Knuckle Finger Print Based Biometric Recognition: A Survey

Samuele Bortolotti (229326), Department of Information Engineering and Computer Science, University of Trento
samuele.bortolotti@studenti.unitn.it

***Abstract*—The automatic use of physiological or behavioral characteristics to determine or verify people identity is an arduous problem in computer vision which has been widely explored by researchers. Human identification has been delved mainly through physiological biometrics, such as finger prints, iris, face and palm prints, and behavioral biometrics, such as voice and gaits. Biometrics combines image acquisition, feature extraction, signal processing and recognition systems and its application scenarios range from logical or physical access control to surveillance and law enforcement. In terms of physical characteristics, the knuckle finger print comprises several different stable peculiar features which have made this surface relevant as a biometric identifier. This paper reviews some of the literature on knuckle finger prints, discusses the methods for their acquisition and illustrates how to develop real-time human identification systems.**

***Index Terms*—Biometrics, knuckle finger print, acquisition systems, recognition systems**

I. Introduction

THE need for reliable user authentication techniques has significantly increased in the wake of heightened concerns about security and authentication [1].

Biometric feature-based person identification methods find wider application than the conventional algorithms like knowledge based techniques, such as password based methods, PIN based methods and token based methods [2] [3] since they cannot be lost, transferred or stolen.

In computer science, biometrics is described as the automated recognition of people based on their physiological or behavioral features [4] which, according to Anil K. Jain *et al.* [5], can qualify as biometric traits if they comply with the following criteria: (i) universality, (ii) uniqueness, (iii) invariance, (iv) collectability, (v) performance, (vi) acceptability and (vii) circumvention. Indeed, a biometric trait has to be universal, namely possessed by each individual, but at the same time unique since it must be sufficiently different among numerous human beings. Furthermore, it must not change over time (invariance) and it must be statistically quantified (collectability). As for its feasibility, a biometric identification system must be precise and quick in its recognition process (performance), as well as strong enough to avoid being easily manipulated through deception (circumvention) [5].

This study focuses on *Knuckle Finger Print* (KFP) which complies with Anil K. Jain *et al.* definition.

According to recent studies [2] [6] [7], KFP constitutes a unique but efficient biometric trait, since it is rich in lines and creases which are reasonably stable over time and particularly distinctive among people. The user acceptability of outer finger surface imaging is high, and data collection is straightforward and affordable. Finally, human hand-based biometric information is particularly trustworthy. Hence, it may be used to accurately identify humans across a wide variety of demographics.

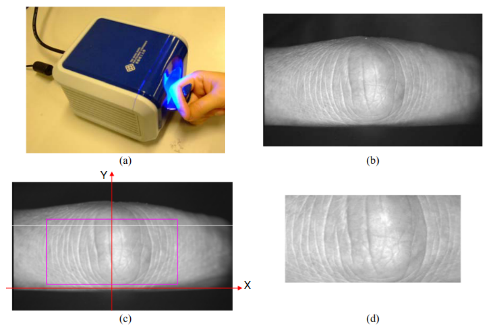

Figure 1. **(a)** KFP image acquisition device; **(b)** a KFP image; **(c)** ROI extraction; **(d)** cropped ROI image in (c). Courtesy of Lin Zhang *et al.*

This paper presents a brief overview of KFP as a biometric descriptor. In particular Section II discusses a possible acquisition method, Section III provides some of the person's identification methods and a few datasets. Finally, Section IV presents the concluding remarks.

II. Acquisition systems

The act of sampling signals, which measure real-world physical conditions, and transforming the samples into digital numeric values is known as data acquisition. This process is possible by the means of sensors, signal conditioning circuitries and analog-to-digital converters.

Due to the lack of available datasets in the early stages of KFP recognition literature, the authors of several studies have built and explained data collection systems which are employed for both data collection and recognition [8] [9].

