Combined SIQT and SSF Matching Score for Feature Extraction Evaluation in Finger Knuckle Print Recognition

KIRTHIKA ALAGAR[1] AND ARUMUGAM SUBBANNA[2]

[1] A/P Dept. of CSE
Affiliated to Anna University, Thangavelu Engineering College
OMR Road, Chennai, Tamilnadu
INDIA
kirthimecse@gmail.com
[2] Chief Executive Officer
Affiliated to Anna University, Nandha College of Technology
Perundurai, Erode, Tamilnadu
INDIA

Abstract:-

Feature selection has been a prevailing part of examine in biometrics, image reclamation, data mining, and text classification. The major design of feature selection is to choose a set of features, by removing the irrelevant as well as the surplus features that are robustly associated. Many classification techniques have been presented for feature extraction process but there has bee no effort for feature selection. The previous work used texture and color intensive biometric (TCIB) for multimodal security that achieves significant presentation even for the huge pose variations with various angles. The matching pattern is done using texture values but the outcome of the image is not as clear as much. To improve the knuckle finger print recognition system, in this paper, we present a narrative grouping of restricted information for a proficient finger-knuckle-print (FKP) based recognition system which is vigorous to extent and rotation. The non-uniform clarity of the FKP due to comparatively curvature surface is accurate and texture is improved. The features of the improved FKP are mined using the Scale Invariant Quality Transform (SIQT) and the Strong Speeded up features (SSF). Consequent features of the register and the query FKPs are coordinated using nearest-neighbor-ratio method and subsequently the consequent SIQT and SSF matching scores are combined using weighted sum rule. An experimental result are carried on the datasets with seven sample images in a substantial pose variations provides enhanced results compared to an existing Texture and Color intensive biometric multimodal security using hand geometry and palm print. The proposed system is evaluated with the set of images for both classification and authentication mode. It is practical that the system achieves with CRR of 100% and EER of 0:215%.

***Key-words*:** Palm print, Hand Geometry, Biometrics, Feature selection, Knuckle finger feature selection, SIQT, SSF, TCIB

1. Introduction

Personal authentication is an ordinary concern to equally industries and academia due to its numerous applications such as physical access organize computer security, banking and law enforcement. Biometrics, which refers to the exclusive physiological or behavioural description of human beings, can be used to discriminate between individuals and hence can serve as an ideal solution to this problem.

The quick development in the exercise of e-commerce applications and dispersion of information technology into the everyday life needs consistent user recognition for efficient and protected access control. The hand-based biometrics has established significant consideration in current years which uses numerous inner and exterior features that are relatively discrete in an entity. The user reception for hand-supported biometrics scheme is very elevated. These systems are appropriate which is more suitable and user-friendly.

Biometric based verification system has been used extensively in profitable and rule enforcement requests. The exercise of different biometric behaviour such as face, fingerprint, ear, iris, palm print, hand geometry and voice has been fine considered. It is accounted that the skin outline on the finger-knuckle is greatly affluent in texture owing to skin folds and enlarges, and therefore, can be measured as a biometric identifier. In addition, advantages of using FKP comprise affluent in texture features, simply available, contact-less image attainment, invariant to emotions and extra behavioral features such as stable features, tiredness and acceptability in the society.

Hand based biometric systems have request rising attention in last ten years. There are numerous approaches which presents talented results from hand geometry, fingerprint, palm print, vein pattern or finger knuckles among other biometrics. The state of the art of knuckle based system goes from the earlier systems. All these approaches present a contact surface to support the user hand during the acquisition. Therefore the conversation between user and device is inevitable.

The use of devices for applications with a large number of users raises clean concerns. The use of without conversation system is the obvious solution to hygienic concerns. The deficiency of contact among the acquisition device and the user addresses the hygienic concerns and recover the user acceptability.

Hand geometry has extended been used for biometric substantiation and classification as of its achievement expediency and good substantiation and classification performance. From image acquisition view, human handed over can be distinguished by its width, thickness, length, geometrical symphony, and geometry of the fingers. The preceding efforts have utilized mixture of these features for detection with unreliable amount of success. Conventionally, pegs are roughly forever used to attach the position of the hand, and the width, length and thickness of the hand are then taken as features. The outline of the hand is mined and is characterized by a group of prominent points, which provide as features in the confirmation process.

