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Finger-Knuckle-Print Based Recognition System using LBP and SURF

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***Abstract*— Finger knuckle bending produces a highly unique texture pattern and it can be used as a distinctive biometric identifier. This paper presents a novel combination of local-local information for an efficient finger-knuckle-print (FKP) based recognition system which is robust to scale and rotation. The non-uniform brightness of the FKP due to relatively curvature surface is corrected and texture is enhanced. The local features of the enhanced FKP are extracted using the LBP histogram and the speeded up robust features (SURF). Corresponding features of the enrolled and the query FKPs are matched using nearest-neighbour-ratio method and then the derived LBP and SURF matching scores are fused using weighted sum rule. The proposed system has been evaluated using PolyU FKP database of 7920 images for both identification mode and verification mode.Its parameters have been tuned to get optimum performance. LBP histograms was used for texture feature extraction of a FKP image. SURF has made the system robust against scale and rotation.**

Keywords- FKP, LBP, SURF, EER, FAR, FRR.

I. Introduction

The term "biometrics" is derived from the Greek words, bio (life) and metric (to measure). Biometrics refers to the automatic identification of a person based on his/her physiological or behavioral characteristics. Verification involves confirming or denying a person's claimed identity while in identification, one has to establish a person's identity. The biometric identifiers have their advantages and disadvantages in terms of the precision and user acceptance. So authentication leads major part in the secured way of communication. Currently, passwords and smart cards are used as the authentication tool for verifying the authorized user. However, passwords are easily cracked by dictionary attacks, as well as the smart cards are stoles by anybody, and then we cannot check who the authorized user is.

A FKP(Finger-Knuckle-Print)recognition system can be either a verification system or an identification system depending on the context of an application. The verification system authenticates a person's identity by comparing the captured image with his/her own template(s) stored in the system. It performs a one to one comparison to determine whether the person presenting herself/himself to the system is the person she/he claims to be. An identification system recognises a person by checking the entire template database for a match. It involves a one to many search. The system will either make a match and subsequently identify the person or it will fail to make a match.

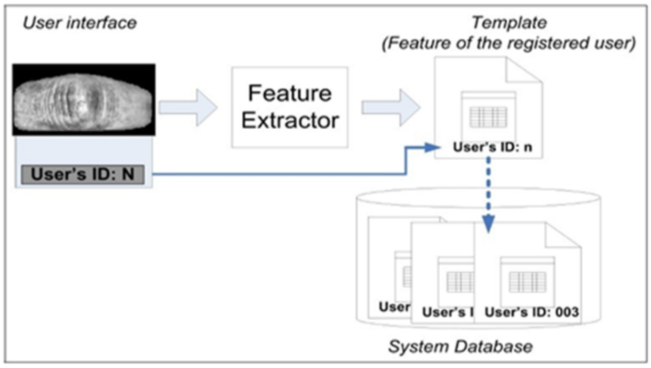

Fig.1. Enrollment

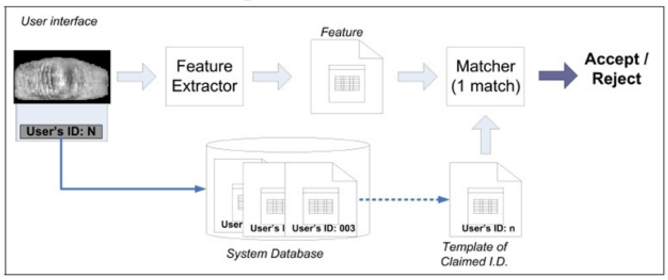

Fig.2. Verification

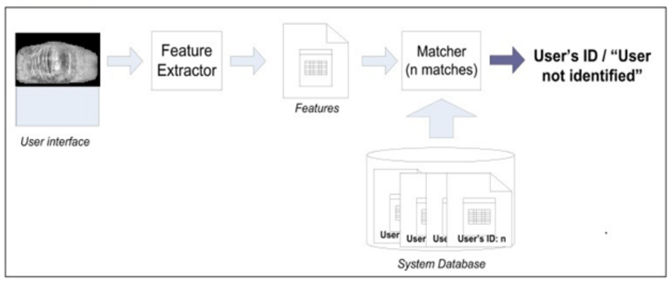

Fig.3. Identification

1. FKP Preprocessing

The backside of finger is to be captured using digital camera. The captured image is then loaded initially to the identification system. Before using this image for processing so that processing can be efficient and accurate

It contains following steps:

1.1 Image Enhancement

The finger surface is highly curved and results in uneven reflection which also generates shadow. The knuckle images therefore have low contrast and uneven illuminations. These undesirable effects are to be reduced using the image enhancement techniques.

