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Local adjacent extrema pattern for fingerprint image classification

Adhiyaman Manickam[1], D Ezhilmaran[1] and Rajkumar Soundrapandiyan[2]
[1]Department of Mathematics, School of Advanced Sciences, VIT University, Vellore-632014, India
[2]Department of Software System, School of Computer Science and Engineering, VIT University, Vellore-632014 , India.

E-mail: adhimsc2013@gmail.com

Abstract. Fingerprint classification is as yet difficult issue due to incomplete information in ridges and low quality images. To address these problems, we propose a new and robust Local Adjacent Extrema Pattern (LAEP) is a feature descriptor for fingerprint classification. The proposed descriptor finds it values based on indexes of local adjacent extremas using first order derivatives. The intensity values of the local extremas are compared with center pixel intensity value to employ the correlation of central pixel with its neighbors. Finally, the descriptor is generated on the support of the indexes and local extremas values. Support Vector Machine (SVM) is utilized for classification of fingerprint images into five classes. To prove the effectiveness of the proposed descriptor, we have tested on Indraprastha Institute of Information Technology (IIIT) - Indian rural fingerprint database for classification. In addition, the classification results of the proposed descriptor are compared with the existing methods. The resultant LAEP descriptor proved better classification accuracy than the previous methods.

1. Introduction

To distinguish the human biometric security is known by two ways such as physical attributes and behavior. There have been different biometric traits were used for recognition. The biometric traits, for example: fingerprint, palm veins, iris recognition, retina, face recognition, Deoxyribonucleic Acid (DNA), palm print, hand geometry, odor, typing rhythm, gait, and voice which is very appropriate for human recognition because of their singularity, integrality and uniformity. Among all other biometric techniques, fingerprints have the elevated amount of dependability and widely utilized by criminological specialists as a part of criminal examinations. To maintain the security is computationally challenging task for large database. Hence, fingerprint indexing scheme is needed for match the query image against every one of the fingerprints in database. Fingerprints are classified into pre specified categories using fingerprint classification algorithms which give an indexing scheme to encourage proficient coordinating for large fingerprint database.

To obtain the index, the following fingerprint features such as incipient ridges, minutiae, pores, singular points, ridge orientation map, singular points, dots and frequency map are used for recognition to identify the person.

The features are inherent in the following three types of patterns like arch, loop and whorl. It has classified in to nine classes such as arch, tent arch, right loop, left loop, double loop, right pocket loop, left pocket loop, whorl, mixed figure [1] (see Figure 1). Among all other feature, singular points are commonly used for classification. Arch - fingerprint do not contains singularities. Left loop, right loop and tented arch fingerprints are containing one loop and one delta. Whorl fingerprint contains two loops and two delta.

A fingerprint classification of the comprehensive survey was explained by Yagar and Amin [2]. It consists different feature extraction and classification techniques for obtain better performance. Fingerprint classification algorithm was proposed by Jung and Lee [3] for ably classify noisy and incomplete fingerprints. Galar et al [4, 5] surveyed complete fingerprint classification based on feature extraction method, learning models and experimental results. Orientation extraction and classification for fingerprint image was proposed by Cao et al [6]. Rule based fingerprint classification was proposed by Guo et al [7]. Li et al [8] proposed combining singular points and constrained nonlinear orientation image information for fingerprint classification. Adaboost learning methodology was used by Liu [9] in fingerprint classification algorithm to model multiple types of singularity features. Karu and Jain [10] proposed fingerprint classification based on extracting the singular points such as core and delta.

Still, many researchers are working on extracting the singular points for classification but it is challenging to obtain the better result. To lead the issue, the texture patterns are used for any image classification. A few researchers are working on fingerprint classification to extract the patterns with learning methodologies such as SVMs, neural network, etc.

