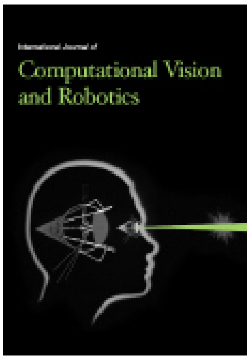

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Holistic knuckle recognition through adept texture representation

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Abstract: In topical years, substantiation of individuals through their finger knuckle patterns has turned into an extremely dynamic area of exploration. Finger knuckle patterns are the inimitable creases existent on the posterior surface of the hand, which is more expedient than other hand related modalities like fingerprint and palmprint, as the posterior surface of hand is less abraded in contrast to interior hand. This work presents an effective knuckle-based recognition framework via fusion of base, minor and major finger knuckle patterns of fingers of the individual for boosted recognition. For this, all the finger knuckle patterns are segmented and features are extracted explicitly using an efficient feature descriptor named curvature Gabor filter (CGF). In order to substantiate the proposed methodology, rigorous investigations have been performed on a publicly accessible large hand dorsal database named PolyU-Hand Dorsal (HD) dataset. Knuckles are integrated in three different ways to investigate the effect of their fusion, named 'fusion over knuckle', 'fusion over finger' and 'fusion over hand'. All the strategies mentioned have supported their magnified performance than individual knuckle recognition framework, whereas 'fusion over hand' outshined with tiniest EER of 0.2009.

Keywords: information security; multimodal biometrics; information fusion; knuckle recognition; score level fusion.

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1 Introduction

Biometrics is involuntary process of authenticating human being by employing physiological and behavioural physiognomies (Jain et al., 2004). In this day and age, biometric systems have been evolved as highly demanded security system for a wide range of applications starting from personal gadgets such as mobile phones to border control of a nation. Several physiognomies have been used as a biometric trait such as face, earprint, palmprint, finger-knuckle-print, iris, voice, gait, handwriting and keystrokes (Jain et al., 2016). The selection of traits depends upon the application where the system is used as some of the traits such as iris, palmprint and fingerprint are used extensively due to their capability to achieve higher authentication rates but these traits have complex acquirement procedure and require the user's active support, while the traits such as face and earprint are easy to acquire but they lag in authentication accuracy. Biometric systems which rely upon one trait are termed as unimodal biometric system. But unimodal biometric systems suffer from various snags such as dissimilarities in the same class, resemblance in dissimilar classes, susceptibility to fraudulent attacks and non-universality (Singh et al., 2019). Biometric systems which rely on more than one trait are termed as multimodal biometric frameworks. To overwhelm the snags of uni-modal biometric framework, multimodal biometric system is an appreciable solution.

To recognise or to authenticate an individual, a biometric framework is used. It involves one to many mapping in identifying an individual and it uses one to one mapping for verifying an individual. For accomplishing authentication a general biometric system has four sections (Jain et al., 2004). These four sections can be described as follows.

1 *Image procurement:* In this section images of biometric traits are acquired using various types of sensors. For example, for capturing iris image an eye sensor is required.

2 *Extraction of features:* In this section key points of a particular trait are extracted using various types of feature descriptors. For example, in case of iris image rifts, rings, stripes, filaments, coronal and furrows are extracted using a suitable feature descriptor.

3 *Matching section:* In this section different types of classifiers are employed to relate the keypoints of inquiry image against the templates already kept in the database, which generate the scores, based upon the similarity between the templates and query image features.

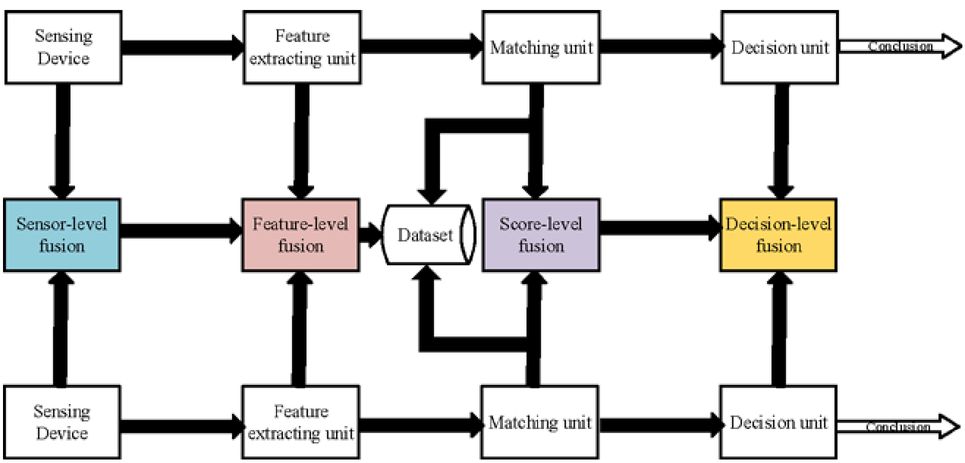
4 *Decision section:* On the basis of scores generated by the classifiers a decision about the identity of a user is taken.

In a multimodal biometric system manifold information is used to authenticate a person which can be acquired using multiple-sensors, multiple-feature extractors, multiple-matchers and multiple-decision sections (Singh et al., 2019).