Initially the noise in the image is removed by using image noise filter. The image is then used for adjustment of brightness and contrast. Resulting image is then converted in to gray scale image to extract exact features of the finger knuckle image.

1.2 Image Resize

The enhanced image will be of large in size, since it is captured through digital camera. The processing of large images will not provide exact result and may take more time. Hence the image is resized according to the requirement.

1.3 Finding ROI

Each of these images requires localization of region of interest for the feature extraction. The region of interest is the region having maximum knuckle creases. It is necessary to construct a local coordinate system for each FKP image. With such a coordinate system, an ROI can be cropped from the original image for reliable feature extraction and matching.

1.4 Pose Reconstruction

The verification scheme is simple and fast, and it leads to acceptable accuracy in FKP verification. If the query FKP image is well aligned after ROI extraction, the proposed scheme can work very well. As we discussed in the introduction section, however, there can be certain degree of variations of the finger pose in the data collection process, which lead to deformations in the FKP images and consequently result in false rejections because algorithm is sensitive to image deformations.

II. SPEEDED UP ROBUST FEATURES

The task of finding correspondences between two images of the same scene or object is part of many computer vision applications. Camera calibration, 3D reconstruction, image registration, and object recognition are just a few. The search for discrete image correspondences – the goal of this work – can be divided into three main steps. First, ‘interest points’ are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability, i.e. whether it reliably finds the same interest points under different viewing conditions. Next, the neighbourhood of every interest point is represented by a feature vector. This descriptor has to be distinctive and, at the same time, robust to noise, detection errors, and geometric and photometric deformations. Finally, the descriptor vectors are matched between different images. The matching is often based on a distance between the vectors, e.g. the Mahalanobis or Euclidean distance.

A wide variety of detectors and descriptors have already been proposed in the literature (e.g. [1–6]). Also, detailed comparisons and evaluations on benchmarking datasets have been performed [7–9]. While constructing our fast detector and descriptor, we built on the insights gained from this previous work in order to get a feel for what are the aspects contributing to performance.

Here, we focus on scale and image rotation invariant detectors and descriptors. These seem to offer a good compromise between feature complexity and robustness to commonly occurring deformations.

SURF is used to extract the local features from a FKP image. It determines scale invariant key-points and then describes these key-points by means of local patterns around key-points. Feature vectors through SURF are formed by means of local patterns around key-points which are detected using scaled up filter [13]. These key-point features remain the same irrespective of the orientation of the FKP image.

Following are the major steps to determine the SURF feature vectors of a given image.

2.1 Key-point detector: At this step, SURF key-points are detected using Hessian matrix approximation. The second order Gaussian derivatives for Hessian matrix are approximated using box filters. Key-points are localized in scale and image space by applying a non-maximum suppression in a 3x3x3 neighbourhood.

2.2 Key-point descriptor: This stage describes the key-points. It fixes a reproducible dominant orientation based on information from a circular region around the interest point. Feature vector of 64 values is computed from the oriented square local image region around key-point.

III. LBP HISTOGRAM

3.1 Local Binary Pattern

Approximately at the same time, the local binary pattern (LBP), the generalised version of Census transform, introduced by Pietik¨ainen et al., offers a powerful and attractive texture descriptor showing excellent results in terms of accuracy and computation complexity in many empirical studies. The most prominent limitation of the Census transform operator is its small spatial support area. A feature computed using a 3 × 3 operator, only relating to a small image structure, that may not necessarily be adept to capturing the key texture characteristic. However, LBP using circular neighbourhoods and linearly interpolating the pixel values allows the choice of any radius, R, and number of pixel in the neighbourhood, P, to form an operator, which can model large scale structure. An illustration of the basic LBP operator is shown in Figure 5 and the corresponding equation is shown in eq.1.

