Score Level Fusion Technique for Human Identification

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Abstract. A multimodal biometric-system based score level fusion technique is proposed to construct a robust human identification system. Feature fusion can be implemented via different methods. In this paper, the score level fusion of face and iris traits are combined and re-classified at Equal Error Rate (EER) value to improve the individual unimodal systems performance for recognizing 80 subjects (40 subject per one face-iris dataset). The multimodal classification results are compared and evaluated comprehensively using four competitive feature extraction methods: Principle Component Analysis (PCA), Fourier Descriptors (FDs), Gray Level Co-occurrence Matrix (GLCM), and Local Binary Pattern (LBP). Also, a low-quality resolution of MMU1 iris database are considered in this work as an additional challenge for system robustness. The accuracy rate of GLCM and LBP methods satisfied 100% with ORL-CASIA-V1 combination datasets, while PCA and GLCM methods achieved 100% with the low-quality ORL-MMU-1 combination datasets, these results provide an evidence of how the multimodal biometric system could improve the overall unimodal systems performance. Also, the GLCM advances all other feature extraction methods by having the highest accuracy rate with ORL-CASIA-V1 and ORL-MMU-1 combined datasets.

1. Introduction
Multimodal biometric system is one of modest security system, it depends on concatenation more than one biometric trait in specific level to produce several advantages like, increasing the biometric security and improving the performance. Also, it solves system dependency on one biometric where each source of information is working separately and independently [1]. If any information source failed, the other one will not be affected [2]. The multi-biometric system can be performed with different techniques to support system performance, it may be a multi-instance, where several images are captured in different instances for the same trait and one sensor is used for performing this type, like captures several images for face in different facial expressions or iris images in different angles [3]. The multi-sensor type is utilized to capture images for same biometric trait [3], and the multi-algorithms which employs multi-classifiers for same biometric trait, and the results from the different matching algorithms are combined to increase the system performance and reduces the dependency on one algorithm [3]. The two or more biometric traits are used for multi-modal human identification. For example, fusion of face and iris trait of same person to perform the identification. The advantage of each biometric system will improve the overall system advantages. Finally, the hybrid type is represented by combined of two or more multi-biometric systems in one system [4].

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Muthana Hamd. an Marwa. M. in [5] proposed feature level fusion between face and iris traits using four feature extraction methods. The LBP, GLCM, FDs, and PCA method were applied for each trait separately to extract the features. The fusion was implemented using serial rule which produces new feature template. The classification stage was performed using ED. Also, three databases were utilized: CASIA-V1, MMU-1, and ORL. The suggested method achieved 100% accuracy rate using (LBP, GLCM) and 97.5% using (FDs, PCA) method. The developed face-iris multimodal biometric system in [6] was implemented by concatenating the two trait features in one vector. It utilized Gabor and LBP as a feature extraction method to form LGXP, also the average matching score was calculated using the distance measure and irrelevant pixels weightage. The experimental results provided better accuracy for multimodal recognition. The facial image information at higher and lower resolution were extracted and combined at different resolution for enhancement purpose [7]. The three fusion techniques: feature level, score level, and decision level were proposed by [8] to fuse the face and iris modalities using Log-Gabor method for feature extraction. Backtracking Search Algorithm was applied to improve the recognition rate by selecting the optimized weights for score level and feature level fusion. The resultant verification rates showed a significant improvement of the three fusion schemes over unimodal and multimodal fusion methods. The developers in [9] applied two optimization techniques to reduce the dimensionality of the iris-signature feature vector. Also, to implement the biometric system, four classifiers and two databases were proposed for more performance evaluation and comparison. The integration of cancellable modalities for Mean-Closure Weighting score-level and Dempster-Shafer based on decision-level fusion for iris and fingerprint were proposed in [10].

2. The proposed method

The six sequential steps that demonstrate the proposed multimodal biometric system are: face-iris image acquisition, feature extraction, classification, score-level fusion, and making the final decision. The four feature extraction methods and their fusion procedure are explained as follows:

2.1 Local binary pattern

The concept of LBP method is based on deference operation between eight neighbours and the center pixel, where the center pixel is considered as a threshold value. If the result of deference operation in equation 1 is zero or positive number, the LBP code is set to one otherwise it is set to zero as in equations(2) and (3)[11, 12].

\[
x_L = g_n - g_c \\
s(x_L) = \begin{cases} 
1 & x_L \geq 0 \\
0 & x_L < 0
\end{cases} \\
LBP_{p,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(x_L) 2^p
\]

Where \(g_n\) and \(g_c\) represent the gray value of neighbours and centre pixel respectively. The two variables \(x_c\) and \(x_n\) are indicated to the coordinates of center pixel. The circle LBP is constructed to provide the flexibility for using different number of neighbours (P) with radius R [12].

