FINGERPRINT RECOGNITION USING LEVEL 3 FEATURE EXTRACTION METHOD AND MATCHING USING SIFT ALGORITH

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***Abstract*—to design fingerprint Level 3 feature extraction method and match using SIFT algorithm. Firstly fingerprint of good quality are acquired by using optical scanner. Image normalization is done using Gaussian blurring and sliding window contrast adjustment. Pores are extracted and estimated. Using these estimated pores, matching is done from template database to stored database using SIFT algorithm. Scale Invariant Features Transform (SIFT) is an algorithm in computer vision to detect and describe local features in images. The features are invariant to image scaling and rotation. They are well localized in both the spatial and frequency domains. The features are highly distinctive, which allows a single feature to be correctly matched with high probability against a large database of features, providing a basis for object and scene recognition**.

Keywords*—Fingerprint recognition, pores, *SIFT technique, pores matching.

INTRODUCTION

Fingerprint recognition is a complex pattern recognition problem. It is difficult to design accurate algorithms capable of extracting salient features and matching them in a robust way, especially in poor quality fingerprint images and when low-cost acquisition devices with small area are adopted. There is a popular misconception that automatic fingerprint recognition is a fully solved problem since it was one of the first applications of machine pattern recognition. On the contrary, fingerprint recognition is still a challenging and important pattern recognition problem.

The real challenge is matching fingerprints affected by:

I) High displacement/or rotation which results in smaller overlap between template and query fingerprints (this case can be treated as similar to matching partial fingerprints).

II) Non-linear distortion caused by the finger plasticity.

III) Different pressure and skin condition

IV) Feature extraction errors which may result in spurious or missing features. The vast majority of contemporary automated fingerprint authentication systems (AFAS) are minutiae (level 2 features) based [1]. Minutiae-based systems generally rely on finding correspondences between the minutia points present in “query” and “reference” fingerprint images.

These systems normally perform well with high quality fingerprint images and a sufficient fingerprint surface area. These conditions, however, may not always be attainable. In many cases, only a small portion of the "query" fingerprint can be compared with the "reference" fingerprints. As a result, the number of minutiae (Level 2 feature of fingerprint) correspondences might be significantly decreases and the matching algorithm would not be able to make a decision with high certainty. This effect is even more marked on intrinsically poor quality fingers, where only a subset of the minutiae can be extracted and used with sufficient reliability. Although minutiae may carry most of the fingerprint's discriminatory information, they do not always constitute the best trade-off between accuracy and robustness.

This has led the designers of fingerprint recognition techniques to search for other fingerprint distinguishing features, beyond minutiae, which may be used in conjunction with minutiae (and not as an alternative) to increase the system accuracy and robustness. It is a known fact that the presence of Level 3 features in fingerprints provides minutiae detail for matching and the potential for increased accuracy. The forensic experts in law enforcement often make use of Level 3 features, such as sweat pores and ridge contours, to compare fingerprint samples when insufficient minutia points are present in the fingerprint image or poor image quality hampers minutiae analysis. That is, experts take advantage of an extended feature set in order to conduct a more effective matching.

Despite their discriminating property, level 3 features are barely utilized in the commercial automated fingerprint authentication systems (AFAS), as a result a large amount of fingerprint information is ignored by such systems. This is mainly because, most of these authentication systems are equipped with 500ppi (pixels per inch) scanners, and reliably (or consistently) extracting, "fine and detailed" Level 3 features require high resolution images. While this may have been the case with many of the older live-scan devices, the current devices are capable of detecting a reasonable amount of level three details even at the relatively limited 500ppi resolution.

Ray et al. [2] have presented a means of modeling and extracting pores (which are considered as highly distinctive Level 3 features) from 500ppi fingerprint images. This study showed that while not every fingerprint image obtained with a 500ppi scanner has evident pores, a substantial number of them do have. Thus, it is a natural step to try to extract Level 3 information, and use them to achieve robust matching decisions. In addition, the fine details of level 3 features could potentially be exploited in circumstances that require high-confidence matches.

