**Information Set based Local Directional Number for Face Recognition**

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**Abstract:** Many algorithms were proposed on face recognition based on the Holistic method, Feature-based method, and also more recently based on local texture patterns. Few local texture patterns utilize the positions of the intensity values like Local Directional Pattern and Local Directional number for obtaining the knowledge (features). This paper proposes the new features based on positions of intensity values and the intensity values in the patch of an image to compute membership function value. The information set concept is used to compute the features that are non-overlapping blocks to restrict the number of features. The proposed method is tested with benchmark databases like ORL and Sheffield and Yale. The classification of the subjects was done with Support Vector Machine (SVM) and K-nearest neighbour Classifier to validate the results. Bio-metric performance curves like Receiver operating Characteristics (ROC) and K-fold validation test is performed. The experimental result shows that the accuracy of recognition has improved over the previously mentioned methods.

**Keywords:** Face recognition; Fuzzy set; Mask set; Information set; SVM; KNN.

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# 1. Introduction

Most of the research in face recognition are classified into two groups: i) Holistic methods in which the entire face(high dimensional) acts as an input to the recognition system, ii) Feature-based schemes which deal with local features such as the eyes, mouth, and nose and their statistics which are fed into the recognition system, and iii) Hybrid schemes, are derived from both the local features as well as the whole facial region are fed into the recognition system. Some popular face recognition approaches in representing the frontal face are as follows. That is Principal component Analysis derived from Eigenvalues and eigenfaces [1], neural networks [2], graph matching [3], hidden Markov model [4], Although appearance-based schemes are widely used because of their simplicity and implementation. The local texture features popular because of their robustness to illumination and other effects like glasses, facial growth, and variations in a pose. The Local-Global Graph algorithm [3] is a face recognition technique which uses Voronoi tessellation, and for segmenting the image, they used Delaunay graphs with this method a graph is built. The geometrical feature matching [5],-based schemes requires the most accurate and highly reliable facial feature detection and tracking algorithms, in many situations, this is difficult to accommodate. The template matching [5] and line edge map [6]. Local appearance-based texture features Local Binary Pattern LBP[7], Local Directional Pattern LDP[8], Local Ternary Pattern LTP[9], and many other variants of LBP have been proposed for face recognition. These approaches have been evaluated in terms of the facial representations adopted by them. The local texture descriptors based on LBP and its variants have widely used because of their sturdiness performance in uninhibited surroundings. LBP computes the local texture features for block or window based on a central pixel within the window. The adjacent pixels are assigned '0' or '1', taking central pixel as the threshold normally for the 3X3 window. We get an 8-bit binary code. In other words, The LBP operator codes the local texture feature of an image by binarizing the neighboring gray levels with respect to center value and thus forms an eight-bit binary pattern. The limitation of LBP is that it performs inadequately in the presence of substantial illumination change and random noise [9], a little variation in the gray level can change the LBP code.

The Local Directional Pattern (LDP) [8] adopts an interesting texture encoding scheme. In this directional edge, response values around a position are used by convolving an image with kirsch masks. In brief, LDP computes the code using kirsch masks set the values are set to '0' or '1' depending upon the responses from masks used. Local Directional Pattern (LDP) gives better results compared to LBP. LDP code dependent on the selection of the number of prominent edge responses, hence it may produce inconsistent patterns in uniform and near-uniform facial regions like forehead and chicks.

The Local Ternary Pattern (LTP) was proposed by Tan and Triggs [9]. It is an advanced version of the LBP code 2-valued to a 3-valued code that provides more consistency in uniform and near-uniform regions.

 (1)

Where is the adjacent pixel with n varies from zero to seven, the middle pixel is in the 3X3 window or patch, and is the threshold value which is chosen subjectively. The range of varies from 3 to 10. The encoding scheme for Local Directional Number (LDN) is based on responses from kirsch masks to find maximum and minimum in a window. They have used eight masks to find direction in which maximum and minimum exist. Much information about this method can be found in [10]. The LDN only uses the directions for encoding, which may fail for local texture features. LDN uses only six bits for generating the code, and the face has smooth texture in a limited area. The extracted features must be highly descremeable, in the sense that they should provide minimal variance within the class and provide large variation within intra classes. Local texture patterns provide a simple and efficient approach for image analysis, which has gained significant popularity for describing the texture characteristics of an image.

