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Novel Approach in Face Recognition Using Hieratical Multiscale Local Binary Pattern with Elm Classifier

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ABSTRACT— This paper presents a efficient facial image recognition based on multi scale local binary pattern (LBP) texture features .It's a fast and simple for implementation, has shown its superiority in face recognition. To extract representative features, "uniform" LBP was proposed and its effectiveness has been validated. However, all "non-uniform" patterns are clustered into one pattern, so lot of useful information is lost. In this study, propose to build a hieratical multiscale LBP histogram for an image. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. The useful information of "non-uniform" patterns at large scale is dug out from its counterpart of small scale, The performance of the proposed method is that it can fully utilize LBP information while it does not need any training step, That classification we introduce ELM classifier with LBP, and then Performance of the feature extraction method to be evaluated by Elm classifier. Which may be sensitive to training samples assessed in the face recognition problem under different challenges, other applications and several extensions are also discussed. The main advantage of the proposed scheme is that it can fully utilize LBP information while it does not need any training steps for extract the features, which may be sensitive to training samples. Experiments on ORL face database data base show the effectiveness of the proposed method.

recognition, texture feature, Extreme Learning machine.

I. INTRODUCTION

Face recognition is an extremely live area of research with a wide variety of real-world applications and in recent years an evidently distinct face-recognition channel has emerged**.** Over the past decade, there has been drastic development in the field of human face recognition due to its importance in broad variety of applications, such as illicit identification, credit card verification, safety system, scene surveillance, entertainments. There are two main stages under face recognition channel: feature extraction and feature classification. The main objective of this paper is to achieve better recognition rate and to reduce the time taken for computation which in turn increases the speed. Face recognition technique needs to be well-built to withstand the image variations caused by the illumination conditions [1]–[2], facial expressions [3]–[4], poses or perspectives [5]–[6], aging [7]–[8], and other factors such as makeup, glasses [9] or hair styles [10]. However, as mentioned in [11], most of the face recognition techniques that exists come across difficulties in the case of large variations. The key outcome of this research is increased accuracy rate, recall, precision and Fmeasure for a face recognition system which has been subjected to varying facial expression, illumination and head pose.

LBP, How to extract discriminate information from an image is one of the key components for biometrics system. There are many different algorithms proposed in the past, such as principal component analysis (PCA) [2], Gabor phase encoding [3], local ternary pattern(LTP) and local binary pattern (LBP) [4-9] for feature extraction. Among them, LBP based method has shown its superiority in face recognition. LBP was originally proposed as a texture descriptor. It owns many advantages, such as it is simple to implement and fast to compute.

In that texture descriptor has been validated that "uniform" patterns play an important role in texture classification [10]. "Uniform" patterns also showed its superiority in face recognition [4-5, 8-9]. Incorporating "uniform" idea, many patterns, which are not "uniform" patterns, are clustered into one "non-uniform" pattern. By this way, many discriminate but "non-uniform" patterns fail to provide useful features. And, the percentage of "non-uniform" patterns increases as the radius increases, so much information is lost. Recently, some works were proposed to address this issue. Many "non-uniform" patterns are isolated from the "non-uniform" cluster [6-7]. However, such methods are learning based algorithms, which require some training samples to discover useful "non-uniform" patterns. Thus, the recognition performance may be related with the training samples. In this paper, we propose a hybrid multiscale LBP algorithm for face recognition. The LBPs for biggest radius is firstly extracted. Then, for those "non- uniform" patterns, the counterpart LBPs of smaller radius is extracted. Among the new LBPs, those "non-uniform" patterns is further proceeded to extract "uniform" patterns in even smaller radius. The procedure is iterated until the smallest radius is proceeded. The proposed scheme could fully utilize the information of "non-uniform" LBPs of bigger radius. Furthermore, this hybrid scheme is totally training free which are not sensitive to the training samples.

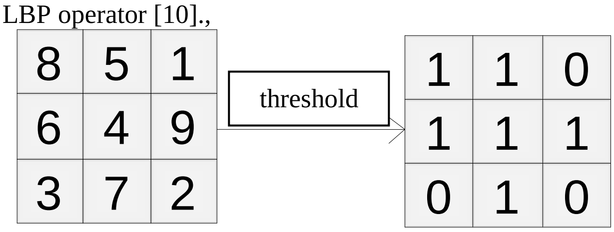
ELM was initially proposed (Huang) for a typical single hidden layer feed forward neural network (with random hidden nodes (random features)).[12][13] ELM gives a combined learning platform with widespread feature mapping types and its ability to apply in multi-class classification and regression applications directly. Rest of that paper organized by review of existing methods like Local binary pattern and proposed work MLBP with ELM classifier, and their result are discussed to below.