BACKGROUND

1) Ray *et al*. (2003) presented a means of modeling and extracting pores (which are considered as highly distinctive Level 3 features) from 500ppi fingerprint images. This paper showed that why not every fingerprint image obtained with a 500ppi scanner has evident pores, a substantial number of them do have. Thus, it is an accepted step to try to extract Level 3 information, and use them in conjunction with minutiae to achieve strong matching decisions. In addition, the fine details of level 3 features could potentially be exploited in circumstances that require high-confidence matches.

2) Anil Jain et al. [10] proposed a Pores and Ridges: Fingerprint Matching Using Level 3 Features. Fingerprint friction ridge details are generally described in a hierarchical order at three levels, namely, Level 1 (pattern), Level 2 (minutiae points) and Level 3 (pores and ridge shape). Although high resolution sensors (~1000dpi) have become commercially available and have made it possible to reliably extract Level 3 features, most Automated Fingerprint Identification Systems (AFIS) employ only Level 1 and Level 2 features. As a result, increasing the scan resolution does not provide any matching performance improvement [17]. They develop a matcher that utilizes Level 3 features, including pores and ridge contours, for 1000dpi fingerprint matching. Level 3 features are automatically extracted using wavelet transform and Gabor filters and are locally matched using the ICP algorithm. Our experiments on a median-sized

database show that Level 3 features carry significant discriminatory information. EER values are reduced (relatively ~20%) when Level 3 features are employed in combination with Level 1 and 2 features.

3) Qijun Zhao et al. [6] proposed an adaptive pore model for fingerprint pore extraction. Sweat pores have been recently employed for automated fingerprint recognition, in which the pores are usually extracted by using a computationally expensive skeletonization method or a unitary scale isotropic pore model. In this paper, however, author shows that real pores are not always isotropic. To accurately and robustly extract pores, they propose an adaptive anisotropic pore model, whose parameters are adjusted adaptively according to the fingerprint ridge direction and period. The fingerprint image is partitioned into blocks and a local pore model is determined for each block. With the local pore model, a matched filter is used to extract the pores within each block. Experiments on a high resolution (1200dpi) fingerprint dataset are performed and the results demonstrate that the proposed pore model and pore extraction method can locate pores more accurately and robustly in comparison with other state-of- the-art pore extractors

PROPOSED WORK

Converse the proposed approach and pores matching using SIFT algorithm. Figure1 shows the block diagram of proposed approach. In this section, the proposed algorithm, its features and other various aspects has been described. Two type of database has been created; first one name samedb1 contains the 10 fingerprints of same person with some variations and other factors such as light, noise etc. Thus samedb1 contains 400 fingerprints of 40 different students. Second database namely diffdb2 contains 150 fingerprints of different students.

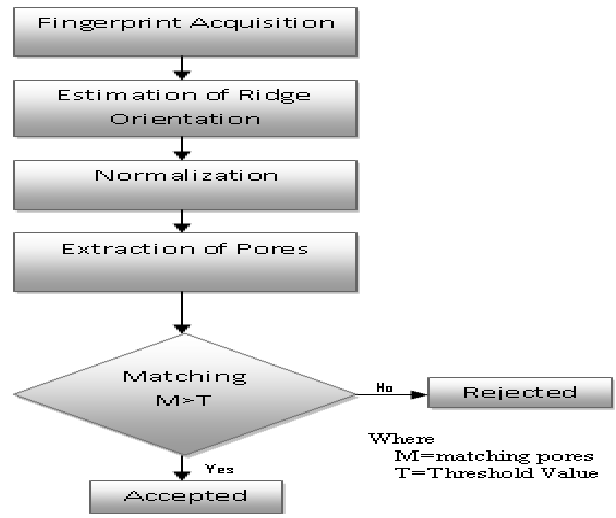

Figure1 Block diagram of proposed approach

Fingerprint Acquisition and Database

The first step in the proposed approach is to acquire fingerprint image of good quality. Thus, Hamster II is use for acquiring fingerprint image. Hamster II is optical fingerprint scanner and use for scanning the finger. Hamster II is used for creating fingerprint database. This database is use for analyzing the accuracy of proposed algorithm and execute the results on the basis of analyze. After acquiring fingerprint, store it in database and also use as input to proposed algorithm. Figure2 shows the acquired fingerprint from optical scanner.