The Local Binary Patterns (LBP) [11] worked based on sign of difference between central pixels with its local neighbours. It helps to illustrate the local feature of the image. Various LBP are exist in the literature such as a Local Ternary Pattern (LTP) [12], Center Symmetric Local Binary Pattern (CSLBP) [13], Data Driven Local Binary Pattern (DDLBP) [14], Local Neighboring Intensity Relationship Pattern (LNIRP) [15], Local Diagonal Extrema Pattern (LDEP)[16], Multichannel Decoded Local Binary Patterns (MDLBP), Directional Extrema Pattern (DEP) [17], Local Ternary Co - Occurrence Patterns (LTCoP) [18] etc. Burges [19] introduced the concepts on support vector machine for pattern recognition. Object recognition, face recognition and text categorization are worked with the help of learning methodology such as SVMs in pattern recognition. Fingerprint matching using SVM-based similarity measure was introduced by Fei et al [20].

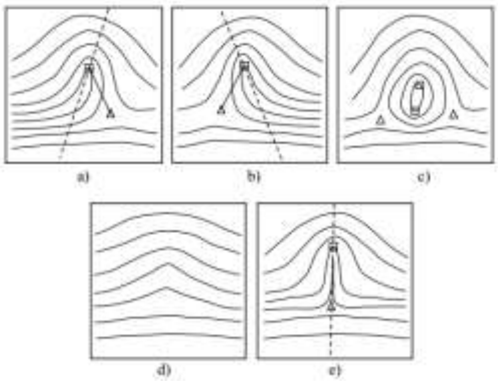

Figure 1. a) Left Loop, B) Right Loop, C) Whorl, D) Arch, and E) Tented Arch; Squares Represents Core and Triangles Represents Delta.

The classification is challenging task because it used to reduce the search time of automatic fingerprint matching in large database as a preliminary stage.

To facilitate high performance classification, in this paper, we used only adjacent neighbours because it reduces the dimension of the descriptor and contain most of the local edge information.

The remaining sections of this research paper include, section 2 proposes a descriptor based fingerprint classification model using local adjacent extrema pattern. Section 3 describes about SVM.

Section 4 presents classification results and performance analysis. Finally, Section 5 concludes the paper.

2. Local Adjacent Extrema Pattern

Local adjacent extrema pattern has derived as a new feature descriptor for fingerprint classification form center pixel and its local neighbours. The first order local adjacent derivative is used to extract the local adjacent extrema (maxima and minima) pattern. The connection of local adjacent extrema with the center pixel plays a major role to encode the LAEP descriptor. Local adjacent extrema are extracted of any center pixel by using first order local adjacent derivatives.