The main difference between conversation and without conversation system lies in the significant intra-class variations generated by the absence of any contact or guiding contact surface. Such variations result from the rotating and conversion variation, projective distortion, level variations, image blurring due to movement during the acquisition. Consequently using improved image normalization but the fundamental question is to ascertain how to extract the features which are invariant and vigorous to such variations from contactless imaging.

Finger knuckle has high textured region. Many samples are obtainable per hand and autonomous to any behavioural aspect. No stigma of possible criminal investigation associated with this approach. Finger knuckle is the reverse surface of finger, it is also acknowledged as dorsum of the hand. The inherent skin patterns of the outer surface roughly the joint of one‟s finger, has high capacity to categorize different individuals.

Such image pattern of finger knuckle is unique and obtaining online, offline for authentication. Extraction of features of knuckle for identification is totally depends upon the user. Some of the researcher extracted the features for authentication. Features are centre of joint, U shaped line around the middle phalanx, Number of lines, length and Spacing between lines.

The characteristic selection on FKP's is finished with an achievement device is developed to confine the FKP images, and a province of attention is produced for feature extraction. A feature extraction plan which integrates both the direction and amount information owing to Gabor filtering is used. The restricted convex path map of the FKP image is mined in based on which a limited synchronized system is recognized to maintain the the FKP confirmation is demoralized, where the direction information mined by the Gabor filters is delighted as the restricted feature and by raising the level of Gabor filters to unbounded, the Fourier change of the image is acquired, and therefore the Fourier change coefficients of the image can be taken as the universal features. In the SIFT (v) is applied after the Gabor enhancement to improve the performance. The finger knuckle identification is undertaken in using the orientation features from the finite Radon change.

In this paper, for the extraction of finger knuckle features, we used Scale Invariant Quality Transform (SIQT) and the Strong Speeded up Features (SSF) to enhance the feature extraction process.

2.Literature Review

In the ancient times, many biometric characteristics have been investigate, including fingerprint, face, iris, retina, voice, gait and signature. Researchers noticed that the texture in the exterior finger surface, particularly in the area approximately the finger cooperative, has the possible to do personal authentication.

It is frequently the case that no particular feature descriptor is rich sufficient to detain all of the classification information accessible in the pattern image. Thus, individual of the solution challenge for improving FKP acknowledgment performance is result and combining competent and discriminative information about FKP patterns. Worth noting, by observing the errors misclassified by the dissimilar approaches, one observe that a certain classifier is improved suitable for the recognition of a certain patterns than another one and consequently, some recognition errors dedicated by the best approach resolved by the inferior methods.

Feature selection plays a leading role in image retrieval, health care, data mining, text categorization and biometrics. The foremost design of characteristic mixture is to pick a deposit of features discarding the irrelevant as well as the unnecessary features that are powerfully connected in hand geometry [13].The characteristic selection on FKP’s is designed. An acquirement device is created to arrest the FKP images, and a region of significance is yielded for feature extraction for multimodal biometric system but not as much efficient [15]. A complete system for ear biometrics includes automated segmentation of the ear in a images. In both local and universal information for profile view image and 3D shape matching for recognition [14]. Evaluated system with largest experimental study date in ear biometrics, achieves a rank-one recognition rate.

In adding up skin outline on the finger-knuckle is highly rich in texture due to skin folds and creases, and hence, considered as a biometric identifier. Further, advantages of using FKP include rich in texture features, effortlessly accessible, contact-less image acquisition, invariant to emotions and other behavioural aspects such as tiredness, steady features and acceptability in the society.

Feature level fusion of finger knuckle prints (FKP's) is implemented to overcome the curse of dimensionality, feature selection using the triangular norms [6]. Feature level fusion is performed by combining the significant features of all FKP. A feature extraction method combines both the direction and extent information owing to Gabor. The restricted curved course map of the FKP image is mined based on which a confined management system is recognized to support the images [16].

Confined and universal information for the FKP substantiation is demoralized, where the direction information mined by the Gabor filters is indulged The Fourier change of the image is achieved, and therefore the Fourier change coefficients of the image can be received as the universal features [8]. The ultimate matching remoteness of two FKPs is a subjective average of confined and total matching distances [12].

