CHARACTERIZING ELEGANCE OF CURVES COMPUTATIONALLY FOR DISTINGUISHING MORRISSEAU PAINTINGS AND THE IMITATIONS

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ABSTRACT

Computerized analysis of paintings has recently gained interest. The rapid technological advancements and the expanding interdisciplinary collaboration present us a promising prospect of computer-assisted authentication. We focus on the characterization of curve elegance. Specifically, we propose measures of curve steadiness and neighborhood coherence from brushstrokes. The technique has been applied to the paintings of renowned aboriginal Canadian artist Norval Morrisseau. Through computerized analysis of his authentic works and the imitations, it is revealed that the curves in his authentic paintings exhibit his commanding painting skills. The smooth and steady flow of the curves show less hesitancy of the artist than the authors of counterfeit works. The tangent angles tend to be more consistent along curves in the authentic paintings than in the imitations.

Index Terms— Image analysis, image line pattern analysis.

1. INTRODUCTION

The art forgery industry has become increasingly sophisticated to target the growing number of art collectors. Factories with assembly lines have been established to forge paintings from well-known artists. Relatively skillful painters and modern technologies are involved in making counterfeits. Despite the use of modern technologies, such as carbon dating, lead dating, X-rays, multispectral imaging, and cross-section microscopy, authenticating visual art is still an open problem.

A connoisseur can tell the authenticity of a painting by analyzing the emotions expressed by the artist. Authentic paintings often stimulate higher emotional responses than forgeries. Traditional painting authentication is a highly subjective and sophisticated appreciation process. Art historians utilize various heuristics and theories [1]. For instance, color, brushwork and composition are some important factors considered in artist attribution, dating, and painting style identification.

In computerized painting analysis, many problems lead to one main issue, that is, numerical characterization of paintings. The numerical features of paintings provide evidence for attribution and can be used for other purposes, e.g., retrieval. One type of digital signature of a painter is based on brushstrokes [1, 4, 6, 5]. The techniques of depiction, such as shading and glazing, suggest that texture-like features may be appropriate for brushstroke analysis [2, 1]. Existing work in the literature is mostly based on analyzing the characteristics of brushstrokes. However, some paintings, such as those by Norval Morrisseau (1932–2007), do not have clearly visible brushstrokes. A new technique has to be developed.

In this paper, we used curves as the main visual content clues. We developed an automated method to detect curves resulting from brushstrokes. Measures of steadiness and neighborhood coherence have been developed and tested on real-world paintings, both authentic ones and forgeries. We found that our measures are good indicators of elegance and skillfulness.

We applied our techniques to the works of Norval Morrisseau, an aboriginal Canadian artist, as well as some known imitations. Figure 1 shows some examples in the dataset. Morrisseau, known as "Picasso of the North," was arguably the greatest aboriginal artist ever to have lived in North America. His subject matter addressed the protection of the environment long before global warming entered our mainstream consciousness. We photographed dozens of authentic paintings and paintings which the artist himself stated as counterfeit using both a digital SLR camera and a medium-format slide film camera.

2. CHARACTERIZING ELEGANCE OF CURVES

Various traits of brushstrokes are by far the main subject for computational comparison of digitized fine art paintings, in large part due to the fact that brushstrokes have been

The material is based upon work supported in part by the National Science Foundation and The Pennsylvania State University. The authors would like to thank the Kinsman Robinson Galleries, Canada, the Norval Morrisseau Heritage Society, Canada, the city of Toronto, Richard H. Baker, John Newman, Paul C. H. Robinson, and John Zemanovich for their assistance.

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Fig. 1. Example authentic and counterfeit paintings from the dataset related to Norval Morrisseau, a native aboriginal painter from Canada.

Fig. 2. Curve detection and linking applied to a painting.

considered to form unique "signatures" by art historians. Although focusing on strokes diminishes the complexity of painting analysis, stroke extraction itself can be a daunting task, the difficulty of which varies tremendously among painters. How strokes were laid down in some paintings can be hard to discern even for human eyes.

In the case of Morrisseau, because he used primitive approaches to painting, specifically, modeling by light and shade does not exist, and edges are always crispy, it is relatively easy to extract the painted areas (which can be the result of one or multiple strokes). Through edge detection, the contour lines of the brushstrokes can be reliably extracted. In our study, we use contour curves acquired by edge detection as the main visual clue in order to capture the painter's artistic characteristics.

A close observation of some works of Norval Morrisseau and several forgeries left us the impression that Morrisseau's work is extraordinary in design and line quality. His lines appear both swift and steady, and the design of figures in his paintings appears harmonious and peaceful. While curves in the forgeries tend to be hesitating and jagged, and the designs lack aesthetics. To quantify such difference, we first find the contour lines by edge detection.

