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Recognition of Persian Handwritten Numbers using LBP-HOG Descriptor

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ABSTRACT
Recognition of handwritten numbers in any language is one of the most important issues attracted many researchers and this is because of the increasing importance of the issue in today's world and in applications such as automatic detection of mail addresses or identification of numbers of bank checks. Given the great interclass diversities and much extra-class similarities between some Persian handwritten numbers, solving the Persian handwritten numbers recognition problem is difficult. In this paper, a new method for recognizing Persian handwritten numbers using a combination of HOG and LBP descriptors is provided. The proposed descriptor enjoys significant advantages of which the important one is the recording of information and features relating to the image (by descriptor LBP)and yet the feature extraction of the image edges (by descriptor HOG). Another advantage of the proposed descriptor is the very small length of the feature vector and the fast calculations. To evaluate the effectiveness of the proposed method the standard data base HODA, a large database of 60,000 images, were used .Experiments carried out on the database show the high effectiveness of the proposed method (with an accuracy of 99.3%) in comparison with other similar methods.
Keywords: *Persian handwritten numbers recognition, descriptor LBP (Local Binary Pattern), descriptor HOG (Histogram of Oriented Gradient), data base HODA.*

INTRODUCTION

Today, automatic recognition of handwritten numbers in different languages of the world is of great importance and this is due to the high potentials of the technology applications. Some of these potentials include automated processing of bank checks, automation of postal addresses, and so on. In Persian language like other languages, there are ten numbers in ten sets. Recognizing and assigning a number to one of the ten sets in Persian language is one of the most difficult pattern recognition problems. Figure 1 shows a sample of ten sets of numbers in Persian language.

0	1	2	3	4	5	6	7	8	9
۰,٥	۱	٢,۲	۳	٤,۴	٥,۵	٦,۶	۷	۸	۹

Figure 1: A sample of ten sets of numbers in Persian language [11]

The difficulty of Persian handwritten numbers Recognition hassome different reasons. For example, some of the numbers in Persian language are very similar to each other (inter-class variation) and on the other handthe numbers of a set can be written in different forms (Figure 2) [11].

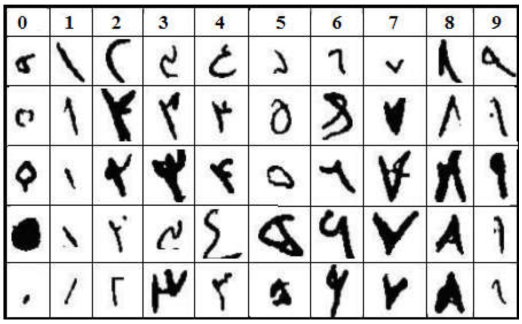

Figure 2: An example of Persian numbervariationsin different sets [11]

Much research has been done so far on the recognition of Latin numbers as the numbers of English language, and researchers in this field have designed systems with very high efficiency [2-5]. But research progress in the recognition of Persian handwritten letters has not enjoyed from an old history and high performance. Persian language is the main language of the countries such as Iran, Afghanistan and Tajikistan, which more than 110 million people speak the language [5]. As noted above, the Persian handwritten numbers are written in different form, size, curvature and direction and that is whythe recognition of these numbers is more challenging compared with the numbers of other languages. Arabic numbers are similar toPersian numbers, small differences between Persian and Arabic languages can be seen in numbers 4 and 6 (Figure 3) [6].

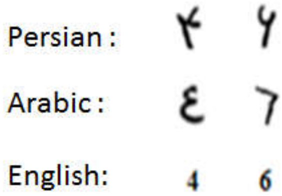

Figure 3: numbers 4 and 6 in Persian and Arabic languages. [6]

Many methods have been presented for identifying Persian handwritten numbers. For example, in [7], the authors using outer profiles, crossing counts and projected histograms in different directions as image features, presented a method for recognizing handwritten Persian numbers.

In [8], the authors used wavelet features for classification and recognition of individual Persian numbers. This paper uses the SVM classifier to classify Persian numbers. In [9], the authors used a template-based approach to extract image features. In this paper,20 templates containing the most important features of Persian/Arabic handwritten images were selected innovatively. Template matching was used to extract features. Then MLP Artificial Neural Network was used for classification and recognition of the images.

