Multimed Tools Appl (2017) 76:1017–1036
DOI 10.1007/s11042-015-3104-5

Orientation judgment for abstract paintings

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Received: 23 April 2015 / Revised: 5 October 2015 / Accepted: 18 November 2015 /
Published online: 26 November 2015

Abstract Artists decide the orientation at which an abstract painting should be hung based on their ideas, but the correct orientation is not obvious to other viewers. Some studies have found that abstract paintings at the correct orientations generally get higher aesthetic ratings from viewers. This encourages us to deal with the problem of orientation judgment for abstract paintings through machine learning. First, we design a group of methods to extract features from paintings based on the theories in abstract art. Then a machine leaning framework is proposed using Naive Bayes classifier and BP neural network classifier for training and orientation testing. Experiments show that it can classify abstract paintings into up and non-up ones with performance comparable to human. This is the first work of orientation judgment for abstract paintings through computer simulation, and the results demonstrate the validity of abstract art theories used for feature definition. This work provides a new scheme for exploring the relationship between aesthetic quality of abstract paintings and their computational visual features.

Keywords Abstract paintings · Image classification · Feature extraction · Orientation judgment · Art theory

1 Introduction

Abstract art uses a visual language of shape, form, color and line to create a composition which may exist with a degree of independence from visual references in the world [2], in

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which the paintings created for the emotion expression are called “heat abstraction”, and the others for the world description in an abstract way are called “cool abstraction”, such as the examples in Fig. 1. When creating an abstract painting, the artist makes a decision of the correct orientation at which the work should be hung based on their aesthetic ideas. Although the correct orientation is often specified on the back of the canvas, it is not obvious to other viewers. Relatively some studies in psychology have addressed the problem about abstract paintings’ orientation [13, 17, 19, 24, 25], for example, if there is sufficient information in an abstract painting for a naive viewer’s judgement to align with the correct orientation, and if the impact or aesthetic value of a work diminished by viewing at an incorrect orientation. Most of the studies addressed such questions agree with that the paintings with correct orientation get higher aesthetic ratings, and experiments in participants show that about half decisions for preferred orientation are in agreement with the artist’s intended orientation, which is well above chance but below perfect performance [19, 24]. All of these provide evidences that painting orientation has relationship with aesthetic quality. The study of orientation judgment can throw some light on the objective rules underlying visual aesthetic evaluation.

With the trend of information digitalization, digital images of paintings can be easily found on the internet. This makes computer-aided painting analysis possible. Various methods on aesthetic assessment have been studied by directly exploring the relationship between aesthetic perceptions of human and the computational visual features [18, 23], but none deals with the problem of aesthetic assessment by focusing on computer-aided orientation judgment.

The results in psychology and development in digitalization of art encourage us to deal with the problem of orientation judgment for abstract paintings by computer simulation. The proposed work aims for a better understanding of what evokes the sense of orientation for abstract paintings, especially when there is no meaningful content, and building the relationship between image visual contents and correct orientation in a frame of machine learning. In particular, we extract a group of features concerning orientation, and trained a Naive Bayes classifier and a BP neural network to predict if a painting is in correct orientation or not. As painting orientation is a factor that has relationship with aesthetic value, the judgment and analysis of orientation for abstract paintings help artists to better understand

(a) Heat abstraction ("Black strokes" by Kandinsky, 1913) (b) Cool abstraction ("Composition" by Mondrian, 1921)

Fig. 1 Examples of abstract paintings (downloaded from http://www.wikiart.org) why their paintings are attractive to viewers and how they can make them more appealing. For researchers, it provides a framework for extracting specific features for abstract painting analysis based on machine learning. Besides, both heat abstraction and cool abstraction are considered in this paper.

The value of this work can be summarized as follow. Evaluations of art works are subjective, particularly for abstract paintings. Various art theories used as the evidence for aesthetic evaluation haven't been verified. In this paper, we provide a computerized system to verify the validity of the art theories for aesthetic evaluation. (1) Psychology studies show that abstract paintings in their original orientations tend to get higher aesthetic ratings. It illustrates that painting orientation is a factor that has relationship with aesthetic value. (2)We extract features from paintings based on the theories in abstract art, and used them in a machine leaning framework for orientation judgment. The system can judge orientations of abstract paintings with performance comparable to human. (3) The performance of this computerized system verifies the validity of the art theories expressed by features, and provides some proved theories for aesthetic evaluation, for example: "if the above of the painting seems looseness and lightness, while the below seems condensation and heaviness, the painting seem more appealing". It provides a new way for exploring the relationship between aesthetic qualities and visual characteristics of paintings.

Our main contributions are: (1) to the best of our knowledge, the problem of orientation judgment for abstract paintings is first studied through computer simulation; (2) we use machine learning to find the factors concerning orientation based on which we give proposals to artists to improve their artworks; (3) the inspiration for selecting features comes from prior knowledge in art, including composition rules in art and theories in abstract art. This work demonstrates the validity of these theories, which can be used as evidence for aesthetic evaluation.

The rest of the paper is organized as follows. Related works are discussed in Section 2. Section 3 describes the basic rules and the proposed method for extracting visual features. Section 4 introduces two classifiers for orientation judgment. The performance of the proposed approach is evaluated in Section 5 and the work is concluded in Section 6.