The LBP has been extended to multiresolution analysis, colour texture analysis.

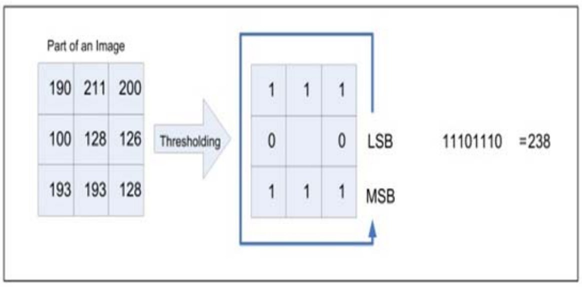

Fig.4. basic of LBP operator

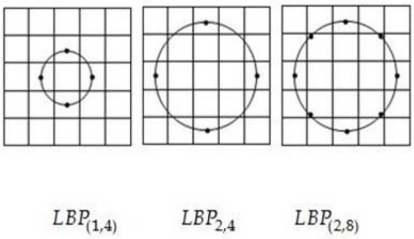

Fig .5. $LBP_{(1,4)}$, $LBP_{(1,4)}$, $LBP_{(1,4)}$

Apart from the orientation features, the FKP images also have many finer texture features, which may convey power discriminative information. In this sub section, we will study the texture information contained in the FKP image in detail.

3.2 LBP Histogram

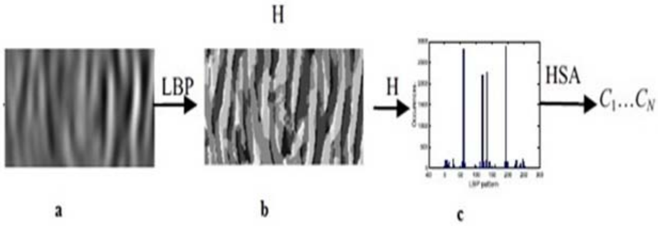

Fig.6. (a) FKP ROI image; (b) corresponding LBP map; (c) corresponding histogram of the map in (b).

In [15], Local Binary Pattern (LBP) histogram was proposed for rotation invariant texture classification. LBP is a gray-scale texture operator which characterizes the spatial structure of the local image texture. It has also been successfully adapted to many applications, such as face recognition [16], dynamic texture recognition [17] and shape localization [18]. Given a central pixel in the image, a pattern number can be computed by comparing its value with those of its neighbourhoods:

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, \quad \mathrm{s(x)} = \left\langle \begin{matrix} 1, x \geq 0 \\ 0, x < 0 \end{matrix} \right\rangle \qquad (1)$$

where g_c is the gray value of the central pixel, g_p is the value of its neighbours, P is the number of neighbours and R is the radius of the neighbourhood.

Suppose that the texture image is NxM. After identifying the LBP pattern of each pixel(i, j), the whole texture image can be represented by a histogram:

$$H(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} \mathrm{f}(LBP_{P,R}(i,j),k), \ \mathrm{k} \in [0, \mathrm{K}] \qquad (2)$$

$$\mathrm{f(x, y)} = \begin{cases} 1 & x = y \\ 0 & other \end{cases} \qquad (3)$$

Where K is the maximal LBP pattern value.

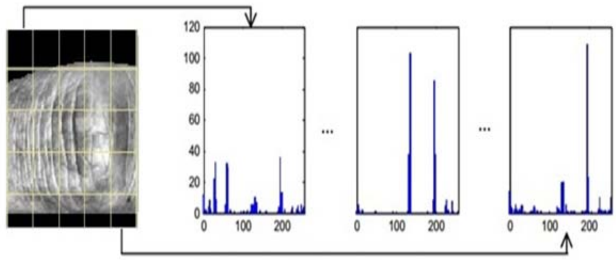

Fig.7. An example of extracting LBPH feature vector

IV. PROPOSED SYSTEM

This section presents a robust FKP based recognition system which is designed by fusing LBP and SURF features at matching score level. Sample of FKP images of Poly U database [1]. The FKP image is subjected for non-uniform brightness correction and contrast enhancement. LBP and SURF features are extracted from the enhanced FKP images. During recognition, corresponding feature vectors of query and enrolled FKPs are matched using nearest-neighbourhood-ratio method [9] to obtain the respective matching scores and these LBP and SURF matching scores are fused using weighted sum rule.

