Visual Complexity of Chinese Ink Paintings

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Abstract

Complexity is a key factor influencing aesthetic judgment of artworks. Using a well-known artist Wu Guanzhong's paintings as examples, we provide quantified methods to gauge three visual attributes which influence the complexity of paintings, i.e. color richness, stroke thickness and white space. By conducting regression analysis, our research validates the influences of given visual attributes on perceived complexity, and distinguishes the complexity measurements for abstract paintings and representational paintings. Specifically, all three factors influence the complexity of abstract paintings; In contrast, mere white space influences that of representational paintings.

CCS CONCEPTS

• **Applied computing → Arts and humanities → Fine arts**

Keywords

Chinese paintings; Complexity; Regression Model; Visual Perception

1 Introduction

The visual complexity of an image refers to the level of details and intricacy contained within the image [Forsythe 2009; Snodgrass et al. 1980]. It influences aesthetic appeal of an art work. Birkhoff defined the beauty of an image as the order, i.e. characteristic of realization of objects such as harmony, symmetry, divided by complexity, assuming the complexity to be the most fundamental determinant [Birkhoff 1933]. Paintings are created either by depicting objects and imitating the reality, or by intentionally constructing non-figurative reality for extending appreciation process and evoking aesthetic experiences. The mimicry and violation of visual objects in daily life govern the mainstream of visual arts which consist of representational paintings and abstract paintings. Representational paintings provide rich details for accessing to the semantic referents. In contrast, abstract paintings, lack of concrete semantic meanings, employ the intricacy to highlight features in style. Beholders appreciate abstract and representational paintings differently in terms of processing complexity related visual information. Existing literature has provided empirical evidences on such a difference. Beholders access to the semantic meanings of representational paintings easily via the precise, detailed and regular forms which are tightly associated with objects in the real world. They are, however, likely to focus on the perceptual dimensions of abstract paintings, such as color [Marković 2011]. It has not been quantitatively verified whether the complexity of two types of paintings are determined by different physical attributes in visual forms. We endeavor to explore the quantified determinants of perceived complexity and their differences in appreciation of representational and abstract paintings and provide empirical evidences.

We adopt Wu Guanzhong's ink paintings as our experimental examples (https://www.wikiart.org/en/wu-guanzhong). Wu is contemporary Chinese painting master. His artworks are featured by the integration of Chinese art and western art, extraordinary simplicity and rich connotations, highly appraised internationally. His exquisite arrangement of white space has been documented in our previous comparative study of his representative ink paintings and oil paintings [Fan et al. 2017]. His works cover diverse themes, and vary in terms of semantic transparency. By focusing on paintings of one artist, we explore the differences in his handling of representational and abstract paintings, while excluding the influences of confounding variables, such as strong personal styles, themes, inclination of color usage and cultural attributes.

Our research provides a computational method to describe multiple visual attributes of Wu's paintings, and indicates how physical attributes influence the perceived complexity of representational and abstract paintings. Our research contributes to the existing literature by:

- Providing quantified methods to gauge visual attributes influencing the complexity of paintings, and highlighting an objective view to understand viewers' perception on complexity, unlike the subjective evidences in psychological research;
- Distinguishing influential visual attributes of perceived complexity for representational and abstract paintings;
- Validating the influences of several visual attributes on perceived complexity.

In the remainder of this paper, Section 2 reviews related work on the role of complexity in the aesthetic judgment, measurements of visual complexity and information processing on paintings. Sections 3 and 4 identify potential visual attributes which might influence perceived complexity, quantify each attribute in a meaningful range, and measure the semantic transparency and the perceived complexity of selected paintings. Section 5 builds regression models based on the reported perceived complexity to validate the

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predictors of perceived complexity, followed by conclusion and discussion in Section 6.

2 Related work

2.1 Complexity in Aesthetic Judgment

Visual complexity relates to the number and quality of basic visual elements, the dissimilarity and organization of the elements [Fiore 2010]. The desire for complexity is considered an important aesthetic experience to activate perceptual system and find regularities.

In the domain of aesthetics, the nature of beauty has been debated for more than 2500 years, and a variety of measurements of beauty have been developed to identify critical contributors to beauty [Frith et al. 1974; Leder et al. 2004; Tatarkiewicz 1970]. One of the most important perceptual features is visual complexity [Berlyne 1970]. As early as 1930s, Birkhoff proposed the well-known model of aesthetic measure. Based on three successive phases of the typical aesthetic experience, he included complexity and order to predict beauty. His insightful understandings encourage continuing efforts in measurements of balance, contrast and harmony in a computational perspective [Zhang et al. 2017].

