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OPTIMIZING SCORE AND DECISION FUSION IN PALM AND FINGER PRINTS USING PARETO OPTIMIZATION TECHNIQUES

M.Ramya 1, Mrs. P.S. Vijayalakshmi [2]

[1,2] Department of Computer Science KG college of Arts and Science , Coimbatore

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Abstract - *A multimodal biometric system integrates information from multiple biometric sources to compensate for the limitations in performance of each individual biometric system. Different approaches have been proposed in the literature for developing unimodal and multimodal biometric systems. Multi-biometric systems are developed by fusing different biometric features pertaining to various biometric modalities at different levels. Many researchers have shown that the multimodal systems outperform the unimodal systems, giving better discrimination of genuine from imposters. In existing system they we present multimodal systems at feature level and score level fusions using our already reported unimodal palm print and fingerprint identifiers. The unimodal finger- and palm print identification systems utilize directional energies of texture as features, extracted using contourlet transform. To improve the optimization in result it can propose the pareto-optimal search method in order to handle the top-k query in the high-dimension record set with that the nearest neighbor search is found and it is used to make dominant relationship between them while fusion. After that the scores of palm print and fingerprint images are multiplied together to produce a new set of values consisting of combined values of both the systems. Then the total number of generated score of test image corresponding to trained database obtained from that decision making will be done.*

1.INTRODUCTION

Multi-biometrics system can be developed by utilizing different approaches: (a) multi-sensor systems combine evidences of different sensors using a single trait, (b) multi-algorithm systems process single biometric modality using multiple algorithms, (c) multiinstance systems consolidate multiple instances of the same body trait, (d) multi-sample systems use multiple samples of same bio-metric modality using a single sensor, (e) multimodal systems are developed by fusing the information of different biometric traits of the individual to establish identity. Fusion at score level demands matching scores generated by comparing input test image with trained database. Feature vectors of palmprint and fingerprint are compared with their respective databases using normalized euclidean distance classifier to generate the matching scores. These scores contain less amount of information as compare to feature vectors. Before fusing scores together, scores should be normalized to a common scale. As normalized energy values are used in both palmprint and fingerprint systems to generate the scores, so generated scores are already on a common scale and hence eliminate the need of using any score normalization technique. Palm and finger scores are combined using two rules: Sum Rule and Product Rule

2. FUSION METHODOLOGY

2.1 Feature Extraction Level

The data obtained from each sensor is used to obtain a feature vector. Features extracted from one biometric trait are independent of those extracted from the other. These features are then combining to form one template.

2.2 Matching Scores Level

Each system provides a matching score indicating the proximity of the feature vector with the template vector. These scores can be combined to assert the veracity of the claimed identity.

2.3 Decision Level

Each sensor can capture multiple biometric data and the resulting feature vectors individually classified into the two classes–accept or reject. Score level fusion is commonly preferred in multimodal biometric systems because matching scores contain sufficient information to make genuine and impostor case distinguishable and they are relatively easy to obtain. Given a number of biometric systems, matching scores for a pre-specified number of users can be generated even with no knowledge of the underlying feature extraction and matching algorithms of each system. Therefore, combining information obtained from individual modalities using score level fusion seems both feasible and practical. Since the scores generated by a biometric system can be either similarity scores or distance scores, one needs to convert these scores into a same nature. Let X denotes these to raw matching scores from a specific matcher, and let $x \in X$. The normalized score of x is then denoted by x'. These normalization schemes can be used to both sum rule-based fusion and SVM- based fusion for improving accuracy.

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2.4 Min–Max Normalization

The normalization maps the raw matching scores to interval and retains the original distribution of matching scores except for a scaling factor. Given that max(X) and min(X) are the maximum and minimum values of the raw matching scores.

3. FEATURE LEVEL FUSION

Joint feature vector is matched with the already stored multimodal database in matching module that consists of Euclidian classifier. Depending upon the threshold, the decision module declares the result as genuine or impostor. Similarly, in case of unimodal identifiers, the extracted features are matched with respective database using a Euclidian classifier in matching module, followed by decision on the basis of selected threshold in the decision module. For feature level fusion of palmprint and fingerprint, feature vectors of palmprint and fingerprints are concatenated together to make combined feature vector similar to Kumar and Zhang. Let P = p1, p2, . . . · pm and F = f1, f2 . . . fn represent feature vectors containing the information extracted from palmprint and fingerprint, respectively. The objective is to combine these two feature sets after normalization in order to yield a joint feature vector (JFV). JFV is obtained by combining P and F feature sets. Problem of compatibility of feature sets is overcome inherently as feature vectors in case of both palm- and fingerprint identifiers consist of normalized energy values. Thus, need for normalizing feature sets is eliminated. One hundred and twenty-four different feature values of palmprint are concatenated with 60 different feature values of fingerprint to give a joint feature vector (JFV) of 184 feature values representing the same individual. JFVs are generated and stored in order to make multimodal database which is subsequently used for identification and verification purpose.

