Palm Vein Recognition based on NonsubSampled Contourlet Transform Features

Amira Oueslati[1], Nadia Feddaoui[2] and Kamel Hamrouni[1]
[1]LR-SITI Laboratory, National Engineering School of Tunis, University ELMAanar, BP 37 Belvedere 1002, Tunis, Tunisia
[2]ISD, University Manouba, 2010 Manouba, Tunisia

Keywords: Palm Veins Recognition, NonsubSampled Contourlet Transform (NSCT), ROI Extraction, Feature Extraction, Feature Matching.

Abstract: This paper presents a novel approach for person recognition by palm vein texture image based on Nonsub-Sampled Contourlet Transform (NSCT). Our approach consists of four steps. First, we reduce noise and enhance contrast in order to produce a better quality of palm vein image then we localize the texture in the ROI. Next, the texture of enhanced image is analyzed by NSCT and obtained features witch are encoded to generate a signature of 676 bytes. Finally, we compute hamming distance in comparison to take decision. The experiments are performed on CASIA Multi-Spectral Palm print Image database. The method evaluation is completed in both verification and identification scenarios and experimental results are compared with other methods. Experiments results prove the effectiveness and the robustness of NSCT method to extract discriminative features of palm veins texture.

1 INTRODUCTION

Biometrics refers to all techniques to identify a person based on its intrinsic characteristics that must be unique and measurable. These features can be physical, biological or behavioral. The most known are fingerprints, voice prints, iris, retina and hand. They offer an irrefutable proof to distinguish one person from another.

Therefore, palm veins recognition represents a new generation of integrated access control system based on the safest biometric technology today. Palms have a large and rich blood vein patterns. It's unique to each person, stable during the person's lifetime and a palm vein image is easily captured by near-infrared rays, without contact and without a trace. This makes this technology non-invasive, hygienic and widely acceptable to users.

In this paper, to obtain a high-performance of palm veins recognition system, we have applied the Non sub sampled Contourlet Transform (NSCT) method which is a shift-invariant, multi-scale, and multi-directional transform. It can capture significant veins features along all directions.

The rest of this paper is structured as follows. In Section 1, existing methods in literature are briefly reviewed, in Section 2 the proposed palm veins recognition method using the NSCT is presented, in Section 3 experimental results of the proposed method are given and discussed. Finally, in Section 4, conclusions are drawn.

2 STATE OF ART

Extensive work has been made on person recognition using palm-vein technology based on many and different type of filtering. For example, In the work presented by (Pan and Kang, 2011) the image is preprocessed by histogram equalization, then three algorithms (Scale Invariant Feature Transform, Speeded-Up Robust Features and Affine-SIFT) were used to extract local features, and finally the matching results were obtained by computing the Euclidean distance.

Palm vein feature extraction from near infrared images is proposed by (Sadeghi and Drygajlo, 2011) an approach based on local texture patterns is proposed. The operators and histograms of multiscale Local Binary Patterns are investigated to identify statistical descriptors for palm vein patterns and novel higher-order local pattern descriptors based on Local Derivative Pattern histograms are then

Oueslati, A., Feddaoui, N. and Hamrouni, K.
Palm Vein Recognition based on NonsubSampled Contourlet Transform Features.
DOI: 10.5220/0005780902490254
In *Proceedings of the 11th Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2016) - Volume 4: VISAPP*, pages 249-254
ISBN: 978-989-758-175-5

investigated for palm vein description. In the work of (Han and Lee, 2013), they proposed an adaptive Gabor filter method to encode the palm vein features in bit string representation. The bit string representation, called VeinCode, offers speedy template matching and enables more effective template storage. The similarity of two VeinCodes is measured by Hamming distance.

In this paper, a new approach is proposed for palm vein recognition with a high performance based on NonsubSampled Contourlet Transform.

3 PROPOSED METHOD

In biometrics, Palm vein technology works by identifying the vein in an individual's palm. When a person's hand is held over a scanner, a near-infrared light locate the veins.