2.2 Visual complexity

In general, the existing literature on visual complexity addresses objective measurements of factors influencing complexity, and the influences of complexity [Donderi 2013]. Prior researches on quantitative measurement of complexity focus on 2D and 3D shapes, web pages and photographs [Harper et al. 2013; Perkiö et al. 2009; Psarra et al. 2001; Purchase et al. 2012. For example, scholars have measured the complexity of web pages using their structural aspects [Harper et al. 2013], complexity of shapes by calculating local characteristics of shape perimeter and degrees of stability [Psarra et al. 2001], and complexity of an image using independent component analysis [Perkiö et al. 2009]. Limited research on the complexity of paintings in a quantitative fashion has identified the influences of color attributes and point of interests on visual complexity among 20 possible factors using machine learning method [Guo et al. 2013]. However, the conceptualization of measurements and its validation are scarcely discussed.

The influence of visual complexity on an individual's perception has been explored. The visual complexity of advertisements caused by dense perceptual features is proved to hurt consumers' attention to the brand and attitude toward the advertisements [Pieters et al. 2013].

2.3 Visual information processing and semantic transparency

Individuals process representational and abstract paintings differently. The evidence on beholders' subjective judgments on paintings' perceptual attributes and semantic components suggests that the processing of representational paintings emphasizes on the illusion of the defined and regular forms resembling objects in the physical world, while the appreciation of abstract paintings has high judgments on color and construction of reality (the opposition of illusion of reality) [Marković 2011]. This means, people pay more attention to semantic components in paintings with higher semantic transparency than in abstract paintings. Evidenced in neural science, the perception of representational and abstract paintings are associated with distinct visual areas of the brain [Kawabata et al. 2004; Lengger et al. 2007], also supports the claimed differences. It is unclear yet, whether individuals, influenced by semantic transparency, rely on different visual attributes to make judgment on visual complexity.

The information carried by paintings can be divided into pictorial information, content information and background information [Marković 2011; Wallraven et al. 2009]. Pictorial information refers to physical visual attributes, including thickness of brush strokes, type of painting materials, color composition of the scene. Content information pertains to depicted objects, types of paintings and subjects, involving the recognition of visual objects and semantic processing. Background information is defined as the information on conventions of expressions and cultural information associated with the paintings. In line with the categories, our research focuses on the influences of pictorial information and content information on the perceived complexity of paintings. On one hand, we explore the influences of pictorial information by computing visual attributes using computational methods. On the other hand, we investigate the influences of content information relying on participants' evaluation of semantic transparency, rather than automatically calculated data. Current methods on scene recognition in representational oil paintings [Condorovici et al. 2013] and script abstraction in Chinese ink paintings [Liu et al. 2012] are incompetent in accurate evaluation on semantic transparency.

3 Computing Complexity

We hypothesize that individuals typically rely on four primary pictorial information, i.e. color (color richness, number of color blocks and variation degree of color pixels [Chan et al. 2004]), stroke (stroke thickness), white space (total area, particularly large pieces, of white space) and layout (horizontal, vertical and diagonal equilibriums) to judge the complexity of paintings. The results show that three variables, color richness, stroke thickness and large pieces of white space are significant in predicting paintings' complexity.

Paintings are viewed as "multilevel hierarchical structure of parts and wholes" [Palmer 1977]. Psychologists have indicated global precedence and the primacy of holistic properties [Kimchi 2015], i.e. the process of perceptual processing is from global structure to local details [Navon 1977]. The perception on complexity as an overall judgment thereby is assumed to be more associated with global information. Therefore, it is necessary to perform a pre-treatment of each painting to eliminate unnecessary details. We applied morphological opening, an algorithm for image enhancement and noise removal [Serra 1982], to each selected painting. After erosion and dilation operations, small subsets of the images that cannot include the translated SEs (structuring elements) [Maragos 2005] are eliminated. Fig. 1 shows the effect of morphological opening on painting *Alienation.* The top-left portion of the image is cropped (as in Fig. 1. (a)) to convey clear details of morphological opening (Fig. 1. (b)). The following calculations of pictorial information are applied to the images processed by morphological opening.

