A NOVEL FINGERPRINT RECOGNITION SYSTEM USING LBP FUZZY FEATURES

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ABSTRACT:

This paper presents a simple, but computationally efficient approach for fingerprint recognition. In this proposed approach fingerprint image is divided into windows of size $3 \times 3$ to extract the fuzzy features. The information at the center of the window is the product of information extracted using Local Binary Pattern (LBP) and fuzzy membership function. Maximization of mutual information between orientation extracted from the test and trainee images is used for alignment of fingerprint images. K-nearest neighbor (KNN) and Support Vector Machine (SVM) classifiers are used for matching on FVC2002 DB2_B databases. The experimental results shows that recognition rate of 97.8% are observed with SVM classifier.

Keywords: Fingerprint recognition, Local Binary Pattern, K-Nearest Neighbor classifier, Information set.

[1] INTRODUCTION

Automatic access control systems require a reliable scheme of person authentication to confirm or determine the identity of an individual requesting for the services like time and attendance, boarding an aircraft, financial transactions, and picking a child from a day care centre etc. Therefore the need for an automatic access has resulted in establishment of new technological area called biometrics [1]. The major objective of biometrics is to provide automatic discrimination between subjects in a reliable way based on one or more physiological (anatomical) and behavioral traits like fingerprint, face, iris, retina, voice, signature etc. [2]. These biometrics traits are also referred as biometrics modalities. From the available biometric modalities fingerprint based authentication has gained an edge over others due to its highest recognition rate and easy acquisition as compared to
other biometrics like face, retinal and iris etc. Various techniques developed over a time for fingerprint recognition are broadly classified as minutiae-based and image-based methods. Minutiae-based techniques represent the fingerprint by its local features, like terminations and bifurcations. This approach has been intensively studied, also is the backbone of the current available fingerprint recognition products [3, 4-6]. The major drawback of minutiae based method is the detection of false minutiae. In image-based matching techniques [7] feature extraction and template generation are based on gray values of ridges and consider the entire image as template. The main disadvantage of image-based method is that matching may be seriously affected by image quality factors and need large storage for templates.

Proposed method address the shortcoming of the above techniques used for fingerprint matching and takes benefits of the Information sets, developed by exploiting the scope of fuzzy sets [8, 9]. The information sets has also exploited in the area of biometric authentication using ears by [10], where, the image after granualization is considered as the information source. The granualization amount is used for partitioning of an image into windows (sub images). The property values, attributes or cues comprising the information sources contained in the windows form the fuzzy sets. The distribution of these information sources in the fuzzy sets requires an appropriate membership function to fit.

We concentrate on extracting the local fuzzy features from images. The idea is not to look at the whole image as a high-dimensional vector, but to consider only the local features of an image. Our goal is to use the approach of Local Binary Patterns (LBP) for features extraction and to fuzzify the same to obtain simple and robust features. These features are tested on SVM and K- Nearest Neighbor classifiers.

The organization of the paper is as follows. Section 2 describes the LBP and fuzzy logic. Section 3 presents the proposed method of fingerprint feature extraction. Experimental setup and results are discussed in Section 4 and conclusion of the paper is presented in Section 5.

[2] LBP AND FUZZY LOGIC

The Local Binary Pattern (LBP) possesses discriminative power for texture classification and is widely used in 2D texture analysis. It was first introduced by Ojala in 2002 [11] and is a non-parametric 3×3 kernel which describes the local spatial structure of an image. At a given pixel position \((x_c, y_c)\), LBP is defined as an ordered set of binary comparisons of pixel intensities between the centre pixel and its eight surrounding pixels. The decimal values of the resulting 8-bit word (LBP code) leads to 28 possible combinations, which are called Local Binary Patterns often abbreviated as LBP codes with as many as 8 surrounding pixels [12]. The basic LBP operator is a fixed 3 × 3 neighborhood as shown in Figure 1.

![The basic Local Binary Pattern (LBP) operator.](image)

The LBP operator can be mathematically expressed as,
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\[ LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \]  

Where \( i_c \) corresponds to the gray value of the centre pixel \((x_c, y_c)\), \( i_n \) to the gray values of the 8 surrounding pixels and function \( s \) is defined as,

\[ s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \]

Let the value of LBP from a window be denoted by \( L_W \).

The extension of conventional (crisp) set theory is Fuzzy Logic theory and it deals with the fuzzy sets having imprecise and uncertain data. It handles the concept of partial truth (truth values between 1 (completely true) and 0 (completely false)). It was introduced by Zadeh to model the vagueness and ambiguity in complex systems for which there is no mathematical model to describe. The Fuzzy Logic theory have been used in almost every domain of computational intelligent systems like, medical imaging control engineering, computer vision, and, document processing, signal processing and image processing.