Lin Zhang *et al.* [8] have provided a contactless 2D KFP biometric identifier for personal identity identification as an effective representation of a KFP acquisition mechanism. The proposed KFP image acquisition device, shown in Figure 1, is composed of a finger bracket, a ring LED light source, a lens, a CCD camera and a frame grabber. The data processing module receives the acquired KFP picture and performs three fundamental steps: *Region Of Interest* (ROI) extraction, feature extraction and feature matching.

The ROI is identified through a 2D coordinate system. To begin with, the finger boundaries are determined by a Canny edge detector. The X-axis is then localized by fitting the finger border as a straight line, whereas the Y-axis is determined by the phalanges' orientation. Finally, the ROI is cropped for the feature extraction [7].

III. Recognition algorithms

In the literature, a KFP recognition algorithm is generally described though two stages: a feature extraction algorithm and a matching algorithm, either based on distances or scores or classifiers.

The performance of a biometric system is typically quantified though a *Receiver Operating Characteristic* (ROC) curve [8] [10]. To evaluate the results, two types of error rates are defined: *False Acceptance Rate* (FAR), namely the probability that the system incorrectly authorizes a non-authorized person, and *False Rejection Rate* (FRR), which is the probability that the system incorrectly rejects access to an authorized person. As a performance measure, the biometric system employs either the *Recognition Rate* (RR) or the *Equal Error Rate* (EER). The RR measures the accuracy of the biometric system, whereas EER is a metric which combines both FRR and FAR, *i.e.* the point in the ROC curve where the FAR is equal to the FRR. A system is considered highly accurate when the EER is low and the RR is high.

With the outbreak and the development of neural networks, the techniques in the biometric recognition field have drastically changed. Therefore, it is possible to distinguish two phases in the literature, which correspond approximately to the period before 2012 and the one after 2012. In the first stage, the approaches were mostly based on traditional techniques such as filters, transforms and texture-based methods, whereas, due to recent advances, the newly proposed systems are based on deep neural networks.

This paper provides a classification of recognition algorithms similar to the one proposed by David Zhang *et al.* [11], which comprises three categories: holistic-based, feature-based and hybrid methods. In addition, this survey presents a brief discussion about the most recent deep neural networks approaches. Finally, the last part of this section describes concisely the available KFP datasets.

A. Holistic-based methods

In the holistic-based recognition approach, the KFP image is wholly used as input of a feature extractor, whose output is subsequently given to a matching algorithm [12] to complete the recognition procedure. Most holistic-based approaches in the literature employ subspace techniques and spectral representation.

1) Subspace methods: Subspace methods are characterized by the detection of spatially localized features in the image [6]. The majority of subspace approaches in the literature are based on unsupervised subspace learning, which reduces data dimensionality while keeping the original data structure [13]. Some of the main techniques are *Principal Component Analysis* (PCA), *Independent Component Analysis* (ICA) and *Linear Discriminate Analysis* (LDA).

As an effective representation, Yang *et al.* [14] have proposed a KFP recognition method based on Gabor filters, PCA and *Orthogonal Linear Discriminant Analysis* (OLDA).

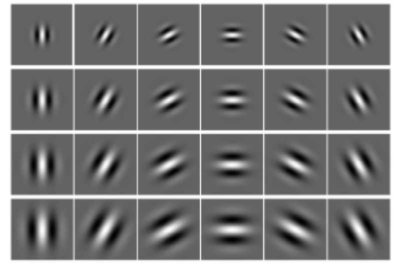

Figure 2. Bank of the 24 2D Gabor filters with four scales and six orientations. Courtesy of Lin Zhang *et al.*

Gabor filters are band-pass filters with different frequencies and orientations. In the literature, those filters have been used to localize and extract local features of the KFP, namely magnitude, phase, and orientation [10] (see Figure 2).

Yang *et al.* have initially constructed an enhanced Gabor feature vector which included all the elements acquired from the Gabor filter. However, since the Gabor feature representation is located in a very high-dimensional space, PCA is used to generate a meaningful low-dimensional representation in order to increase pattern matching computational efficiency and conserve space. Yang *et al.* have employed a LDA extension called OLDA with the aim of learning the subspace on which the classification is performed. The major issue of the standard LDA is that its formulation demands non-singular scatter matrices. However, when the data dimension is substantially bigger than the sample size, all scatter matrices are singular, thus LDA inevitably fails [15]. Due to the orthogonalization provided by its constraints, OLDA solves the singularity problem. Immediately after the feature extraction, a nearest neighbor classifier based on cosine distance is employed to perform the prediction. Yang *et al.* have evaluated the proposed technique on the Poly-U database [16] achieving a maximum RR of 98.67% and a minimum RR of 90%.

