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Towards Automatic Painting Authentication

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Abstract

This work investigates pattern recognition techniques that can be used to identify the author of fine art paintings. The methodology proposed consists of four sequential phases: image acquisition, segmentation, feature extraction, and classification. Brushstrokes are segmented assuming that hue is uniform within a single brushstroke. Using a wavelet-based technique, textures are measured and used as features to describe the brustrokes in the painting. Classification is performed through two distinct non-parametric algorithms: Fuzzy KNN and Kohonen Map. A system was built to evaluate the proposed approach in discriminating between two different painters. A database consisting of images from 31 paintings was used in the experiments. The system was able to attain a recognition rate better than 99%.

Keywords: wavelet transform; computer vision; authentication; KNN fuzzy, neural network, Kohonen maps, pattern recognition

1 Introduction

Signature and calligraphy have been used for decades as a particular sign of an individual. Underlying these methods is the fact that every person has its own singular way of moving the hand while writing. Therefore it's reasonable to think that every painter has its own way of striking the painting board with his brush, leaving a personal pattern of "geographical accidents", which could be used to identify him or her.

This reasoning gives birth to the idea of applying computer vision to recognize patterns specific to each painter. Some previous studies exploring this idea have been done producing interesting results [i].

This paper presents the preliminary results of a method to establish the authenticity of fine art paintings. A new procedure for segmenting the strokes on a painting along with a texture measurement technique to capture the signatures on the strokes is proposed. Moreover, the work investigates the use of non-parametric classification procedures to discriminate between potential authors. The proposed method is evaluated in a set of experiments with the goal of discriminating between two well-known Brazilian painters: Portinari and Bianco.

The research on methods for authorship recognition is one of the activities in the Portinari Project [ii] that has organized the digitization of over 5000 paintings, other printed documents and audio material to create a multimedia database.

The paper is organized in the following way. Section 2 presents the proposed methodology and a general description of the proposed system. Section 3 describes the experiments performed to evaluate the method. Section 4 presents the conclusions obtained from this work

2 Methodology

2.1 General System Description

Figure 1 presents the sequential steps to recognize painting authorship. The first step is the image acquisition. Segmentation is performed in the second step. It aims at locating regions in the image containing a single brushstroke. The algorithm proposed assumes that regions with a small hue variation are entirely enclosed in a brushstroke. The subsequent step consists of measuring texture attributes from each segmented brushstroke. By applying a wavelet approach, ten-dimensional texture vectors are obtained.

The final decision concerning the authorship of a painting is taken by a classifier based on the texture information obtained in the previous step. Two classifiers were considered in this work: a Fuzzy KNN algorithm, and Kohonen Maps.

These steps are now described in detail.

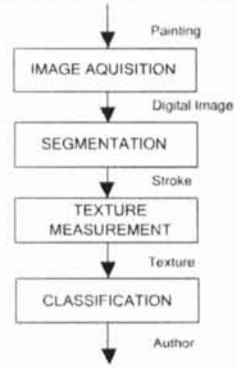

Figure 1: Sequential tasks performed by the author identification system

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2.1 *Image Acquisition*

In the present work the images of paintings were obtained with traditional color film, using a macro lens to select small regions. The same magnification was used for all paintings, which were subsequently digitized with the same resolution

2.2 *Segmentation*

In this step, areas from the painting image are selected where one expects to find the signs of authors identity. This work assumes that such "signs" are contained in contiguous regions of the painting having low hue variation. Although it does not correspond accurately to the usual meaning of the term, such areas are called in this text brushstrokes. The segmentation of brushstrokes involves the following steps:

1. Divide the close up image in blocks of 32×32 pixels;
2. Change the color space from RGB to HSV, picking up only the hue component.
3. Use the region-growing algorithm based on the standard deviation of hue in each block, to find regions with uniform hue.

2.3 *Wavelet Based Texture Measurement*

The texture of the brushstrokes obtained in the procedure outlined in the previous section is measured on the hue component using a wavelet based approach, as described in full detail in [iii] and [iv].

Wavelets are short duration waves with zero mean value. They can be scaled and translated, breaking two-dimensional images into different scales to obtain greater or lower information of some image detail. When global image information is required, larger scales are used while lower scales are used for detail information.

Different from a continuous transform, the discrete wavelet transform is computed using scales and positions given by powers of two.