From a period of time, fingerprint and facial images have been used by forensic science as biometric identifier to identify convicts of sombre criminality. However in several cases where evidence images of these traits are not of sufficient quality, it becomes challenging task to identify a convict. In such cases hand dorsal images can play a substantial role in identification. The unique creases existent on the rear side of fingers are termed as finger knuckle prints. Dependent upon the location of creases on different joints of the finger there are three types of knuckles prints termed as major, minor and base knuckles. Finger knuckle patterns are expedient than other hand related modalities like fingerprint and palmprint as the posterior surface of hand is less abraded in contrast to interior hand (Kumar and Ravikanth, 2009). Alike fingerprints, finger knuckle patterns possess ample amount of stable unique surface creases which can act as effective biometric identifier (Kumar and Xu, 2016). In fact, in recent years the finger knuckle print based recognition frameworks have been drawing extensive consideration of researchers. An enormous numbers of research works illustrate that biometric fusion can extraordinarily further augment the authentication percentage of the biometric framework.

In multimodal biometric systems information from different traits are integrated at various stages like, fusion at device stage (integration of images captured from different sensing units), fusion at feature stage (integration of key points extracted from several traits), fusion at score stage (integration of matching score obtained using different classifiers), fusion at decision stage (integration of decisions of several classifiers), fusion at rank stage (integration of ranks obtained from different matchers) and fusion using hybrid stage (employing manifold fusion techniques) (Kabir et al., 2018). Figure 1 presents the schematic block diagram of general multimodal biometric system. This figure clearly depicts that biometrics fusion can take place at multiple levels of the processing pipeline, where sensor-level, feature-level, score-level and decision-level fusions are few popular terms used in the literature (Singh et al., 2019).

Figure 1 Schematic block diagram of general multimodal biometric system (see online version for colours)



Due to high processing time and lesser compatibility of images acquired using multiple sensors, in state-of-art works there is very less amount of research works based on fusion at device stage. Rank level fusion cannot be used in verification; it can only be used in identifying an individual hence till now there is very little implementation of multimodal biometric system has been done using rank level fusion. Decision level is also less renowned in integrating the traits because in this stage of fusion, the decisive results of various decision units are integrated to reach at final conclusion about the identity of an individual. So there is no sufficient information to be fused to get augmented authentication rate. Substantial works have been using feature level fusion techniques, since key points possess rich extent of information related to biometric modalities that are to be fused. As fusion at feature stage of traits is accomplished just by concatenating the feature vectors of several traits which results in a feature vector of huge dimensionality, so it become very difficult to process the fused feature vector. The most protruding method of fusing various traits is score level fusion, as it requires only the matching scores of traits to be fused, which are easy to process and fuse (Ammour et al., 2018).

Moreover, score level fusion provides better recognition rate as the matching scores of different traits have ample amount of information about the traits.

This paper presents fusion of knuckle patterns to attain augmented percentage of authentication. In this work initially major, minor and base knuckle creases of four fingers (index, middle, ring and little finger) are segmented followed by extraction of features, which has been accomplished using curvature Gabor filter (CGF). Afterwards, performance of all the 12 individual cases of the four fingers has been evaluated. Then to augment the recognition accuracy three kind of strategies for score level fusion of knuckle patterns have been proposed i.e., fusion over knuckles, fusion over finger, fusion over hand.

This work aims to accomplish the following objectives:

1 extract most distinctive textural features of knuckles

2 achieve augmented percentage of authentication via score level fusion of knuckles

3 determine optimal fusion strategy of fusing knuckles.

Moreover, the scope of this work includes fusion of finger knuckles at score level using three strategies named 'fusion over knuckle', 'fusion over finger', 'fusion over hand'. To demonstrate the superior performance of the suggested methodology, a thorough set of experiments using the PolyU hand-dorsal (HD) dataset, a publicly available knuckle dataset, were carried out. These experiments involved tailoring different suitable measures, including EER, DI, GAR, and ROC.

Remainder of the paper is systematised as follows. In Section 2 we provide a concise summary of some recent works related to finger knuckle patterns. Section 3 exhibits the suggested methodology. This section portrays the structure of multimodal biometric framework, segmenting procedure of major, minor and base knuckles, feature extraction of modalities, score level fusion of modalities. Furthermore, Section 4 refers to experimentations performed to validate the proposed approach. This section depicts the details of dataset used for confirmation of the proposed work, Receiver Operating Characteristics (ROC) curves obtained for all set of experimentations. Section 5 presents the discussion and Section 6 concludes the proposed work.

2 Related work

In swotting finger knuckle patterns as biometric identifier, the foremost work was by Woodard and Flynn (2005); they demonstrated that fine creases on rear side of fingers can be used in biometric identification. Additionally, authors used shape index based on curvature to epitomise the surface of finger. Kumar (2014) proposed an automated procedure for segmenting major and minor knuckles from contact-free hand dorsal images. Bahmed and Mammar (2021) introduced a basic finger knuckle pattern as an effective biometric trait and employed ALLBP as feature descriptor. To boost the quality of FKP images a novel technique named CLAHE was introduced by Hana and Maulida (2021). They employed SURF AND PCA as feature descriptors. To decrease the time complexity a deep learning based automated approach for finger knuckle patterns was presented by Vyas et al. (2021).

Fusion at feature stage of knuckle patterns and finger veins based on hash learning was proposed by Li et al. (2021). Relative evaluation of several feature descriptors to handpick the superlative feature descriptor for knuckle patterns was introduced by Singh et al. (2022) and after rigorous experimentations they concluded that SURF, KAZE and ORB descriptors outperforms other descriptors such as MAZE and BRISK. Heidari and Chalechale (2022) proposed transfer learning based approach to fuse knuckle patterns and fingernails at rank level. Additionally, they proved that use of AlexNet results in decreased computational cost. Zohrevand et al. (2021) compared different CNN based models such as VGG16, AlexNet, ResNet34, GoogleNet in terms of recognition accuracy for finger knuckle patterns as well as introduced a novel CNN based model which outperforms the other exiting models.

