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NEW LOCAL BINARY PATTERN FEATURE EXTRACTOR WITH ADAPTIVE THRESHOLD FOR FACE RECOGNITION APPLICATIONS

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ABSTRACT

This paper represents a feature extraction method constructed on the local binary pattern (LBP) structure. The proposed method introduces a new adaptive thresholding function to the LBP method replacing the fixed thresholding at zero. The introduced function is a Gaussian Distribution Function (GDF) variation. The proposed technique uses the global and local information of the image and image blocks to perform the adaptation. The adaptive function adds to the on-hand im-age's features by preserving the information of the amplitude of the pixel difference rather than just considering the sign of the pixel difference in the process of LBP coding. This feature improves the accuracy of the face recognition system by providing additional information. The proposed method demonstrates a higher recognition rate than other presented techniques (%97.75). The proposed method was also tested with different types of noise to demonstrate its effectiveness in the presence of various levels of noise. The Extended Yale B dataset was used for the testing along with Support Vector Machine (SVM) as classifier.

KEYWORDS

Face Recognition, Pre-processing, CLAHE, Gamma Correction, LBP.

1. INTRODUCTION

Face recognition as a non-intrusive biometric system shows a promising future in terms of the scope of application. All these together make face recognition a desirable research topic. Over the past few decades, significant improvements have been brought to face recognition systems. The early methods were slow, complicated, and relatively unreliable, with a low accuracy rate.

These days, face recognition systems are far more trustworthy, consistence, easier to implement, and comparatively fast. These systems can be found vastly in any number of practical applications, from security to marketing and customer service to safety. However, there is still plenty of room available to make enhancements. For instance, one of the most important parameters of a face recognition system is that system's accuracy. In most applications, accuracy is preferred over speed. Recently, methods and approaches have been introduced to the field that provide a promising recognition. Figure 1 demonstrates the block diagram of a general face recognition algorithm.

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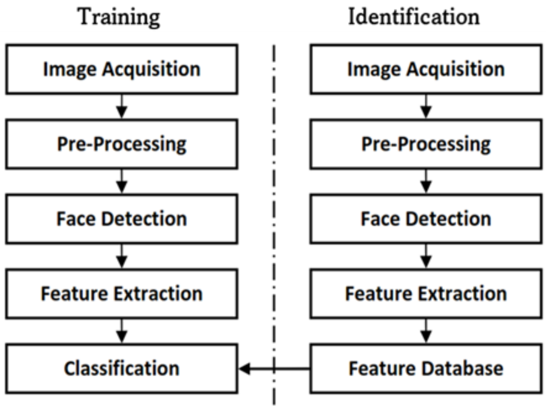


Figure.1. Steps of a face recognition system

As figure 1 shows, the four main stages of the algorithm that are in reality involved in the computation are 1) pre-processing, 2) face detection, 3) feature extraction, and 4) Classification. Improving the operation of any of these stages could result in a system with a higher recognition rate. For the pre-processing stage, [1] and [2] suggested methods to enhance the illumination of the image while preserving the texture information and by creating a more uniform global brightness on the image and therefore increasing the features, boosting the recognition rate. Techniques employed in the face detection section [3] and [4] promote the accuracy of the system by removing the unnecessary and excess information from the face image, such as background, hair, and sometimes even forehead, to reduce the computational load of the system as well as decrease the chance of error by narrowing down the choices for the system. Other approaches [5] and [6] try to utilize the most suitable classifier based on the type of dataset that they are working with to optimize the system's operation and improve the rate by that.

The feature extractor has the highest weight in defining the complexity of the system. In addition to that, some of the system's properties directly come from this stage, features such as robustness against noise, speed, and most of the computational complexity. Feature extraction, mainly, can be divided into two major categories: 1) holistic-based methods, which tend to reduce the dimensionality of the face image while maintaining the essential required information. Principle component analysis (PCA) [7], linear discriminant analysis (LDA) [8], and local binary pattern [9] are examples of this approach. 2) Methods that are based on the features of the frequency space of the image, such as discrete cosine transform (DCT) [10] and Gabor wavelet [11].

