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SEPARATION OF ORIGINAL PAINTINGS OF MATISSE AND HIS FAKES USING WAVELET AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In recent years, with the latest developments in computer technology, wavelet and Artificial Neural Networks (ANN) are being widely used in different fields and disciplines. Especially, wavelet followed by ANN applications has produced successful results in image processing. In this paper, we have applied wavelet followed by ANN to obtain an objective approach in seperating original paintings of Matisse and fakes. In art environment, the term of fake can be explained as producing new paintings resembling to the artist's painting style. The works of Matisse have been especially chosen since his paintings are mostly faked. Here, wavelet is utilized for feature extraction of 2D paintings. Thus, important properties of input image are extracted while reducing input parameters with minimum loss of information. ANN is then applied in separation process between paintings. At the end of the overall separation task, we obtained 88 % classification accuracy.

Keywords: *Henri Matisse, Painting separation, Wavelet transform, Artificial Neural Networks*

1. INTRODUCTION

In recent years, many image processing algorithms are started in evaluation of 2D paintings as new developments are involved in computer technology. There are many studies about classification problem in 2D images [1- 4]. One of the main problems in art researches is the separation of paintings with similar criteria i.e. same art movement, same century, masterpieces, fakes and visual content etc [1, 2]. Another main problem in art researches is art forgery. Art forgery refers to creating and, in particular, selling works of art that are falsely attributed to be work of another, usually more famous artist.

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Here are a few available techniques used against art forgery. The first and commonly use of them is carbon-14 dating used to measure the age of an object up to 10,000 years old [5]. The other is "White Lead" dating used to determine the age of an object up to 1,600 years old [6].

To detect the work of a skilled forger, investigators must rely on other methods such as digital authentication. Using the technique called wavelet decomposition can be a new method to detect forgeries. Using wavelet decomposition; a picture is broken down into a collection of more basic images called sub-bands.

These sub-bands are analyzed to determine textures, assigning a frequency to each sub-band. Then these data are used as input into Artificial Neural Networks for testing.

For this testing, the works of Matisse have been used since its high ratio of fakes. He was born in 1869 at Northern France. He obtained a diploma in law and worked as a lawyer's assistant for a period of time. In 1896, he exhibited four paintings at the *Salon de la Societe Nationale* and sold two of them [7].

In this paper, Matisse and his fakes are separated by two consecutive approaches; wavelet and ANN in evaluation of high capacity 2D painting images. In high resolution images, one step direct image processing is almost impractical because of time consuming long iterations. The first approach is based on compression with minimum loss via feature extraction. The second is classification of original Matisse paintings and his fakes by ANN, where extracted features are taken as input.

We have proposed a supervised classifier to construct and evaluate Matisse's paintings and his fakes done by different forgers. We have transformed the raw data of the images into a wavelet basis, and then used special sets of the coefficients as the features tailored by ANN towards separating each of those classes. At first, we have acquired original and fake paintings of Matisse as in Figure 1. To achieve separation, we have extracted essential features from paintings using Discrete Wavelet Transform (DWT) [8, 9]. In wavelet approach, we have chosen (mean, minimum, maximum, variance, standart deviation) values of approximation, vertical, horizontal and diagonal wavelet coefficients of the whole paintings. Then these 20 feature vectors were taken as input of ANN structure. Thus, both compression and unification is achieved with constant length of vector for various paintings with different sizes. The overview of our system is shown at Figure 2.

2. MATERIAL

We focus on original and fake paintings of Matisse and try to separate original and fake paintings objectively and automatically using Wavelet and ANN approaches consecutively. In this section, artististic works of Matisse and fakes of him will be given, which helps us to identify the problem.

Matisse produced an enormous volume of work in fouvist styles. He created thousands of paintings, prints and sculptures during his life [7, 10-12]. There are also lots of fake of Matisse. He was especially faked by Elmyr de Hory who was a well-known art forger of the 20^{th} century. He eventually became known worldwide as one of the most talented and greatest art forger. The Hungarian art forger claimed to have sold lots of fakes to galleries and museums around the world during his career. His insistence that he had passed off paintings by such artists as Picasso, Modigliani and Matisse caused a scandal in the world of art and its experts. We used some fakes of Matisse from de Hory for training and testing. Here, we have chosen 60 original painting images from fouvist period of Matisse and 15 fakes.

