JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review on Person Verification with Finger-Vein Identification Approaches.

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Abstract: Person verification with finger-vein has attracted lots of respect from researchers around the world in recent years. Different type of approaches has been proposed to improve the results. In this paper approaches gathered from different research on pre-processing, feature extraction and classification stage specifically for recognizing identity of person. The strengths and fragility of finger veins are critically reviewed. The classification approach using machine learning method is highlighted to determine the future direction and to fill the research gap in this field. A Review on Person Verification with Finger-Vein Identification Approaches
Keywords: Biometric, Classification, Feature Extraction, Finger-Vein, Machine Learning, Pre- processing

I.INTRODUCTION

With our progress toward a globalize information society, the average person's life has at the same time become threatened by crime occurrences that can originate anywhere in the world. The biometric identification systems that are based on behavioral patterns the system that are based on physiological patterns such as face and fingerprint. Those systems somehow have several disadvantages3, 4. The features can be copied fraudulently as they are visible to human eye. In addition, the accuracy of face identification is very sensitive towards illumination invariance, facial expressions, poses and occlusions5. Table 1 summarizes the characteristics of the previously mentioned methods. A Finger vein 13biometric authentication is a recent identification system in this modern era. This technology is used for wide variety of applications including credit card authentication, automobile security, employee time and attendance tracking, computer and network authentication, and so on. Like fingerprints 12or iris patterns, finger vein-based blood vessel patterns are unique for each individual. Finger vein-based blood vessel pattern have high security because the veins are located under the surface of the skin. The fingerprints can be cheated by dummy finger fitted with a copied fingerprint, but the finger vein-based identification system is highly secure for authentication. The finger-vein patterns are not obscured nor it easily to be replicated or damaged because it is located underneath the human’s skin. The vein pattern images are captured non-invasively. The device using a contactless sensors concept ensuring convenience and hygiene for the user. Every individual commonly has ten available fingers. Therefore, if something unforeseen incident happens to any one of the fingers, other fingers be used as replacement for authentication6, 7. Finger- veins can only be captured from a living body, hence, if a person is dead, it is impossible to steal his identity there are challenges that still need to be dealt with in order to achieve the higher performance required in real-world. Firstly, the finger- vein image acquisition device has a great impact on the quality of the finger-vein images. During the capturing process, the distance between the finger and camera is very close to one another. This close position could cause optical blurring on the captured image9. In addition, the lighting of the capturing device is a very crucial attribute for the system. Poor lighting may cause the image to appear extremely dark or extremely bright10 besides that, the position guidance of the finger is also important. Other than that, the thickness of bones and skin varied for every individual. Therefore, light scattering may happen as the human’s skin layer is not consistent7. The noise on the captured images needs to be eliminated as much as possible. Consequently, to overcome those issues, the conventional finger vein recognition methods implemented complex image preprocessing algorithms to the system1.

II.EXISTING APPROACHES FOR PREPROCESSING, FEATURE EXTRACTION, AND CLASSIFICATION

Finger-vein recognition system can be realized through three approaches. The first approach is by applying a series of image processing modules known as a con- venational method. The second approach is by applying machine learning technique that is commonly known as AI method. The final approach is the combination of conventional and machine learning approach. Research have shown that the finger- vein images captured using Near Infrared (NIR) technique are sensitive towards illumination change and different thickness of finger for each individual. The low image quality of NIR images is attributed by motion blur and low contrast. Hence, conventional methods commonly applied various complex preprocessing algorithms to improve the quality of the captured image as reported by18, 19. In other cases, when the simple preprocessing stage is applied, expensive and precise mathematical model is required to describe the biometric characteristics as reported in20. The efficient classifier also plays a role in enhancing the recognition rate. The work in3, 21, 22 has proposed their own classifier to classify the biometric traits. When there are many stages of preprocessing and complex feature extraction and classifier algorithm, this will result in high computational time to identify an unknown subject. Thus, this approach is impractical when execution time is taken into consideration23. In fact, the algorithms deployed are very problem specific in which if another variant of finger-vein samples exist, there will be a possibility to modify the designed algorithms. Table 3 summarizes the algorithms applied by the conventional approach and detail information on the data samples. From Table 3, we can see that conventional approach involves with several stages of image processing modules to cope with the challenges encountered by finger-vein data samples.