2 Related works

2.1 Psychology study on abstraction orientation

Is there any visual information in an abstract painting for a naive viewer to judge its correct orientation? Does the aesthetic value of an abstract painting vary by viewing at different orientations? Some studies in psychology have addressed these questions by asking human subjects. In [19], a group of professional artists and a group of nonartists were asked to indicate their preferred orientations using different sets of abstract paintings. For each group, about half were in agreement with the artists' intended orientations. In [17], the effect of the orientation of Mondrian's paintings on their aesthetic appeal was examined. Participants showed a preference for the original orientation and a preference for pictures presented with component horizontal and vertical lines than oblique ones. In [25], Plumhoff and Schirillo illustrated that observers prefer Mondrianś paintings in their original orientation compared to the rotated by testing eye movements. They confirmed that an abstract painting becomes more aesthetically pleasing if it shows both a greater amount of diversive/specific types of image exploration and balance. In [13], when viewing variations in paintings by Mondrian, aesthetic preferences correlated with pupil size were studied. They found evidence for the higher preference for the original orientation than a rotated position. George's study [24] was in agreement with [19], the judgements of nonexpert viewers accorded with the intended orientation for abstract or semiabstract art at levels well above chance (48 % in experiments) and orientation judgements were mediated at least in part by some appreciation of meaningful content in the image.

The studies in Psychology illustrate that painting orientation is a factor that has relationship with aesthetic value. Original orientations of abstract paintings tend to get higher aesthetic ratings, and no mater professional artists or nonexpert viewers appreciate the correct orientations well above chance but below perfect performance.

2.2 Image orientation judgment

There are some works for natural images' orientation judgment. Hollitt et al. [9] estimated the roll orientation of a camera system using the power spectral density of an image to find the excess of vertical textures in the environment, and using the Hough transform to find the directions of lines in the image. They dealt with the problem of camera parameter estimation while our method concerns image classification. Lyu [20] proposed a method for determining image orientations using low-level image features including a set of natural image statistics collected from multi-scale multi-orientation image decomposition. This method was designed for natural image classification and aimed at optimal performance while our method aims at feature design and art theory demonstration. Gossweiler et al. [7] presented a CAPTCHA based on the identification of an image's upright orientation. They used a suite of automated orientation detectors to prune those images that can be automatically set upright easily. Image orientation identification was used as a tool for CAPTCHA design in [7], while in our paper, painting orientation identification is used as a tool for art theory demonstration.

2.3 Computer methods on painting analysis

In recent years, a number of computer methods in computer vision, pattern recognition, image processing, computer graphics have been developed for painting analysis, including traditional pixel-based methods such as color adjustment, area-based processes involving filtering and analysis of brush strokes, computer vision methods such as perspective and lighting analysis, and three-dimensional modeling using computer graphics methods [29]. The basic approach of painting analysis is using pattern recognition techniques to deal with the image properties for estimating ages of the prints [8], better understanding the choices of artists [28], or assessing aesthetic visual qualities [18].

For aesthetic visual quality assessment, by extracting certain visual features from images, Ke et al. [16] classified between high quality professional photos and low quality snapshots, Datta et al. [6] assessed the aesthetic quality of photographs as a machine learning problem, and Li et al. [18] classified painting qualities based on prior knowledge and painting-rating survey. [11] and [23] used Bag-of-Visual-Words framework for aesthetics prediction.

Including visual quality assessment, some problems in painting analysis can be solved through image classification, such as the classification of traditional Chinese versus non-traditional Chinese [12], Gongbi versus Xieyi, high-quality versus low-quality [18], etc. The features used include: edge direction, color histogram, brightness, hue, texture, etc. Various classifiers include: K-nearest neighbor classifier, SVM, Decision tree, Bayesian classification framework, hidden Markov model (HMM), adaboost training algorithms, neural network, etc.

In the fields of painting analysis, especially aesthetic assessment, we don't find any previous work dealing with painting orientation judgement through computer methods to our best knowledge. Although these works of paining analysis are not directly related to our study, they do inspire us on how to extract features in paintings and build the framework for learning and testing.

2.4 Abstract art evaluation

As a member of modern art, abstract art seems a puzzle to common viewers. Wassily Kandinsky is the pioneer of abstract art on painting (An example is shown in Fig. 1a) and theory. His writings such as "On the spiritual in art" and "Point and line to plane" have great importance in abstract art. In "Point and line to plane" [15]. Kandinsky analyzes the painting elements on the point of view of their inner effect on the living subjectivity of the observer who looks at them. In our work, some features comes from the theories of Kandinsky.

Some works analyze dripped painting based on fractals. For the works of American abstract expressionist Jackson Pollock, Taylor et al. [30] pointed that Pollock's drip paintings are fractal, however, some works questioned the claim that fractal dimension can distinguish Pollock's paintings from others [14]. In addition, Irfan et al. [10] used traditional image measures to analyze Pollock's works.

Abstract paintings are analyzed using statistical methods in some works. Victoria et al. [31] employed statistical analysis and eye tracking for analyzing the emotion of abstract paintings. In [22], perceptual contrast and statistical properties were studied using behavioral and objective approach in the field of empirical aesthetics.

Some works for emotion analysis use features inspired by art theory. Sartori et al. [27] used statistical analysis and art theory in a recognition system to find the associated statistical patterns for positive and negative emotions on professional and amateur abstract artworks. For understanding the relationship between artistic principles and emotions, Zhao et al. [32] extracted principles-of-art-based emotion features to classify and score image emotions. Machajdik et al. [21] exploited concepts from psychology and art theory to define image features, and used them for image emotion classification. Our features for orientation judgments in this paper are also based on art theories.

These works give us more information about abstract paintings, and provide prior knowledge for feature definition.

In this paper, we deal with the problem of orientation judgment through classifying the abstract paintings into up versus non-up ones, using Naive Bayes and BP neural network as classifiers. First, we extract various image features of digitalized abstract paintings based on art theories, and then use a machine leaning framework for feature learning and orientation testing. This work provides a new viewpoint for the aesthetic assessment of abstract paintings.

