

Optimal Block Selection for Vein Based Multimodal Biometrics

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Abstract: Vein based multi-modal biometric recognition is becoming an emerging need in order to have better security. Here, we have utilized dorsal and finger vein biometrics present in the hand. After preprocessing, the necessary features are extracted from dorsal vein images using automatic thresholding and from finger vein images using hyper analytic wavelet transform. Once the vein features are extracted, vein patterns are generated based on the vein location. The vein pattern is large in length, so the selection of blocks from the large length vein patterns is important without affecting the accuracy. Here, firefly algorithm is utilized to select the optimal blocks. After selecting the optimal blocks, the location and size of blocks are fixed. Using these blocks matching is done with the block features stored in the database. The experimentation is carried out using the standard data bases of finger and dorsal hand vein images. The performance of the proposed technique is evaluated using the false acceptance and false rejection rates. The experimental results show that the proposed method achieved improved performance compared to the existing techniques.

Key words: Finger vein, dorsal vein, feature extraction, optimal block selection, score level fusion, multi-modal biometric recognition

INTRODUCTION

Biometric recognition is a common and reliable way to authenticate the identity of a person through physical measurements of unique human characteristics or behavior. A physiological characteristic is a relatively stable physical characteristic, such as fingerprint, iris pattern, facial feature, hand silhouette and more (Jain *et al.*, 2004). Biometric technology offers the secure method to make highly accurate verifications of individuals. Here the most important task is the selection of right modality for authentication. However, the best biometrics is still facing numerous problems, some of them inherent to the technology itself. Multimodal biometrics (Ross and Jain, 2004; Raghavendra *et al.*, 2010; Yadav and Gothwal, 2011) are fairly a good approach to overcome those problems which combines information from multiple modalities to arrive at a decision. The main concept of the multimodal biometric system is the fusion (Ross and Jain, 2003) of various modalities. The fusion can be done at the sensor level, feature level (Chin *et al.*, 2014; Kaur, 2012) score level (Hanmandlu *et al.*, 2011; Sim *et al.*, 2014) and decision level (Saleh and Alzoubiady, 2014).

The score level fusion approach based on triangular norm with four finger biometric modalities was utilized by (Peng *et al.*, 2014). They proposed a multimodal biometric authentication system that combines finger vein, finger

print, finger shape, and knuckle print features of a finger. Their experimental results show that the score level fusion approach achieve slower error rates. The fusion of palm print and palm vein images at the matching score level was done (Zhang *et al.*, 2011) in order to increase the Genuine Acceptance Rate of the biometric system. The palm vein and signature modalities are fused at the feature level (Soliman *et al.*, 2012) and they have discrete cosine transform for dimensionality reduction of feature vectors. The authors utilized morphological operations and Scale invariant feature transform for extracting features from the palm vein and signature images. The fusion of knuckle print, finger geometry and palm print at decision level was carried out by Zhu and Zhang (2010). They have used logical AND rule to fuse the features to improve the accuracy of the system.

A multimodal biometric system based on finger vein and dorsal vein of the hand is proposed here. The vein biometrics has its own merits such as: Universality and uniqueness. The vein is beneath the skin, so it is very difficult to forge. Hence, the recognition technology based on vein features becomes a current emerging direction of biometrics. A wide line detector for extracting the precise width information of the finger vein was presented (Huang *et al.*, 2010) in order to improve the information of the extracted feature from the low quality image. The distortion caused by variance of the finger

