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A New Offline Persian Hand Writer Recognition based on 2D-Wavelet Transforms

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***Abstract*—**All the works on writer's handwritten letters detection was based on the western languages and partly Chinese and Hindi, and there is a little study on Persian handwritten letters detection. Accordingly, in this paper a method is proposed to distinguish scanned Persian handwritten texts with image processing techniques. The proposed method assumes that the writer's handwritten are available in separate letters. The system trains with features extraction of these separate letters and then the trained system is used to detect individual handwritten among some indistinctive handwritten texts. The characteristics of our proposed method including high-speed of training in too much number of handwritten, is the content inattention and visual features considering. The results of procedures on 100 persons also admitted that the proposed method has a very good performance on Persian handwritten texts detection.

***Index Terms*—**Writers' handwritten identification; handwritten; wavelet transform; nearest neighbor search.

I. INTRODUCTION

In recent years, studies on the biometric security algorithms are one of the fields that have expanded rapidly due to development of computer systems, authentication and encryption.

In addition, according to the judgment and justice concerns, the assessment to identify the writers' handwriting is needed, which now mostly has done by human experts and graphologists. Among behavioral features, the individual handwriting is easily obtainable and in addition, studies have shown that different people have different handwritings that are usually constant for a period of literacy in writing [1, 2]. According to the above description, human identification using their handwritten texts had been a research topic in recent years. Identification based on the handwriting, compared with physiological characteristics such as fingerprints and iris patterns, is less accurate. Where only this information is available, in order to enhance the efficiency of security systems and help graphologists is efficient. The equipment required for doing this, is cheaper, more readily available, and does not require the presence of the person. In the identification problem, we have a handwritten text, and want to determine its author.

Writers' detection methods are divided into two general categories:

Offline Methods: In these methods, only scanned images of handwritten characters are available and the features are extracted due to the whole image or word structure. Obviously, in these methods, much dynamic information, such as pen pressure, writing speed or direction, which relate to the writing style is lost and this is more difficult than online methods. Offline or out of line methods are divided into two general groups, including text-dependent and text independent. In text-dependent methods, the author should write a constant text, in order to determine his identity, but in the text independent methods, the author's identity is determined with any kind of handwritten text. Text independent methods are more complex and more useful.

Online Methods: In these methods, in addition to the visual characteristics, the dynamic information such as pen pressure, the writing priority, the writing speed, the form of the pen hits, the time when pen not lift the paper etc. is used and identification is done more accurately, due to having more information. But, these methods have limited applications, for example, these methods do not apply in identifying sign or judicial applications.

Based on the little study on Persian handwritten letters detection, in this paper a method is proposed to distinguish scanned Persian handwritten texts with image processing techniques.

The rest of this paper is organized as follows. In Section II the literature review for the problem is presented. The wavelet transform theory is described in Section III. In Section IV our proposed algorithm consisting of feature extraction and classification and the pseudo-code of it is presented. Finally, Section V is devoted to the study of the output of our algorithm and several conclusions are reported.

II. LITERATURE REVIEW

Context-based data retrieval is one of the works on the identification of the writer in the English language. The authors of [3] determined the writer's identification with a reasonable accuracy by using image texture features of handwritten. [4] used the repetitive bending or curvature form of the Latin alphabet and by using their repeatability, achieved a probabilistic model for the individual. Finally, using the probability of bending properties was able to determine the identity of the writer. [5] used a combination of genetic algorithms and fuzzy logic to identify the writer. With regard to the fuzzy logic form of text and handwriting, obviously, fuzzy logic can help in improving the efficiency of writer's identification methods. In [6], the interconnected contour of the constituent handwritings components is used and with their histogram, a method for forming a codebook for each person proposed. Finally, this codebook is saved for each person and is used to identify the writer.

In contrast to previous references, in [7], an online method is proposed based on the Bayes criterion. In this method, the features of online and offline methods used at the same time and it is a hierarchal like method that each step determines the procedure.

[8] is provided an efficient method based on English and Greek handwritten. The method used support vector machine and nearest neighborhood to classify features and forming appropriate discriminator.

