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GABOR FILTER-BASED FEATURE LEVEL FUSION OF PALM VEIN AND FINGERPRINT RECOGNITION SYSTEM

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ABSTRACT

Biometrics fusion entails using two or more physiological or behavioral traits to improve the performance of biometric systems. Most existing works investigated effects of fusion of multiple features at image, matching score and decision levels for biometric recognition systems. In this paper, an efficient Gabor Filter-based Feature Level (GFFL) fusion of palm vein and fingerprint recognition system was developed. Four hundred images consisting of five palm vein and fingerprint images each across 40 individuals were acquired. Two hundred and ten images were used for training while the remaining 190 images were used for testing purposes. These images were preprocessed using histogram equalization while the extraction of features from the region of interest of the images was carried out using Gabor filter algorithm. The extracted features were fused through concatenation and subjected to Fisher Linear Discriminant Analysis for dimensionality reduction. Euclidean distance was used in the classification of the images. The system was implemented using Matrix Laboratory 7.1. The performance of the developed feature level fusion system was evaluated at varying thresholds (0.2 - 0.8) by comparing it with matching score level fusion biometric system as well as existing Fingerprint and Palm vein unimodal systems based on recognition accuracy, sensitivity, specificity and false positive rate. The evaluation results revealed that the developed GFFL fusion of palm vein and fingerprint recognition system outperformed the existing unimodal systems in terms of the aforementioned metrics. The system could be adopted as effective recognition system in access control systems or any other related systems.

KEYWORDS: Recognition system, Feature level, Fusion, Palm vein, Fingerprint, Gabor Filter.

1. INTRODUCTION

Biometric refers to the identification (or verification) of an individual (or a claimed identity) by using certain physiological or behavioural traits associated with the person. Biometric systems make use of hand, iris, retina, palm, facial thermograms, signature or voiceprint to verify a person's identity (Jain *et al.*, 2010). Among the various biometric characteristics, the human hand is the oldest and the most successful form of biometric technology (Hand-based biometrics, 2003). The rich sets of biometric features that can be extracted from hand include: fingerprint, hand geometry, palmprint and palm vein. These properties are stable and reliable. Fingerprint biometrics uses the features of fingerprint, that is, ridges and minutia points (Ankur and Vikas, 2013). The palm region has a very rich texture and is much larger than the fingertip region. Therefore, the research possibilities for palm features extraction are very extensive. From application point of view, forensic and non-forensic fingerprint recognition can be distinguished.

Also, Palm has a broad and complicated vascular pattern and thus contains a wealth of differentiating features for personal identification. As the blood vessels are believed to be "hard-wired" into the body at birth, even twins have unique vein pattern. The pattern of blood veins is unique to every individual; this does not change significantly from the age of ten (Vein recognition in Europe, 2004). External conditions like grease and dirt, wear and tear, dry and wet hands do not affect the vein structure. The properties of stability, uniqueness, and spoof-resilient make hand vein a potentially good biometrics for personal authentication. The benefits of palm vein technique are that it is difficult to forge, highly accurate, capable of one to one (1:1) and one to many (1: many) training, contactless, hygienic and non-invasive. However, biometric systems based on a single source of information (unimodal systems) suffer from limitations; they have to contend with a variety of problems such as noisy data, intra-class variation, restricted degree of freedom, non-universality, spoof attack, and unacceptable error rates. A robust identification system may require fusion of several modalities (multimodal system); ambiguities in one modality caused by illumination problem of fingerprint may be compensated by another modality like vein features. Multimodal identification techniques hence promise to perform better than any one of its individual components. Biometrics fusion involves the use of two or more physiological or behavioural traits to improve the accuracy and performance of biometric systems. Fusion can be achieved at Image level, Feature level, Matching score level or Decision level with different fusion models (Jain *et al*., 2010). Fusion at the matching score level means involves combining the matching scores emanating from different biometric systems in order to get classification results. Fusion at the matching score level draws more attention due to the easier actualization, and its main fusion methods include sum rule, decision trees, linear discriminant and so on (Ross and Jain, 2003). Fusion at the decision level is easiest, because classification results from different biometric systems are integrated to make the final classification using appropriate rules such as OR rule and AND rule. Fusion at the feature extraction level is to combine biometric features from different biometric systems, and the corresponding original feature vectors are integrated into one higher-dimensional feature vector. Multimodal biometric system provides optimal False Acceptance Rate (FAR) and False Rejection Rate (FRR), which consequently improves system accuracy and reliability.