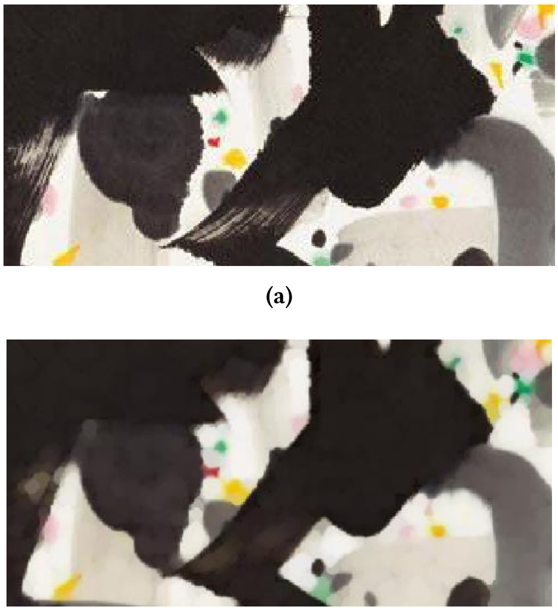
3.1 White Space

White space, as a typical feature in traditional Chinese paintings, is intentionally left blank for viewers' imagination. Generally, the unoccupied area simplifies the composition of paintings than those fully covered [Fan et al. 2017]. White space is typically used to refer to sky, cloud, river and lake in scenic views, as the background of highlighted figures, or play a role as a component exclusively functional in term of style but indicating nothing concrete. The former is usually featured as white regions, and the latter scattered white pieces. Regarding the paintings' denotation, white regions are more likely to be processed as meaningful objects than scattered white pieces, which are shown as trivial details, hardly influencing viewers' holistic impression of the paintings. Similar to scattered small white pieces, connected small white pieces are also insignificant visually. Therefore, only large areas of white regions on a painting can be attributed to complexity and indicate that a limited space is used for figures, i.e. the painting is likely to be simple. White space, as a visual attribute, is hard to demarcate from the denotations of the painting.

We capture white regions in the paintings by applying quadtree decomposition to them. Quadtree is a tree data structure where each node has four children [Finkel et al. 1974]. The quadtree algorithm proceeds to recursively divide a two-dimensional space into four regions until all divided regions cannot be further divided when reaching a particular criterion. Fig. 2. (a) illustrates the recursive partitioning of an image into quadrates with some regions undivided.

The quadtree decomposition is performed as following. First, we re-size a rectangular image as a square, of which each side is sized 1024. Second, we convert the RGB images to a gray image. Third, we set a threshold (at 20 through several experiments) and start decomposition. The image is split into four quadrates if the difference between their the maximum and the minimum gray values, among the pixels in this image, is greater than the threshold. Fourth, we compute the difference of four new quadtrates and then compare it with the threshold. The pseudo-code is shown below:

```
WHITESPACE (Image)
Resize Image to 1024*1024;
Convert Image from RGB to HSV;
S ⟵ matrix of saturation
V ⟵ matrix of lightness
for i from 1 to 1024
   for j from 1 to 1024
      if  S[i,j] < 20 and S[i,j] > 80
         Mark this pixel as white pixel;
   end if
end for
Convert Image to gray-scale;
Decompose gray-scale image with quadtree threshold at 20;
Calculate the number of quadtrates sized 128 and 64 as
NumOfQuadrates128 and NumOfQuadrates64;
Calculate proportion of white space in each quadrate sized 128 and
64 and store in matrices ProportionOfWhiteSpace128,
ProportionOfWhiteSpace64;
while q < NumberOfQuadrates128
     if PropotionOfWhiteSpace128[q] < 0.3
        NumOfQuadrates128 ⟵ NumOfQuadrates128 - 1;
     end if
 end while
 Repeat the same loop operation as above to quadrates sized 64
and obtain NumOfQuadrates64;
 LargeWhiteSpace=128*128*NumOfQuadrates128
+64*64*NumOfQuadrates64;
 Output: LargeWhiteSpace
```



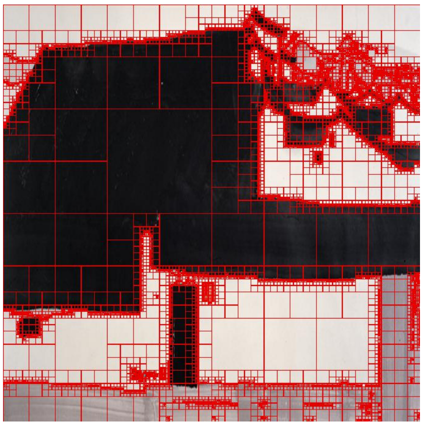
(a)