Figure2 Acquired fingerprint from optical scanner

Estimation of ridge orientation

Next process is the estimation of the ridge orientation. The local ridge orientation is determined by the least square estimate method. This data is utilized later in the representation of pores. Analysis of the developed fingerprint matching system has revealed a number of interesting conclusions. It can be stated that segmentation is the critical stage of fingerprint pores recognition, since areas that are wrongly identified as pores regions will corrupt biometric templates resulting in very poor recognition. Segmentation can be the most difficult stage of pores recognition because its success is dependent on the imaging quality of fingerprint images. 95% of the fingerprint database images segmented correctly. Another interesting finding was that the encoding process only required one Gabor filter to provide accurate recognition, since the open literature mentions the use of multi-scale representation in the encoding process.

Figure3 Ridge orientation of fingerprint

Normalization

To compensate for the variations in lighting, contrast and other inconsistencies, three preprocessing steps are used: Gaussian blur, sliding window contrast adjustment, and histogram based intensity level correction. Gaussian blurring is used to remove any noise introduced by the sensor. Normalizes image values to 0-1, or to desired mean and variance. Offsets and rescales image so that the minimum value is 0 and the maximum value is 1. Result is returned in n. If the image is color the image is converted to HSV and the value/intensity component is normalized to 0-1 before being converted back to RGB.
The lighting inconsistencies are adjusted by using sliding-window contrast adjustment on the Gaussian blurred image. To further enhance the ridges and valley a final intensity correction is made by using Histogram-based Intensity Level Adjustment.

The image can divide into small processing blocks (32 by 32 pixels) and perform the Fourier transform according to:

$$F(u, v)=\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y) \times \exp\left\{-j2\pi\times\left(\frac{ux}{M}+\frac{vy}{N}\right)\right\}$$

…………… (1)

For u = 0, 1, 2... 31 and v = 0, 1, 2... 31.

In order to enhance a specific block by its dominant frequencies, multiply the FFT of the block by its magnitude a set of times. Where the magnitude of the original FFT = abs (F(u, v)) = |F(u, v)|.

Get the enhanced block according to

$$g(x, y) = F^{-1}\{F(u, v)\times|F(u, v)|^k\}$$

…………. (2)

Where $F^{-1}(F(u, v))$ is done by:

$$F(x, y)=\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y) \times \exp\left\{j2\pi\times\left(\frac{ux}{M}+\frac{vy}{N}\right)\right\}$$

……………. (3)

For x = 0, 1, 2... 31 and y = 0, 1, 2... 31.

The k in formula (2) is an experimentally determined constant, which can choose k=0.45 to calculate. While having a higher "k" improves the appearance of the ridges, filling up small holes in ridges, having too high a "k" can result in false joining of ridges. Thus a termination might become a bifurcation.

The enhanced image after FFT has the improvements to connect some falsely broken points on ridges and to remove some spurious connections between ridges. The side effect of each block is obvious but it has no harm to the further operations because resultant image after consecutive binarization operation is pretty good as long as the side effect is not too rigorous

For the fingerprint image preprocessing stage, Fourier Transform can be use to image enhancement. And then the fingerprint image is binarized using the locally adaptive threshold method. The image segmentation task is fulfilled by a three-step approach: block direction estimation, segmentation by direction intensity and Region of Interest extraction by Morphological operations. Most methods used in the preprocessing stage are developed by other researchers but they form a brand new combination in our paper through trial and error. Also the morphological operations for extraction ROI are introduced to fingerprint image segmentation in this paper.

Figure4 Normalized image

Pores estimation and extraction approach

Extract level 3 features in ROI. The pores are distributed over ridges and using orientation detail can provide additional information for matching. During tracing, the algorithm classifies the contour information into pores and ridges.

A blob of size greater than 2 pixels and less than 45 pixels is classified as a pore. Therefore, noisy contours, which are sometimes wrongly extracted, are not included in the feature set. A pore is approximated with a circle and the center is used as the pore feature. The fingerprint image is threshold with a single-point threshold (T). After this step the pores have an intensity of 255. The pores are then extracted by a blob detector which locates groups of connected pixels (pores) with an intensity of 255 and with size within a pre-determined range. Each pore thus extracted is represented by the coordinates of the central pixel and an orientation, which is the ridge orientation at that particular location.