In [10] Roshnoudi et al used Fourier coefficients to extract features. The advantage of the method is the very small feature vector generated (154 minutes). In [11] Salimi and Givaki introduced a new recognition system based on PSO (particle swarm optimization) algorithm and SVD (singular value decomposition) classifier. The advantage of their method was the high generalization potential. The method compared with other proposed methods of Persian handwritten numbers recognition uses much smaller training set to train classifiers. In [12] Mozaffari et al defined a framework for each Persian handwritten number and then extracted features from each number using an innovative method. This method is very creative and noise-sensitive. One of the most obvious disadvantages of the existing methods for recognizing handwritten Persian numbersis the providing of innovative algorithms for feature extraction and the high sensitivity of the algorithms to noise and lack of considering the final characteristic whicha good descriptor should benefit from.For example, a good descriptor should be as resistant as possible to situations, such as transfer, rotation, scaling, and noise. Some of these articles do not refer to the characteristics and properties of the descriptor used. In this paper, a set of features are extracted from Persian handwritten images using advanced image descriptors so that the proposed model reaches high performance. For this purpose we will use HOG and LBP descriptors. Experiments on HODA database show the superiority of the above method over other existing methods in the problem of recognition and classification Persian handwritten numbers and this is due to the proper use of two different sets of descriptors so that these descriptors are complementary. LBP descriptor is resistant to rotation. The descriptor properly records the information about the image texture. On the other hand, HOG descriptor records the distribution of image edges in different directions. If different Persian numbers are carefully considered, it can be seen that the edges of the images contain very important information associated with number images. On the other hand, the LBP and HOG descriptors are local descriptors and thus enjoy high discrimination power. Section 2 reviews the descriptors used. In Section 3, the proposed method for

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recognizing Persian handwritten numbers is provided. In Section 4, the results of the implementation of the proposed method will be presented and the paper is summarized and concluded in section 5.

An overview of LBP and HOG descriptors

In this section we will briefly review the HOG and LBP descriptors.

LBP descriptor

LBP is a machine vision values used to classify and recognize objects. The descriptor is a particular kind of spectral texture model that could well project the image texture information. [16]. LBP feature vector records visual features of an image around a pixel. Initial LBP acts on windows of 3 × 3 around each pixel of the image and compares the pixel with neighboring pixels. These comparisons are placed together and make an 8-bit string that is interpreted as a decimal number: LBP feature vector is a histogram of these numbers. The number of strings of length 8 bits is equal to 256. The number is reduced to 58 in LBP method. Assuming that $LBP_{P,R}(x, y)$represents the LBP descriptor on a pixel (x, y), P is the number of points on a circle of radius R, similar to (Figure 4).

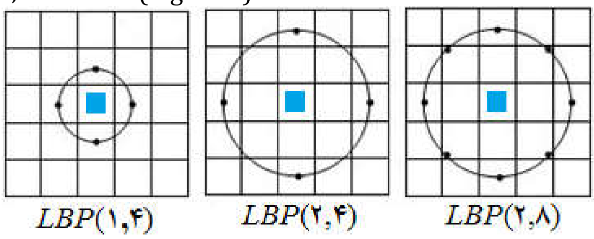

Figure 4: An example of $LBP_{P,R}(x, y)$ with different P and R

In this case, the LBP feature is calculated as follows:

$$LBP_{P,R}(x, y) = \sum_{i=0}^{p-1} s(g_i - g_c)2^i \qquad (1)$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} (2)$$

Where, g_c is central pixel value and g_i is the value of i_{th}pixel on the circle. One type of LBP is its uniform pattern. $LBP^u_{P,R}(x, y)$is called uniform binary pattern if there are two changes from one to zero and zero to one. Tests show that $LBP^u_{8,1}(x, y)$and $LBP_{8,1}$ (x, y) have the same performance. Uniform LBP histogram considers only one space for non-uniform patterns and the feature vector is thus obtained equal to 59. In this paper, the normal version of the LBP i.e. $LBP_{8,1}$ (x, y) has been used.

HOG descriptor

One of the most commonly used descriptors processing machine vision values is HOG descriptor. HOG is well-suited for detecting objects in images. In HOG the amount and the type of gradient angle at local areas of the image is calculated that can effectively capture the features of an image. HOG method divides the image into small square cells, and for each cell, gradient angle histogram vector is computed. Then, using a block model, results of each cell are normalized and a feature vector is formed, and finally for each block a histogram of features will be the final descriptor of the image (Figure 5) [17].