Attia et al. (2021a) presented an automated deep rule based knuckle recognition framework, they extracted features of knuckle patterns employing two feature descriptors named BSIF and Gabor filter and integrates the patterns at score level afterwards. Hamidi et al. (2021) presented a framework which employed VGG16 and VGG19 for extracting features of finger knuckle patterns and then fused them at score level. Anbari and Fotouhi (2021) suggested a three layered model for extracting dominant feature from LBP images. Attia et al. (2021b) presented fusion of local and global features extracted using BSIF form minor and major knuckle patterns. Alghamdi et al. (2022) recommended a framework for fusion of finger knuckles and fingernails using DenseNet201 model of CNN and Bray-Curtis as a classifier. Tarawneh et al. (2022) several classifiers based on machine learning such as ANN, KNN, RF and NB were employed for knuckle identification.

In another recent work, a proficient technique for automatically localising knuckle patterns by collaborating several object detecting systems was described by Vyas et al. (2022). Benmalek et al. (2022) presented a robust deep rule based SSDRB classifying algorithm for knuckle recognition. This algorithm employed BSIF for extracting discriminative features. Chaa et al. (2022) presented kernel fisher analysis based contact-free recognition by fusing two and three dimensional knuckle patterns at score level. They employed tans and Triggs procedure for extracting features. An optimisation algorithm for KNN based feature selection approach was described by Jayapriya and Umamaheswari (2022). Lakshmanan et al. (2022) proposed an efficient feature extraction technique (M-LPQ) for extricating the key points of knuckles. Another transfer learning based fusion of traits was introduced by Attia et al. (2022). In this work authors have extracted features of finger knuckles as well as palmprints by employing PCANet and subsequently fused these traits at score level for augmented recognition. Another recent work presented by Gupta et al. (2020) has employed local directional peak valley binary pattern (LDPVBP) for texture analysis of images. This approach is an amalgamation of two another approaches namely local binary pattern (LBP) and local extrema peak valley pattern (LEPVP). Results offered have evidently revealed the outpacing performance of the proposed approach. Bhunia et al. (2020) proposed an exclusive feature extracting method for real time systems, which collectively uses colour as well as textural information present in the image for extracting distinctive features. For performance validation of the proposed approach experimentations have been completed on five benchmark datasets. Furthermore, Ghose et al. (2020) introduced a CNN based model for real time systems, which utilises textural information for recognising the ground–terrain images. This work has been compared with existing techniques on three mobile datasets. The results presented revealed the superior performance of the proposed approach. Hammouche et al. (2022) employed BSIF for extracting the distinctive features of major and minor knuckles and fused these at score level in order to develop an effective recognition system. Srivastava et al. (2022) extracted the features of the traits using SIFT, SURF and LOG Gabor wavelet and subsequently employed a neuro-fuzzy classifier to attain the scores of Iris and finger-knuckle-print. Score level fusion of above said traits result in an efficient multimodal biometric recognition system. The explored related works have been summarised in Table 1.

Table 1 Summary table presenting the feature extractor and performance metrics in various related works

Author	*Employed feature extraction method*	*Metrics for performance evaluation*
Woodard and Flynn (2005)	Curvature based shape index	EER = 5.5%
Kumar (2014)	LBP, ILBP, BLPOC, 1-D LOG Gabor filter	EER = 6.29%
Bahmed and Mammar (2021)	ALLBP	FRR = 0%, FAR = 0.03%
Hana and Maulida (2021)	SURF	Accuracy = 97%
Vyas et al. (2021)	CNN based model	EER = 1.0 to 1.9%, DI = 5.04–5.83
Li et al. (2021)	Learning based model	EER = 0.63%
Singh et al. (2022)	MSER, BRISK, SURF, KAZE, ORB	EER = 0.0010%, DI = 6.4645
Heidari and Chalechale (2022)	CNN based model	Accuracy = 94.75%
Zohrevand et al. (2021)	CNN based model	Accuracy = 99.83%
Attia et al. (2021a)	BSIF, Gabor filter	EER = 0.19%, Accuracy = 99.65%
Hamidi et al. (2021)	VGG-16, VGG-19	EER = 0.00%
Anbari and Fotouhi (2021)	Learning based model	EER = 0.91%
Attia et al. (2021b)	BSIF	Rank-1 = 99.60%, EER = 0.00%
Alghamdi et al. (2022)	CNN based model	Rank-1 Score = 93.81%
Tarawneh et al. (2022)	VGG-19	EER = 0.23%
Vyas et al. (2022)	CNN based model	Mean EER = 4.05%, Mean AUC = 99.04%
Benmalek et al. (2022)	BSIF	Rank-1 = 99.90%, EER = 0.00%
Chaa et al. (2022)	MLPQ	Rank-1 = 99.52%, EER = 0.16%
Jayapriya and Umamaheswari (2022)	PCA-LDA	Accuracy = 99.67%
Lakshmanan et al. (2022)	M-LPQ	RR = 99.90%, EER = 0.01%
Li (2022)	PCA, LBP	RR = 99.6%
Attia et al. (2022)	PCANet deep learning method	Rank-1 = 100%, EER = 0.00%
Gupta et al. (2020)	LDPVBP	Feature vector length = 56, image retrieval rate = 5–10%
Bhunia et al. (2020)	Diagonally symmetric local binary co-occurrence pattern	Precision = 24.57–94.19, Recall Rate = 23.33–99.36
Ghose et al. (2020)	CNN based model	Classification accuracy = 85.3%
Hammouche et al. (2022)	BSIF	Rank-1 = 94%, EER = 1.89%
Srivastava et al. (2022)	SIFT, SURF, LOG Gabor wavelet	Accuracy = 99.68%

