region_i} \tag{28}$$

3. The blurring degree for the i^{th} region: $B_R(i)$. When calculating $B_R(i)$ for the i^{th} region, the other regions on the image are masked. Then the method introduced in the “Blurring Effect” part in the previous “Global Features” section is applied to get the blurring feature. i.e.

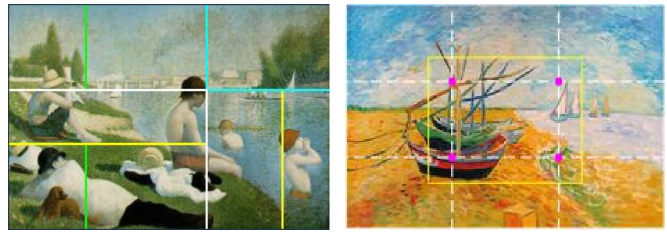


Fig. 6. (a) Left: Example of Golden Section; (b) Right: utilize “Rule of thirds” to define a focus region.

$$B_R(i) = \max\left(\frac{2(m - \lfloor \frac{M}{2} \rfloor)}{M}, \frac{2(n - \lfloor \frac{N}{2} \rfloor)}{N} \right), \tag{29}$$

where (m,n) satisfies $|\zeta_i(m,n)| = |FFT(I_i^b)| > \varepsilon$, and ε is manually controlled. I_i^b is the masked image leaving only the i^{th} region unmasked.

With the above features for different regions, four contrast features between segments are calculated as below:

Hue Contrast:

$$f_{34} = \max\left\{ \| H_R(i) - H_R(j) \| \right\},\quad i,j = 1,2,\cdots 5 \tag{30}$$

Saturation Contrast:

$$f_{35} = \max\left\{ | S_R(i) - S_R(j) | \right\},\quad i,j = 1,2,\cdots 5 \tag{31}$$

Brightness Contrast:

$$f_{36} = \max\left\{ | L_R(i) - L_R(j) | \right\},\quad i,j = 1,2,\cdots 5 \tag{32}$$

Blurring Contrast:

$$f_{37} = \max\left\{ | B_R(i) - B_R(j) | \right\},\quad i,j = 1,2,\cdots 5 \tag{33}$$

In the above equations, $\| \bullet \|$ refers to the arc-length distance on the hue wheel and $| \bullet |$ refers to Euclidian distance.

In previous works of aesthetic quality assessment, features are extracted either based on all pixels of the image or of a certain region. Here in our work, the contrast features between segments are different from the previous two types, which indicate the relationship between major regions of a painting.

4) *Focus Region*

Another way to separate special region out of the whole painting is to cut out a focus region based on rules.

Golden Section is a classic rule in mathematics and also a tool for many other fields including art. Since it is commonly found in the balance and beauty of nature, it can also be used to achieve beauty and balance in the design of art. “This is only a tool though, and not a rule, for composition.”[14] Many examples can be found to show that this rule is commonly used by artists to organize objects in the paintings. Fig. 6 (a) gives an example of the match between the rule and a real painting by the impressionist painter Georges Pierre Seurat, who is said to have "attacked every canvas by the golden section”. On Fig. 6 (a), “the horizon falls exactly at the golden section of the height of the painting. The trees and people are placed at golden sections of smaller sections of the painting [14].”

TABLE I
PROPOSED FEATURES IN OUR METHOD
(ROWS IN SHADOWS CORRESPOND TO GLOBAL FEATURES; OTHERS CORRESPOND TO LOCAL FEATURES)

Feature	Meaning of Feature	Characteristics	Feature	Meaning of Feature	Characteristics
f_1	Average hue across the whole image	Color	f_2	Average saturation across the whole image	Color
f_3	Number of quantized hues present in the image	Color	f_4	Number of pixels that belong to the most frequent hue	Color
f_5	Hue contrast across the whole image	Color	f_6	Hue model the painting fits with	Color
f_7	Saturation-Lightness model the painting fits with	Color	f_8	Arithmetic average brightness	Brightness
f_9	Logarithmic average brightness	Brightness	f_{10}	Brightness contrast across the whole image	Brightness
f_{11}	Blurring Effect across the whole image	Composition	f_{12}	Edge distribution metric	Composition
f_{13}	Horizontal coordinate of the mass center for the largest segment	Composition	f_{14}	Horizontal coordinate of the mass center for the largest segment	Composition
f_{15}	Horizontal coordinate of the mass center for the 3rd largest segment	Composition	f_{16}	Vertical coordinate of the mass center for the largest segment	Composition
f_{17}	Vertical coordinate of the mass center for the 2nd largest segment	Composition	f_{18}	Vertical coordinate of the mass center for the 3rd largest segment	Composition
f_{19}	Mass variance for the largest segment	Composition	f_{20}	Mass variance for the 2nd largest segment	Composition
f_{21}	Mass variance for the 3rd largest segment	Composition	f_{22}	Mass skewness for the largest segment	Composition
f_{23}	Mass skewness for the 2nd largest segment	Composition	f_{24}	Mass skewness for the 3rd largest segment	Composition
f_{25}	Average hue for the largest segment	Color	f_{26}	Average hue for the 2nd largest segment	Color
f_{27}	Average hue for the 3rd largest segment	Color	f_{28}	Average saturation for the largest segment	Color
f_{29}	Average saturation for the 2nd largest segment	Color	f_{30}	Average saturation for the 3rd largest segment	Color
f_{31}	Average brightness for the largest segment	Brightness	f_{32}	Average brightness for the 2nd largest segment	Brightness
f_{33}	Average brightness for the 3rd largest segment	Brightness	f_{34}	Hue contrast between segments	Color / Comp
f_{35}	Saturation contrast between segments	Color / Comp	f_{36}	Brightness contrast between segments	Brightness / Comp
f_{37}	Blurring contrast between segments	Composition	f_{38}	Average hue for the focus region	Color
f_{39}	Average saturation for the focus region	Color	f_{40}	Average lightness for the focus region	Brightness

