Analysis of the Performance Improvement Obtained by a Genetic Algorithm-based Approach on a Hand Geometry Dataset

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Abstract— *Biometric recognition by hand geometry has a large number of measurements that may be used for authentication. The higher number of attributes, the harder is to define the importance of each one. In this paper, we analyze the use of a Genetic Algorithm-based approach in improving Equal Error Rate (EER) performance for biometric authentication by hand geometry. We used an own data set of dorsal and palm images of hand in a controlled environment to validate our approach. As the best results, the genetic algorithm decreased the equal error rate up to 0% in the training set and 0.01% for the test set. Additionally, a relative improvement of 90.91% was achieved by GA in the best case for the test set.*

Keywords: genetic algorithms, hand geometry, palm, optimization, EER

1. Introduction

Reliable identification systems have become a key issue for applications that authenticate users. Traditional methods to establish user's identity include mechanisms based upon knowledge (e.g., passwords) or tokens (e.g., identification cards). However, such mechanisms may be lost, stolen or even manipulated to spoof the system. In such a context, biometrics rises as an alternative. [15].

The biometry allows the identification of individual based on anatomical and behavioral features. There are many examples of biometric traits used to recognize a person, e.g., fingerprint, handprint, hand geometry, hand veins, face, voice, and iris. Those features can be used alone or combined (multi-biometric). Because biometric identifiers cannot be easily misplaced, forged, or shared, they are considered more reliable for person recognition than a traditional token or knowledge-based methods. Thus, biometric recognition systems are increasingly being deployed in many government and civilian application [14].

For human hands, a large number of features may be extracted, such hand print, the pattern of hand veins and hand geometry. Hand geometry refers to features like the shape of the hand, size palm, length and width of the fingers [11]. Such process has some advantages when compared with other methods [16], including easy to use; low cost, requires only an average resolution camera (no special sensors are necessary); and low computational cost, allowing faster results.

In biometric systems, a matching algorithm is used to compare two templates and generates a score value to indicate the degree of similarity between the templates. Such score depends on factors and constant weights are generally assigned to each factor. In the most of cases, these weights are computed empirically or statically. The optimization of these weights can be a hard task for a large N-dimensional features space.

Genetic Algorithms (GA) are an approach to optimization based on the principle of natural selection of Charles Darwin. These algorithms input is an N-dimensional vector that will be optimized according to a fitness function. GAs proved to be quite successful in finding good solutions to such complex problems as the traveling salesman, the knapsack problem, large scheduling problems and others [5].

The most used method to compare biometric systems is Equal Error Rate (EER) [19] [20] [12] [10]. To compute EER, two values are necessary: the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). The FAR is the probability that an impostor is falsely accepted as a genuine use, while the FRR is the probability that a genuine user is falsely rejected by the system. Thus, the EER is the point where FAR and FRR are equal. The lower EER, the better the system.

This work analyzes a Genetic Algorithm [8] approach in order to improve EER performance in a hand geometry data set. To validate our study, an own data set of hand images were used.

2. Related Works

In this section, we list some related works that may be useful to the reader. First, the work of John Holland [9] was the first to describe evolutionary algorithms. Such work provides a good background about Holland's goal of understanding the life adaptation as like it occurs in nature and the ways of developing systems based on these principles.

For a good theoretical foundation for evolutionary algorithms Back et al. [1] provides an overview of the three main branches of evolutionary algorithms (EA): evolution strategies, evolutionary programming, and genetic algorithms. In their work, certain characteristic components of EAs are considered: the representation scheme of object variables, mutation, recombination, and selection operators.

The paper [2] describes a method to optimal feature selection for a speech signal of people with unilateral vocal fold paralysis. The GA is used in order to find an optimal set of features that maximize the recognition rate of support vector machine classifier. The results show that entropy feature, in comparison with energy, demonstrates a more efficient description of such pathological voices and provides a valuable tool for clinical diagnosis of unilateral laryngeal paralysis.

Considering the importance of parameter optimization on biometric systems, the work by Goranin et al. [7] analyzes a GA application in such context. According to it, the use of evolutionary algorithms may ensure a qualitative increase of biometric system parameters, such as speed, error rate, and flexibility.

