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Multimodal Biometrics Recognition by using Modified Unconstrained Cohort Normalisation under Unconstrained Setting

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Abstract

Objective: The main intention of this research is to provide secured authentication on mobile devices with the use of multimodal based biometric authentication system under unconstrained settings. **Methods:** Method used in this research is pattern recognition algorithm namely modified unconstrained cohort normalisation (MUCN) is introduced into the score-level fusion process of multi-biometric system. The goal of proposed MUCN is normalizing the unconstraint modalities by correcting the misclassified scores occur in the UCN. Score normalization of multimodal biometric is enhanced and investigated for improving the accuracy performance of the multimodal biometric in an unconstraint setting. **Results:** The result of presented pattern recognition algorithm performs well in terms of recognition accuracy when compared to existing schemes.From the comparative evaluation on WVU multimodal data set, the proposed MUCN based Score level fusion achieves 89.2 % of overall recognition rate and out-performs existing state-of-art techniques. **Conclusion:** The present work demonstrates that the result obtained by MUCN can considerably improve the accuracy of fused biometrics. Thus it can be concluded that with respect to the obtained comparison results from the experiment, the proposed method provides highest recognization rate when compare with other conventional methods of biometric recognition system.

Keywords: Joint Sparse Representation, Modified Unconstrained Cohort Normalisation, Multimodal Biometrics, Score-Level-Fusion

1. Introduction

Automatic recognition of human identities has gained significant importance in various appliances such as teleshopping, physical access control and telebanking. The advantages in biometrics make it an efficient choice than the conventional methods. The conventional methods are mostly utilized manually which means the recognition of individuals is time consuming and low matching. Recently, the usage of multiple modalities has gained significant interest. Single modality biometric authentication methods depend on a single source of information namely fingerprint or face or iris for human validation[1]. However, these methods suffer from the following unavoidable problems[2].

1.1 Noisy Data

The instance of noisy data occurs with low lights on a user's occlusion, face during capturing.

1.2 Non-Universality

This is defined as when biometric method relied on a unimodal confirmation which might not be capable of capturing important data from the users. For example, biometric system based on iris might not extract correct

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iris texture patterns for some of the users caused due to the occurrence of contact lenses.

1.3 Intra-Class Variations

This type of variations occurs in case of fingerprint recognition; the existence of wet wrinkles[3] can form these variations which often arise when a user mistakenly interact with the sensor.

1.4 Spoof Attack

Hand inscription forgery is an example of this attack.

Some limitations of unimodal biometric systems can be tackled by deploying multimodal biometric methods which integrates the proof from multiple sources of information such as iris, fingerprints, and face.

Normally, multimodal biometrics is developed based on the idea that the sets of data obtained from various modalities are corresponding to each other[4]. Classification in multi-biometric methods is done by combining data from various biometric modalities. Data fusion can be performed at various levels, broadly divided into feature-level, score-level, and rank-/decision level fusion. Subsequently, a suitable combination of data sets could be more useful than using the data from any single modality. Many data combinations are considered for this purpose. Feature level, score level and decision level[4] are some of the examples. But still the most efficient multimodal biometrics approach is developed through the score level[5] fusion of data.

One of the most important problems related with both multimodal and unimodal technique is the occurrence of undesired variations in the biometric informations. Such variations are reflected in the corresponding biometric scores, and thereby can adversely influence the overall effectiveness of biometric recognition. The said variations can arise due to the effects of data capturing apparatus and various non-ideal operating conditions such as background noise and ambient lighting effects.

In this research, multimodal biometric recognition system is done on unconstrained setting. The proposed system uses pattern recognition algorithms using input signals obtained under unconstrained settings. A pattern recognition algorithm namely Modified Unconstrained Cohort Normalisation (MUCN) is introduced in the into the score-level fusion process of multi-biometric. MCUN eliminates or discards the misclassified score obtained in UCN approach. Score normalization of multimodal biometric is enhanced and investigated for improving the accuracy performance of the multimodal biometric in an unconstraint setting. Using quality assessment and information fusion algorithms a multimodal system with improved recognition performance is developed. The proposed approach utilized the capabilities afforded by MUCN which can increase the accuracy of fused biometrics.