Computational complexity is a parameter that plays a determining role in selecting an extraction technique. Due to its computational simplicity, strength against illumination variation, and ease of implementation, the local binary pattern (LBP) is one of the most popular techniques for face recognition. Though the conventional local binary pattern has its downsides, nevertheless, the advantages outweigh the shortcomings. This paper proposes a new approach to LBP for face recognition using a new adaptive function in the operator's structure. The new operator is modified to adapt based on a variation of the gaussian distribution function. The idea for this improvement comes from a conventional LPB's weaknesses: having a fixed threshold.

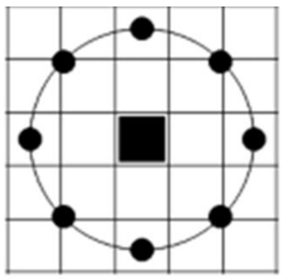
The contributions of the proposed method are 1) The new adaptive threshold by replacing the traditional way of thresholding at zero, maintains the information that is hidden in the amplitude of the pixel difference, 2) The proposed method improves the accuracy of the system by introducing the adaptive thresh-old function and a new error function to replace the fixed zero thresholding in conventional LBP, 3) In addition to that, the proposed method improves the robustness of the system against the noise.

The rest of this chapter is structured as follows: Section 2 briefly explains the theory of LBP. The shape of the proposed system is explained in detail in section 3. Section 4 includes the results of the experiment with the proposed method. Finally, the conclusion is stated in section 5.

2. LOCAL BINARY PATTERN

Among different existing methods of feature extraction, LBP is one the most widely used techniques, especially in face recognition applications, due to its ease of implementation and successful outcomes. The LBP is a local appearance-based method that extracts the image's texture features by comparing each pixel with its neighbours. There is no training requirement which makes it fast and easily integrable into the new data sets, and also, it is robust to rotation, scaling, and illumination variation.

Local pattern and grayscale contrast are two paired elements that are used to form the histogram. The idea was first introduced by Ojala et al. in 1996 [12]. The initial LBP operator considers a 3 by 3 window of neighbouring pixels to assign a tag to a pixel. This is called LBP coding. The three neighbouring pixels provide $2^8 = 256$ levels to form the histogram as the feature map. Later on, the system was modified to adopt a different window size than the original 3x3. Furthermore, a circular area, as well as bilinear interpolation, were introduced to improve the freedom of choice for selecting the neighbours' number. The figure 2 shows the concept of the LBP neighbour selection process.



R = 2 & P = 8

Figure.2. Radius and number of neighbouring pixels in LBP

P and R are the number of pixels and radius of the circle, respectively. These two parameters determine the pixels that are used to be compared with the center to create the LBP code. Now that the algorithm specified the pixels involved in the process, the next step is finding the difference between the reference pixel in the center and other pixels. The calculated pixel difference ultimately denotes the LBP code based on the equation (1). Figure 3 depicts this step for a sample.

$$b_p = \begin{cases} 1 \ if \ D_p \geq 0 \\ 0 \ if \ D_p \leq 0 \end{cases} \quad p = 1,2, \dots, N \tag{1}$$

where b_p is the LBP code of the pixel p, N is the number of pixels, and D_p is pixel difference.

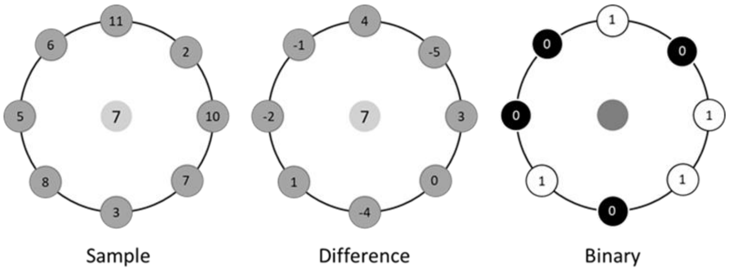


Figure.3. An example of LBP coding execution

Finally, a decimal number is calculated based on the binary code created by the algorithm. The following equation shows the process of computing this value.

$$LPB_i = \sum_{p=1}^{N} b_p(D_p) \times 2^{p-1} \quad (2)$$

The other variable in this setting is the direction of rotation which defines the sequence of the pixels and gets two values, clockwise and counter clockwise. We also can set the starting point in the process of decimal production, which should be the same for all the pixels of the image.

Now that the image is converted into a series of decimal values created based on the relationship between each pixel and its neighbours, the next step is generating the image's histogram. Albeit the histogram development is done on the blocks of the image rather than the whole image. The diagram of these steps can be seen in figure 4.