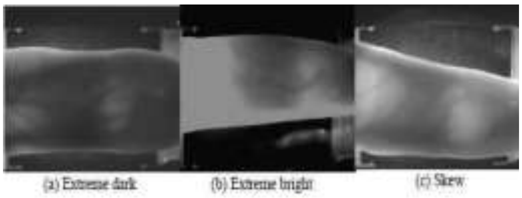


Figure 1: Non-ideal finger-vein samples of SDUMLA-HMT finger -vein database

Table 1: Summary of existing biometric traits[5]

Biometric trait	**Main Advantage**	**Disadvantage**	**Security Level**	**Sensor**	**Cost**
Voice	Natural and convenient	Noise	Normal	Non-Contact	Low
Face	Remote capture	Lighting conditions	Normal	Non-Contact	Low
Finger print	Widely applied	Skin	Good	Contact	Low
Iris	High precision	Glasses	Excellent	Non-Contact	High
Finger-vein	High-security level	Few	Excellent	Non-Contact	Low

Table 2. The existing public finger-vein databases[8]

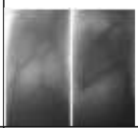
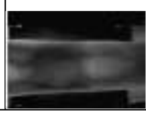
Database	**No of images**	**No of Subject**	**Finger Number per Subject**	**Image Number per Finger**	**Image resolution**	**Format**	**Typical Image**
THU-FVFDT1[13]	440	220	1	1	720x576pxl (raw)	.BMP	
UTFV[14]	1440	60	6 (Index, ring, middle, of both hands)	4	672x380pxl	8 bit gray scale .PNG	
MMCBNU_6000[15]	6000	100	6 (Index, ring, middle, of both hands)	10	480x640pxl	.BMP	
HKPU-FV[16]	6264	156	3 (Index, ring, middle of left hand)	12/6*	513x256pxl	.BMP	
SDMULA-HMT[17]	3816	106	6 (Index, ring, middle, of both hands)	6	320x240pxl	.BMP	

Table 3:Conventional methods of finger-vein identification

Reference	**Preprocessing**	**Segmentation, Feature extraction**	**Classifier**	**Accuracy/ EER(%)**
Liu et al., 2010[12]	1. ROI Detection 2.Imageenhancement(Multi- resolution) 3. Size normalization	Orthogonal Neighborhood Preserving Projections (ONPP)Manifold Learning	Image manifold distance for recognition	97.80
Guan et al., 2010[27]	-	BWMB2DPCA	Nearest Neighbor	97.73

Yang et al., 2010[28]	1. Interphalangeal joint prior 2. Vein ROI segmentation	Steerable filter	Nearest Neighbor	98.70
Lee et al., 2011[4]	Gaussian high-pass filter	1. Simple Binarization 2. Local Binary Pattern(LBP) 3. LDP	Hamming Distance (HD)	(2.32, 1.53, 0.89)*

Wenming et al.,2011[18]	1. Background 2. Elimination 3. Noise reduction 4. Image enhancement 5. Size normalization 6. Brightness 7. Normalization	1. Local dynamic thresholding 2. Median filter 3. Morphological operation4. Vein location and direction coding	Template matching	100.00
Mobarakeh et al., 2012[22]	1. ROI extraction 2. Image resize 3. Gaussian HPF	Kernel PCA	Weighted K- nearest centroid neighbor (WKNCN)	99.7
Damavandinejadmonfar ed et al., 2012[30]	1. ROI extraction 2. Contrast Limited Adaptive Equalization (CLAHE) 3. Normalization	Linear Kernel Entropy Component Analysis (KECA)	Euclidian Distance	98.00
Yang et al., 2012[32]	1. Image Gray Processing 2. ROI extraction 3. Normalization (Size and Gray)	Personalized Best Bit Map (PBBM)	Matching	0.0038

Conventional approaches are less robust to noise and misalignment, therefore, the image processing tasks applied to the conventional system is to reduce the risk of the mentioned problems. One approach to reducing the number of preprocessing stages is by applying adaptive image acquisition technique to ensure that the captured image is in appropriate lighting condition [30, 31].

III.MACHINE LEARNING APPROACH FOR FINGER-VEIN IDENTIFICATION SYSTEM

Biometric matching is a “fuzzy comparison”. It is because biometric traits captured a second time is never exactly the same as the first time. This characteristic of biometric matching has led to the usage of machine learning techniques, such as Neural Networks, fuzzy logic, evolutionary computing, etc., in biometric algorithms. Machine learning possesses key properties of being robust to noise and can efficiently solve complex pattern recognition prob- lems. In addition, machine learning is orderly adaptive and commonly have a parallel computational architecture. It models the complex biometric characteristics very adaptively, without making many assumptions using precise mathematical model. With these properties, machine learning proved to be an effective method for biometric feature extraction and matching process. There are few researches applying machine learning approach in vascular biometric recognition. However, all previous works on finger-vein recognition are based on their own developed in-house finger-vein database, since standard finger-vein database is not publicly available.

Table 4 lists out the algorithms applied in each existing machine learning work and Table 4 gives the accuracy achieved by each existing work. There are not many existing works implemented machine learning techniques for finger-vein identification problem. Wu and Liu proposed finger-vein pattern identification using SVM in 20115. The database includes 10 people with 1samples for each finger. The accuracy of the classification using SVM is 98.00% and only takes 0.015 seconds. Wu and Liu proposed a finger- vein identification using PCA as the feature extraction and neuro-fuzzy inference system (ANFIS) as the classifier in 201121 the work in[26] presented the identification by applying SVM. Global matching is used to fasten the matching scheme, using extracted features by LBPV.