Multibiometric systems have succeeded in minimizing some of the drawbacks of the uni-biometric systems by integrating the multiple sources of information (Sasidhar *et al.*, 2010). However, it has been observed that a multibiometric system that integrates information at an earlier stage of processing is expected to provide more accurate results than the systems that integrate information at later stage(s), because of the availability of richer information. Since the feature set contains much richer information on the source data than any of the later levels (the matching score or decision), fusion at the feature level is expected to provide better recognition performances. Researchers have worked on different levels of fusion; however, fusion at feature level is a relatively understudied problem. Generally, it is noticed that fusion at feature level is relatively difficult to achieve because multiple modalities may have incompatible feature sets and relating different feature spaces may be very difficult to achieve (Rattani *et al.*, 2007). However, the unique features of palm vein and fingerprint technologies in personal recognition cannot be overemphasized. These include (i) High level of accuracy due to uniqueness and complexity of the vein and fingerprint pattern and (ii) Both fingerprint and palm vein have stable features. Hence, in this paper, a Gabor filter-based feature level fusion of palm vein and fingerprints recognition system was developed.

2. RELATED WORKS

A number of studies showing the advantages of multimodal biometrics fusion were reported in literature. Brunelli and Falavigna (1995) used hyperbolic tangent (tanh) for normalization and weighted geometric average for fusion of voice and face biometrics; a hierarchical combination scheme for a multimodal identification system was proposed. Also, Kittler and Duin (2002) experimented several fusion techniques for face and voice biometrics, which include sum, product, minimum, median, and maximum rules. The results of the experiment revealed that sum rule outperformed other contemporary rules; it was also reported that the sum rule was not significantly affected by the probability estimation errors. Ross and Jain (2003) combined face, fingerprint and hand geometry biometrics with sum, decision tree and linear discriminant-based methods and reported that sum rule performed better than others.

As an effort to increasing the accuracy of biometric systems, Singh *et al.* (2004) fused infrared-based face recognition with visible based face recognition at feature level, reporting a substantial improvement in recognition performance as compared to matching individual sensor modalities. Also, Ross and Govindarajan (2005) proposed a method for the fusion of hand and face biometrics at feature extraction level while Ziou and Bhanu (2006) proposed a multibiometric system based on the fusion of face features with gait features at feature level. Furthermore, Deepamalar and Madheswaran (2010) developed a palm vein recognition system using multimodal features and Adaptive sequential floating forward search (ASFFS) neural network; the effects of fusion of multiple features at various levels were demonstrated. Also, a team of researchers built a multimodal identification system based on fusion of the palm print and palm vein at image level using integrated line preserving and contrast enhancement fusion method (Wang *et al.*, 2008). Similarly, David *et al.* (2011) combined the palm print and palm vein. The method that is used to extract the vein is matching filter. The EER to the system is 0.3091%. However, they fused the palm print with palm vein features to evaluate the system.

Furthermore, Hassan *et al.* (2012) developed a multimodal biometric identification system with emphasis on feature level fusion of palm veins and signature; feature of both modalities were extracted using morphological operations and scale invariant features transform algorithm. Also, Omidiora *et al.* (2008) established that physiological (Palm vein) and behavioural (signature) characteristics are unstable for identification since they are emotional-based; signature of same individual can vary and also depends on the emotional status of the individual.

3. MATERIALS AND METHODS

In order to develop an efficient method to extract features from the sub-images of fingerprint and palm vein, Histogram equalization and Gabor filter algorithm were used at pre-processing and feature extraction levels respectively; fusion was achieved by concatenating the two features. Fisher linear discriminant analysis was employed in dimensionality reduction of the extracted features. The parameters used to measure and evaluate the overall performance of the developed system are recognition accuracy, recognition time, sensitivity, specificity and false rejection rate.