2) Spectral representation: In spectral representation-based approaches the picture is converted from the spatial domain to another domain (Fourier, Gabor, *etc.*), either to improve the image quality, or to extract the features' coefficients which will be employed in the recognition process [12].

Meraoumia *et al.* [2] have suggested a robust spectral representation-based recognition system developed on the Fourier transform which considers two modalities: KFP and palm print. To perform the recognition, Meraoumia *et al.* have used the *Phase-Correlation Function* (PCF), a well-known picture alignment approach. When two images are comparable, PCF produces a sharp peak, dramatically declining when they are not similar. As a result, the height of the PCF peak has been employed as the similarity metric for matching the 2D discrete Fourier transform of the KFP and palm print pictures. During the first stage, KFP and palm print pictures have been compared to those already stored in the database. When the two unimodal biometric matching scores are computed, they are fused together employing a score level fusion based on the sum rule. Score level fusion refers to the combination of various matching scores provided by the unimodal classifiers. However, before proceeding to the fusion stage, the matching scores must be normalized; to accomplish this, Meraoumia *et al.* have used the Min-Max method.

Assume the score vector is $D_i = [D_{i0}, D_{i1}, D_{i2}, \ldots D_{iN}]$, where N depicts the size of the system database and i indicates the picture on which the method is being tested. The normalized scores are calculated as follows:

$$DN_i = \frac{D_i - \min(D_i)}{\max(D_i) - \min(D_i)}$$

where DN_i is the normalized vector. The final decision is made according to the score obtained from the sum rule: for instance, if D_0 and D_1 represent the normalized scores associated to the FKP and to the palm print modalities, then the final score, SF, is defined as the sum between D_0 and D_1.

Meraoumia *et al.* have evaluated the suggested technique on the Poly-U KFP database [16] in combination with the palm print database, which is provided by the same university, achieving a RR of 97.417% and an EER of 5.688%.

B. Feature-based

Feature-based methods consist in the extraction of local prominent characteristics (such as edges, lines, *etc.*) from the KFP images, and in the comparison with the stored templates by the means of a matching algorithm. In the literature, the feature-based approaches are mostly either coding-based or texture-based.

1) Coding-based methods: Coding-based systems use binary coding to encode the representation of KFP pictures. These techniques are frequently implemented using Wavelets or Gabor filters [12].

In order to extract the local features of the KFP, Lin Zhang *et al.* [8] have applied a simple and cost-effective coding method based on Gabor filters (see Figure 2). The orientation information retrieved by the Gabor filter is then coded using a competitive coding scheme, referred as CompCode [10]. CompCode involves the convolution operation between the points of the pre-processed image and the real part of the Gabor filter allowing to retrieve robust and brightness-independent features. To determine whether two KFP images refer to the same finger, Lin Zhang *et al.* have employed a matching algorithm on top of the extracted competitive code maps using the angular distance, namely a normalized hamming distance between the competitive codes. As a result, the final matching distance is the minimum of the resulting distances.

The verification phase has been performed on their proprietary database; through their experiments, Lin Zhang *et al.* have achieved an EER of 1.09% and a RR of 97.96

2) Texture-based methods: Texture-based approaches are feature-based methods which extract useful picture descriptors based on the image typical patterns.

Morales *et al.* [17] have suggested a method for FKP authentication based on Gabor filters and on the *Scale Invariant Feature Transform* (SIFT) algorithm as an effective representation.

SIFT is a prominent texture identification approach which is invariant to picture scaling, rotation, and partial changes in illumination.