(b)

Figure 1: (a) A small cropped portion of *Alienation*. (b) The cropped portion of *Alienation* after applying morphological opening. (Images processed by authors as fair use from wikiart.org)

The images are resized as 1024*1024 pixels, and then applied with the quadtree algorithm to obtain quadrates sized 2^N pixels (N=0..9). We judge whether a pixel is a "white" pixel or an "ink" pixel by setting thresholds on saturation and lightness in HSV color space. Saturation and lightness can be each divided into three levels, with 33 and 67 as two break points [Smith et al. 1995]. However, special properties in Chinese rice paper make "white" parts not pure white, but beige, and thus white pixels not statistically white (hue: 0, saturation: 0, lightness: 100). Also, there are large amount of ink regions in light gray. Hence saturation below 20 and lightness over 80 are suitable for recognizing white space in Chinese ink paintings. For the divided quadrates, we define 128*128 and 64*64 quadrates as large regions because few paintings have quadrates larger than 128 and quadrates less than 64*64 are likely to be regarded as scattered pieces and hard to notice. We then differentiate the large quadrates filled by white pixels, by calculating the number of "white" pixels, from those filled by ink pixels. If the proportion of"white"pixels is over 70% of the quadrate, we determine this divided quadrate as a white one. In other words, this quadrate is included in one of the painting's white regions. We mark white quadrates with red lines on the paintings (see Fig. 2. (b), *A Big Manor*. We sum the areas of 128*128 white quadrates and 64*64 white quadrates, representing the large pieces of white space in each painting.

As two representational paintings, *Parrot Haven* has a higher rating on perceived complexity than *Swallows Before the Hall*, which means the former is more complex than the latter, while the former has a larger ratio of "white" pixels than the latter. But we find 34% of the large pieces of white space in *Swallows Before the Hall*, much more than 12% of *Parrot Haven*, where white space is separated by many brushstrokes. For abstract paintings, beholders pay more attention to large white regions than scattered white pieces. *Within and Without the Window* has a lower rating on complexity than *Red, Green* though both paintings have similar percentages of white pixels. But the former has more white quadrates than the latter.



(a)

(b)

Figure 2: (a) An example of a quadtree decomposition on *A Big Manor.* (b) The quadtree decomposition result of white space in A Big Manor. (Images processed by authors as fair use from wikiart.org)

3.2 Stroke Thickness

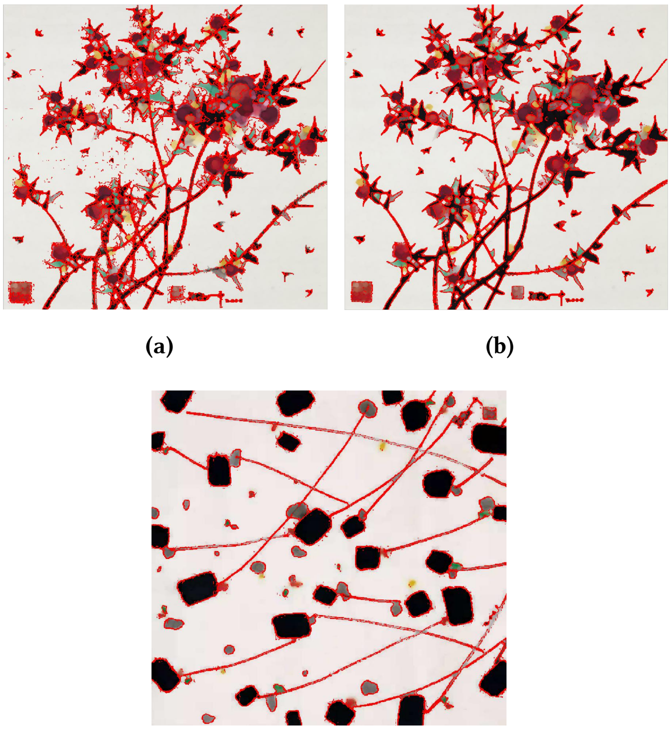
Stroke thickness is usually associated with the intricacy of paintings. One can visually distinguish thin strokes and tiny points in paintings, such as *Spring Song*, and figure out large slices (thick brush strokes) in paintings such as *Waterfall*. Generally, large number of thin strokes can increase the perceived complexity, while a few thick strokes can decrease complexity.