3. METHODS

In this section, wavelet and ANN will be explained. The main mathematical formulas of each will be given.

3.1. WAVELET BASED FEATURE EXTRACTION

Wavelets decompose data into different frequency sub-bands components and then study each component with a resolution matched to its scale. Wavelets have come out as powerful new mathematical tools for analysis of complex datasets. In classical approach, Fourier transform provides representation of an image based only on its frequency contents. Hence this representation is not spatially localized while wavelet functions are localized in space. While Fourier transform groups a signal into a spectrum of frequencies whereas the wavelet analysis decomposes into a hierarchy of scales ranging from the coarset scale. Hence wavelet transform which provides representation of an image at various resolutions is a better tool for feature extraction from images [4, 13]. The wavelet transform is a useful mathematical tool that currently has received a great attention in different applications like compression and feature extraction. Feature extraction is defined that extraction some important features from the image and obtaining feature vector. Wavelet transform is used as a feature extractor in this study.

Since our raw data is discrete, we use Discrete Wavelet Transform which employs a discrete set of the wavelet scales and translation obeying some defined rules as an implementation of the wavelet transform. Here, both of scale and translation parameters are discrete. Thus, DWT can be represented in Eq.(1),

$$W[m,n] = \sum_{x} f[x]\psi_{m,n}[x] \tag{1}$$

where, discretized scale and translation parameters are given by, $a = 2^j$ ve $b = k2^j$ ($k, j \in Z$). Then, wavelet basis function is writen in Eq.(2),

$$\psi_{j,k}[x] = 2^{-j/2}\psi(2^j x - k) \quad (2)$$

One-dimentional transforms are easily extended to 2-dimensional functions like images. In this case, the DWT is applied to each dimension separately. This yield a multiresolution decomposition of the image into four subbands called the approximation (low frequency component) and details (high frequency component). The approximation (A) indicates a low resolution of the original image. The detail coefficients are horizontal (H), vertical (V) and diagonal (D). Figure 3 presents process of painting image being decomposed into approximate and detailed components.

At each decomposition level, the length of the decomposed image is half the length of the signal in the previous stage. The first level decomposition of an $N \times N$ image is $N / 2 \times N / 2$ and the second level decomposition is $N / 4 \times N / 4$.

3.2. ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Artificial Neural Network is also highly parallel systems that process information through many interconnected neurons that respond to inputs through modifiable weights, thresholds and mathematical transfer functions. Each unit processes the pattern of activity it receives from other units, than broadcasts its response to still other units. An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns [14]. A unit in the output layer determines its activity by following a two step procedure:
First, it computes the total weighted input x_j, using the formula:

$$X_j = \sum_i y_i W_{ij} \quad (3)$$

where y_i is the activity level of the j^{th} unit in the previous layer and W_{ij} is the weight of the connection between the ith and the j^{th} unit.

Second, the unit calculates the activity y_j using some function of the total weighted input. Typically we use the sigmoid function:

$$y_j = \frac{1}{1 + e^{-x_j}} \quad (4)$$

Once the activities of all output units have been determined, the network computes the error *E*, which is defined by the expression:

$$E = \frac{1}{2}\sum_i (y_i - d_i)^2 \quad (5)$$

Where is the activity level of the j^{th} unit in the top layer and di is the desired output of the j^{th} unit.

