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Survey of Finger Knuckle Print Recognition and Authentication

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Abstract

Background: Finger knuckle (FK) has gained significant attention as a biometric characteristic in recent years. Its unique features, such as visible lines, wrinkles, and ridges on the external surface of finger knuckles, make it an economically viable option for human identification. FK serves as the foundation for many biometric systems. Aim: This report presents a comprehensive analysis of relevant FK research. The typical FK identification system consists of four steps: image acquisition, image preprocessing, feature extraction, and matching. Various methods have been employed at each stage in this research. Result: The paper highlight state-of-art methods utilized for the recognition of FK.

Keywords: Finger knuckle, Biometric, finger knuckle print, subspace methods, Coding methods

Introduction

Biometric-based person identification methods, known for their reliability and accuracy, have gained broader application compared to conventional approaches like password or PIN-based methods, as well as token-based methods such as passport ID cards (Gbolagade, Hambali, Abdulganiyu, Lawrence, 2022; Hambali and Jimoh, 2015; Saheed, Hambali, Aderibigbe and Akeem, 2017). Physical and behavioral characteristics like fingerprints, face, palm prints, iris, voice, and gait are widely used in biometric systems. Among these traits, hand geometry-based methods such as fingerprints and palm prints are particularly popular due to their high user acceptance rates (Saheed et al., 2017). Recently, it has been discovered through extensive experimentation that the creases and folds in the skin pattern around the joints of the outer finger knuckle print (FKP) are highly unique and can serve as distinctive biometric identifiers (AL-Janabi and AL-Juboori, 2022). FKP offers user-centric, contactless, and unrestricted access control. Its texture and statistical features can be easily extracted, making it independent of any behavioral aspects (Xiaoyuan, Li, Lan, Fang & Xi, 2011; Meraoumia, Chitroub & Bouridane, 2011; Sharaiatmadar and Faez, 2011).

Biometric-based methods for person identification are widely adopted due to their superior reliability and accuracy compared to traditional approaches like password or PIN-based methods, as well as token-based methods such as passport ID cards (Gbolagade et al., 2022; Hambali and Jimoh, 2015; Saheed et al., 2017). Various physical and behavioral characteristics, including fingerprints, face, palm prints, iris, voice, and gait, are extensively utilized in biometric systems. Among these biometric traits, hand geometry-based methods like fingerprints and palm prints are particularly popular due to their high level of user acceptance (Saheed et al., 2017). Recent experiments have revealed that the creases and folds in the skin pattern around the joints of the outer finger knuckle print (FKP) possess exceptional uniqueness, making them ideal for distinct biometric identification (AL-Janabi and AL-Juboori, 2022). FKP offers user-centric, contactless, and unrestricted access control. Its texture and statistical features are readily available and can be easily extracted. Importantly, FKP is independent of any behavioral aspects (Xiaoyuan et al., 2011; Meraoumia et al., 2011; Sharaiatmadar and Faez, 2011).

Selecting the appropriate biometric modality poses a significant challenge for researchers. It is essential to understand the requirements before implementing biometric-based authentication systems. These requirements encompass security levels, unattended system capabilities, anti-spoofing measures, and reliability. Despite being a promising modality, finger knuckle print (FKP) has not received significant attention from researchers. FKP offers several advantages, such as being user-centric, contactless, and enabling unrestricted access control. Its contactless nature eliminates the need for proof of physical presence, mitigating spoofing risks. FKP features a highly textured region, and multiple samples can be obtained per hand, making it independent of behavioral aspects. Additionally, FKP does not carry the stigma associated with potential criminal investigations, unlike other biometric modalities like fingerprints (Goh, Connie, and Andrew, 2010). Comparatively, FKP holds several advantages over fingerprints: it is less prone to damage since it predominantly uses the inner surface of the hand, it is not commonly associated with criminal activities, and it is difficult to forge due to the lack of trace residue left on touched objects. Moreover, FKP exhibits rich texture and has the potential to serve as a reliable biometric identifier (Esther and Shanmugalakshmi, 2013). Figure 1 depicts the finger knuckle images.