Texture is measured by using a pyramidal algorithm [v] that applies low-pass and high-pass filters to the original image generating four sub-images as shown in Figure 2. The original image is the input to a column low-pass filter and to a column high-pass filter. The output of each filter is applied to two further row filters producing four outputs: a) the approximation, b) the horizontal detail, c) vertical detail, and d) diagonal detail. Each time a wavelet filter is applied, a down sampling of the output images is performed so that the total amount of data points is kept constant.

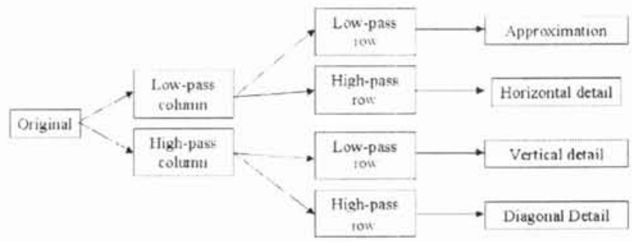

Figure 2: Pyramidal algorithm for texture measurement

This pyramidal algorithm can be applied recursively to the output of the low-pass filter, called image approximation (a). The output produced after each new execution of this algorithm is called a level. Texture attributes are obtained by computing the variance, standard deviation, entropy or any other similar measurement over the outputs b) to d) of each level.

In this work three levels of analysis were used, each of them producing three variance measurements for horizontal, vertical and diagonal texture characteristics. There is also a last value corresponding to the variance of the final image approximation. Therefore, the texture of a block from a brushstroke is represented in this work by a ten-dimensional texture vector.

In this work the Daubechies orthogonal wavelets [vi] were used. They are constructed based on orthogonalization and factorization conditions. They have compact support, are non-symmetric but work with a wide range of tensorial moments.

The vector describing a single brushstroke is given by averaging the texture vectors of its blocks.

2.4 *Classification Procedures*

This work explores two distinct classification procedures for comparison purposes. The first classification procedure uses the fuzzy KNN Classifier **[vii].**

The conventional K-Nearest Neighbor (KNN) algorithm consists basically of measuring the distance between the patterns of an unknown class and every training pattern, and choosing the class that has the highest number of representatives among the K nearest ones.

The fuzzy version of KNN does not assign the input pattern to a single class, but produces instead category memberships for all classes.

The membership $u_i(\mathbf{x})$ of a pattern $\mathbf{x}$ in relation to the class i is computed with the formula [viii]:

$$u_i(\mathbf{x}) = \frac{\sum_{j=1}^{K} u_{ij} \left(\frac{1}{\|\mathbf{x} - \mathbf{x}_j\|^{\frac{2}{(m-1)}}} \right)}{\sum_{j=1}^{K} \left(\frac{1}{\|\mathbf{x} - \mathbf{x}_j\|^{\frac{2}{(m-1)}}} \right)} \qquad (1)$$

where u_{ij} is 1 if the j-th neighbor belongs to class i, and is zero otherwise, and m is the fuzzy exponent which defines the fuzziness level of the classifier.

The second classification procedure applied is a neural network approach known as Kohonen Maps. These nets consist of a two dimensional layer of nodes connected to all the inputs. Each node is connected to the neurons contained in its N_4 neighborhood. The classification decision is based on the topological maps formed by the neurons that were activated during the training phase of the network. This map corresponds to the division of the feature space between the pattern classes. A full description of Kohonen Maps can be found in [ix].

Both classifiers assign a class to each brushstroke. The individual classification results of each stroke must be combined to produce a classification result for the entire painting. Different strategies can be employed for this purpose [x]. The investigation of such strategies in the context of paintings authorship identification is beyond the scope of this work. In this work a voting algorithm was applied that favors the class having the largest number of brushstrokes assigned to it.

3 Results

Experiments were performed to estimate the system ability to discriminate between paintings according to their authorship, using the methodology described above.

3.1 Database

Ideally, the database should include images both from authentic and fake paintings. Since forgeries were difficult to obtain, paintings from a Portinari disciple, named Bianco, along with genuine Portinaris were used in the evaluation. It is expected that the disciple has used the techniques that he learned from his master, so that their paintings would be similar in some sense. Images from 23 Portinaris and 5 Biancos were used in the experiments.

In the average 9 regions with 768x512 pixels were cropped from each painting, resulting in a total of 252 samples from Portinari and 45 samples from Bianco. Such regions are denoted hereafter as macro-strokes. During the process of digitization care was taken so that the pixel size was approximately the same for all paintings. The segmentation step generated:

- 1199 strokes in 23 paintings of Portinari, and
- 280 strokes in 5 paintings of Bianco.

Figure 3 shows an example of the result produced by the segmentation algorithm.