4. EXPERIMENTAL RESULTS

Wavelet coefficients of 75 (60 originals, 15 fakes) images are calculated. After decomposition with Discrete Wavelet Transform, we have four coefficients for each image; approximation, vertical, horizontal and diagonal. Level-1 DAUB4 and HAAR type wavelet decompositions are preferred. The first level decomposition vector size is too large to be given as an input to a classifier. Since high dimensional of feature vectors increased computational complexity and hence, in order to reduce to dimensionality of the extracted feature vectors, statistics over the wavelet coefficients are used. Then the following statistical features were chosen as follows;

- Maximum values of the approximation, vertical, horizontal and diagonal coefficients
- Minimum values of the approximation, vertical, horizontal and diagonal coefficients
- Mean values of the approximation, vertical, horizontal and diagonal coefficients
- Variance values of the approximation, vertical, horizontal and diagonal coefficients
- Standard deviation values of the approximation, vertical, horizontal and diagonal coefficients.

The computed statistical features of discrete wavelet coefficients are used as the inputs of the network of ANN. The output of the model was defined as 0 for original paintings of Matisse and 1 for fakes. In this paper multilayer perceptron (MLP) ANN was used and we treat the separations of painting images between original and fakes as a two class pattern classification problem. MLP-

ANN was trained and tested Backpropagation learning algorithms. For the training, the most suitable network configuration found was 15 neurons in hidden layer. 5 statistical features for each subband coding, totally 20 inputs for each painting were used. On the other hand, ANN structure has 20 input neurons, 15 hidden neurons and 1 output, in other presentation it can be modeled as (20, 15 ,1). ANN structure is given in Figure 4.

During the training procedure; we considered 20 different features of 50 paintings as input set. In testing procedure; we chose 20 different features of the remaining 25 paintings. We reached 88 % correct estimation in testing stage with HAAR type wavelet coefficients.

5. CONCLUSION

In this study, we have classified paintings of original Matisse and his fakes with the help of wavelet transform and ANN, which are used for feature extraction and supervised machine learning approaches. We have preferred wavelet type is Level-1 Daub4 and Haar after experimental study. Since, in the first level decomposition, the vector size is too large to be given as an input to ANN. So only some statistics of first level wavelet coefficients are used as an input of ANN. These are; {maximum, minimum, mean, variance and standard deviation values of the approximation, vertical, horizontal and diagonal coefficients}. Our experimentation showed that classification accuracy has reached up to 88 % by HAAR type Wavelet. This statistic suggests that our combined approach may be used to facilitate separation from orginal painting to its fakes.

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FIGURES

Henry Matisse, "The Music Lesson" (La lecon de musique), 1917, Oil on canvas, 96 3/8 x 79 in. (244.7 x 200.7 cm) Barnes Foundation, Merion, PA © Succession H. Matisse, Paris	**Elmyr de Hory**, "Fake of Matisse"

Figure 1. Overview of the similarity

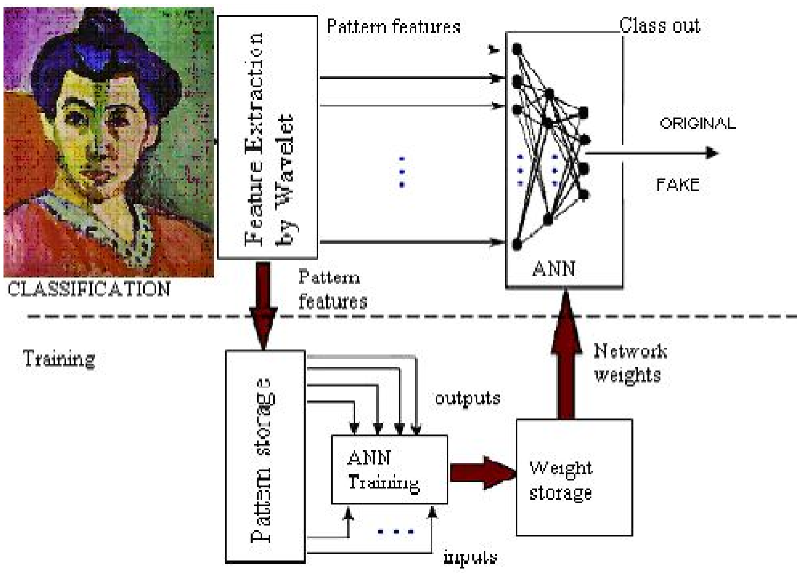

Figure 2. Overview of the separation system.