Minutiae-based automatic fingerprint identification algorithm provides a score with a pair of fingerprints [11]. Scores were computed for corresponding fingers from both twins and non-twins. Multimodal Palm print and hand geometry features which are concurrently extracted from the users pose normalized textured 3-D hand which is used for matching. The influence of electrolysis on galvanic metal corrosion was explored found that the clarity of the fingerprints was time sensitive and improved as acid concentration increased with lower duration of electrolysis [3].

The SIFT (Scale Invariant Feature Transform) is useful behind the Gabor improvement to develop the performance [2]. The finger knuckle recognition is assumed using the direction features from the restricted radon transform [10]. The texture organization is completed with Joint Distributions of Local Patterns with Gaussian Mixture [5]. Techniques for characteristic subset collection can be categorized into the subsequent categories such as embedded, wrapper, filter and hybrid. The wrapper strategy needs one organization model and it chooses features with intend of enhancing the overview recital of that form.

An algorithm uses a beneficial approach concerning association information while choosing features and shaping [1]. A novel method for feature mixture, builds a human central finger using partial parts of the knuckle surfaces [9].The technique uses an instruction algorithm called ANOVA and Functional Networks. It pursues a backward non-sequential policy on the complete set of features and is capable to arbitrator multivariate relations among features. A SIQT and SSF feature is designed for extracting the features of the finger knuckle recognition system.

Neural Network architectures for individual verification are used for the purpose of finger knuckle recognition system [7]. Texture and Color Intensive Biometric (TCIB) for multimodal security is presented which achieves considerable performance even for the large pose variations with diverse angles but the image is not clear [4].

Therefore the Fourier change coefficients of the image are taken as the universal features. In Scale Invariant Quality Transform (SIQT) is applied after the Gabor enhancement improves the performance. The finger knuckle identification is undertaken using the direction features from the finite radon change. For the extraction of finger knuckle features, used a Scale Invariant Quality Transform (SIQT) and the Strong Speeded up Features (SSF) to enhance the feature extraction process.

3. Feature Extraction for FKP recognition using SIQT and SSF

The schematic plan of FKP based individual verification system is collected of a data acquisition component and a data processing component. The data acquisition module is collected of a finger bracket, a ring LED brightness source, a lens, a CCD camera and a frame grabber. The confine FKP image is inputted to the data processing module, which contains three primary steps namely Region of Interest extraction, feature extraction and coding, and matching. The outlook of FKP image acquisition device with overall size is 180mm×145mm×120mm.

A significant issue in data acquisition is to create the data collection environment as stable and consistent as possible so that variations among images collected from the same finger reduced to the minimum. In general, a stable image acquisition process successfully reduces the complication of the data processing algorithms and recovers the image recognition accurateness.

Meanwhile, a diminutive constraint is probable on the users in order for high user friendliness of the system. With the above considerations, a semi-closed data collection environment is designed in system. The LED light source and the CCD camera are covered in a box so that the enlightenment is almost constant. One complex difficulty is how to create the signal of the finger which is almost stable so that the captured FKP images from the indistinguishable finger are consistent.

A fundamental and triangular block is used to restore the position of the finger knuckle united. In data acquisition, the user easily put his/her finger on the basic block with the middle phalanx and the proximal phalanx poignant the two incline of the triangular block. Such a intend aims at dropping the spatial position variations of the finger in dissimilar capturing sessions. The triangular block is also used to restrict the position between the proximal phalanx and the centre phalanx to a definite magnitude so that line features of the finger knuckle surface clearly imaged.

After the image is captured, it is send to the data processing unit for pre-processing, feature extraction and matching. Two images are shown below in which the fig.1 (a) and (b) are from one finger and fig.2 (a) and (b) are from another finger.