The work [17] presents an optimization approach for authentication of fingerprint biometric system. The GA described in the paper is used in order to find the set of parameters that optimize the equal error rate. In the best case,their work reached a relative improvement of 40% in the equal error rate.

In a biometric system based on hand geometry, the work of [13] present a fusion approach of palmprint and hand geometry features in a verification system. The data set of hand images is built without pegs and controlled illumination, only using a digital camera. The results show that when the fusion of features is used, the error rates achieve lower values than when the features works alone (each palmprint or hand geometry).

Finally, the closest work in comparison with ours is the work of [6]. Such work describes an approach for biometric recognition based on hand geometry. Different classification and training methods are applied to measure results. The database used in this work is the same of ours. Additionally, their results are competitive when compared to other state-of-the-art methods.

3. Genetic Algorithms

Genetic algorithms were proposed by [8] as a tool to find solutions to optimization problems in poorly understood large spaces. They are based on the genetic processes of biological organisms, especially on the principle of natural selection by Charles Darwin [4]. Although, this slogan seems to be slightly tautological in the natural environment, where fitness is defined as the ability to survive, it makes good sense in the world of optimization problems where fitness of a string is given as the value of the function to be optimized at the argument encoded by the string.

Typically, a genetic algorithm works on a population of individuals. Each individual is represented by one chromosome formed by a set of genes representing the parameters to be optimized. Some operations are realized in order to produce new generations of individuals based on their capability to generate good results: crossover, selection and mutation.

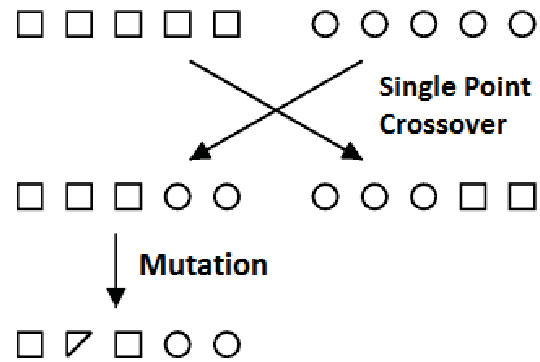

Fig. 1: Example of Crossover and Mutation operators

The crossover is the key operator to generate new individuals in the population. Inspired by the example of nature, crossover is intended to join the genetic material of chromosomes with a high fitness in order to produce even better individuals.

The selection operator is intended to implement the idea of "survival of the fittest". It basically determines which of the chromosomes in the current population is allowed to inherit their genetic material to the next generation.

The mutation operator should allow the GA to find solutions which contain genes values that are non-existent in the initial population. The parameter governing this operator is called mutation probability. Whereas the selection operator reduces the diversity in the population, the mutation operator increases it again. The higher the mutation probability, the smaller is the danger of premature convergence. A high mutation probability, however, transforms a GA into a pure random search algorithm, which is of course not the intention of this.

Let P be a random population of N chromossomes (x_1, x_2, ..., x_n) and *f(x)* a fitness function. The following pseudocode describes the steps of genetic algorithms.

1) Create a random population P of N chromosomes (candidate solutions for the problem).
2) Evaluate *f(x)* of each chromossome *x* in the population.
3) Generate a new population by repeating the following steps until the new population reaches population N:
   a) Select two parent chromosomes from the population, giving preference to highly fit chromosomes (high *f(x)* values). Automatically copy the fittest chromosome to the next generation.
   b) With a given crossover probability, crossover the parent chromosomes to form two new offspring. If no crossover was performed, offspring is an exact copy of parents.
   c) With a given mutation probability, randomly swap two genes in the offspring.
   d) Copy the new offspring into a new population.
4) Copy the newly generated population over the previous

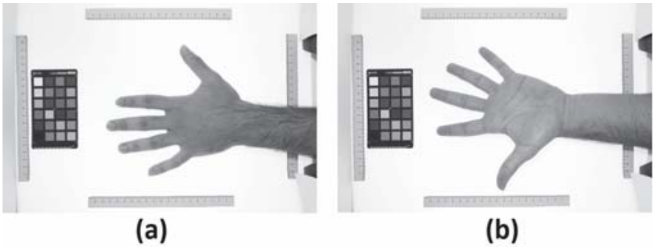

Fig. 2: Image samples of the data set used. (a) dorso (palm down). (b) palm (palm up).