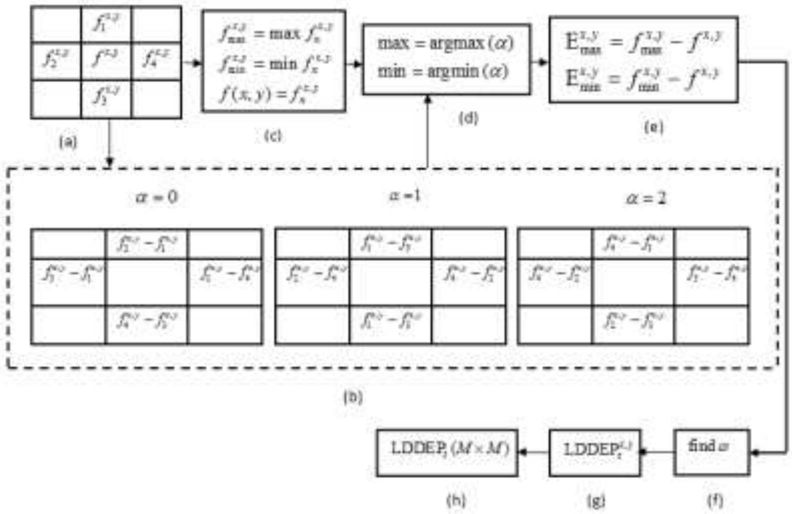

Figure 2. The computation of $LAEP^{i,j}$ pattern for center pixel $Q^{i,j}$

Let $Q^{i,j}$ be the center pixel and its corresponding n^{th} diagonal neighbours $Q_n^{i,j}$ at a distance D, where $n \in [1,4]$ and $Q^{i,j}$ is the pixel at i^{th} row and j^{th} column of any gray scaled image M having m_1 rows and m_2 columns. Let $I_n^{i,j}$ and $I^{i,j}$ be the intensity value of $Q_n^{i,j}$ and $Q^{i,j}$ respectively as shown in Figure 2(a).

We define $f_n^{x,y}$ as: $f_n^{x,y} = f^{(x+\alpha),(y+\beta)}$

Where α and β are the constant having the values either $+D$ or $-D$ depending upon the value of n as,

$$\alpha, \beta = \begin{cases} 0, \quad \text{-D} & n = 1 \\ \text{-D}, \quad 0 & n = 2 \\ 0, \quad \text{+D} & n = 3 \\ \text{+D}, \quad 0 & n = 4 \end{cases}$$

We used three directions (clock wise $\alpha = 0$, diagonal $\alpha = 1$ and anticlockwise $\alpha = 2$) to encode the relationship of each diagonal from $Q_n^{i,j}$ for find the local diagonal maxima and minima. Figure 2 (b) depicts the first order adjacent derivatives for $\alpha = 0$, 1 and 2 respectively. Figure 2(c) shows the values of the local diagonal extremas and center pixel.

$$I_{n,\gamma}^{i,j} = I_{(1+\text{mod}(\text{n}+\gamma,4))}^{i,j} - I_n^{i,j}$$

Where $n \in [1,4]$, $\gamma \in [0,2]$. The local adjacent maxima and minima of the center pixel $Q^{i,j}$ are represented by the value $f_{\max}^{i,j}$ and $f_{\min}^{i,j}$ of the intensity pixel values respectively, where $\max$ and $\min$ are the indexes of the local adjacent maxima and minima of $Q^{i,j}$ respectively. Figure 2(d) displayed the indexes of the local adjacent extremas and defined as follows,

$$\max = \arg\max(sign(\alpha) = 0 \;\forall \alpha \in [0,2]$$
$$\min = \arg\min(sign(\alpha) = 1 \;\forall \alpha \in [0,2]$$

where $sign$ is a function and the formula to find the sign of a pixel values and given as follows,

$$sign(\alpha) = \begin{Bmatrix} 1, & \alpha \geq 0 \\ 0, & \alpha < 0 \end{Bmatrix}$$

The values and indexes of the local adjacent extremas has derived for finding the local adjacent extrema pattern. We represented the LAEP for $Q^{i,j}$ with a binary pattern $LAEP^{i,j}$ when the local diagonal neighbors at a distance D are considered and generated as follows,

$$LAEP^{i,j} = (LAEP_1^{i,j}, LAEP_2^{i,j}, \ldots, LAEP_{\dim}^{i,j})$$

where $\dim$ is the length of the $LAEP$ pattern and $LAEP_t^{i,j}$ is the t^{th} element of the $LAEP^{i,j}$ and given using following formulae,

$$LAEP_t^{i,j} = \begin{cases} 1, & if\; t = (\max + 8\omega)\, or\; t = (\min + 4 + 8\omega) \\ 0, & else \end{cases}$$

