SVM BASED CLASSIFICATION AND IMPROVEMENT OF FINGERPRINT VERIFICATION

Alka Rani[1], Palvee[2], Deepak Sharma[3]

Abstract: - Fingerprints are the oldest and most widely used form of biometric identification. This recognition system is having the problem in terms of extraction of the fingerprint. One of such problems is the rotational aspect. There is also a problem of accuracy in identification and verification. The traditional PST and PCT rotational techniques do not provide 100 percent accuracy. In this proposed work, SVM classification along with the PST is used to get 100 percent accuracy and rotational invariency. The aim of this paper is to use the ability of SVM in pattern recognition and classification with PHT to improve the false acceptance rate (FAR) and false rejection rate (FRR). To give an objective assessment to the approach, both international and domestic fingerprint verification databases have been used for the evaluation. Afterwards, the training of data and data classifications has been done. Experimental results showed the substantial improvements in the accuracy and performance of fingerprint verification as well as in false acceptance rate (FAR) and false rejection rate (FRR) as compared to simple PST or PCT for image classification.

Keyword: - Fingerprint minutiae, PHT, FAR, FRR, SVM, Classification

I. INTRODUCTION

Biometrics refers to ways of identifying people by using physical human features. There have been several kinds of biometric recognition systems such as fingerprint, face, iris, hand vein etc. However, these conventional systems have some problems in terms of convenience and performance. In fingerprint and hand vein recognition systems, users have to touch the surface of the input sensor by their finger and hand. This can cause much inconvenience for the user and it is also possible to steal latent information from the fingerprint sensor. In addition, the condition of the finger surface (e.g. sweat, dryness) and skin distortion can cause degraded recognition accuracy. For face recognition, performance highly depends on facial expressions and illuminations, which can change. Iris recognition is most reliable in terms of accuracy, but the capturing device is expensive and can be inconvenient compared to other biometric systems.

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A fingerprint is the feature pattern of one finger. It is believed with strong evidences that each fingerprint is unique. The each person has his own fingerprints with the permanent uniqueness. The fingerprints have being used for identification and forensic investigation for a long time [1].A fingerprint composed of many ridges and furrows. These ridges and furrows represent good similarities in each small local window such as parallelism and average width. The fingerprints are not distinguished by their ridges and furrows. The minutia is some abnormal points on the ridges by intensive research on fingerprint recognition. The variety of minutia types reported in two are mostly significant and in heavy usage: one is called termination in which is the immediate ending of a ridge and the other is called bifurcation in which is the point on the ridge from which two branches derive [2] [3].

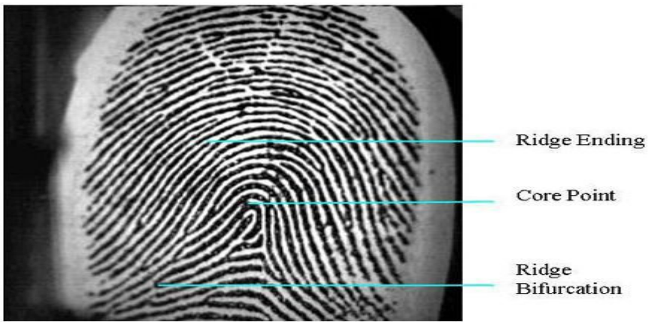

Fig.1 Ridge ending, core point and ridge bifurcation [9]

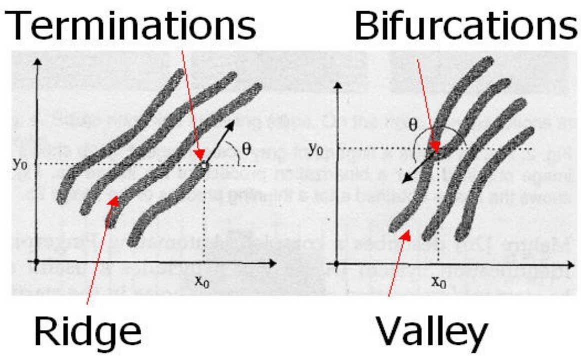

Fig.2 Minutia (Terminations and Bifurcations)

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II. IDENTIFICATION AND VERIFICATION

Identification: In an identification system, an individual is recognized by comparing with an entire database of templates to find a match. The system conducts one-to-many comparisons to establish the identity of the individual. The individual to be identified does not have to claim an identity (*Who am I?)* [1].

