Abstract—In this paper, we use Genetic and Evolutionary Computation (GEC) to optimize the weights assigned to the biometric modalities of a multi-biometric system for score-level fusion. Our results show that GEC-based multi-biometric fusion provides a significant improvement in the recognition accuracy over evenly fused biometric modalities, increasing the accuracy from 90.77% to 95.24%.

Keywords- Eigenface, Fusion, Local Binary Pattern, Multi-Biometrics, Steady-State Genetic Algorithms

I. INTRODUCTION

Multi-biometric systems that fuse multiple biometric modalities have proven to be more reliable than biometric systems that use only a single modality [1, 2, 3, 10, 13, 15]. Research has shown that multi-biometric systems can achieve higher recognition accuracies and are also able to address many of the problems that can affect single modality biometric systems (i.e. noisy sensor data and spoof attacks) [2].

Multi-biometric fusion can occur at several levels. Sanderson and Paliwal [11] proposed classifying fusion techniques into two categories: pre-mapping and post-mapping fusion. Pre-mapping fusion techniques, such as sensor-level and feature-level fusion, perform fusion before matching. Post-mapping fusion techniques, such as rank-level, decision-level, and match score-level fusion, perform fusion after matching.

Of the various fusion levels, match score-level fusion (also known as measurement or confidence level fusion) is the most commonly used [1]. The match score is the measure of the similarity between a probe and gallery feature set [4]. Match score-level fusion combines the individual match scores obtained by the different biometric modality matchers into a single match score which is used to determine whether the probe and gallery sets match. If the match scores generated are not homogeneous (e.g. different measurement techniques or different numerical ranges), score normalization must be performed before the combination of the match scores [1].

In [3], Ross et al. proposed using the Sum Rule to fuse the match scores obtained for a multi-biometric system that used face, fingerprint, and hand geometry modalities. Assigning each biometric modality equal weights, the fused match score using the sum rule is the average of the scores obtained by the multiple modalities. In [13], Wang et al. proposed using the Weighted Sum Rule to fuse match scores returned for a multi-biometric system that used iris and face modalities, and compared its performance to that of the Sum Rule. For the Weighted Sum Rule, different weights are assigned to each biometric matcher based on its false accept rate (FAR) and false reject rate (FRR). Essentially, higher weights are given to biometric matchers that result in smaller error rates. The results showed that the Weighted Sum Rule performs better than the Sum Rule at increasing the accuracy of multi-biometric recognition.

In this paper, we propose the use of Genetic and Evolutionary Computation (GEC) to optimize the weights assigned to the modalities used in our multi-biometric system for score-level fusion. GECs use evolutionary concepts to find optimal or near optimal solutions to a problem and typically work as follows. First, an initial population of candidate solutions to the problem is randomly generated. Each candidate solution is assigned a fitness based on a user-defined evaluation function. Parents are selected from the population, usually based on their fitness, and reproduce creating new candidate solutions. These new candidate solutions are evaluated and integrated into the population, typically replacing the candidate solutions in the population with lower fitnesses. This process is continued until the population converges, a user-specified threshold is reached, or a user-specified number of function evaluations are performed.

The modalities tested were face and periocular biometrics. The facial features were extracted using the Eigenface method [14], and the periocular features were extracted using Local Binary Patterns (LBP) [7, 11].

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The remainder of this paper is as follows. In the following section, a brief overview of the feature extractors used for our experiments is given. In Section III we describe how GEC was used to determine the weights used by each biometric modality for score level fusion. Section IV presents our experiments, and Section V presents our results. In Section VI we provide a brief discussion of our results and our conclusions and future work are presented in Section VII.

II. FEATURE EXTRACTION AND RECOGNITION

Eigenface [9, 14] is a feature extraction method that uses Principal Component Analysis (PCA) [6], a well-known statistical method, to encode images of faces. The number of pixels in an image of a face is typically large, however since all faces have similar structures, they will be concentrated within the same region in a high dimensional image space. Eigenface uses PCA to reduce the dimensionality of the image space into the facespace. Only those dimensions required for efficient representation of the face are used. For each image, the feature template is obtained by projecting the image onto the facespace.