The extrema-center relationship factor is denoted by ω. The $LAEP^{i,j}$ pattern is all 0's and 1's. The positions of the 1 are determined by the relationship of local extrema with the centre pixel. The extrema-centre relationship factor can be defined as equation

$$\omega = \begin{cases} 0, & if\; (sign(\Omega_{\max}^{i,j})) = 0\, and\; (sign(\Omega_{\min}^{i,j})) = 0 \\ 1, & if\; (sign(\Omega_{\max}^{i,j})) = 1\, and\; (sign(\Omega_{\min}^{i,j})) = 1 \\ 2 & else \end{cases}$$

where $\Omega_{\max}^{i,j}$ and $\Omega_{\min}^{i,j}$ are the local diagonal and extrema-center pixel difference factor for $f_{\max}^{i,j}$ and $f_{\min}^{i,j}$ respectively and computed as follows (see Figure 2 (e)),

$$\Omega_{\max}^{i,j} = f_{\max}^{i,j} - f^{i,j}$$
$$\Omega_{\min}^{i,j} = f_{\min}^{i,j} - f^{i,j}$$

The maximum possible value of t is 24 and it depends on the values of $\min$ and ω. The binary $LAEP^{i,j}$ pattern is a 24 bit number, where twenty two places hold the value 0 and the remaining two places have the value 1.

The computed local adjacent extrema pattern for the pixel $P^{i,j}$ is $LAEP^{i,j}$. The enhanced adjacent extrema pattern over the image (M) as below,

$$LAEP = (LAEP_1, LAEP_2, \ldots, LAEP_{\dim})$$

Where $LAEP_t$ is the t^{th} element of $LAEP$ given as follows,

$$LAEP_t = \frac{1}{(m_1 - 2D)(m_2 - 2D)} \sum_{i=D+1}^{m_1 - D} \sum_{j=D+1}^{m_2 - D} LAEP_t^{i,j}$$

3. SVM classification

Support Vector Machine (SVM) has been used for recognizing two class problems by the separating hyper plane with maximal distance to the closest points of the training set. Increase the margin between the classes and classification and classification error is reduced with the help of SVM.
Linear kernel function is given as below

$$K(x_i, x_j) = x_i^{'} x_j$$

where $K(x_i, x_j)$ is the kernel function and x_i is the training data. $x_i^{'}$ is the transform of the training data.

4. Experimental results and performance analysis

4.1. Dataset used

The proposed method is tested on public available database namely Indraprastha Institute of Information Technology (IIIT) Rural Indian Fingerprint database. It contains 75 subjects (for each individual, we capture right and left index finger). Each subject has 10 samples. Each image is of 508 × 661 pixel in size and has been scanned at 1000 pixels per inch as a gray - scale image. Total number of images in rural database is 1500. The challenges in this dataset is having non feature (such as singular points) images. It motivates us to derive the extrema pattern for classification. As far as we know, the classification work has not yet been carried out on this database.

4.2. Perfomance evaluation measures

The performance evaluation is carried out on the basis of recall, precision and accuracy metrics. They have found extensive use in many forensic applications for evaluating the individual recognition.
Quantity is measured by recall and defined as follows

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Precision is a measure of fidelity. If false positive is less then high precision for classification. It defined as follows

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Classification problem is evaluated on the basis of accuracy and provided as follows

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{False Negative} + \text{True Negative}}$$

4.3. Experimental results

We used five major fingerprint classes for classification such as arch, tented arch, left loop, right loop and whorl. Classification is executed SVM linear kernel function. For training 200 images having the classes and 1300 images having the non-classes were used.

To test the robustness of our algorithm, we have compared with previous popular feature based classification methods such as Gray-Level Co-occurrence Matrix (GLCM) [21], Local Binary Pattern (LBP) [13], Local Directional Pattern (LDP) [22], Local Diagonal Extrema Pattern (LDEP) [16] using SVM with linear kernel function. The feature descriptors, namely, GLCM, LBP and LDP are generally used in computer vision and image processing for pattern recognition. LBP and LDP is simple and efficient texture descriptor. GLCM is texture descriptor which works for highly textured images. Recall, precision and accuracy are used to conclude the performance of the results.

In this experiment, we have tested for classification with different combination of images such as test-1, 2 and 3 respectively. Test -1 contains 1050 images for training and 450 images for testing. Similarly test -2 contains 900 images for training and 600 images for testing and test -3 contains 750 images for training and 750 images for testing. As far as we know, the dataset used in classification results are not yet reported. Due to this reason, we have used this dataset for experiment and classification results are carried out. Table 1 show that the LAEP descriptor method performs better than the existing methods.