(existing) population.

5) If the loop termination condition is satisfied, then stop and return the best solution in current population. Otherwise, go to Step 2.

4. Proposed Technique

In this paper, we use a GA-based approach to optimizing the EER performance of a hand geometry authentication algorithm. Detailed description of the database used and the methods developed are described in subsections below.

4.1 Database

The database for our work was the same described in [6]. The images were acquired using a device built with a negatoscope, a wooden box, and a DSLR camera. This device has lighting conditions controlled. Each individual places his hand inside the box through a hole in the bottom. The camera capture images 5184x3456 pixels in raw format. The Fig. 2 shows an two images from this data set.

This database is composed of 1200 images divided into 100 different class, where each class represents a person. Each person has 12 hand images, 7 dorsal images, and 5 palm images. Thus, the database has 700 dorsal images and 500 images with palm up.

For each hand image, we use eight measurements from each finger: area, perimeter, length, bottom width, convex area (the area of the smallest convex polygon that contains the finger), eccentricity and the axes of the ellipse that has the same normalized second central moments as the finger image. Of all the fingers, except the thumb, are extracted two angles between three segments that are used to determine the natural inclination of the fingers.

Six measurements are also extracted from hand images: area, perimeter, convex area, eccentricity and the axes of the ellipse (calculated similarly to the fingers). To sum up, there is a total of 54 features which are used as an attributes vector for classification.

For this work, we also extracted 31 more measurements for each palm up image: 6 width information for each finger and hand width. Thus, we use 85 measurements in total for each palm image. Tests were performed to compare the GA performance using 54 and 85 measurements.

4.2 GALib

The GALib library [18] was chosen as a framework to apply the genetic algorithm in this work. It is an open source library written in Java and very easy to use.

In our method, the genetic algorithm was used to compute the weights to optimize our matching algorithm (see section 4.3) concerning to decrease the EER. For this, the initial population of the genetic algorithm is a set of coefficients that represent the importance of each attribute to classification. These coefficients multiply the values of attributes giving importance to each one in the classification. The Equal Error Rate (EER) is used as a fitness function. The Coefficients that generate lower values of EER on classification are more indicated to next generations.

In our work, we have chosen the initial chromosome population of GA equals to 1,000 in order to do an exhaustive search on the search space. Moreover, we also defined 1,000 as the number of generations to be generated by GA and the crossover type was set to *uniform* because preliminary tests have shown this crossover type converges faster than the other two. All the other GALib parameters were left as default.

4.3 The Matching Algorithm

The matching algorithm of this work computes the score between two templates using the score function defined by Eq.(1). A template is defined as the set of measurements of a hand or palm image.

$$d_{1,2} = \sum_{i=0}^{N} w_i . \left| a_i^1 - a_i^2 \right| \tag{1}$$

Where a_i^1 and a_i^2 represent the *i*-th measurement from template 1 and 2, respectively; w_i represents the *i*-th multiplier coefficient; N is the number of measurements; and $d_{1,2}$ is the distance between templates 1 and 2. The lower the distance, the more similar templates 1 and 2.

The main goal of genetic algorithm in this work is to find all the weights $\{w_1, w_2, w_3, ..., w_N\}$ that minimize the EER performance for training set.

4.4 Validation

To validate our method, a cross-validation was performed in the database used. For hand templates, 4 templates of each class were used for training and 3 templates were used for test. For palm templates, 3 templates of each class were used for training and the 2 remaining templates were used for test. The relative performance improved by GA is also analyzed. Table 1 summarize the tests applied.

Each combination was performed three times in training and the best result was stored. The use of GA for test cases of both hand and palm templates means the matching algorithm was applied using the weights computed by GA in corresponding training set.