3.1 Stages of Palm vein and fingerprint Recognition System Development

The stages explored in developing palm vein and fingerprint recognition system are: (i) Palm vein and Fingerprint Acquisition; (ii) Location of Region of Interest (ROI); (iii) Palm vein and fingerprint Pre-processing; (iv) Texture Feature Extraction Based on Gabor Filter; (v) Feature Concatenation and Dimensionality Reduction; (vi) Training and Classification; and (vii) Recognition/Testing.

3.1.1 Image acquisition

Palm vein pattern is not easily seen in visible light and thus cannot be captured by ordinary camera. Therefore, near infrared CCD sensitive camera and fingerprint reader were used to capture forty (40) individuals' palm vein and fingerprint respectively. During the image acquisition process, the users are required to stretch their palm straight on the platform of the scanner. The images were acquired in 256RGB colours (8 bits per channel) format, with resolution of 640 x 480 pixels and 260 x 300 pixels for palm vein and fingerprint respectively. The three colour components are important in the pre-processing stage as it can distinguish the background, rings and shadow from the hand images. The colour distinction helped to trace the hand more accurately and reliably. For each individual, five palm vein and fingerprint images were captured (40*5*2 equals 400 images). Two hundred and ten (210) images (105 palm vein and 105 fingerprints) were used for training the system while one hundred and ninety (190) images were used to test the system and finally saved in jpeg format.

3.1.2 Locate the Region of Interest (ROI)

After image capturing, a small area (71*71 pixels) of fingerprint and palm vein image was located as the Region of Interest (ROI) to extract the features and to compare different palms and fingers. Using the features within ROI for recognition can improve the computational efficiency significantly. Further, because this ROI normalized coordinate based on the palm boundaries, the recognition errors caused by users who slightly rotated or shifted his/her hands were minimized.

3.1.3 Palm vein and fingerprint pre-processing

Before feature extraction, it is necessary to ensure noise reduction, contrast enhancement and elimination of the variations caused by rotation and translation. The technique being used for both fingerprint and palm vein enhancement is histogram equalization which usually increases the global contrast of an image.

3.1.4 Fingerprint and palm vein feature extraction based on Gabor Filter algorithm

This is the process of using the most important information of the cropped palm vein and fingerprint images for classification purpose. The feature extraction was carried out using Gabor filter (a band pass filter) which is characterized by orientation-selective and frequency-selective features.

3.1.5 Feature concatenation and dimensionality reduction

The feature level fusion is performed by concatenating the two feature pointsets (SP_{norm} and SS_{norm}). These results in a fused feature pointsetconcat= (SPlnorm, SP2norm, SPnnorm,…, SSlnorm, SS2norm, SSmnorm). Fisher linear discriminant analysis was used for dimensionality reduction.

3.1.6 Training and classification stage

Three images per person from each modality (fingerprint and palm vein), two hundreds and ten (210) images were used to train the fused system out of which one hundred and five (105) images were used to train each unimodal system. The training was done for each of the Unimodal sub-system and for both traits. Computed fisherpalms (fishervectors) were ordered at this stage to form fisherspace. The centred training image vectors were projected onto the fisherpalm space. Euclidean distance is used as classifier. Palm vein and fingerprint recognition classifier takes place by setting a threshold value for the system. Threshold is the acceptance or rejection of a template match which is dependent on the matching score falling above or below the threshold. The threshold was adjustable within the recognition system. The performance of the classifier was tested by using Receiver Operating Characteristic (ROC) which is a metric used to check the quality of classifiers. For each class of classifier, ROC applies threshold values across the interval of 0 to 1. The ROC curve describes the performance of a model across the entire range of classification thresholds.