Approximately, there is a rule for photography and some art creations that is called “Rule of Thirds”. This rule specifies that the focus (center of the interest) should lie at one of the four intersections as shown in Fig. 6 (b). The pink points are considered to be probable focus by “Rule of Thirds”. One more intuitive assumption is that human eyes are often placed on the center part of the painting. Therefore, we try to cut out a rectangle region that stretch from the center of the image to a little further than the four intersections, as the yellow frame indicates in Fig. 6 (b). The reason for extending the frame a little more outside the intersections is that there may still be imprecision even the artist intended to apply the same rule so a small neighborhood around the intersection points should be equally important.

On the focus region we cut out, we calculate its basic color features: the average H, S, L characteristics.

$$f_{38} = \frac{1}{\#of\{(m,n)\,|\,(m,n)\in FR\}} \sum_{(m,n)\in FR} I_H(m,n) \tag{34}$$

$$f_{39} = \frac{1}{\#of\{(m,n)\,|\,(m,n)\in FR\}} \sum_{(m,n)\in FR} I_S(m,n) \tag{35}$$

$$f_{40} = \frac{1}{\#of\{(m,n)\,|\,(m,n)\in FR\}} \sum_{(m,n)\in FR} I_L(m,n) \tag{36}$$

where FR means Focus Region.

In summary, 40 features are extracted from a painting image to help represent its aesthetic quality, globally and locally, as listed in Table I. Global features are marked with a shadow in the table. Moreover, the table also tells what kind of characteristics each feature represents. These features are selected based on rules and methodology in art, and also some intuitive assumptions on human vision and psychology. They are proved efficient through experiments which will be introduced in Section IV.

III. PAINTING-RATING SURVEY

Being treated as a data-based learning problem, this assessment work highly relies on the data used for learning. Unlike those works on photographs, it is hard to find a website of paintings with ratings by a large community. It seems that currently the assessment authority is mainly placed on the minority of artists and connoisseurs. However, as mentioned in the introduction, the prevalence of art among common people raises the need of evaluation in accordance with their eyes. Therefore, we lead a survey by our own to collect quality labels for the paintings we collected. As a starting point for research, we try to eliminate the variance from different art styles and different contents. Moreover, none of the participants in the survey are in art-specialty. A general description about the survey is given in the following and more details can be found in the Appendix.

Fig. 7. Examples that are labeled as “high-quality” and “low-quality” based on the average scores on them given by human. The paintings on the upper row are labeled as “high-quality” and those on the bottom row are labeled as “low-quality”.

We collected 100 image copies of paintings which are all in the impressionistic style with the landscape content for experiments. Most of the paintings in the survey are from famous artists, such as Van Gogh, Monet and so on. This does not mean all of the paintings are of high aesthetic quality in common people’s eyes. As we know, multiple factors can make a painting brilliant and famous, like history meanings, originality, etc. Participants were also asked whether they feel familiar with the painting or recognize the author of the painting when they rate each painting. For each painting used in our experiment, no more than three participants recognize its author or feel familiar with the painting. This ensures the ratings are rarely relevant to the painting’s fame or its author’s fame.

The survey contains two parts, which are carried on in different periods. The first part is a questionnaire. 23 subjects participate in this part. In the questionnaire part every participants is asked to list more than two factors which are important for them to evaluate the aesthetic quality of a painting in their everyday life. The top 4 important factors that are considered by participants to affect their decisions most are: “Color”, “Composition”, “Meaning” and “Texture”. Texture mentioned here refers to “brushstrokes” according to the participants. Other factors mentioned by people include “Shape”, “Perspective”, “Feeling of Motion”, “Balance”, “Style”, etc. These answers served as reference for the design of the following rating survey and also provided some inspiration for feature selection.

A website is set up for the rating survey and 42 subjects (23 of them attended the previous questionnaire) enrolled individually to give ratings to the painting images. An example rating page can be seen in the Appendix. A subject is required to give four scores for evaluating four aspects of a painting: “General”, “Color”, “Composition”, and “Texture”.

Score for ‘General’ is to describe the total impression of the whole painting, ranging from 1 to 5, where higher score means higher quality. Scores for the other parts – “Color”, “Composition” and “Texture” – are to describe the feelings towards the respective aspects of that painting, ranging from 1 to 5 and a “No Concern” option is also available to indicate this factor is not considered when a decision is made. We give literal directions at the beginning of the survey. Before starting the survey, we also gave an oral introduction to all participants so that they can focus more on the measurement of the aesthetic quality defined in our work.