 Despite having so many methods, face recognition still suffers when there is variation illumination, pose, age, and expression conditions. Non-monotonic and random noise also affects performance. To overcome the problems associated with face recognition, the soft computing technique (neural network, Support Vector Machine, Fuzzy logic, and genetic algorithms) will be beneficial. The limitation of the Fuzzy logic theory is that membership function value and source data (intensity value of the image) are treated separately [11]. The said limitation of Fuzzy logic can be overcome by applying the Information set concept proposed by Hanmandlu et al. [12].

In this paper, we have presented an effective local texture feature-based on the central pixel and directional number with modified kirsch masks, which represent local Feature in a simple and efficient manner. To evaluate the features, we have used empirically two well-known machine learning methods, Support Vector Machine (SVM) and k nearest neighbour K-NN classifiers are used for classification. Experimental results show that the classification rate of the proposed method is appreciable. The rest of the paper is organized as follows: Section II Information set and Local directional number (ILDN), III Results and discussion. Finally, the conclusion is presented in section IV.

# 2. Information Set & Local Directional Number

***Information set***: The information set is used to enlarge the scope of the fuzzy set. The information set concept is simple to understand and easy to implement. The fuzzy logic (FL) deals with vagueness in the data and produces the degree of belongingness between '0' to '1'. FL is also used for building a mathematical model for a complex system. In building the membership function, the information values are used. Once the membership value is obtained, the information source value is ignored. Hanmandlu et al. have introduced the Information set. The concept is just the multiplication of normalized information source values with corresponding membership function. This concept is similar to the prospect theory proposed by Nobel laureate D Kahneman.[13] It has been proved that effective results were obtained by designing their own membership function than using popular membership functions like Gaussian, Sigmoidal, Trapezoidal, etc. The computing of Membership value and LDN code is explained with the help of a 3X3 patch or micro pattern.

The example of a micro pattern taken is taken as

**Fig. 1** Micro pattern or patch

To compute the membership function we use

 (1)

Where membership of the image pixel, is the minimum value and is the average value defined in the micro pattern. For the above pattern =20,, and

 (2)

Since is a very small value. We take a complement of the membership function. And it is represented by

 (3)

 for the above case.

 Local directional number (LDN), was proposed by Adin Ramirez et al. in their work, they have used kirsch mask the masks consist of -3,0,5 they have used eight masks. They have convolved these face images with the masks to produce eight responses and used a total of 6 bits for the representation of code. In this paper, we propose the method (1) instead of convolving the mask with the image, which takes considerable time to give the same result. We take element by element multiplication mask with micro pattern or window or block, and these are non-overlapping type. Our method takes very less amount of time. The time comparison is also made. 2) we build an 8-bit code instead 6-bit code to have more discriminative power for the Feature. (3) we develop our own mask set, which is a combination of -1,0,1. (4) Instead of computing the histogram and ambiguity of finding the bins, we go with non-overlapping windows to reduce the number of features. The results are compared with kirsch mask sets. The kirsch masks are given in Fig2.

East (M0) North East(M1)

 North( M2) North West (M3)

 West( M4) South West (M5)

South (M6) South East (M7)

**Fig.2** Kirsch Masks.

The filter responses they have obtained are the central values after convolving micropattern with masks the responses that they have got is (1)for East is

similarly, for North East the response that they have obtained

Similarly, the responses are obtained for the rest of the mask. The point to be noted is they have convolved and used central value. We obtained the same result which is fast to compute and done with the element by element multiplication for the same micropattern with the mask in the direction East is given in figure 1 after element by element multiplication we get

 =-1100. Similarly for the North East, the response we have got is

 =140. The eight responses obtained are-1100(East), 140(North East), 1220 (North), 1364(North West), 1444(West), 308(South West),-1036(South), and -2340(south East) the direction of maximum is west. We represent it with decimal 4 in a binary form we represent by 0100.and the direction of the minimum is southeast, and it represented by 1111, here the point is -7, represented by 1111 in the binary form to add more discriminative power. We combine to form (01001111)2=79. The advantage of using 8 bits is that we will get a maximum of 255. The Kirsch mask set is modified. Fig 3 shows the modified masks. The responses are boosted five times in one direction and three times in the opposite direction to obtain these masks. We modified to respond by the same magnitude in one direction and oppose it by the same in the opposite direction. The goal of any mask is that the response should be zero for uniform intensity region. And the sum within the mask should always be zero. Pragmatically we have got better results as compared to Kirsch mask

Set and information set.