3 Feature extraction

Extracting features to judge the orientation of an abstract artwork is a crucial part of this work. With knowledge and experiences in art, we believe some factors can be especially helpful for assessing the orientation of a painting. While looking for efficient features, we refer to the theories of art, especially the rules of composition and the theories of abstract art to find what factors can affect human's judgment on the orientation of a painting. Inspired by the theories in art, and based on intuition, we extract a number of features in this section and then evaluate whether the extracted features are useful or not in Section 5.

3.1 Rules in art

3.1.1 Stability

The sense of stability is a visual and aesthetic habit of human formed in long terms of living. Although abstract paintings contain abstract contents, they are still the reflections of the world. “Stability” (including “balance”, “symmetry”, etc.), as a basic rule in painting composition, could also be applied to abstract paintings. Human’s sense of weight comes from the visualization of different areas, shapes, colors and movement states, as is the source of “stability” in art. Low brightness with high saturation gives an impression of heaviness, while high brightness with low saturation gives an impression of lightness. Besides, high brightness with warm colors results in the sense of expansion. “Symmetry” is the most simple “stability” in art, which means that the left part is similar to the right part. From intuition, light and small expansion at above, heavy and big expansion at below, and symmetry in right and left give us a sense of stability. For orientation judgment, stability is a basic rule for our feature extraction.

3.1.2 Line and plane

In his writings [15], Kandinsky analyzes the geometrical elements which compose every painting, namely the point, the line and the basic plane.

He analyzes on the point of view of their inner effect on the observers. In his theory, the tonality of a painting is determined by the relative importance of horizontal and vertical lines, the horizontals giving a calm and cold tonality to the basic plane, while the verticals give it a calm and warm tonality. The artist possesses the intuition of this inner effect of the canvas format and dimensions, which he chooses according to the tonality he wants to give to his work. These points make us pay more attention to horizontal and vertical lines, which are related to painting orientation.

According to [15], every part of the basic plane possesses a proper affective coloration which influences the tonality of the pictorial elements that will be drawn on it. The above of the basic plane corresponds to the looseness and lightness, while the below evokes the condensation and heaviness. The left of the basic plane is the continuation of the above, while the right is the continue of the below. In other words, The left of the basic plane corresponds to the lightness and freedom in lighter degree than the above, while the right of the basic plane, similar to the below, corresponds to the heaviness and denseness in a lighter degree. These theories about different parts of the plane can be used as a director for painting’s orientation.

3.2 Features

Based on the theories in Section 3.1, a group of features are extracted. In our analysis we represent paintings in Lab color space and HIS color space. The Lab color space plots image data in three dimensions, “L” for brightness, while “a” and “b” for different color opponents. Lab color space is used in the calculation of texture complexity in Sections 3.2.1 and 3.2.2. HSI color space is chosen, as hue(H) , saturation(S) and intensity(I) make sense for human's vision. HSI color space is used in the calculation of color features mainly in Section 3.2.5.

For feature calculation, we divide an abstract image I first into two parts from the middle, i.e. the above part and the below part, denoted by images A and B, and then divide I into the left and right ones from the middle, denoted by images L and R. The feature values for each part are calculated and compared as the following details in Sections 3.2.1 to 3.2.5.

3.2.1 Complexity

Based on the plane theories of Kandinsky in Section 3.1.2, features f_1 and f_2 are defined to describe the texture complexity of different parts of a painting.

According to the plane theories, in a painting, the above and left parts are loose and light, while the below and right evoke the sense of condensation and heaviness. Based on these, features f_1 and f_2 are extracted in (1) and (2), where "*complexity*" is defined to decribe the degree of texture complexity, which could cause the sense of looseness or heaviness.

$$f_1 = complexity(A) \leqslant complexity(B) \tag{1}$$

$$f_2 = complexity(L) \leqslant complexity(R) \tag{2}$$

The $complexity$ in (1) and (2) is based on the maximum gradient image G_{max}, and can be calculated as the following details.

First, in Lab color space, a gradient image G_{max} of image I is generated according to (3) based on the maximum gradient magnitudes in the L, a and b color channels.

$$G_{max}(x, y) = max(\|\nabla I_L(x, y)\|, \|\nabla I_a(x, y)\|, \|\nabla I_b(x, y)\|) \tag{3}$$

In (3), $\nabla I_L(x, y)$, $\nabla I_a(x, y)$, and $\nabla I_b(x, y)$ are the gradients at pixel (x, y) for the L, a, and b channels respectively.

Then, according to the method of [26], the $complexity$ of different parts of image I, viz. $I_x = A, B, L, R$, is defined as the mean value of image G_{max} in (4).

$$complexity(I_x) = \frac{1}{PixelNum(I_x)} \sum_{(x,y)\in I_x} G_{max}(x, y) \tag{4}$$

In (4), G_{max} is the maximum gradient image of I, and $PixelNum(I_x)$ is the total pixel number of image part I_x. The mean value over the maximum gradient image G_{max} is used as a prediction on texture complexity. The higher the value of $complexity(I_x)$ is, the more complex the image part I_x is.

3.2.2 Similarity

From the plane theories and the rules of stability, features f_3, f_4 and f_5 are defined to describe the texture similarity of different parts of a painting.