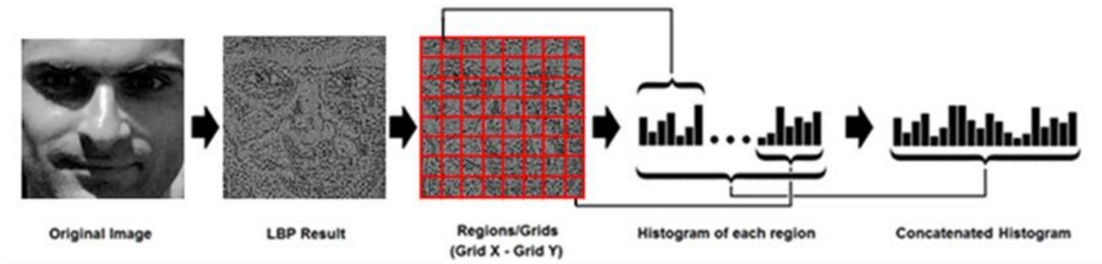


Figure.4. Histogram of an image based on the LBP code

2.1. Pros and Cons of The Conventional LBP

As mentioned before, LBP is considered one of the most reliable texture feature extraction methods. Many researchers in the field of face recognition employed LBP as the feature extractor for their system. The features like simplicity and robustness against monotonic changes in the image, such as illumination variation, rotation, and scaling, help in that regard. However, when it comes to maximum potential, one major flaw is that the conventional LBP employs a fixed zero threshold for the pixel difference, only considers the sign of the D_p, and dismisses the amplitude. A fixed zero threshold increases the sensitivity of the system to noise, and important information in the amplitude is missed, which decreases the accuracy of the method.

3. PROPOSED METHOD

Monotonic changes in the face image are the most affecting occurrences that alter the final results of the face recognition algorithm. Illumination variation, as one of these changes, shifts the pixel intensity of the image and thus changes the pixel difference D_p. However, it can be determined from (1) that this variation is not completely reflected since the algorithm only considers the sign of the difference and omits amplitude. Needless to say, that important information about the image can be extracted from the dismissed amplitude. In addition to that, the fixed zero threshold in conventional LBP adds sensitivity to noise and makes the system vulnerable. This comes from the fact that an added noise can change the binary bits from zero to one or vice versa by bringing a slight alteration. To overcome these issues, we propose to replace the zero thresholding for the pixel difference with an adaptive function, as is shown follows:

$$b_p^i = \begin{cases} 1 & if \ D_p \geq T_i \\ 0 & if \ D_p < T_i \end{cases} \qquad p = 1,2,\ldots,N \tag{5}$$

Here i refers to the block number, N is the number of pixels, and T_i is the adaptive threshold function.

The block size and numbers are fixed in our proposed method. But the threshold adapts to the global and local information of the image and blocks. We based the threshold function on the cumulative density function (CDF) of the Gaussian distribution function anticipating having both strong and responsive LBP features, as below:

$$f_i = {}^1\!/_2 \left[1 + \operatorname{erf}\left(\frac{\sigma_i}{\sigma\sqrt{2}\sqrt{|\mu-\mu_i|}}\right)\right], \qquad i = 1,\ldots,M \tag{6}$$

Where M is the number of image blocks, σ and μ are standard deviation and global mean, and μ_i and σ_i are the mean and standard deviation in a frame of the image. The error function is defined by $\operatorname{erf}(x)$ as below:

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt \tag{7}$$

Figure 5 illustrates the proposed adaptive threshold for different values of μ and σ.

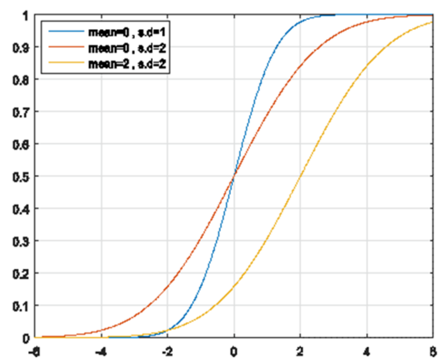


Figure.5. The proposed adaptive thresholding function with three different mean and standard deviation values

Finally, substituting (4) into the main framework of the LBP in (3) provides the ultimate LBP coding of the proposed method (A_dT-LBP):

$$b_p = \begin{cases} 1 & if \ D_p \geq f_i \\ 0 & if \ D_p < f_i \end{cases} \quad (8)$$

Also, worth mentioning that noise properties have a governing role in the development of the threshold function. Increases in the noise will result in a rise in the value of the threshold function and vice versa, which can be translated to more robust LBP features.