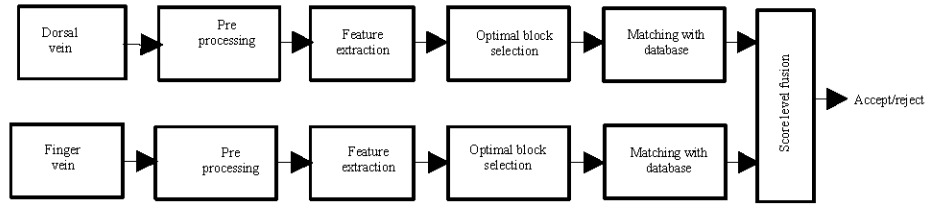


Fig. 1: Block diagram of the proposed method

pose is eliminated by a new pattern normalization method. By means of a simple modified webcam. Distler *et al.* (2011) have proposed a low cost hand vein based biometric recognition system. A blob removal algorithm is introduced by them that makes the results of the segmentation attractive and uses a modified version of Hausdorff distance for feature matching and recognition purposes. The statistical processing of hand vein patterns has been proposed by Yuksel *et al.* (2011). A combination of geometric and appearance-based techniques were used by them. Their technique gave a superior identification performance on the database. Finger vein based biometrics for personal identification has been presented by Yang and Shi (2012) and Wu and Liu (2011). They have addressed the problems of the finger vein region of interest localization, vein ridge enhancement and vein restoration for recognition. A personal verification approach using palm vein patterns based on modified two directional two-dimensional linear discriminant analysis was proposed by Lee (2015).

On the other hand, vein based biometric system also face many problems during the extraction of vein features. Most commonly occurred problems are: degradation unable to extract pixels and invisibility of vein features. By these problems, it is very challenging to extract the required vein features. Hence in this study, we introduce a new approach in order to overcome the above problems. Here, we suggest a method for optimal block selection from finger and dorsal hand vein patterns for multi-modal biometric recognition.

At first, input images are preprocessed in order to make them more suitable to extract the necessary features. In hand vein extraction process, an automatic thresholding method is used to extract veins from hand vein and in finger vein extraction process, the hyper analytic wavelet transform (Adam *et al.*, 2007) and pixel frequency table method are used. In our proposed work, firefly algorithm is used for optimal block selection from finger and hand vein patterns. In our proposed work, the feature extracted vein image is divided into blocks and each individual block has more pixels. The fitness value is measured in these blocks by means of pixels. Wherever, the fitness value is high, the vein is present and that block

is selected. In the recognition phase, the test sample feature is matched with the features stored in the database in order to find whether the input images are matched with the database.

MATERIALS AND METHODS

The block diagram of the proposed method is shown in Fig. 1. Extraction of the most significant features from the input traits is essential for efficient multimodal recognition. Here the optimal block is selected from the primarily extracted vein images using firefly algorithm. Initially, the input vein images are preprocessed so as to extract the required features. Automatic thresholding technique is used to extract features from dorsal hand vein images and hyper analytic wavelet transform and pixel frequency table method are used to extract features from finger vein images. From these extracted vein images optimal blocks are selected to extract the most significant features for matching.

Optimal block selection: The most significant features are extracted by selecting optimum blocks from the primarily extracted features of vein images. Here this process is carried out by using a meta-heuristic algorithm, called firefly algorithm which is motivated by the flashing behavior of fireflies. The Firefly Algorithm is a population-based method for finding the global optimal solution based on swarm intelligence and enquiring the foraging behavior of fireflies. The important function of the firefly's flash isto operate as an indication technique in order to catch the attention of other fireflies. Steps of block selection using Firefly algorithm is described as follows:

- Get the feature extracted image
- Split the image into blocks so that each block has different values of pixels
- Each pixel is assigned to a random value
- The fitness value is measured in these blocks' pixels and it is done using euclidian distance measure calculation
- The fitness value is used to analyze the quality of vein in each block. Wherever, the fitness value is high that block is selected

