Analyzing the Cross-Generalization Ability of a Hybrid Genetic & Evolutionary Application for Multibiometric Feature Weighting and Selection

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ABSTRACT

Genetic & Evolutionary Biometrics (GEB) is a new field of study devoted to the use of Genetic & Evolutionary Computations to solve some of the traditional problems within the field of biometrics. In this paper, we evaluate the performances of two GEB applications, Genetic & Evolutionary Fusion (GEF) and Genetic & Evolutionary Feature Weighting/Selection—Machine Learning (GEFeWS$_{ML}$), on the FRGC and MORPH databases. We then investigate the ability of the evolved weights and feature masks (FMs) to generalize across datasets. Our results showed that the GEB applications were robust, achieving high recognition accuracies across the datasets. In addition, the FMs achieved these recognition accuracies while using less than 50% of the originally extracted features.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search– *Heuristic methods.*

General Terms

Algorithm, Performance, Experimentation, Security

Keywords

Biometrics, Feature Selection, Feature Weighting

1. INTRODUCTION

Recently, there has been an increase in the use of Genetic & Evolutionary Computations (GECs) [7, 8, 9] to solve some of the traditional problems within the field of biometrics, giving rise to a new field of study referred to as Genetic & Evolutionary Biometrics (GEB) [1, 2, 3]. Alford et al. [1, 3] proposed several GEB applications for multibiometric recognition. One application, Genetic & Evolutionary Fusion (GEF) [1, 3], evolved weights for multibiometric score-level fusion in an attempt to increase the recognition accuracy. Another technique, known as Genetic & Evolutionary Feature Weighting/Selection—Machine Learning (GEFeWS$_{ML}$) [3], evolved feature masks (FMs) in an attempt to reduce the dimensionality of the feature templates, increase the recognition accuracy, and also generalize well to unseen instances.

In their previous research, Alford et al. applied their techniques to templates formed from the facial and periocular images extracted from the Face Recognition Grand Challenge (FRGC) [5] database. In this paper, we evaluate the performance of the two applications on a subset of images extracted from the Craniofacial Longitudinal Morphological Face (MORPH) [6] database. Unlike the FRGC images, the MORPH images were captured over a period of time. In addition, we test the performance of the resulting FMs for each dataset on the alternative dataset. This process, which is referred to as cross-generalization [4], attempts to determine how well artifacts (in this case, FMs) trained on one dataset generalize to another dataset. This property is important for biometric systems because new individuals may be added to the system incrementally and the individuals currently in the system will definitely begin to exhibit signs of aging. Therefore, having the ability to generalize well to unseen subjects across datasets will reduce the need for future retraining of the techniques over time.

The remainder of this paper is as follows. In Section 2, we describe our experiments; in Section 3, we provide a discussion of our results; in Section 4, we present our conclusions and future work.

2. EXPERIMENTS

For our experiments, images were selected from two facial databases: the FRGC database and the MORPH database. A total of 309 subjects were selected from the FRGC database, and a total of 100 subjects were selected from the MORPH database. Three datasets were then formed for each database: a training set, a validation set, and a test set. The FRGC subjects were segmented as follows: 105 of the subjects were used to form the training set, which will be referred to as FRGC-105; An additional 105 subjects were used to form the validation set, which will be referred to as FRGC-105b; The remaining 99 subjects were used to form the test set, which will be referred to as FRGC-99. The MORPH subjects were divided as follows: 50 subjects were used to form the training set, which will be referred to as MORPH-50; 25 subjects were used to form the validation set, which will be referred to as MORPH-25a; the remaining 25 subjects were used to form the test set which will be referred to as MORPH-25b.

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For each dataset, three frontal facial images of each subject were selected and used to form the probe and gallery sets. The probe sets consisted of one image per subject, and the gallery sets consisted of the two remaining images per subject. The Local Binary Patterns (LBP) [10] method was then used to extract 2124 (*36* patches × *59* bins) facial features and 2832 (*24* patches × *59* bins per periocular region) periocular features from each image in the probe and gallery sets.

Next, two experiments were performed. For the first experiment, $GEFeWS_{ML}$ was used to evolve FMs for the FRGC and MORPH face-only, periocular-only, and face + periocular templates within the training sets. This will be referred to as *'Optimization'* because we are attempting to maximize the recognition accuracy while minimizing the percentage of features used. The resulting FMs (FM^{ts}s and FM^{*}s) were then applied to the test sets in order to evaluate how well they generalized to unseen subjects within the respective test sets. The application of the FM^{ts}s will be referred to as *'Opt-Gen'* because we are taking the FMs that were optimized for a training set and evaluating their generalization ability. Similarly, the application of the FM^{*}s to the test sets will be referred to as *'Val-Gen'* because we are evaluating how well the best performing FMs on the validation sets generalize to the test sets. In addition, GEF was used to evolve weights for the face + periocular feature templates for both datasets with the goal of minimizing the number of recognition errors.

For the second experiment, we evaluated the cross-generalization ability of the returned FMs as well as the weights optimized by GEF. To do so, the FMs returned for the FRGC templates were applied to the MORPH test set and the FMs returned for the MORPH templates were applied to the FRGC test set. In addition, the optimized weights for each dataset were tested on the opposite dataset.

3. DISCUSSION OF RESULTS

For Experiment I, our results along with the previous results by Alford *et al.* [4] showed that for both datasets, $GEFeWS_{ML}$ used less than 50% of the features to and achieved higher recognition accuracies than the baseline method. In addition, the resulting FMs generalized well to the unseen subjects within the test sets.

For Experiment II, our results showed that the resulting FMs were also able to generalize well on subjects presented from an entirely different database. In addition, the FMs that resulted from applying $GEFeWS_{ML}$ to the MORPH dataset generalized better to the FRGC dataset than the FRGC FMs did to the MORPH dataset. This may indicate that the FMs returned for the MORPH dataset were able to latch on to some features that were more discriminative for recognition due to the variability of pose, expression, and age of the subjects within the dataset.

4. CONCLUSION AND FUTURE WORK

In this paper, we applied two GEB applications, GEF and $GEFeWS_{ML}$, to two different databases and evaluated the ability of the resulting weights and FMs to generalize to another test set. Our results showed that not only could $GEFeWS_{ML}$ be used to reduce the number of features necessary for recognition and increase the recognition accuracy for a specific database, but that the resulting FMs could also generalize well to unseen images from a different database. GEF was also robust, increasing the recognition accuracy over the baseline method for the training set, while not reducing the accuracy on the various test sets.

For our future work, we would like to analyze the effect training GEF and $GEFeWS_{ML}$ on datasets that consist of templates extracted from various databases would have on the generalization performances. We believe that this would result in better cross-generalization performances.

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