In view of the literature stated above, it can be inferred that the fusion of knuckles is not a well-studied research topic. Moreover, very less amount of work has been done to demonstrate the localisation of knuckle regions through a learning-based technique which can work in a more generalised way. Besides, the proposed feature descriptor is developed keeping in mind the general appearances of the knuckle creases which happen to be curved lines/wrinkles. This is the reason addition of curvature property to the Gabor filter is utilised to apprehend those curvilinear features more effectively.

3 Proposed methodology

The comprehensive structure of proposed approach for finger knuckle pattern-based identification is illustrated in Figure 2 in the form of a flowchart. R-CNN model is used for localising objects in the hand dorsal images. As this model possess robustness against pose and illumination alterations related to traditional models for knuckle localisation. Subsequently, an improved X-OR sum code (IXSC) is used to extract key points of the knuckle patterns and then the yielded scores are fused in three different styles named as 'fusion over knuckle', 'fusion over finger', 'fusion over hand'. The detailed explanation of proposed methodology is given as follows:

3.1 Knuckle localisation

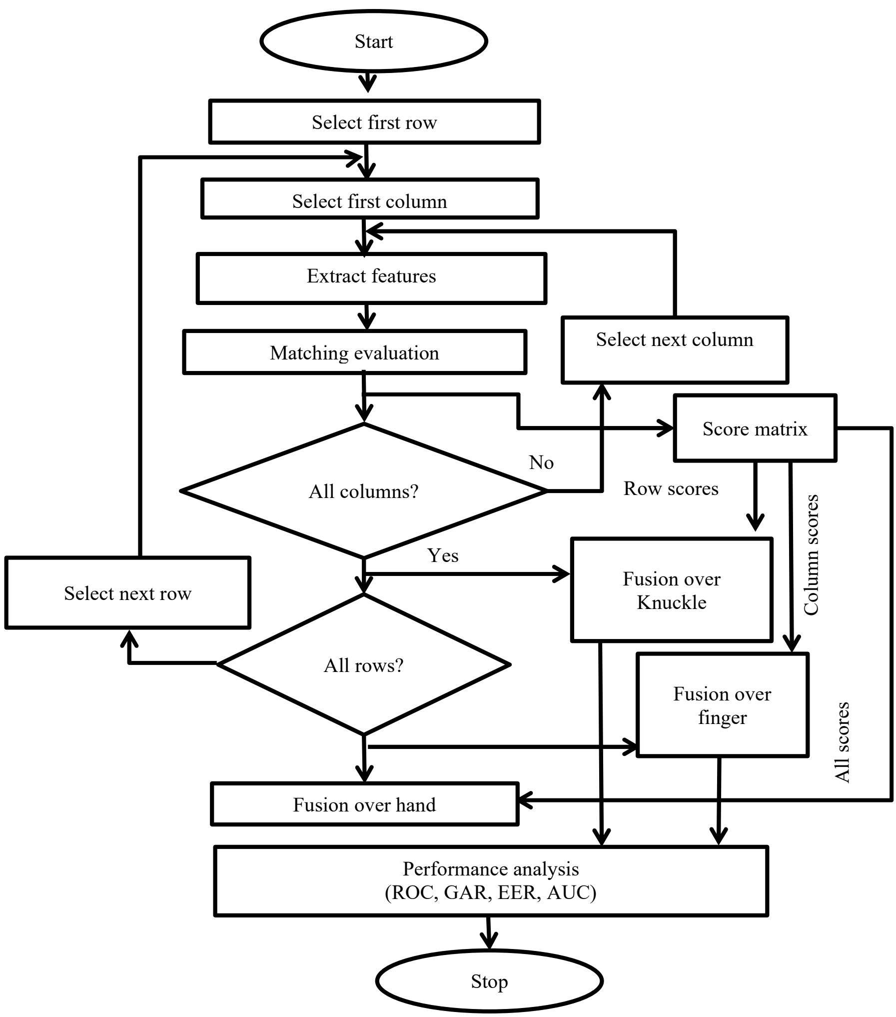
In most of the existing work, knuckle patterns are extracted manually form the images reliant upon their characteristics and explicit pose, so it is very cumbersome task to extract every knuckle manually. Hence, in real time forensic applications, a robust automated localisation approach is usually preferred. Faster region based convolutional neural network (R-CNN) model (Vyas et al., 2021) is used for localising knuckles in the hand dorsal image. This model possesses robustness to pose variations, skin-tone variations and illumination variations. Additionally, this model is proficient in yielding bounding boxes of the aimed object swiftly and precisely from the input image. Several variants of the R-CNN models exist in the literature but aforementioned faster model outperforms the others as its working procedure is not reliant on the selective searching.