4.1 Feature Extraction

Features are extracted from all FKP images. LBP and SURF are used to extract the local features of FKP. Both LBP and SURF have been designed for extracting highly distinctive invariant features from images. Further, extracted feature vectors are found to be distinct, robust to scale, robust to rotation and partially invariant to illumination. Thus features can be matched correctly with high probability against features from a large database of FKPs. SURF key-points extracted from the FKP images are shown in Fig. 3.6.

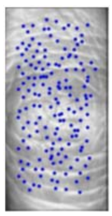

Fig.8. Key-points

4.2 Matching and Fusion

Feature template of the FKP is represented by two local feature vectors extracted using LBP and SURF. During recognition, LBP and SURF features of the query FKP are matched with the corresponding features of all the knuckle-prints in the database. The matching scores between corresponding feature vectors are computed using nearest-neighbour-ratio method [14] as follows.

Let Q and E be vector arrays of key-points of the query and the enrolled FKP respectively obtained using either LBP or SURF

$$Q = \{q_1; q_2; q_3; \_\_\_ q_m\} \qquad (4)$$

$$E = \{e_1; e_2; e_3; \_\_\_ e_n\} \qquad (5)$$

where q_i and e_j are the feature vectors of key-point i in Q and that of key-point j in E respectively. If $||q_i - e_j||$ and $||q_i - e_k||$ are the Euclidean distance between q_i and its first nearest-neighbour e_j and that between q_i and its second nearest-neighbour of e_k respectively, then

$$q_i = \begin{cases} \text{Matched with } e_j & \text{if } \frac{\|q_i - e_j\|}{\|q_i - e_k\|} < T \\ \text{Unmatched} & \text{Otherwise} \end{cases} \qquad (6)$$

Where T is a predefined threshold.
The matched key-points q_i and e_j are removed from Q and E respectively. The matching process is continued until there are no more matching points either in Q or E. Total number of matching pairs M is considered as the matching score. More the number of matching pairs between two images, greater is the similarity between them. Matching between FKP images of same user is called genuine matching while that of different users is known as imposter matching.
Let M_L and M_S be LBP and SURF matching scores respectively between the query and an enrolled FKP. These LBP and SURF matching scores are fused by weighted sum (WS) rule to obtain the final matching score S as

$$S = W_L * M_L + W_S * M_S \qquad (7)$$

Where W_L and W_S are weights assigned to LBP matching score M_L and SURF matching score M_S respectively, with $W_L + W_S = 1$. In this paper, $W_L = C_L / (C_L + C_S)$ and $W_S = C_S / (C_L + C_S)$ are considered where C_L and C_S are the correct recognition rate (CRR) of the system using LBP alone and SURF alone respectively.

$$CRR = (N_1/N_2) * 100 \qquad (8)$$

Where N_1 denotes the number of correct (Non-False) recognitions of FKP images and N_2 is the total number of FKP images in the testing set.

V. EXPERIMENTAL RESULT

During recognition, the corresponding features of enrolled and query FKPs are matched using nearest-neighbourhood-ratio method and the derived LBP and SURF matching scores are fused using weighted sum rule to obtain fused matching score. The proposed system has been evaluated using publicly available PolyU database [1] images.
Weights assigned to SURF score and LBP score were tuned to get optimum accuracy, EER. ROC has been drawn viz. Accuracy vs Threshold, FAR vs FRR, GAR vs FAR. The accuracy and EER of the system has been evaluated as 11.87%, 90.0% respectively.