The red blood cells in the palm veins absorb the rays and show up on the map as black lines, whereas the hand structure shows up as white. This vein pattern is then verified to authenticate the individual.

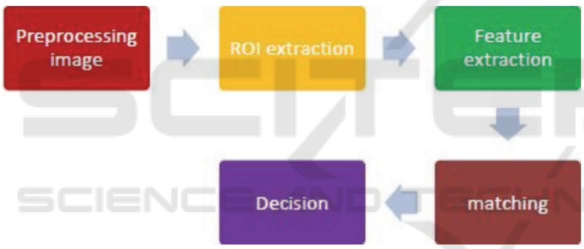


Figure 1: The process of the Palm veins recognition.

Figure 1 shows the general process of the recognition model using Palm veins biometrics. This palm vein recognition system consists of four steps: palm veins region localization, preprocessing, feature extraction, and matching.

3.1 Preprocessing

First, to segment the input image from the background we have applied a threshold. The smaller objects due to the noise are removed through connected components labeling. To normalize the contour of the hand image a morphological operator closing is carried out with a square structuring element.

3.2 ROI Extraction

This process has many important aims; first, it serves to remove the rotation, translation and scale (RST) variations of palm vein images. Second, it allows extracting the most informative area in the palm vein image.

In the proposed palm vein recognition method, we apply the method of (Feng et al. 2011). The four steps to obtaining the square area ROI are described as follows:

1) Line up the key point $C^1$and the key point C^3 to get the X-axis of image and then make a line through the key point C^2, perpendicular to the Y-axis, and the intersection is d^1.

2) Calculate the mean δ distance between the points C^1, C^2, C^3 and make:

$$d^1d^2 = \frac{\delta}{2} \quad (1)$$

3) Locate the square $a^1a^2a^3a^4$, a^1a^2 and C^1C^3 are parallel, and make:

$$a^1a^2 = \sigma \times \frac{3}{2}, \frac{a^1d^2}{d^2a^2} = \frac{C^1C^2}{C^2C^3} \quad (2)$$

4) Get the ROI from the original image, and transform it into a grey image of fit size.

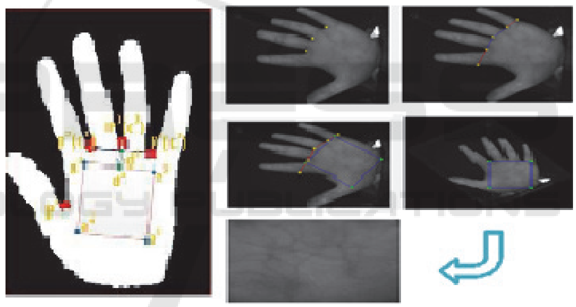


Figure 2: Region of interest (ROI) of palm vein image.

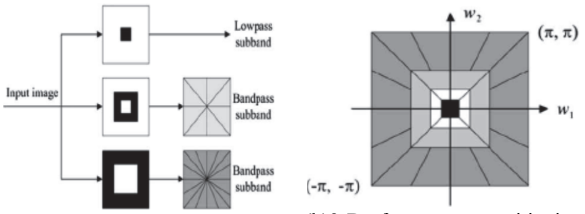
3.3 Palm Veins Feature Extraction

We analyze the texture to detect the most distinctive characteristics using NSCT to extract texture features.

3.3.1 Texture Description based on NSCT

NSCT is composed of two-channel nonsubsampled filter bank (NSFB). One is the Nonsubsampled directional filter banks (NSDFB) that provide the directionality and the other one is the Nonsubsampled pyramid (NSP) that ensures the multi-scale property (Gonzalez et al., 2010). The structure of the NSCT (Fig. 3) ensures the shift-invariant property. Figure 3(a) shows the structure of the two-channel NSFB, and Figure 3(b) shows a 2-D frequency domain split into a number of subbands. The NSP consists on a high-pass (HP) subband and a low-pass (LP) subband, and the NSDFB decomposes the HP subband into a number of directional subbands.