Recently various methods have been used established for recognization of multimodal biometrics. Feature-level fusion methods in[6,7] have been explored by A. A. Ross et al and A. Rattani et al. The reason is that the differences in extracted features from diverse sensors in terms of kinds and proportions. Generally the features have large dimensions, and fusion turns into difficult at the feature stage. The prevalent process is feature concatenation, which has been used for diverse multi-biometric settings. But, for high-dimensional feature vectors, uncomplicated feature concatenation may be inefficient and non-robust. Later on this Multiple Kernel Learning (MKL) based methods in[8] by Gonen and Alpaydn. This method plans to incorporate information from different features by learning a weighted combination of individual kernels. But, for multimodal systems, weight estimation during testing is vital, based on the worth of modalities. Also, a corrupted test sample from a modality must be discarded by the algorithm. Such a framework is not yet practicable in the MKL settings and it is not clear for the extension of multiple view based multimodal biometrics. So Diethes et al in[9] presented a Fisher discriminant analysis-based method has also been proposed for integrating multiple views in but it is also similar to MKL with kernel Fisher discriminant analysis as the base beginner.

Most recently compressed sensing and sparse representation has been presented in[10] by Patel for proficient processing of multimodal data in non-conventional ways. However performance lacks which is due to presence of various artifacts such as random pixel corruption, disguise, illumination variations and occlusion. Then in[11] the seminal sparse representation-based classification (SRC) algorithm is presented by Wright et al. for face recognition. This work is extended in[12] by Pillai et al. which presents robust cancellable algorithm for iris recognition. However the issues occur in these methods is recognition not performed under different illumination scenario. By addressing this issue, a dictionary-based method is presented in[13] by Patel et al. for face recognition under varying illumination. However these methods support only for unimodal based biometric recognition. By extending the work of these methods a multitask sparse linear regression is presented by Yan et al in[14] for multimodal based biometric image classification Since this technique uses group sparsity to unite various aspects of an object for classification, the limitation occurs in these methods are recognition accuracy degrades when multimodal recognition is performed under unconstrained settings.

2. Methods and Materials

In this section, the methods used for authentication of multi-biometric under unconstrained settings are discussed below:

Initially the training set of images is pre-processed and features are extracted from multimodal biometric training sets. Robust pre-processing of images was performed before feature extraction. Iris images can be segmented using the proposed scheme. Then, 25 × 240 iris templates are created by resampling. Fingerprint images were improved using the filtering process, and then the core point was identified from the improved images. Then the features are extracted near the identified core point.

2.1 Feature Extraction

In this section, features of multi-biometric are extracted. Gabor features were extracted from the processed images as they have been shown to give good performance on both fingerprints and iris. For fingerprint samples, the processed images were convolved with Gabor filters at eight different orientations. Circular tessellations were extracted around the core point for all the filtered images. The tessellation consisted of 15 concentric bands, each of width 5 pixels and divided into 30 sectors. The mean values for each sector were concatenated to form the feature vector of size 3,600 × 1. Features for iris images were formed by convolving the templates with a log-Gabor filter at a single scale, and vectorizing the template to give a 6000 × 1 dimensional feature.

2.2 Modified Unconstrained Cohort Normalisation in Score Level Fusion (MUCN-SLF)

The normalisation methods considered for unconstraint setting of multimodal biometrics are Cohort Normalisation (CN), Unconstrained Cohort Normalisation (UCN), Universal Background Model (UBM) normalisation, T-norm and Z-norm. The results based on the use of decoupled reference modelling, have shown that UCN is the best performing normalisation approach. In conventional Unconstrained Cohort Normalisation (UCN), misclassified scores of modalities occur. For example during authentication, Misclassified scores occur in user side and it will be moved towards the impostor class whereas the misclassified impostor scores will be shifted towards the user/client class. The proposed MUCN approach solves the misclassified score by transforming all the modalities to log domain by using log transformation. Then obtain the normalized score of each modality and average the normalized score. The distance between those logarithm score and normalisation term for the target model is then measured. With some predefined threshold value and based on the obtained distance, the level of degradation under unconstraint setting is determined.

Initially transform the modalities into log domain by using log transform after that average the normalized of all modalities.

In MUCN, p(x) is approximated as

$$\mathrm{P(x)} \approx \prod_{\mathrm{K=1}}^{\mathrm{K}} \left[\mathrm{p}\left(\mathrm{x} \middle| \lambda_{\mathrm{k}}\right) \right]^{\frac{1}{\mathrm{K}}} \tag{1}$$

Where $p(x|\lambda_k)$, k = 1............K ,are the top *K* probabilities obtained for the observation, using a set of *M* background unconstraint models (M>K).