According to the plane theories in Section 3.1.2, in a painting, the left of the basic plane is the continuation of the above, while the right is the continue of the below, viz. the above and left parts of a painting are more similar than the above and right, while the below and right parts are more similar than the below and left parts. Based on these theories, features f_3 and f_4 are defined in (5) and (6). From the rule of symmetry, we know that the left and right parts of a painting are more similar than the above and below parts. Then the feature f_5 is extracted in (7).

$$f_3 = similarity(A, L) \geqslant similarity(A, R) \tag{5}$$

$$f_4 = similarity(B, R) \geqslant similarity(B, L) \tag{6}$$

$$f_5 = similarity(L, R) \geqslant similarity(A, B) \tag{7}$$

For the calculation of “similarity”, we compare the HOG (Histograms of Orientation Gradients) features of one image with another using a similar method of [26] (PHOG features, viz. Pyramid of Histograms of Orientation Gradients were used in [26] for the calculation of self-similarity). Details of similarity calculation are discussed below.

The *similarity* calculation is based on HOG [5] and PHOG [1, 4, 26]. Redies et al. [26] use PHOG for the measurement of image aesthetic quality. We use the method of [26] for *similarity* calculation using a simple form of HOG. First, the maximum gradient image G_{max} is calculated as in (3). Then the simplified HOG features of each part image I_x ($I_x = A, B, L, R$) is calculated, by seeing image I_x as one cell with 8 bins for binning the orientations. The normalized values of the bins represent the orientation strengths in each direction. The similarity between two images is calculated through Histogram Intersection Kernel [3] in (8), where $I_1 \neq I_2, I_1, I_2 \in A, B, L, R$.

$$similarity(I_1, I_2) = \sum_{i=1}^{m} min(h(i)_1, h'(i)_2) \tag{8}$$

In (8), h_1 and h_2' are the corresponding normalized histograms of images I_1 and I_2 respectively, and m is the number of bins present in the HOG features. In features f_3, f_4, and f_5, the similarity values of each two parts (A, B, L and R) are calculated according to (8), and are compared according to (5), (6) and (7).

3.2.3 Horizontal and vertical lines

Based on the theories of lines, features f_6 and f_7 about the horizontal and vertical lines in a painting are defined.

Kandinsky in his writings [15] (in Section 3.1.2) points that tonality is determined by the relative importance of horizontal and vertical lines, chosen by the artist according to his expression. This makes us pay attention to horizontal and vertical lines, which are related to painting orientations. Features f_6 and f_7 are defined to describe the relative amount and energy of horizontal and vertical lines.

$$f_6 = amount(vertical) \geqslant amount(horizontal) \tag{9}$$

$$f_7 = energy(vertical) \geqslant energy(horizontal) \tag{10}$$

In feature f_6, we compare the amount of vertical lines and horizontal lines. The vertical and horizontal lines are extracted by wavelet decomposition, through which image I is decomposed into vertical, horizontal and oblique lines. We extract the amount of lines in different orientations by calculating its wavelet coefficients. In feature f_7, image I's central energies in vertical and horizontal directions are compared. Central energies are obtained by calculating the average intensities along vertical and horizonal center lines in a painting image.

3.2.4 Edge

From the rules of stability, f_8 and f_9 are features concerning edge characteristics, including edge length and texture.

Length and texture differences along four edges of image I are compared. First, the width and height of the painting image I are compared in feature f_8 in (11), where $width(I)$ and $height(I)$ stand for the width and height of a painting image I respectively.

$$f_8 = width(I) \geqslant height(I) \tag{11}$$

$$f_9 = TexDiff(Ae, Be) \geqslant TexDiff(Le, Re) \tag{12}$$

Then texture difference along edges are compared in feature f_9 (12), where Ae, Be, Le, and Re are four lines along but with certain distance to the above, below, left and right edges respectively. $TexDiff$ stands for the texture difference along two of these lines.

$TexDiff$ is calculated through edge detection and pixel comparison along two lines Ae, Be or Le, Re in the following way.

First, the texture edges of image I are extracted through edge detection. The image I is then changed into a binary image with pixels in texture edges represented by 1 and pixels in other areas represented by 0. Finally, as in (13), $TexDiff$ is calculated through comparing the values of pixel pairs along two lines (Ae, Be) or (Le, Re), at the same height horizontally (for (Le, Re)) or at the same width vertically (for (Ae, Be)), and get the total number of pixel pairs with different values. In (13), (E_1, E_2) represents (Le, Re) or (Ae, Be).

$$TexDiff(E_1, E_2) = \sum_{E_1, E_2 = begin}^{end} PixelNum(E_1 \neq E_2) \tag{13}$$

3.2.5 Color

According to the theories in Section 3.1.1 that color has relationship with the sense of weight, features from f_{10} to f_{25} are extracted. Here the hue, saturation and intensity values of a painting in HSI color space are used to describe the sense of human's vision.

In these features, f_{10} to f_{12}, f_{19}, f_{21}, and f_{23} to f_{25} are based on the rules of stability, while f_{13} to f_{18}, f_{20} and f_{22} are based on the plane theories.

Based on the rules of stability, the color difference of left and right is generally smaller than the color difference of above and below, which are expressed in f_{10} to f_{12}.

$$f_{10} = \|hue(A) - hue(B)\| \geqslant \|hue(L) - hue(R)\| \tag{14}$$

$$f_{11} = \|sat(A) - sat(B)\| \geqslant \|sat(L) - sat(R)\| \tag{15}$$

$$f_{12} = \|int(A) - int(B)\| \geqslant \|int(L) - int(R)\| \tag{16}$$

In (14) to (22) $hue()$, $sat()$, and $int()$ are the average hue, saturation and intensity values of images respectively.

