Oil Painting Classification

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Abstraction

In this project, a neural network-driven digital image processing method is studied to identify and classify the oil paintings. Traditionally, this authentication work is often entrusted to human experts, whereas it is becoming harder with even more forgeries emerging. Based on the previously contributions of digital image processing and neural network methods, I believe the combination will given us a better and possibly practical solution. To replace the human work with algorithms, we could process a large amount of data at same time and obtain the most objective results. Furthermore, different feature selection procedure would ensure us with a certain degree of flexibility.

Keywords: **feature extraction, Fourier Transform, Wavelet Transform, statistics, covariance, neural network, Multi Layer Perceptron (MLP)**

I. INTRODUCTION

The Paintings are of great values in art as well as the history. The 18^{th} – 19^{th} century period is the most productive epoch in terms of all kinds of oil paintings, the emerging of abstract expressionism, cubism, impressionism, etc., have given us a lot to learn and appreciate. It was probably not very later that art forgeries appeared after the value of paintings has been discovered [1]. It then becomes significant for art experts to identify various paintings of different painters. Traditionally, these approaches are accomplished by human labors, in terms of identifying the signatures of painters, deducing the date of the paintings, studying the canvas producers and recognizing the brushwork of painters.

However, with even growing amount of forgeries, it is becoming more difficult to distinguish the authentic works by merely human experts. Fortunately, based on the differences among painters in terms of canvas textures, pigments, and brushstroke styles [2], it has been discovered that the mathematical analysis of the digital representation of paintings could assist the art experts in this authentication work [3], [4]. Recently, the painting identification by digital image processing techniques has become popular and various approaches have been proposed [4] – [6].

Although the ultimate goal is for authentication as mentioned before, in this project, I will focus on distinguishing different paintings from the same painter from each other. More specifically, an eight X-rayed paintings from Leonardo da Vinci will be used as my data base, for each of the paintings, features will be extracted and a certain dimension of testing space will be built. Based on these spaces, a randomly chose testing space will be formed by using the same dimension of features. Next, the Multi Layer Perceptron Method will be employed to execute the whole classification procedure. The classification results will be provided at the end, and future work is expected due to the limitation of data and method in this pilot project.

One important point is that distinguishing the paintings of the same painter is intuitively more difficult that authentication. The reason is that one painter tends to use similar approaches to paint even if these paintings may not even related to each other. However, my confidence is because a painter may not use the exact same brushes, canvases, and painting styles for different paintings. The variances exist. And also a worth-mentioning issue is that the authentication result may be better than that of this project, i.e., classification of paintings that are from the same painter.

II. APPROACH

Generally there are three steps, patch selection, feature extraction, and neural network build and test, I will introduce each step in the following sections.

1) Patch selection

Patches are selected randomly from the X-rayed paintings, two kinds of patches are selected, 50 by 50 pixels and 100 by 100 pixels. For convenience, they will be called patch 1 and patch 2 in the following statement. For each of the two kinds of patches, 25 patches will be selected to build the space for patch-wisely feature selection.

2) Feature extraction

To achieve a generally satisfied classification result, one of the crucial steps is feature selection [7], [8]. A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a patter. Features are use to represent patterns with the goal of minimizing the loss of important information. Features are very important that they must satisfy the following requirements [9]. First, intra-class variance must be small, which means the features extracted from different patches of the same painting should be close (e.g., numerically close if numerical features are selected). Secondly, the inter-class separation should be large, i.e., features extracted from different patches of different paintings should be independent of the size, orientation, and location of the pattern. This requirement can be tested by randomly choose the patches from the paintings.

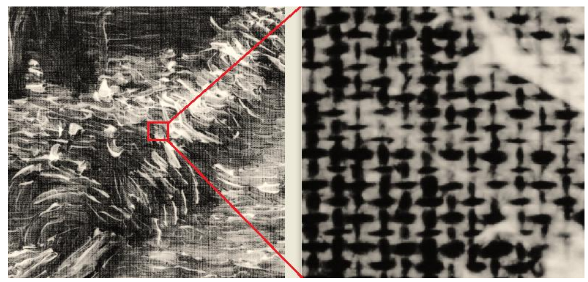

Fig. 1. Brush work of Leonardo da Vinci

An example is shown in the above figure, by the left figure of Fig. 1, we could observe the brushwork of painter; by the micro-view figure (right), we could observe certain weaving style of the canvas. The following four features are well-representing these structures.

i) *Fourier Transform*

Fourier transform is one of the most important approaches for feature extraction. It can describe the brushwork of the painting in terms of frequency representation in the frequency domain. More specifically, smaller brush strokes will have higher frequencies, which could be observed by extracting the indices of corresponding large frequency values.