Figure 1: Sample Image of Finger Knuckle (Source: Mourad, 2020)

Finger Knuckle Anatomy

Each finger has three joints .There are three bones in each finger called the proximal phalanx, the middle phalanx and the distal phalanx. The first joint is where the finger joins the hand called the proximal phalanx. The second joint is the proximal inter phalangeal joint, or PIP joint. The last joint of the finger is called the distal inter phalangeal joint, or DIP as shown figure 2.

Figure 2: Finger Knuckle Anatomy (Source: Kulkarni and Rout, 2012).

Finger knuckle is the back surface of finger, it is also known as dorsum of the hand (fig 1). The inherent skin patterns of the outer surface around the phalangeal joint of one's finger, has high capability to discriminate different individuals. Such image pattern of finger knuckle is unique and can be 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 as shown in figure 3 and 4. Features are center of phalangeal joint, U shaped line around the middle phalanx, Number of lines, length and Spacing between lines (Kulkarni and Rout, 2012).

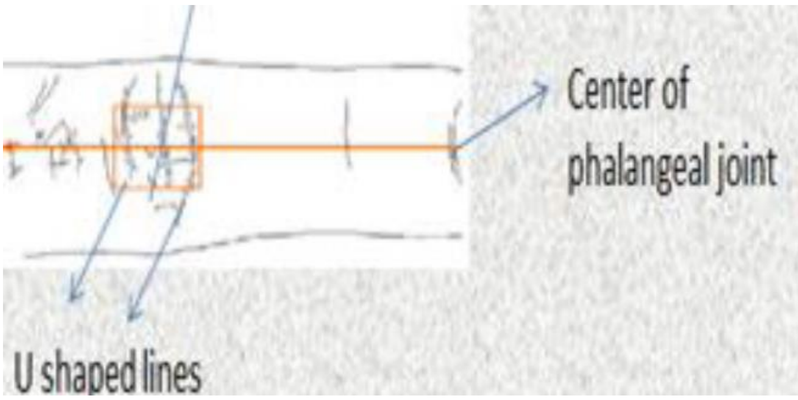


Figure 3: Finger Knuckle Features (Source: Kulkarni and Rout, 2012).

Knuckle crease patterns and stray marks as a means of photographic identification. Such features are unique and can use for identification.

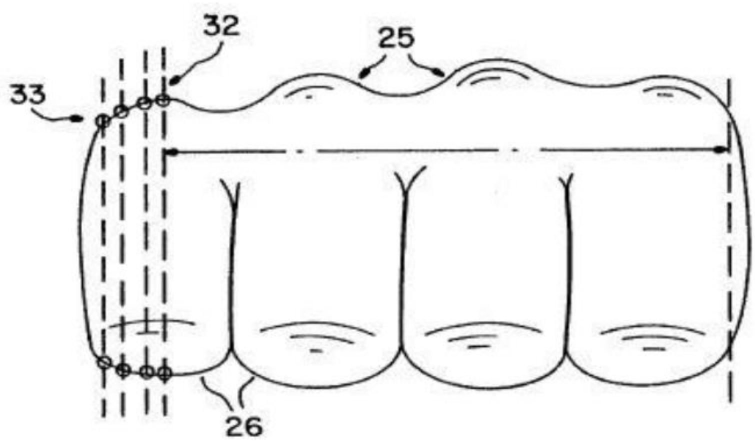


Figure 4: Finger Knuckle Features (Source: Kulkarni and Rout, 2012).

The Finger-Knuckle-Print (FKP) Recognition System

The schematic diagram of most FKP based personal recognition and authentication system (fig 5) is composed of a data acquisition module and a data processing module. The data acquisition module is composed of a finger bracket, a ring LED light source, a lens, a CCD camera and a frame grabber. The captured FKP image is inputted to the data processing module, which comprises three basic steps: ROI (region of interest) extraction, feature extraction and coding, and matching (Zhanga, Lei, David and Hailong, 2010).