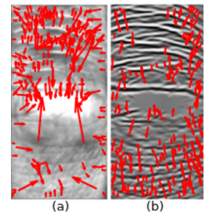

Figure 3. **(a)** SIFT over a FKP grayscale image; **(b)** SIFT over the pre-processed FKP grayscale image. Courtesy of Morales *et al.*

Firstly, SIFT applies a Gaussian low-pass filter to the Gabor-processed KFP picture, which is then equalized using a histogram equalization technique (CLAHE). Secondly, the image keypoints are extracted (see Figure 3). Finally, the keypoints are used to extract the orientations and gradient magnitudes, namely the image descriptors. The Euclidean distance between keypoint descriptors is used as a similarity metric during the matching phase.

In summary, the analyzed KFP picture is linked to the closest match individual.

Morales *et al.* have tested the proposed approach on the Poly-U database [16] obtaining an EER of 0.43%.

C. Hybrid methods

Hybrid methods consists in the application of both holistic and local features in order to improve the recognition accuracy and enhance the identification speed.

As an effective representation, Lin Zhang *et al.* [10] have provided an extension of their previous work, enriching their coding method based on competitive coding scheme [8] with global features provided by the Fourier transform coefficients. The recognition process is performed by combining two distances. The first one is the angular distance based on the normalized hamming distance for the local orientation features. The second one is obtained with the *Band-Limited Phase-Only Correlation* (BLPOC), a variation of the *Phase-Only Correlation* (POC). Such distance measures the similarity of the two Fourier transforms obtained from the ROI of both of the KFP images. The BLPOC aims to estimate the relative translative offset between two similar images in the Fourier domain, avoiding noisy high frequency components. Once the local and global distances have been obtained, they are fused together by the means of a matcher-weighting rule distance; the resulting distance is subsequently used in the matching phase. Moreover, BLPOC is employed at the beginning of the process in order to align the KFP of the two evaluated pictures according to the location of the peak.

Lin Zhang *et al.* have performed the verification phase on their own proprietary dataset achieving an EER of 0.402% a FRR of 1.5236% and a FAR of 0.0515%.

D. Deep neural networks methods

Due to recent advances in Artificial Intelligence, deep neural networks have increasingly aroused interest in biometric identification. In the literature, those methods are mainly based on a *Convolutional Neural Network* (CNN), a deep neural network architecture characterized by the combination of convolution and pooling layers.

A CNN is used either for feature extraction or classification; those tasks are commonly accomplished with the employment of a pre-trained model (*e.g.* VGG or ResNet) trained on a big dataset such as ImageNet.

Tarawneh *et al.* [18] have developed a KFP recognition pipeline based on the features extracted from the first two fully connected layers of VGG-19. Following the features extraction, PCA is used to decrease the data dimensionality, preserving 95 percent of data variance. As a classifier, an *Artificial Neural Network* (ANN), specifically a multilayer perceptron, has been trained and subsequently tested employing 5-fold-cross-validation. The suggested technique outperforms well-known architectures such as Resnet18, while the state-of-the-art EfficientNet performs marginally better.

Tarawneh *et al.* have performed the verification phase on the IIT Delhi Finger Knuckle Database [19] achieving an EER of 0.23%.

E. Datasets

In order to test the performances of KFP recognition systems, several datasets have been introduced. In this section, the paper aims to provide a brief overview of the most relevant ones in the field of KFP.

1) Poly-U Finger-Knuckle Database [16]: Provided by the Hong Kong Polytechnic University, the Poly-U Finger-Knuckle Database is one of the first KFP dataset to test human recognition algorithms. Altogether, the database contains 7,920 images from 660 different fingers obtained by 165 different individuals aged between 20 and 30 years old. The database contains KFP of the same finger acquired in two different sessions 4 to 7 years apart.

2) Lin Zhang et al. dataset [10]: Lin Zhang *et al.* have established their own proprietary KFP dataset in order to evaluate their proposed KFP recognition techniques. The database contains 5,760 images from 480 different fingers obtained by 120 different individuals, aged between 30 and 50 years old. The dataset contains KFP of the same finger acquired in two different sessions 14 to 76 days apart.