In Faster R-CNN, object detection proposals are produced using region proposal networks (RPNs). Analogous to traditional convolutional neural networks these RPNs use anchor boxes at different scales and aspect rations as reference while envisaging the region proposals for wide-ranging scales and aspect ratio. Therefore, in this work to locate three categories (base, minor and major knuckles) from four fingers (index, middle, ring and little) Faster R-CNN model is incorporated. Thus in total 12 instances of four fingers are detected in this work. This generates a collection of bounding boxes for each knuckle then a threshold based non-maximal suppression tactic is used to eradicate the overlapping bounding boxes to localise knuckles precisely.

3.2 Feature extraction

An effective feature descriptor selection becomes the important task in subsequent to localisation of knuckle patterns. Improved X-OR sum code (IXSC) technique (Bala et al., 2021) is employed to accomplish this task. In this, an effective feature descriptor named CGF is applied for efficiently extracting textural information existing in the knuckle patterns. In contrast to the conformist Gabor filter descriptor which only extracts the orientation information, it extracts the curvature information too. As a consequence of the additional information more distinctive features are obtained. Prior to feature extraction, to diminish the dimension of pre-processed images conserving the latent textural information present in them Haar wavelet is applied, which decomposes the images into four subsections: H-H, H-L, L-H and L-L, where L-L subsection contains greatest energy and key information of the image. So, at next level only this subsection is further processed. Gabor filter has capability of human visual perception and it is used effectively to apprehend textural information existent in the biometric images. But there are common challenges to traditional Gabor filter such as variations in illumination, enormous reflections, blurred and off-focus, which affects the performance of traditional Gabor filter. In this paper, CGF is used to extract textural information existing in all the three traits, as it is proficient in analysing textural evidences prevailing in an image.

Figure 2 Flowchart depicting the proposed holistic knuckle representation approach for embraced different fusion strategies



In CGF there is an extra curvature parameter as compared to traditional Gabor filter, which makes it more effective in extracting vital information from any image. Equation (1) epitomises mathematical manifestation of the CGF (Wang et al., 2019):

$$\xi(M,\ \mathrm{N},\ \sigma,\ \mathrm{v},\ \varphi,\ \mathrm{c}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{\frac{m^2+n^2}{2\sigma^2}\right\} * \exp\left\{2\pi i\left(v\left(m\cos(\phi)+n\sin(\phi)\right)+c\sqrt{m^2+n^2}\right)\right\} \tag{1}$$

where (MxN), σ, v, φ, c symbolises, the kernel size, standard deviation, frequency of sinusoidal function, phase offset,and curvature parameter respectively.

Real and imaginary part of CGF is convolved with the image, which results in real and imaginary filtered images. Then binarisation of filtered images is done using 0 as threshold. Then to merge the binarised real and imaginary filtered images, X-OR operator is used for all the orientations. Furthermore, texture feature vector is obtained, by adding the outputs of X-OR operator computed for different orientations (Tamrakar and Khanna, 2015; Wang et al., 2019; Bala et al., 2021; Srivastava et al., 2022; Hammouche et al., 2022). Subsequently, extracted textural feature vector is encoded and Hamming Distance based approach is used for matching and recognition of traits. To match the feature vectors of binary images the utmost expedient tactic is Hamming distance. It provides genuine and imposter scores after matching similar and non-similar images respectively.

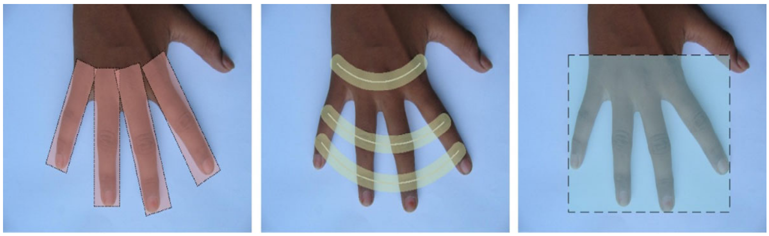
3.3 Fusion

The effectiveness of any multimodal biometric recognition framework is governed by the efficacy of applied fusion approach. There are various fusion schemes such as fusion at device stage, fusion at feature stage, fusion at score stage, fusion at rank stage and fusion at decision stage. In proposed work, we have chosen fusion of traits at score stage as this stage of fusion is realistically flexible, simple and efficient scheme, the only prerequisite for the fusion at score stage is that the quantity of scores must be equal for all traits to be fused. Score level fusion can be achieved using various methods like min strategy, max strategy, sum strategy, product strategy; weighted sum strategy provided diverse classifiers or traits. In this paper to integrate the matched scores of knuckle patterns, sum strategy is employed. The normalised score is designated as B_i^m for m classifiers and *i* volunteers. The integrated score (F_i) for user *i* is epitomised as follows:

$$F_i = \sum_{m=1}^{M} b_i^m, \quad \forall i \tag{2}$$

Different styles of fusion adopted for the current work are illustrated in Figure 3.

Figure 3 Illustration of different categories of knuckle fusion employed in the proposed approach, (a) fusion over fingers (i.e. fusing the base, major and minor knuckles of individual fingers) (b) fusion over knuckle type (i.e. fusing all the base, major and minor knuckles with similar knuckles from other fingers) (c) fusion over hand (i.e. fusing all 12 knuckle regions from the four fingers) (see online version for colours)



(a) (b) (c)

3.3.1 Fusion over finger

In this section, the fusion is performed for all the fingers (index, middle, ring and little finger) individually. The scores obtained from minor, major and base knuckles of index fingers are fused, similarly the scores of minor, major and base knuckles of all the fingers are fused. The notable augmentation in performance of framework is professed form Table 1.