II. Review Of The Existing Method

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

A. Feature Extraction Using LBP:

The original LBP operator labels the pixels of an image by thresholding a 3 × 3 neighborhood of each pixel with the center value and considering the results as a binary operator. Converting the binary code into a decimal one. Figure 1 gives an illustration for the basic LBP Based on the operator, each pixel of an image is labeled with an LBP code. The 256-bin histogram of the labels contains the density of each label and can be used as a texture descriptor of the considered region. The procedure of extracting LBP features for facial LBP approach can obtain the relationship among the original LBP operator [10].,



Binary pattern: 11010101

Fig.1.Fundamental LBP operator

LBP [10] is a gray-scale texture operator that characterizes the local spatial structure of the image texture. Given a central pixel in the image, a pattern code is computed by comparing it with its neighbors:

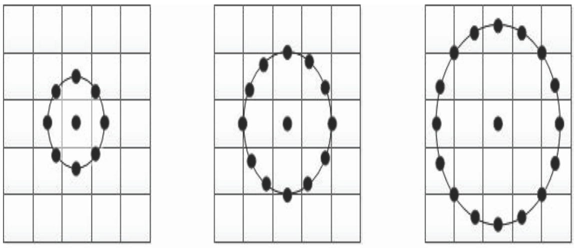
$$LBP_{N,R} = \sum_{p=1}^{p} s(g_n - g_c)2^{n-1} \text{ ---------------- (1)}$$

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

where gc is the gray value of the central pixel, gn is the value of its neighbors, N is the total number of involved neighbors and R is the radius of the neighborhood. Suppose the coordinate of gc is (0, 0), then the coordinates of gn are (R*cos(2πn/N),R*sin(2πn/N)). Fig. 1 gives examples of circularly symmetric neighbor sets for different configurations of (N,R). The gray values of neighbors that are not in the center of grids can be estimated by interpolation.

B. Feature Extraction Using MLBP:

The performance of single LBP operator is limited. Multi scale or multi resolution could represent more image feature under different settings. Traditionally, LBP features of different scale are extracted first, and then the histograms are concatenated into a long feature. Joint distribution could contain more information, but it suffers from huge feature dimension. As shown in Section 2, (2^P -P*(P-1)-2) "non-uniform" patterns are clustered into one "non-uniform" pattern. By applying this scheme, much information is lost. And, as the radius increases, the percentage of "non-uniform" pattern increases. For example, Table I shows the percentage of "non-uniform" patterns in images.



(P=8, R=1.0) (P=12, R=2.0) (P=16, R=3.0)

Fig.2. Example of proposed Modified multiscale LBP

TABLE .I

PERCENTAGE (%) OF "NON-UNIFORM" PATTERNS IN ORL DATABASE.

	R=1	R=2	R=3
P=8	15.82	23.68	29.86

be estimated by interpolation where g_c is the gray value of the central pixel, g_p is the value of its neighbors, P is the total number of involved neighbors and R is the radius of the neighborhood. Suppose the coordinate of g_c is (0, 0), then the coordinates of g_p are (R*cos(2πp/P),R*sin(2πp/P)). Fig. 1 gives examples of circularly symmetric neighbor sets for different configurations of (P, R). The gray values of neighbours that are not in the center of grids can be estimated by interpolation.

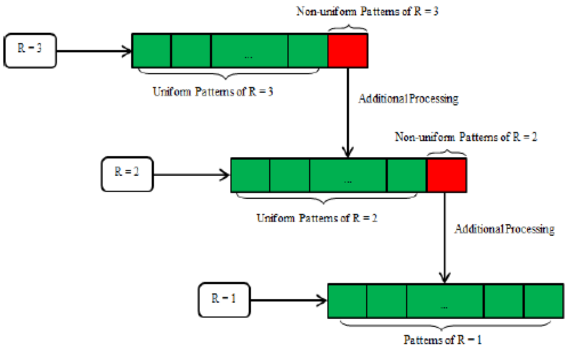


Fig 3.An example of the proposed Modified multiscale LBP scheme

As shown in Table I, around one third information is wasted by using previous method. To extract more useful feature from the image, some works were proposed to dig out information from these "non-uniform" patterns. However, such methods require a training step to learn which patterns are useful. The recognition accuracy may be dependent on the training samples. Fig. 2 shows an example. The pattern of a bigger radius is "non-uniform", but its counterpart in a smaller radius is "uniform". Thus, it is possible to classify the "non-uniform" patterns according to their counterpart of smaller radius.

