GEFeWS: A Hybrid Genetic-Based Feature Weighting and Selection Algorithm for Multi-Biometric Recognition

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Abstract

In this paper, we investigate the use of a hybrid genetic feature weighting and selection (GEFeWS) algorithm for multi-biometric recognition. Our results show that GEFeWS is able to achieve higher recognition accuracies than using genetic-based feature selection (GEFeS) alone, while using significantly fewer features to achieve approximately the same accuracies as using genetic-based feature weighting (GEFeW).

Introduction

A biometric system is a pattern recognition system that uses physiological and behavioral traits, characteristics that are unique for every individual, to perform recognition (Jain, Ross, and Prabhakar 2004). The value of a biometric system depends largely on its ability to accurately authenticate an individual. Thus, the recognition accuracy is a major concern and is a key area of research for the biometrics community (Deepika and Kandaswamy 2009).

Researchers have shown that biometric systems that use only one biometric modality can produce highly accurate results (Adams et al. 2010; Dozier et al. 2009; Miller et al. 2010; Ross 2007). However, when these systems are applied to real-world applications, their performance can be affected by numerous factors such as noisy sensor data due to dust or lighting conditions and spoofing. Multi-biometric systems that fuse multiple biometric modalities have been shown to be more robust, able to counter many of the aforementioned limitations, and are also capable of achieving higher recognition accuracies (Jain, Nandakumar, Ross 2005; Ross 2007; Eshwarappa and Latte 2010).

Feature selection and weighting have also been proven as successful methods of improving the accuracy rates of biometric systems (Adams et al. 2010; Dozier et al. 2009; Gentile, Ratha, and Connell 2009; Mumtazah and Ahmad 2007). The goal of feature selection is to reduce the dimensionality of a data set by discarding features that are inconsistent, irrelevant, or redundant; thus keeping those features that are more discriminative and contribute the most to recognition accuracy. Feature weighting is a more general case of feature selection, with each feature being assigned a weight based on its relevance (Yang and Honavar 1998).

Genetic and Evolutionary Computation (GEC) has been utilized by researchers to optimize feature selection and weighting (Hussein et al. 2001; Yang and Honavar 1998; Yu and Liu 2003; Tahir et al. 2006; Raymer et al. 2000) and has also been used by the biometrics community to optimize the recognition accuracy (Dozier et al. 2009; Adams et al. 2010; Giot, El-Abed, and Rosenberger 2010). The goal of GEC is to find the optimal or near optimal solution to a problem, and typically works as follows. A population of candidate solutions is generated randomly and assigned a fitness based on a user-defined function. Using this fitness, members of the population are chosen and reproduce. The resulting offspring are then evaluated and typically replace candidate solutions within the population that have a lower fitness. This evolutionary process is continued until the population converges, a user-specified number of evaluations have completed, or no solution can be found.

In this paper, we use a hybrid GEC-based feature weighting and selection (GEFeWS) technique for multi-biometric recognition. Our goal is to reduce the number of features necessary for biometric recognition and increase the recognition accuracy. The performance of GEFeWS is compared with the performances of genetic-based feature selection (GEFeS) and weighting (GEFeW) techniques individually. The modalities tested were face and periocular biometrics. The facial features were extracted using the Eigenface method (Turk and Pentland 1991; Lata et al. 2009), and the periocular features were extracted using Local Binary Patterns (LBP) (Adams et al. 2010; Miller et al. 2010).

This research is inspired in part by the proposal of a hierarchical two-stage system, presented by Gentile et al. for iris recognition (2009). This system used a reduced feature set size in an effort to reduce the total number of feature checks required for an iris-based biometric recognition system. For a conventional biometric recognition system, a probe, p, is compared to every individual within a biometric database. The number of feature checks performed by a conventional biometric system, f_c, is:

$$f_c = nm$$

where n is the number of individuals in the database and m is the number of features used to represent an individual. A hierarchical biometric system reduces the number of feature checks performed by first using the reduced length biometric template to select a subset of the r closest matches to the probe p. The subset is then compared to p using all of the m features. The number of feature checks performed by a hierarchical system, f_h, is the summation of the calculations of the two stages, represented by:

$$f_h = nk + rm$$

where, once again, n represents the number of individuals in the database, k is the number of features in the reduced feature set, r is the subset of the closest r-individuals to the probe, p, and m is the number of features used to represent an individual. The savings gained by using the hierarchical biometric system, f_s, instead of the conventional biometric system is:

$$f_s = \frac{f_h}{f_c} = \frac{nk + rm}{nm} = \frac{k}{m} + \frac{r}{n}$$

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. GEFeS, GEFeW, and GEFeWS are then described, followed by a description of our experiments, the presentation of our results, and finally, our conclusions and future work.

