The Visual Computer
https://doi.org/10.1007/s00371-022-02408-2

ORIGINAL ARTICLE

A comparative study of oil paintings and Chinese ink paintings on composition

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Accepted: 4 January 2022

Abstract

In this study, we compare Western oil paintings and Chinese ink paintings on their composition, by extracting and computing 28 composition features of the paintings, including visual balance and relationships between different regions (segments). Among the extracted segments, we compute average distance and rule-based features based on three layout rules, *rule of thirds*, *golden mean* and *golden triangle*. A total of 2253 paintings including 1138 oil paintings and 1115 Chinese ink paintings are collected. By comparing the results of the features on these paintings, our study investigates the difference and similarity between the two types of paintings on composition. Their composition designs are similar in visual balance and their tendency of composing along two diagonal lines, but are fairly different on many other aspects. For example, oil paintings are inclined to place objects on the bottom horizontal dividing lines of *rule of thirds* and *golden mean*. Having discovered the most important features that can differentiate the two types of paintings, we analyze the differences in the features and discuss their possible relationships to the culture and artists' backgrounds.

Keywords Paintings · Composition · Visual Balance · Layout Rules

1 Introduction

Visual order is one of the important factors influencing aesthetic beauty. It is a multi-faceted concept, considered in different dimensions, such as orientation, color, size, shape, and spatial composition. In this work, we investigate visual order in two types of paintings, oil paintings and Chinese ink paintings, and particularly compare their characteristics in spatial composition.

Different cultures may have different traditions in representing the world via their artworks and thus have varied aesthetic preferences. Existing studies investigate the relationships between various sources of paintings and cultural groups and find a significant interaction between them. Different traditions in paintings' representations influence aesthetic preferences in corresponding cultural groups [1]. Viewers with different cultural backgrounds also have distinct aesthetic experience on the same visual representation [2]. There are comparative studies investigating differences between visual arts, such as comparing abstract and representational paintings on perceptual, semantic and affective dimensions [3], Eastern and Western paintings on aesthetic preference [1]. But few works use quantitative methods to measure and visualize differences between visual arts, i.e., Eastern and Western paintings. By computing layout features, we can map representations of visual arts into mathematical features. It helps us understand cultural preferences at a detailed level, how these preferences are reflected in layouts of paintings, and understand existing art theories from a computational perspective. The layout features that best distinguish certain visual arts can be applied in online galleries and help automatically classify the genres of artworks.

Our study mainly focuses on the difference in the visual order, specifically composition, of Western oil paintings vs. Chinese ink paintings. As discussed in art theory, Western and Eastern artists use different ways to represent what they see in the visual world [4]. Western paintings represent the world

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Published online: 19 February 2022

with a central perspective and pay attention to salient objects in the scene since the Renaissance [5, 6], while Chinese paintings favor a dynamic perspective and mainly focus on the contextual information [7]. Western artists prefer object-centered scenes, while Chinese artists emphasize the context [8].

Interpreting beauty differently, different cultures use their own ways of representations to create aesthetically appealing artworks. To compare the two types of paintings in a uniform fashion, we extract features based on a generally accepted term determining the aesthetic appreciation, i.e., visual order. We focus on one of the most important dimensions of visual order, i.e., composition, and extract features on visual balance, segmental relationships, and layout rules. The extracted features map theory to computation and quantify the cultural differences. We explore the difference between oil paintings and Chinese ink paintings by comparing statistical distributions of the features and evaluate if the results are consistent with the existing subjective intuitions and theories. In summary, this work is conducted in three steps. First, we extract 28 features, in which feature $f_1 - f_2$ measure visual balance, $f_3 - f_6$ are about segmental relationships, while $f_7 - f_{28}$ are based on layout rules. Second, we compare extracted features and discuss their differences and similarities on the two types of paintings. Third, the classification methods are used to classify the two types of paintings and extract features that best distinguish two types of paintings.

Overall, our research contributes to the existing literature by.

- Comparing Western and Chinese paintings on multiple aspects of composition in a quantified way;
- Highlighting the differences of cultural representations and backgrounds in two genres of artworks;
- Shedding light on understanding and computing visual order in the artworks.

In the remainder of this paper, Sect. 2 reviews related work on visual order and composition. Section 3 presents the extracted layout features and Sects. 4 compares these features on two types of paintings. Sections 5 concludes the paper, followed by a discussion on the limitation and future research.

2 Related work

2.1 Visual order

In the fields of perception and psychological aesthetics, order is mainly defined by two variables—symmetry and complexity. Information theory was early used as a conceptual and metric framework for quantitative description of symmetry [9, 10]. Within this framework, symmetry is defined as a means of increasing redundancy by reducing the amount of information that the stimulus pattern carries. According to this approach, the perceptual and cognitive systems prefer redundancy, i.e., symmetrical patterns because they are easily and efficiently processed in the perceptual, memory and cognitive system [10, 11]. Many studies find that aesthetic preference increases linearly with symmetry and other forms of regularity [12–16]. Our work also finds that visual order increases linearly with local symmetry in Chinese ink paintings [17].