An edge of a ridge is defined as the ridge contour. Each row of the ridge feature represents x; y coordinates of the pixel and direction of the contour at that pixel. Here edges will remove by using morphological operation and extract only pores whose pixel value is greater than 15. In other words, there is assumption that pores can be classified as combination of 2 or more pixels. Using this assumption, we consider only those pores who are grouping of more than 15 but less than 45 pixels. Rest pixels will remove from normalized image. Thus it is possible to remove the contour ridges and extract pores. Figure 5 shows the extracted pores from normalized image.

The pixel intensity values in the fingerprint image are typically non-invariant over the time of capture and there is need to determine salient feature of input fingerprint image that can be discriminate between identities as well as remain invariant for a given individual. Thus the problem of representation is to determine a measurement (features) space in which fingerprint image belonging to the same finger form a compact cluster and those belonging to the different finger occupy different portions of space.

The last step is to remove possible spurious pores. We apply the following constraints to post-processing the initial pore extraction results.

(I) Pores should reside on ridges only. To implement this constraint, we use the binary ridge image as a mask to filter the extracted pores.

(II) Pores should be within a range of valid sizes. We measure the size of a pore by counting the pixels in its region.

(III) The mean intensity of a true pore should be large enough. In our experiments, we discarded the last 5% pores (i.e. those with lowest intensity). Finally, we record the extracted pores' locations as the coordinates of their mass centers.

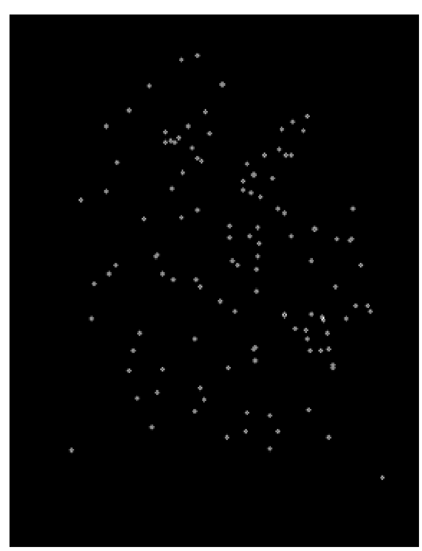

Figure 5 Extracted pores from normalized image

Pores based fingerprint matching

In latent print comparison, when Level 1 or Level 2 features are similar between the template and the query, a forensic expert often investigates Level 3 details. To be compatible with current AFIS systems, our matching using Level 2 and Level 3 features is done separately, except using the Level 2 information (minutiae) for initial alignment for Level 3 matching. Then a score-level fusion of both the matching stages is performed using the sum rule and min-max normalization. The best candidate match for each keypoint is found by identifying its nearest neighbor in the database of keypoints from training images. The nearest neighbor is defined as the keypoint with minimum Euclidean distance for the invariant descriptor vector as was described in Chapter 5. A global threshold on distance to the closest feature does not perform well, as some descriptors are much more discriminative than others.

A more effective measure is obtained by comparing the distance of the closest neighbor to that of the second-closest neighbor. If there are multiple training images of the same object, then it can be defined the second-closest neighbor as being the closest neighbor that is known to come from a different object than the first, such as by only using images known to contain different objects. This measure performs well because correct matches need to have the closest neighbor significantly closer than the closest incorrect match to achieve reliable matching. For false matches, there will likely be a number of other false matches within similar distances due to the high dimensionality of the feature space. We can think of the second-closest match as providing an estimate of the density of false matches within this portion of the feature space and at the same time identifying specific instances of feature ambiguity. No algorithms are known that can identify the exact nearest neighbors of points in high dimensional spaces that are any more efficient than exhaustive search.