2.2 Gray level co-occurrence matrix

The idea of GLCM method is based on the counting of specific pair’s pixel value with specific distance and direction angle over the whole image. The GLCM second order features can be extracted in different direction angles, where each angle determines specific relationship such as: 90°, 0°, 45°, and 135°. More than six features can be produced by GLCM, they are: contrast, homogeneity, energy, entropy, correlation, and autocorrelation [13, 14].
2.3 Principle component analysis
The concept of PCA is relayed on computing the eigenvalues and eigenvectors from the covariance matrix where the dimension of feature vector is reduced with maintaining the important values. The covariance matrix, eigenvalues, and eigenvectors can be computed as in equations (4) to (6) [14]:

\[
\text{mean } (\bar{A}) = \frac{1}{n} \sum_{i=1}^{n} a_i
\]

\[
\text{cov}(a,b) = \frac{\sum_{i=1}^{n} (a_i - \bar{A}_i)(b_i - \bar{B}_i)}{n}
\]

\[
\det(\text{cov}_{ab} - \lambda I) = 0
\]

Where \(\bar{A}_i\) and \(\bar{B}_i\) represent the mean value of vector, while the two parameters \(a_i\) and \(b_i\) refer to the present value of vector a and b. The variable \(n\) indicates to the number of rows.

2.4 Fourier descriptors
It is essential method to describe the shape despite its position, rotation, and scale. There are three major steps for implementing the FDs method as in equations (7) to (9) [5].

\[
r(t) = \sqrt{(x(t) - x)^2 + (y(t) - y)^2}
\]

\[
x = \frac{1}{N} \sum_{t=0}^{N-1} x(t), \quad y = \frac{1}{N} \sum_{t=0}^{N-1} y(t)
\]

\[
\text{FD}_n = \frac{1}{N} \sum_{t=0}^{N-1} r(t) \exp\left(-\frac{j2\pi nt}{N}\right)
\]

Where the two variables \(x\) and \(y\) refer to the centred of the shape, while \(x(t)\) and \(y(t)\) refer to the border points as a complex number. \(N\) represents the number of sampling.

2.5 Score Level Fusion
This technique is applied to improve the overall biometric system performance. Firstly, the classification process is performed for face and iris features separately using Euclidean Distance (ED). The second step is normalizing the face and iris scores that are produced from previous step as in equation (10). Third step is fusing the scores using the sum rule as in equation (11) [15]. Figure 1 shows the steps of building a multimodal system based on the score-level fusion technique.

\[
S_{Ni} = \frac{S_i - \text{max}_{si}}{\text{max}_{si} - \text{min}_{si}}
\]

\[
F_{\text{Score}} = \sum_{i}^{M} S_{Ni}
\]

Where \(S_i, S_{Ni}\) are the score value and score normalization of sample \(i\). \(\text{max}_{si}, \text{min}_{si}\) represent the maximum and minimum value of the score vector for sample \(i\). \(M\) refers to the number of biometric systems that have been used.
3. Results and discussion
The performance results of the five different modal systems are tabulated in Table 1. The maximum recognition accuracy is 100\% and it is achieved by the GLCM, LBP, and PCA methods. The lowest accuracy rate is detected with ORL-MMU-I dataset which contains blurred iris images. It is clearly noticed from Table 1 how much the score-level has improved the accuracy of the unimodal systems, where the rate limits are (95-100)\%, these results have advanced the score-level of [8] that has rate limits (81.17 – 95)\%, although [8] implemented its score-fusion system using the right and left iris images with Log-Gabor and LDA feature extraction methods.
Table 1. Performance of unimodal systems and its score-level fusion for 120 subjects

| Method | Recognition Rate(%) |
|--------|---------------------|
|        | Three unimodal systems | Two multimodal system |
|        | ORL-CASIA-V1-MMU-1 | ORL-CASIA-V1 | ORL-MMU-1 |
| GLCM   | 100                 | 62.5         | 60         | 100 |
| LBP    | 100                 | 95           | 85         | 100 |
| FDs    | 90                  | 92.5         | 50         | 97.5 |
| PCA    | 92.5                | 87.5         | 75         | 97.5 |

4. Conclusion
The experimental results showed that the score-fusion based multi-biometric system has been succeed improving the recognition accuracy of both unimodal systems like face-based recognition and iris-based recognition systems, even with presence of blurred iris images in the ORL-MMU-1 face-iris dataset, the fusion technique satisfied significant accuracy rates (95% and 100%) for classifying 40 subjects. However the GLCM advances all other feature extraction methods by achieving 100% accuracy for both combinational datasets. The score-level fusion of face-iris traits has approved in this work its robustness in classifying the normal and difficult images with promising accuracy rate values.

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