3.3.2 Fusion over Knuckle

In this section, the fusion is performed for individual knuckles i.e., major knuckles, minor knuckles and base knuckles of all the four fingers (index, middle, ring and little finger) are fused at score level. For this, major knuckles of all the fingers are fused, likewise minor knuckle of all the fingers and base knuckles of all the fingers are fused. The notable augmentation in performance of framework is ostensible form Table 1.

3.3.3 Fusion over hand

All the 12 instances of fingers (major, minor and base knuckles of all the four fingers) are fused here. The notable augmentation in performance of framework is ostensible form Table 1. The results evidently demonstrate that fusion over hand strategy outperforms than both other strategies.

4 Results and discussion

4.1 Dataset used

The proposed knuckle based biometric framework is verified on a publically accessible largest hand dorsal database entitled PolyU-Hand Dorsal (HD) dataset. It comprises of 4650 right hand dorsal images acquired from 501 subjects. Every single image of the dataset possesses same pose and a resolution of 1600 × 1200. A hand-held device is used for capturing these images in indoor and outdoor environments. Figure 4 portrays a few specimen images of this dataset.

Figure 4 Sample images of the PolyU-HD dataset (see online version for colours)

Figure 4 Sample images of the PolyU-HD dataset (continued) (see online version for colours)

4.2 Experimental results

To gain insight into the performance of proposed approach rigorous experimentations have been performed on a publically accessible knuckle dataset named PolyU hand-dorsal (HD) dataset. All images from the dataset have been localised using Faster R-CNN model. Subsequently improved X-OR Sum code is used for extracting features of the knuckles. At the outset we started with performance evaluation of the each of the 12 instances of the fingers. Afterwards performance evaluations of three frameworks named 'fusion over knuckle', 'fusion over finger', 'fusion over hand' have been done. Results and receiver operating characteristics curves (ROC) of corresponding knuckles are portrayed in Table 2 and Figure 5.

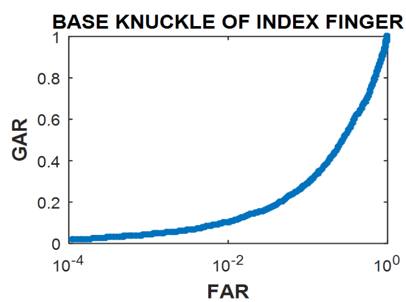
Table 2 Performance metrics (AUC, DI, EER and GAR) for individual knuckles and the employed fusion strategies

Finger	*Knuckle*	*AUC*	*DI*	*EER*	*GAR*
Index	Base	0.6429	0.5708	0.3916	0.61
	Major	0.685	0.7116	0.3726	0.6315
	Minor	0.6831	0.7097	0.3642	0.6325
Middle	Base	0.6082	0.4575	0.4242	0.5715
	Major	0.693	0.7426	0.3668	0.6385
	Minor	0.6643	0.6536	0.38	0.6175
Ring	Base	0.637	0.5543	0.4046	0.594
	Major	0.6979	0.7558	0.3671	0.642
	Minor	0.6641	0.6625	0.389	0.6155
Little	Base	0.6321	0.5379	0.4039	0.6
	Major	0.6758	0.7034	0.3785	0.6235
	Minor	0.7105	0.8261	0.3478	0.6535

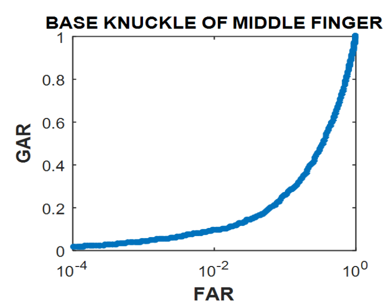
Table 2 Performance metrics (AUC, DI, EER and GAR) for individual knuckles and the employed fusion strategies (continued)

Finger	*Knuckle*	*AUC*	*DI*	*EER*	*GAR*
Fusion over Knuckle	Knuckle	AUC	DI	EER	GAR
	Major	0.8214	0.8977	0.2603	0.7365
	Minor	0.8154	0.8855	0.263	0.737
	Base	0.7404	0.6619	0.3389	0.6745
Fusion over Finger	Finger	AUC	DI	EER	GAR
	Index	0.739	0.6535	0.3219	0.6755
	Middle	0.741	0.6572	0.3212	0.6825
	Ring	0.7647	0.7192	0.3025	0.693
	Little	0.7726	0.7328	0.2952	0.706
Fusion over hand	Finger	AUC	DI	EER	GAR
	All	0.8803	1.1348	0.2009	0.793

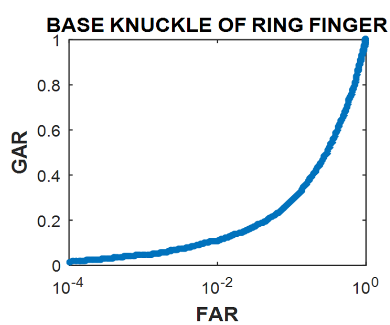
Figure 5 ROC curves for (a–d) Base knuckles of all fingers (e–h)Major knuckles of all fingers (i–l) Minor knuckles of all fingers (m) fusion over knuckles (n) fusion over finger (o) fusion over hand (p) comparison of three strategies (see online version for colours)