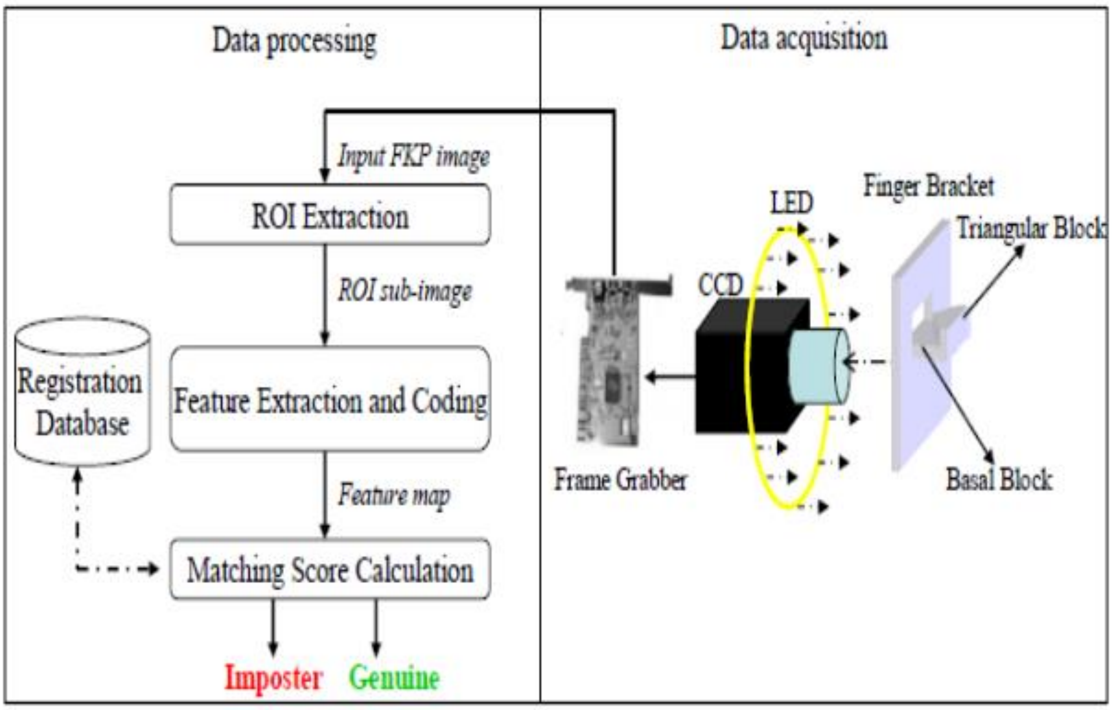
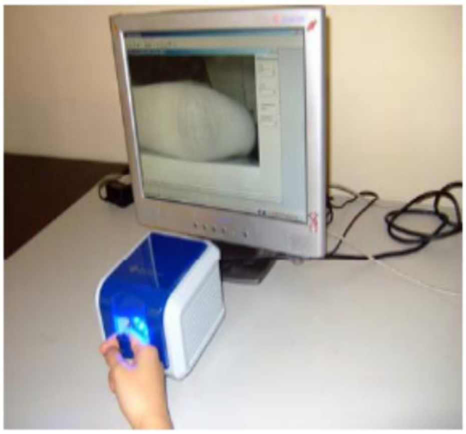


Figure 5: Structure of a FKP-based personal authentication system
(Source: Zhanga et al., 2010).

In general, a stable image FKP acquisition process can effectively reduce the complexity of the data processing algorithms and improve the image recognition accuracy, so as to put as little constraint as possible on the users in order for high user friendliness of the system. In view of this considerations, a semi-closed data collection environment is designed in our system. The LED light source and the CCD camera are enclosed in a box so that the illumination is nearly constant. One difficult problem is how to make the gesture of the finger be nearly constant so that the captured FKP images from the same finger are consistent. In the recognition system, the finger bracket is designed for this purpose.

As shown in Figure 6(a) and Fig 6(b), a basal block and a triangular block are used to fix the position of the finger joint. In data acquisition, the user can easily put his/her finger on the basal block with the middle phalanx and the proximal phalanx touching the two slopes of the triangular block. Such a design aims at reducing the spatial position variations of the finger in different capturing sessions. The triangular block is also used to constrain the angle between the proximal phalanx and the middle phalanx to a certain magnitude so that line features of the finger knuckle surface can be clearly imaged.



(a) The outlook of the developed FKP image acquisition device (b) The device is being used to collect FKP samples

Figure 6: Structure of a FKP-based personal authentication system (Zhanga et al., 2010).

The General Scheme of Biometric System

The biometric authentication process is divided into three main functionalities:

Enrolment: It constitutes the initial process of collecting biometric data samples from a person and subsequently creates a reference template representing a user's identity to be used for later comparison. An example of users' templates of different modalities is given Figure 7.