One may extract description of brush strokes from representational paintings by applying segmentation techniques and using a brush stroke library [Xu et al. 2006], which is complex and time consuming. In this paper, we use a fast approach by simply calculating color changes among adjacent pixels, to measure stroke thickness. We scan each entire painting image line by line, vertically and horizontally, and count the number of changes in color. Obviously, for a given sized image, a great number of color changes suggest many thin lines and small areas. We use the ratio of times of color changes to the total number of pixels to indicate a painting's stroke thickness. For example, *Spring Song* has 14% of color changes compared to 21% for *Construction of a Building.*

The calculation is performed in three steps. The image is first transformed from the RGB color scheme to the HSV color scheme. We choose the HSV color space because it separates hue, saturation, lightness into three equal channels and its linearity in transforming to the RGB color space in both the forward and reverse processes [Wyszecki et al. 1967]. In the second step, we set a threshold for each of hue, saturation and lightness, and a change is recorded if the difference between each of hue, saturation and lightness for two neighboring pixels is larger than the corresponding threshold. In the HSV color space, color can be differentiated by separating color into 18 angles of 20 degree and using 33 and 67 as two break points in saturation and lightness channel [Smith et al. 1995]. Fig. 3. (a) shows the calculated results using thresholds mentioned above.

This method cannot be directly used for Wu's paintings because the usage of ink makes black and gray dominant colors in ink paintings and, in contrast, the hue difference is obvious. To a viewer, white and light gray and black and dark gray are visually different colors. But these two sets of colors are similar in their values in the HSV color space. We adjust the breakpoints in three channels and determine two pixels to have different colors if their numerical differences in hue, saturation, and lightness are more than 30, 2 and 3, respectively. If the difference in lightness alone surpasses 9, two pixels are also considered having different colors. Fig. 3. (b) and (c) show the calculation results for *Fruit Tree* and *Spring Breeze* respectively. We mark a pixel in red if it has a different color compared to its top pixel or left pixel. The third step calculates the ratio of the number of changes over the total number of pixels in each image. The pseudo-code is shown below:

```
STROKETHICKNESS (Image)
  m ← height of Image
  n ← width of Image
  NumOfPixels = m*n
  ChangNum ← 0
  Convert Image from RGB to HSV;
  H ← matrix of hue
  S ← matrix of saturation
  V ← matrix of lightness
  for i from 1 to m
    for j from 1 to n-1
      if (H[i, j+1]-H[i, j] > 30 and S[i, j+1]-S[i, j] > 2 and V[i, j+1]
       -V[i, j] > 3) or V[i, j+1]-V[i, j] > 9
        ChangNum ← ChangNum + 1
      end if
    end for
  end for
  for p from 1 to n
    for q from 1 to n-1
      If (H[q+1, p]-H[q, p] > 30 and S[q+1, p]-S[q, p] > 2 and V[q+1, p]
      -V[q, p] > 3) or V[q+1, p]-V[q, p] > 9
        ChangNum ← ChangNum + 1
      end if
    end for
  end for
  ChangeRatio=ChangNum/NumOfPixels
  Output : ChangeRatio
```



(a) (b)

(c)

Figure 3: (a) Smith and Chang's method [Smith et al. 1995] applied to *Fruit Tree*. (b) Our method applied *Fruit Tree*. (c) Our method applied to *Spring Breeze*. (Images processed as fair use from wikiart.org)

3.3 Color Richness

Rich colors can increase complexity of paintings. We measure the number of distinct colors used in each painting and check the results by generating its hue histogram. First, we convert images from RGB to HSV color space, with $H(x,y)$, $S(x,y)$, and $V(x,y)$ denoting hue, saturation and lightness. We obtain the numbers and positions of pixels with hue equaling h. Second, we determine whether each pixel with hue of h is a colored pixel or a neutral pixel (gray scale, black or white pixel) by a saturation threshold, and remove neutral pixels. Third, we count the number of pixels on six color bands by dividing the 360-degree hue scale into six intervals representing red, yellow, green, blue, cyan and magenta. If the quantity ratio of pixels of a color is large than 0.1% of the total pixel number, the color is determined to be used in this painting. This threshold of 0.1 is determined to be most appropriate via comprehensive experiments with a range of numbers.

In the second step, we set a saturation threshold because a color of low saturation can be represented by a gray value controlled by the lightness, while a color of high saturation can be represented by hue. A saturation threshold can determine the transition between hue and lightness. The threshold is depended on the lightness because a color of low lightness is always close to the gray scale.