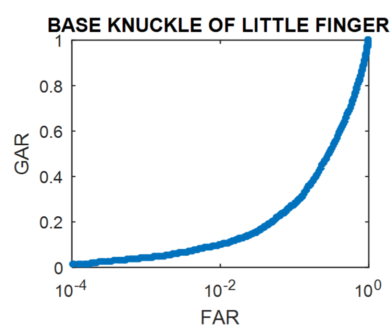
(a)



(b)

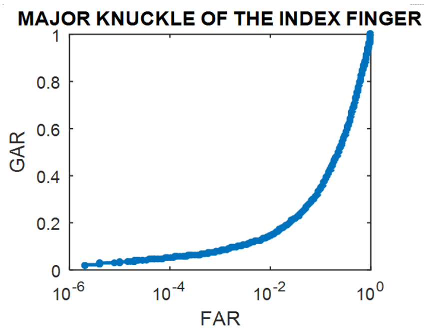


(c)

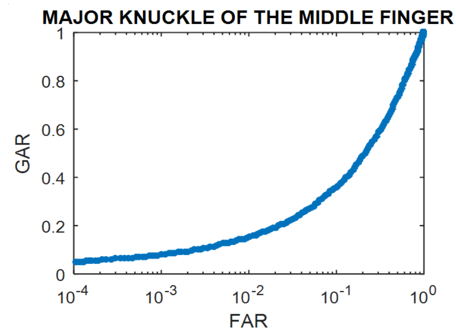


(d)

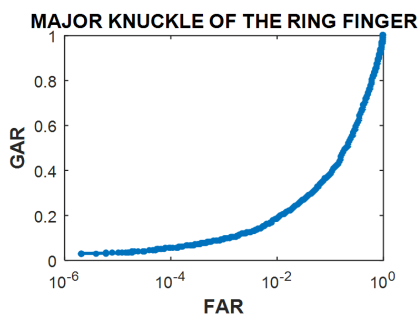
Figure 5 ROC curves for (a–d) Base knuckles of all fingers (e–h)Major knuckles of all fingers (i–l) Minor knuckles of all fingers (m) fusion over knuckles (n) fusion over finger (o) fusion over hand (p) comparison of three strategies (continued) (see online version for colours)



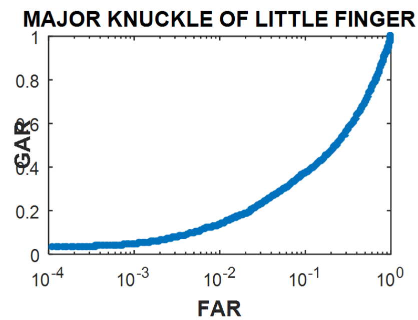
(e)



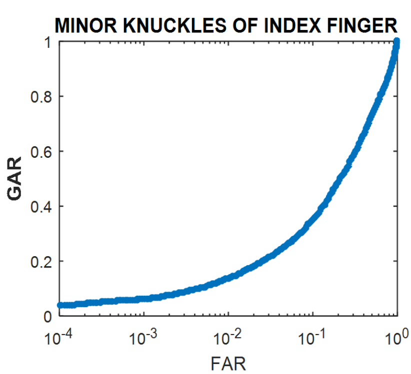
(f)



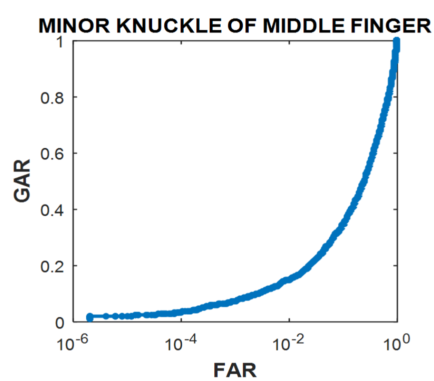
(g)



(h)