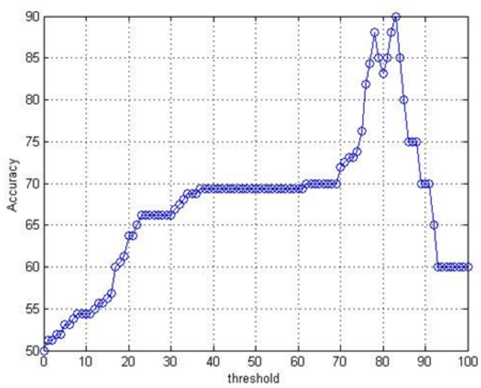

Fig.9. Accuracy vs Threshold graph

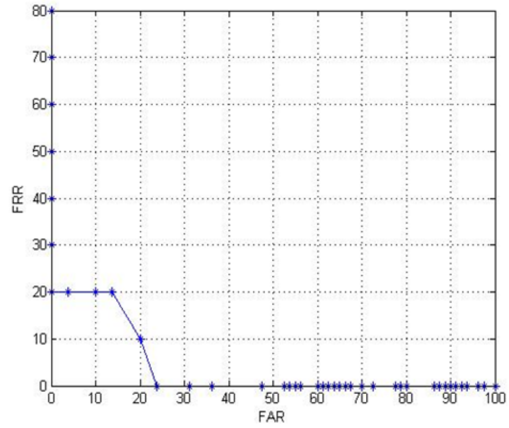

Fig.10. FAR vs FRR graph

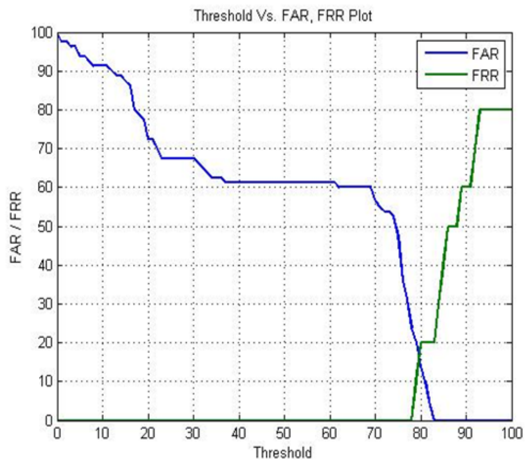

Fig.11. Threshold vs FAR/FRR

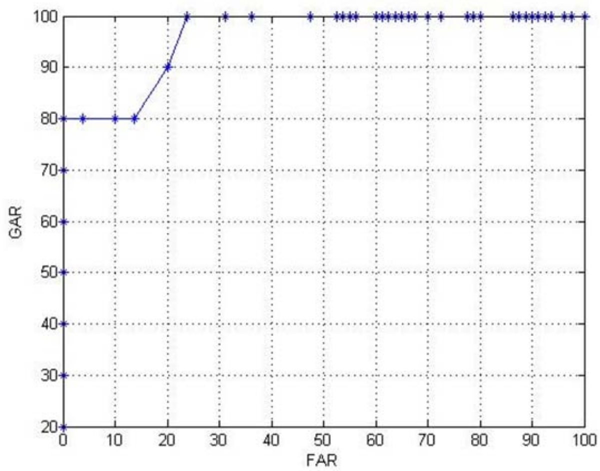

Fig.12. FAR vs GAR graph

EER	16.80%
Optimal Threshold	83
Accuracy	90.0%
FRR	20%
FAR	0.0%

VI. Conclusions

The aim of this dissertation is to develop an FKP based recognition system which is robust to scale and rotation. Local information of the FKP are extracted using LBP and SURF and they are fused at matching score level. During recognition, the corresponding features of enrolled and query FKPs are matched using nearest-neighbourhood-ratio method and the derived LBP and SURF matching scores are fused using weighted sum rule to obtain fused matching score. The proposed system will be evaluated using publicly available PolyU database [1] images.

Weights assigned to SURF score and LBP score were tuned toget optimum accuracy, EER. ROC has been drawn viz. Accuracy vs Threshold, FAR vs FRR, GAR vs FAR. The accuracy and EER of the system has been evaluated as 11.87%, 90.0% respectively.

Apart from this system's performance can be further increased by using advanced version of SURF and by tuning its parameters. LBP parameter tuning can be done or advanced LBP algorithm can be used. More Enhanements can be applied to images so that its score calculation can be accurate.

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