3.2 Performance Measures of the Developed System

The performance of trained and recognized subjects was measured against recognition accuracy, total training time, sensitivity, specificity and false positive rate. The performances of the developed system were evaluated based on the following metrics:

False Positive Rate = $\frac{FP}{FP+TP}$;

Sensitivity = $\frac{TP}{TP+FN}$;

Specificity = $\frac{TN}{FP+TN}$;

Overall Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

3.3 Palm vein and Fingerprint Recognition /Testing Stage

Testing and recognition of the developed system were performed using two training images per individual; five untrained subjects were used as imposters. Total numbers of 190 images were used to test the developed system. Testing was conducted by using the system as unimodal for each trait and as multimodal as shown in Figure 1. The performance of the system was evaluated and compared with developed fusion at matching score level and each intrinsic unimodal systems. Two modules were employed as enumerated hereunder:

(i) Feature level fusion-based palm vein and fingerprint recognition module

(ii) Matching score level fusion-based palm vein and fingerprint recognition module

3.3.1 Unimodal recognition module

As depicted in Figure 1, the developed multimodal system has ability to perform as unimodal system. The system GUI allows the user to switch among the modes of the system and load fingerprint or palm vein images from the database; pre-processing, feature extraction, matching score, training and testing activities would be done as a biometric system and then visualize the result of each step of unimodal recognition system. The identification process in unimodal recognition system consists of matching the generated code of the input image with all codes stored in the database. The performance of each unimodal system (palm vein and fingerprint) was evaluated and compared with the developed system (multimodal).

3.3.2 Multimodal recognition module

Two algorithms were implemented for the multimodal system; first is the system that fuses the evidences from palm vein and fingerprint at feature level and second is the system that fuses the evidence from palm vein and fingerprint at matching score level. The GUI allows the user to switch between the two systems. Both verification and identification processes were implemented. Performance comparison between developed system and fusion at matching score level was carried out and recorded.