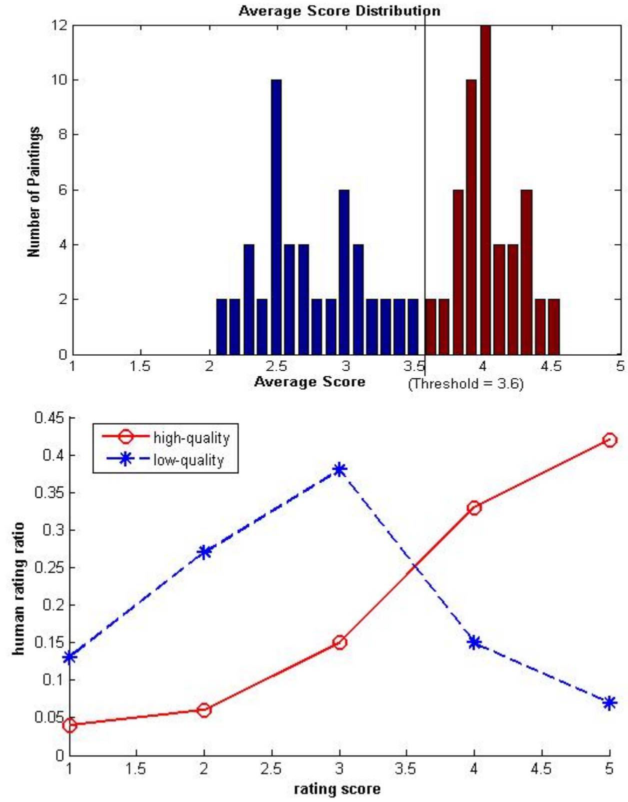


Fig. 8. Score distribution. (a) The upper histogram shows the distribution of the average scores for the 100 paintings. A threshold divides the paintings into two categories. (b) The bottom graph shows the human rating distributions for each category, e.g. the blue curve shows the ratio of population that gives a certain score to the paintings that are categorized as “low-quality” in the upper histogram.

From the survey results, the median of the “General” scores over all paintings is 3.6, which is selected as the threshold for labeling images as “low-quality” and “high-quality”, as shown in the upper histogram of Fig. 8. A painting is labeled as “low-quality” if its average general score is lower than 3.6. Vice versa, a painting is labeled as “high-quality” if its average general score is higher than 3.6. Fig. 7 gives several examples that are labeled as “high-quality” paintings and “low-quality” paintings, respectively. What need emphasizing is that these labels only represent the relative aesthetic quality within the database and in the eyes of most participants. They are not judgments given by art-specialists and are not necessarily relevant with the paintings’ fames or art values.

Only the ‘General’ scores are used in the classification experiment. The other aspects of scores are used for other analysis where we got some interesting results. Fig. 8 and Table II show some statistic data for the human rating scores.

Fig. 8 shows the score distribution. The upper part is a distribution of the average scores of all the paintings. With the threshold, the paintings are categorized as “low-quality” or “high-quality” according to their average score. The bottom part of Fig. 8 shows the human rating distribution for both categories. For example, the blue curve shows the ratio of population that gives a certain score to the paintings that are categorized as

TABLE II
CORRELATIONS BETWEEN SCORES ON DIFFERENT ASPECTS

	General	Color	Composition	Texture
General	**1.0000**	**0.8937**	**0.9160**	**0.8651**
Color	0.8937	1.0000	0.8229	0.8341
Composition	0.9160	0.8229	1.0000	0.8190
Texture	0.8651	0.8341	0.8190	1.0000

"low-quality" due to their average scores. This figure can be understood on two sides. One side is that the peaks for the two classes are obviously separated, which confirms the first assumption for this work – The majority of people tend to have similar opinions towards many paintings. However, on the other side, we can also see that there is still a large overlapping region between the two distributions, which means there is always a considerate variance in human ratings. This again indicates what we try to solve is a really subjective problem.

Table II shows the relationship between scores in measure of different aspects. In this table, each element indicates the correlation coefficient between the scores for the specific factors described respectively by the label of that row and the label of that column.

The correlation coefficients are calculated as below:

Suppose S_G, S_{Cr}, S_{Cn}, S_T are sets of average scores for all paintings, respectively in the sense of "General", "Color", "Composition" and "Texture". e.g. $S_G = [s_G^1, s_G^2, \cdots, s_G^N]^T$, where s_G^i means the average score across users for the i^{th} painting in the sense of "General". N is the number of paintings. Let $\tilde{S}_G, \tilde{S}_{Cr}, \tilde{S}_{Cn}, \tilde{S}_T$ be the sets corresponding to the sets S_G, S_{Cr}, S_{Cn}, S_T with their averages subtracted, e.g. $\tilde{S}_G = [s_G^1 - \overline{s}_G, s_G^2 - \overline{s}_G, \cdots, s_G^N - \overline{s}_G]^T$, where $\overline{s}_G = mean(s_G^i)$. So the element at position (i, j) of the correlation coefficient matrix is calculated as:

$$Coef\_mat(i, j) = \frac{\mathbf{S}(:,i) \cdot \mathbf{S}(:,j)^T}{norm(\mathbf{S}(:,i)) \cdot norm(\mathbf{S}(:,j))} \quad (37)$$

where $\mathbf{S} = \begin{bmatrix} \tilde{S}_G & \tilde{S}_{Cr} & \tilde{S}_{Cn} & \tilde{S}_T \end{bmatrix}$.

Since we use the "General" scores for experiment, what we care most is how the different factors are related to the "General" scores. It is shown in the first row of Table II, the three factors to be correlated with the "General" score ranks as "Composition", "Color" and "Texture" in descending order. The high score shows consistency with the questionnaire result that these three factors are considered important factors for judging a painting's aesthetic quality.

IV. EXPERIMENTS

The aesthetic visual quality assessment work is highly subjective. Therefore, instead of expecting the computer to give exact scores on paintings, we simplify the problem into a two-class problem. That is, to distinguish between paintings with high aesthetic quality and those with low aesthetic quality.

The classification performance can be measured by the Receiver Operating Characteristic (ROC) curve, which is dependent on the False Reject Rate (FRR) and False Accept Rate (FAR). In this application, the two indicators are calculated as:

$$FAR = \frac{\#test\ images\ with\ "low"\ label\ but\ classified\ as\ "high"}{\#test\ images\ with\ "low"\ label} \quad (38)$$

$$FRR = \frac{\#test\ images\ with\ "high"\ label\ but\ classified\ as\ "low"}{\#test\ images\ with\ "high"\ label} \quad (39)$$

Different pairs of FAR and FRR can be obtained by changing the decision threshold of a classification method.