f_{13} to f_{18} are defined based on the theories of plane that the left is the continuation of the above, while the right is the continue of the below:

$$f_{13} = \|hue(A) - hue(L)\| \leqslant \|hue(A) - hue(R)\| \tag{17}$$

$$f_{14} = \|sat(A) - sat(L)\| \leqslant \|sat(A) - sat(R)\| \tag{18}$$

$$f_{15} = \|int(A) - int(L)\| \leqslant \|int(A) - int(R)\| \tag{19}$$

$$f_{16} = \|hue(B) - hue(R)\| \leqslant \|hue(B) - hue(L)\| \tag{20}$$

$$f_{17} = \|sat(B) - sat(R)\| \leqslant \|sat(B) - sat(L)\| \tag{21}$$

$$f_{18} = \|int(B) - int(R)\| \leqslant \|int(B) - int(L)\| \tag{22}$$

Based on the rules of stability - low brightness with high saturation gives an impression of heaviness, while high brightness with low saturation gives an impression of lightness, feature f_{19} and f_{21} are defined. Based on the plane theories - the above is similar to the left, while the below is similar to the right, f_{20} and f_{22} are extracted.

$$f_{19} = sat(A) \leqslant sat(B) \tag{23}$$

$$f_{20} = sat(L) \leqslant sat(R) \tag{24}$$

$$f_{21} = IMaxNum(A) \geqslant IMaxNum(B) \tag{25}$$

$$f_{22} = IMaxNum(L) \geqslant IMaxNum(R) \tag{26}$$

In (23) and (24), $sat()$ is the average saturation value of a image, and in (25) and (26), $IMaxNum()$ calculates the number of pixels with maximal intensities in a image (We select the highest 20 % in the intensity range in our experiments).

Based on the stability rules, small expansion at the above with big expansion at the below give us a sense of stability. Features f_{23} to f_{25} are defined.

$$\begin{aligned} f_{23} = \|(hue(Al) + hue(Ar))/2 - hue(Am)\| \geqslant \\ \|(hue(Bl) + hue(Br))/2 - hue(Bm)\| \end{aligned} \tag{27}$$

$$\begin{aligned} f_{24} = \|(sat(Al) + sat(Ar))/2 - sat(Am)\| \geqslant \\ \|(sat(Bl) + sat(Br))/2 - sat(Bm)\| \end{aligned} \tag{28}$$

$$\begin{aligned} f_{25} = \|(int(Al) + int(Ar))/2 - int(Am)\| \geqslant \\ \|(int(Bl) + int(Br))/2 - int(Bm)\| \end{aligned} \tag{29}$$

In (27) to (29), we divide A (the above part of image I) further into three parts. Al is the left part of A, Ar is the right part of A, and Am is the middle part of A. Similarly, B is divided into Bl, Br, and Bm.

All features mentioned in Section 3.2 are listed in Table 1, where ”V” and ”H” stand for ”vertical” and ”horizontal” respectively, and ”As” and ”Bs” represent ”Al+Ar” and ”Bl+Br” respectively.

4 Classification

The problem of orientation judgment is a two-class problem. That is, to distinguish between paintings of up directions and those of non-up directions. Using the set of features extracted in Section 3.2, we choose Naive Bayes Classifier and BP neural network Classifier for classification.

4.1 Naive Bayes classifier

Assuming that the different features discussed in Section 3.2 are independent, we have

$$\frac{P(C_1|X)}{P(C_2|X)} = \frac{P(X|C_1)P(C_1)}{P(X|C_2)P(C_2)} = \frac{P(C_1)\prod_{i=1}^{25} P(f_i|C_1)}{P(C_2)\prod_{i=1}^{25} P(f_i|C_2)} \tag{30}$$

In (30), $X = [f_1, f_2, \ldots, f_{25}]$ represents the feature vector of a painting image I, C_1 represents the up-direction class, and C_2 is the non-up-direction class. $P(C_1)$ and $P(C_2)$ are prior probabilities for the two classes respectively.

Note that all the features are discrete, and $P(f_i|C_j)$ $(i = 1, 2, \cdots, 25, j = 1, 2)$ is coincident with 0-1 distribution. The conditional probabilities $P(f_i|C_j)$ for the states of each feature can be computed in the training stage. The Naive Bayes method is introduced

Table 1 Proposed features in our method

Feature	Meaning	Theory/Character
f_1	Complexity of A vs B	plane/texture
f_2	Complexity of L vs R	plane/texture
f_3	Similarity of(A,L) vs (A,R)	plane/texture
f_4	Similarity of(B,R) vs (B,L)	plane/texture
f_5	Similarity of(L,R) vs (A,B)	stability/texture
f_6	Line amount (V) vs (H)	line/texture
f_7	Energy (V)vs (H)	line/color
f_8	Length of image(V)vs (H)	stability/texture
f_9	Tex Diff of (Ae,Be)vs (Le,Re)	stability/texture
f_{10}	Hue diff of (A,B)vs (L,R)	stability/color
f_{11}	Sat diff of (A,B)vs (L,R)	stability/color
f_{12}	Int diff of (A,B)vs (L,R)	stability/color
f_{13}	Hue diff of (A,L)vs (A,R)	plane/color
f_{14}	Sat diff of (A,L)vs (A,R)	plane/color
f_{15}	Int diff of (A,L)vs (A,R)	plane/color
f_{16}	Hue diff of (B,R)vs (B,L)	plane/color
f_{17}	Sat diff of (B,R)vs (B,L)	plane/color
f_{18}	Int diff of (B,R)vs (B,L)	plane/color
f_{19}	Sat (A) vs (B)	stability/color
f_{20}	Sat (L) vs (R)	plane/color
f_{21}	Int Max Num(A)vs(B)	stability/color
f_{22}	Int Max Num(L)vs(R)	plane/color
f_{23}	Hue diff(As,Am)vs(Bs,Bm)	stability/color
f_{24}	Sat diff(As,Am)vs(Bs,Bm)	stability/color
f_{25}	Int diff(As,Am)vs(Bs,Bm)	stability/color

to provide a simple but efficient way to combine the features. In the forecasting stage, the posterior probability ratio can be computed and compared in (31) to decide which class the new painting I with feature X should be classified into. In (31), T is the threshold, and different values of T can be used for classification performance evaluation.