For continuous function, the Fourier Transform and Inverse Fourier Transform is defined as

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt$$

$$x(t) = \int_{-\infty}^{\infty} X(f) e^{j2\pi ft} df$$

For discrete signals, the definition of Fourier series is

$$x(t) = \sum_{n=-\infty}^{\infty} x_n e^{j2\pi \frac{n}{T_0} t}$$

$$x_n = \frac{1}{T_0} \int_{\alpha}^{\alpha+T_0} x(t) e^{-j2\pi \frac{n}{T_0} t} dt$$

where the x_n is the Fourier Coefficients.

ii) *Wavelet Transform*

The Wavelet Transform is designed to address the problem of non-stationary signals. It represents a function in time domain in terms of simple fixed building blocks, termed wavelets.

The wavelet transform can be categorized into continues and discrete. The Continuous Wavelet Transform (CWT) is defined as [10]

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^{*}(t) dt$$

where x(t) represents the analyzed signal, a and b represent the scaling factor (dilatation/compression coefficient) and translation along the time axis (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation. $\psi_{a,b}(\bullet)$ is obtained by scaling the wavelet at time b and scale a:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right)$$

The normalized wavelet and scale basis functions $\varphi_{i,l}(k), \psi_{i,l}(k)$ can be defined as

$$\varphi_{i,l}(k) = 2^{i/2} h_i (k - 2^i l)$$
$$\psi_{i,l}(k) = 2^{i/2} g_i (k - 2^i l)$$

where the factor is an inner product normalization, i and l are the scale parameter and the translation parameter, respectively. The Discrete Wavelet Transform (DWT) decomposition can be described as

$$a_{(i)}(l) = x(k) * \varphi_{i,l}(k)$$
$$d_{(i)}(l) = x(k) * \psi_{i,l}(k)$$

where $a_{(i)}(l), d_{(i)}(l)$ are the approximation coefficients and the detail coefficients at resolution i, respectively.

iii) *Statistical Momentum*

One of the simplest approaches for describing texture is to use statistical moments of the gray-levels and let $p(z_i), i = 0,1,2,...,L-1$, be the corresponding histogram, where L is the number of distinct gray levels. The n-th moments of z about the mean is:

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i)$$

where m is the mean value of z (the average gray level):

$$m = \sum_{i=0}^{L-1} z_i p(z_i)$$

It is worth-mentioning that the second moment (the variance $\delta^2(z) = \mu_2(z)$) is of particular importance in texture description. It is a measure of gray-level contrast that can be used to establish descriptors of relative smoothness.

For a 2-D continuous function $f(x,y)$, the moment of order (p + q) is defined as

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy$$

for p, q = 0, 1, 2, ….

The central moments are defined as

$$u_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy$$

where

$$\bar{x} = \frac{m_{10}}{m_{00}}, \bar{y} = \frac{m_{10}}{m_{00}}$$

If $f(x,y)$ is a digital image, the above equation becomes

$$u_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y)$$

iv) *Covariance Matrix*

The Covariance Matrix is a good descriptor to boundaries and regions; it can be used as the basis for describing sets of images that are registered spatially, but whose corresponding pixel values are different (e.g., the three component images of a color RGB image).

The covariance matrix of the vector population is defined as

$$C_x = E\{(x-m_x)(x-m_x)^T\}$$

Because x is n dimensional, the C_x and $(x-m_x)(x-m_x)^T$ are matrices of order n by n.

3) Multi Layer Perceptron

A Multi Layer Perceptron is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. MLP utilizes a supervised learning technique called back propagation for training the network.

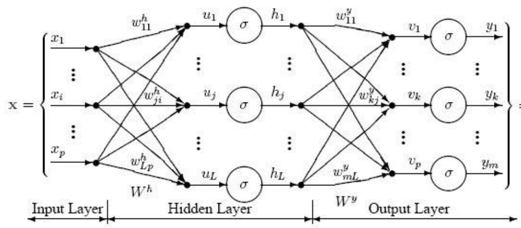

Fig. 2, A structure view of MLP

Figure 2 is a typical MLP network structure. Using back propagation, the weights are updating after each epoch. For weight w connecting to the output layer, we have

$$-\frac{\partial E}{\partial w_{ij}^{(L)}} = -\sum_{k=1}^{K} \frac{\partial E}{\partial z_i^{(L)}(k)} \frac{\partial z_i^{(L)}(k)}{\partial w_{ij}^{(L)}}$$