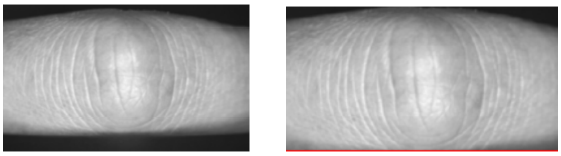

Fig.1 (a) (b)

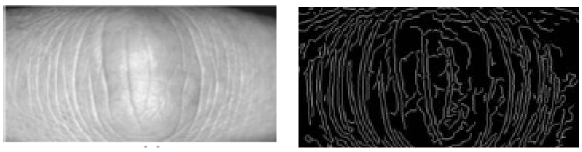

Fig.2 (a) (b)

The above images are illustrated for the same finger was capture at two diverse collection sessions with an interval of 45 days. The developed system, images from the same finger but collected at different times are very similar to each other. Meanwhile, images from different fingers are very dissimilar, which imply that FKP has the possible for personal identification.

The proposed FKP based identification system is considered by combining SIQT and SSF features based on equivalent gain level. Model of FKP images are taken for testing the feature extraction process. The FKP image is intended for a distinct clarity improvement and contrast improvement. SIQT and SSF feature extraction is done by the improved FKP images. Through identification, analogous feature vectors of query are harmonized. FKP registered using nearest neighborhood ratio method to attain the individual equivalent scores and the features of SIQT and SSF matching scores are combined using weighted average rule. The architecture diagram of the proposed FKP based system for recognition is shown in Fig.3.

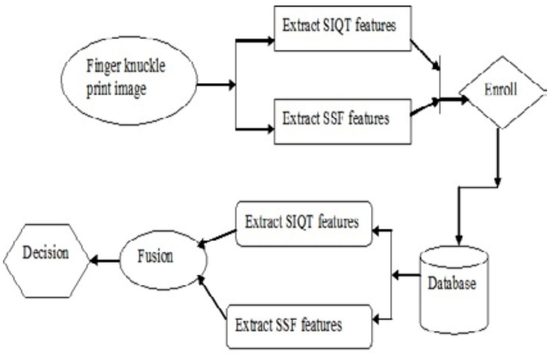

Fig. 3. Architecture diagram of the proposed FKP based system for recognition

The finger-knuckle surface symbolizes a moderately bend surface and outcomes in non-uniform mirror image. FKP has low disparity and non-uniform intensity. To achieve the well dispersed texture image subsequent operations are practical on FKP. FKP image is normally divided into sub-blocks. Representation of each block is designed which guess the expression of the block. The probable coarse reflection is prolonged to the innovative size of the FKP image using bi-cubic exclamation. For the common estimation of reflection, if the block size is very little, the estimation is roughly similar as the mined FKP and if the block size is elevated, the estimation becomes inappropriate.

3.1 Different Types of Feature Extraction Method

Different Types of feature extraction algorithms are based on both confined and universal appearance descriptors, block-based Discrete Cosine Transform (DCT) and uniform Local Binary Patterns (LBP). An overview of these two algorithms is given.

3.1.1 Discrete Cosine Transform

DCT is a predominant tool and it was widely used as a feature extraction and compression in various applications on signal and image processing and analysis due to its fine properties, i.e., de-correlation, energy compaction, reparability, symmetry and orthogonality. In finger knuckle recognition, DCTs are used to diminish image information redundancy since only a subset of the change coefficients is necessary to conserve the most significant finger knuckle features.

The confined information of a contestant FKP obtained by using block-based DCT. A FKP finger knuckle image is removed into blocks of 8 by 8 pixels size. Each block is then symbolized by its DCT coefficients. From the obtained DCT coefficients only a minute, generic feature set is reserved in each block. It proved that the maximum information necessary to achieve high categorization accuracy in the first low incidence DCT coefficients finger knuckle feature extraction via zigzag scanning [9].

3.1.2 Local Binary Pattern

The Local Binary Pattern operator showed the maximum discriminative energy of this operator for texture classification in finger knuckle biometric. The original LBP operator labels the pixels of an image by threshold the 3*3 neighbourhood of each pixel with the centre assessment and considering the result as a binary string or a decimal number and uses the resulting binary-valued image patch as a local image descriptor [16]. It originally defined for 3*3 neighbourhoods, generous 8 bit codes based on the 8 pixels around the middle one.

