Multimodal Biometric System for Identification of a Person

Trupti Pawshere

Abstract— A biometric identification system is an automatic pattern recognition system that recognizes a person by determining the authenticity of a specific physiological and/or behavioural characteristic (biometric) possessed by that person. Unimodal biometric systems often face significant limitations due to sensitivity to noise, intraclass variability, data quality, nonuniversality, and other factors. To improve the performance of individual matchers in such situations may not prove to be highly effective. Multibiometrics systems seek to alleviate some of these problems by providing multiple pieces of evidence of the same identity. These systems help achieve an increase in performance that may not be possible using a single-biometric indicator. An effective fusion scheme that combines information presented by multiple domain experts based on the rank-level fusion integration method. The developed multimodal biometric system possesses a number of unique qualities, starting from utilizing principal component analysis and Fisher's linear discriminant methods for individual matchers (face, ear, and signature) identity authentication and utilizing the novel rank-level fusion method in order to consolidate the results obtained from different bio- metric matchers. The ranks of individual matchers are combined using the highest rank, Borda count, and logistic regression approaches. The results indicate that fusion of individual modalities can improve the overall performance of the biometric system, even in the presence of low quality data. Moreover better performance can be obtained by using ICP algorithm for ear database.

Index Terms— Biometric identification system, logistic regression, multibiometrics system, pattern recognition, principal component analysis (PCA), rank-level fusion

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1 INTRODUCTION

Automatic person identification is an important task in our day to- day life. The traditional method of establishing a person's identity include knowledge based like password or token based like ID cards, but representation of these identity can easily be lost, stolen or shared. Therefore they are not sufficient for identity verification. Therefore biometric systems are used to overcome the limitations of traditional methods. The survey of biometric and multimodal biometric systems is therefore necessary for high security applications. Biometric information system is one of the finest examples of computer system that tries to imitate the decisions that humans make in their everyday life, specifically concerning people identification and matching tasks.

The main goal and contribution of this system is to present a comprehensive analysis of various biometric fusion techniques in combination with advanced biometric feature extraction mechanisms that improve the performance of the biometric information system in the challenging and not resolved problem of people identification.

Physiological biometric identifiers include fingerprints, hand geometry, ear patterns, eye patterns (iris and retina), facial features, and other physical characteristics. Behavioural identifiers include voice, signature, typing patterns, and others.

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In recent years, biometric authentication has seen considerable improvements in reliability and accuracy, with some biometrics offering reasonably good overall performance. Multibiometric systems can significantly improve the recognition performance in addition to improving population coverage, deterring spoof
attacks, increasing the degrees of freedom, and reducing the failure-to-enroll rate.

The key to successful Multibiometric system is in an effective fusion scheme, which is necessary to combine the information presented by multiple domain experts. The goal of fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts. A decision made by a biometric system is either a ―genuine individual‖ type of decision or an ―impostor‖ type of decision. [1] The genuine distribution and the impostor distribution, which are used to establish the following two error rates.

1) False acceptance rate (FAR), which is defined as the probability of an impostor being accepted as a genuine individual. It is measured as the fraction of impostor score exceeding the predefined threshold.

2) False rejection rate (FRR), which is defined as the probability of a genuine individual being rejected as an impostor. It is measured as the fraction of genuine score below the predefined threshold.

A FAR of zero means that no impostor is accepted as a genuine individual. Sometimes, another term, genuine accept rate (GAR), is used to measure the accuracy of a biometric system.

2 Related Work

In 1998, a bimodal approach was proposed by Hong and Jain for a PCA based face and a minutiae-based fingerprint identification system with a fusion method at the decision level. [1] At a FAR of 0.01%, the monomodal systems obtained FRRs of 61.2% and 10.6% for face and fingerprint, respectively. For the same FAR, the fusion approach obtained an FRR of 6.6%. In 2000, Frischholz and Dieckmann [2] developed a commercial multimodal approach, BioID, for a model-based face classifier, a VQ-based voice classifier, and an opticalow based lip movement classifier for verifying persons. Lip motion and face images were extracted from a video sequence and the voice from an audio signal.

Accordingly to the security level, experiments on 150 persons demonstrated a decrease below 1% of the FAR In 2003, Fierrez-Aguilar and Ortega-Garcia [3] proposed a multimodal approach including a face verification system based on a global appearance representation scheme, a minutiae-based fingerprint verification system, and an online signature verification system based on HMM modeling of temporal functions with fusion methods, i.e., sum-rule and support vector machine (SVM) user independent and user dependent, at the score level. In the same year, Kumar et al [4] proposed a multimodal approach for palmprint and hand geometry, with fusion methods at the feature level by combining the feature vectors by concatenation, and the matching score level by using max rule.

Only the fusion approach at the matching score level outperforms the monomodal systems. For an FRR of 1.41%, the multimodal approach obtained a FAR of 0%, while the palmprint-based verification system, the best monomodal approach in this study, obtained a FAR of 4.49% at an FRR of 2.04%. In 2004, Toh et al. [6] developed a system using hand geometry, fingerprint, and voice biometric with weightedsum rule-based match-score-level fusion. They treated the multimodal biometric decision fusion problem as a two-stage problem: learning and decision. Experiments on fingerprint, speech, and hand-geometry biometric data showed that local learning alone can improve verification ERRs of about 50%.

In 2005, Snelick et al. [7] developed a multimodal approach for face and fingerprint, with fusion methods at the score level. Three fingerprint recognition commercial systems and one face recognition commercial system were used in this study. The EERs of the best fingerprint system and the face recognition system were 2.16% and 3.76%, respectively, while the max-score fusion approach on quadric-line quadric normalized scores obtained an EER of 0.63%.