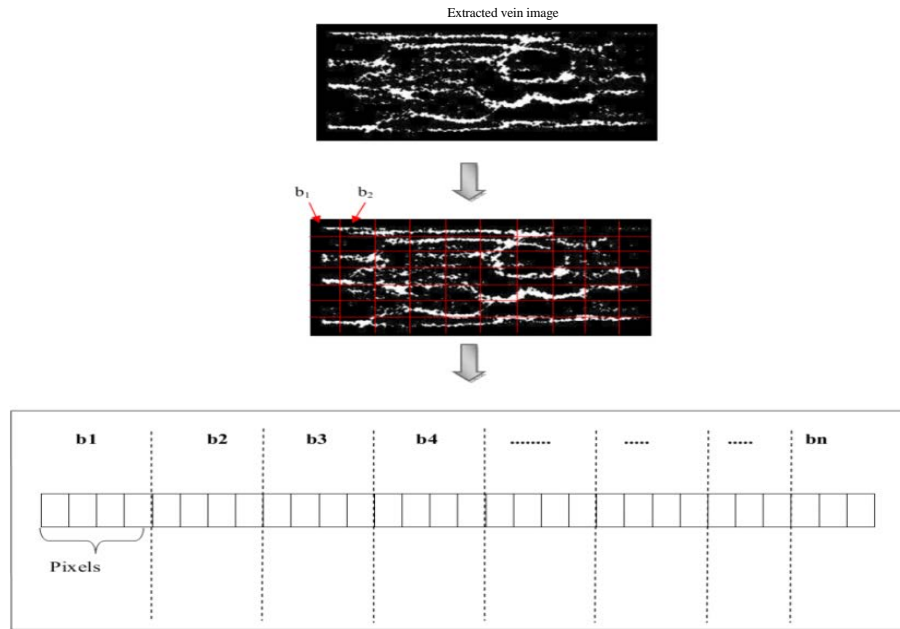


Fig. 2: Split block using grid form

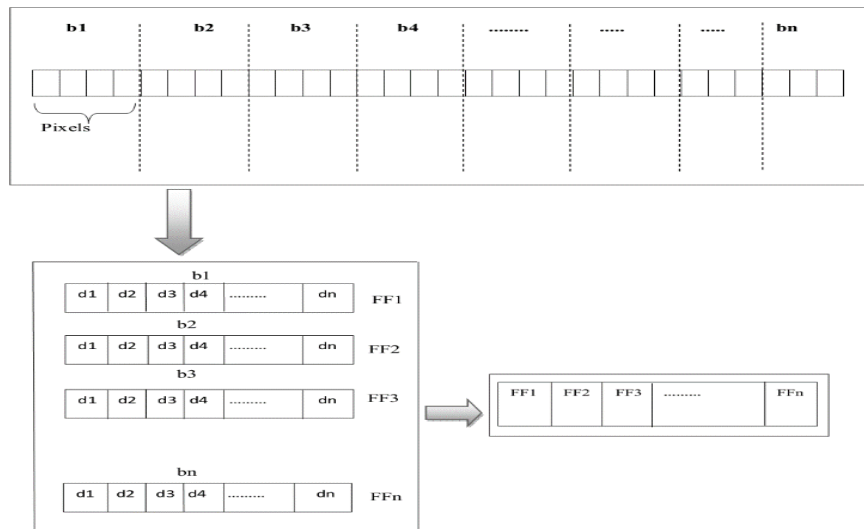


Fig. 3: Block selection with pixel

The above process is explained in detail as follows: At first, the primarily extracted features of the vein image is partitioned into different blocks. Each block has different number of pixels and they are assigned to random values. Figure 2 illustrates the block splitting of the feature extracted vein images.

Then, the fitness value is measured in these blocks from the pixels individually and it is done by Euclidian

distance calculation. The fitness value is calculated in each pixel, then it is compared with all the fitness values of every block. The block with high fitness value contains the maximum number of vein pixels and that block is selected as the optimal block. The block selection process in illustrated in Fig. 3.