An addition to the original operator was made and called consistent patterns. An LBP is uniform if it encloses at most two bitwise conversions from 0 to 1 or vice versa. In a substance of information this means that a uniform pattern has no transitions or two transitions. Only one evolution is not probable, since the binary string needs to be considered circular. The design following the LBP uniform is to detect characteristic (local) textures in image, similar to spots, column ends, edges and corners.

During its current extensions, the LBP operator has been completed into an actually controlling measure of finger knuckle image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. Computational time is considerably condensed and additionally, LBP's are resistant to lighting possessions in the sense that they are invariant to monotonic gray-level transformations, and they have been shown to have high discriminative power for texture classification.

3.2 Feature Extraction

Feature vectors through SIQT are formed by means of confined patterns around key-points from level space images. Following are the major steps to generate SIQT features of a given image.

Level space Extreme recognition: The initial action of calculation searches above all scales and image position. It is realized economically by using a Difference-of-Gaussian function to classify possible interest points that are invariant to level.

Key point localization: At each contestant position, a detailed model is fitted to determine position and scale. Key-points are certain based on method of their stability.

Orientation transfer: Consistent orientation is assigned to the key-point subsequent confined image properties to create the key-point descriptor rotation invariant.

Key-point descriptor: Feature vector of 128 values is calculated from the confined image region around the key-point.

Feature vectors through SSF are formed by means of confined patterns around key-points which are detected using level up filter. Following are the major steps to determine the SSF feature vectors of a given image.

Key-point detector: At this step, SSF key-points are detected using matrix approximation. The second order Gaussian derivatives for matrix are approximated using filters. Key-points are restricted in level and image space by applying non-maximum suppression. It has a 3*3*3 region of SSF key points.

Key-point descriptor: This stage describes the key-points. It fixes a reproducible central direction based on information from a round region around the interest point. Feature vector of 64 values is compute from the orient rectangle confined image region approximately key point.

FKP images are extracted for receiving the features. SIQT and SSF are utilized to haul out the restricted features of FKP. Both SIQT and SSF have been planned for mining extremely characteristic invariant features from images. An auxiliary, mined aspect vectors are established to be discrete, tough to balance, robust to alternation and moderately invariant to clarification. Thus features can be coordinated suitably with elevated probability beside features from a large database of FKPs. SIQT and SSF key-points extracted from the FKP images.

3.3 Matching and Fusion

Score level fusion refers to the mixture of matching scores provide by the dissimilar classifiers to produce a single scalar score which is then used to make the finishing decision. Since the matching scores generated by the dissimilar modalities are heterogeneous, normalization is necessary to change these scores into a normal area before merge them. Normalization performed using the Min-Max and Gaussian normalization as described below. Some of the rules used to join the classifiers at the score level are Sum rule, Product rule, Max rule and Min rule.

Next to the feature vectors, the matching scores production by the classifiers enclose the more satisfied information about the contribution pattern. In proposed FKP based system for recognition uses the sum rule to perform the feature extraction.

Feature template of the FKP is characterized by two restricted feature vectors mined using SIQT and SSF. During identification, SIQT and SSF aspects of the query FKP are coordinated with the analogous features of all the knuckle-prints in the database. The identical scores among analogous feature vectors are calculated using nearest-neighbor ratio method as follows.

Let A and B be vector arrays of key-points of the query and the registered FKP correspondingly obtained using either SIQT or SSF

$$A = \{a_1; a_2; a_3; \_\,\_\,\_\ a_m\} \text{…….. Equation (1)}$$

$$B = \{b_1; b_2; b_3; \_\,\_\,\_\ b_n\} \text{…….. Equation (2)}$$

Where a_i and b_j are the feature vectors of key-point i in Q and that of key-point j in E correspondingly. If $\|a_i - b_j\|$ and $\|a_i - b_k\|$ are the Euclidean distance between a_i and its first nearest-neighbor b_j

and that between ai and its second nearest-neighbor of b_k correspondingly, then

$$ai = \{Matchedwithbj \quad \text{If } \frac{a_i - b_j}{a_i - b_k} \quad \text{...Equation (3)}$$

Unmatched Otherwise

The matched key-points a_i and b_j are removed from A and B correspondingly. The equivalent process is continued until no more matching points occurs in A and B. Total number of matching pairs M is considered as the matching score. The more number of identical pairs among two images are greater and they are parallel among them. Matching among FKP images of similar user is called authentic matching with dissimilar users is known as imposter matching.