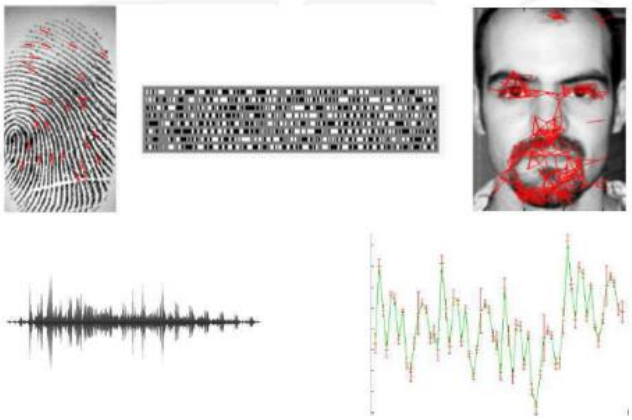


Figure 7: An example of biometric templates. From left to right, top to bottom, extracted minutia from a fingerprint, iris code, facial-based graph using key points, vocal and keystroke dynamics signals. (Source: Mahier, Pasquet, Rosenberger and Cuozzo, 2008)

Verification: It provides a matching score between the biometric samples provided by the user and his/her template. The matching score is defined between 0% and 100% (100% is quite impossible to be reached).

Identification: It consists of determining the identity of an unknown individual from a database of individuals. In this case, the system can then either attribute the identity corresponding to the most similar profile found in the database to the unknown individual (or a list of the most similar profiles), or reject the individual according (Mahier et al., 2008).

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FKP Recognition Algorithms

A biometrics system which is designed for the identification of the person can recognize the person on the basis of the algorithm on which it is designed. Two types of recognition algorithm are most widely used-

i. Template based- This method work by computing the template of the user and then comparing this template with the template already stored in the database. This method is called one to many matching.

ii. Verification based- This type of system generally requires identity proof of the user such as ID card, ID number, Smart card etc. for authentication. The user identity is then matched with the master template for authentication. This is known as the one to one matching. The algorithm used for recognition or identification must be accurate and fast (Ross and Jain, 2003).

Recognition algorithms based on the FKP can be divided in to the following categories: Subspace based method, Coding method, Fusion method and other methods.

Subspace Method

In the subspace method, spatially localized features are created. This method is attracting a lot of attention by researchers. Since the localized feature are efficient for implementing the region based identification so this method is assumed to be more tolerant to the occlusion (Kumar and Ravikanth, 2009). Principal component analysis (PCA), Independent component analysis (ICA) and Linear discriminate analysis are some of the methods which are used in this method. In this method sub space coefficients are used as the feature vector. For matching purpose, classifier or distance measure is used. This method is also used for reducing the dimension. Zhang, Lei & David, (2010) proposed weighted linear embedding technique (WLE) which is s new feature extraction algorithm. This method is the combination of the fisher criterion and manifold learning criterion such as local discriminate embedding analysis. Manifold learning theory clearly suggests that non local information carry less information than the local information and hence can be used as feature vector and can be extracted. For combining the local and non-local information Gaussian weighting is used in this method.

Wanknou, Changyin and Sun (2011) adopted WLE for finding the mapping vector in such a way that the ratio of weighted class vector to weight within class vector has maximum values. Nearest neighborhood classifier is used for classification purpose in this method. Same algorithms have also been tested on palm-print and comparative study of PCA, LDA WLE and LDE has been accomplished. Accuracy of about 78% is achieved by applying the WLE on the right index fingers of about 1000 people.

Wanknou, Changyin & Zhongxi (2011) proposed another recognition method based on the finger knuckle print. In his method the authors used the Gabor features of the finger knuckle. This work was inspired by the fact that the Gabor wavelet has been used earlier in the image analysis and pattern recognition task. PCA was used in this algorithm for reducing the dimensional space of the Gabor features. PCA was used to transform Gabor features in to low dimensional space. Further orthogonal linear discriminant analysis (OLDA) transformation in PCA subspace is done and classified using nearest neighbor classifier and efficiency as high as 98% was obtained. This paper compares the performance of the individual fingers and shows that the left index finger provides better performance.