III. PROPOSED ALGORITHM

A. Hieratical Multiscale LBP With ELM Classifier:

Here we propose to build multi scale LBP histogram from big radius to small radius, then that LBP map for each pixel in biggest radius, That pixels are divided into two types of patterns like Uniform pattern and Non-Uniform pattern ,A Sub histogram is build for uniform pattern. Those pixels in Non-uniform pattern are further processed at another small radius, When the new pattern contains full of uniform that process will be stop, and remaining pixels are continued to extract LBP pattern at smaller radius. Fig. 3 shows an example of the proposed hierarchical multi scale LBP scheme. The LBP histogram for R=3 is first built. For those "non-uniform" patterns by R=3 operator, a new histogram is built by R=2 operator. Then, the "non- uniform" patterns of R=2 are further proceeded to build a histogram R=1operator .Final ly , three histograms are concatenated into one mul t i scale histogram. There are mainly two differences compared with traditional multi scale LBP. Suppose the number of scale is S, the dimension of the proposed scheme is smaller than traditionally scheme by S-1. Second, sum of frequencies of the proposed histogram is 1/S of traditional one.

The ELM algorithm is based on the subsequent two principles.

1. When the number of training samples and the number of hidden nodes are equal, i.e.,$N = \tilde{N}$, then the parameters of hidden nodes can be randomly assigned (the input weights and biases for additive hidden nodes or the centers and impact factors for RBF) and based on this computation of the output weights by just inverting H and recognizing zero training error can be done logically. Computation of the output weights is a single step process. There is no need for any extensive training method where the network parameters are in tune interactively with suitably selected control parameters (learning rate and learning epochs, etc.).

2.When the amount of training samples is larger than the number of hidden nodes, i.e., $N > \tilde{N}$,one can still arbitrarily assign the parameters of hidden nodes and compute the output weights by using a pseudo inverse of H, to give a small nonzero training error $\in >$. Here also computation of the output weights is a single step process and no lengthy training process is required.

The standard SLFNs with $\tilde{N}$ hidden nodes and activation function $g(x)$ can approximate these N samples with zero error means by $\sum_{i-1}^{N\prime} ||\mathrm{oj} - \mathrm{tj}|| = 0$ i.e., there exist βi, wi and bi such that

$$\sum_{i-1}^{N\prime} \beta_i\, g_i(w_i x_j + b_i) = o_j,\ j = 1,2 \ldots .N \quad (3)$$

The above equations can be rewritten efficiently as

$$H\beta = T \quad (4)$$

$$H(w_1, \ldots w_{\widetilde{N}}, b_1, \ldots, b_{\widehat{N}}, x_1, \ldots\ldots, x_N) \quad (5)$$

where

$$\begin{bmatrix} g(w_1 x_1 + b_1) \ldots & g(w_{\widehat{N}} x_1 + b_{\widehat{N}}) \\ g(w_1 x_{\widehat{N}} + b_1) \ldots & g(w_1 x_{\widehat{N}} + b_1) \end{bmatrix}_{N*\widehat{N}} \quad (6)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \beta_{\widehat{N}}^T \end{bmatrix}_{\widetilde{N*m}} \quad (7)$$

$$T = \begin{bmatrix} t_1^T \\ t_N^T \end{bmatrix}_{N*m}$$

III. RESULTS AND DISCUSSION

A.Face Database:

The ORL database contains images from 40 individuals, each providing 10 different images. For some Subjects, the images were taken at different times. The facial expressions (open or closed eyes, smiling or non smiling) and facial details (glasses or no glasses) also vary. The images were taken with a tolerance for some tilting and rotation of the face of up to 20 degrees. Moreover, there is also some variation in the scale of upo about 10 percent. All images are grayscale and normalized to a resolution of 92 x 112 pixels.