Table 4. Algorithms applied by machine learning approach for finger-vein identification

Reference	**Preprocessing**	**Segmentation, Feature extraction**	**Classifier**	**Accuracy/ EER (%)**
Liu et al., 2010[12]	1. ROI Detection 2.Imageenhancement(Multi-resolution) 3. Size normalization	Orthogonal Neighborhood Preserving Projections (ONPP)Manifold Learning	Image manifold distance for recognition	97.80
Guan et al., 2010[29]	-	BWMB2DPCA	Nearest Neighbor	97.73
Yang et al., 2010[27]	1. Interphalangeal joint prior 2. Vein ROI segmentation	Steerable filter	Nearest Neighbor	98.70

Lee et al., 2011[4]	Gaussian high-pass filter	4. Simple Binarization 5. Local Binary Pattern(LBP) 6. LDP	Hamming Distance (HD)	(2.32, 1.53, 0.89)*
Wenming et al.,2011[18]	8. Background 9. Elimination 10. Noise reduction 11. Image enhancement 12. Size normalization 13. Brightness 14. Normalization	4. Local dynamic thresholding 5. Median filter 6. Morphological operation4. Vein location and direction coding	Template matching	100.00
Mobarakeh et al., 2012[22]	4. ROI extraction 5. Image resize 6. Gaussian HPF	Kernel PCA	Weighted K- nearest centroid neighbor (WKNCN)	99.7
Yang et al., 2012[31]	4. Image Gray Processing 5. ROI extraction 6. Normalization (Size and Gray)	Personalized Best Bit Map (PBBM)	Matching	0.0038
Harsha et al., 2012[32]	1. Bucolic Interpolation 2. Histogram Equalization	1. Fractal dimension 2. Wavelet Transform	1. Wavelet transformation 2. Energy feature	99.30
Meng et al., 2012[33]	1. Image Gray Processing 2. ROI extraction 3. Normalization (Size and Gray)	Local Directional Code (LDC-00 & LDC-45)	Matching	100.00

System achieved 98.75% of 20 subjects and 48 test samples. The similarity of these works is that machine learning is applied to the classifier of the system instead of using machine learning as the feature extraction method. Hence, the biometric features are not adaptively modelled by the machine learning method. Table 5 depicts the number of subjects, the number of test samples and accuracy achieved by existing works using machine learning method. Besides the ability of a finger-vein recognition to efficiently extract distinct features and classify samples with high recognition rate, high recognition speed is also required to make the system more practical for real-world applications. Table 6 reports on recognition speed stated by other researches on machine learning approach. The approach mentioned is based on the feature extraction method they applied. The speed is measured starting from the preprocessing until classifier stage. Table 7 summarizes the weaknesses of other researches on machine learning approach. Most of the researches tested on a very few number of subjects. The weaknesses may be caused by the output of preprocessing or feature extraction stages. However, it shows that the machine learning has limitations.

Table 5. Accuracy achieved by machine learning method for finger-vein identification

Reference	Number of subject ts	Number of test samples	Accuracy (%)
Wu and Liu, 2011[5]	**10**	**100**	**98.00**
Hoshyar et al., 2011[34]	**7**	**14**	**93.00**
Kuan-Quan et al., 2012[35]	**10**	**800**	**79.00-96.00***
Souad et al., 2014[36]	**20**	**48**	**98.75**
Syafeeza et al., 2014[37]	**81**	**162**	**99.38**

Table 6. Execution time achieved by machine learning-based for finger-vein identification

Reference	Machine Learning Approach	Execution time (s)
Wu and Liu, 2011 [5]	SVM	0.0150
Hoshyar et al., 2011 34	SVM	—
Kuan-Quan et al., 2012 [35]	SVM	—

Souad et al., 2014 [36]	SVM	—
Syafeeza et al., 2014 [37]	CNN	0.1574

Table 7. Weaknesses of existing machine learning method for finger-vein identification

Reference	Number of subjects	Number of test samples	Weaknesses
Wu and Liu, 2011 [5]	10	100	Too few number of subjects, SVM is sensitive to noise. .
Hoshyaral.,34	7	14	Too few number of subjects, low accuracy
Kuan-Quan et al.., 35	10	800	Too few number of subjects, low Accuracy as for middle and little fingers.
Souad etal.., 2014 ,36	20	48	Too few number of subjects.
Syafeeza etal.., 37	81	162	Not suitable for non-ideal finger-vein cases

IV.CONCLUSION

We have work on a few existing public databases. Although there are databases publicly available, most of the existing works developed their own in-house databases. This matter possibly due to the inappropriate type of finger vein images to their application in need. The highlight of this paper is that we have reviewed a significant number of papers to cover the existing approaches of finger-vein identification. We have discussed the preprocessing, feature extraction and classification stage of finger-vein identification techniques. In the classification stage, we focused on machine learning techniques. This technique has a high potential to be the future research direction in this field. A new method of finger-vein References

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