Symmetry serves as an effective means of information simplification—the more symmetrical the stimulus pattern is, the more redundant or informationally simple it is, while with decreasing symmetry the pattern becomes more complex [10, 11]. However, symmetry and complexity overlap only partially, for instance, the complexity of a pattern can increase while keeping its symmetry constant. Complexity of visual patterns is standardly defined as a number of different segments of visual patterns [18, 19]. The number and thickness of strokes also positively influence visual complexity of paintings [20].

Starting from the concept of Prägnanz or figural goodness, Gestalt psychologists expect that aesthetic preference increases with symmetry (regularity, order) and simplicity (homogeneity, coherence) in the organization of form or pattern [21–23]. The first attempt to formalize this relationship is found in Birkhoff, who brings the aesthetic measure M into relation with order O and complexity C, so that M increases with O and decreases with C, that is, $M = O/C$ [24]. Birkhoff measures order through symmetry and rectangularity, and complexity through the number of constituent elements of the pattern (number of polygon sides). Based on his study, Hans Eysenck concludes that the empirical predictability of Birkhoff's formula is weak and proposes his own formula according to which the aesthetic measure (M) is a product of order (O) and complexity (C), that is $M = O \cdot C$ [25, 26]. In other words, unlike Birkhoff, Eysenck redefines the role of complexity in aesthetic preference—-complex stimulus leads to increase, not a decrease in liking. The results of numerous later studies support Eysenck's formula [27–30].

Order occurs with respect to different dimensions like orientation, color, size, shape, spatial composition/configuration, etc. [31]. It can also be divided into conceptual and semantic dimensions, or, formal and connotative order [24, 50]. Formal order refers to physical properties of stimulus like repetition, balance, contrast, similarity, while connotative order consists of all properties not only at the formal level. Conceptual and semantic factors are the most important ones that determine aesthetic appreciation [32]. In this study, we solely focus on the conceptual/formal dimension of visual order.

2.2 Composition

Visual composition is a characteristic geometric-spatial arrangement of components within the visual scene. Starting from Ross's idea that the visual field functions as a real physical field [33], Arnheim defines the structural or compositional skeleton of perceptual forces in the visual field [21, 34]. According to Arnheim's study, certain positions within this field are privileged by giving the impression of greater weights of objects placed on them. The weight is determined by various visual properties, such as brightness, color, and density of details: The darker, larger, more saturated and richer in detail an object or region, the greater the weight; bright, pastel colors, tiny shapes and scattered details make the composition lighter [21]. Empirical findings are in line with Arnheim's intuitions showing that the center of mass is dominant, followed by cardinal axes, sides, and so on [35–37].

In addition, aesthetic pleasing composition also emerges when positions in the visual scene follow the layout rules which define the optimal positions to place the focus points of an image. Researchers find the effects of so-called *rule of third* by participants' subjective scores on photographs and paintings [38] and extract rule-based composition in the aesthetic computation on photographs [39, 40]. Compared to laypersons, artists adhere more closely to the so-called *rule of third* when designing composition of abstract art [49]. Also, balance is important in the image composition [21, 41]. Many studies show that participants are sensitive to balance in original works of art, such as Mondrian's works, compared to their modified or disturbed versions of those works [42–44]. The objective balance and deviation of the mass center from the geometric center largely influence subjective preference of images [45, 46]. Balance is not always positively or negatively correlated to aesthetic preference and is interpreted differently depending on the stimulus type [53]. On the photo-sharing platform, Instagram, balance in posted photographs is closely related to the number of Likes, but is negatively related in "2D" photographs and positively in "3D" photographs [51]. In Japanese calligraphies, researchers also find correlation between liking and certain balance measures, but reliable only for atypical calligraphies [52].

3 Composition features

This section describes the features to be computed on Western oil painting and Chinese ink paintings. The results will be compared in Sect. 4.

In visual design, composition is interchangeable with various terms including visual order. The layout of a painting is closely related to visual order and different cultural backgrounds may prefer different compositions. Artists elaborately arrange the objects in artworks to bring them into certain relationships that can create aesthetic beauty, such as the simplicity and unity of the scene, visual balance and symmetry. We extract composition features including visual balance and relationships between different regions. Inspired by the work of composition in photographs [39], we further compute the composition features using the established rules, i.e., *golden mean*, *golden triangles* and *rule of thirds*, as detailed below.

Visual Balance Paintings can be "well-balanced" or "poorly-balanced" and aestheticians are unanimous on picture balance as an important and necessary factor in aesthetic composition [21, 47]. Mass center represents the balance point in an image. Our previous work investigates the influence of Chinese ink paintings' mass centers on visual order and found that paintings not balanced in the exact middle are more ordered than the ones strictly balanced [17]. Chinese ink paintings do not show a preference to balance on the left or right side but their mass centers tend to be off-center vertically and slightly biased toward the bottom. We are interested in learning whether oil paintings have similar preference.

We convert each painting image to grayscale and calculate the coordinates of its mass center using the intensity values (lightness value), along y-axis and x-axis in relation to the physical center of the painting assumed at (0, 0).

$$f_1 = \frac{M_y}{h}$$

$$f_2 = \frac{M_x}{w}$$

where (M_x, M_y) is the mass center.