We use the EDISON edge detection algorithm to obtain edge maps for paintings [3]. Input parameters of the algorithm are adjusted so that most of the contour lines are extracted by the program, while edges of low contrast such as within-stroke edges and noisy edges are not detected. An edge linking procedure is applied on edge maps to remove short edges and record coordinates of the pixels along curves in the right order (Figure 2).

2.1. Measure of Curve Steadiness

Fig. 3. The edge map of a counterfeit painting.

Figure 3 shows the edge map of a forgery. Many contour lines are jagged. This observation leads us to believe that the extent of jaggedness in the contour curves reflects the steadiness of the painter's hand. A painter of great draftsmanship, especially one that masters line work like Morrisseau, distinguishes himself from unskillful painters in this quality.

We characterize the steadiness of curves using the extent of jaggedness. Figure 4 illustrates the basic ideas. The pixels of interest are highlighted by red circles. In the first case, the spanning angles of a corner point tend to decrease as the spanning edge increases. For a point at the tip of a spiky curve, the spanning angles tend to increase. While in the last case, for a point in a zigzag curve, the spanning angles tend to vary unmonotonically.

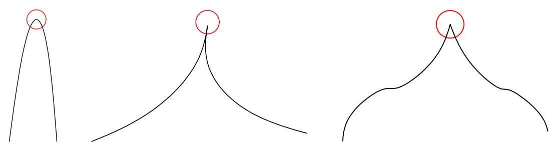


Fig. 4. Edge points under different conditions.

Denote a straight line segment connecting two points i and j by $L_{i,j}$. At a given spanning length k, to compute the spanning angle at edge point i, $L_{i-k,i}$ and $L_{i,i+k}$ are formed. The angle between the two is then called the spanning angle of i at spanning length k. Let $\beta_i^{(k)}$ represent the spanning angle for point i on a curve when the spanning length is k. The value of k is set to 3, 5, and 7 respectively. So we have three sequences of spanning angles for each curve. The measure for steadiness is defined as the ratio of points whose spanning angles across spanning lengths (or scales) do not vary monotonically. Again, let i be the index for points on a curve, and j the index for curves in a painting. Define

$$d_i' = \beta_i^{(5)} - \beta_i^{(3)} , \quad d_i'' = \beta_i^{(7)} - \beta_i^{(5)} .$$

Let s_i be the indicator whether d_i' and d_i'' have the same sign. Then

$$r_j = \frac{\sum_i s_i}{length(j)} ,$$

where $length(j)$ is the length of the jth curve (number of points contained). Finally, the measure for the overall painting is the mean of r_j:

$$m_1 = mean(r_j) .$$

2.2. Measures of Coherence by Tangent Directions

We define two measures to characterize the coherence of tangent directions of curves. The tangents along the detected curves are estimated approximately by the sum of the backward and forward vectors. If the spanning length is k, the backward vector is pointing from the $(i-k)$th point to the ith point and the forward vector is from the ith point to the $(i+k)$th point. We estimated the tangent direction of the ith point by the sum of these two vectors. Similar to the color histogram, we use tangent angle histogram to describe tangent distribution of the curves in a painting. If the curves in a painting appear to flow in similar directions, the histogram tends to have high peaks in some bins. Otherwise, a random distribution of tangents is more likely to give a balanced histogram. In the tangent angle histogram, y axis represents the ratio of points whose tangent angles fall in the range of the bin. Since the exact tangent direction of majority points is unimportant, only the variance of the ratios are used to describe the distribution of tangents.

The aforementioned measure describes the flow of curves in a global way. We now attempt to characterize tangent coherence locally. For each edge point, we check other edge points in its neighborhood. If the tangent angle difference between the current point and the neighboring point is below a threshold, we claim the neighboring point is coherent with the current point. In this way, we can calculate the ratio of coherent neighboring points for any point on a curve, and use the average ratio as a coherence measure for the painting.

The first measure of coherence m_2 is to characterize the distribution of tangent angles. The angles range from -180 °to 180°. The tangent angle histogram is divided evenly into 24 bins. The descriptor we use is the variance of the 24 bins in the histogram. For the second coherence measure, let s_j represent the ratio of neighboring points which are coherent with the jth point, t_j be the tangent angle, n_j be the number of neighboring edge points, T be the threshold of coherence which is set to be 15 in our experiment, and n be the total number of points. Define

$$s_j = \frac{\sum_{k=1}^{n_j} I(|t_j - t_k| < T)}{n_j} , \; m_3 = \frac{\sum_{j=1}^{n} s_j}{n} .$$