Using equation (1) the normalised score can be stated in the log domain as

$$\mathrm{Scorenorm_{MUCN}} = \log \mathrm{P(x|\lambda)} - \mathrm{L(x)} \tag{2}$$

$$\mathrm{Avg(Scorenorm_{MUCN})} = \frac{1}{N} \sum_{n=1}^{N} \log p_n^i \tag{3}$$

Where p_n^i is the score obtained of the all modalities and L(.) = log p (.). i.e score obtained for target modal. This equation recommends that the effects of data degradation could be considerably reduced if there are reflected similarly in *L(x)* and the target model score. At last normalised matching score obtained using MUCN can be stated as follows:

$$\mathrm{MUCN\ (i)} = \log\ \mathrm{p^i_{Target}} - \mathrm{Avg(Scorenorm_{MUCN})} \tag{4}$$

This proposed MCUN method works efficiently in spite of whether the functioning structure is non-probabilistic or probabilistic. As a result, provided MUCN shows related characteristics with other types of biometrics, its appliance to multimodal biometric fusion could be of significant value for enhancing the reliability of the process in uncontrolled or varied operational conditions. This is because the proposed method gives a useful approach by appropriately providing the individual biometric scores for a client, without any earlier awareness of the level of degradation of each biometric data type absorbed.

2.3 Joint Sparse Representation

Consider a multimodal C-class classification problem with D diverse biometric traits. Assuming there are $p = \sum_{j=1}^{c} p_j$ training samples in each biometric trait, where p_j is the number of training samples in class j. For each biometric trait i = 1. ...D we denote

$$X^i = \left[X_1^i, X_2^i, ...X_c^i\right] \tag{5}$$

as an $n_i \times p$ dictionary of training samples consisting of C sub dictionaries X_k^i subsequent to C diverse classes. Each sub dictionary

$$X_j^i = \left[X_{j,1}^i, X_{j,1}^i, ...X_{j,p(j)}^i\right] \in R^{n(i)\times p(j)} \tag{6}$$

A set of training data is represented from the i'th modality labelled with the jth class. The n(i) is the feature aspect of each sample. Components of the dictionary are often referred to as atoms.

In multimodal biometrics recognition problem, provided test samples Y that consists of D diverse modalities.

$$\left\{Y^1, Y^2, ...Y^D\right\} \tag{7}$$

Where all samples Y^i consists of d_i observations.

2.4 Reconstruction Error based Classification

Preferably, a fusion mechanism has to give more weights to the more dependable modalities. Therefore, the notion of quality is vital in multimodal fusion. A quality measure based on sparse representation was established for faces. To select a given sample as good or bad, its Sparsity concentration index (SCI) was calculated. Given a coefficient vector $\gamma \in IR^p$, the SCI is given as

$$SCI(\gamma) = \left(\left(C \cdot \max_{(j\in\{1,\ldots\ldots C\})} \left\|\delta_j(\gamma)\right\|_1\right) \Big/ \left(\|\gamma\|1\right) - 1\right) \Big/ (C-1) \tag{8}$$

where δ_j is the pointer function keeping the coefficients related to the jth class and setting remaining coefficients to nil. SCI values near to 1 relate to the case where the test sample can be corresponding to well using the samples of a single class, therefore of high quality. Similarly, samples with SCI close to 0 are not related to any of the classes, and therefore are of poor quality. This can be easily extended to the multimodal case using the joint sparse illustration matrix $\widehat{\Gamma}$. In this case, we could characterize the quality, q_j^i, for sample y_j^i as

$$\widehat{\Gamma} = \arg\min \Gamma 1/2 \sum_{(i=1)}^{D} \left\|Y^i - X^i\Gamma^i\right\|_F^2 + \lambda \left\|\Gamma\right\|_{1,q} \tag{9}$$

By knowing this quality measure, the classification rule could be adapted to incorporate the quality measure as follows:

$$\hat{j} = \arg\min_j \sum_{i=1}^{D} \sum_{k=1}^{d(i)} q_k^i \,||\, y_k^i - X^i \delta_j(\Gamma_k^i) \,||(2@F) \tag{10}$$

$$q_j^i = SCI(\widehat{\Gamma}_j^i) \tag{11}$$

where $\widehat{\Gamma}_j^i$ is the jth column of $\widehat{\Gamma}^i$, δ_j is the pointer function for maintaining the coefficients consequent to jth class.

3. Experimental Results

In this section the experimental analysis of proposed scheme with existing method is performed. The dataset used in the present work is described briefly in the following section.

The WVU multimodal data set is a comprehensive set of different biometric modalities namely fingerprint, iris, palm print, hand geometry, and voice from individuals of different age, gender, and traditions, as illustrated in Table 1. It is a challenging data set, because many of these samples are corrupted with blur, occlusion, and sensor

Table 1. Cumulative Recognition Rate (CRR) comparison

Methods	Iris	Fingerprint	All modalities
SMBR	76.5 ± 1.6	97.9 ± 0.4	98.7 ± 0.2
MUCN-SLF	78.2 ± 1.2	98.1 ± 0.6	99.1 ± 0.8

noise, as shown in Figure 2. Only the iris and fingerprint modalities are utilized in the proposed scheme for testing. Totally two iris (right and left iris) and four fingerprint modalities are utilized. Also, the estimation was performed on a subset of 219 subjects having samples in both modalities.