$$\begin{cases} \frac{P(C_1|X)}{P(C_2|X)} \geqslant T \Rightarrow I \in C_1 \\ \frac{P(C_1|X)}{P(C_2|X)} < T \Rightarrow I \in C_2 \end{cases} \tag{31}$$

If four copies of image I with different orientations are called ”up”, ”down”, ”turn left”, and ”turn right”, and they are seen as a group, there is one image with up orientation and three images in non-up directions in each group. We get the up one based on the ratio of two posterior probabilities as in (32).

$$\gamma_\theta = \frac{P(C_1|X_\theta)}{P(C_2|X_\theta)} \, (\theta = 1, 2, 3, 4) \tag{32}$$

In (32), X_θ is the feature vector of each copy, and γ_θ is the posterior probability ratio for each image in a group. We compare the γ_θ in each group, and select the image with the maximum γ_θ as the up one.

4.2 BP neural network classifier

Back Propagation (BP) network is also chosen for classification. As a kind of multilayer feedforward network, BP neural network is made up of an input layer, one or several hidden layers and an output layer, and trained by error back propagation algorithm. It could learn and store large numbers of relationships between the inputs and outputs, and could be used to approach a mapping equation. Weights in the network are adjusted through error back propagation to minimize the error square sum. In our system, a BP network classifier noted as Net is built and trained for orientation judgement.

The input of Net is the feature vector $X = [f_1, f_2, \ldots, f_{25}]$ extracted in Section 3.2, and the output is the result of orientation. Sigmoid function $f(x) = 1/[1 + exp(-x)]$ is used as the activation function. In this way, we build a BP neural network of three layers, with node numbers 25-30-1. As in the training stage, the output of "up" is represented by "1", while "non-up" is represented by "0", a new painting I can be classified into "up" class or "non-up" class by comparing the output value of the network with "1" and "0", and classify it in to a class based on (33), where T' is the threshold,

$$\begin{cases} \frac{\|Net_{output}-1\|}{\|Net_{output}-0\|} \geqslant T' \Rightarrow I \in C_1 \\ \frac{\|Net_{output}-1\|}{\|Net_{output}-0\|} < T' \Rightarrow I \in C_2 \end{cases} \tag{33}$$

5 Method performance

We select 500 images of abstract paintings from internet (http://www.wikiart.org) in experiments. The artworks were realized between 1910 to 1970 by 74 artists. We copy each image and rotate it into 4 orientations, and then there are 2000 images totally for experiments. We randomly select some images for training, and the remainders for testing, using Naive Bayes classifier and BP neural network classifier respectively. As a two-class problem, in the test stage, we predict the orientation of each painting to be "up" or "non-up".

To evaluate the classification performance, we adopt the "leave-N-out" cross validation method for experiment. We replicate the following course for ten times: randomly select 1400 images for training, 600 for testing, and lead an independent experiment for training and testing.

5.1 Total performance

The average accuracy for the two-class classification (classify the images into "up" ones or "non-up" ones) are 74 % and the average accuracy for the four-choose-one classification (viz. selecting an up image from four copies - "up", "down", "turn left", and "turn right") are 42 % with the standard deviation 3.6 %. In [24], experiments in participants show that the correct orientation was selected in 48 % of trials on average (selecting an up image from four copies). Our results (42 %) has a comparable performance to human, with a little minor accuracy.

In the four-choose-one classification, the experiments show that the correct orientation was selected at average rate 42 %, significantly above the chance level 25 %, and the other available orientations were selected much less frequently. As the four orientations are named "up", "down", "turn left", and "turn right", in our experiments, the "down" is predicted much frequently (at average rate 24 %) than "turn left" and "turn right" (at average rate

17 % respectively). We can see that "down" is the most easily confused orientation for this method.

5.2 Method analysis

The classification performance can be measured by the Receiver Operating Characteristic (ROC) curve, which is dependent on False Accept Rate (FAR) and False Reject Rate(FRR). In this application, the two values are defined in (34), where "Num" means "The number of".

$$\begin{cases} FAR = \frac{Num(\text{“non−up” labeled images but classified as “up”})}{Num(\text{“non−up” labeled images})} \\ FRR = \frac{Num(\text{“up” labeled images but classified as “non−up”})}{Num(\text{“up” labeled images})} \end{cases} \tag{34}$$

To evaluate the performance of the two classification methods, different threshold T in (31) and T' in (33) are selected between $[T_{min}, T_{max}]$ to calculate FAR and 1-FRR pairs. In Fig. 2, the ROC curves show the classification performance by using different classifiers with all features. We can see that both Naive Bayes classifier and BP neural network classifier perform better than a random chance system, and the Naive Bayes classifier generally performs better than the BP neural network classifier over most thresholds.

According to the theories based on, all the proposed features are classified into three categories: 11 features $\{f_i \mid i = 5, 8, 9, 10, 11, 12, 19, 21, 23, 24, 25\}$) are based on the rules of stability, 12 features $\{f_i \mid i = 1 \le i \le 4, 13 \le i \le 18, 20, 22\}$) are based on Kandinsky' theories of plane (the relationships of the above &left/below&right parts of the plane) and 2 features $\{f_i \mid i = 6, 7\}$) are based on Kandinsky' theories of lines. Figure 3 shows the classification performance by using different categories of features and demonstrates that the features from theories of stability, plane, and lines all have contributions to the final performance of classification.