Xiaoyuan et al. (2011) simultaneously considered distances and angles between image data vectors to measure data similarities in hope of more sufficiently capturing the manifold structure. In order to highlight the distinction among angles between different data and enhance the complimentary information of angles compared with distance, a new type of image angle measurement in a shifted image space that is cantered at the data mean is proposed. Both angle and distance are fused using the parallel fusion strategy based on which the complex locality preserving projection is used extract the low dimensional feature that can better preserve the manifold structure of the input data set. In order to remove the redundant information, orthogonal complex locality preserving projections (OCLPP) is used. Four images were randomly selected during the training process and recognition rate of 88% was achieved for the left index finger. This method is compared with other subspace methods like PCA, CPCA, LPP, CLPP and OCLPP in their proposed work (Shubhangi, Kamal and Zadgaonkar, 2013).

Coding Methods

Different coding algorithms have been adopted by different researches of which iris code is the basic foundation of these coding algorithms. These coding techniques have been used widely used for palm print recognition by (Kong and Zhang, 2002; Kong & D, 2004; Kong, Zhang, and Kamel, 2006; Zhang, Kong, You and Wong, 2003; Kumar and Zhou, 2009) and have provided good recognition results. The finger knuckle surface is highly rich in lines and creases which are curved but are highly unique in individuals. Hence, Ajay and Yingbo (2009) relied on the local feature instead of the global information for better performance in their work. Pre-processing steps in his method take care of the illumination variation. In order to avoid the wrap around due to the intrinsic modulo operation, instead of the finite radon transform (FRT), Modified finite radon transform (MFRT) to effectively and efficiently locate the orientation of the lines and the crease around a local neighborhood. The dominant direction is then coded using binary bits which are considered as the knuckle code. For similarity measurement, hamming distance is computed which gives the accuracy of about 98.6%.

Yin, Jingbo and Yang, (2010) evolved a framework to secure FKP images and offered a strategy for adjusting the FKP pictures by adaptively building a neighborhood arrange framework for each image. The base of the FKP image is steady because of securing technique embraced. Thus this is expected as X axis of the ROI facilitate framework by fitting this limit as a straight line. A curve model for FKP was then settled and the convexity extent is resolved. This greatness was achieved base on the focal point of the joint and this position can be utilized to set the Y axis of the organize framework. When this organizes framework is settled then a ROI sub image of 110 x 220 is extricated. Gabor filtering is utilized from which the introduction data is extricated and represented as Competitive Code. Precise separation is utilized for coordinating and an EER of 1.09% was accomplished.

Rui, Kunlun, Ming & Xue, (2009) proposed a fast feature extraction and coding method called the Monogenic code based on the Monogenic signal theory and is used for FKP recognition. For a two dimensional signal f(x) the monogenic signal is defined as the combination of f and its Ritz transform which is a vector valued extension of the Hilbert transform in the 2D Euclidean space. The code represents each pixel as a 3 bit code obtained by extracting the signs of the three components of the monogenic signal. It reflects the local orientation and phase information of the pixel under consideration. This method is shown to achieve similar verification accuracy in comparison to the state of art FKP verification methods.

Zhang, Lei, Zhang and Zhu, (2011) applied the coding method because of the merits like high accuracy, robustness high matching speed along with the compactness. Hence, based on the capability of the Ritz transform to characterize the visual pattern, their research work offered an encoding the visual pattern of the FKP by second order Ritz transforms. The code scheme is called the Ritz comp code which is six (6) bit code scheme. This code actually carries the advantage of the Ritz transform and the comp code for representing the local image feature together. Matching process is accomplished by computing the hamming distance. This coding is said to have a better performance as far as verification accuracy is concerned and make it better among the coding method.