A. Classification Methods

Given the set of features, we need to build proper classifier to combine the features together. Since the metrics based on different features are not necessarily linear, simple weighted combination may not work. A straightforward method we use here is the Naive Bayes Classifier.

1) Naive Bayes Classifier:

Assuming independence between different features and equal prior probability for both classes, i.e. $P(w_1) = P(w_2)$, we have:

$$\frac{P(w_1 | X)}{P(w_2 | X)} = \frac{P(X | w_1)P(w_1)}{P(X | w_2)P(w_2)} = \frac{P(X | w_1)}{P(X | w_2)} = \frac{\prod_{i=1}^{40} P(f_i | w_1)}{\prod_{i=1}^{40} P(f_i | w_2)} \quad (40)$$

In (39), X represents the feature vector of a painting image. w_1, w_2 represent the high-quality class and low-quality class, respectively.

Suppose $P(f_i | w_j)$ is coincident with Gaussian distribution, i.e. $P(f_i | w_j) \sim N(\mu_i^j, (\sigma_i^j)^2)$. μ_i^j and σ_i^j can be computed in the training stage. This Gaussian assumption is made only for simplification. Rationally the distributions for different features should be considered individually. The Gaussian assumption may decrease the discriminative ability of some features, especially those with a distribution containing multiple clusters. Though unitary Gaussian may not be enough to model the real distribution of a feature, its two parameters (mean and variance) do help the classification. For some special case like the hue harmony model feature, the numerical value used to indicate the type of a model can be manually selected. Since we found in training that high-quality paintings tend to fit with the L-type, I-type, Y-type and X-type better, we assigned consecutive number (1, 2, 3, 4) for these four models to better satisfy the Gaussian assumption. Similar implementation is taken for the S-L model feature. For other features whose numerical values are automatically computed, we do not make any intervention on them. Further investigation of modeling feature distribution and designing classifier is left for future study. In the test stage, the posterior probability ratio can be computed as Equation (40) and compared to a threshold in order to make a decision, i.e.

$$\begin{cases} \dfrac{P(w_1 | X)}{P(w_2 | X)} \geq T \Rightarrow w_{test} = w_1 \\ \dfrac{P(w_1 | X)}{P(w_2 | X)} < T \Rightarrow w_{test} = w_2 \end{cases} \quad (41)$$

By changing the threshold T, we can get a number of (FAR, FRR) pairs.

Note here that not all the features are independent, for example, some features of the largest segment can be correlated with the global features. Furthermore, the contrast features between segments may also be highly relevant with the global contrast. However, the Naive Bayes Method is introduced here to serve as a baseline classifier, providing a simple but efficient way to combine the features.

2) Adaptive Boosting Classifier:

In the Naive Bayes Method, all features are given the same weight on the final decision. This neglects the fact that some features may be more powerful while others may be weaker. Therefore, in order to make better use of the features, we apply the Adaptive Boosting (AdaBoost) method [18] to adaptively assign different weights to different features. One feature is chosen to construct a weak Bayes classifier based on a unitary Gaussian model.

Finally all the weak classifiers work as a strong classifier, which can be expressed as:

$$h(X) = \sum_{i=1}^{K} \alpha_i h_i(f_i) \tag{42}$$

where $X = \{ f_i \mid 1 \le i \le K \}$, K is the number of weak learners.

$h_i(x_i)$ is the corresponding weak classifier to the feature f_i and α_i is the weight for this weak classifier. So the total number of weak classifiers equals to the number of features. Therefore, the decision strategy is:

$$\begin{cases} h(X) \ge T \Rightarrow w_{test} = w_1 \\ h(X) < T \Rightarrow w_{test} = w_2 \end{cases} \tag{43}$$

Similarly to the previous part, changing the threshold T can lead to different (FAR, FRR) pairs.

B. Classification Performance

To evaluate the classification performance, we split the paintings into two groups as descried in the "Rating Survey" in Section III. With the ratings from the survey, fifty images are labeled as "high-quality" and the rest fifty are labeled as "low-quality". Since the quantity of images is limited, we adopt the "leave-N-out" cross validation method for experiment. We replicate the following course for ten times: From each class, we randomly select 30 images for training, and 20 for testing. Each time we lead an independent experiment for training and testing. In each time's experiment the threshold T will go through values between $[T_{\min}, T_{\max}]$, with an interval:

$$\Delta T = \frac{T_{\max} - T_{\min}}{K} \tag{44}$$

K is selected to be 20 in our experiment. For different methods, $T_{\min}$ and $T_{\max}$ can be selected differently. The performances for the each time are recorded and summarized according to the thresholds after completing the ten-time experiments.

Figures in this section will show the performance of our proposed approach in different viewpoints.