Let MF and MR be SIQT and SSF equivalent scores correspondingly among the query and a joined FKP. These SIQT and SSF matching scores are merged by weighted sum rule to acquire the ultimate equivalent score S as

$$S = W_T * M_T + W_S * M_S \quad \text{........ (Equation 4)}$$

Where W_T and W_S are weights consigned to SIQT matching score M_T and SSF matching score M_S correspondingly, with $W_T + W_S = 1$.

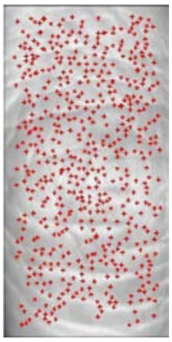

Fig .4 SIQT Matching score

SIQT matching score points M_T are multiplied with the weight points of W_T to attain the equivalent score 'S' as shown in Equation (4). Fig 4 describes the matching key points of SIQT, through which the genuine matching detected with $W_T + W_S$ is set to be unity.

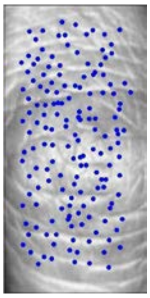

Fig.5 SSF Matching score

SSF matching score as shown in Fig.5 describes the M_S respectively. SSF matching score points M_S are multiplied with the weight points of W_T. It attain the equivalent score 'S' by adding up the SIQT and the SSF equivalent score as shown in Equation (4).

FKP uses the $W_T = C_T / (C_T + C_S)$ and $W_S = C_S / (C_T + C_S)$ measurement where C_T and C_S are the Correct Recognition Rate (CRR) of the scheme using SIQT and SSF correspondingly. By the way of using the equivalent score levels of SIQT and SSF, the similar images are identified efficiently with the training set samples by extracting the features.

Finger Knuckle print is raising tool of biometrics and consisted of a integer of curvature points in finger knuckle image. The process extraction in SIQT Histogram has each suitable key point characterized by two parameters namely x-coordinate and y-coordinate. The initial process of feature extraction is histogram equalization, which is used to improve the input image of FKP in order to get hold of the spatial characters precisely. Histogram equalization is used to improve the visualization effect by raising the pixel size.

The subsequently step of feature extraction is to extract the key points from finger knuckle print using the scale invariant feature transform by SIQT. The SIQT and SSF algorithm is mainly used for image matching purpose. Scale invariant quality transform is used for detection and extracting local features of an image. The first step of SIQT process is to find the difference of Gaussian function convoluted with the finger knuckle print image to detect the key point locations which is invariant to level change.

3.4 Algorithmic Flow of FKP Feature Extraction

It is necessary to construct a confined synchronize system for each FKP image. With such a coordinate system, a feature extracted from the original image for reliable feature extraction. The detailed steps for pointing out such a coordinate system are as follows.

Step 1: Determine X-axis of the synchronize system. The bottom limit of the finger effortlessly is extracted by edge detector. Really, this bottom boundary is approximately reliable to all FKP images because all the fingers are position totally on the blocks in information acquirement. By appropriate this limit as a straight line; the X-axis of the confined synchronize system is determined.

Step 2: Crop a sub-image of IS and the left and right borders of IS are two fixed values evaluate empirically. The top and bottom borders are estimated according to the boundary of real fingers and they get hold of by edge detector.

Step 3: Edge detection applied to obtain the edge map IE.

Step 4: Convex direction coding for IE describe a perfect model for FKP “curves”. In FKP extraction using SIQT and SSF model, an FKP curve is either convex leftward or convex rightward. The pixels on rounded leftward curves as “1”, pixels on rounded rightward curves as “-1”, and the other pixels not on any curves as “0”

Step 5: Determine the Y-axis of the coordinate system. For an FKP image, curves on the left part of are mainly convex leftward and those on the right part are chiefly rounded rightward. Meanwhile, “curves” in a small area around the joint do not have obvious convex directions. Based on this inspection, at a horizontal position x (x represents the column) of an FKP image.