The following equation is used to determine whether a pixel is dominant by its lightness or hue [Su et al. 2011].

$$th_{sat} = 1.0 - 0.9 * V \tag{1}$$

In the above equation, when a pixel's saturation (S) is greater than th_{sat}, the pixel is a colored one and can be represented by hue. If its saturation is less than th_{sat}, it is represented by its lightness(V) and thus not a colored pixel. A painting's hue histogram after removing neutral pixels is shown in Fig. 4. (a) and (c). Hue in the HSV color space is defined as an angle in the range of 0 to 2π. The angle represents different colors. But certain successive angles are visually in the same band of colors. Hue can thus be composed of six color bands [Sural et al. 2002] including three primary colors, red (range: 330~360 and 1~29), green (range: 80~159), and blue (range: 210~269), and three secondary colors, yellow (range: 30~79), cyan (range: 160~209) and magenta (range: 270~329). Six color bands are enough to describe colors in the selected paintings (Fig. 4. (b) and (d) mark different colored regions in two paintings). Fig. 4. (a) and (c) show hue histograms of two abstract paintings, *Within and Without the Window* and *Jasper*.

The pseudo-code is shown below:

```
COLORRICHNESS(Image)
    Convert Image from RGB to HSV;
    Assign the values of hue, saturation and lightness to matrices H,
S, V;
    Modify outlier pixels whose S =1 to average of sums of 8
    surrounding pixels;
    for i from 1 to 360
        row_hue ⟵ x-coordinate of pixels whose hue values equal to i
        col_hue ⟵ y-coordinate of pixels whose hue values equal to i
        card ⟵ length of row_hue/col_hue
        for j from 1 to card
            th_sat ⟵ 1 - 0.9*V(row_hue(j), col_hue(j))
            if S(row_hue(j), col_hue(j)) >= th_sat
                Number of pixels whose hue = i + 1;
            end if
        end for
        hue_h(i) ⟵ number of pixels whose hue = i;
    end for
    PixelNumOfColorBand(k) = sum the number of color pixels in
    each (k=0..5)
    Ratio(k) = PixelNumOfColorBand(k)/Total of pixels in Image;
    NumberOfColor=0;
    for k from 1 to 6
        If Ratio(k) >= 0.1%
            NumberOfColor=NumberOfColor+1;
        end if
    end for
    Output : NumberOfColor
```

4 Semantic Transparency and Perceived Complexity

We selected Wu's 40 ink paintings as samples, of which 26 are abstract paintings and 14 are representational paintings. We recruited 97 Chinese participants in a major university to evaluate the perceived complexity of the paintings using 7 point Likert scale (1= not simple, 7=very complex). No participant is color blinded. Although some participants may have heard of Wu Guanzhong, none is a professional artist, or familiar with his paintings. Each participant was tested individually with a computer to view each painting and then rate the perceived complexity and semantic transparency. Their education levels and genders are also recorded. The reported data are used in our regression model discussed next.

Fig. 5 shows the distribution of the average Likert ratings of 40 paintings on visual complexity, in which orange bars refer to representational paintings while blue bars refer to abstract paintings.

Except one painting, *The Bridge*, representational paintings all have lower ratings than abstract paintings.

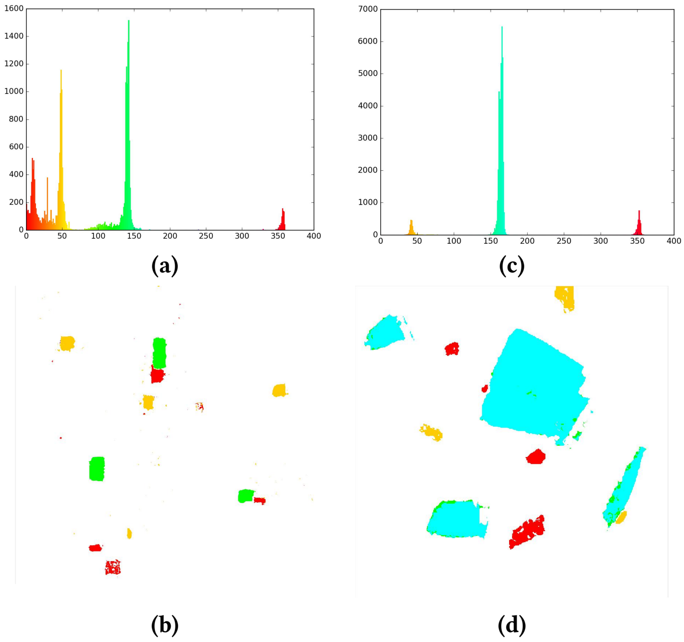


Figure 4: (a) Hue histogram of *Within and Without the Window.* (b) The calculated color regions of *Within and Without the Window.* (c) Hue histogram of *Jasper.* (d) The calculated color regions of *Jasper.*