3) IIT Delhi Finger Knuckle Database [19]: The IIT Delhi established a KFP dataset including 790 images obtained by 158 different individuals aged between 16 and 55 years old.

IV. Conclusion

This survey presented a brief description of the KFP-based biometric recognition, its definitions, a potential acquisition mechanism and an overview of some popular KFP datasets.

The purpose was to provide a general introduction of how a KFP recognition system works by discussing the major steps, from acquisition to image classification, as well as the main idea behind the various methodologies which may be used to fulfill the KFP recognition task.

As for the methods accuracy, all the presented KFP recognition algorithm categories have achieved astonishing results regardless of the methodologies employed, as illustrated in Table I.

Table I
Accuracy Comparison of Different Recognition Methods based on KFP

Authors	Method[a]	Techniques[b]	Dataset	Accuracy (%) [c]	
				EER	RR
Yang	Subspace	GF+OLDA	Poly-U	-	98.67
Meraoumia	Spectral	2D-DFT	Poly-U	5.688	97.417
Lin Zhang	Coding	GF+CC	Lin Zhang	1.09	97.96
Morales	Texture	GF+SIFT	Poly-U	0.43	-
Lin Zhang	Hybrid	CC+BLPOC	Lin Zhang	0.402	-
Tarawneh	DNN	VGG-19+ANN	IIT Delhi	0.23	-

[a] DNN: Deep Neural Network
[b] GF: Gabor Filters; DTF: Discrete Fourier Transform; CC: Competitive Code; SIFT: Scale Invariant Feature Transform; BLPOC: Band-Limited Phase-Only Correlation; ANN: Artificial Neural Network
[c] -: Not Recorded; RR: Recognition Rate; EER: Equal Error Rate;

Despite their simplicity, holistic-based techniques have shown great results, namely RRs of 98.67% and 97.417%. Moreover, features retrieved by subspace-based approaches are stable to changes such as illumination and position variation, however, the data has high dimensionality [20].

Furthermore, Meraoumia *et al.* [2] have demonstrated that KFP may be employed in contexts with high security standards when combined with other unimodal biometrics, such as palm print.

On the other hand, feature-based methods are entirely dependent on how features are retrieved. As an effective representation, coding-based techniques have the advantage of having short feature length, a fast feature extraction and matching phase and of being robust to illumination variation. However, if two images are not perfectly aligned, their code maps may differ and the user may not be recognized [12]. Despite this, the results are astounding (Lin Zhang *et al.* EER 1.09% and RR 97.96%, Morales *et al.* EER 0.43%).

As for hybrid approaches, they combine both local and global characteristics, thus they are more robust and accurate compared to the method listed above as demonstrated by Lin Zhang *et al.* [8] system (EER 0.402%).

Despite the high computational cost of training and testing a CNN and the challenge in understanding the features learned from a neural network, the results achieved from these models are remarkable. Tarawneh *et al.* [18] have presented an interesting and low-resources strategy based on the use of VGG-19 as a feature extractor, which has the highest performance among the methods presented in this paper (EER 0.23%). In fact, thanks to the dimensionality reduction, the ANN training becomes faster, hence more classifiers can be employed in order to choose the better performing one.

To conclude, KFP is a new, interesting and efficient biometric trait which can be used in high-security authentication systems and may gain popularity due to recent improvements in recognition systems and to the increased data availability.

References

[1] A. Ometov, S. Bezzateev, N. Mäkitalo, S. Andreev, T. Mikkonen, and Y. Koucheryavy, "Multi-factor authentication: A survey," *Cryptography*, vol. 2, no. 1, 2018. [Online]. Available: https://www.mdpi.com/2410-387X/2/1/1

[2] A. Meraoumia, S. Chitroub, and A. Bouridane, "Fusion of finger-knuckle-print and palmprint for an efficient multi-biometric system of person recognition," in *2011 IEEE International Conference on Communications (ICC)*, 2011, pp. 1–5.

[3] D. Zhang, W.-K. Kong, J. You, and M. Wong, "Online palmprint identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 9, pp. 1041–1050, 2003.