4. Experimental Results

In this section, we conduct two experiments and simulations and compare the results with other existing approaches to evaluate the effectiveness of the proposed method over the others. We first need to define a face recognition system based on the diagram in figure 1. For the pre-processing, our system employs a simple image resize and normalization. The feature extraction obviously is the method proposed in this paper (A_dT-LBP), and finally, for the classifier, we decided to go with the support vector machine (SVM). The selected dataset for the experiments is Extended Yale B. The first experiment compares the recognition rates of several existing face recognition systems with different feature extraction methods with the results of the proposed technique. In the second simulation, two different types of random noise (Salt & Pepper and Gaussian) are added to the database, and the effect of these noises on the accuracy is investigated for the previous approaches as well as the proposed method (A_dT-LBP). In the following, a brief introduction to the SVM and dataset is presented before we get into the results.

4.1. Extended Yale Dataset [14]

The Extended Yale Dataset of face images contains a 28-subject expansion of the original Yale B Dataset. The dataset includes 21888 photos from a mono lighting setup. Thirty-eight individuals participated in the experiment, with a total number of 576 viewing conditions. For each member, a sample with background illumination was captured, accompanied by a specific head pose of that person. Extended Yale B Dataset is divided into 5 distinct subgroups based on the angle between the light source, direction and the camera axis, and lighting situation. Subgroup 5, based on our experience, has the most challenging lighting condition and, in most cases, shows the lowest recognition rate.

4.2. Experimental Setup

4.2.1. First Experiment

In the first experiment, we compare the accuracy of the proposed system with other face recognition methods. The Extended Yale B dataset is selected for the experiment. Our proposed system uses SVM as the classifier. All the images of the database are resized to 64x64 prior to being fed to the algorithm. We used 40 random samples for training and 40 random for the test. Table 1 contains the results of the simulation. These results are gathered from the average of 20 runs of the algorithm on the dataset.

Table.1. %Recognition rate of different methods

Method	Recognition Rate
LDA+IPMML [15]	81.74
MRF [16]	78.11
LBP + SVM [17]	84.38
SVD+HMM [18]	95.56
Proposed Method	**97.75**

As we can see, the proposed method has a higher recognition rate than other techniques.

4.2.2. Second Experiment

In this simulation, the algorithm is tested against image noise. Two different types of noise, salt and pepper and Gaussian noise, are added to the samples, and their effects on the recognition rate are investigated. These two noises are categorized into two groups. Noise #1 is Gaussian noise with mean = 0 and variance = 0.05. Noise #2 is Salt and Pepper noise with noise density = 0.06. Note that these noises are also added to the inputs for other methods. The proposed system in this experiment has the LBP as the feature extractor and SVM as the classifier. We used the Extended Yale B database for training and testing. All the images of the database are resized to 64x64 prior to being fed to the algorithm. We used 40 random samples for training and 40 random for the test. Table 2 contains the results of the simulation.

Table.2. %Recognition rate of several face recognition systems in the presence of two different types of noise compared to the proposed method

Method	Recognition Rate	Noise #1	Noise #2
LDA+IPMML [15]	81.74	73.53 ↓8.21	66.2 ↓15.54
MRF [16]	78.11	66.93 ↓11.18	60.75 ↓17.36
LBP + SVM [17]	84.38	74.56 ↓9.82	68.79 ↓15.59
SVD+HMM [18]	95.56	87.94 ↓7.62	83.35 ↓12.21
Proposed Method	**97.75**	**96.38 ↓1.37**	**93.2 ↓4.55**

The second experiment shows that the proposed method has the lowest decrease in the recognition rate with the added noise.