Feature Extraction

Feature extraction is one of the essential tasks performed by a biometric system. After a biometric sample is acquired from an individual, feature extraction is performed to extract a set of features, termed a feature template, which is used to represent the individual and is used in the comparisons to determine recognition (Jain, Ross, and Prabhakar 2004).

In this paper, we use two feature extraction schemes. The Eigenface method is used to extract features from the face (Turk and Pentland 1991; Lata et al. 2009). Local Binary Patterns (LBP) is used to extract features from the periocular region (Adams et al. 2010; Miller et al. 2010).

Eigenface is based on the concept of Principal Component Analysis (PCA) and has been proven successful for facial recognition (Turk and Pentland 1991; Lata et al. 2009). PCA is a method used to reduce the dimensionality of a dataset while retaining most of the variation found among the data (Jolliffe 2005). For the Eigenface method, PCA is used to find the principal components, or eigenfaces, of the distribution of the face images within the entire image space, which is called the face space.

LBP is a method used for texture analysis that has been used in many biometric applications, including the extraction and analysis of periocular features for identification (Adams et al. 2010; Miller et al. 2010). LBP descriptors of each periocular region are formed by first segmenting the image into a grid of 24 evenly sized patches. Every internal pixel within the patch is used as a center pixel. The intensity change of the pixels around the center pixel is measured by subtracting the intensity value of the center pixel from each of the P neighboring pixels. For our experiments, the neighborhood size, P, was 8. If the resulting value is greater than or equal to 0, a 1 would be concatenated to the binary string representing the texture, otherwise a 0. The texture is then encoded into a histogram where each bin represents the number of times a particular binary string appears in a patch. For optimization purposes, only uniform patterns are considered. These are binary string patterns with at most two bitwise changes when the pattern is traversed circularly. Therefore, our histogram consisted of 59 bins (instead of 2^P=256 bins), 58 for the possible uniform patterns and 1 for the non-uniform patterns.

GEFeS, GEFeW, and GEFeWS

The genetic and evolutionary techniques used within this paper are based on the eXploratory Toolset for the Optimization of Launch and Space Systems (X-TOOLSS) (Tinker, Dozier, and Garrett 2010), and are an instance of the X-TOOLSS Steady-State Genetic Algorithm (SSGA).

For GEFeS, a SSGA is used to evolve a feature mask that selects the most salient biometric features. For each real-valued candidate solution that is generated by the SSGA, a masking threshold of 0.5 is used to determine if the feature is used. If the values of the features within the mask are less than the masking threshold, the feature is turned off by setting the mask value to 0. Otherwise, the feature is turned on by setting the mask value to 1, resulting in a binary coded feature mask.

For GEFeW, a SSGA is used to evolve a real-valued feature mask composed of values between 0.0 and 1.0. The resulting feature mask value is multiplied by each feature value to provide the weighted feature.

GEFeWS is a hybrid of GEFeW and GEFeS. Like GEFeW, a SSGA is used to evolve the weight of the features. However, if the weight is less than the masking threshold of 0.5, then the feature is not included, basically being turned off as done by GEFeS. Otherwise, the feature is weighted as done by GEFeW.

Associated with each candidate feature mask, *i*, there were two weights, w_{ip} and w_{if}, which are weights for the periocular and face feature submasks to allow for score-level fusion. The weights ranged from [0..1] and were co-evolved with the rest of the feature mask.

Experiment

To test our algorithms, we used a subset of 315 images taken from the first 105 subjects of the Face Recognition Grand Challenge (FRGC) dataset (Phillips et al. 2005). These images were used to form a probe set of 105 images (one of each subject) and a gallery set of 210 images (two of each subject). For each of the images in the probe and gallery set, the Eigenface method was used to extract 210 face features, and the LBP method was used to extract 2832 periocular features (1416 features for each eye).