LBP [7] is a mechanism for texture and pattern recognition and has been proven successful by Miller et al. [10] for extraction of periocular features. Initially, an image is segmented into a grid of evenly sized regions termed patches. LBP is applied to the pixels within each patch by measuring the intensity change of the P pixels surrounding a center pixel with a radius R. For our research, the periocular image is segmented into 24 patches, the neighborhood size P is 8, and the radius R is 1, thus only interior pixels are used as center pixels. If the intensity change is greater than or equal to 0, it is represented by a 1, otherwise a 0. The texture formed by concatenating these binary values is then used to update a histogram for the image, where each bin represents the number of times a particular binary string appears in a patch. Only uniform patterns, texture patterns with at most two bitwise changes when the pattern is traversed circularly (e.g. 10000001), are differentiated in our histograms for optimization purposes. For our research using a neighborhood size of 8, each histogram contained 58 bins for each of the optimization purposes. The resulting histograms from each patch are concatenated together to form the image's feature template consisting of 1416 (24 patches × 59 bins) features.

Manhattan distance is used to compare a probe template to the templates in the gallery set. The subject of the template within the gallery set with the smallest Manhattan distance is considered a match for the probe.

III. GEC-BASED SCORE-LEVEL FUSION

The genetic and evolutionary technique used within this paper is based on the eXploratory Toolset for the Optimization of Launch and Space Systems (X-TOOLSS) [1]. X-TOOLSS is a suite of twelve GECs which interface with evaluation functions specified as modules written in any language. The GEC used to generate the results in this paper is an instance of the X-TOOLSS Steady-State Genetic Algorithm (SSGA).

Consider a multi-biometric system that uses N biometric modalities, \( b_1, b_2, \ldots, b_N \), to authenticate an individual. Assume that \( s_j \) is the normalized match score returned by the matcher for \( b_j \). Using the Weighted Sum Rule, the fused match score, \( S \), is:

\[
S = \sum_{i=1}^{N} w_i s_i
\]

where \( w_i \) is the weight assigned to \( b_i \) and is within the range [0.0, 1.0] such that

\[
\sum_{i=1}^{N} w_i = 1
\]

The weights are assigned such that more reliable biometric traits are given higher weights.

If equal weights are assigned to all of the biometric modalities, the fused match score, \( S \), is the average of the match scores:

\[
S = \frac{1}{N} \sum_{i=1}^{N} s_i.
\]

For GEC-based score-level fusion, a SSGA is used to evolve a weight within the range [0.0, 1.0] for each of the biometric modalities, so that the number of recognition errors is minimized. Binary tournament selection is used to select the parents and offspring are created using uniform crossover and Gaussian mutation. The returned weights are normalized so that the summation of the weights equaled 1 using the following formula:

\[
w_i^* = \frac{w_i}{\sum_{j=1}^{N} w_j}
\]

where \( w_i^* \) is the normalized weight.

IV. EXPERIMENT

A subset of 105 subjects from the Face Recognition Grand Challenge (FRGC) dataset was used for our experiments [10]. The probe set consisted of one image of each subject. The gallery set consisted of two different images of each subject. The images used were frontal views of the subjects with neutral facial expressions and no occlusions (e.g. eyeglasses).

The tested biometric modalities for the experiments were face, periocular, and face plus periocular. The Eigenface method was used to extract 210 face features from each image, and LBP was used to extract 2832 periocular features (1416 features from the left and right periocular regions).

For the multi-biometric experiment, because the number of features used to represent each biometric modality was different, the match scores returned by the Manhattan distance were normalized. Score normalization was performed as follows:

\[
s_{ij} = \frac{d_{ij}}{d_{max}}
\]

where \( s_{ij} \) is the normalized score for probe template \( i \) and gallery template \( j \), \( d_{ij} \) is the Manhattan distance between probe template \( i \) and gallery template \( j \), and \( d_{max} \) is the maximum Manhattan distance obtained for that specific biometric modality.
V. RESULTS

For our experiments, the SSGA used to evolve the weights for each biometric modality had a population size of 20, a crossover rate of 1.0, a mutation rate of 1.0, and a Gaussian mutation range of 0.2. The GEC was run 30 times, and a maximum of 1000 function evaluations were performed for each run.