Consequently, the NSCT is effective in representing well the detailed characteristics of the strong palm vein texture along the radial and angular directions. (Zhou et al., 2012); (Tang et al., 2007); (Yang et al., 2007).



(a) NSFB that implements the NSCT

(b)2-D frequency partitioning domain into a number of subbands

Figure 3: NSCT structure (Gonzalez et al., 2010).

3.3.2 Palm Vein Features Extraction using the NSCT

The binary vein image Fig 4(c) is used as the input of the NSCT. After filtering by the NSCT, all of the NSCT coefficients are used to define the palm vein features.

The NSCT coefficients in all the subbands can be defined as:

$$\{W^J, W_i^j\}\begin{cases} 1 \le j \le J \\ 1 \le i \le d_j \end{cases} \tag{3}$$

(J) is the total number of scale decomposition; (dj) is the number of directions at j-th scale. W^J Represents the low-frequency coefficients and W_i^j represent the mid/high-frequency coefficients in the i-th directional subband of the j-th scale level.

To capture strong distinct directional characteristics of the palm vein, the coefficients in the HP subbands W_i^j at scale j are used as the palm vein features. Little directional information is contained because the pyramid subband is an approximation and contains LP information. Therefore, the LP coefficients are W^J excluded in the palm vein feature extraction process. (Gonzalez et al. 2010)

Consequently, only the coefficients W_i^j in mid- and HP subbands are used as palm vein features.The results of the decompositions is shown in Fig4.

Then, a binary feature vector must be created, the signs of the NSCT coefficients W_i^j in each subband are used to generate the binary code (BC):

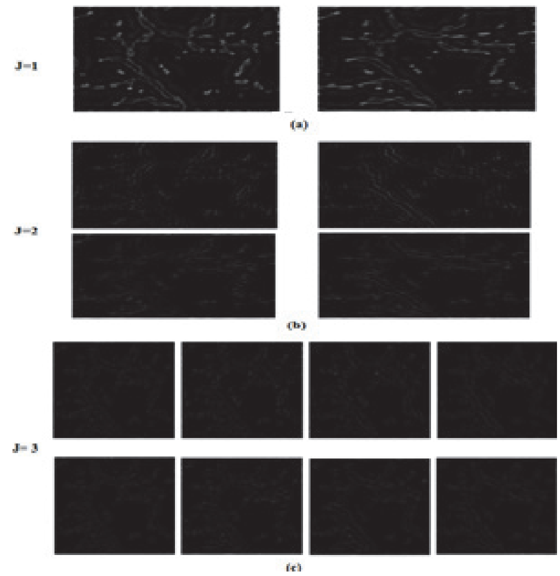


Figure 4: the Directional subband images at three different scale levels. (a) Scale 1, two directions (d1=2), (b) Scale 2 Four directions (d2=4), (c) Scale 3 Eight directions (d3=8).

$$bc_i^j(x,y) = \begin{cases} 1, & \text{if } W_i^j(x,y) > 0 \\ 0, & \text{else} \end{cases} ; 1 \le i \le d_j \tag{4}$$

(x,y) represent the coordinates in each nonsubsampled subband image W_i^j. It is known that the resulting (BC) contains sign information in each NSCT subband. All the directional characteristics in both multi-directions and multi-scale are considered in the generated (BC). The final binary palm vein vector is expressed as:

$$V(x,y) = \left[bc_1^1(x,y) \cdots bc_{d_1}^1(x,y) \vdots bc_1^2(x,y) \cdots bc_{d_2}^2(x,y) \vdots \cdots \vdots bc_1^J(x,y) \cdots bc_{d_J}^J(x,y)\right]^T \tag{5}$$

3.4 Palm Vein Feature Matching

In order to match two palm vein feature vectors, the Hamming distance (HD) is used. The HD measure between two palm vein feature vectors V^1 and V^2 can be defined as: (Daugman, 1993)

$$HD = \frac{1}{XY} \sum_{x=1;y=1}^{XY} V^1(x,y) \oplus V^2(x,y) \tag{6}$$

Where (x, y) represents the pixel coordinates in the X×Y subband image. The HD measure between two palm vein vectors calculates how many bits are different, if the value of the HD is closer to ‘0’, it means that the two palm vein vectors come from the same subject, and vice versa.