Fusion Method

The accuracy of the biometrics system can be improved further by incorporating the fusion techniques (Ross and Jain, 2003). Different fusion methods (Wanknou et al., 2011; Ross and Jain, 2003; Meraoumia et al., 2011; Yanqiang et al., 2010; Zhu, 2011) are used for different biometrics traits. There are four different fusion techniques such as sensor level fusion, feature level fusion, rank level fusion and score level fusion. Out of these methods, score level fusion method has been used widely. Sharaiatmadar and Faez, (2011) offered another efficient method which uses information fusion at different level. Two feature vectors are extracted from each image. The ROI was segmented into twenty two division of 1100 pixel each, Average Absolute Deviation (AAD) was computed on individual division. Five scale and ten orientations are obtained for each of these images and again the computation of the AAD is carried out. By this process 110 features were extracted. In order to reduce the dimension, PCA along with LDA is used which gives the 164 most suitable features. Minimum Euclidean distance was used for comparison of the combination of the two features. Two different experiments were carried out in which each individual finger are first tested for the accuracy and then the combination of different fingers were also carried out to check the recognition rate. Left index finger was found to give the highest accuracy of 89.9% while the fusion of the entire four finger provided an accuracy of the 96.56%.

The research work of Meraoumia et al., (2011) suggested another fusion based biometrics recognition system in which fusion of FKP and palm print modalities were carried out. Phase correlation function (PCF) is used in this scheme for matching purpose. Two dimensional Discrete Fourier Transform DFT of the palm print image was obtained. The cross correlation of the two dimensional inverse DFT of the phase component is also carried out. This is known as the PCF. The distinct impulse of the PCF is used for matching. For two similar images, PCF gives the two sharp distinct peak and for two dissimilar images, PCF peak significantly drops. Extensive analysis is carried out for separate fingers and the right index finger is said to have the better performer.

Rui et al. (2009) in their work, tried to find out the various way to improve the accuracy of the recognition by combining the multiple hand based biometrics and FKP. In this method first of all the Gabor feature is extracted from the palm print image and then it is convolved with a group of wavelets of distinct frequencies, orientations and scales. A two bit code which represents the local feature of the image is defined. Similar process is adopted for FKP images also and fusion code is then derived. Scores obtained from both the strategy are combined at the decision level. Similarity between the two subjects is determined by computing the hamming distance.

Yanqiang, Dongmei & Zhengding, (2010) offered another fusion based method which is obtained by fusing the two biometrics i.e middle inner surface of the finger and the palm print features. Statistical information and the structural information are used to derive the discriminant features of both the modalities. Locality preserving projection (LPP) which is based on the wavelet transform are used to extract the features. This step reduces the effect of the affine transform. In order to improve the discriminant ability of high frequency sub-bands of the palm print, mean filtering is used for enhancing the structural information. Both the features are fused at score level for recognition of the person.99.56% of accuracy is said to have obtained.

Arunachalam and Amuthan (2020) present a novel method for personal identification, accompanied by a proposed approach for secure data storage. The authentication process involves transforming features using a 2D Log Gabor filter and representing them through Eigen values in Multi-Manifold Discriminant Analysis (MMDA) of Finger Knuckle Print (FKP). These features are then grouped using k-means clustering for both identification and verification purposes. The proposed system is built upon the FKP framework without relying on a template, utilizing the concept of the fuzzy vault for secure key storage. This ensures the protection of the secret key even in the presence of random numbers, known as chaff points.

Deep Learning Method

Deep learning is a branch of machine learning algorithms that harnesses the power of artificial neural networks to autonomously acquire knowledge. In numerous instances, deep learning has achieved outcomes that rival or even surpass human accuracy in various domains. For instance, when trained on vast amounts of images, these networks exhibit remarkable precision in tasks related to image comprehension, such as assessing image aesthetics. In this passage, we delve into several key elements involved in estimating image aesthetics using deep learning techniques.

AlexNet, proposed by Zhang, Zhang, Zhang, and Zhu (2011) is among the prominent models in the field of convolutional neural networks (CNN). VGGNet, explored by (Chlaoua, Meraoumia, Aiadi and Korichi, 2019), investigated the effectiveness of using a small filter size, specifically 3×3, to extract robust features. Deep learning methods excel at automatically extracting features, with CNN being a pivotal model in this domain. Consequently, CNN models were employed for finger knuckle print (FKP) recognition in the second category. Chalabi, Attia and Bouziane (2020) proposed a methodology that involves incorporating finger knuckle notches using the SVM technique.