All the results in Fig. 3 are gained through Naive Bayes classifier. The magenta curve is based on the features from the rules of stability, and the green curve is based on the features

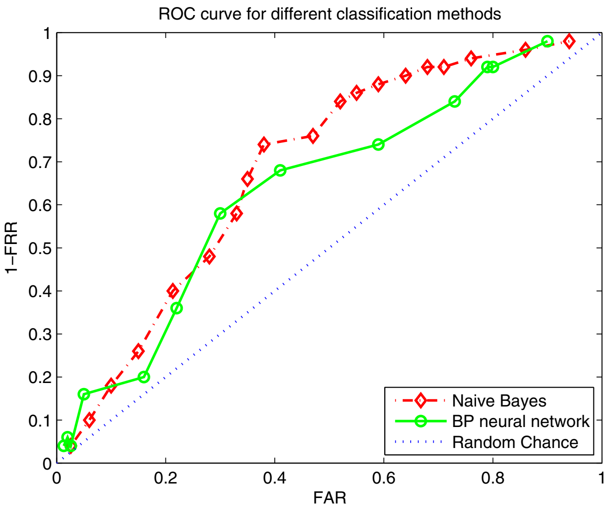

Fig. 2 Performance for two classification methods

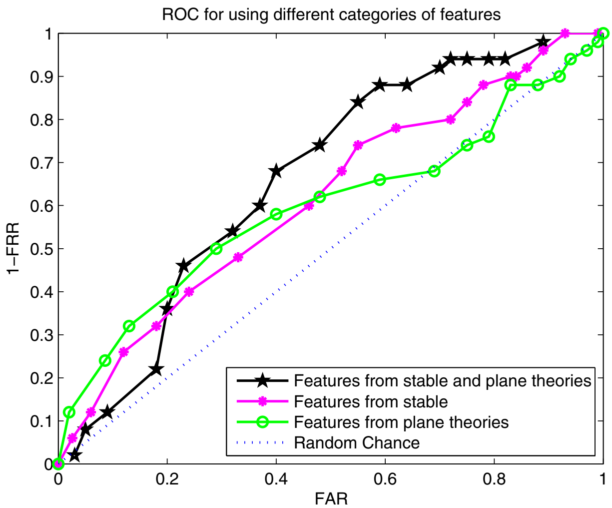

Fig. 3 Performance by using different features

from the theories of plane, while the black curve indicates the result by using the two groups of features. The features from stability perform more stable than the features from plane theories in different thresholds, while the features from plane theories have better performance when FAR is low. Moreover, combing the two categories of features can improve the performance. In Fig. 4, the black curve shows the performance of all features except 2 features from theories of lines ($\{f_i \mid i = 6, 7\}$), while the red curve indicates the result by combing all features. We can see that features from theories of lines can improve the performance.

According to their characteristics, all features are classified into two categories: 8 features $\{f_i \mid i = 1, 2, 3, 4, 5, 6, 8, 9\}$) related to image texture (shape and complexity), and the

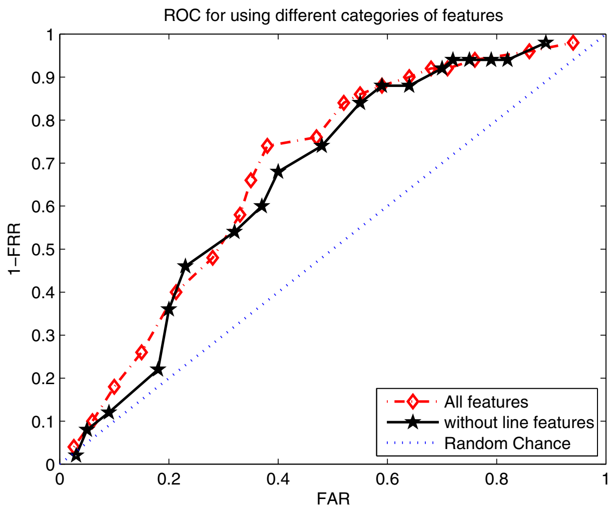

Fig. 4 Performance by using different features

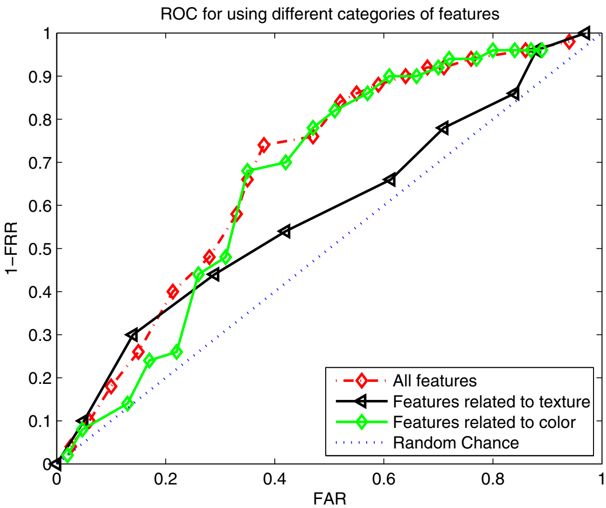

Fig. 5 Performance by using different features

remaining 17 features $\{f_i \mid i = 7, 10 \le i \le 25\}$) related to image colors (hue, intensity, and saturation). Figure 5 compares the performance of these two categories. The comparison is tested based on Naive Bayes classifier. The color features perform better than the texture features, but we should notice that the texture group contains fewer features than the color group. These two groups of features concerning color and texture both have contributions to the final performance.