Table 1: Combination parameters for hand templates

Combination	Templates (Training)	Templates (Test)
1	$1^{st},2^{nd},3^{rd},4^{th}$	$5^{th},6^{th},7^{th}$
2	$1^{st},2^{nd},3^{rd},5^{th}$	$4^{th},6^{th},7^{th}$
3	$1^{st},2^{nd},3^{rd},6^{th}$	$4^{th},5^{th},7^{th}$
4	$1^{st},2^{nd},3^{rd},7^{th}$	$4^{th},5^{th},6^{th}$
5	$1^{st},2^{nd},4^{th},5^{th}$	$3^{rd},6^{th},7^{th}$
6	$1^{st},2^{nd},4^{th},6^{th}$	$3^{rd},5^{th},7^{th}$
7	$1^{st},2^{nd},4^{th},7^{th}$	$3^{rd},5^{th},6^{th}$
8	$1^{st},2^{nd},5^{th},6^{th}$	$3^{rd},4^{th},7^{th}$
9	$1^{st},2^{nd},5^{th},7^{th}$	$3^{rd},4^{th},6^{th}$
10	$1^{st},2^{nd},6^{th},7^{th}$	$3^{rd},4^{th},5^{th}$
11	$1^{st},3^{rd},4^{th},5^{th}$	$2^{nd},6^{th},7^{th}$
12	$1^{st},3^{rd},4^{th},6^{th}$	$2^{nd},5^{th},7^{th}$
13	$1^{st},3^{rd},4^{th},7^{th}$	$2^{nd},5^{th},6^{th}$
14	$1^{st},3^{rd},5^{th},6^{th}$	$2^{nd},4^{th},7^{th}$
15	$1^{st},3^{rd},6^{th},7^{th}$	$2^{nd},4^{th},5^{th}$
16	$1^{st},3^{rd},5^{th},7^{th}$	$2^{nd},4^{th},6^{th}$
17	$1^{st},4^{th},5^{th},6^{th}$	$2^{nd},3^{rd},7^{th}$
18	$1^{st},4^{th},5^{th},7^{th}$	$2^{nd},3^{rd},6^{th}$
19	$1^{st},4^{th},6^{th},7^{th}$	$2^{nd},3^{rd},5^{th}$
20	$1^{st},5^{th},6^{th},7^{th}$	$2^{nd},3^{rd},4^{th}$
21	$2^{nd},3^{rd},4^{th},5^{th}$	$1^{st},6^{th},7^{th}$
22	$2^{nd},3^{rd},4^{th},6^{th}$	$1^{st},5^{th},7^{th}$
23	$2^{nd},3^{rd},4^{th},7^{th}$	$1^{st},5^{th},6^{th}$
24	$2^{nd},3^{rd},5^{th},6^{th}$	$1^{st},4^{th},7^{th}$
25	$2^{nd},3^{rd},5^{th},7^{th}$	$1^{st},4^{th},6^{th}$
26	$2^{nd},3^{rd},6^{th},7^{th}$	$1^{st},4^{th},5^{th}$
27	$2^{nd},4^{th},5^{th},6^{th}$	$1^{st},3^{rd},7^{th}$
28	$2^{nd},4^{th},5^{th},7^{th}$	$1^{st},3^{rd},6^{th}$
29	$2^{nd},4^{th},6^{th},7^{th}$	$1^{st},3^{rd},5^{th}$
30	$2^{nd},5^{th},6^{th},7^{th}$	$1^{st},3^{rd},4^{th}$
31	$3^{rd},4^{th},5^{th},6^{th}$	$1^{st},2^{nd},7^{th}$
32	$3^{rd},4^{th},5^{th},7^{th}$	$1^{st},2^{nd},6^{th}$
33	$3^{rd},4^{th},6^{th},7^{th}$	$1^{st},2^{nd},5^{th}$
34	$3^{rd},5^{th},6^{th},7^{th}$	$1^{st},2^{nd},4^{th}$
35	$4^{th},5^{th},6^{th},7^{th}$	$1^{st},2^{nd},3^{rd}$

5. Results and Discussions

To evaluate our method, 45 combinations of tests were performed on 1200 images (700 hands and 500 palms) divided into 100 classes. Furthermore, for each hand and palm template, 54 and 85 measures were extracted respectively. Subsets of each class are used for training and the remaining are used for test. Genetic algorithms are applied to analyze the EER improvement.

Figure 3 shows the results of the application of GA to all combinations performed in the training set of hand templates. As it can be clearly seen, the genetic algorithm improved the EER for all combinations. As depicted in Table 3, such improvement is at least 86.2694% (combination 32). In some cases (combinations 6, 16, 18, 19, 28, and 31), the improvement obtained by GA acquires 100.0%.