Segmental relationships Visually depicting united or scattered elements, a painting is composed of a number of connected regions, which will be termed *segments* in the remaining part of the paper. We extract connected regions as segments in each painting and count them as f_3.

The ways these segments are composed is closely related to the aesthetic appeal of a painting [21]. The centroids of segments extracted in f_3 are used to represent the segments' positions and shown in red on a painting in Fig. 1a,b.

To discover the relationships among segments, we compute average distance between the centroids of each pair of segments as f_5 and normalize it by the diagonal length of the painting image as f_4.

$$f_5 = \frac{\sum_{i,j} \sqrt{(C_{x_i} - C_{x_j})^2 + (C_{y_i} - C_{y_j})^2}}{N_{seg}}$$

where (C_{x_i}, C_{y_i}) is the centroid of the i^{th} extracted segment and N_{seg} is the number of segments.

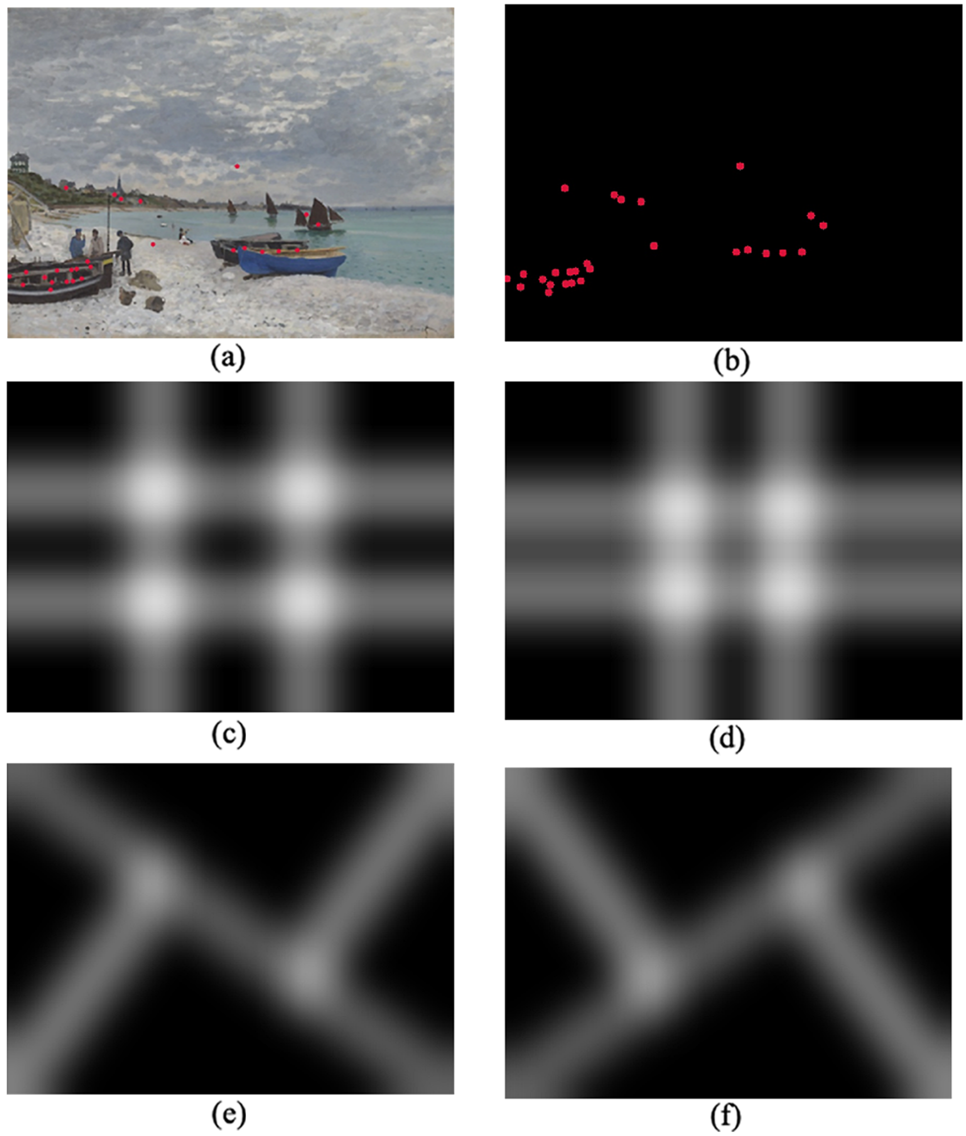

Fig. 1 **a** Image segmentation on the painting, the beach at Sainte-Adresse (centroids of segments are marked in red (**b**)). Rule templates: **c** rule of thirds, **d** golden mean, **e** golden triangles, **f** a rotation of golden triangles

$$f_4 = \frac{f_5}{\sqrt{h^2 + w^2}}$$

where h and w are the height and width of the painting. We compute the circle of equal area size to each segment, centered at the segment's mass center and derive the average shortest distance between them as f_6.

$$f_6 = \frac{\sum_{i,j}\left(\sqrt{(C_{x_i} - C_{x_j})^2 + (C_{y_i} - C_{y_j})^2} - r_i - r_j\right)}{N_{seg}}$$

$$r_i = \sqrt{\frac{S_i}{\pi}}\; r_j = \sqrt{\frac{S_j}{\pi}}$$

where S_i is the area of the ith segment and r_i is the radius of the corresponding circle.