3 Proposed Work

This section deals with the development procedures of the proposed multimodal biometric system through the rank level fusion method. Rank-level fusion is a relatively new fusion approach.

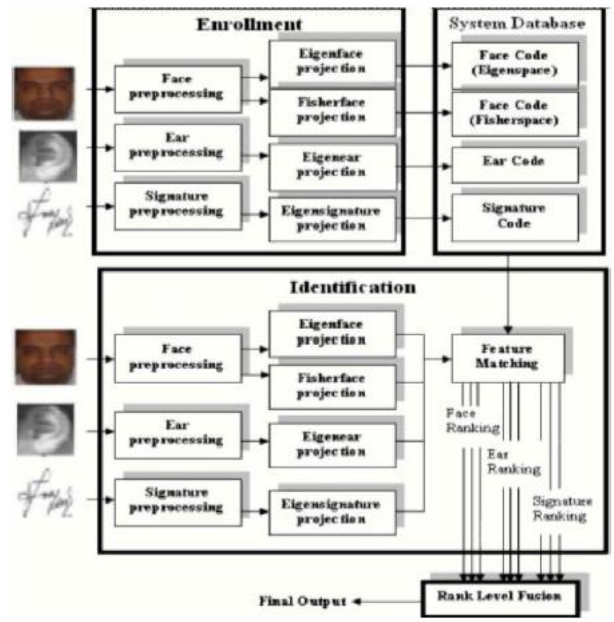

Fig1: Block diagram of Multibiometric system.

The goal of rank-level fusion is to consolidate the rank output by individual biometric subsystems (matchers) in order to derive a consensus rank for each identity. There are basically two types of recognition approaches appearance based and model based. PCA and LDA are examples of appearance-based recognition approaches. PCA is a statistical method which involves analysis of n- -dimensional data. PCA observes correspondence between different dimensions and determines principal dimensions, along which the variation of the data is high.

3.1 Recognition Using Eigen image

Eigenimage feature extraction is based on the K–L transform [8] and is used to obtain the most important features from the face, ear, and signature subimages in our system. These features are obtained by projecting the original subimages into the corresponding subspaces. The process of obtaining these subspaces and projecting the subimages into them is identical for all subspaces.

The system is first initialized with a set of training images. Eigenvectors and eigenvalues are computed on the covariance matrix of these images according to the standard procedure. The higher the eigenvalue, the more characteristic features of an image the particular eigenvector describes. Eigenimages with low eigenvalues can be omitted. Finally, the known images are projected onto the image space, and their weights are stored. This process is repeated as necessary. The steps for the recognition process

1) Project the test image into the eigenspace, and measure the distance between the unknown image's position in the eigenspace and all the known image's positions in the eigenspace.

2) Select the image closest to the unknown image in the eigenspace as the match.

3.2 Recognition Using Fisherface

Eigenspace representation is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. When substantial changes in illumination and expression are present in any image, much of the variation in data is due to these changes [9], and the eigenimage technique, in this case, cannot give highly reliable results.

To overcome this, a new method called fisherface method is adopted. The fisherface method uses both PCA and LDA to produce a subspace projection matrix, similar to that used in the eigen face method. However, the fisherface method is able to take advantage of within-class information, minimizing variation within each class, yet still maximizing class separation. Scatter matrices, representing the within class (S W), between-class (S B), and total (S T) distributions are

$$S_W = \sum_{i=1}^{C} \sum_{\Gamma_k \varepsilon X_i} (\Gamma k - \Psi_i)(\Gamma k - \Psi_i)^T$$

$$S_B = \sum_{i=1}^{C} |X_i| (\Psi_i - \Psi)(\Psi_i - \Psi)^T$$

$$S_T = \sum_{n=1}^{M} (\Gamma_n - \Psi)(\Gamma_n - \Psi)^T$$

Where, $\varphi = (1|M) \sum_{n=2}^{M} \tau_n$ is the average image vector of the entire training set and $\varphi_t = (1||X_t|) \sum_{\in X\tau_i} \tau_t$ is the average of each individual class Xi.

3.3 Fusing Rank Information

This can be applied after those methods. After getting the identification results with ranks by the FLD based unimodal system, it's compared with the results obtained from the eigenface-based subsystem. The ranked output of these three matchers is then consolidated by using the highest rank, Borda count, and logistic regression methods. Choose 0.3, 0.4, and 0.3 as the weights for face, ear, and signature, respectively. The more the weight, the less the recognition rate of the system. This means that the ear matcher gives us less accurate results than the face or signature matchers. These weights are chosen by reviewing the previous research, examining the quality of the database and by consequently executing the system.

4 Conclusion

Multibiometrics is a new and exciting area of information science research for accurate and reliable personal information representation for matching. This is specifically focused to find a good combination of multiple biometric traits and various fusion methods to get the optimal identification results.

In this a comparison between various rank-level fusion methods are obtained. Between the three rank-level fusion approaches, the logistic regression method gives us the better performance in terms of error rates. The main reason for this is that, in this approach, weights are assigned to different matchers according to their performance.

In future, a better result can be obtained by improving the genuine acceptance rate and decreasing the false acceptance rate. This can be done by using some specific algorithm for each database.

In future the multimodal biometric systems is to be designed such that, design and prototype of the embedded recognizer in which integrating feature acquisition and processing in a smart device without transmitting the data through different stages of the biometric system.

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