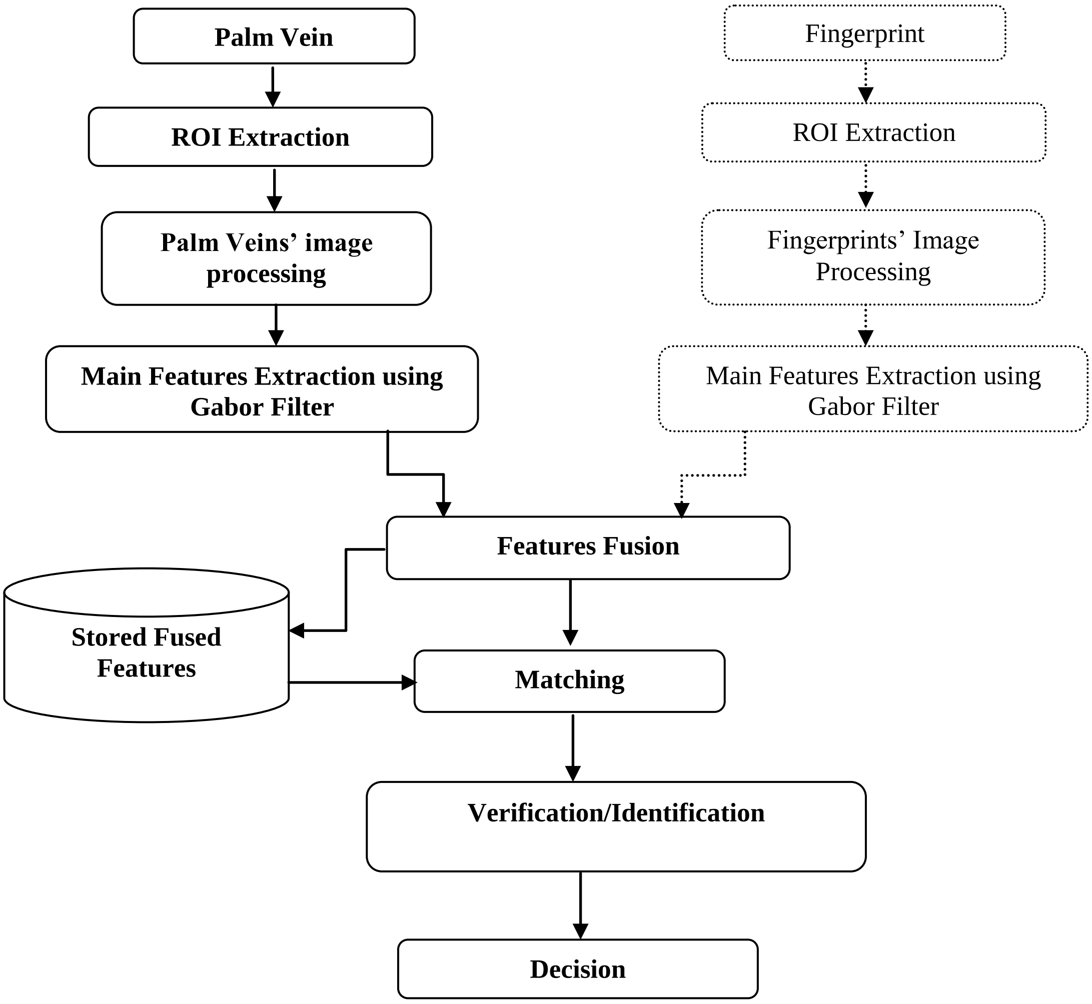

Figure 1: Framework of the developed system.

4. RESULTS AND DISCUSSION

The results of evaluation of the developed system (feature level fusion) with fusion at matching score level and individual unimodal systems were generated and reported hereunder.

4.1 Results of Evaluation of Unimodal Palm Vein Recognition System

The performance of the palm vein recognition system was evaluated using the following parameters: Training time, Recognition rates, Recognition accuracy and Number of unidentified images. The results are presented in Table 1(a) at varying threshold values 0.2, 0.4, 0.6 and 0.8. It was observed that the accuracy and performance of the palm vein recognition system improves at higher threshold value as threshold increases. Recognition accuracy (83.2% - 91.6%) and sensitivity of the system (88.1% - 94.2%) were recorded at threshold value (0.2 - 0.8). It was also noticed that FPR reduces (14.8% - 5.6%) as threshold value increases (0.2– 0.8).

The performance of the fingerprint recognition system was evaluated using the following parameters: Training time, Recognition rates, Recognition accuracy and Number of unidentified images. The results are presented in Table 1 (b) at varying threshold values 0.2, 0.4, 0.6 and 0.8. It was observed that the accuracy and performance of the palm vein recognition system improves at higher threshold value as threshold increases. Recognition accuracy (82.47% - 91.58%) and sensitivity of the system (89.83% - 92.96%) were recorded at threshold value (0.2 - 0.8). It was also noticed that FPR reduces (14.52% - 5.71%) as threshold value increases (0.2– 0.8).

It was observed from Tables 1(a) and 1(b) that average recognition time of palm vein (5.20 - 5.26secs) is higher than that of fingerprint recognition (4.43 – 4.48secs) at all the threshold values. This is further corroborating the fact that complexity inherent in palm vein texture (in term of pixel level) is more than that of fingerprint. This contributed to the higher accuracy in all the thresholds considered when palm vein was evaluated with fingerprint system.

Table 1(a): Parameters Considered for the Palm Vein Recognition System.

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Average Recognition Time (Sec)
0.2	52	9	7	27	14.754	88.136	75.000	83.158	5.200
0.4	60	6	4	25	9.091	93.750	80.645	89.526	5.190
0.6	64	5	4	22	7.246	94.118	81.481	90.526	5.224
0.8	67	4	4	20	5.634	94.366	83.333	91.579	5.259

Table 1(b): Parameters Considered for the Fingerprint Recognition System.

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Average Recognition Time (Sec)
0.2	53	9	6	26	14.516	89.831	74.286	82.474	4.429
0.4	59	8	3	25	11.940	95.161	75.758	88.421	4.421

0.6	61	6	4	25	8.955	93.842	80.645	89.583	4.450
0.8	66	4	5	20	5.714	92.958	83.333	90.526	4.480