4 EXPERIMENTAL RESULTS

In this section, we will introduce the performance measurement of our algorithm in verification and identification scenarios. Then we will try to compare our results with results of well-known veins recognition methods found in the literature. Tests are carried out on left and right hands images of CASIA Multi-Spectral Palm print database (CASIA Multispectral Palmprint Database).

The CASIA database contains large RST variations since it was acquired using a non-contact sensor, it has 200 identities, 6 samples per identity witch give us 1200 palm veins.

Verification experiments and identification experiments are detailed in the Section below.

4.1 Verification Mode

We perform verification experiments by reporting the inter-class and intra-class curves, Receiver Operating Characteristic (ROC) curves, the decidability (MD), the degree of freedom (DOF) and the equal error rate (EER).

In verification mode, all images in the database are matched to all other images which commonly named as “all versus all” in the literature.

After the calculation of the hamming distances of all templates comparisons, which is a fractional measure of dissimilarity; 0 would represent a perfect match, the Intra-Class and the Inter-Class distribution are found. The Inter-Class distribution of the hamming distances is generated by comparing between templates of the different persons. Intra-Class distribution is generated by comparing between different templates of the same sample. The number of operations is 359400, 3100 of genuines and 716 300 of imposters.

To test the separability of the veins recognition system, the decidability index MD proposed by (Daugman, 1993) is used. The mean and the standard deviation of intra-class and inter-class distributions are calculated in order to calculate the decidability, If their two mean values are μ1 and μ2, and their two standard deviations are σ1 and σ2, then ‘MD’ is defined as:

$$MD = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}} \quad (7)$$

We introduce also the uniqueness of the vein patterns which means that there is an independent variation in the vein details (Sun et al., 2005); we can determine the vein uniqueness by examining the Inter-Class distribution and calculating the degree of freedom ‘DOF’ defined as:

$$DOF = \frac{\mu_2(1 - \mu_2)}{\sigma_2^2} \quad (8)$$

To choose the best number of decomposition k, we have varied k form 2 to 4 and for each stage we have generated the intra class and inter class distributions as shown in Fig. 5. The obtained decidabilities and the degrees of freedom are given in Table 1.

Table 1: Decidability ‘MD’ and degree of freedom ‘DOF’.

Stage k	MD	DOF
k = 2	1.22	11.06
k = 3	3.46	72.12
k = 4	3.43	50.67

The measure of decidability achieved high value on CASIA database from k equal to 3; it reflects the perfect separation between the two distributions which don’t overlap. So the less error is found which allows for more accurate recognition. We will focus our study on the number of decomposition stages k=3.

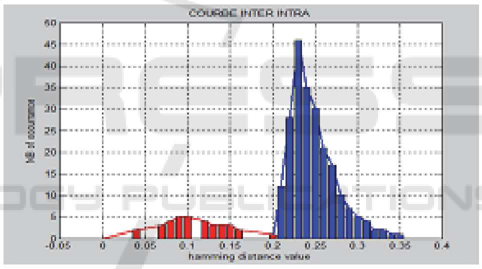


Figure 5: Intra class and Inter class distributions.

The highest HD of the intra-class distribution is 0.21 and the smallest HD of the inter-class distribution is 0.2. Thus, a decision criterion of 0.2 can perfectly separate the dual distribution. The error rates FAR (False Accepted Rate) and FRR (False rejected Rate) will be 0.2% at that threshold.