Verification (authentication): In a verification system, the individual to be identified has to claim his/her identity (*Am I whom I claim to be?)* and this template is then compared to the individual's biometric characteristics. The system conducts one-to-one comparisons to establish the identity of the individual. Before a system is able to verify/identify the specific biometrics of a person, the system requires something to compare it with. Therefore, a profile or template containing the biometric properties is stored in the system. Recording the characteristics of a person is called *enrollment*. The processes of enrollment, verification, and identification are depicted graphically in fig. 3[1].

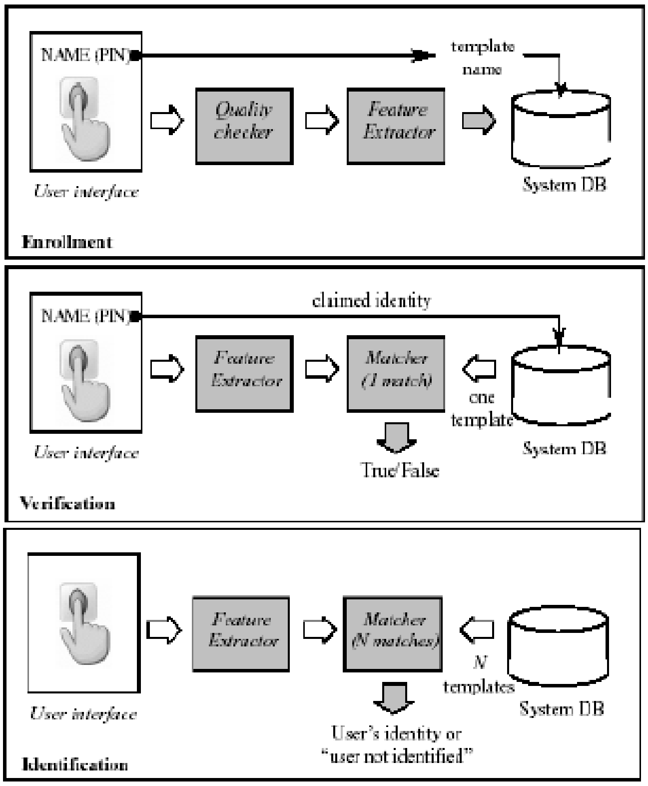

Fig.3 Block diagrams of enrollment, verification, and identification tasks [1].

A. *Results from identification and verification procedures* When results from identification or verification procedures are discussed, the following terms will be used in this report:

Success rate: The rate at which successful verifications or identifications are made compared to the total number of trials [11].

False rejection rate (FRR): The rate at which the system falsely rejects a registered user compared to the total number of trials [11].

False acceptance rate (FAR): The rate at which the system falsely accepts a nonregistered (or another registered) user as a registered one compared to the total number of trials. The FAR is in this report used in the identification version, as a contrast to verification procedures, where it measures if a user is accepted under a false claimed identity [11].

Equal error rate (EER): The common value of the FAR and FRR when the FAR equals the FRR. This is the value where both the FAR and FRR are kept as low as possible at the same time (see fig. 2). A low EER value indicates a high accuracy of the system [11].

III. LITERATURE SURVEY

Reliably matching fingerprint images is an extremely difficult problem, mainly due to the large variability in different impressions of the same finger (i.e., large intra-class variations).The main factors responsible for the intra-class variations are: displacement, rotation, partial overlap, non-linear distortion, variable pressure, changing skin condition, noise, and feature extraction errors. Therefore, fingerprints from the same finger may sometimes look quite different whereas fingerprints from different fingers may appear quite similar [1].