Layout Rules Using the method for photograph composition [39], we compute rule-based features based on three layout rules, *rule of thirds*, *golden mean* and *golden triangles*, to measure the layout of extracted segments. *Rule of thirds* divides an image into nine equal parts by two horizontal and two vertical lines and important objects should be placed along the lines or on the intersections (see Fig. 1c). Widely used in paintings since Renaissance, *golden mean* applies golden ratio ($\varphi = \frac{1+\sqrt{5}}{2} \approx 1.618$) that is first studied by mathematicians in Ancient Greek. *Golden mean* divides an image using similar lines as in *rule of thirds*. Each of four lines divides two parallel sides of the image into two short sides equaling a and two long sides equaling b and $\frac{a}{b} = \frac{b}{a+b} = \varphi^{-1}$ (see Fig. 1d). Rule of *Golden triangles* draws a diagonal line from the top left corner to the bottom right corner and two more lines from the bottom left corner and the top right corner to the diagonal line that intersect

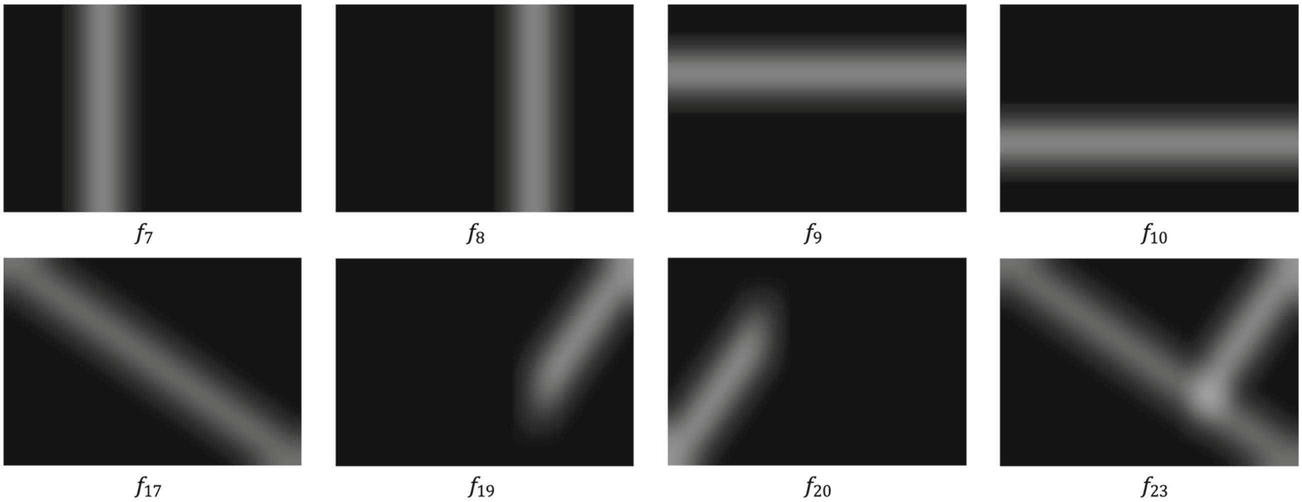

Fig. 2 Rule-based features on one dividing line and on two dividing lines

the diagonal at right angles and create two intersections (see Fig. 1e).

A template is defined for each specified layout rule n and l_n^i defines the i^{th} dividing line in the rule n. It is convolved with a 2D Gaussian kernel with standard deviation $\sigma = \frac{L_{max}}{20}$, where L_{max} is the length of the longer side of a painting image. The composition template is defined as [39]:

$$T_n(x, y) = K \sum_{i=1}^{M} e^{-\frac{x^2+y^2}{2\sigma^2}} \cdot l_n^i(x, y)$$

where K is a normalization factor and M is the number of dividing lines. Then, the layout feature is defined as:

$$f_n = \sum_{j=1}^{N} T_n\left(C_{x_j}, C_{y_j}\right)$$

where N is the number of extracted segments, C_{x_j} and C_{y_j} represent x and y coordinates of the segment j's centroid. It sums up the values of all segments with the centroid of each segment as inputs to $T_n(x, y)$.

Figure 1c, d, e and f illustrate the templates of the three layout rules, and Fig. 1e and f are two rotations of *golden triangles*. We will call the template in Fig. 1e *golden triangles* and that in Fig. 1f a rotation of *golden triangles* in the remaining part of the paper. Twenty-two layout features are extracted on the three rules: five features on *rule of thirds* as f_7–f_{11}, five on *golden mean* as f_{12}–f_{16} and twelve on *golden triangles* as f_{17}–f_{28}. We extract features f_{11}, f_{16}, f_{27} and f_{28} for the entire templates in Fig. 1c, d, e and f, respectively, and also with each of the dividing lines. Figure 2 shows examples of features with one dividing line and with two dividing lines. Feature f_7 only considers the left vertical dividing line of *rule of thirds* and f_8 only considers the right vertical dividing line, while f_9 is measured on the top horizontal dividing line while f_{10} on the bottom horizontal dividing line. Feature f_{11} is computed on the entire template of *rule of thirds* which adds up f_7, f_8, f_9 and f_{10}. Features on *golden mean* ($f_{12} - f_{16}$) take the same sequence as those on *rule of thirds* ($f_7 - f_{11}$). Features f_{17}, f_{19} and f_{20} are computed on each of the dividing lines of *golden triangles* and f_{23} is one of their combinations, which sums up f_{17} and f_{19}.