4. Experimental Evaluations

The proposed FKP for hand geometry and palm print using SIQT and SSF features is implemented by using Java platform. The experiments were run on an Intel P-IV machine with 2 GB memory and 3 GHz dual processor CPU. The experiments are carried over with sets of sample images. In order to estimate the performance of the proposed FKP for hand geometry and palm print, the proposed features are applied to those sample sets of images with SIQT and SSF approaches. Based on Scale Invariant Quality Transform (SIQT) and the Strong Speeded up Features (SSF), the texture values are generated and features are efficiently extracted in a secure manner.

After that, it would match the template values and proficiently identify the given image similarity. The proposed FKP for hand geometry and palm print is efficiently designed for identifying the similarity of image (hand geometry/palm print) and improved the multimodal biometric security using SIQT and SSF features. The performance of the proposed FKP for hand geometry and palm print in multimodal biometric security using SIQT and SSF is measured in terms of

i) Feature Extraction rate
ii) Matching
iii) Error rate

5. Results

The experiments are evaluated on how the palm print/hand geometry image similarity are identified by extracting the features using the proposed FKP for hand geometry and palm print in multimodal biometric security with SIQT and SSF features and contrast with an existing TCIB approach written in mainstream languages such as Java. A set of sample test images are used with diverse postures to estimate proposed FKP using SIQT and SSF. The comparison results shown that proposed FKP for multimodal biometric security using SIQT and SSF outperforms well. The below table and graph describes the process of the FKP for hand geometry and palm print in multimodal biometric security with SIQT and SSF features.

5.1 Feature Extraction Rate

It is defined as the special form of dimensionality reduction in biometric system. Transforming the input data into the set of features is called feature extraction. It is measured in terms of percentage (%).

The table (Table 1) describes the process of extraction of features in the given sample set of images. The results of FKP for multimodal biometric security using SIQT and SSF are compared with an existing TCIB approach.

No. of users	Feature Extraction rate (%)	
	Proposed FKP technique	Existing TCIB
1	12	9
2	28	18
3	35	27
4	48	34
5	56	40

Table 1 No. of users vs. Feature Extraction Rate

Fig 6 shows the process of feature extraction from the given set of images and the results are compared with an existing TCIB and proposed FKP using SIQT and SSF features for hand geometry/palm print features. In order to reveal effectiveness of the proposed FKP using SIQT and SSF features for knuckle feature extraction print matching concepts, have plotted the number of user and feature extraction process in terms of rate.

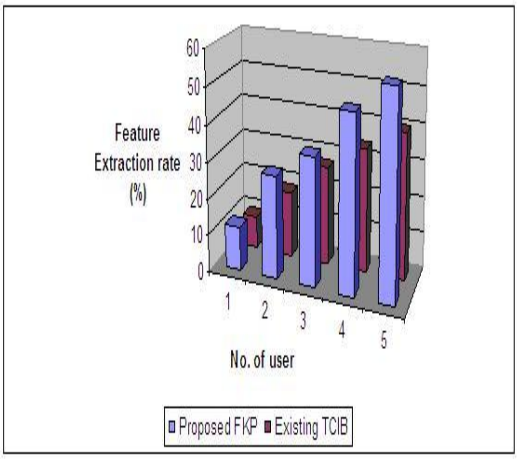

Fig.6 No. of user vs. Feature Extraction rate

The general matching graphs for proposed FKP for multimodal biometric security using SIQT and SSF is plotted for number of user versus matching (%) for different users. It is practical from the graph that matching (%) obtained for the proposed FKP for multimodal biometric security using SIQT and SSF are coordinated with the analogous features which is 20 – 30 % higher when compared to existing TCIB approach.

5.2 Matching

It is defined as the rate of matching the input biometric finger knuckle palm print with the stored database information. It is measured in terms of percentage (%).

No. of users	Matching (%)	
	Proposed FKP technique	Existing TCIB
1	16	12
2	30	20
3	42	32
4	50	40
5	62	51

Table 2 No. of user vs. Matching

The above table (Table 2) describes the process of matching factor of the given sample set of images. The results of FKP for multimodal biometric security using SIQT and SSF are compared with an existing TCIB approach.