Manufacturers of fingerprint scanners currently cannot deliver convincing evidence that they can make a distinction between a real, living finger and a dummy created from silicone rubber or any other material. Therefore, our advice is not to use fingerprint verification with applications where the identification serves as proof of presence. Comparing all biometric verification possibilities, fingerprint scanners are (perhaps apart from keystroke dynamics) the least secure means of verification. It is the only system where the biometrical characteristic can be stolen without the owner noticing it or reasonably being able to prevent it [8].

- Minutiae-based matching: minutiae are extracted from the two fingerprints and stored as sets of points in the two-dimensional plane. Minutiae matching essentially consist of finding the alignment between the template and the input minutiae sets that result in the maximum number of minutiae pairings [1].

Statistical learning theory was introduced in the late 1960's. Until the 1990's it was a purely theoretical analysis of the problem of function estimation from a given collection of data. In the middle of the 1990's new types of learning algorithms (called support vector machines) based on the developed theory were proposed. This made statistical learning theory not only a tool for the theoretical analysis but also a tool for creating practical algorithms for estimating multidimensional functions [6].

Support Vector Machines:

To evaluate the potentiality of SVM on image recognition and image classification tasks Intuitively, given a set of points which belong to either of two classes, a linear SVM finds the hyperplane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyperplane. This hyperplane minimizes the risk of misclassifying examples of the test set.The potential of the SVM is illustrated on a 3D object recognition task using the Coil database and on a image classification task using the Corel database. The images are either representated by a matrix of their pixel values (bitmap representation) or by a color histogram. In both cases, the proposed system does not require feature

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extraction and performs recognition on images regarded as points of a space of high dimension. We also purpose an extension of the basic color histogram which keeps more about the information contained in the images [12].

The support-vector network is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high-dimension feature space. In this feature space a linear decision surface is constructed. This algorithm works well for both the linearly separable and non-separable categories by looking for the hyper-plane that separates the classes optimally in the feature space [3-4].B. Boser **suggests** a training algorithm that maximizes the margin between the training patterns and the decision boundary is presented. The approach consists of combining the filtering techniques for feature space extraction and information gain. Further, using the structural risk minimization principle, the best classifier was extracted that maximizes the distance of the hyper-plane from the supports vectors and minimizes the generalized error [5].

Polar Harmonic Transforms for Invariant Image Representation:

A set of 2D transforms, based on a set of orthogonal projection bases, to generate a set of features which are invariant to rotation. We call these transforms Polar Harmonic Transforms (PHTs). Unlike the well-known Zernike and pseudo-Zernike moments, the kernel computation of PHTs is extremely simple and has no numerical stability issue whatsoever. This implies that PHTs encompass the orthogonality and invariance advantages of Zernike and pseudo-Zernike moments, but are free from their inherent limitations. This also means that PHTs are well suited for application where maximal discriminant information is needed.

Furthermore, PHTs make available a large set of features for further feature selection in the process of seeking for the best discriminative or representative features for a particular application.Polar Harmonic Transforms1 (PHTs), which can be used to generate rotation-invariant features. The computation of the PHT kernels is significantly simpler compared with that of ZMs and PZMs, and can hence be performed at a much higher speed. With PHTs, there is also no numerical instability issue, as with ZMs and PZMs, which often limits their practical usefulness [13].

IV. PROPOSED WORK

Fingerprint identification has a number of advantages which make it a popular method of identification in settings ranging from police stations to secured facilities. This method of identification is accomplished by comparing fingerprints from someone against a database of known fingerprints. If the sample fingerprints match fingerprints in the database, it is considered a positive match. While working with the fingerprint recognition there are so many difficulties and challenges which are to be faced. One of those challenges is the rotation of the fingerprint image. It is not always possible to take it in same orientation as of source fingerprint. Because of this there is the requirement of the rotation of fingerprint under different angle so that actual orientation will be obtained [8]. In proposed methodology, SVM classifier with the PST rotation algorithm is used to improve the results of recognition system.