All of these 28 features are annotated and normalized by the number of segments in each painting in Table 1. Section 4 discusses and compares the results of these features on the two genres of paintings.

4 Results

4.1 Painting set

Our study compares Western oil paintings and Chinese ink paintings on composition. We have collected a total of 2253 paintings including 1138 oil paintings from the Art Institute of Chicago (https://www.artic.edu/collection), National Gallery of Art (https://www.nga.gov/collection/paintings.html) and Artsy (https://www.artsy.net) and 1115 Chinese ink paintings from Artnet (http://www.artnet.com). For a better comparison of two types of paintings, we only select paintings containing obvious semantic meanings, mostly landscape paintings depicting scenery and people. The painting set is available in the online archive.

Table 1 Mean and standard deviation of extracted features on two types of paintings

Feature	Chinese ink paintings		Oil paintings		Feature	Chinese ink paintings		Oil paintings	
	Mean	Std. deviation	Mean	Std. deviation		Mean	Std. deviation	Mean	Std. deviation
f_1: vertical position of mass center	− 0.017	0.063	− 0.029	0.043	f_{15}: bottom horizontal dividing line of *Golden mean*	16.343	15.726	26.037	15.538
f_2: horizontal position of mass center	0.005	0.049	− 0.001	0.024	f_{16}: entire template of *Golden mean*	84.835	26.332	78.239	23.777
f_3: Number of segments	10.990	12.435	24.080	17.161	f_{17}: diagonal line of *Golden triangle*	38.383	22.699	22.053	12.937
f_4: normalized average distance between segments	0.189	0.087	0.279	0.079	f_{18}: diagonal line of rotated *Golden triangle*	40.566	22.913	22.533	13.516
f_5: unnormalized average distance between segments	72.233	41.843	137.115	44.849	f_{19}: dividing line from the top right corner to the diagonal of *Golden triangle*	4.570	8.362	8.471	8.669
f_6: average shortest distance between segments	50.092	24.776	85.560	27.342	f_{20}: dividing line from the bottom left corner to the diagonal of *Golden triangle*	5.969	9.666	12.199	10.280
f_7: left vertical dividing line of *Rule of thirds*	19.087	13.416	14.966	10.549	f_{21}: dividing line from the top left corner to the diagonal of rotated *Golden triangle*	4.091	7.705	8.250	8.333
f_8: right vertical dividing line of *Rule of thirds*	20.890	15.129	15.206	11.008	f_{22}: dividing line from the bottom right corner to the diagonal of rotated *Golden triangle*	5.309	8.438	11.947	9.678
f_9: top horizontal dividing line of *Rule of thirds*	12.113	13.910	15.576	11.794	f_{23}: combination of f_{17} and f_{19}	42.953	23.756	30.524	15.434
f_{10}: bottom horizontal dividing line of *Rule of thirds*	14.022	15.305	26.935	16.203	f_{24}: combination of f_{17} and f_{20}	44.352	23.281	34.252	15.224
f_{11}: entire template of *Rule of thirds*	66.112	21.942	72.684	21.388	f_{25}: combination of f_{18} and f_{21}	44.657	24.180	30.784	15.693
f_{12}: left vertical dividing line of *Golden mean*	26.659	15.316	17.223	11.464	f_{26}: Combination of f_{18} and f_{22}	45.875	23.247	34.481	15.393
.f_{13}.: right vertical dividing line of *Golden mean*	26.805	15.670	17.106	11.496	f_{27}: entire template of *Golden triangle*	48.922	24.919	42.724	16.633
f_{14}: top horizontal dividing line of *Golden mean*	15.027	14.771	17.873	12.572	f_{28}: entire template of rotated *Golden triangle*	49.967	25.026	42.731	16.690