Then firefly training process is carried out to select the features for further processing. Figure 4 illustrates the

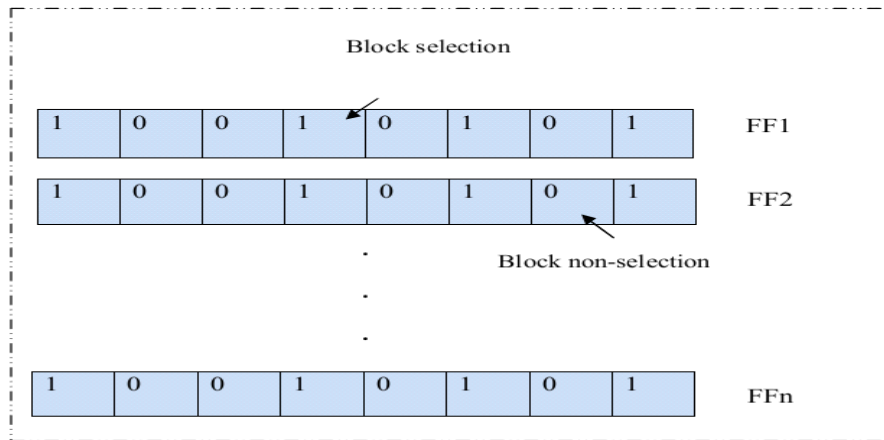


Fig. 4: Sample firefly training generation process

firefly attributes which contains ‘1’s’ and ‘0’s’, where ‘1’s’ represents the block selection and ‘0’s’ represents block non-selection.

In this way, we have developed a modified dataset from the training dataset for the fitness selection process. The modified dataset contains only identified attributes (‘1’s’). This is created based on the firefly training and this dataset is used for classification.

Fuzzy score level fusion: After extracting the necessary features and selecting optimal blocks from the dorsal hand vein and finger vein images, the fusion of them is done at the score level using fuzzy logic. In the recognition phase, we computed the matching score of vein images using the Euclidean distance measure. Let $d_t = (d_{t1}, d_{t2}, \dots, d_{tn})$ is the feature vector of the trained dorsal vein images, $d_r = (d_{r1}, d_{r2}, \dots, d_{rn})$ is the feature vector of the test dorsal vein images, $f_t = (f_{t1}, f_{t2}, \dots, f_{tn})$ be the feature vector of trained finger vein images and $f_r = (f_{r1}, f_{r2}, \dots, f_{rn})$ be the feature vector of test finger vein images. The corresponding score values of the vein images can be computed based on the Euclidean distance using the following formulations.

$$S_1 = D(d_t, d_r) = \sqrt{(d_{t1} - d_{r1})^2 + (d_{t2} - d_{r2})^2 + \dots + (d_{tn} - d_{rn})^2} \tag{1}$$

$$= \sqrt{\sum_{i=1}^n (d_{ti} - d_{ri})^2}$$

$$S_2 = D(f_t, f_r) = \sqrt{(f_{t1} - f_{r1})^2 + (f_{t2} - f_{r2})^2 + \dots + (f_{tn} - f_{rn})^2} \tag{2}$$

$$= \sqrt{\sum_{i=1}^n (f_{ti} - f_{ri})^2}$$

After getting the score values of input images, the final score value will be computed to identify that whether the person is authorized or not. To combine the score values, we have used fuzzy logic that provides the final score value of the input images and it is used to recognize a person. Defining the fuzzy if-then rules serves as the major significant module in any fuzzy system. Here, two input variables such as S1 and S2 and one output variable are used. The rule defined in the rule base is: IF S1 value is High (H) and S2 value is High (H), then the output is recognized.

RESULTS AND DISCUSSION

The experimental results of the proposed method, for extracting the finger and dorsal vein-based multi-modal biometric recognition is discussed here. The database utilized for our experimentation is taken from standard data bases (hand vein database, Finger vein database) of hand vein and finger vein images. For experimental evaluation, we have taken False Acceptance Rate, False Rejection Rate and Accuracy as evaluation metrics shown in Fig. 6 and 7.