Furthermore, Thapar, Jaswal, and Nigam (2019) developed a deep learning system for individual recognition using the filled finger dorsal surface. Their approach utilized a finger knuckle picture matching network, a Siamese CNN matching structure. In a similar vein, Cheng and Kumar (2020) introduced a deep neural network for 3D finger knuckle identification. They employed the HKPolyU 3D Finger Knuckle Image dataset and extracted features by encoding and combining deep features at multiple scales. These collaborative feature representations incorporated an effective alignment technique to enhance the accuracy of matching between registered and test images. However, a drawback of their method is the increased computational time compared to traditional approaches, owing to the additional alignment scheme. Acknowledging these challenges, it was observed that the deep learning approach performed slightly better with an average accuracy of 98.8%, surpassing other approaches. CNN categorization ranked second, while the remaining groups showed comparable performance. The relatively small difference between the best and worst-performing groups suggests relative success for all proposed methods.

Hamidi, Khemgani, and Bensid (2021) introduced a convolutional neural network method called VGG, which utilizes transfer learning features. VGG has demonstrated impressive achievements in feature extraction, image recognition, and computer vision tasks. The researchers proposed a multimodal identification system that incorporates finger knuckle prints (FKP) from different samples, including Left Index Fingers (LIF), Left Middle Fingers (LMF), Right Index Fingers (RIF), and Right Middle Fingers (RMF), during the matching score stage. To extract FKP features, they employed the VGG transfer learning method. The experimental findings demonstrate that the fusion of finger modalities images outperforms the use of a single finger modality. The system achieves a remarkably low Equal Error Rate (EER) of 0.00% in open-set identification and a high Rate-One Recognition (ROR) of 100% in closed-set identification.

Other Methods

From work of Zhu (2011) and Sharaiatmadar and Faez, (2011) used different techniques of image processing which was applied to extract the feature like texture, line feature of local and global region in finger knuckle print. The combinations of the local and global information are bound to give better recognition accuracy.

During the exploration of the FKP recognition technology Zhu (2011) in the paper titled "Finger Knuckle print recognition based on SURF algorithm" offered a novel feature presentation as well as the matching method of the FKP which was based on the speeded-up robust feature (SURF). It is an improvement over the scale invariant feature transform. In this method, a coordination system is set on the basis of the convex direction map of FKP for alignment of the image and feature extraction is carried out by ROI cropping. In the next step, Fast Hessian detector is applied to extract the key point for which the orientation is assigned according to the Haar wavelets inside the neighbor circle area of the key points. This results in to a construction of the orientation invariants descriptor for each key points. In matching process, the distance between the closest and the second closest neighbor are compared and distance ratio is computed. So all the matches in which the distance ratio is less 0.6 is retained. This process is accomplished to find the correspondence between the key point set of training images and the template. Geometric constraint is applied by using the Random Sample Consensus (RANSAC) which removes the false matching probability. This method is robust against the rotation variation and view point changes which prove its robustness. An accuracy of 90.63% for verification and the accuracy of the 96.91% for identification is obtained through this method.

Zhang, Lei, Davind and Hailong, (2011) suggested that both global and local features are vital for image perception. His above findings was based on the psychophysics and neurophysiology studies of the FKP. On the basis of the above mentioned cause he offered a Local Global Information combination (LGIC) technique. Gabor filter is used to extract the orientation information using four scale and six orientations. This orientation information is coded using the competitive coding scheme. All the image having the abundant like line structure suits this method and give the high accuracy, robustness variation in illumination and fast matching. Fourier transform of the FKP image is obtained by increasing the scale of the Gabor filter to infinity. The Fourier coefficient obtained by applying the Fourier transforms work like a global feature. In order to match the two competitive code maps, angular distance based on the normalized hamming distance is applied. Similarity measurement of the global information of the two images obtained by the Fourier transform is carried out using the BLPOC (Band limited phase only correlation). So in this method, two different matching operations is performed for local and the global feature and the two distance obtained as d1 and d2. These two distance are fused by applying the matcher weighting (MW) rule distance. This technique is able to achieve the EER as low as 0.402.