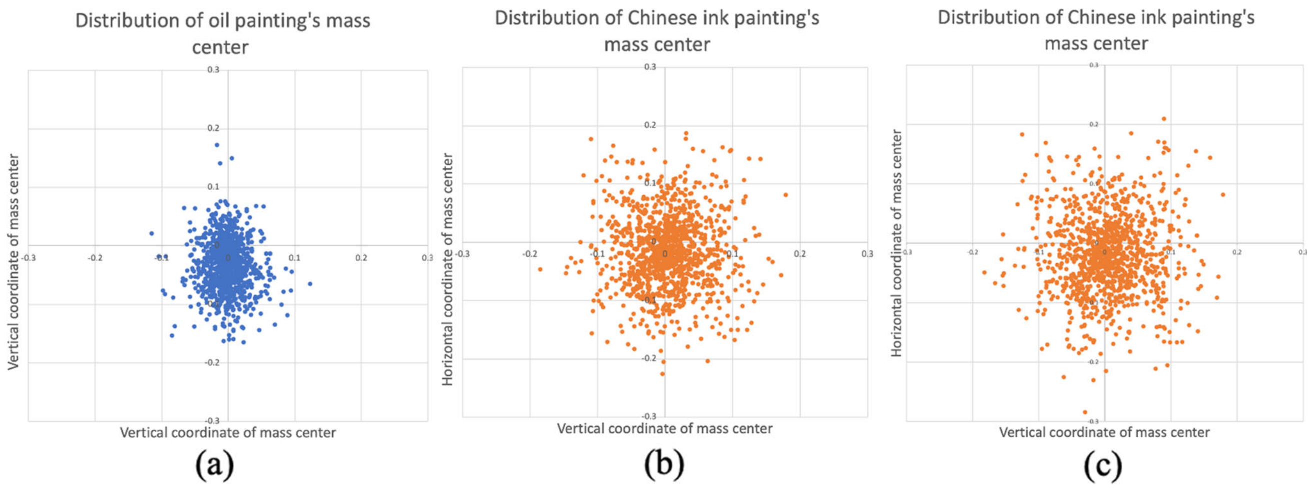

Fig. 3 The distribution of coordinates of mass centers in two types of paintings

4.2 Comparison on features

Table 1 reports the mean and variance of each feature, and Fig. 4 illustrates the distribution of feature values on the two types of paintings.

Features f_1 and f_2 represent the mass center of a painting. Figure 3 shows the distributions of mass centers of the two types of paintings. Chinese ink paintings tend to place the balance points slightly below the paintings' physical centers, consistent with the experimental results of our previous work [17]. In Fig. 3b, 690 of 1138 Chinese ink paintings place the mass centers below their physical centers while 425 paintings' mass centers are above the centers. This preference is more obvious in oil paintings, 845 of 1115 oil paintings place their mass centers below their physical centers. Comparing the distributions of the two types of paintings in Fig. 3a,b and the plot in Fig. 4a, mass centers in Chinese ink paintings are more evenly distributed and more off-center than oil paintings. The average distance of mass centers to the physical centers of Chinese ink paintings is 0.0669 while that of oil paintings is 0.0465.

Chinese ink paintings include special components, inscriptions and seals, frequently found to be interspersed with pictorial imagery of Chinese ink paintings and can be unfamiliar to western viewers. An inscription is a narrative text/calligraphy that an artist writes on a painting. Together with pictorial imagery, an inscription tells an entire story and expresses the emotion and mind of the artist. Seals are stamps with artists' names, or meaningful words when not placed on the bottom left. Inscriptions and seals help balance composition in paintings. In our collected painting set, 934 of 1138 Chinese ink paintings include inscriptions. We remove these inscriptions and seals and re-compute the paintings' balance points and Fig. 3c shows the distributions. Generally, 709 of 934 paintings' centers of gravity become further away from their physical centers after eliminating the inscriptions and seals.

Feature f_3 counts the number of segments in a painting. As shown in Table 1 and Fig. 4b, Chinese ink paintings (mean = 10.990, std. dev = 12.435) include fewer number of segments than oil paintings (mean = 24.080, std. dev = 17.161), implying that, the former have simplified visual compositions and contain a few segments while the latter are composed of plentiful details and many segments.

Features f_4, f_5 and f_6 reflect the relationships among extracted segments by measuring their mutual distances. The distribution of feature values in Fig. 4b implies that segments in oil paintings are more visually scattered than those in Chinese ink painting. The average distance between segments in oil paintings (f_4: mean = 0.279, std. dev = 0.079; f_5: mean = 137.115, std. dev = 44.849; f_6: mean = 85.560, std. dev = 27.342) is higher than that in Chinese ink paintings (f_4: mean = 0.189, std. dev = 0.087; f_5: mean = 72.233, std. dev = 41.843; f_6: mean = 50.092, std. dev = 41.843).

Features $f_7 - f_{28}$ are based on the three layout rules, whose distributions are shown in Fig. 4c, d, e and f. If a feature on a dividing line ($f_7 - f_{10}$, $f_{12} - f_{15}$, $f_{17} - f_{22}$) in a rule template has a value higher than other features, the centroids of segments are closer to this line than others. In order to check if the two types of paintings have different preferences to compose along certain dividing lines in each of the layout rules, in Table 2, we count the number of paintings having the largest values among all the features on one dividing line, grouped by layout rules.

In the template of *rule of thirds*, oil paintings are more inclined to place objects on the bottom horizontal dividing line (f_{10}), while Chinese ink paintings tend to compose along two vertical dividing lines (f_7 and f_8). 602 of 1115 oil paintings have the largest value in f_{10}, significantly higher than 192 for Chinese ink paintings, while 369 and 400 of