For test set of hand templates, the relative improvement of EER ranged from 25.2396% (combination 11) to 84.4985% (combination 2). Such results can be noticed in Table 3 and observed graphically in Fig. 4. Overall, the use of GA improved EER performance for all combinations of tests where GA is not applied.

Table 2: Combination parameters for palm templates

Combination	Templates (Training)	Templates (Test)
1	$1^{st},2^{nd},3^{rd}$	$4^{th},5^{th}$
2	$1^{st},2^{nd},4^{th}$	$3^{rd},5^{th}$
3	$1^{st},2^{nd},5^{th}$	$3^{rd},4^{th}$
4	$1^{st},3^{rd},4^{th}$	$2^{nd},5^{th}$
5	$1^{st},3^{rd},5^{th}$	$2^{nd},4^{th}$
6	$1^{st},4^{th},5^{th}$	$2^{nd},3^{rd}$
7	$2^{nd},3^{rd},4^{th}$	$1^{st},5^{th}$
8	$2^{nd},3^{rd},5^{th}$	$1^{st},4^{th}$
9	$2^{nd},4^{th},5^{th}$	$1^{st},3^{rd}$
10	$3^{rd},4^{th},5^{th}$	$1^{st},2^{nd}$

Similar to hand templates, the application of GA achieved a significant improvement in EER performance on training sets of palm templates (see Fig. 5 and Table 4). In this respect, the performance improvement ranged from 33.99% (combination 5) to 98.51% (combination 8).

In Figure 6 and in Table 4 is possible to see the results accomplished by genetic algorithms in all test sets of palm templates. The best performance improvement were around 90.91% (combination 2). However, only in these tests there was a worsening of the EER performance in some cases (combinations, 1, 7, and 9). Figure 6 shows this worsening is lower than 1%, in practice, though.

6. Conclusion

This paper analyzes the EER performance improvement obtained by a GA-based approach. A cross-validation was performed on a database with high-quality images of palm down and palm up hands to evaluate your method. The genetic algorithm was used to optimize weights present in the matching algorithm in order to improve EER performance, thus, improving the authentication of system.

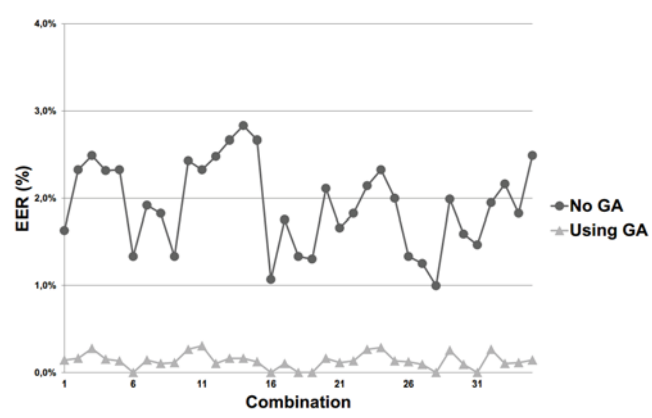

Fig. 3: Results of application of GA for all combinations performed on training set of hand templates.

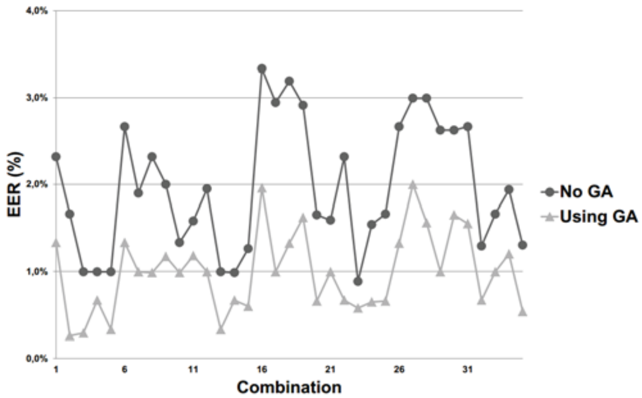

Fig. 4: Results of application of GA for all combinations performed on test set of hand templates.