Fig. 9 gives the overall performance with all the features. The curves in "red" and "blue" show the average performances in twenty-time experiments with Naive Bayes classifier and

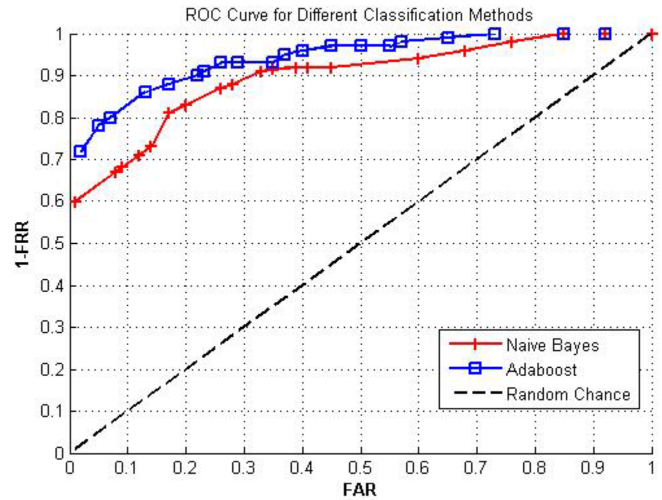


Fig. 9. Performance for the two classification methods

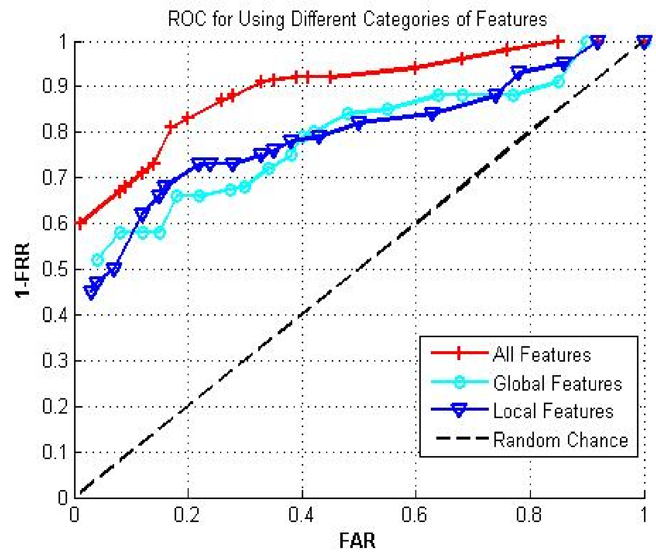


Fig. 10. Classification performances by using different features

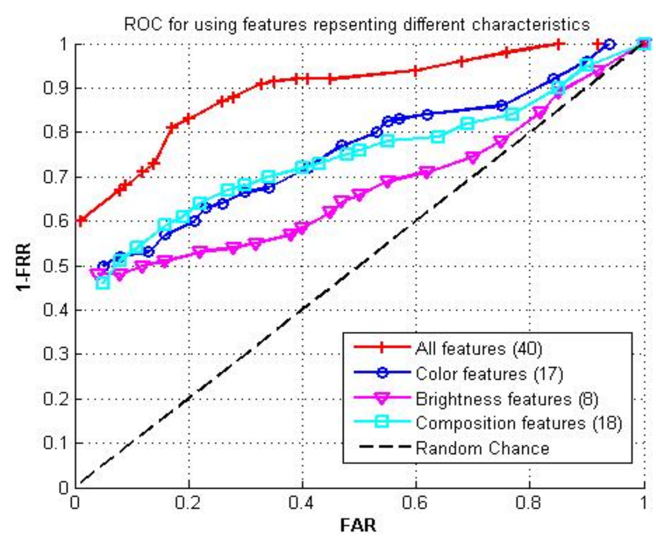


Fig. 11. Classification performances by using different categories of features

AdaBoost classifier, respectively. The black line indicating FAR=1-FRR gives the performance that can be achieved by a random chance system, which serves as a reference to see how much better the proposed methods can achieve. We can see that both Naive Bayes classifier and AdaBoost classifer perform distinctly better than a random chance system.

Fig. 10 shows classification performances by using different categories of features. All the results in Fig. 10 are gained through Naive Bayes Classifier. The red curve indicates the result by using all the proposed features $\{f_i \mid 1 \le i \le 40\}$, while the other two curves are based on the global features $\{f_i \mid 1 \le i \le 12\}$ and local features $\{f_i \mid 13 \le i \le 40\}$, respectively. The global features and the local features achieve similar performance, respectively. Moreover, combining the two categories of features can significantly improve the performance. In Ref [1], only global features are used to assess photographs. In Ref [2], local features are considered in a separable way. However, in our work, we not only consider both global and local features, but also consider the local contrast between different local parts. The obvious improvement in performance by combining all features proves that our global features and local features are complementary.

In Fig. 11, we compare the performance by using features representing different kind of characteristics. In Table I, we divide the features into three categories, representing color, brightness and composition. Some features may relate to more than one category at the same time. The color features and composition features perform better than the brightness features. But we should notice that the brightness group contains fewer features than the other two and all three groups perform comparably when the FAR is low.

To look into the role that every individual feature plays, we study the classification error rates for each weak learner in the AdaBoost classifier in Fig. 12. The total iteration number for the AdaBoost classifier is 46 since some features are used more than once. We can see that the first weak learner has a 26%-round error rate while the 46th weak learner has a 43%-around error rate. Random selection can achieve no larger than 50% error rate. It tells us that some features may be playing little roles and it is likely to achieve similar performance by using fewer features.

Fig. 13 compares classification performance by using different number of weak learners. This comparison is tested based on AdaBoost Classifier. Using the top 31 weak learners can reach similar performance with using all the weak learners. Those cut-out weak learners may correspond to different features when using different experiment sets.