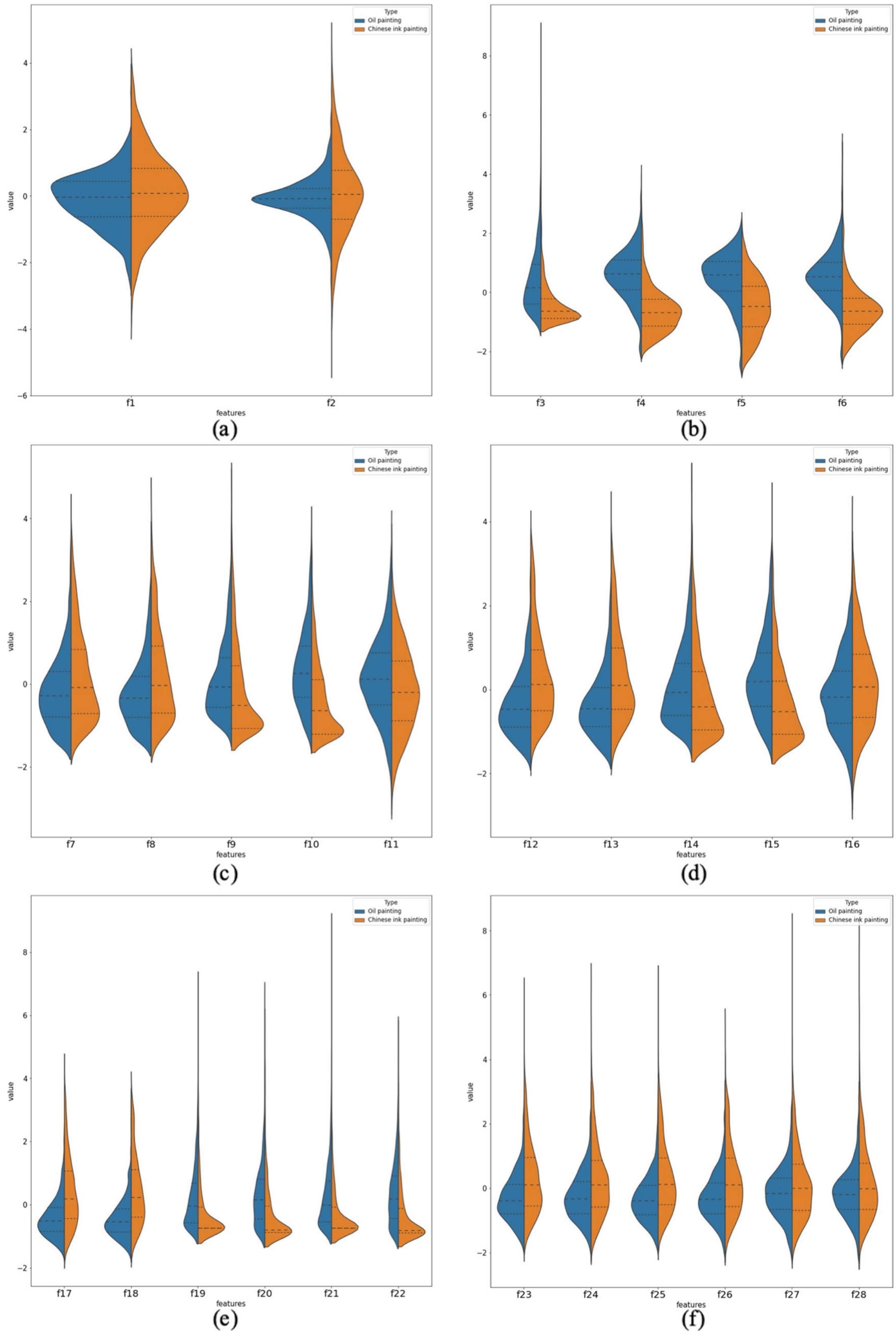

Fig. 4 Distribution of feature values of Oil paintings (blue) and Chinese ink paintings (orange)

Table 2 The number of paintings composed along dividing lines in each of the layout rules

Layout rule	Rule of thirds				Golden mean				Golden triangles					
Feature	f_7	f_8	f_9	f_{10}	f_{12}	f_{13}	f_{14}	f_{15}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}
Chinese paintings	369	400	154	192	405	399	136	175	501	572	10	17	6	9
Western paintings	142	164	230	602	189	194	237	518	427	412	44	99	56	100

Table 3 The number of paintings composed along the dividing lines in all three layout rules

Feature	f_7	f_8	f_9	f_{10}	f_{12}	f_{13}	f_{14}	f_{15}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}
Chinese paintings	25	42	27	41	93	86	40	60	334	360	2	5	0	0
Western paintings	32	27	56	281	58	64	92	139	109	132	10	14	11	13

1138 Chinese ink paintings have the largest values in f_7 and f_8, respectively. Features on the template of *golden mean* ($f_{12} - f_{15}$) also show consistent results.

In the template of *golden triangles* and its rotation, the two types of paintings show the same tendency in composing along two diagonal dividing lines. This is evidenced by 1073 of 1138 Chinese ink paintings and 839 of 1115 oil paintings that have the largest values in f_{17} and f_{18} among all the other features. Furthermore, Fig. 4e shows that the values of f_{17} and f_{18} in Chinese ink paintings distribute on higher ranges than those in oil paintings, implying that the former tend to be closer to the dividing lines than the latter. It also shows the values of $f_{19} - f_{22}$ with slightly opposite results.

Table 2 compares the importance of each of the dividing lines within each layout rule. Table 3 shows the number of paintings having the largest values on one dividing line among all features of the three layout rules. By comparing these dividing lines together, we find that two diagonal dividing lines have stronger influence than other dividing lines in Chinese ink paintings; and in oil paintings, the lower horizontal dividing line in *rule of thirds* is the most dominant one.