[9] used uncommon handwriting features to identify writer and set the evaluation criteria based on this matter. The idea is very interesting due to the probability of slope events or abnormal curvatures of each person's handwriting. [10] is one of the last few cases in which worked on Persian handwritten and designed based on the Gabor filter. With regard to the large number of Persian curving letters, this article is used the Gabor filter that is proper for curvature recognition and reached an acceptable accuracy in a limited database.

[11] presents a complete survey of several feature extraction methods and compare them under different conditions, scenarios and classifiers. This survey evaluate the performance of feature extraction methods in the image classification fields in both two and multiclass conditions. The results of [11] are used in classification process. [12] analyzed wavelet domain techniques and filters as one of the most active research areas in image processing. They review on the state-of-the-art techniques for wavelet based feature extraction methods in images. In addition [12] showed some essential criteria and issues related to performance assessment of different resolution enhancement techniques.

III. Wavelet Transform Theory

Wavelet analysis is one of the strong achievement in pure mathematical which is based on decades of research on harmonic analysis and today has important applications in many fields of science and engineering and new possibilities has provided for understanding its mathematical aspects and applications.

Wavelet transform plays an important role in image classification and analysis. Wavelet transform decomposed an image into low-resolution image. The advantage of transform is mainly due to good presentation of one-dimensional piecewise softening functions. Wavelet transform is also performing very well at getting singularities.

In wavelet analysis, such as Fourier analysis dealing with the functions expansion, but this expansion is done by wavelet. Wavelet is an assumed specific function with mean zero and the expansion is done based on this function transform. Wavelet analysis locally in the space unlike the polynomial trigonometric, and thus, closer connection is possible between certain functions and their coefficients, and more numerical stability provided in reconstruction and calculations. Every application based on the Fast Fourier transform can be formulated using wavelet and achieve more local spatial information. Generally, this problem addressed on signal and image processing, and fast numerical algorithm for calculating the integral operators.

Wavelet transform is a combination of low-pass and high-pass filter that apply on the signal at each stage. The lower scales images represent high frequency components and details and higher scales images, represent the low-frequency components and generalized.

If $\psi(x)$ is the wavelet function and $\psi(x) \in L^2(\Re)$, continuous and discrete wavelet transform correlation can be written as follows:

$$\int_{-\infty}^{+\infty} \psi(x)dx = 0 \tag{1}$$

$$Wf(s,u) = \int_{-\infty}^{+\infty} f(x)\,\psi_{s,u}(x)\,dx \tag{2}$$

That W represents $f(x)$ signal of wavelet transform, x is integral variable, which is considered with energy spectrum and $\psi_{s,u}(x)$ shows the mother wavelet or analyzing wavelet that is obtained from the equation (3):

$$\psi_{s,u}(x) = s^{-1/2}\psi\left(\frac{x-u}{s}\right) \tag{3}$$

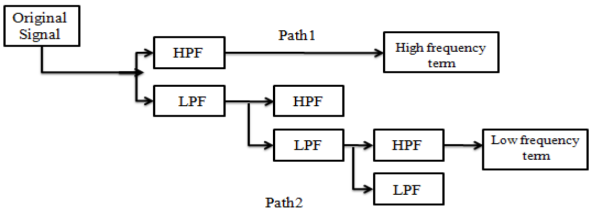

Fig.1. Block diagram of wavelet transform performance

That u and s respectively represent the transmission and the scale parameters. The concept of wavelet is the same as transmission in the short time Fourier transform which determines the displacement of the window. Obviously, includes transform time information, but unlike short time Fourier transform, in wavelet transform we have no frequency parameter. Instead, we have the scale parameter, which is inversely related to the frequency. In other words S is 1/f. Figure 1 shows the block diagram of wavelet transform.

Formula (4) shows another way of specifying the wavelet transform in which f(x) is the original signal. A determines the approximate low frequency signal and D determines the details of high-frequency signal.

According to the above formula, it is obvious that the information in the jth scale consists of information in the (j+1)th scale of decomposition, and the information in the (j+1)th scale of decomposition consists of information in the (j+2)th scale of decomposition. Decomposition in the other scales is done in the same way. Figure 2 shows this decomposition in two levels.