We also test the performance for each individual feature by using Bayes Classifier based on unitary Gaussian model. The features with the top 10 performance are listed below:

$$\{f_{36}, f_{13}, f_{10}, f_{12}, f_{28}, f_6, f_{25}, f_{39}, f_{11}, f_5\}$$

Also we can see from the result of the AdaBoost algorithm, the 10 largest weights are assigned to the following features:

$$\{f_{36}, f_{10}, f_6, f_{11}, f_{13}, f_{17}, f_{32}, f_{39}, f_3, f_{28}\}$$

The above two sets share 7 common features, which play important roles to the classification in both methods. The meanings of the seven features are listed in Table III and their computation methods can be referred to Section II. These results help us understand further about which features are more powerful for the aesthetic quality assessment. Fig. 14 gives an

TABLE III
IMPORTANT FEATURES FOR CLASSIFICATION

Feature	Meaning of Feature	Global / Local
f_{36}	Brightness contrast between segments	Local
f_{10}	Brightness contrast across the whole image	Global
f_6	Hue model the painting fits with	Global
f_{11}	Blurring Effect across the whole image	Global
f_{13}	Horizontal coordinate of the mass center for the largest segment	Local
f_{39}	Average saturation for the focus region	Local
f_{28}	Average saturation for the largest segment	Local

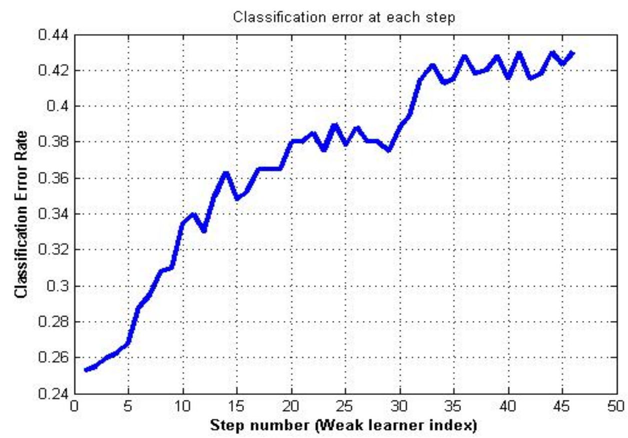


Fig. 12. Classification errors rates for each weak learner in the AdaBoost Classifier. There are totally 46 weak learners. Some features are selected more than once since in different iterations training samples are given different weights and the threshold changes even when using the same feature.

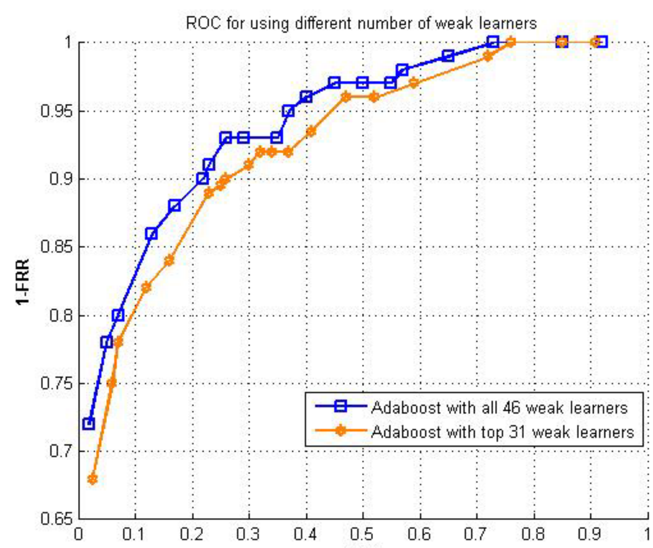


Fig. 13. Classification performances by using different number of weak learners

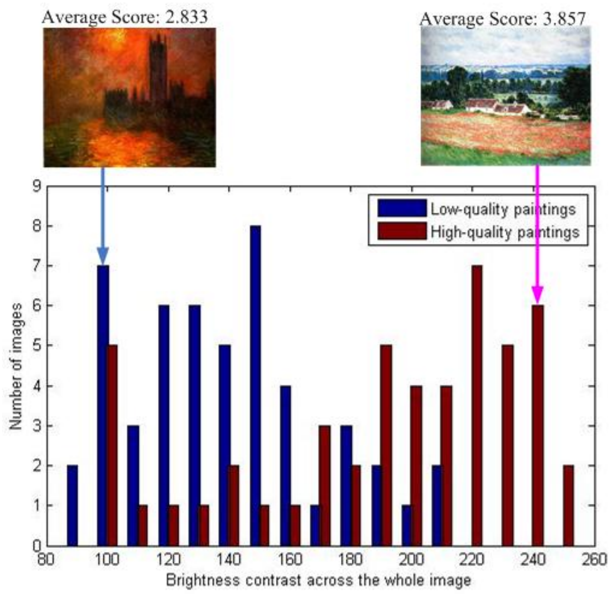


Fig. 14. Brightness contrast feature value distribution for both classes. Above the histogram, two example paintings belonging to different classes are shown. The arrows relate the paintings to the zones where their "Brightness contrast" values lie in.

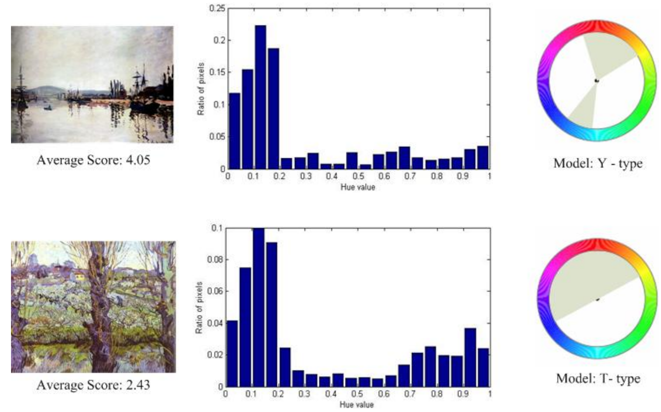


Fig. 15. Comparison of the discriminability of simple hue histogram and the hue model. The two paintings are with different quality, but the bottom image has the most similar hue histogram with that of the upper one. Thus using only the hue histogram leads to wrong classification. However, the models they fit with are different. By training, Y-type is favorable for the high-quality paintings, thus the hue model here works.

example to show the feature value distribution of the "Brightness contrast" feature for both classes. We can see that paintings with high brightness contrast are more likely to be of high-quality.