A. SVM Algorithm:

Proposed algorithm maintains a candidate Support Vector set. It initializes the set with the closest pair of points from opposite classes like the Direct SVM algorithm. As soon as the algorithm finds a violating point in the dataset it greedily adds it to the candidate set. It may so happen that addition of the violating point as a Support Vector may be prevented by other candidate Support Vectors already present in the set. We simply prune away all such points from the candidate set. To ensure that the KKT conditions are satisfied we make repeated passes through the dataset until no violators can be found [2]. We use the quadratic penalty formulation to ensure linear sap arability of the data points in the kernel space.

a) Finding the Closest Pair of Points

First of all, we observe that finding the closest pair of points in kernel space requires n2 kernel computations where n2 represents the total number of data points. But, in case we use a distance preserving kernel like the exponential kernel the nearest neighbors in the feature space are the same as the nearest neighbors in the kernel space. Hence we need not perform any costly kernel evaluations for the initialization step.

b) Adding a Point to the Support Vector Set

Given a set S which contains only Support Vectors, we wish to add another Support Vector c to S. From Equations below we get the change in gi due to addition of a new point c as

$$\Delta g_i = Q_{ic}\Delta\alpha_c + \sum_{j\in S} Q_{ij}\Delta\alpha_j + y_i\Delta b$$

And

$$0 = y_c\Delta\alpha_c + \sum_{j\in S} y_j\Delta\alpha_j$$

Where $\Delta\alpha_i$ is the change in the value of αi and Δb is the change in the value of b. We start off with $\alpha_c = 0$ and update αc as we go along.

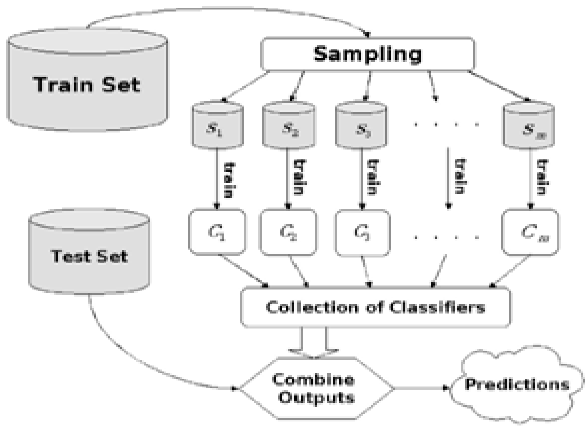

Fig.4 Working of SVM classifier

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B. Polar Harmonic Transform

Polar harmonic transform (PHT), which are used to generate rotation invariant features. The computation of the PHT kernels is significantly simpler compared with that of ZMs and PZMs and hence can be performed at a much higher speed [13]. With PHTs, there is also no numerical instability issue, as with ZM and PZMs which often limits their practical usefulness. A large part of the computation of the PHT kernel scan be recomputed and stored. In the end, for each pixel, as little as three multiplications, one addition operation, and one cosine and/or sine evaluation are needed to obtain the final kernel value. Three different transforms will be introduced, namely, Polar Complex Exponential Transform (PCET), Polar Cosine Transform (PCT), and Polar Sine Transform (PST). We have grouped them under the name Polar Harmonic Transform as the kernels of these transforms are harmonic in nature, that is, they are basic waves. In our proposed work we have used these rotation invariance techniques.

C. Algorithm

1. Take reference image from the database.
2. Apply filter effect and watershed on the images for enhancement of image
3. Next step is to crop the image in circular section
4. After cropping apply feature extraction algorithm
5. Take these features to train the SVM classifier
6. Provide testing images from data set
7. Extract the same feature of testing image
8. Pass this to SVM for classification
9. Repeat the steps for multiple images at multiple angles
10. Finally calculate parameters as FAR and FRR for accuracy testing

V. EXPERIMENTAL RESULTS

We have used MATLAB software to implement the proposed approach. As per implementation the results which are obtained in our proposed methodology are shown below:

There is a comparative analysis of our proposed methodology i.e. SVM classifier with PST for fingerprint matching accuracy analysis.