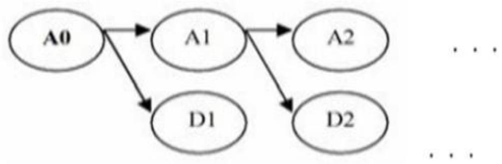

Fig.2. Approximation and detail spectrum of wavelet transform tree diagram

Now, we consider the wavelet transform in two dimensions. In any two-dimensional signal that is the image, we have a matrix consisting of different rows and columns.

$$f_j(x) = A_j f = A_{j+1} f + D_{j+1} f = A_{j+2} f + D_{j+2} f + D_{j+1} f = \dots \quad (4)$$

In order to apply two-dimensional wavelet transform to the image, the one-dimensional wavelet transform is applied to the rows and then columns are down sampled with rate of 2, until just even samples remain. In this case, again one-dimensional wavelet transform is applied to the columns and finally, rows are down sampled with rate of 2. Thus, 4 different subbands are obtained as wavelet transform coefficients. Figure 3 shows these subbands.

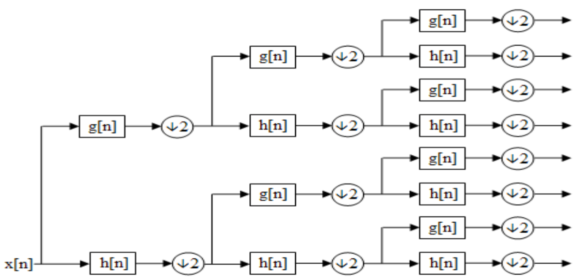

Fig.3. Two steps of two-dimensional wavelet transform filter bank representation

Similar to the one-dimensional case, the first subband of wavelet transform coefficients is related to the approximation coefficients that are similar to the original image in terms of value and appearance.

We have 3 detail subbands except approximation subband, in which one of them is related to the horizontal details, one is related to vertical details and the last subband is related to the other details in the image, which is called diagonal details (see Figure 4). Wavelet transform has various types, like Haar, Daubechies, Coiflet, cubic splines and. . . .

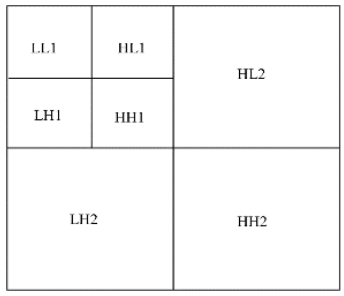

Fig.4. Wavelet transform subbands representation

IV. The Proposed Algorithm

A. Feature Extraction

Based on the capability of wavelet transform in simultaneously detecting time-varying frequency variations, in new applications of image processing, Fourier transform which works with a constant frequency characteristics, is replaced by a wavelet transform. Wavelet preference in extracting the detail of frequency bands can show different writers handwriting in a very specific way.

The only ambiguity in the application of wavelet transform in such applications is consists of the number of selected wavelet levels, the algorithm that performs filtering and a window that the wavelet transform is to be applied to it.

According to the above description, we've used several of these transformations include Daubechies (level 1 to 45), Coiflets (level 1 to 5) and Symlets (level 2 to 45) that listed in Table 1, which at the end of these functions, the best result regarding the separation obtained by db8 algorithm.

Table 1. Experimented wavelet filters for feature extraction

Filters	Experimented Levels
Daubechies	db1 - db 12
Coiflets	coif1 - coif 5
Symlets	sym2 – sym8

24 different cases have been tested and the best answer was db8. Finally, the best two-dimensional wavelet filter is applied to the image and the level transform number is selected as N = 1.

We have 4 extracted images from the original image that these extracted sets from the wavelet transform are used for features extraction.