In Table I, the performance of the algorithms for each of the tested modalities is shown. The first column represents the tested biometric modalities, the second column represents the type of algorithm used, and the last column represents the recognition accuracy. For the algorithms used for the Face + Periocular experiment, the subscripts denote the normalized weights assigned to each biometric modality. The result of assigning equal weights (0.5) to each biometric modality served as a baseline for the experiment. The average of the weights returned by the 30 runs performed by the GEC for each biometric modality was used for GEC-based score-level fusion.

When the GEC was used to find the weights for each of the biometric modalities, more weight was given to the more accurate biometric trait, the periocular modality. The average of the weights returned by the 30 runs performed by the GEC was normalized. The periocular features were therefore assigned a weight of 0.89 and the face features were assigned a weight of 0.11. As a result, the recognition accuracy increased to 95.24%, a significant improvement over the evenly weighted fusion algorithm.

Figure 1 shows the effect of varying the normalized weight assigned to the periocular biometric modality for the multimodal experiment on the recognition accuracy. When the weight was 0, the recognition accuracy is equivalent to the Face-Only experiment. As the normalized weight increases, the recognition accuracy increases, reaching a peak recognition accuracy of 95.24% between the weights of 0.81 and 0.99. The weights evolved by the GEC for each of the 30 runs were within this range. When the weight is 1.0 (equivalent to Periocular-Only experiment), the recognition accuracy decreases to 94.29%.

VI. DISCUSSION

For our research, we performed strict matching between the probe and gallery feature set. Therefore, our results were based on the recognition accuracies. In [15], Wang et al. assigned weights based on the FAR and FRR. To obtain weights in a similar manner, we propose a modified weighted sum rule that perhaps can achieve higher recognition rates:

\[
w_l = 1 - \left( \frac{\text{Error}_l}{\sum_{j=1}^{m} \text{Error}_j} \right) \tag{6}
\]

where \(\text{Error}_l\) is the percentage of errors obtained by biometric modality \(b_i\). When this formula is applied to the results shown in Table I, the weight assigned to the periocular modality is 0.82, and the recognition accuracy is still 95.24%. It would be interesting to see what would happen when more biometric modalities are used.

The Periocular-Only experiment obtained a higher accuracy than the Face-Only experiment. The recognition accuracy of the Face-Only experiment was only 64.76%. The recognition accuracy of the Periocular-Only experiment was 94.29%. When the two biometric modalities are evenly weighted, the recognition accuracy was 90.77%, higher than the Face-Only experiment but lower than the Periocular-Only experiment.

![Effect of Varying the Weight Assigned to a Biometric Modality on the Recognition Accuracy](image)

Fig. 1. The effect of varying the weight assigned to the periocular biometric modality on the recognition accuracy.
VII. CONCLUSION

Our results show that GEC can be used to assign weights to the biometric modalities of a multi-biometric system, resulting in an improvement in the recognition accuracy. Using only the face features results in an accuracy of 64.76% and using only the periocular features results in an accuracy of 94.29%. Fusing these biometric modalities evenly resulted in a lower recognition accuracy than the periocular modality alone. Using GEC to optimize the weights assigned to each biometric modality, we were able to increase the recognition accuracy to 95.24% by assigning a higher weight to the biometric modality that produces the highest recognition accuracy.

Our future work will include applying GEC-based multi-biometric fusion on a multi-biometric system consisting of the face and the left and right periocular regions individually. In addition, we will apply GEC-based multi-biometric fusion on images from other datasets, including the Face Recognition Technology (FERET) [16], Essex [18], and the Yale [19] databases. We also plan on applying the modified weighted sum rule, shown in (6), to the work of [15].

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