The present method is experimentally evaluated based on Cumulative Recognition Rate (CRR) and overall recognition rate for Iris, fingerprint and all modalities. In this section the proposed method of MUCN-SLF based multimodal recognition is compared with existing Sparse Multimodal Biometrics Recognition (SMBR). The proposed MUCN-SLF based recognition approach outperforms existing classification techniques. The following comparative Table 1 and Table 2 shows CRR and overall recognition rate values obtained for proposed MUCN-SLF and SMBR approach by using WVU multimodal data set.

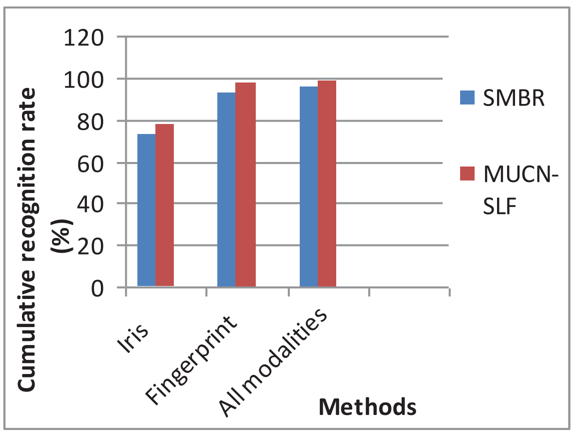

Figure 1. Cumulative recognition rate comparison.

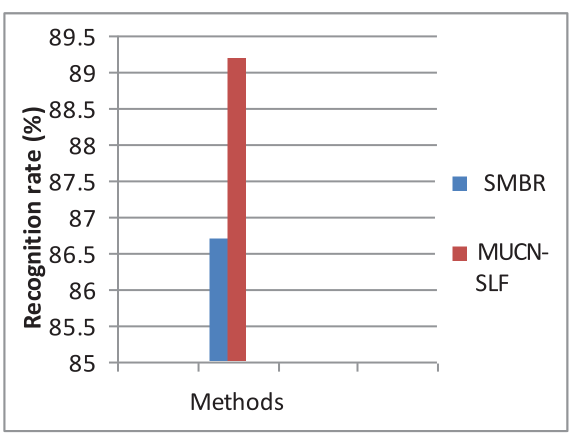

Figure 2. Overall Recognition rate comparison.

Table 2. Overall recognition rate comparison

S. NO.	Method	Recognition rate (%)
1	SMBR	86.7
2	MUCN-SLF	89.2

The comparative graph can be drawn for differentiating the recognition rate achieved for MUCN-SLF based multimodal and SMBR based recognition.

The above graph in Figure 1 and Figure 2 shows the cumulative recognition rate and overall recognition rate comparison of SMBR and MUCN-SLF based multi-biometric authentication system. In X-axis diverse modalities namely Iris, Fingerprint and all modalities are compared with SMBR and MUCN-SLF methods on WVU multimodal data set respectively. The proposed method illustrates superior performance on all the modalities. The existing system of SMBR achieved satisfied recognition rates still lacks in performance when compared with proposed methods because recognition of modalities under unconstrained settings are not performed. So the existing system lacks flexibility while training samples. Thus from the graph it has been observed that the proposed MUCN-SLF based recognition achieves high recognition rate when compare with existing system.

4. Conclusion

The present work proposes pattern recognition algorithms using input signals obtained under unconstrained settings for multi-biometric system. A pattern recognition algorithm namely Modified Unconstrained Cohort Normalisation (MUCN) is introduced in the into the score-level fusion process of multi-biometric. MUCN discards the misclassified scores obtained score obtained from the conventional UCN approach. Score Normalization of multimodal biometric is enhanced and investigated for improving the accuracy performance of the multimodal biometric in an unconstraint setting. Using quality assessment and information fusion algorithms a multimodal system with improved recognition performance is developed. Then joint Sparsity-based feature level fusion algorithm is used for multimodal biometrics recognition. The algorithm is robust as it precisely includes both noise and occlusion terms. A competent algorithm based on the substitute direction was suggested for solving the optimization problem. Experimental result of proposed system improves the overall recognition accuracy rate when compare with the existing system. In future work, a perfect secured biometric scheme possesses various properties such as security; privacy-reservation, cross matching resistance etc need to be considered.

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