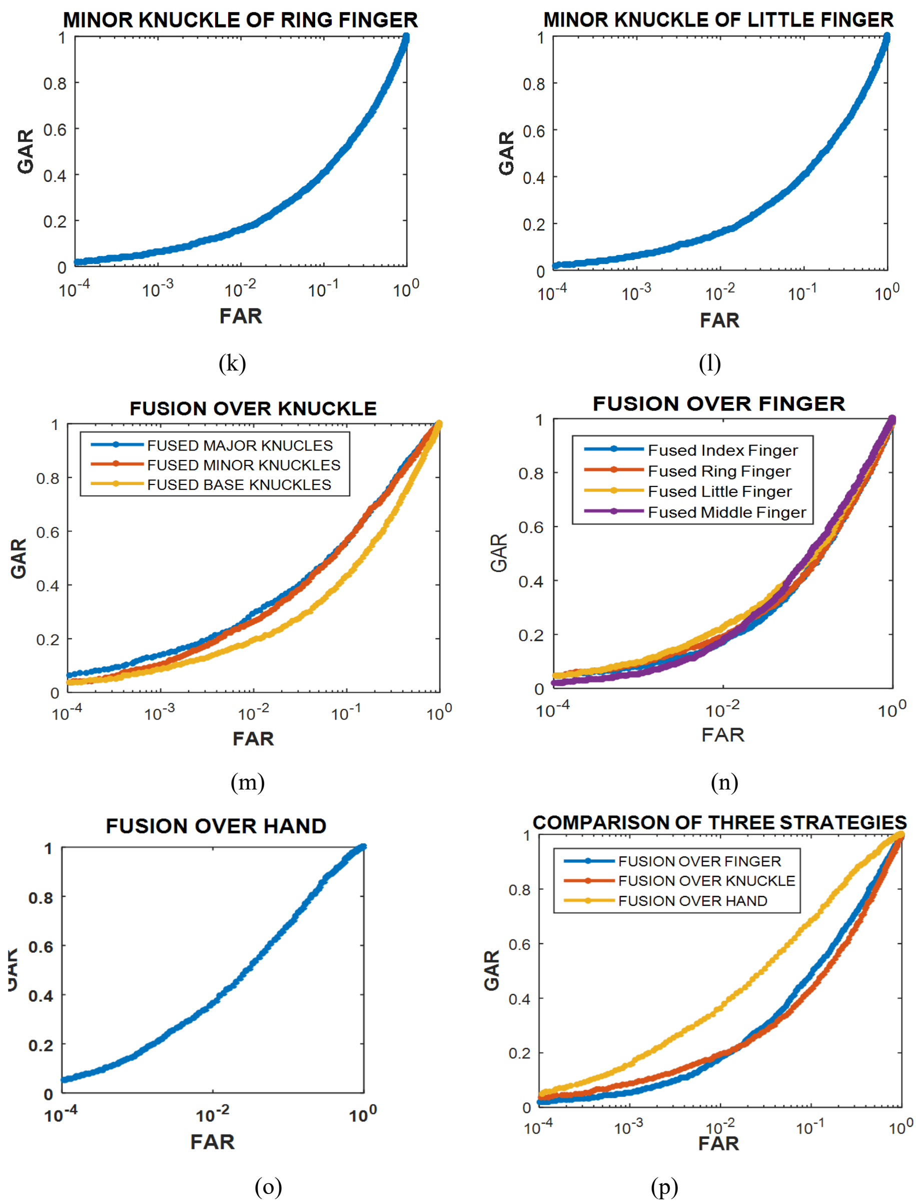


(i)



(j)

Figure 5 ROC curves for (a–d) Base knuckles of all fingers (e–h)Major knuckles of all fingers (i–l) Minor knuckles of all fingers (m) fusion over knuckles (n) fusion over finger (o) fusion over hand (p) comparison of three strategies (continued) (see online version for colours)



5 Discussion

In this work, at the outset faster R-CNN model has been employed for localising the knuckle images. An effective feature descriptor named Improved X-OR Sum Code

(IXSC) has been employed to attain most distinctive texture features of three types of knuckles i.e. base knuckles, minor knuckles and major knuckles of four fingers (index, middle, ring, little). Individual unimodal biometric systems have been developed for all the 12 cases. It can be seen clearly form Table 2 that minor knuckles of little finger outperforms than other unimodal systems with AUC = 0.7105, DI = 0.8261, EER = 0.3478, GAR = 0.6535. Subsequently, to fuse these knuckles at score level three strategies have been employed. In one strategy named 'Fusion over Knuckle' major knuckles of all the fingers have been fused, likewise minor knuckles of all the fingers and base knuckles of all fingers have been fused. In this strategy fusion of knuckles outperformed better than others with AUC = 0.8214, DI = 0.8977, EER = 0.2603, GAR = 0.7365. In another strategy named 'Fusion over Finger' base, minor and major knuckles are fused for each finger. Little finger outperformed than other fingers with AUC = 0.7726, DI = 0.7328, EER = 0.2952, GAR = 0.706. Afterwards, in one more strategy named 'Fusion over Hand' all the knuckles of all the fingers have been fused with AUC = 0.8803, DI = 1.1348, EER = 0.2009, GAR = 0.793. It can be seen clearly from Table 2 that out of above said three strategies of fusion 'Fusion over Hand' gave best performance. Moreover, the proposed approach is easy to be implemented on devices equipped with nominal hardware resources, for instance computers with CPUs only. As there is no requirement of parallel processing on GPUs and TPUs like other learning based approaches.

6 Conclusions

This paper intends an effective knuckle based recognition framework via fusion of base, minor and major finger knuckle patterns of the individual for boosted recognition. The idea behind development of this knuckle base recognition framework includes learning based proficient knuckle localisation, efficient feature extraction and subsequently three strategies for integrating these knuckles. Comprehensive set of experimentations on publicly accessible knuckle dataset named PolyU hand-dorsal (HD) dataset to tailor various appropriate metrics such as EER, DI, GAR and ROC have been accomplished in order to substantiate the outpacing performance of the proposed methodology. The proposed texture representation approach extracts the discerning features from the knuckles and the performance of the base, major and minor knuckle regions vary for different fingers. Additionally, the major knuckle is observed to be outperforming the other two knuckles in terms of the various performance metrics. However, the individual performance of the knuckle recognition is still not up to the mark, which can be due to the imaging modality which captures the hand dorsal images using a contactless setup. Besides, the fusion of scores produced for different fingers and knuckles result into a significant improvement in the performance. The same can be corroborated from the AUC values listed in Table 2, where fusion of all major knuckles from the four fingers improve the AUC to 82.14% for the major knuckle, which is approximately 18% better than the AUC achieved in the individual major knuckle recognition of the ring finger (with AUC of 68.8%). On the other hand, the improvement in AUC is even more notable when we combine the scores of knuckles from all over the hand, where the AUC rises to 88.03% (which is 24% better than the individual best AUC of 71.05%). These statistics clearly demonstrate that the proposed approach can result in improved overall performance of the knuckle recognition framework. However, we still believe that the performance can further be enhanced if some effective image registration techniques can be employed, which would result in increased correlation between the intra-class samples leading to better separation of genuine and imposter scores. This can be considered as a potential future avenue of the proposed work.

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