The major drawback of fuzzy sets is that they treat the attribute or property values which we say information source values and their membership function values separately for all the problems dealing with the fuzzy logic theory. The membership function value provides the degree of association of a particular information source value in any given fuzzy set [10]. The proposed work seeks to combine the information source values and their membership values together referred to as information values and often constitutes to Information set. Moreover, to provide higher flexibility to the membership function, it is treated as an agent (\( \mu \)) by empowering with more power than that possible with the usual membership function. The sum of information values give the information or uncertainty existing in the information set derived from the original fuzzy set [14]. To give an example of agent, consider a student set graded on the performance of the class topper serving as the benchmark and the student’s individual performance (information source value) is determined by comparing his performance with that of the topper (\( \mu \)).

[3] THE PROPOSED METHOD

In the case of images the uncertainty appears in the gray values. Gray level fingerprint images are divided into non overlapping windows of size 3×3 and LBP method is used to extract their local information. The membership function for each window using their central pixel is computed as follows:

\[ \mu_{\text{window}} = \frac{i_c}{\sum i(x,y)} \]

Where \( i_c \) represent the central pixel of the window and \( \sum i(x,y) \) is the sum of the gray values of that window. The use of membership function in (3) is to take care for the central gray value which is ignored while computing LBP value over a window.

In the proposed method, two types of information is computed: (i) the scaled information at the central pixel of a window and (ii) the information derived from LBP of a window. The total information is taken to be the product of these two.

The resulting information at the central pixel is given by the product of the membership value and central pixel value as per the concept of information value explained in [10].

\[ I_c = \mu_{\text{window}} \times i_c \]

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This information is modified by a scale factor $\lambda F_{\text{max}}$. The resultant scaled information is

$$H_s = \lambda F_{\text{max}} H_c \quad (5)$$

Where $\lambda$ is a scaling parameter which is greater than one ($\lambda > 1$). For our implementation we have taken it as 2.5 and $F_{\text{max}} = 0.5$. $F_{\text{max}}$ is the maximum frequency and $\sqrt{2}$ (half octave) is the spacing factor between different central frequencies. According to the Nyquist sampling theory, a signal containing frequencies higher than half of the sampling frequency cannot be reconstructed correctly. Therefore the upper limit of frequency for a 2D image is 0.5 cycle/pixels, while the low limit is Zero. As a result we set $F_{\text{max}} = 0.5$ [15].

In order to take account of the information from the neighbourhood pixels (information sources), we compute the LBP value for the window. This is given by

$$L_W = \text{LBP}(x_c, y_c) \quad (6)$$

It may be noted that while computing $L_W$ which is a decimal value, the central pixel value is ignored. By taking a clue from the communication theory, the information about the neighbourhood pixels is taken to be the log of the decimal value:

$$H_N = \log L_W \quad (7)$$

As we have the information at the central pixel and the neighborhood pixels, the total information is taken as the product of these two types of information, given by

$$H = H_s H_N \quad (8)$$

The contribution of this method is to eliminate the shortcoming of LBP approach that ignores the central pixel value by accounting for the information of both the central and the neighbourhood pixels.

[[4] EXPERIMENTAL SETUP AND RESULTS]

The image processing toolbox of MATLAB 7.12.0 was used for implementation in this paper on Intel core i5 with 4GB RAM. Experiments are performed on FVC2002 DB2_B public dataset [13], which contains 80 fingerprint images of 10 subjects. Fingerprint images are normalize over the gray (pixel) values by dividing them by the maximum gray value in that image. So the pixel values lie in the range 0 to 1 (also known as, the normalized information source values). Region of interest (ROI) of size $100 \times 100$ is then extracted.

We have padded each fingerprint image with zeros to make rows and columns divisible by 3 in order not to lose any information while dividing the fingerprint image into windows. The procedure to extract the feature information is as follows:

1. Divide the image into $3 \times 3$ non-overlapping windows.
2. For each $3 \times 3$ window, compute the sum of window as
   $$D_{\text{sum}} = \sum I_{ij}$$
3. Compute the membership value, $\mu_{\text{window}}$ using Eqn. (3).
4. Using the specified values of scale parameter, the information at the central pixel is calculated using

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\[ \mu_{\text{window}} = \frac{ic}{\sum f(x, y)} \]

5. Compute the LBP value from a window using
\[ L_W = \text{LBP}(x_c, y_c) \]

6. Compute the information about the neighborhood pixels by using
\[ H_N = \log L_W \]

7. Total information is computed as the product of information at the central and the neighboring pixels.

This total information is a feature extracted from each window.

All features are stored as an array for each fingerprint image. For an image of size 100×100, we get an array of 1156 features. Total 80 features are extracted from 80 images, each one of size 1×1156. The complete set of 80 features is then divided into training and test sets. We have used K-Nearest Neighbor and SVM classifiers [16] for matching. The flow chart of implementation of the proposed method is shown in Figure 2.

Figure 2. A flowchart of Implementation

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A. **KNN Classifier**

The simplest among all the machine learning techniques is the k-Nearest Neighbor classifier. It is a non-parametric technique used for classification of the data objects. It is non-parametric in the sense that we should not take care of its underlying structure rather we can readily use it. It gives the measure of the closeness of test feature vector to the training feature in the feature space for classification. Any data object is classified based on its closeness to the neighbors. If the value of k is equality, the object is simply assigned to the class of its nearest neighbor. The flowchart for KNN is shown in Figure 3.