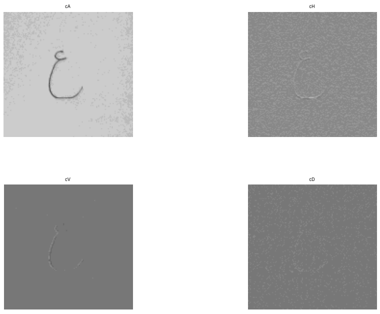

Fig.5. Wavelet transform of ع character

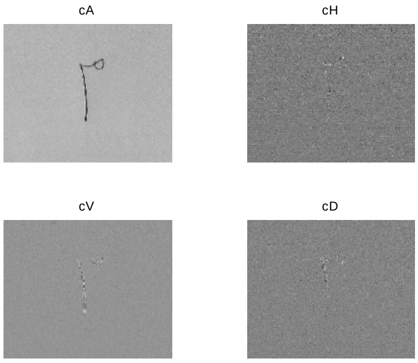

Fig.6. Wavelet transform of 'م' character

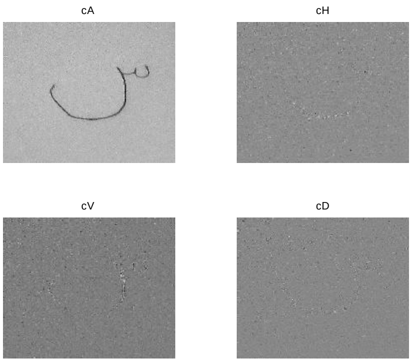

Fig.7. Wavelet transform of 'س' character

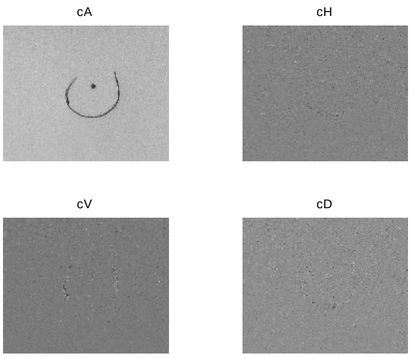

Fig.8. Wavelet transform of ن character

Figures 5 to 10 show the output of wavelet transform of each character in level 1. In fact these images are used in feature extraction process.

The features must have the same size to compare the features criteria in different dimensions images. For doing this, if the output images are M*N, for extracting features, it should be used a formula which remove the dimension.

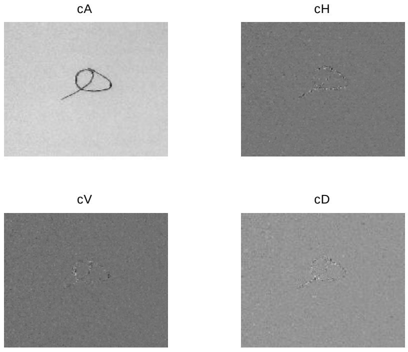

Fig.9. Wavelet transform of 'ه' character

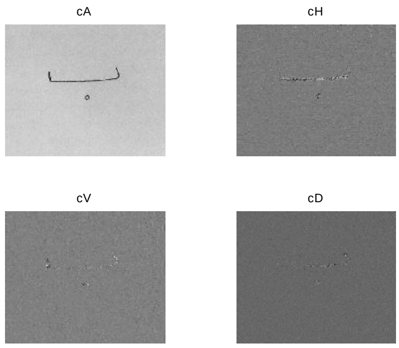

Fig.10. Wavelet transform of 'ب' character

So we used entropy formula, energy in x and y directions and Cluster tendency. These features formulas are presented in Table 2. Basic formulas (5) and (6) used for creating input and extracting triple features based on texture, in which respectively p represents the sum of the probability of an $M \times N$ window and μ is the sum of the absolute values of the probability.

Table 2. Extracted features descriptors

Formula	descriptors
$f_1 = \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j)\log(p(i,j))$	entropy
$f_2 = \sum_{i=1}^{M} \sum_{j=1}^{N} [p(i,j)]^2$	energy
$f_3 = \sum_{i=1}^{M} \sum_{j=1}^{N} (i+j-2\mu)^2 p(i,j)$	Cluster tendency

$$p_{x+y}(k) = \sum_{\substack{i=1 \\ i+j=k}}^{M} \sum_{j=1}^{N} p(i,j) \qquad k = 2,3,\ldots,M+N \tag{5}$$

$$\mu = \sum_{i=1}^{M} \sum_{j=1}^{N} |\, p(i,j)| \tag{6}$$

Given the level of wavelet functions, we had 4 images which from each of the 4 images, 3 features and totally 12 features were extracted.