Three biometric modalities were tested: face, periocular, and face plus periocular. For each of the three biometric modalities, GEFeS, GEFeW, and GEFeWS were used. The biometric modalities were also tested using all of the originally extracted features without the use of GECs. This served as a control/baseline for our experiments.

Results

For our experiments, the SSGA had a population size of 20 and a Gaussian mutation range of 0.2. The algorithm was run 30 times, and a maximum of 1000 evaluations were performed on each run.

In Table I, the average performance of the three experiments is shown. The first column represents the tested biometric modalities. The second column represents the type of algorithm that was used. The third column represents the average percentage of features used, and the last column represents the average accuracy of the 30 runs.

Table I shows the performance comparison of GEFeS, GEFeW, and GEFeWS. The results using the feature extractors without the GECs were also included to serve as a baseline for the experiments. When the face and periocular biometrics were fused, they both were weighted evenly.

For the Face-Only experiment, GEFeW performed the best in terms of accuracy, having an average accuracy of 87.59%. Based on the results of the ANOVA and t-test, GEFeWS was in the second equivalence class in terms of average accuracy, but there was only a 1.21% difference in the average accuracy for the two algorithms. In terms of the percentage of features used, GEFeWS was in the first equivalence class, along with GEFeS. GEFeWS was able to obtain an average accuracy of 86.38%, while using only 51.71% of the features.

For the Periocular-Only experiment, GEFeWS performed the best in terms of accuracy and the percentage of features used, having an average accuracy of 96.15% while using only 45.39% of the features. These results were confirmed using an ANOVA and t-test. GEFeW was in the second equivalence class in terms of average accuracy. In terms of the percentage of features used, GEFeS and GEFeW were in the second and third equivalence classes respectively.

For the Face + Periocular experiment, GEFeW performed the best in terms of accuracy, while GEFeWS was in the second equivalence class. However, in terms of the percentage of features used, GEFeWS was in the first equivalence class, using only 46.24% of the features to achieve an average accuracy of 98.48% (only a 0.5% difference when compared to GEFeW). GEFeS and GEFeW were in the second and third equivalence classes respectively.

The Face + Periocular experiment performed the best in terms of accuracy for all the algorithms used, followed by the Periocular-Only experiment and the Face-Only experiment.

Modalities Tested	**Algorithms Used**	**Average % of Features Used**	**Average Accuracy**
Face Only	Eigenface	100.00%	64.76%
	Eigenface + GEFeS	51.03%	77.87%
	Eigenface + GEFeW	87.71%	87.59%
	Eigenface + GEFeWS	51.71%	86.38%
Periocular Only	LBP	100.00%	94.29%
	LBP + GEFeS	48.03%	95.14%
	LBP + GEFeW	86.22%	95.46%
	LBP + GEFeWS	45.39%	96.15%
Face + Periocular	Eigenface + LBP [evenly fused]	100.00%	90.77%
	Eigenface + LBP + GEFeS	48.18%	97.40%
	Eigenface + LBP + GEFeW	87.59%	98.98%
	Eigenface + LBP + GEFeWS	46.24%	98.48%

Table 1. *Comparison of the performances of GEFeS, GEFeW, and GEFeWS.*

For the percentage of features used, GEFeWS used the least amount of features for the Periocular-Only and Face + Periocular experiments, and there was no statistical significance between GEFeWS and GEFeS for the Face-Only experiment. GEFeW used the highest percentage of features for all three experiments.

Conclusion

Our results show that the hybrid GEC, GEFeWS, is able to achieve higher recognition accuracies than GEFeS, while using about the same amount of features. GEFeWS is also able to use a significantly lesser amount of features than GEFeS while achieving approximately the same average recognition accuracy. Overall, the Face + Periocular performed better in terms of accuracy when compared to the Face-Only and Periocular-Only experiments. Our future work will include investigating additional multi-biometric fusion techniques as well as additional GECs in an effort to further improve the performance of multi-biometric recognition. In addition, we will investigate applying these algorithms to a larger dataset to see how well they generalize.

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