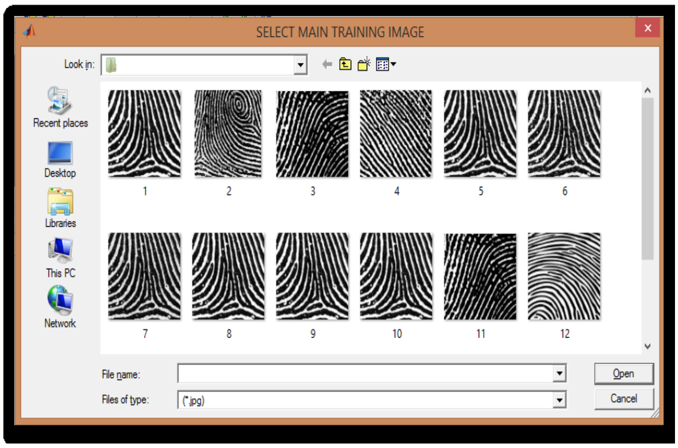

Fig.5 Database of Fingerprints Used In Proposed Work

Figure 5 shows the database of the fingerprint images. There are 14 different fingerprint images in database, out of which seven images are wrong and seven images are same but affected with noise.

There are three experimental results shown below. Figure 6 shows the results of PCT algorithm for fingerprint classification as shown in diagram its matching ratio is 3:11, which means it matches the 3 images out of the 7 same images.

Figure 7 shows the PST classification in which the ratio of matching is 6:8.

Whereas figure 8 shows the result of our proposed methodology (SVM-PST) which indicates that the ratio of matching is 7:7, which is 100%.

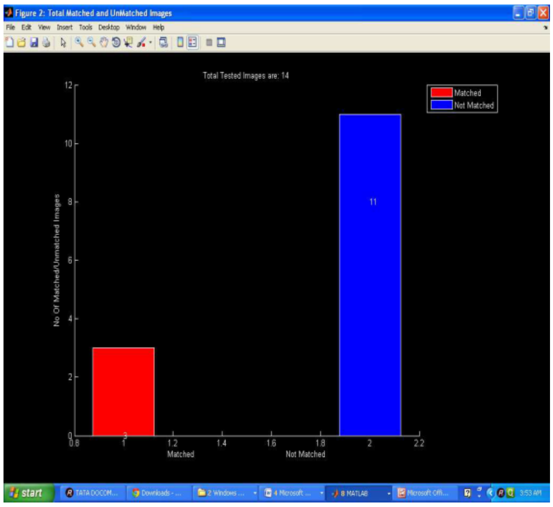

Fig. 6- Results simple PCT for classification [7]

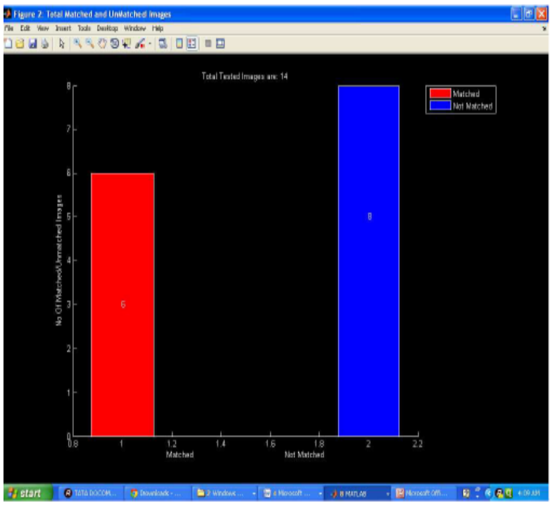

Fig. 7- Results simple PST for classification [7]