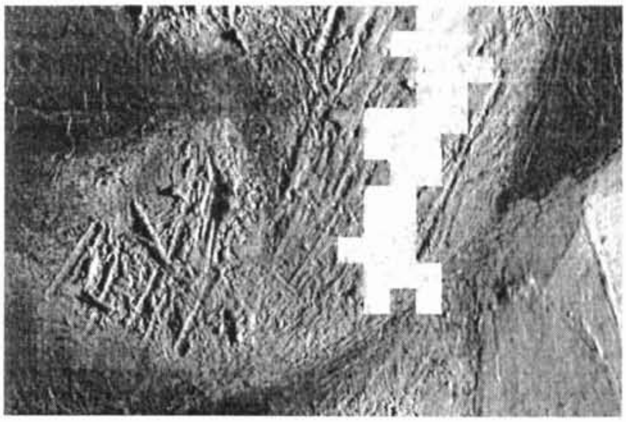

Figure 3: Example of the result produced by the segmentation algorithm

The training data used in the evaluation consisted of 196 samples from each painter selected randomly among the available strokes produced by the segmentation. The strokes not selected for training were used for validation.

3.2 System Performance

In all experiments to evaluate the system performance a training set and a validation set were built according to the following procedure.

From the brushstrokes obtained by the segmentation step from Bianco paintings, 70% were randomly selected as training patterns. The same amount of brushstrokes from Portinari paintings was randomly taken for training. The remaining brushstrokes from both painters were used for validation.

This procedure was performed 100 times for the Fuzzy KNN classifier, each time using a different random choice of training and validation patterns.

Table 1 shows the average results obtained in these experiments. The first column on the left indicates the true author, while the next column presents the proportion of correctly classified paintings in each case. The system was able to recognize the true painter for 99.8% and 97.48% of the paintings from Bianco and Portinari, respectively.

The third column contains the average recognition rates for brushstrokes. Even though these rates are below the values obtained for painting recognition they still indicate that the texture of the segmented brushstroke actually encloses some characteristic that is particular to each painter.

The last two columns on the right show the standard deviations of the recognition rate for paintings as well as for brushstrokes. These rates reveal that the system performance is quite insensitive to the particular choice of the training and validation patterns.

Due to the comparatively longer training time, the evaluation for the Kohonen classifier was performed just once for a single random choice of the training and validation sets according to the procedure outlined before. Table 2 shows the results obtained by using a 5×5 configuration, which produced the best results.

Table 1: Results from the fuzzy KNN classifier.

Author	Recognition rate for Paintings	Recognition rate for Brushstrokes	Standard Deviation (Paintings)	Standard Deviation (Brushstrokes)
Bianco	99.80%	75.71%	2.10%	3.62%
Portinari	97.48%	77.91%	2.33%	1.52%

Table 2: Results from the Kohonen Map classifier.

Author	Recognition rate for Paintings	Recognition rate for Brushstrokes
Bianco	100.0%	72.0%
Portinari	95.7%	74.3%

Comparing the results for both classifiers it is not possible to state the superiority of one over the other as far as the recognition rates are concerned.

The computational load associated to the training of the Fuzzy-KNN classifier is much lower than for the Kohonen Map. Once the training step is concluded, the computational time for the classification is similar for both classifiers.

An interesting byproduct of the Kohonen Map is a pictorial representation of its outcome that may allow some semantic interpretation concerning the pattern classes considered in the application. This aspect was not explored in the present work.

Although a system to establish the authenticity of paintings still lies far in the future, the results obtained with this approach are encouraging, as the figures in Tables 1 and 2 attest. These results show that the texture attributes are able to capture the distinguishing characteristics of each painter.

4 Conclusions

This work presented an approach for authorship recognition in paintings. It is based on a segmentation procedure that locates regions of the painting having low hue variation. Texture measurements are performed for each region using a wavelet based algorithm. The texture features are then applied to a classifier, which discriminates among the potential authors. Two classifiers were considered in the work: a fuzzy KNN and a Kohonen Map.

The proposed approach was evaluated by experiments using paintings from two different authors, Portinari and Bianco. The system failed to recognize the true author in less than 3% for the Fuzzy-KNN classifier. Similar performance was obtained for the Kohonen classifier.

The final system will probably require the inclusion of attributes other than texture. In this work the hue was only used in the segmentation step, but some art experts suggest that the hue combination on a painting may also be a distinguishing characteristic of its author.

It will be also important to evaluate the proposed method for a large database having not only more paintings but also a larger number of painters represented in it.

Acknowledgements

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