Considering the three layout rules, features f_{11}, f_{16}, f_{27} and f_{28} do not differ significantly in their value distributions on the two types of paintings (see Fig. 4c, d, f). This implies that neither culture may prefer a specific layout rule.

4.3 Distinctive features

As we compare features in Sect. 4.2, two types of paintings are apparently different on certain features. Though not focusing on classification of the two types of paintings in this work, we use classification techniques to check if our selected features can distinguish the two types of paintings. Using 70% of the painting set as training data and 30% as testing data, we use four machine learning methods, Random forest, XGBoost, KNN, and GBDT, to classify the paintings. Table 4 shows that the computed features can classify the two types of paintings in consistent accuracies.

Table 4 Accuracy of different classification techniques

Method	Accuracy
Random forest	0.8314
XGBoost	0.8372
KNN	0.8373
GBDT	0.8476

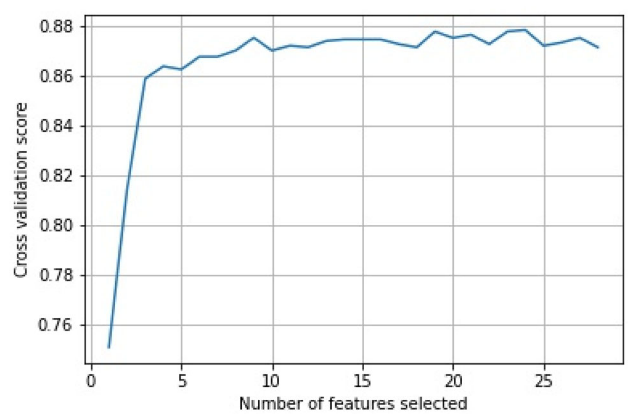

Fig. 5 Cross validation score of recursive feature elimination

We use recursive feature elimination (RFE) with random forest to find the most important features in classification. RFE assigns weight to each feature and eliminates the feature with the least importance from the feature set. Then, it repeats this process and re-evaluates feature importance until an optimal combination of features is found. A total of 2253 paintings are used for classification. Figure 5 shows scores of recursive elimination with cross validation and nine is an optimal number to achieve good accuracy. The 9 top features are: f_2, f_3,f_4, f_5, f_6, f_9, f_{10}, f_{13}, f_{18}. These features combined could best distinguish oil paintings and Chinese ink paintings.

5 Conclusion and discussion

Different cultures may demonstrate different aesthetic preferences in artworks [1]. Our study investigates the difference and similarity between Western oil paintings and Chinese ink paintings on composition. Their composition designs are similar in visual balance, but are fairly different on many other aspects, as described in Sect. 4, relevant to their cultural backgrounds.

The balance points of most of the collected paintings are slightly below their physical centers. This should be attributed to the typical spatial arrangements of objects in a vertical manner, distant objects are drawn in the upper part and nearby objects appear in the lower part. Landscape oil paintings prefer geometrically correct representations of real scenes by painting the sky and cloud in the upper part of the canvas and foreground objects like boats, rivers, trees, streets and people in the lower part. Chinese ink paintings use white space to represent the sky and cloud and put them in the upper part. So the two types of paintings are visually light in their upper parts.

Since the Renaissance, Western artists have explored the criteria in visual displays by developing mathematical rules to organize spaces and objects to create precise spatial layouts. Chinese paintings, however, do not follow rules and geometrically correct representations but emphasize dynamic arrangements of spatial information [48]. Our experimental results show the distinct preferences of composition in the two types of paintings. Oil paintings tend to place objects near the bottom dividing lines in the *rule of thirds* and *golden mean*, while Chinese ink paintings do not show the same tendency on these two rules but tend to compose along diagonals. Emphasizing a dynamic structure, Chinese artists place the main objects on one side of diagonal of canvas to create a strong contrast and bring viewers a feeling of change and dynamics.

Despite the proclaimed importance of mathematical rules in artistic composition, different cultures produce different artistic representations and aesthetic preferences. It is hard to find a uniform and universal composition criterion that is applicable to all types of paintings. For example, existing study in psychology finds the layout rule, *rule of thirds*, playing only a minor role in large sets of high-quality photographs and paintings [38]. Although the visual quality of a painting could degrade if its objects deviate from dividing lines and intersections, it may still be aesthetically appealing if it has a balanced layout.

Our study explores the visual order in composition on two types of paintings. Visual order can also be reflected on other dimensions, such as color harmony, shape, symmetry, and size. These other dimensions of visual order are to be studied in our future work. Only focusing on order in the objective dimension and ignoring the semantic meanings, we extract segments in the paintings and investigate the relationships and organizations between them. Meaningful objects in a painting could play a more significant role than simple segments and how easy viewers can recognize the objects influences the connotative visual order. In the future work, we plan to investigate the semantics of various objects in paintings.

Funding Not applicable.

Data availability The data that support the findings of this study are available from the first author, Zhen-Bao Fan, upon reasonable request.

Declarations

Conflict of interest Not applicable.

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