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East (M0 ) North East (M1)

 North( M2) North West (M3)

 West( M4) South West(M5)

 South (M6) South East (M7)

**Fig.3** Modified Kirsch Masks

The final computation of the Feature for 3X3 as an example is based on complement membership function. and the LDN code computed is 79. Let the final Feature for kth window be represented by

 (4)

For the above example , The procedure is adopted for the next patch. Thus each patch will produce one Feature. If an image is of size 63X63, the features obtained are 441. These features are concatenated to form an array. The purpose of using modified Shannon entropy is, An image having a single intensity will have low entropy; it poses very little information, i.e., it has low discrimination power for classification. On the other hand, an image having different intensity values will have high entropy. For a face region, the variation of intensity is small. Hence instead of using probability, the membership function is used. The recognition rates are given in section III.

# 3. Results And Discussions

 Performance evaluation of FLDN for face recognition is done through the experiments conducted on ORL, Sheffield, and Yale datasets. ORL database has face images from 40 subjects, for each subject, ten images giving a total of 400 face images. The images were normalized first. All the face images are resized into images of 63x63 pixels for proper characterizing the directional information. The size of the images was made into integer multiplication of 3. To avoid padding of zeros for rows and columns. The 63X63 image produces the 441 feature vector per image.

The Sheffield Face Database consists of 564 images of 20 individuals, both male and female. The images are not equal in number for each subject. These folders contain a minimum of 23 images and a maximum of 58 images. We have used 23 images per folder, and each image resized to 99X99, which generates 1089 features.

Whereas for Yale database has 165 images of 15 subjects, and each subject has 11 images. The face images are center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised, and wink. Yale is having a fixed pose but different light illumination condition and expression. The Yale database images are cropped to face region and resized to the size of 63X63. The 63X63 image to produce 441 feature vector. The feature vectors are partitioned into training and test set before applying the classifier.



**Fig. 3** Grayscale face images of some of the subject in ORL database.

Table 1 and 2 shows the recognition rate and K-fold results obtained from ORL, Sheffield, and Yale databases. With 50% training and 50% test, there is an improvement in recognition of 9% on ORL database with SVM polynomial degree1on Modified Kirsch Mask set, and for the same, the KNN classifier has shown an increase of 9%.



**Fig. 4.** Gray scale face images of some of the subjects in Sheffield database.



**Fig. 5**: some original images from Yale face Database.

 SVM classifier with a polynomial 1 and polynomial 2 is used for training the classifier. To validate empirically, we have used the KNN classifier with proposed similarity measure .further the K fold results were plotted using SVM on the train and test vectors.

**Table 1** recognition accuracy and K-fold results with 50% training and 50% testing With Kirsch Masks and information set.

|  |  |  |  |
| --- | --- | --- | --- |
| Database | SVM POLY1 | SVMPOLY2 | KNN |
| ORL | 84 | 82.5 | 88.50 |
| Sheffield | 78.75 | 75.41 | 86.81 |
| YALE | 76 | 69.33 | 82.66 |
| K-FOLD RESULTS |
| Database | MIN | MAX | AVG |
| ORL | 77.5 | 97.5 | 90.90 |
| Sheffield | 95 | 100 | 99.50 |
| YALE | 20 | 93 | 78 |

**Table2** recognition accuracy and K-fold results with 50% training and 50% testing with Modified Kirsch Masks with information set.

|  |  |  |  |
| --- | --- | --- | --- |
| Database | SVM POLY1 | SVMPOLY2 | KNN |
| ORL | 95 | 93 | 97.50 |
| Sheffield | 88.91 | 85.75 | 88 |
| YALE | 92 | 89.33 | 90.66 |
| K -FOLD RESULTS |
| Database | MIN | MAX | AVG |
| ORL | 82.5 | 97.5 | 89.75 |
| Sheffield | 95 | 100 | 99.50 |
| YALE | 32 | 93.33 | 78 |

For the same condition on Sheffield Database, there is an improvement of nearly 10%. On Yale database with KNN, there is an improvement of 8%. Similarly, we can find improvement in the K-fold results. To plot the k-fold results, the SVM classifier is used.