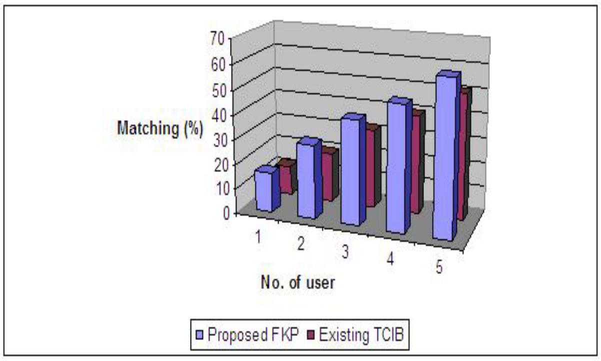

Fig.7 No. of user vs. Matching

Fig 7 shows the performance of general matching work done for the existing TCIB and proposed FKP for multimodal biometric security using SIQT and SSF. In order to exhibit effectiveness of proposed work FKP for multimodal biometric security using SIQT and SSF. It plots the number of user and matching in terms of rate. The general matching curve for the proposed FKP for multimodal biometric security using SIQT and SSF is plotted for number of user versus matching (%) for different users. It is known from the graph that matching (%) obtained for the proposed FKP probable coarse reflection in SSF is 10 – 20 % prolonged higher when compared to existing TCIB approach.

5.3 Error rate

Error rate is the term which defines the amount of error (i.e.) the biometric mismatches. The error rate is measured in terms of percentage (%).

No. of users	Error rate (%)	
	Proposed FKP technique	Existing TCIB
1	2.3	5.8
2	4.6	9.3
3	6.2	8.6
4	5.4	12.5
5	6.9	15.4

Table 3 No. of users vs. Error rate

The above table (Table 3) describes the error rate occurred during the feature extraction process. The results of FKP for multimodal biometric security using SIQT and SSF are compared with an existing TCIB approach.

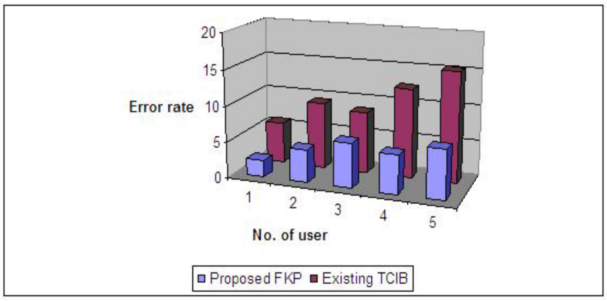

Fig. 8 No. of user vs. Error rate

Fig 8 shows error rate occur during the proposed FKP for multimodal biometric security using SIQT and SSF. Since the SIQT has been used for improving the features of identifying the knuckle feature extraction process, the feature extraction is done efficiently with low error rate. To improve the performance of the proposed FKP for multimodal biometric security using SIQT and SSF, the error rate has been found.

The general Error rate curve for the proposed FKP for multimodal biometric security using SIQT and SSF is plotted for number of user versus error (%) for different users. From the graph, it is identified that the error rate is 40 – 50 % reduced in proposed FKP, which uses $W_T = C_T / (C_T + C_S)$ for multimodal biometric security when compared to existing TCIB approach.

At last, it is concluded that the proposed FKP for multimodal biometric security using SIQT and SSF is efficiently designed and the knuckle features are extracted in a reliable manner with less error rate. After the features are extracted from the knuckle fingerprint, the matching has been done with the training set of images.

6. Conclusion

A FKP approach efficiently extracts the features from knuckle finger print pose invariant biometric identification using Palm print and hand geometry images. FKP is acquired through a combined value imaging set up. The proposed FKP approach used the required hand images to guess the track of the hand. The estimated direction information of the given image is then developed to correct pose of the obtained 3-D as well as 2-D hand. FKP also developed a SIQT and SSF features for proficiently extracted hand features together for palm print matching features. The proposed FKP for multimodal biometric security using SIQT and SSF efficiently matched scores with an existing TCIB feature sets. The experimental results demonstrated that the proposed FKP for multimodal biometric security using SIQT and SSF approach significantly better in terms of the feature extraction process. The results also showed that the FKP for multimodal biometric security using SIQT and SSF constantly outperforms in terms of feature extraction and matching factor with less rate.

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