[4] J. Unar, W. C. Seng, and A. Abbasi, "A review of biometric technology along with trends and prospects," *Pattern Recognition*, vol. 47, no. 8, pp. 2673–2688, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S003132031400034X

[5] A. Jain, A. Ross, and S. Prabhakar, "An introduction to biometric recognition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 1, pp. 4–20, 2004.

[6] A. Kumar and Y. Zhou, "Personal identification using finger knuckle orientation features," *Electronics Letters*, vol. 45, pp. 1023–1025, 10 2009.

[7] W. Li, "Biometric recognition of finger knuckle print based on the fusion of global features and local features," *Journal of Healthcare Engineering.*, vol. 2022, 2022.

[8] L. Zhang, L. Zhang, and D. Zhang, "Finger-knuckle-print: A new biometric identifier," in *2009 16th IEEE International Conference on Image Processing (ICIP)*, 2009, pp. 1981–1984.

[9] A. Kumar and C. Ravikanth, "Personal authentication using finger knuckle surface," *IEEE Transactions on Information Forensics and Security*, vol. 4, no. 1, pp. 98–110, 2009.

[10] L. Zhang, L. Zhang, D. Zhang, and H. Zhu, "Ensemble of local and global information for finger–knuckle-print recognition," *Pattern Recognition*, vol. 44, no. 9, pp. 1990–1998, 2011, computer Analysis of Images and Patterns. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0031320310002712

[11] D. Zhang, W. Zuo, and S. Yue, "A comparative study of palmprint recognition algorithms," *ACM Comput. Surv.*, vol. 44, p. 2, 01 2012.

[12] M. A. Sadik, M. N. Al-Berry, and M. Roushdy, "A survey on the finger knuckle prints biometrie," in *2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS)*, 2017, pp. 197–204.

[13] X. Jing, W. Li, C. Lan, Y. Yao, X. Cheng, and L. Han, "Orthogonal complex locality preserving projections based on image space metric for finger-knuckle-print recognition," in *2011 International Conference on Hand-Based Biometrics*, 2011, pp. 1–6.

[14] Z. W. Wankou YANG, Changyin SUN, "Finger-knuckle-print recognition using gabor feature and mmda," *Frontiers of Electrical and Electronic Engineering*, vol. 6, no. 2, p. 374, 2011. [Online]. Available: https://journal.hep.com.cn/fee/EN/abstract/article_1669.shtml

[15] J. Ye and T. Xiong, "Null space versus orthogonal linear discriminant analysis," in *Proceedings of the 23rd International Conference on Machine Learning*, ser. ICML '06. New York, NY, USA: Association for Computing Machinery, 2006, p. 1073–1080. [Online]. Available: https://doi.org/10.1145/1143844.1143979

[16] T. H. K. P. U. campus, *PolyU Finger-Knuckle-Print Database*, 2006-2013. [Online]. Available: http://www.comp.polyu.edu.hk/~biometrics

[17] A. Morales, C. Travieso, M. Ferrer, and J. Alonso, "Improved finger-knuckle-print authentication based on orientation enhancement," *Electronics Letters*, vol. 47, no. 6, pp. 380–381, 2011.

[18] A. S. Tarawneh, A. B. Hassanat, E. Alkafaween, B. Sarayrah, S. Mnasri, G. A. Altarawneh, M. Alrashidi, M. Alghamdi, and A. Almuhaimeed, "Deepknuckle: Deep learning for finger knuckle print recognition," *Electronics*, vol. 11, no. 4, p. 513, 2022.

[19] I. Delhi, *IIT Delhi Finger Knuckle Database*, 2006-2007. [Online]. Available: http://www4.comp.polyu.edu.hk/~csajaykr/IITD/iitd_knuckle.htm

[20] M. Imran, S. Noushath, A. Abdesselam, K. Jetly *et al.*, "Efficient multi-algorithmic approaches for face recognition using subspace methods," in *2013 1st International Conference on Communications, Signal Processing, and their Applications (ICCSPA)*. IEEE, 2013, pp. 1–6.