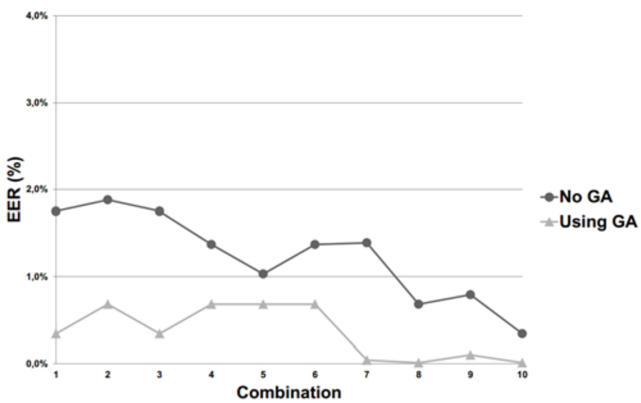

Fig. 5: Results of application of GA for all combinations performed on training set of palm templates.

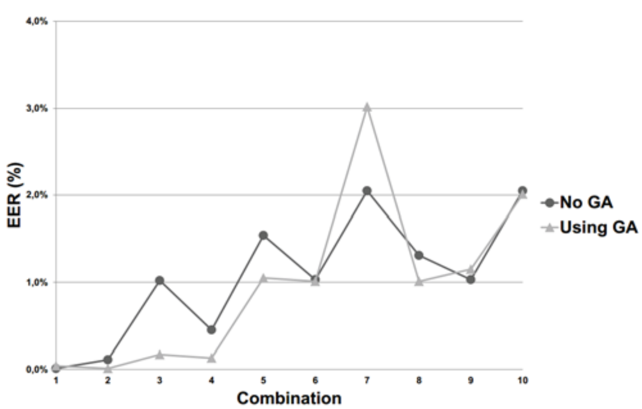

Fig. 6: Results of application of GA for all combinations performed on test set of palm templates.

Table 3: Relative improvement for training and test sets of hand templates.

Combination	Rel. Improv. (Training)	Rel. Improv. (Test)
1	91.176471%	42.483660%
2	92.950108%	84.498480%
3	88.855117%	71.065990%
4	93.355120%	32.994924%
5	94.251627%	67.005076%
6	100.000000%	50.000000%
7	92.500000%	47.606383%
8	94.329184%	57.516340%
9	91.477273%	41.414141%
10	88.992731%	26.136364%
11	86.767896%	25.239617%
12	95.829095%	48.963731%
13	93.844697%	67.005076%
14	94.201606%	32.307692%
15	95.359848%	52.800000%
16	100.000000%	41.212121%
17	94.100719%	66.209262%
18	100.000000%	58.544304%
19	100.000000%	44.367418%
20	92.234170%	60.244648%
21	93.161094%	37.460317%
22	92.669433%	71.241830%
23	87.514723%	62.857143%
24	87.635575%	58.032787%
25	93.308081%	60.486322%
26	90.719697%	50.378788%
27	92.540323%	33.220911%
28	100.000000%	47.892074%
29	87.055838%	62.115385%
30	94.126984%	37.115385%
31	100.000000%	41.856061%
32	86.269430%	48.437500%
33	95.215869%	40.121581%
34	93.775934%	38.020833%
35	94.224924%	58.914729%

The results show that our approach produces a significant improvement when GA is used. For the training set, all the 45 combinations had an improvement in EER performance. In the most of cases, the relative improvement was above 80%. For the test set, i.e. samples not used for GA training, the relative improvement has occurred in 42 of 45 cases.

For future works, we intend to test our approach with other databases to verify whether GA also improve their results. Furthermore, we also expect to test other evolutionary algorithms and optimization metaheuristics, as ant colony, particle swarm, and greedy randomized adaptive search procedure, comparing their results with the results presented in this paper.

Although hand geometry recognition is not usual yet, the experiments performed in this work can indicate evolutionary algorithms as a tool to improve the equal error rate and the quality of biometric systems.

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Table 4: Relative improvement for training and test sets of palm templates.

Combination	Rel. Improv. (Training)	Rel. Improv. (Test)
1	80.69%	-300.00%
2	64.08%	90.91%
3	80.69%	83.09%
4	50.74%	71.11%
5	33.99%	32.13%
6	50.74%	1.97%
7	97.10%	-47.04%
8	98.51%	23.17%
9	87.18%	-11.82%
10	97.02%	1.97%

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