In this experiment we are used 40 subjects each subject have 10 different images for a same person, during first experiment we give 5 images for train the system, that is train data set, remaining 5 images for testing in this experiment we are vary on class 5-40 class, according to this experiment results are tabulated on Table II, MLBP, LBP, HMLBP algorithms with ELM classifier,

TABLE II

OUTPUT OF ELM CLASSIFIER WITH HMLBP FOR THE ORL DATABASE ACCORDING TO VARYING CLASS

Class	Recall	Precision	Elapsed time(sec)	F measure	Recognition Efficiency
5	90	90.666	0.018000	90.3322	90
10	90	90.666	0.022001	90.3322	90
15	89.33	89.095	0.024186	89.7128	89
20	93	94.476	0.036073	93.7323	89
25	87.40	87.581	0.037154	87.9868	88
30	87	87.095	0.049413	87.5444	87
35	86.78	86.540	0.050826	86.9091	87
40	86.2	87.192	0.072008	87.892	86

EXPERIMENT-I

conducted by according to varying training and testing data set, initially we are taken 5 images for testing and remaining 5 for training like this way decrease the training samples and increase the test samples.

EXPERIMENT-II

conducted by according to varying the class initially 5 class are taken for measure the performance of the system and then increase the class upto 40 class for evaluate the performance of the system.

Calculate the recognition rate for HLBP with Elm classifier and then compare the results with exsisting methods like LBP and MLBP feature extraction methods with Elm classifier and calculate elapsed time also.

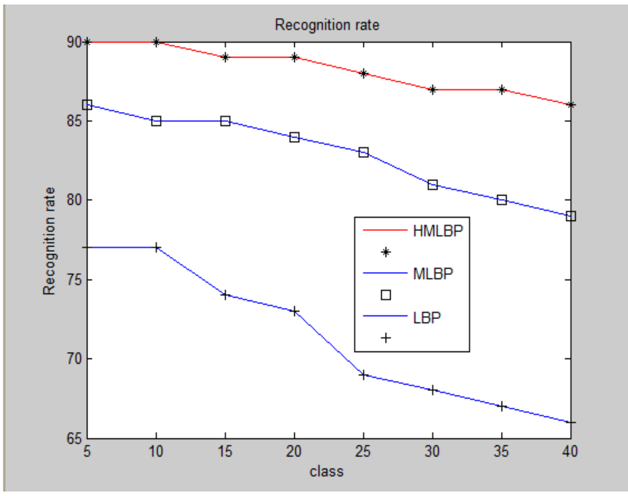


Fig 4: Comparison Of Recognition Rates According To Various Feature Extraction Methods With Elm Classifiers

TABLE III

COMPARISON OF RECOGNITION RATES ACCORDING TO VARIOUS FEATURE EXTRACTION METHODS WITH ELM CLASSIFIERS

Class	LBP+ELM	MLBP+ELM	HMLBP+ELM
5	77	86	90
10	77	85	90
15	74	85	89
20	73	84	89
25	69	83	88
30	68	81	87
35	67	80	87
40	66	79	86

Similar findings as Table II could be found from Table III, such as both multiscale schemes could significantly improve the recognition accuracy and the proposed multiscale scheme is better than traditional one.

it only gets around 2% drop from the first experiment to the second experiment. It is a very good property in many applications, as getting enough training samples is not a trivial issue. However, there is one disadvantage of the proposed scheme. The feature dimension of multiscale LBP is a little higher.

IV. CONCLUSION

Face recognition technology has come a long way in the last twenty years. Today, machines are able to automatically verify identity information for secure transactions, for surveillance and security tasks, and for access control to buildings etc. These applications usually works in a controlled environment and recognition algorithms can take advantage of the environmental constraints to obtain high recognition accuracy. However, next generation face recognition systems are going to have widespread application in smart environments, where computers and machines are more like a helpful assistant. To achieve these goals computers must be able to reliably identify nearby people in a manner that fits naturally within the pattern of normal human interactions. They should not require special interactions and should conform to human intuitions about when recognition is needed. This implies that future smart environments should use the same modalities as humans, and have approximately the same limitations. These goals are now seems to be achieved, however some substantial research remains to be done to make person recognition technology and that should work reliably in widely varying conditions using information from single or multiple modalities.

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