Clearly, the probability of not making a false match for single one-to-one verification trials is 99.70%, so we can conclude that the probability of making at least one false match when searching a database of N unrelated patterns is 0.30%.

The veins recognition system error rates, FAR and FRR, are dependent on the adjustable adopted threshold. Our algorithm will then compute the HDs that will be sorted in ascending order and vary the threshold from 0 to 1 then determine in each case the corresponding FAR and FRR which will be used to construct the ROC curve shown in Fig. 6.

When we increase threshold value, the FAR will increase and FRR will decrease. When FAR is equal to FRR, this value is called ERR (Equal Error Rate).

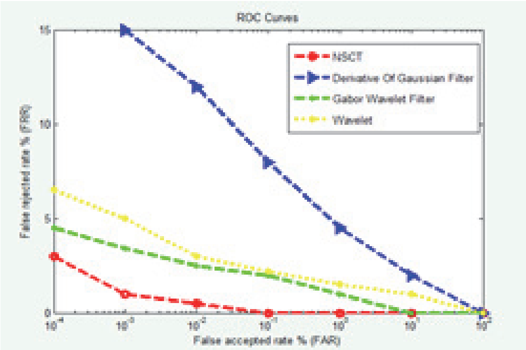


Figure 6: Comparison of ROC curves with other techniques.

The TAR (True Acceptance Rate) can be used as an alternative to FRR while reporting the performance of a biometric verification system.

The results show a 99.70% of TAR in our proposed system.

4.2 Identification Mode

The methodology we have followed consists on randomly selecting one of palm veins images per subject to form the gallery and treats all the remaining images as probes. The training set is composed of 200 Right/200Left samples and the testing set is composed of 400 Right/400Left.

We report cumulative Match Characteristic "CMC" curve (fig. 7). This system achieved 99.80% of rank-one identification rate.

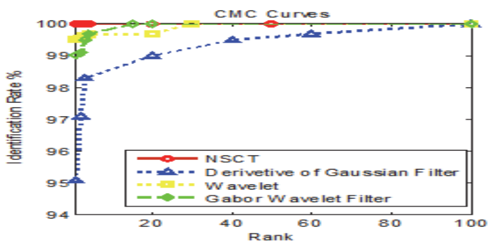


Figure 7: Comparison of CMC curves with other techniques.

4.3 Comparison with State-of-the-Art Methods

We compare the performance of the proposed method with three state-of-the-art ones namely Wavelet (Kong et al., 2004) Gabor Wavelet Filter (Sun et al., 2005) and Derivative of Gaussian Filter (Wu et al., 2006). Tests are carried out on CASIA database.

A direct comparison on ROC curves is shown in Fig. 6 and the results of the Equal Error Rate (EER) and the TAR are summarized in Table 2.

Table 2: EERs and TARs of the different techniques.

Method	EER %	TAR %
NSCT	**0,2000**	**99,70**
Derivative Of Gaussian Filter	2.8887	92.01
Gabor Wavelet Filter	0.8660	98.40
Wavelet	0.4999	98.66

We can observe that our method gives perfect results. Indeed, the NSCT ROC curve coincides with coordinate axis. When the threshold is low, FAR will be 0 and FRR vary from 1 to 0.When the threshold is high, FRR will be 0 and FAR vary from 0 to 1. When the threshold is about 0.2, FAR and FRR will intersect at the 0.2 position, so the EER rate will be 0.2000% and the TAR will be 99.70% witch consistently outperforms all other techniques for CASIA database. We observe clearly that our proposed method achieves an important EER reduction compared to the nearest competitor, Wavelet method.

Figure 7 shows a comparison of the CMC curves of these several techniques and Table 3 summarizes the results of rank-1 identification rates and time processing of different techniques.

Table 3: Comparison of different algorithms.