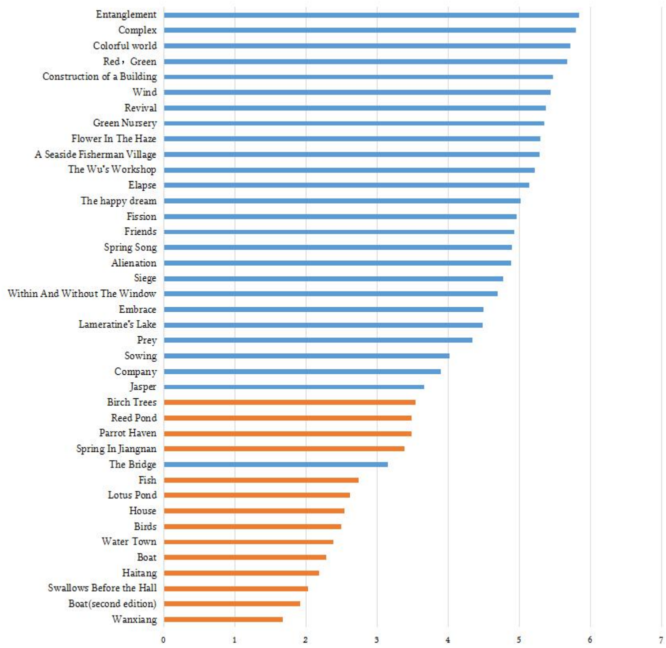


Figure 5: Distribution of the Likert ratings of visual complexity.

5 Regression Model of Perceived Complexity

We assume that different levels of semantic transparency would lead individuals to rely on other pictorial information in their judgment of complexity [Marković 2011; Wallraven et al. 2009]. According to the participants'reported data, semantic components largely influence viewers' perceived complexity. So we categorize our paintings into high vs. low semantic transparency. Then we build two models accordingly to explore the influential factors of perceived complexity, using the calculated color richness, stroke thickness and proportion of white space as independent variables and perceived complexity as a dependent variable.

Abstract paintings do not depict objects in the physical world, leading viewers to pay attention to formal attributes. Therefore, we hypothesize that the three visual attributes would influence the perceived complexity of abstract paintings. The statistics of the regression model are shown in Table 1.

This regression model indicates the three physical predictors explaining 67% of abstract paintings' perceived complexity.

In contrast, representational paintings portray objects in the physical world and provide semantic cues for viewers to organize visual attributes. Color and stroke attributes serve the organizing and sense making purposes. Once viewers recognize the visual objects, they would rarely rely on such attributes. The areas of white space indicating things or certain background scenic information would potentially predict the perceived complexity of representational paintings.

Table 1: Statistics of regression model for abstract paintings using three variables

Model Summary				
R^2=0.715 adj. R^2=0.675 F=17.591 Sig. =0.000				
Variable	*Regression Coefficient*	*Standard Error*	*Significance*	*VIF*
Stroke Thickness	0.317	0.081	0.001	1.114
White Space	-0.265	0.089	0.007	1.174
Color Richness	0.304	0.343	0.01	1.075
Constant	4.82	0.084	0.000	

Therefore, the regression model for the complexity of representational paintings is as below:

$$Complexity = 2.625 - 0.422 \times WhiteSpace \quad (3)$$

The results in Table 2 validate this model.

Table 2: Statistics of regression model for representational paintings using one variable.

Model Summary			
R^2=0.455 adj. R^2=0.410 F=10.023 Sig. =0.008			
Variable	*Regression Coefficient*	*Standard Error.*	*Significance*
WhiteSpace	*-0.422*	*0.133*	*0.008*
Constant	*2.625*	*0.128*	*0.000*

For representational paintings, the variable white space explains 41% of complexity.