The performance graph of FAR, FRR, ROC and Accuracy curve is plotted in Fig. 8. Here, the proposed technique is compared with fuzzy existing method of vein extraction for multi-modal biometric recognition. From the graph shown in Fig. 8a and b, we observe that the FAR and FRR of the proposed system are lower compared with existing fuzzy method. Also, from Fig. 8c, we say that the proposed method achieves high accuracy of around 90% at the threshold of 0.2. The Receiver operating Characteristics (ROC) curve provides the relation between the FAR and FRR. From the ROC graph, Fig. 8d, we can see that the Equal Error Rate (EER) of the proposed

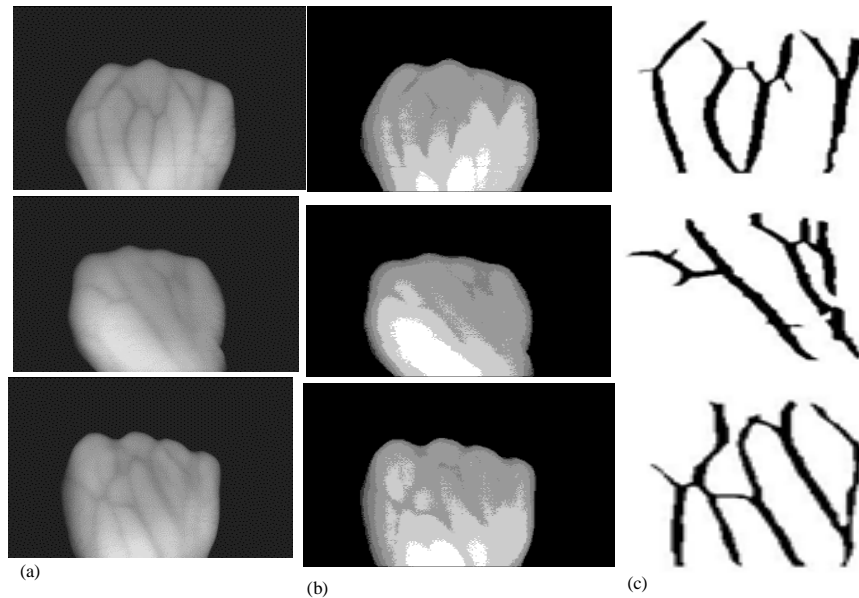


Fig. 6: Hand vein output at various stages: a) Input images; b) Preprocessed images and c) Extracted vein images

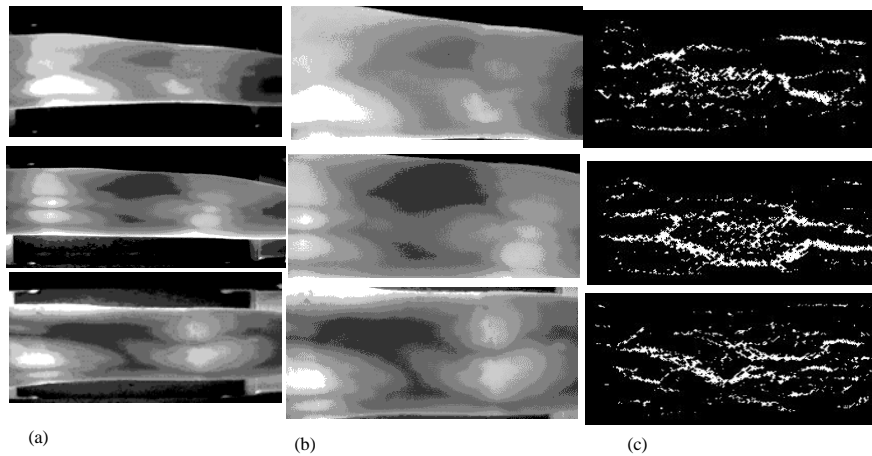


Fig. 7: Finger vein output at various stages: a) Input images; b) Preprocessed images and c) Extracted vein images

system is lower value as 0.1, compared with the existing techniques. By analyzing the above results, our proposed method of optimal block selection from finger and dorsal hand vein patterns for multi-modal biometric recognition shows good performance.