Our keypoint descriptor has a 128-dimensional feature vector, and the best algorithms, such as the k-d tree provide no speedup over exhaustive search for more than about 10 dimensional spaces. Therefore, we have used an approximate algorithm, called the Best-Bin-First (BBF) algorithm Lowe [41]. This is approximate in the sense that it returns the closest 20 neighbor with high probability. The BBF algorithm uses a modified search ordering for the k-d tree algorithm so that bins in feature space are searched in the order of their closest distance from the query location. In this thesis, we cut off search after checking the first 200 nearest-neighbor candidates. One reason the BBF algorithm works particularly well for this problem is that we only consider matches in which the nearest neighbor is less than 0.8 times the distance to the second-nearest neighbor (as described in the previous section), and therefore there is no need to exactly solve the most difficult cases in which many neighbors are at very similar distances.

Figure5 shows the pores matching result. As we set threshold value i.e. 25, when SIFT matching more than 25 keypoints then it can be accepted fingerprint image otherwise fingerprint will be rejected.

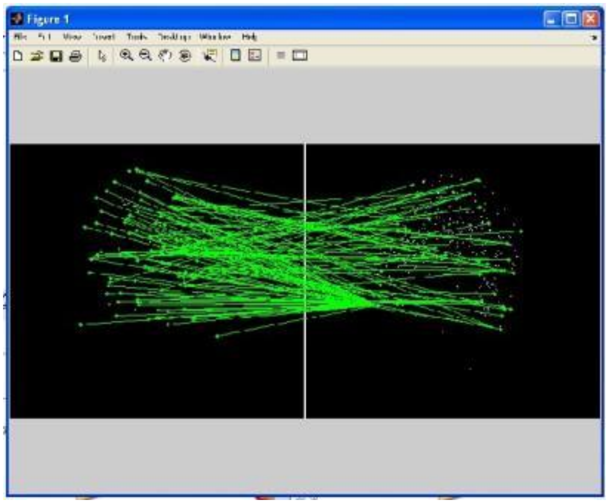

Figure6 Matching Pores (keypoints)

RESULT

In this Chapter, we have analyzed the Performance of the proposed technique known as pores matching using SIFT algorithm. As this is a novel approach, so for this reason we have chosen the images of fingerprint from Hamster fingerprint scanner. We have taken here total 100 images, and consider two to eight images of each finger with respect to variations in images for analysis and key points detection same user, so it will become 500 fingerprint images are collected in a database.

We create two types of database; first one name samedb1 contains the 10 fingerprints of same person with some variations and other factors such as light, noise etc. Thus samedb1 contains 400 fingerprints of 40 different students. Second database namely diffdb2 contains 150 fingerprints of different students. These fingerprints acquire using Hamster II optical fingerprint scanner. Fingerprints are acquired after taking some interval of time. There is another database name fprintdb that was downloaded from FVC 2002 for analysis.

Experimental results are obtained using the cross validation approach. We perform experiments by evaluation of the proposed level-3 feature extraction algorithm. We first compute the verification performance of the proposed level-3 feature extraction algorithm and compare it with existing level-3 feature based verification algorithms.

Genuine Acceptance Rate

The graph plots in Figure7 and Genuine Acceptance Rate in Table1 summarize the results of this experiment and comparison the results with other existing approaches given by other researchers. The proposed level-3 feature extraction algorithm yields a verification accuracy of 94% which is 2–7% better than existing algorithms.

Table1 GAR of proposed approach

Threshold	25	35	45	70
Accepted images	188	181	149	82

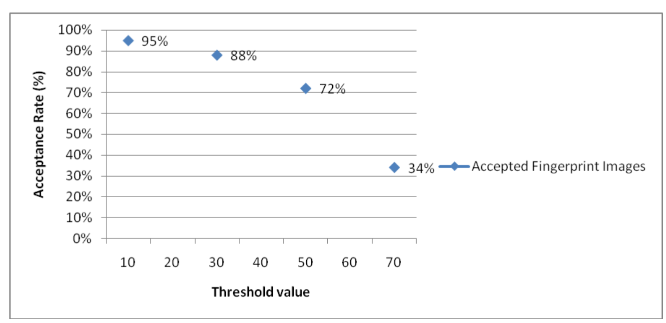

Figure7 GAR graph of proposed approach

Finally we will take another database in account to compare the proposed results with existing results, for this we have chosen database of images from FVC 2002 and examining the proposed technique with it. So the result shows that the proposed technique will give better results.