Method	Rank 1 identification rate	Time(s)
NSCT	**99,80**	**0.0010**
Derivative Of Gaussian Filter	95.10	0.0900
Gabor Wavelet Filter	99.01	0.1519
Wavelet	99.63	0.1214

The NSCT code achieved 99.80% identification rate for rank-1. It is fair to deduce that the proposed method performs better for identification in comparison to state-of-the art techniques. We make also a comparison on the time of execution shown in Table 3 which demonstrates that our approach is very quick and perfect.

5 CONCLUSIONS

This paper proposes a palm vein recognition method, in which shift-invariant, multi-scale, and multi-directional NSCT coefficients are used as effective palm vein features.

We apply a pre-processing of the image to eliminate the noise and the unwanted points.

Next, all the NSCT coefficients in each directional subband are used to extract palm vein features. The created palm vein vector extracts desirable characteristics of features in both multi-scale and multi-directions. These features are encoded to generate a signature of 676 bytes. Finally, hamming distance is computed in comparison.

Experimental results show the effectiveness of the proposed NSCT feature based method in verification and identification modes. We obtain an excellent results of 99,80% of rank one recognition rate and 0.2000% of EER.

Future research will focus on the improvement of the execution time and the performance of the proposed algorithm fusion with the multimodality of palm and dorsal parts of hand.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences for their supply of Casia Multi-Spectral Palm print image database.

REFERENCES

M. Pan, W. Kang, 2011. *Palm Vein Recognition Based on Three Local Invariant Feature Extraction Algorithms Biometric Recognition*, Lecture Notes in Computer Science, Vol. 7098.

M. M. sadeghi, L. Drygajlo, A. , Oct. 2011. *Palm vein recognition with Local Binary Patterns and Local Derivative Patterns*, International Joint Conference on Biometrics Compendium (IJCB), 11-13, Washington.

W.Y. Han, J. Ch. Lee, March 2013.*Palm vein recognition using adaptive Gabor filter*, Expert Systems with Applications, Vol. 40.

YiFeng,Jingwen Li, YiFeng, Jingwen Li, Lei Huang, and Changping Liu, 2011. "*Real-time ROI Acquisition for Unsupervised andTouch-less Palmprint,"* World Academy of Science, Engineering and Technology 54.

R. C. Gonzalez and R. E. Woods, 2010. *Digital image processing*, (Pearson Education Inc., Upper Saddle River), NJ, USA, 3rd edn.

J.G. Daugman, Nov.1993. *High confidence visual recognition of persons by a test of statistical independence*, IEEE Trans. Pattern Anal. Machine Intell, vol. 15, no. 11.

Y. Zhou and J. Wang, Nov. 2012. *Image denoising based on the symmetric normal inverse Gaussian model and NSCT*, IET Image Processing, Vol. 6, no. 8.

L. Tang, F. Zhao and Z. G. Zhao, Nov. 2007. *The nonsubsampled contourlet transform for image fusion*, Proc. Int.Conf. Wavelet Analysis and Pattern Recognition, Beijing, China.

B. Yang, S. T. Li and F. M. Sun, Aug. 2007. *Image fusion using nonsubsampled contourlet transform*, Proc. Fourth Int. Conf. Image and Graphics, SiChuan, China.

"CASIA Multispectral Palmprint Database." [Online]. Available:http://www.cbsr.ia.ac.cn/MS Palmprint Database.asp.

A.-K. Kong and D. Zhang, August 2004. *Competitive coding scheme for palmprint verification*, International Conference on Pattern Recognition, Cambridge UK.

Z. Sun, T. Tan, Y. Wang, and S. Z. Li, June 2005. *Ordinal palmprint representation for personal identification*, Computer Vision and Pattern Recognition CVPR, San Diego.

X. Wu, K. Wang, and D. Zhang, Nov. 2006. *Palmprint texture analysis using derivative of gaussian filters*, International Conference Computational Intelligence and Security, New York.