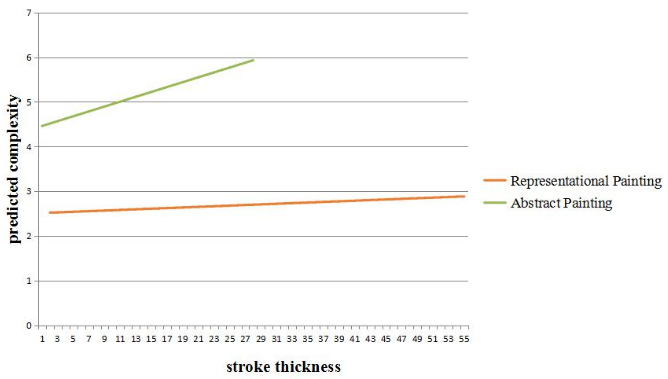
The regression models confirm that viewers judge the complexity of abstract paintings relying on color richness, stroke thickness and white space. They, however, judge representational paintings relying on white space exclusively.

Our further exploration on moderation effect of semantic transparency in the influence of stroke thickness on perceived complexity also provides evidence on the difference in processing abstract paintings and representational paintings (see Fig. 6. (a) and (b)). We build the regression model using stroke, semantic transparency and their interaction as independent variables, and perceived complexity as a dependent variable.

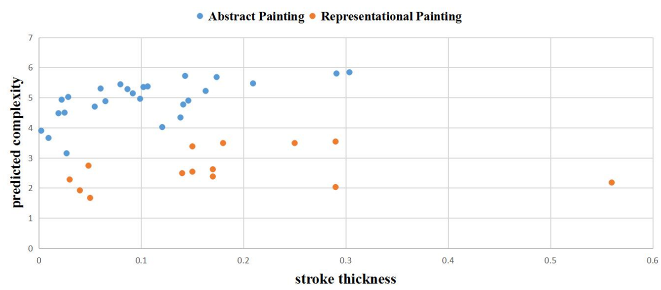
$$\begin{aligned} Complexity = &-1.85 \times Abstraction + 5.45 \times StrokeThickness \\ &-4.76 \times Abstraction \times StrokeThickness + 4.35 \end{aligned} \tag{4}$$

where *Abstraction* is a categorical variable, representing an abstract painting when it is 0 and representational painting when it is 1.

As a result, semantic transparency is confirmed as the moderator of the influence of strokes on complexity (p=.08, significant in 90% interval).



(a)



(b)

Figure 6: Moderation effect of semantic transparency in stroke thickness

6 Conclusion and Discussion

By calculating color richness, stroke thickness and white space in regression analysis, our research distinguishes the influence of objective visual features on perceived complexity. Specifically, all three factors influence the complexity of abstract paintings, and exclusively white space influences that of representational paintings.

Our research gauges visual attributes influencing the complexity of paintings, and provides an objective view to understand viewers' visual information processing, different from the often reported findings in psychology. Comparing to the existing research on objective measurement of paintings, which identifies color attributes as influential factors on the complexity of oil paintings [Guo et al. 2013], our research provides evidences from different genre of paintings, and conceptualizes new factors.

Complementing the findings of the differences in processing representational and abstract paintings in psychology [Marković 2011], we provide empirical evidences to validate such a difference. The results confirm that abstract paintings emphasize on pictorial arrangements while representational paintings focus on depicting reality. High semantic transparency provides meanings as cues to organize visual stimuli, leading to less influence of forms, e.g. color richness and stroke thickness.

Our research explores the influences of attributes in form on perceived complexity when clear semantic meaning is absent or easy to access, and provide insight to the understanding of aesthetics. As indicated in Birkhoff's aesthetic measurement formula: **M** = **O/C**, where **C** denotes complexity and **O** is order [Birkhoff 1933]. Complexity and order are twin poles of aesthetic [Gombrich 1980]. On one hand, people have the desire for complexity to resist boredom [Reber et al. 2004]. On the other hand, they are looking for orders among chaos. Therefore, an ordered complexity is pursued. In our research, the readily accessible semantic meaning provides a quick approach for order, leading to little desire to seek for order using forms. Such an understanding might provide an explanation to support the evolvement of art history, i.e., from representational expressions to the violation against reality. By carefully removing semantic meanings, artists create a detour around to avoid abruption in appreciation of visual forms. Such abruption is likely caused by a quick access to available semantic meanings, consistent with our conclusions.

Our study is limited to Wu's paintings and we plan to include paintings in other genres and validate the general applicability of our conclusions. We aim at eventually being able to predict a painting's complexity. Meanwhile, future work would possibly provide biological evidences to the influences of complexity on the appreciation of paintings with high vs low semantic transparency. To generalize our model in measuring the complexity of a wide range of paintings, we need to take into account many other variables and conduct much larger experiments. This is our long term future work.

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