We try to explain these results in the following ways, by connecting with some art knowledge and psychology theory.

1) f_{36} , f_{10} : It is intuitively rational that brightness contrast affects people's impression on a painting. The contrast brings more information than the objects themselves. Large brightness contrast can create much spatial perception. As said in [7], "All gradients have the power to create depth, and gradients of brightness are among the most efficient".

2) f_6 : High quality paintings are more likely to fit with these four models: L-type, I-type, Y-type and X-type, especially the latter three. The latter three all represent the mixture of complementary colors. The use of complementary colors is an important aspect of aesthetically pleasing art and graphic design. When placed next to each other, complements make each other appear brighter. When blended the small brushstrokes in complementary colors together, it creates neutral color and achieves harmony. We spent a lot of efforts for fitting these models. Fig. 15 gives an example that this model wins over the method of simply using the hue histogram. The two paintings belonging to different quality class have the most similar histogram. But the models they fit best are different and are discriminative for the classification. Table IV gives results by using the two methods.

3) f_{11} : Blurring is sometimes a favorable effect for paintings. It brings feelings of motion and depth, etc. Professional photographers try to control the blurring effect at some degree to keep the moving feel without being too blurred. The result in our work for this feature is similar. It is likely to be a low-quality painting when the blurring effect is very large or very small.

TABLE IV
CLASSIFICATION PERFORMANCE OF HUE HISTOGRAM AND HUE MODEL

Methods	Classification Error rate
Hue histogram (20-d) + Nearest Neighbor	39.3 %
Hue histogram (20-d) + Naive Bayes	42.0 %
Fitted hue model (1-d) + Bayes	33.8 %

4) f_{13} : The relative horizontal coordinate (normalized by the image width) of the mass center for the largest segment is more likely to be smaller than 0.5. It can be linked to the *"Right and left" balance* in visual psychology. It is discussed in the book [7] that objects with the size seem to have more weight when put on the right. So its size needs increasing when put on the left. That is , larger objects on the left can balance with smaller objects on the right. It is also said that the important objects are set a bit left from the center in order to emphasize its importance since a picture is often read from "left" to "right".

5) f_{39} , f_{28} : for oil painting, saturation varies due to the quantity of white pigment mixed in. The saturation for the focus region tends to be high and that for the largest region tends to be low for high-quality paintings. Higher saturation is for emphasizing. However, for large segments, lower saturation may lead to better harmony and peace.

V. CONCLUSIONS AND FUTURE WORK

In this paper we proposed a framework to assess the aesthetic visual quality of paintings. We treat this subjective problem as a data-driven machine learning problem. We first conduct a questionnaire survey to study the factors that affect human's judgments. Later in a rating survey we have human subjects score 100 painting images with similar content and in the similar style. With statistic computation on the rating results, the paintings are split into two categories relatively with "high-quality" and "low-quality" labels. Thus the problem is defined as a two-class classification problem.

To solve the problem, we extract a group of perception-related features, representing both global

TABLE V
DIRECTIONS FOR THE RATING SURVEY

Please score each image based on your aesthetic visual feeling instead of judging the art value. **Scores:** 1 - 5, 5 means the highest quality while 1 means the lowest quality. A score is required for the "General" item. For the other items, you could either give a score or choose "No Concern" to mention you don't consider the corresponding property in your decision process. You are given 25 seconds to look at the paintings. There is a timing bar on every page. After that, the painting will disappear, but you can still continue answering the questions on the page. Press the "next" button to score the next painting when you finish answering the current page. **"General":** your whole feeling on this painting at the first sight. **"Color":** your feeling on the color present in this painting. **"Composition":** your feeling on the organization of objects in the painting. **"Texture":** your feeling on the brushstrokes, the marks given to paint by contact with the bristles of a brush.

characteristics and local characteristics of a painting. Inspiration for these features comes from our prior knowledge in art and the criteria mentioned by human subjects in the questionnaire. These features represent the color, brightness and composition concepts in a painting. In the classification stage, two types of classifiers are tested: Naive Bayes classifier and AdaBoost classifier. Experiments show that both classifiers are robust to produce good accuracy using the 40 extracted visual features in discriminating high-rated and low-rated paintings. Importance of individual feature on the classification performance is also analyzed, which can help us to decrease the number of features without significant loss on performance.

This work provides a machine learning scheme for assessing visual quality in the sense of aesthetics. It aims to explore the relationship between aesthetic perceptions of human and the computational visual features extracted from paintings. Building a connection between human perception on art works and computational visual features extracted from the art works is a challenging multidisciplinary problem. Our work is not meant to provide a full solution, but rather to inspire more interests in this new and amazing research direction. Furthermore, the experiment results show that even for such a subjective problem, with efficient features it is still feasible to teach the computer to complete the task.

To develop efficient feature metrics is a crucial part for this research. Although most features extracted here are low-level, many of them implicitly express important art concepts such as harmony, balance, complementation, etc. We will keep our efforts on discovering semantic features in the future. At the same time, we believe further cooperation with the art community will provide in-depth vision into the problem. Also, well-designed psychology survey will assist us to know more about the tendency in human assessment of paintings, and further to find related features in the paintings.

Although the assessment is simplified into a two-class classification task in this work, estimating a quality score for each painting by regression methods will be part of the future work. Estimating a quality score can be much helpful for developing a painting auto-recommendation system.