4. SCORE LEVEL FUSION

Fusion at score level demands matching scores generated by comparing input test image with trained database. Feature vectors of palmprint and fingerprint are compared with their respective databases using normalized euclidean distance classifier to generate the matching scores. These scores contain less amount of information as compare to feature vectors. Before fusing scores together, scores should be normalized to a common scale. As normalized energy values are used in both palmprint and fingerprint systems to generate the scores, so generated scores are already on a common scale and hence eliminate the need of using any score normalization technique. Palm and finger scores are combined using two rules: Sum Rule and Product Rule.

4.1. Sum Rule

According to sum rule, the scores of palmprint and fingerprint input images are added together to yield a new set of values. Thus, the new set of values contains more amount of information as compared to the individual unimodal systems, hence, giving more information to identify a person. Finally, the decision of input claim is established on the basis of preset threshold by the classifier. Suppose P = p1, p2, . . . pm and F = f1, f2 . . . fn give the scores of palm and finger images, respectively, then according to the sum rule, the combined score vector $sskk$ is obtained $sskk = ppkk + ffkk$. Here, 'k' represents the total number of generated score of test image corresponding to trained database. sk is the combined score which is used for decision making.

4.2. Product Rule

The scores of palmprint and fingerprint images are multiplied together to produce a new set of values consisting of combined values of both the systems. Suppose P = p1, p2, . . . pm and F = f1, f2 . . . fn give the scores of palm and finger images, respectively, then according to the product rule the combined score vector gk is obtained as: $gk = pk + fk$ Here, 'k' represents the total number of generated score of test image corresponding to trained database, and gk is the combined score which is used for decision making.

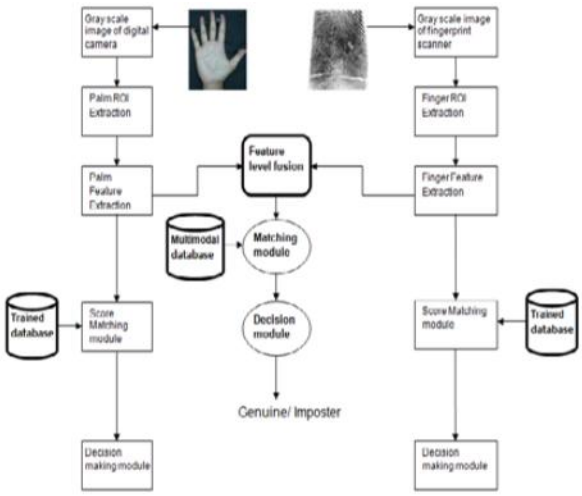

Fig -1: Methodology of feature level and score level Palm-Finger multimodal system

5. FINGERPRINT AND PALMPRINT RECOGNITION

Fingerprint and Palmprint are unique and permanent throughout a person's life. The fusion of Minutia Score Matching method for fingerprint and alignment based minutiae matching algorithm for palmprints. A fingerprint is comprised of ridges and valleys. The ridges are the dark area of the fingerprint and the valleys are the white area that exists between the ridges. Many classifications are given to patterns that can arise in the ridges and some examples are given in the figure to the right. These points are also known as the minutiae of the fingerprint. The most commonly used minutiae in current fingerprint recognition technologies are ridge endings and bifurcations because they can be easily detected by only looking at points that surround them. Most modern fingerprint matching technologies use minutiae matching.

The idea being if you can find enough minutiae in one image that have corresponding minutiae in another image then the images are most likely from the same fingerprint. Minutiae are usually matched together by their distance relative to other minutiae around it. If multiple points in one image have similar distances between them then multiple points in another image then the points are said to match up. It is the idea of this paper to add the constraint that the regions and possibly edges between the minutiae should be the approximately the same as well. Minutia Code and alignment-based minutia matching algorithm is used to match two palmprints. A match score estimate is calculated using the local ridge direction and frequency in palmprints. The distinctive information around each minutia is calculated using the fixed length minutiae descriptor.

6. PALM FEATURE EXTRACTOR

In this module the image acquisition setup is provided with two flat plates. The camera and the light source are fixed on the upper plate, while the bottom plate is used to place the hand for image acquisition with fixed pegs. To minimize any mismatch due to scale variance, the distance between these two plates is kept constant. After empirical testing, the distance between the plates is kept. The palmprint image is binarized using Hysteresis thresholding isolating the foreground of palmprint from the background. The binarized palmprint is complemented and distance transform is calculated.