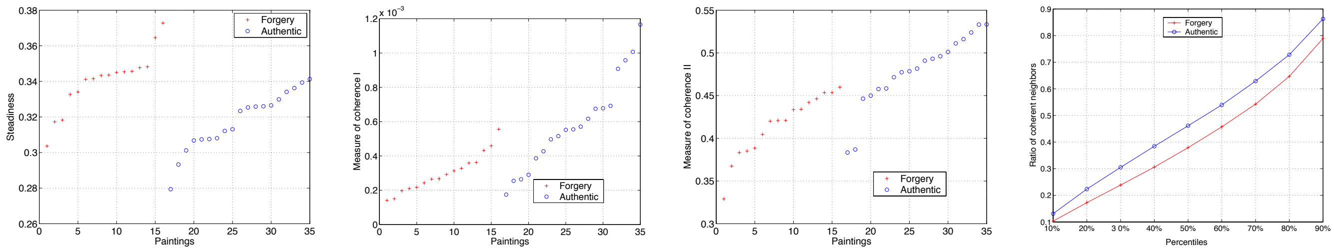
To demonstrate authentic paintings have better neighborhood coherence, we also analyze the percentiles of coherence ratios (coherence measure II). The $p\%$ percentile is a value that is greater than $p\%$ of the coherence ratios. Experiment results show that authentic works do have greater percentiles than forgeries, which means the coherence ratio distribution of authentic ones tends to be more left-skewed.

2.3. Classification Results

We compute the steadiness and the coherence of contours for 35 digitized paintings, among which 19 are authentic Morrisseau and 16 are forgeries as confirmed by Morrisseau himself. Figure 5 shows the values of these measures. Clearly, most paintings of Morrisseau have better values for the three measures (i.e., smaller m_1 and greater m_2 and m_3).

Percentiles are calculated for the coherence ratios from which we obtained the second coherence measure. In order to see the difference, we do a 95% 2-sample t-test for the 9 percentiles as well as the three measures mentioned above. The results for the t-tests are given in Table 1. The first column of the table shows different measures we calculated, among which $10\% - 90\%$ are the percentiles and m_1, m_2, m_3 are measures for steadiness and coherence. Figure 5(d) shows the 9 percentiles.

In order to further demonstrate the distinguishing power of the features, we do a cross-validation using the SVM$^{\text{light}}$ [7]. Features are normalized to have zero means and unit variances. Default parameters provided by the program are used for training. We divide the 35 paintings into four groups through random permutation of painting indices. Each of the first three groups has four forgeries and five authentic



(a) Steadiness (b) Coherence I (c) Coherence II (d) Percentiles of coherence ratios

Fig. 5. Calculated measures for the 19 Morrisseau paintings and 16 forgeries. Values in (a)-(c) are sorted.

Table 1. Results of 2-sample t-test

	Forgery	**Genuine**	**Difference**	**P-value**
10%	0.10326	0.13096	-0.027697	0.003
20%	0.17271	0.22356	-0.050856	0.000
30%	0.23864	0.3052	-0.066522	0.000
40%	0.3061	0.3843	-0.078155	0.000
50%	0.3790	0.4613	-0.082282	0.000
60%	0.4574	0.5396	-0.082218	0.000
70%	0.5426	0.6290	-0.086442	0.000
80%	0.6467	0.7280	-0.081236	0.000
90%	0.7895	0.8628	-0.073310	0.000
m_1	0.3403	0.3177	0.022556	0.000
m_2	0.000299	0.000589	-0.000289	0.000
m_3	0.41514	0.47846	-0.063318	0.000

Table 2. SVM cross-validation error rates

Test group	**Error on training set** misclassified / total	**Error on test set** misclassified / total
1	1/26 or 3.8%	2/9 or 22%
2	4/26 or 15%	0/9 or 0%
3	3/26 or 12%	0/9 or 0%
4	2/27 or 7.4%	2/8 or 25%

paintings while the fourth group has four forgeries and four authentic works. Each experiment involves one group as the test set and the other three as the training set. Table 2 provides the results of the cross-validation experiment.

3. CONCLUSIONS AND FUTURE WORK

We have developed an approach to characterize steadiness and coherence of contour lines in paintings. Existing techniques on painting authentication have been primarily based on brushstroke characteristics and cannot be applied to certain styles of paintings when individual brushstrokes are not clearly visible. We argue that the steadiness of the contour lines reflects the draftsmanship of a painter in line work. And the coherence measures we defined can be used to distinguish the authentic works from the forgeries. Paintings by Morrisseau and forgeries are analyzed. It is found that Morrisseau's paintings consistently demonstrate higher level of steadiness and coherence in curves.

Whereas the techniques demonstrate their power on this dataset, they may be insufficient in identifying skillfully forged paintings. A study involving forgeries from additional sources will be desired. Finally, it is clear that the presented techniques may not be suitable for analyzing some styles of paintings. We plan to further study the applicability of these techniques for other painting styles.

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