4.2 Results of Evaluation of Multimodal Biometric Recognition System (Feature Level Fusion of Palm Vein and Fingerprint)

Multimodal system was empirically considered using the same threshold range. The performance of the developed feature level fusion of palm vein and fingerprint recognition system was also evaluated using the following parameters: training time, recognition rates, recognition accuracy and number of unidentified images. The results are as presented in Table 2 at varying threshold values 0.2, 0.4, 0.6 and 0.8. It was observed that as threshold value increases, the average recognition time increases 10.82; 10.80; 10.87; 10.94 sec (except at threshold value 0.4 where 10.80 was recorded), True Positive (TP) increases 44; 51; 58; 60 while False Positive (FP) 8; 6; 5; 4, and True Negative (TN) 37; 35; 30; 29 reduce. It could be deduced that the developed multimodal biometric system (feature level fusion of palm vein and fingerprint) demonstrated an improved performance over the two unimodal systems (pam vein and fingerprint) with respect to each of the threshold considered as observed in Tables 1 and 2. Feature Level Fusion gave higher recognition accuracy (93.68%), sensitivity (98.36%), and specificity (85.29%) against palm vein and fingerprint unimodal systems of Recognition accuracy (91.58% and 90.53%), sensitivity (92.96% and 94.37%), and specificity (83.33% and 83.3%).

Table 2: Parameters Considered for the Multimodal Recognition System (Feature level fusion).

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Average Recognition Time (Sec)
0.2	44	8	6	37	15.380	88.000	82.222	85.263	10.819
0.4	51	6	3	35	10.530	94.444	85.366	90.526	10.800
0.6	58	5	2	30	7.940	96.667	85.714	92.632	10.871
0.8	60	5	1	29	7.690	98.361	85.294	93.684	10.943

4.3 Results of Evaluation of Feature Level Fusion and Matching Score Level Fusion

The comparisons of the developed system and matching score level fusion were based on false positive rate, sensitivity (True positive rate), specificity (True negative rate), recognition accuracy, average recognition time and total training time. Results were generated based on TP, False Negative (FN), FP, and TN. As shown in Table 3, the following were observed: At threshold value 0.8, Feature Level Fusion gave higher Recognition accuracy (93.68%), sensitivity (98.36%), and specificity (85.29%) against Matching Score Level Fusion of

Recognition accuracy (93.53%), sensitivity (93.65%), and specificity (84.4%). However, higher false positive rate of matching score level fusion (7.81) was observed over feature level fusion (7.69); also higher average recognition time was observed in feature level fusion (10.94secs) compared to matching score level fusion (10.90secs). Overall, feature level fusion gave better performance than matching score level fusion because only extracted features are richer in useful textual information that is more useful for personal identification and verification than combining both traits at matching level, which fused only scores and not the textual information fusion.

Table 3: Comparison Results between Feature level fusion (FF) and matching score level fusion (FM).

Threshold	Total Number of Images used in Testing		False Positive Rate		Sensitivity (%)		Specificity (%)		Recognition Accuracy (%)		Average Recognition Time (Secs)	
	FF	FM	FF	FM	FF	FM	FF	FM	FF	FM	FF	FM
0.2	210	210	15.380	21.570	88.000	83.330	82.220	76.600	85.260	80.000	10.819	10.295
0.4	210	210	10.530	18.180	94.440	86.540	85.370	76.700	90.530	82.110	10.800	10.271
0.6	210	210	7.940	11.860	96.670	89.660	85.710	81.100	92.630	86.320	10.871	10.776
0.8	210	210	7.690	7.810	98.360	93.650	85.290	84.400	93.680	90.530	10.943	10.895

5. CONCLUSION AND FUTURE WORK

Multimodal biometric is popular due to its performance and its effectiveness in personal identification, verification and access control. In this paper, fusion at feature extraction level was studied. The development of the multimodal recognition system was separated into four major sections: image acquisition and standardization, feature level fusion, dimensionality reduction as well as training and testing for recognition. The system performance evaluation carried out revealed the effectiveness and accuracy of multimodal feature level fusion over the unimodal and matching score level fusion. The results obtained could provide baseline information for researchers targeting fusion of palm vein and fingerprint in access control systems or other related systems. It is recommended that future work may be geared towards comparing the effect of structural based features with the global based features and evaluating the performance of other existing algorithms with the considered ones.

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