Obviously, at this stage, adding more features, may be able to help increasing the accuracy but regarding the various functions that we've added, the best case in terms of run-time, algorithm complexity, efficiency and accuracy were obtained with these 12 features The only disadvantage of defined features is that they are very high in amplitude. The problem is resolved by taking decimal logarithm before learning. Tables 3 and 4 show two sets of all extracted features for 'ع' character for two persons before and after mapping. The large amount of all features is obviously shown in Table 3.

Table 3. Some samples of extracted features for two persons

	Person no.1			Person no. 2	
1	239613.2	245188.0		243610.6	238999.6
2	1977.6	1358.1		1296.0	1383.9
3	521.4	417.4		1023.6	1276.8
4	818.1	463.1		1227.1	1157.8
5	113209.6	106183.5		98688.1	171316.8
6	172435.7	121105.1		143964.9	151895.0
7	12946.8	13208.2		8648.1	15852.0
8	32977.7	23737.9		14971.8	24308.0
9	5464.8	5024.1		15049.8	15712.3
10	4845.3	4772.6		13549.5	11600.5
11	9747.5	4196.4		14134.4	13504.3
12	13694.4	4947.2		20003.5	16053.7

Table 4. The table 3 features after mapping by decimal logarithm

	Person no1			Person no 2	
1	5.380	5.389		5.387	5.378
2	3.296	3.133		3.113	3.141
3	2.717	2.621		3.010	3.106
4	2.913	2.666		3.089	3.064
5	5.054	5.026		4.994	5.234
6	5.237	5.083		5.158	5.182
7	4.112	4.121		3.937	4.200
8	4.518	4.375		4.175	4.386
9	3.738	3.701		4.178	4.196
10	3.685	3.679		4.132	4.064
11	3.989	3.623		4.150	4.130
12	4.137	3.694		4.301	4.206

The values of all features in each character are similar in two persons, but some different details can be marked.

B. Classification Algorithm

For classification, K-Nearest Neighbor (KNN) algorithm is used. This is a supervised learning algorithm. In general case, it is used for two purposes. First, to estimate the density distribution of the training data and then to classify the test data, based on training phase.

a. Density distribution estimation of the data using KNN algorithm

To estimate P (X) from n training samples by KNN algorithm, we can create a cell with center x and allow the radius extends such that it contains Kn training samples. These samples are x`s Kn nearest neighbors.

In general, the density distribution for each point in the cell with the center of x is calculated by the following equation:

$$P_n(x) = \frac{K_n / n}{V_n} \tag{7}$$

If, with the increasing n, the value of K_n increases, so that when n tends to infinity, K_n tends to infinity, then we can be sure that is a good approximation of the probability of a point being in a cell with volume V_n . Therefore, the following equations are necessary and sufficient conditions for $P_n(x)$ to converge to P(x) at the end.

$$\lim_{n\to\infty} K_n / n = 0 \tag{8}$$

$$\lim_{n\to\infty} K_n = \infty \tag{9}$$

b. Estimating the probability of the next steps

The technique described in the previous section can be used to estimate the next conditional probability P (w_i | x) of a set of n labeled samples.

Suppose that a volume V is drawn around x such that it contains k input samples and k_i samples of them belongs to class w_i. Therefore, an estimate for the probability p (x, w_i) is

$$P_n(X,\omega_i) = \frac{K_i / n}{V} \tag{10}$$

Therefore, we have:

$$P_n(\omega_i, X) = \frac{P_n(X,\omega_i)}{\sum_{j=1}^{c} P_n(X,\omega_j)} = \frac{\frac{K_i / n}{V}}{\sum_{j=1}^{c} \frac{K_j / n}{V}} = \frac{K_i}{K} \tag{11}$$

It means that, in order to minimize the error rate, the test sample is immersed in a category that is most frequent in the cell. If the samples are large enough and the cells are small enough, the choice is the best choice in terms of performance.