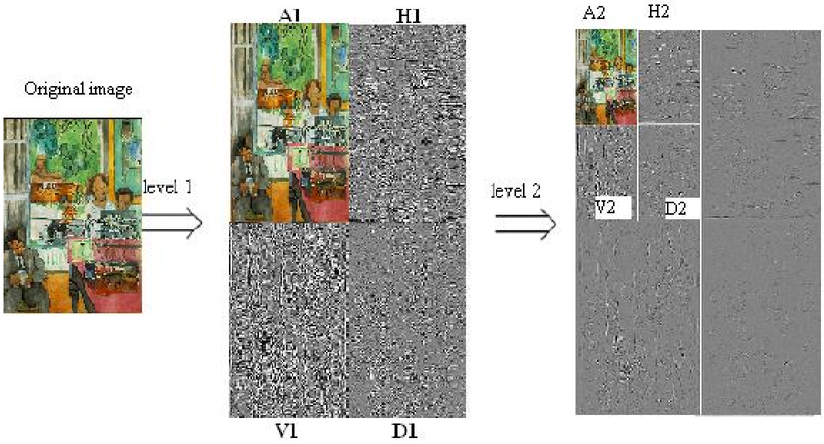

Figure 3. One and Two Level Decomposition of Pantings with DWT

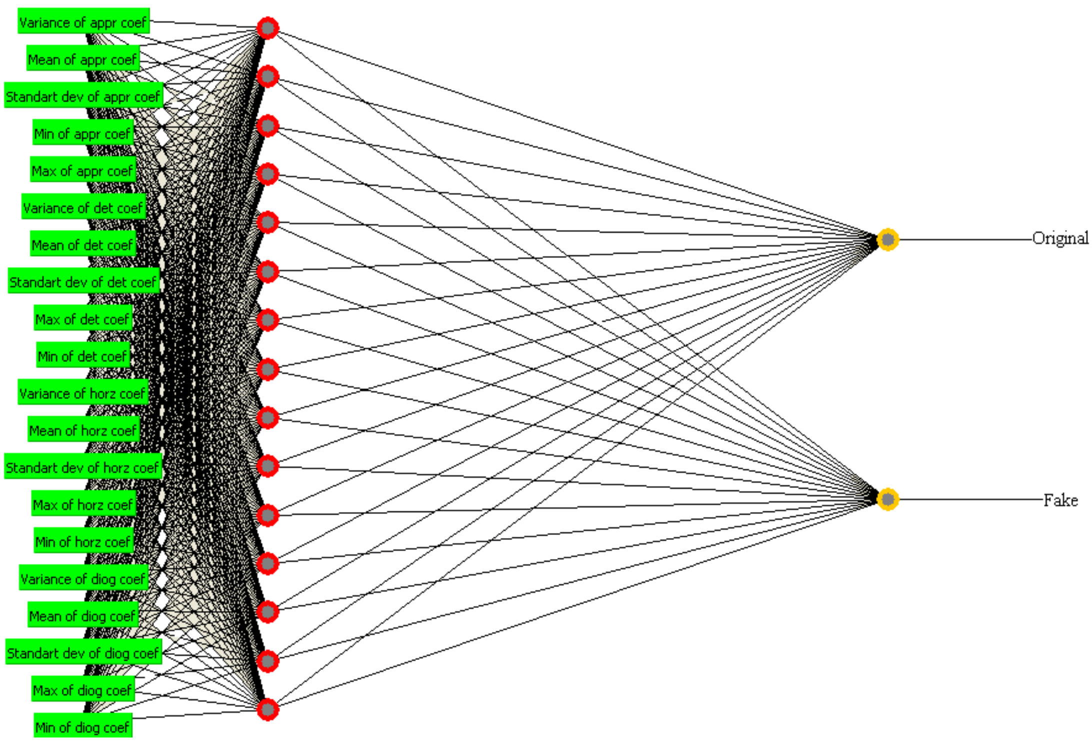

Figure 4. ANN Structure (20,15,1)