**Fig 6.** The Accuracy Vs. K-fold with Kirsch Masks.



**Fig 7.** The Accuracy Vs. K-fold with Modified Kirsch Masks.



**Fig 8.** The ROC with Kirsch Masks and Information Set



**Fig 9.** The ROC with Modified Kirsch Masks and Information Set

Fig.8 and Fig. 9 show the ROC with Kirsch masks and information set and Modified Kirsch masks and information set, respectively. To plot the ROC, we have used the KNN classifier with cosine distance measure is used. The ROC curves clearly show the improvement in the recognition rate. Comparing with the existing methods, the Authors in [14] have used the Haar wavelets with different de-noising levels on the ORL database. They have obtained a recognition rate of 65.36 to 67.14 % at FAR of 0.1, and our obtained results are better.

# 4. Conclusion

We developed a novel method for face recognition that makes use of membership function to enlarge the scope of fuzzy set, LDN code, and Shannon entropy in the modified form. We have presented the local directional number with eight bits, i.e., four-bit for the representation of the maximum number and four-bit for the minimum number. In this work, membership function and LDN code are combined with a modified form of Shannon entropy. A new mask set that gives better results is also developed. Validated the results of the SVM and K-nearest neighbour classifier, both the classifier has given approximately the same results. The further work can be carried by changing the membership function, building the new classifier. One can think of using the type-2 fuzzy set for improving the recognition rate.

# References

1. Jolliffe, Ian. Principal component analysis. John Wiley & Sons, Ltd, 2002.
2. Lawrence, Steve, et al. "Face recognition: A convolutional neural-network approach." Neural Networks, IEEE Transactions on 8.1 (1997): 98-113.
3. Wiskott, Laurenz, et al. "Face recognition by elastic bunch graph matching."Pattern Analysis and Machine Intelligence, IEEE Transactions on 19.7 (1997): 775-779.
4. Samaria, Ferdinando Silvestro. Face recognition using hidden Markov models. Diss. University of Cambridge, 1994.
5. Brunelli, Roberto, and Tomaso Poggio. "Face recognition: Features versus templates." IEEE Transactions on Pattern Analysis & Machine Intelligence10 (1993): 1042-1052.
6. Gao, Yongsheng, and Maylor KH Leung. "Face recognition using line edge map." Pattern Analysis and Machine Intelligence, IEEE Transactions on24.6 (2002): 764-779.
7. Ahonen, Timo, Abdenour Hadid, and Matti Pietikainen. "Face description with local binary patterns: Application to face recognition." Pattern Analysis and Machine Intelligence, IEEE Transactions on 28.12 (2006): 2037-2041.
8. Jabid, Taskeed, Md Hasanul Kabir, and Oksam Chae. "Local directional pattern (LDP) for face recognition." 2010 Digest of Technical Papers International Conference on Consumer Electronics (ICCE). 2010.
9. Tan, Xiaoyang, and Bill Triggs. "Enhanced local texture feature sets for face recognition under difficult lighting conditions." Analysis and Modeling of Faces and Gestures. Springer Berlin Heidelberg, 2007. 168-182.
10. Ramirez Rivera, Adin, Jorge Rojas Castillo, and Oksam Chae. "Local directional number pattern for face analysis: Face and expression recognition." Image Processing, IEEE Transactions on 22.5 (2013): 1740-1752.
11. Gubbi, Abdullah, M. Hanmandlu, and M. F. Azeem. "A novel LBP fuzzy feature extraction method for face recognition." India Conference (INDICON), 2013 Annual IEEE. IEEE, 2013.
12. Hanmandlu, Madasu, Devendra Jha, and Rochak Sharma. "Colo rimage enhancement by fuzzy intensification
13. ." Pattern Recognition Letters 24.1 (2003): 81-87.
14. Kahneman, Daniel, and Amos Tversky. "Prospect theory: An analysis of decision under risk." Econometrica: Journal of the Econometric Society(1979): 263-291.
15. Isra'a Abdul-Ameer Abdul-Jabbar, Jieqing Tan, Zhengfeng Hou "Wavelet Based Image De-noising to Enhance the Face Recognition Rate" IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 1, No 3, January 2013: 1694-0814