Table 1. Recall, Precision and Accuracy of the fingerprint classification for all the sequences

Name	Test -1			Test-2			Test-3		
	TPR (%)	PPV (%)	ACC (%)	TPR (%)	PPV (%)	ACC (%)	TPR (%)	PPV (%)	ACC (%)
GLCM	66.47	63.21	51.21	67.28	61.21	53.23	65.21	60.23	52.31
LBP	73.00	73.00	58.02	75.12	73.00	59.08	71.08	71.02	55.13
LDP	74.21	73.01	58.33	73.31	72.21	60.01	71.29	71.09	55.12
LDEP	74.44	72.00	58.26	74.13	73.09	59.18	71.31	70.13	55.25
LAEP	75.00	74.13	59.72	76.12	73.97	60.92	72.00	71.42	56.00

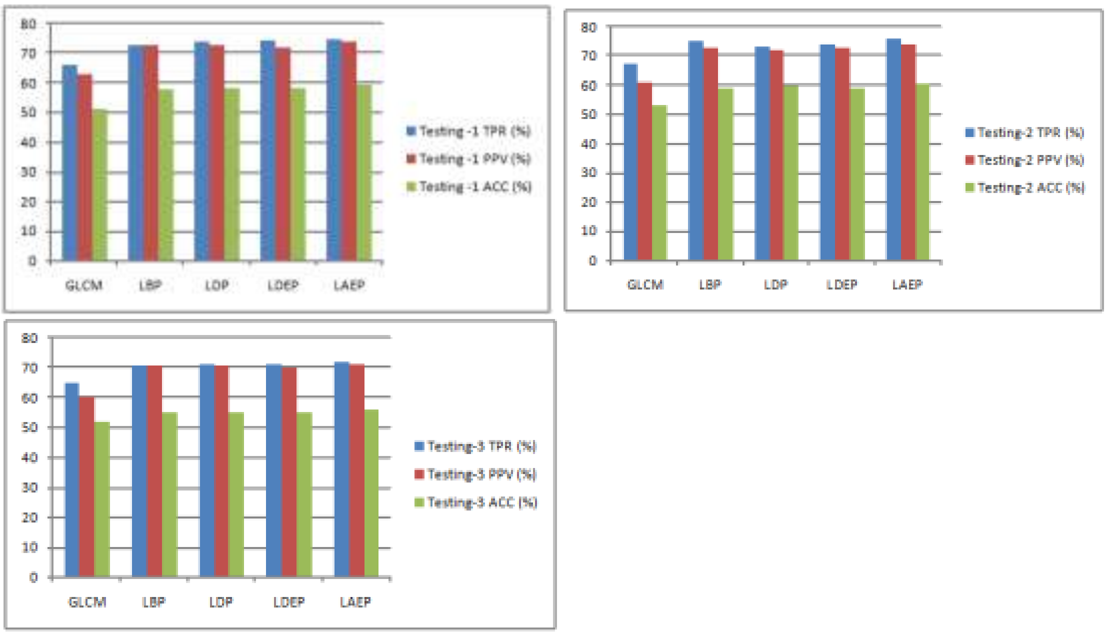

Figure 3. (a), (b) and (c) Comparison of TPR, PPV and ACC values of the different features in the classification stage for total sequences

5. Conclusions

In this paper, fingerprint classification is carried out by LAEP with the help of SVM classifiers. The values and indexes of the local and adjacent extrema patterns are computed by using first order adjacent extrema pattern. The descriptor is formed based on the indexes and local adjacent extremas values. The proposed feature is a local structuring element based descriptor. The proposed descriptor was compared with existing descriptor (see Figure 3(a), (b) and (c)) and it shows better classification results.

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