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A flowchart of KNN Classifier
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B. **SVM CLASSIFIER**

Currently, the SVM has gained popularity as a supervised machine learning algorithm particularly to solve the classification problems almost in all domains. SVM is also used in order to classify the input fingerprints feature vector into the corresponding class.
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Least Square-SVM is a variant of SVM which is designed in order to solve the indefinite linear sets of equations. LS-SVM and SVM both are designed for making binary classification however, a multi class system can also be designed by combination of the two class SVMs. Given a set of training samples, each given class number as belonging to one of two classes, an SVM training algorithm constructs a model that assigns new samples into one class or the other. Figure 4 shows support vectors built by SVM (Linear SVM image, 2011) [17].

![Figure 4. Linear SVM; Curtsey (Linear SVM image, 2011)](image)

C. MULTICLASS SVM

Multiclass SVM uses support vectors in order to allocate labels to instances. Here the labels are taken from a limited set of elements and the multiclass problem is then converted to multiple binary classification problems. This can be accomplished in two ways:

1. One-versus-all
2. One-versus-one

Categorization of new samples in the case of one-versus-all is achieved by a winner-takes-all approach, and the classifier which possesses the maximum output function assigns the class. Categorization in the one-versus-one case is achieved by a max-win voting approach where every classifier assigns the sample to one of the two classes, and then increasing the vote count by one, and lastly the sample classification is determined by the class with the majority votes.

In our proposed system, one-versus-all approach is used in order to classify between each class and all the remaining classes. We have adopted the second strategy for multi-class classification because we are interested in computing FAR. The grid-search adjusts the testing parameters using the hyper parameter space in the 100-fold cross validation using the training sequence.

Though the various new kernels are being proposed but the linear, polynomial, and radial basis function (RBF) are the most frequently used? In our experiments, we have used the RBF kernel given by

\[ k(x, x') = \exp(-\gamma ||x - x'||^2), \gamma > 0. \]  

As our feature vector is formed by concatenating the histograms, which lead to a very large feature vector for training a classifier. Discrete cosine transform (DCT) is used for the dimensionality reduction [18].

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For classification, the feature vectors are separated into training and testing sets. Each example of the training set contains one target value (i.e. the class labels) and several attributes (dimension of feature vector). The goal of SVM is to produce a model (based on the training data) for predicting the target values of the test data given only the test data attributes. The feature vector for each dataset is separated into the training to test ratio of 75:25 i.e. for each subject 6 images are chosen for training and remaining two for testing at random. Each set is then normalized in the range [-1, 1].

For the training to test ratio of 75:25, we obtain highest recognition rate of 97.8% using SVM with the polynomials of degrees 1 and 2 and the KNN gives 95.6% for the same ratio. The detailed results obtained from the experiments are shown in Table 1.

<table>
<thead>
<tr>
<th>FVC2002 DB2_B</th>
<th>SVM</th>
<th>KNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training images 6.</td>
<td>97.8%</td>
<td>95.6%</td>
</tr>
<tr>
<td>Testing images 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training images 5.</td>
<td>94.2%</td>
<td>92.4%</td>
</tr>
<tr>
<td>Testing images 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training images 4.</td>
<td>89.5%</td>
<td>87%</td>
</tr>
<tr>
<td>Testing images4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The table clearly shows that the recognition rate obtained from SVM is better in comparison to the KNN. It is also observed that the recognition rate is better for the higher size of training dataset for both the classifiers. The SVM classifier accuracy is comparable with those of obtained in the literature.

[5] CONCLUSION

This proposed approach extract the information from both the central pixel and the neighborhood pixels of a fingerprint image while matching test sample with the training samples in the fingerprint recognition process thus eliminating the drawback of LBP approach which accounts for the neighboring pixels alone in the representation of texture in a window. Our approach is based on the recent theory on information sets presented in [8, 10] where the information value is defined as the product of information source value and its membership function value. The information LBP value is framed from the communication theory where the information is defined as the log of the decimal value of a signal. In this work the information from LBP value is coupled with the concept of information sets in the multiplicative manner. The advantage of this approach is that the information sets allow the information to be modified in different ways. One of the ways to change the information is suggested in this paper using the scale factor derived from the knowledge of frequency components.

A comparison of performance of the proposed approach is made with that of two classifiers KNN and SVM. Better results are reported with SVM.

The proposed approach is found to be effective on images having variation in expression, illumination and pose. Further work needs to be done by changing the membership function values. This is possible one way by employing type-2 membership functions in which one of the parameters is changed.

The experiment is conducted on FVC2002 DB2_B public dataset [13]. The new features are the result of better representation of the uncertainty in the local area like a window, which preserves
the information of complete window. The experiments reveal that better the representation of the uncertainty, better will be the recognition rates.

References