To analyze the validity of the features, we further classify them into "complexity" ($\{f_1, f_2\}$), "similarity" ($\{f_3, f_4, f_5\}$), "line" ($\{f_6, f_7\}$), "edge" ($\{f_8, f_9\}$), and "color" ($\{f_i \mid$

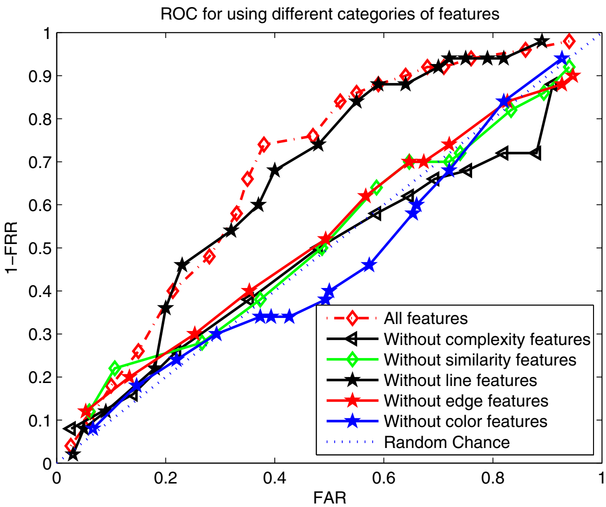

Fig. 6 Performance by using different features

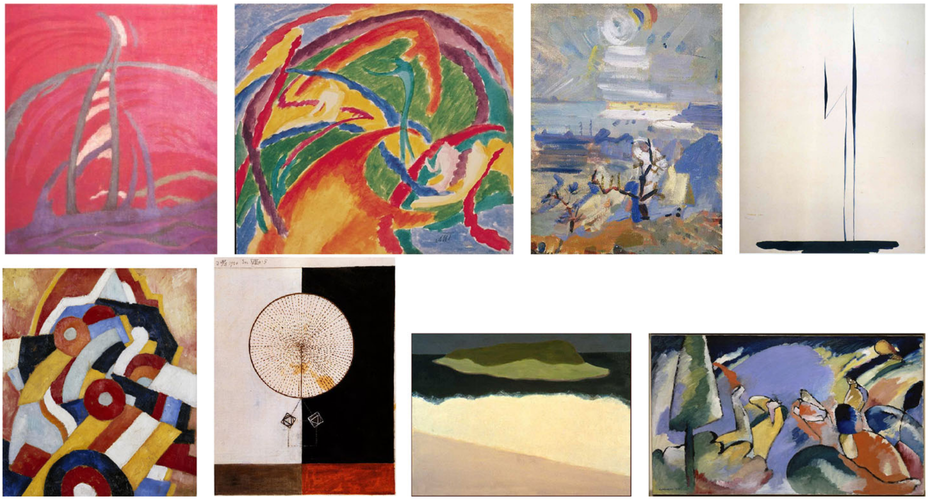

Fig. 7 Examples of correctly judged paintings by this method

$i = 10 \leq i \leq 25\}$) groups corresponding to their sources. Figure 6 compares the performance of these categories. The comparison is tested based on Naive Bayes classifier. Each feature group is analyzed in classification by leaving this group out. The difference between "without xx features" curve and "all features" curve illustrates the contribution of xx feature group. The feature groups concerning complexity, similarity, line, edge and color all have contributions to the final performance. The "color" features make the greatest contribution, while the "line" features contribute the minimum.

Fig. 8 Examples of incorrectly judged paintings by this method (difficult for eyes)

Fig. 9 Examples of incorrectly judged paintings by this method (easy for eyes)

By analyzing the classified painting images, we find that the paintings with clear contents whose orientation may be obvious for eyes are more prone to be distinguished (some examples are shown in Fig. 7) while the ones with orientations difficult for eyes to judge always make mistakes (see Fig. 8), although a few paintings exist that are easy for eyes but are mistaken by machine (Fig. 9). From this, we can conclude that mechanism of this work for orientation judgment is similar to human's.

The performance of the work illustrates the validity of the art theories the work based on. As orientation judgment has relationship with painting aesthetic quality, it also illustrates that "stability in composition", and "style designing for different parts of a painting" are both important factors for the aesthetic qualities of abstract paintings. These can be provided as proposals to artists to improve their artworks and be used as the verified evidence for aesthetic evaluation.

6 Conclusion

In this paper, we deal with the problem of orientation judgment through classifying the abstract paintings into up versus non-up ones, using Bayesian and neural network as classifiers. A group of features are extracted based on the composition rules in art and theories in abstract art. Experiments shows that this work can judge orientations of abstract paintings with performance comparable to humans.

In the future, more features derived from art theories could be extracted and analyzed to improve the judgment accuracy, and questionnaire survey could be introduced to find more factors in human's judgement for abstraction orientation.

This work illustrates that the "stability in composition", and "style designing for different parts of a painting" are important factors for aesthetic quality, as can be used as the verified evidence for aesthetic evaluation. It provides a new way for exploring the relationship between aesthetic qualities and visual characteristics of paintings.

Acknowledgments This work is supported by the National Natural Science Foundation of China with project No. 61172104.

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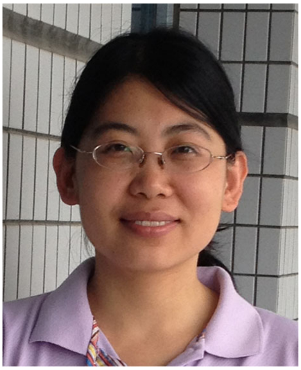

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