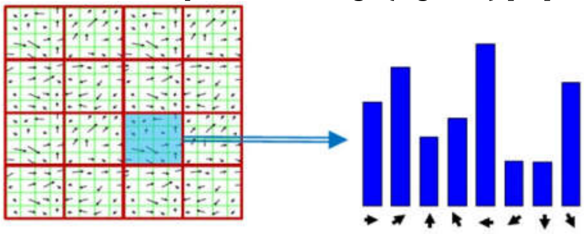

Figure 5: the construction of feature vectors by HOG

By taking the feature vectors of the cells together a larger feature vector is made that is the final feature vector of the HOG.

The proposed method

For recognition of Persian handwritten numbers, HODA database, one of the largest and the most challenging Persian databases was used [18]. In this database images are divided into two categories: training and testing. In the proposed method first all feature vectors are extracted for each training image to build a model of Persian handwritten numbers recognition. Thus the feature vector of an image like *I* will be equal to $\vec{V} = (\vec{V}_{LBP}, \vec{V}_{HOG})$,this means for each image the feature vector is achieved by combination of two feature vectors $\vec{V}_{LBP}$ (feature vector extracted by LBP descriptor) and $\vec{V}_{HOG}$ (feature vector extracted by HOG descriptor). Then all feature vectors extracted from the training images are normalized. LBP method produces 58-dimensional feature vectors for each image. In this paper, to increase the effectiveness of LBP method, the image is first divided into 9 blocks, and then feature vectors of LBP

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descriptor are extracted from every 9 blocks and thus $\vec{V}_{LBP}$ will be a 522-D vector and on the other hand, HOG descriptor produces 279-dimensional feature vector $\vec{V}_{HOG}$ for each image. In general, the proposed method produces the 801-dimensional feature vector $\vec{V} = (\vec{V}_{LBP}, \vec{V}_{HOG})$ for each image. Figure 6 shows the steps of the proposed method for the recognition of Persian handwritten numbers.

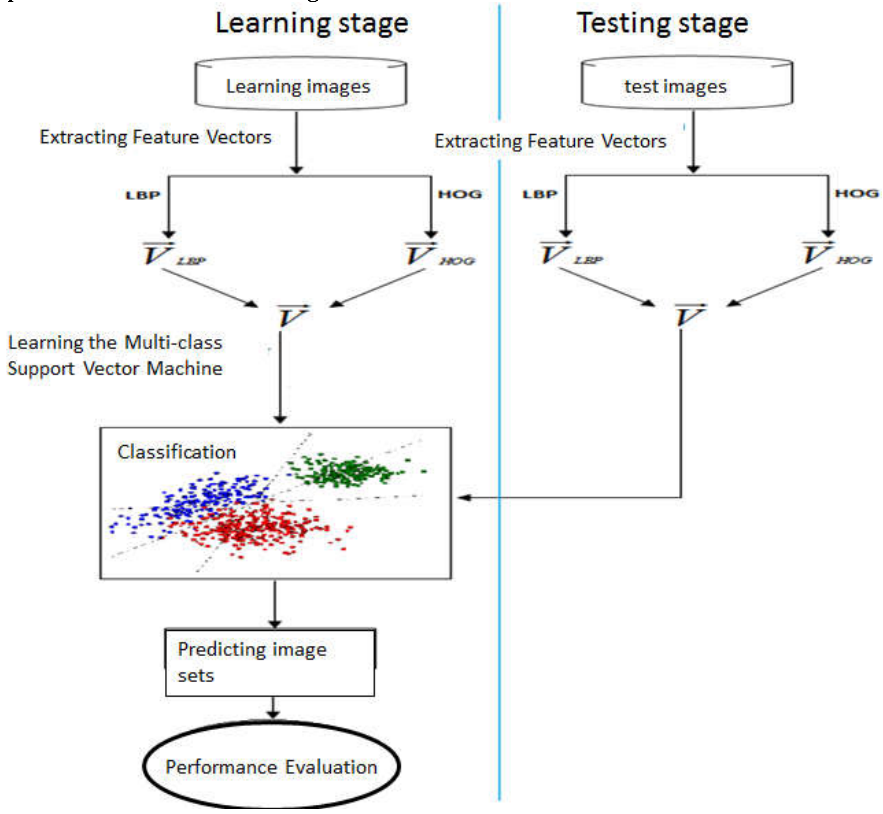

Figure (6): the steps of the proposed method for recognizing handwritten Persian numbers

As it can be seen in Figure 6, after extracting all features from training images, these features are learned by using multi-class SVM (M-SVM) classifier. After training M-SVM, the classifier is able to predict the class of images. After training the classifier, features of testing images are extracted and feature vectors are stored. Now all features enter M-SVM and the effectiveness of the proposed model is assessed by M-SVM with respect to predictions made.