C. Nearest Neighbor Rule

In the definition of k-nearest neighbors, suppose that k is one to ease.

If $D^n = x_1, ..., x_n$ is a set of n input pattern and $X' \in D^n$ is the closest pattern to the test input x, then the nearest neighbor rule classifies it in the same class with class X'.

Usually, the nearest neighbor rule`s error is more than the Bayesian error rate which is the least possible error rate. It could be proved that in case of infinity input samples, in the worst case, error rate is more than twice the Bayesian error rate. K nearest neighbor rule is the generalization form of nearest neighbor rule. It`s obvious that this rule classified x into the class with more similar data. According to the simulation results, at this stage, the best value for k is 2.

D. Pseudo-code of our algorithm

Summarizing our above discussions, our algorithm is included here briefly.

1. Read image and its label.
2. Apply 2d-wavelet to image with db8 method.
3. Extract features from all wavelet outputs using Table 2.
4. Repeat reading items (Step 1) for all database images.
5. Save features and their labels.
6. Map all outputs for limiting values and enhance classifier accuracy.
7. Select randomly, train and test set.
8. Select 6 images of each character randomly and average all features to eliminate the human variability.
9. Repeat Step 8, 40 times for each character from each PERSON.
10. Apply KNN classifier.
11. Test classifier output.
12. Compute accuracy.

V. Results

For showing the validity of proposed method, it is analyzed in two cases.

- First case:

In this part, characters were used separately. It means that for each classifier the input vector is a vector of 12 bits instead of 72 bits. The goal was to make the characters more suitable for the detection of specific writers and weaker characters got known at this stage. The final result is shown in Table 5.

From Table 5 we can see that in this case, characters “س” and “ب” had the best accuracy. In other words, to identify the writer in different people, the distinction between these two letters is greater than the other letters. Letters “ه”and “ع” letters are the worst letters. The similarity between these two letters is higher than the others are and are not suitable for the separation of the author.

Table 5. The result of train and test for characters

	test	train
ع	48.63	48.73
ب	55.91	54.23
ه	47.39	46.36
ن	51.13	50.62
س	58.04	56.80
م	49.66	50.10

- Second case:

In this part, this combination of all features in a vector is applied to the classifier. Obviously, the features length in this case is 72. The rest of the conditions is assumed like the first case. Table 6 shows the results for a total of 72 features in ten different runs.

Table 6. Test and train results for all letters in ten different runs

Train	Test
100.00	85.98
100.00	85.57
100.00	86.46
99.97	86.01
99.83	85.98
99.93	86.25
99.93	85.53
100.00	86.56
99.97	85.64
100.00	84.74

As it is clear from Table 6, the proposed method, in a set of features, almost 100% in train, and a good percentage (85% average) in test, were able to classify the writers compared to similar methods, very good (For example 67% in [10]). Although the difference between the consideration of the letters and nothing specific was done on the handwritten, exact comparison of methods is not possible.

VI. Conclusion

This work presents a computationally efficient method designed for automatic segmentation of color images with varied complexities. Firstly, the original image is divide into rectangular image blocks which are not overlapped; then, the mean and variance of each image black was calculated in CIE$L^*a^*b^*$ color space, and the image blocks were divided into homogeneous color blocks and texture blocks by their variance. The initial seed regions are automatically selected depending on calculating the homogeneous color blocks' color difference in CIE$L^*a^*b^*$ color space and spatial and adjacent information. The color contrast gradient of the texture blocks need to calculate and the information of boundary pixels are storage. Finally, the region growing and merging algorithm was to use and achieve the segmentation result.

The meaningful experiment results of color image segmentation hold favorable consistency in terms of human perception and satisfy the content-based image retrieval and recognition process. There are mainly two disadvantages in our algorithm. First, although using the fixed threshold values can produce reasonably good results, it may not generate the best results for all the images. Second, when an image is highly color textured (i.e. there are numerous tiny objects with mixed colors), our algorithm may fail to obtain satisfied results because the mean value and variance could not represent the property of the region well. How to combine other properties such as texture into the algorithm to improve segmentation performance is the point of our further research.

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