In Table 1, the comparative analysis of the optimal block selection from finger and dorsal hand vein patterns for multi-modal biometric recognition and the existing techniques. In the previous method, the equal error rate for 25 people is making available at 13%, whereas in our proposed method optimal block selection from finger and hand vein patterns for multi-modal

Table 1: Comparative analysis

Methodologies	EER	
	25 users	50 users
Sum rule based score level fusion	0.16	0.14
Fuzzy score level fusion with hyper analytic wavelet transform	0.13	0.12
Fuzzy score level fusion with genetic algorithm	0.11	0.102
Proposed fuzzy score level fusion with firefly algorithm	0.1	0.093

biometric recognition of fuzzy genetic and fuzzy firefly has achieved 11 and 10%. Due to the optimal block selection using firefly algorithm used which extracts only

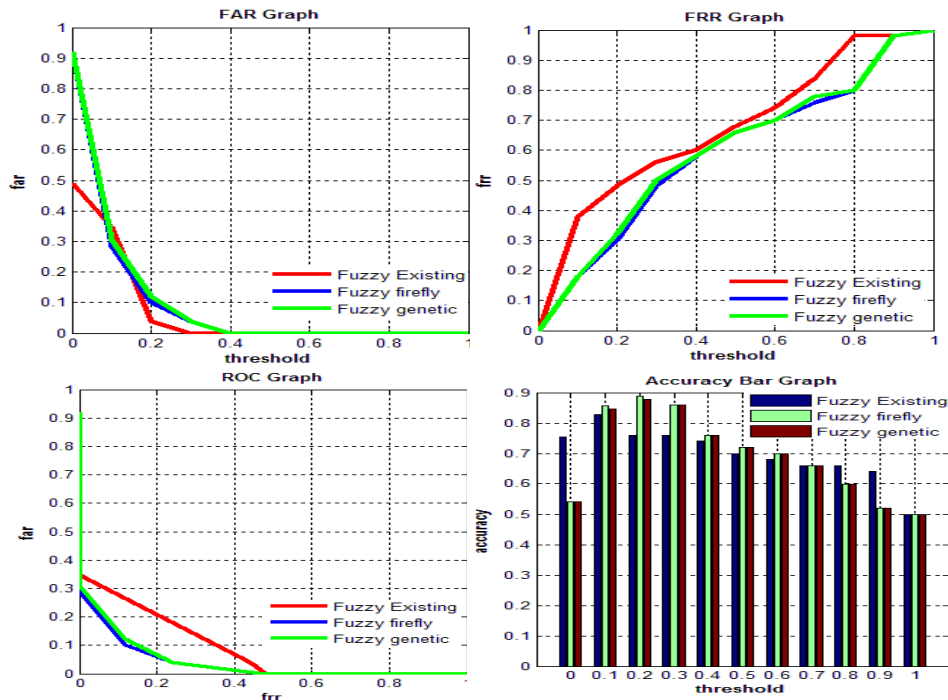


Fig. 8: Performance analysis of the proposed system: a) Plot of FAR; b) Plot of FRR; c) Plot of ROC and d) Plot of accuracy

the maximum vein features presented in the block clearly, the performance of the proposed method is improved.

CONCLUSION

We have developed multi-modal biometric recognition technique using dorsal vein and finger vein of the hand. The input images were preprocessed in order to make the images more suitable to extract the relevant features. The features are extracted from the dorsal and finger vein images using automatic thresholding technique and hyper analytic wavelet transform and pixel frequency table method respectively. From these extracted vein images optimal blocks are selected using firefly algorithm. The fitness value was measured in these blocks by means of pixels and selected blocks depend upon the fitness values. In recognition phase, test sample feature was matched with the features stored in the database using fuzzy score level fusion, to found whether, the input images were matched with the database. Finally, the experimental results show that there is an improved performance of the proposed system in terms of low FAR and FRR.

REFERENCES

Adam, J., C. Nafomita, J.M. Boucher and A. Isar, 2007. A new implementation of the hyperanalytic wavelet transform. Proceeding of the 2007 International Symposium on Signals, Circuits and Systems, July 13-14, 2007, IEEE, Timisoara, Romania, ISBN:1-4244-0968-3, pp: 1-4.