Zhao, Kunlun, Liu & Xue, (2009) presented a novel approach of person recognition using the single knuckle print only. This method uses light database to train the classifier and hence reduce the burden of the large database. The edge of the image can be defined as the discontinuity in the gray level values of the pixel. So the main lines in the finger knuckle are due to the discontinuity in the gray level. So in order to extract the main lines and to remove the effect of the noise a predefined template of the dimension 3x5 is used as the gradient operator for extracting the edge information and hence the line features of the FKP. In order to reduce the possibility of getting wrong recognition which may be due to the variation in the precise location while acquiring the different standing postures, eight different images were obtained by applying the translational operation. Original image and the eight different translational image makes total of nine images which are used to confirm the user identity by maximization of the cross correlation. This method confirms the FKP as one of the biometrics trait for recognizing the person with the recognition accuracy of about 95.68%.

Sharaiatmadar et al., (2011) proposed a recognition method based on the orientation features of the FKP and PCA and LDA for this purpose. Orientation of the image is acquired by the Gabor filter. Eight different orientation and five different scales are used for extracting the orientation information from FKP. PCA is used here for dimensional reduction by PCA (Principal component analysis) analysis. Since the PCA and LDA combination provides good performance therefore LDA is applied on the PCA weight.

Euclidean distance is computed for matching operation. Though this method is tested for all the four fingers but it was found that the right middle finger provides the highest accuracy of about 75.35%. By incorporating the fusion of the feature level information for different finger combination, recognition rate of 98.8% can be obtained.

Kumar and Ravikanth (2009) devised a novel approach to normalize the finger knuckle surface, minimizing the influence of scale, translation, and rotation. Their system introduced peg-free imaging for each knuckle image, utilizing Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) techniques to calculate matching scores for identification purposes.

Feizollah et al. (2014) evaluated the performance of clustering algorithms, specifically k-means and Minibatch k-means, for detecting normal and malicious results in Malgenome data samples.

Badrinath et al. (2011) presented a combination of local information for FKP, incorporating scale, rotation, and features extracted using the Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) transforms. They employed the nearest neighbor-ratio method and fused the results with a weighted sum-rule system, achieving a Crossover Rate (CRR) of 100% and an Equal Error Rate (EER) of 0.215%.

Jules and Sudan (2006) developed the fuzzy vault, a cryptographic construction that deals with order invariance against unbounded attackers. Koptyra and Ogiela (2015) extended the concept of the fuzzy vault to hide noisy data using a multi-biometric cryptosystem, offering a choice of authentication accuracy relevant to a cryptosystem based on a single biometric.

Bae et al. (2003) focused on encoding iris codes to improve performance, specifically the Equal Error Rate (EER), taking into account iris size and processing time. Uludag and Jain (2006) aimed to enhance the security and privacy of biometric systems by transforming templates into a cryptographic framework, utilizing the orientation field of helper data for fingerprint extraction.

Yang et al. (2011) proposed a dimensionality reduction method based on graph embedded learning for pattern recognition. However, this technique is not suitable for small-sized problems. To address this limitation, they introduced the calculation of Maximum Mean Discrepancy (MMDA) for eigenvectors and eigenvalue representations. Yang et al. (2012) further explored the application of MMDA against Gabor features.

Certain Fuzzy vault systems (Jules and Sudan, 2006) are based on local iris features extracted from an unordered set using the shift matching technique.

Zhang, Wang, Ding, Ma, and Hao (2019) proposed an improved method for edge detection in Finger Knuckle Print (FKP) images based on the enhanced Canny operator. The approach consists of several steps. Firstly, the region of interest (ROI) in the FKP image is identified. Next, the method optimizes the edge detection process by addressing two aspects: traditional Canny algorithm filtering and gradient direction. To overcome the limitations of the Gaussian filter used in the traditional Canny algorithm, which struggles with removing Gaussian noise and preserving edge details, an Adaptive Median Filtering technique is employed instead of Gaussian filtering for the purpose of filtering. Additionally, to tackle the issue of false edge detection commonly associated with the Canny algorithm, the edge detection process is refined by incorporating a gradient direction template during the calculation of the image's gradient direction. The effectiveness of the proposed algorithm is evaluated using information entropy. In comparison to traditional operators, this method demonstrates superior stability and robustness.

Conclusion

This paper presents a comprehensive overview of various stages, methods and advancements in the field of finger knuckle technology, which has emerged as an alternative biometric feature in recent years. Finger knuckle patterns exhibit unique trace-like structures and are characterized by texture information on the rear surface of the finger knuckles. The paper also discusses the deep learning to the recognition of finger knuckle print which are the new approach in the image process domain.

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