5. CONCLUSION

This research proposed a new adaptive thresholding function for the LBP feature extractor in face recognition applications. The new function is based on a variation of the Gaussian distribution function. The proposed approach eliminates the shortcomings of employing fixed thresholding at zero in conventional LBP. The proposed technique amplifies the resistance of the LBP against noise by changing the threshold from zero to an adaptive function. Also, by considering the amplitude of the pixel difference and utilizing it in the computations of the LBP code, the proposed system preserves a significant part of the image information previously neglected in conventional LBP. In the course of this research, the new adaptive thresholding approach is evaluated by comparing the accuracy of a face recognition system that makes use of the introduced feature extraction technique and SVM classifier with other existing methods. The Extended Yale B dataset is used as the test set. The proposed method shows a higher recognition rate than other existing techniques. Also, to evaluate the system's behaviour against noise, we added two types of Gaussian and Salt and Pepper noise to the dataset and measured the new recognition rate of the system. The proposed method also improves the robustness of the system against the noise.

REFERENCES

[1] Ayyavoo, Thamizharasi, and Jayasudha John Suseela. "Illumination pre-processing method for face recognition using 2D DWT and CLAHE." *Iet Biometrics* 7.4 (2018): 380-390.

[2] Starovoitov, V. V., et al. "Image enhancement for face recognition." *International Conference on Iconics*. 2003.

[3] Fu, Limei, and Xinxin Shao. "Reseach and Implementation of Face Detection, Tracking and Recognition Based on Video." *2020 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*. IEEE, 2020.

[4] Li, Chong, et al. "Face detection based on YOLOv3." *Recent Trends in Intelligent Computing, Communication and Devices*. Springer, Singapore, 2020. 277-284.

[5] Gong, Sixue, Xiaoming Liu, and Anil K. Jain. "Mitigating face recognition bias via group adaptive classifier." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021.

[6] Ibrahim, Abdelhameed, et al. "Optimized superpixel and AdaBoost classifier for human thermal face recognition." *Signal, Image and Video Processing* 12.4 (2018): 711-719.

[7] Gottumukkal, Rajkiran, and Vijayan K. Asari. "An improved face recognition technique based on modular PCA approach." *Pattern Recognition Letters* 25.4 (2004): 429-436.

[8] Lu, Juwei, Konstantinos N. Plataniotis, and Anastasios N. Venetsanopoulos. "Face recognition using LDA-based algorithms." *IEEE Transactions on Neural networks* 14.1 (2003): 195-200.

[9] Rahim, Md Abdur, et al. "Face recognition using local binary patterns (LBP)." *Global Journal of Computer Science and Technology* (2013).

[10] Kohir, Vinayadatt V., and Uday B. Desai. "Face recognition using a DCT-HMM approach." *Proceedings Fourth IEEE Workshop on Applications of Computer Vision. WACV'98 (Cat. No. 98EX201)*. IEEE, 1998.

[11] Choi, Wing-Pong, et al. "Simplified Gabor wavelets for human face recognition." *Pattern Recognition* 41.3 (2008): 1186-1199.

[12] Ojala, Timo, Matti Pietikäinen, and David Harwood. "A comparative study of texture measures with classification based on featured distributions." *Pattern recognition* 29.1 (1996): 51-59.

[13] Suthaharan, Shan. "Support vector machine." *Machine learning models and algorithms for big data classification*. Springer, Boston, MA, 2016. 207-235.

[14] Georghiades, Athinodoros S., Peter N. Belhumeur, and David J. Kriegman. "From few to many: Illumination cone models for face recognition under variable lighting and pose." *IEEE transactions on pattern analysis and machine intelligence* 23.6 (2001): 643-660.

[15] Zhou, Lijian, et al. "Face recognition based on local binary pattern and improved pairwise-constrained multiple metric learning." *Multimedia Tools and Applications* 79.1 (2020): 675-691.

[16] Huang, Rui, Vladimir Pavlovic, and Dimitris N. Metaxas. "A hybrid face recognition method using markov random fields." *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004.*. Vol. 3. IEEE, 2004.

[17] Luo, Yuan, Cai-ming Wu, and Yi Zhang. "Facial expression recognition based on fusion feature of PCA and LBP with SVM." *Optik-International Journal for Light and Electron Optics* 124.17 (2013): 2767-2770.

[18] Kiani, Kourosh, Sepideh Rezaeirad, and Razieh Rastgoo. "HMM-based face recognition using SVD and half of the face image." *Modeling and Simulation in Electrical and Electronics Engineering* 1.2 (2021): 45-50.

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