Table 2 Comparison of Genuine Acceptance Rate (GAR) with other existing approaches.

(threshold value: 40)

	Kryszczuk's	Level 2	M. Vatsa	Proposed

jain's				
88.07	84.03	89.11	91.41	93

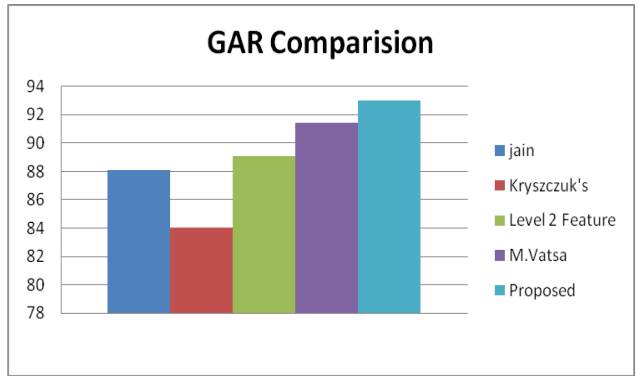

Figure8 Comparison Graph

False Rejection Rate:

Fraction of attempts for which a fingerprint system denies access to a valid user. Each sample in a database is matched against the remaining samples of the same finger to compute the False Rejection Rate (FRR). To calculate FRR, we use samedb1 database. The FRR is the fraction of genuine fingerprints which are rejected and is calculated as follows

$$FRR = \frac{\text{Number of genuine fingerprints rejected}}{\text{Total number of genuine tests}}$$

The total number of genuine tests is 115 and 215 for Hamster II database, FVC 2002 Database respectively. Table 3 summarizes the FRR and Figure 9 shows the graph of FRR of proposed approach. As table 3 summarize the result of this analyzing process, we conclude that, as the threshold value is increases, false rejection rate is also increases.

Table3 False Rejection Rate (FRR) of proposed approach.

Threshold	25		35		45		70
FRR	7%		12%		28%		66%

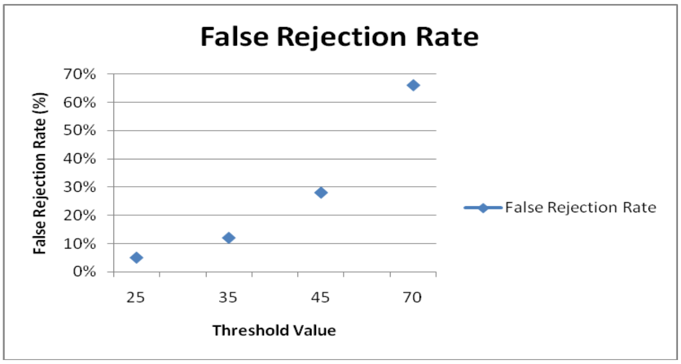

Figure9 False Rejection Rate of proposed approach.

CONCLUSION

This dissertation presents a concise introduction of fingerprint level 3 features extraction and matching approach which is a novel approach, its characteristics, design issues and applications. It also describes an overview of Level 1 and level 2 features, in the literature and their functionalities. Along with that, it has through discussion of SIFT algorithm. Finally, it presents an novel approach for level 3 feature extraction and matching algorithm. Since the technology is going to its zenith, the way of its journey is not smooth and many loopholes are there.

The proposed work is an attempt to overcome some weakness regarding security concern of the system. The experimental results demonstrate that the proposed approach and its associated pore extraction method can detect pores more accurately and robustly, and can help to improve the verification accuracy of pore based fingerprint recognition systems. There are many method exists to make it unextractable by adversaries, like one is to use multi-biometric traits under a single process, but it need extra sensors setup for each kind of traits, the proposed technique gives an extra edge to such systems which use single type of sensor and give more security.

This approach will give the technology new amplitude in order to provide a secure way of authentication, in which the pores are logically extracted. The proposed algorithm performs better than existing recognition algorithms and fusion algorithms. Along with other advantages, in all biometric systems fingerprint based systems are more efficient than other multimodal system, so it minimizes FAR and FRR.

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