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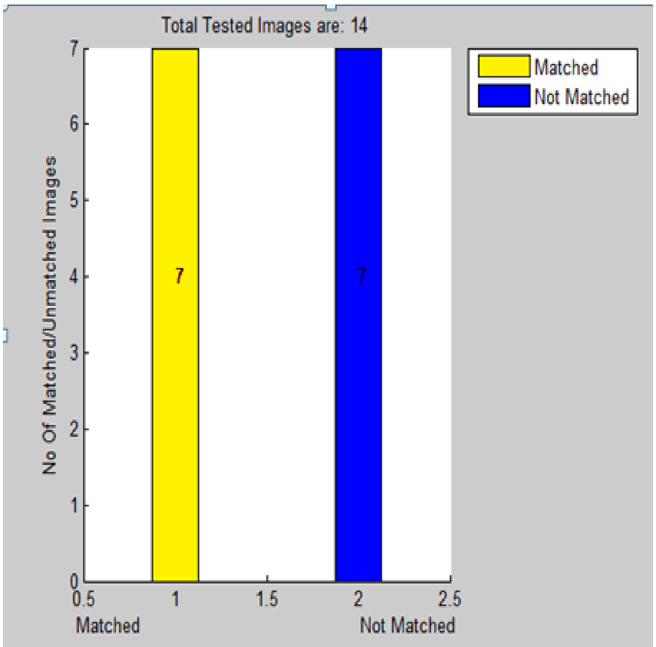

Fig. 8 Results proposed SVM classifier with PST for classification

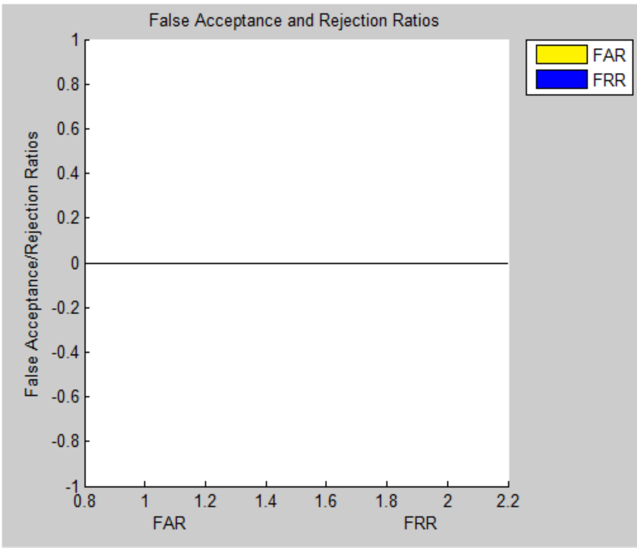

Fig.9 FAR and FRR of Proposed Work

Figure 9 shows the FAR (False Acceptance Rate) and FRR (False Rejection Rate) of proposed work.

5.2 Improvement made

- **Initial improvement with PST:**

1. Reduced FAR (False Acceptance Rate) and FRR (False Rejection Rate).
2. The Polar Harmonic Transform provides more accuracy in pattern matching technique.
3. Fast calculation.

- **Improvement made using SVM-PST:**

1. Better FAR (False Acceptance Rate) and FRR (False Rejection Rate). They have been reduced to zero.
2. Limit is set on Euclidean distance.
3. Training is introduced.
4. Classification is also done.

VI. DISCUSSIONS AND FUTURE WORK

Using support vector machine (SVM) fingerprint match has been improved with respect to the polar harmonic transform (PHT). SVM has improved false rejection ratio (FRR) as well as false acceptance ratio (FAR).Besides that the accuracy of system has also been enhanced. Initially without using the classification algorithms, the training time was less because training of data was not done. But with the use of a classification algorithm like support vector machine, although training time has been increased but there has been significant improvement in the overall performance of fingerprint classification and verification. There are prevalent ways to extend the proposed work. Superiorities can be shown by using Fast polar harmonic transforms (FPHT) and Fast polar complex exponential transforms (FPCET).

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