$$= \sum_{k=1}^{K} [d_i(k) - z_i^{(L)}(k)] f'[u_i^{(L)}(k)] \frac{\partial u_i^{(L)}(k)}{\partial w_{ij}^{(L)}}$$

$$= \sum_{k=1}^{K} \delta_i^{(L)}(k) z_j^{(L-1)}(k)$$

where the delta-error is defined as

$$\delta_i^{(L)}(k) \equiv \frac{\partial E}{\partial u_i^{(L)}(k)}$$

$$= [d_i(k) - z_i^{(L)}(k)] f'[u_i^{(L)}(k)]$$

For weight $w(l)$ connecting 1st and $l-th$ layer, we have

$$-\frac{\partial E}{\partial w_{ij}^{(L)}} = -\sum_{k=1}^{K} \frac{\partial E}{\partial u_i^{(L)}(k)} \frac{\partial u_i^{(L)}(k)}{\partial w_{ij}^{(L)}}$$

$$= \sum_{k=1}^{K} \delta_i^{(l)}(k) z_j^{(l-1)}(k)$$

Here the delta error for the internal layer is also defined as

$$\delta_i^{(l)}(k) \equiv \frac{\partial E}{\partial u_i^{(l)}(k)}$$

To sum up, for the Feed-forward pass

$$z_0^{(l-1)} \equiv 1$$
$$z_i^{(l)}(k) = f(u_i^{(l)}(k))$$
$$u_i^{(l)}(k) = \sum_{j=0}^{N} w_{ij}^{(l)}(t) z_i^{(l-1)}(k)$$

and the delta error (in Error-back-propagation pass) as shown below

$$\delta_i^{(l)}(k) = \begin{cases} f'\left(u_i^{(l)}(k)\right) \cdot \sum_{m=1}^{N(l+1)} \delta_m^{(l+1)}(k) \cdot w_{mi}^{(l+1)}(t), l < L \\ f'\left(u_i^{(l)}(k)\right) \cdot [d_i(k) - z_i^{(L)}(k)], l = L \end{cases}$$

and the weight update pass: for k = l to K, l = 1 to L, i = l to N(l),

$$-\frac{\partial E}{\partial w_{ij}^{(l)}(t)} = \sum_{k=1}^{K} \delta_i^{(l)}(k) z_j^{(l-1)}(k)$$
$$w_{ij}^{(l)}(t+1) = w_{ij}^{(l)}(t) - \eta \frac{\partial E}{\partial w_{ij}^{(l)}(t)} + \mu(w_{ij}^{(l)}(t) - w_{ij}^{(l)}(t-1))$$

III. RESULT

1) Experimental result

The final testing result is shown in figure 3.

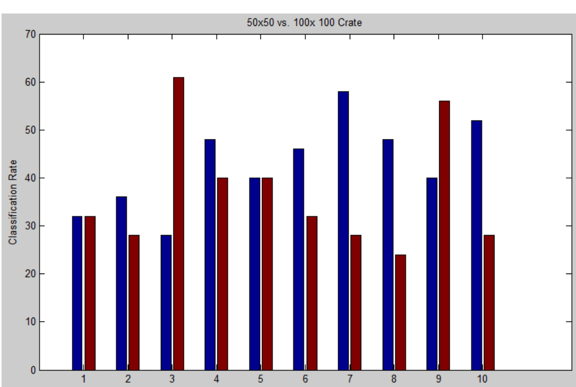

Fig. 3, Comparison of two kinds of patches

In the above figure, the blue bars represent the classification rate of patch 1, while the red bars represent that of patch 2. Generally speaking, I have achieved a classification rate range from 40% to 60%. And furthermore, we can observe that, patch 1 based space will give us a more promised and stable results than patch 2 space does, and the best classification rate of patch 1 is achieved by choosing the number of neurons in hidden layer to be 6 – 8. One of the reasons is that there are totally eight classes of data.

2) Future work

This experiment has some limitations on the data and methods. Hence, I could improve the final result by doing the following: firstly, the real colored paintings could be used, rather than the grey level images I used here; secondly, more features are expected to better represent the characteristics of the painting, e.g., higher orders of wavelet transform are expected; thirdly, more neural network approaches are to be tested, and hopefully, a better network structure would be explored.

IV. CONCLUSION

In this project, I accomplish a pattern classification work of several oil paintings from Leonardo da Vince. The result suggests that by my method, it is possible to distinguish paintings from each other. The advantage of this digital image processing method is that we could processing large amount of data simultaneously with a certain level of satisfied result. Furthermore, it is possible to do the painting authentication based on this method, and the result is expected to be better.

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