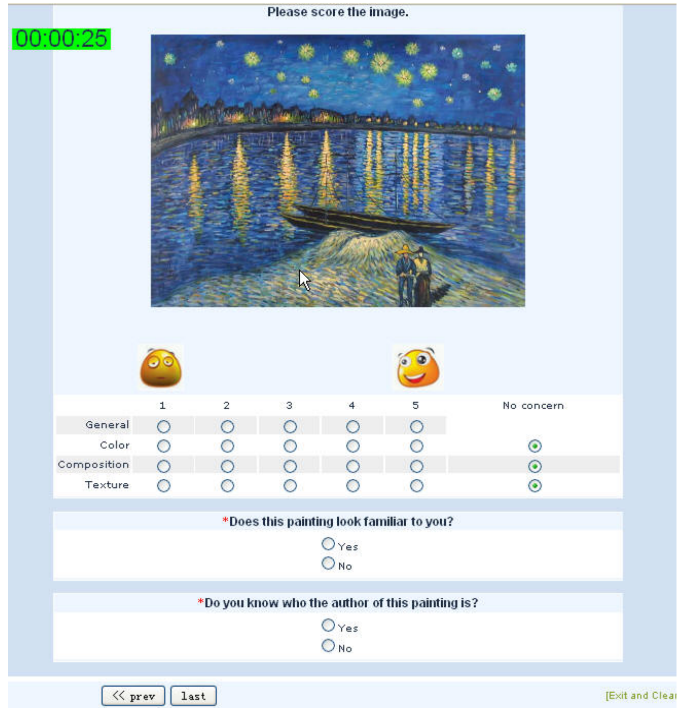


Fig. 16. An example page of the survey. When the time decreases to 00:00:00, the painting becomes invisible while the questions remain until the user clicks the “next” button. The “happy-face” and “unhappy-face” are used to remind user that higher score corresponds to higher quality.

APPENDIX

The complementary details about the survey are given in this appendix. General introduction has been given in Session III.

The survey includes two parts. Part I is a questionnaire. It is done before Part II of the survey. 23 subjects participate in the questionnaire. In this part, subjects are asked to list at least two factors which are important for them to evaluate the aesthetic quality of a painting in everyday life. Answers can be ranked according to their frequency of being mentioned: Color, Composition /Structure /Form, Meaning /Content, Texture /Brushstrokes, Shape, Perspective, Feeling of Motion / Dynamics, Balance, Style, Mood, Originality, Unity, etc.

Part II is a rating survey. We have totally 42 subjects (including the 23 subjects attending Part I) participate in the rating survey. None of the participants in the survey are in art-specialty. Age of the participants varies from 21 to 37. All of them are with a bachelor’s degree or above and have normal ability of distinguishing colors. They are asked before the survey about their preference on painting style. They generally show neutral feelings on impressionistic style of painting, neither too enthusiastic nor repulsive.

The rating survey requires each participant to rate at 100 paintings, which are all in the impressionist-style and with the landscape content. The paintings are downloaded through “Google image search” with careful selection on size and definition. The width of the painting images ranges from 768 to 1024 pixels. All paintings are in the JPEG format. Each painting has an independent rating page. The order of presenting the paintings to each participant is randomly generated. Table V shows the instructions on a page before the ratings. It directs the subjects how to rate on the following section and clarifies terms that are used in the survey.

Fig. 16 shows an example page for rating a painting. A participant is required to rate a painting in four aspects, following the rules described in Table V. The participant also needs to answer whether they know the author of a painting and whether they feel familiar with a painting. For each painting used in our experiment, no more than three participants give "yes" answer to either question. A painting is shown for 25 seconds. After 25 seconds, the painting will disappear. However, the participant can still complete answering the questions until he/she presses the "Next" button to go to next painting. This rule is set to prevent subjects thinking much of the meaning of the painting. The first sight on a painting is highly related to the visual perception. As time goes on, human try to combine the visual feeling with the knowledge in the mind.

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Congcong Li is a Ph.D. candidate in Department of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania. She received her B.E. Degree and M.S. Degree at Department of Electronic Engineering, Tsinghua University, Beijing, P.R. China, respectively in 2005 and 2007. Her research interests include image processing, computer vision and pattern recognition.

Tsuhan Chen has been with the School of Electrical and Computer Engineering, Cornell University, Ithaca, New York, since January 2009, where he is Professor and Director. From October 1997 to December 2008, he was with the Department of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania, as Professor and Associate Department Head. From August 1993 to October 1997, he worked at AT&T Bell Laboratories, Holmdel, New Jersey. He received the M.S. and Ph.D. degrees in electrical engineering from the California Institute of Technology, Pasadena, California, in 1990 and 1993, respectively. He received the B.S. degree in electrical engineering from the National Taiwan University in 1987.

Tsuhan served as the Editor-in-Chief for IEEE Transactions on Multimedia in 2002-2004. He also served in the Editorial Board of IEEE Signal Processing Magazine and as Associate Editor for IEEE Trans. on Circuits and Systems for Video Technology, IEEE Trans. on Image Processing, IEEE Trans. on Signal Processing, and IEEE Trans. on Multimedia. He co-edited a book titled Multimedia Systems, Standards, and Networks.

Tsuhan received the Charles Wilts Prize at the California Institute of Technology in 1993. He was a recipient of the National Science Foundation CAREER Award, from 2000 to 2003. He received the Benjamin Richard Teare Teaching Award in 2006, and the Eta Kappa Nu Award for Outstanding Faculty Teaching in 2007. He was elected to the Board of Governors, IEEE Signal Processing Society, 2007-2009, and a Distinguished Lecturer, IEEE Signal Processing Society, 2007-2008. He is a member of the Phi Tau Phi Scholastic Honor Society, and Fellow of IEEE.