For each pixel in the binary image, the distance transform assigns a number that is the distance between that pixel and the nearest nonzero pixel. The maximum distance obtained from the distance transform is estimated as the centre of palmprint. Although during image acquisition stage of the database development an effort was made to acquire standard palmprint images, a rotational alignment is incorporated in our proposed approach to cater any inadvertent small rotations. The longest line in a palm passes through the middle finger, and any rotation is considered with reference to this line. The second-order moment helps analyzing the elongation or eccentricity of any binary shape. By finding the Eigen values and eigenvectors, we determine the eccentricity of the shape by analyzing the ratio of the Eigen values. The second-order normalized moments a, b and c of the pixels in the image P(x, y) are calculated using the following equations:

$$a = \frac{\sum_{(x,y)\epsilon P}(y-v)^2 \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)}$$

$$b = \frac{\sum_{(x,y)\epsilon P}(x-u)^2 \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)}$$

$$c = \frac{\sum_{(x,y)\epsilon P}(x-u)\cdot(y-v) \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)}$$

7. FINGER PRINT FEATURE EXTRACTOR

In the module the input image is pre-processed using histogram equalization, adaptive thresholding, Fourier transform and adaptive binarization. In order to extract region of interest (ROI) from the input image, core point is used as the reference point. Core point is the point located on the inner most ridges having the maximum curvature as depicted. Region of interest (ROI) of 128×128 pixels size around the core point is extracted from input image and contourlet transform is subsequently used for its textural analysis. With the help of Directional Filter Banks (DFBs), 2-D spectrum is fragmented into fine slices. Let Skθ denotes the sub-band image at k level. Core point located to the extreme margin of the image and θ direction. Similarly, let σθk denotes the standard deviation of the kth block in the θ direction sub-band image and cθk (x, y) is the contourlet coefficient value at pixel (x, y) in the sub-band block $S_{k\theta}$, then the value for directional energy $E_{k\theta}$ for that sub-band block is calculated using following equation:

$$E_{k\theta} = n\ \mathrm{int}\left(\frac{255(\sigma_{\theta k} - \sigma_{\min})}{\sigma_{\max} - \sigma_{\min}}\right)$$

where

$$\sigma_{\theta k} = \sqrt{\left(\frac{1}{n}\right) \sum_{x,y \in S_{k\theta}} (c_{k\theta}(x,y) - \overline{c_{k\theta}})^2}$$

n int (x) is the function that returns the nearest integer value to x, σ max and σ min are the maximum and minimum standard deviation values for a particular sub-block. Feature set for fingerprint comprises of core and delta points along with the ridge and valley orientations which have strong directionality. Euclidian distance classifier is finally employed for fingerprint matching.

8. FUSION BASED ON PARETO-OPTIMAL SEARCH METHOD

In this module before fusing scores together, scores should be normalized to a common scale. As normalized energy values are used in both palmprint and fingerprint systems to generate the scores, so generated scores are already on a common scale and hence eliminate the need of using any score normalization technique. Palm and finger scores are combined using two rules: Sum Rule and Product Rule. From that the decision making process will be done. In that fusion we are using the pareto-optimal search method which is the features of feature level and score level from that finding the dominating feature and from that finding the nearest neighboring feature and then find the dominating feature for proceeding the decision making process.

9. PERFORMANCE EVALUATION

Fingerprint images were collected using Digital Persona Fingerprint scanner 4000B, while palmprints with the help of developed platform. A database consisting of palm and finger images of 55 individuals has been constructed. Sixteen prints are collected from single individual with 8 records per biometric modality. Thus, multimodal database consists of 16×55 = 880 records, consisting of 440 palmprint and 440 fingerprint records. The database is developed in two sessions with an average interval of two months to focus on performance of developed multimodal system. User training is conducted prior to data acquisition phase for both palm and fingerprints. In our experiments, the developed database is divided into two non-overlapping sets: training and validationsets of 440 images each (220 for each modality). Validation data set is then used to evaluate the performance of trained system.

10. CONCLUSION

Under the framework, a hybrid fusion method is proposed, which combines the score-level fusion and the decision-level fusion, and takes advantage of both with the palm and fingerprint. By identifying Pareto- optimal features in a feature extraction phase we can guarantee that the best fusion method can be achieved for the personal identification. It uses a combination of depth first traversals of the lattice to efficiently find the Pareto-optimal feature selection. Results show that the proposed system has the potential to identify all Pareto-optimal features with a small percentage of feature evaluations.

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