Experiments and results

As mentioned in the previous section experiments were carried out on HODA database. The database contains 80,000 images. 60,000 are selected as training images, and 20,000 as testing images. Images are in various sizes and no change in the size or preprocessing has been used for the experiments. Figure 7 shows the results of the implementation of the proposed method by confusion matrix. At all experiments, the classification M-SVM (multi-class SVM) was used for classification. For the SVM classifier, exponential kernel as exp-αd has been used, where d is the Euclidean distance between the vectors, scalar number α as described in [19] is determined. (LIBSVM library in [19] was used.) One-versus-all method was used for classification where each classifier is trained to separate each class from other classes. According to confusion matrix the proposed method had the highest recognition rate for number "0". The method also had the lowest performance for recognition of numbers "2", "3" and "4", "6" and "9".This is because some of these numbers are very similar to each others that in many cases it is very difficult to distinguish the two numbers due to various handwriting of individuals. Even in some cases, Persian individuals are themselves unable to distinguish and recognize these numbers.

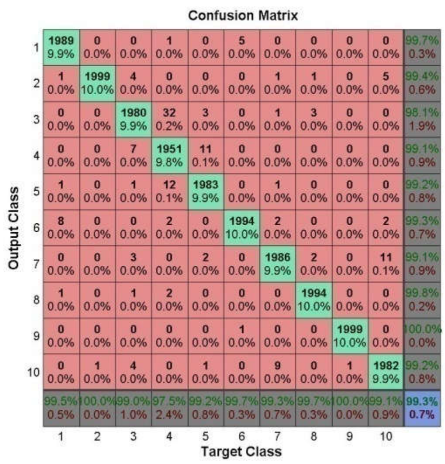

Figure (7): the confusion matrix of the proposed method

To compare with other well-known and valid methods, Table 1 is provided. According to Table 1, the first point is that some methods are implemented on databases other than HODA database and since we did not have access to those databases, evaluation of the effectiveness of the proposed method on the databases was impossible. On the other hand, it can be seen from Table 1that some methods have selected a subset of training and testing randomly because of the large size of HODA database and have implemented their methods on the data subset. According to table, the proposed method of this paper has the highest recognition rate, which is equal to 99.3%. The method proposed in [20] has the maximum effectiveness equal to 98.71% following the method proposed in this paper,

Table 1: Results of the comparison between the proposed method and other methods

Algorithm	Database	Database size		Accuracy (%)
		Training	Testing	
The proposed method in[7]	Non-HODA	4979	3939	99.57
The proposed method in[8]	Non-HODA	2240	1600	92.44
The proposed method in[9]	Non-HODA	6000	4000	97.65
The proposed method in[21]	Non-HODA	2600	1300	97.8
The proposed method in[22]	Non-HODA	6000	4000	97.01
The proposed method in[23]	Non-HODA	230	500	97.60
The proposed method in[24]	Non-HODA	2240	1600	91.88
The proposed method in[25]	Non-HODA	2240	1600	91.37
The proposed method in[26]	Non-HODA	7390	3035	94.14
The proposed method in[20]	HODA	60000	20000	98.71
The proposed method in[27]	HODA	6000	2000	95.30
The proposed method in[28]	HODA	6000	2000	97.10
The proposed method in[29]	HODA	30000	10000	9512
The proposed method in[11]	HODA	1000	5000	97.30
The proposed method in this paper	HODA	60000	20000	993

CONCLUSIONS

This paper introduces a new method for Persian handwritten numbers recognition on HODA large database. The method uses a new combination of image texture and edge features so that the high accuracy of 99.3% on 20,000 testing image is achieved.This result enjoys much higher effectiveness compared to most of the advanced methods available for the recognition of Persian handwritten numbers and this is because of the proper use and combination of image features. Local descriptors have been used and as we know local descriptors have high discrimination power. The extracted features by the descriptors then lead to a higher recognition rate. On the other hand, these features are complementary.LBP descriptor measures images texture and HOG descriptor measures the distribution of the edges of images. Another advantage of the proposed method is its small feature vector (801-dimensional vector).

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