Chin, Y.J., T.S. Ong, A.B.J. Teoh and K.O.M. Goh, 2014. Integrated biometrics template protection technique based on fingerprint and palmprint feature-level fusion. *Inf. Fusion*, 18: 161-174.

Distler, M., S.H.N. Jensen, N.G. Myrtue, C. Petitimbret and K. Nasrollahi et al., 2011. Low-cost hand vein pattern recognition. Proceeding of the IEEE International Conference on Signal and Information Processing, November 22-22, 2016, CSIP, Alborg, Denmark, pp: 1-4.

Hammandlu, M., J. Grover, A. Gureja and H.M. Gupta, 2011. Score level fusion of multimodal biometrics using triangular norms. *Pattern Recognit. Lett.*, 32: 1843-1850.

- Huang, B., Y. Dai, R. Li, D. Tang and W. Li, 2010. Finger-vein authentication based on wide line detector and pattern normalization. Proceeding of the 2010 20th International Conference on Pattern Recognition, August 23-26, 2010, IEEE, Beijing, China, ISBN:978-1-4244-7541-4, pp: 1269-1272.
- Jain, A.K., A. Ross and S. Prabhakar, 2004. An introduction to biometric recognition. IEEE Trans. Circuits Syst. Video Technol., 14: 4-20.
- Kaur, M., 2012. K-Nearest neighbor classification approach for face and fingerprint at feature level fusion. Int. J. Comput. Appl., 60: 13-17.
- Lee, Y.P., 2015. Palm vein recognition based on a modified (2D)2 LDA. Signal Image Video Process., 9: 229-242.
- Peng, J., E.A.A.A. Latif, Q. Li and X. Niu, 2014. Multimodal biometric authentication based on score level fusion of finger biometrics. Opt. Int. J. Light Electron. Opt., 125: 6891-6897.
- Raghavendra, R., M. Imran, A. Rao and G.H. Kumar, 2010. Multimodal biometrics: Analysis of handvein and palmprint combination used for person verification. Proceeding of the 2010 3rd International Conference on Emerging Trends in Engineering and Technology, November 19-21, 2010, IEEE, Mysore, India, ISBN:978-1-4244-8481-2, pp: 526-530.
- Ross, A. and A.K. Jain, 2003. Information fusion in biometrics. Pattern Recog. Lett., 24: 2115-2125.
- Ross, A. and A.K. Jain, 2004. Multimodal biometrics: An overview. Proceedings of the 12th European Signal Processing Conference, September 6-10, 2004, Vienna, Austria, pp: 1221-1224.
- Saleh, I.A. and L.M. Alzoubiady, 2014. Decision level fusion of Iris and signature biometrics for personal identification using ant colony optimization. Int. J. Eng. Innovative Technol., 3: 35-42.
- Sim, H.M., H. Asmuni, R. Hassan and R.M. Othman, 2014. Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images. Expert Syst. Appl., 41: 5390-5404.
- Soliman, H., A.S. Mohamed and A. Atwan, 2012. Feature level fusion of palm veins and signature biometrics. Int. J. Video Image Process. Network Secur. Ijvipns Ijens, 12: 28-39.
- Wu, J.D. and C.T. Liu, 2011. Finger-vein pattern identification using SVM and neural network technique. Expert Syst. Appl., 38: 14284-14289.
- Yang, J. and Y. Shi, 2012. Finger-vein ROI localization and vein ridge enhancement. Pattern Recognit. Lett., 33: 1569-1579.
- Yuksel, A., L. Akarun and B. Sankur, 2011. Hand vein biometry based on geometry and appearance methods. IET Comput. Vision, 5: 398-406.
- Zhang, D., Z. Guo, G. Lu, L. Zhang, Y. Liu and W. Zuo, 2011. Online joint palmprint and palmvein verification. Expert Syst. Appl., 38: 2621-2631.
- Zhu, L.Q. and S.Y. Zhang, 2010. Multimodal biometric identification system based on finger geometry, knuckle print and palm print. Pattern Recognit. Lett., 31: 1641-1649.