Genetic Algorithm based Palm Recognition Method for Biometric Authentication Systems

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***Abstract*—Biometric authentication systems are steadily becoming a solution to wide number of authentication and identity management problems. Unique parts of human body that can be recognized and used as a mean to identify a person include fingerprints, iris, lips, etc. Though fingerprint and facial recognition systems are most widely used and developed, most of the systems and methods are slow or require expensive technical equipment. In this article genetic algorithm based palm recognition method is proposed, which does not require special equipment and can be used in systems where fast detection is needed. Method is compared to other existing methods. Method description, test results and evaluation are provided.**

***Index Terms*—Genetic algorithms, palm recognition, biometric authentication, fingerprint recognition.**

I. INTRODUCTION

Biometrics is the science of establishing the identity of an individual based on the physical, chemical or behavioural attributes of the person. The relevance of biometrics in modern society has been reinforced by the need for large-scale identity management systems whose functionality relies on the accurate determination of an individual's identity in the context of several different applications [1]. Biometrics is seen by many as a solution to a lot of user identification and security problems in today's networks. Either intentional or inadvertent, misuse or abuse of passwords is a gaping hole in the present day security system [2]. The most common biometric method to identify the individuals is through fingerprint [3] recognition though in recent years the interest in other techniques of biometric has grown. These techniques rely on: DNA, hand geometry, palm print, face, iris, retina, signature, ear shape, odor, keystroke entry pattern, gait, and voice [4].

Biometric system implementation for person identity verification purposes, terrorist acts prevention measures, authentication process simplification in computer systems and many other tasks has raised significant attention to reliability and efficiency of biometric systems [5]. In this article our goal is to present a biometric palm recognition technique, based on genetic algorithms, which mainly aims at express authentication systems. Genetic algorithms were

selected for method implementation as a quick search method.

II. GENETIC ALGORITHM BASED RECOGNITION METHODS

Genetic algorithms are considered to be a part of evolutionary algorithms that are inspired by Darwinian evolution mechanisms. Genetic algorithms are nondeterministic methods that employ crossover and mutation operators for deriving offspring. The power of GA lies in its ability to exploit, in highly efficient manner, information about a large number of individuals [6].

III. GENETIC ALGORITHMS AND GENETIC PROGRAMMING FOR FINGERPRINT MATCHING

Fingerprint has been researched the longest period of time and shows the most promising future in real-world applications [7]. Due to the persistence and individuality of fingerprints, fingerprint recognition has become a popular personal identification technique [8] though this method has its own weaknesses such as fingerprint recognition because of complex distortions in images and fingerprint registration, creation and usage of fingerprint test databases [9] and others.

According to [7] image registration can be divided into two categories: area based methods and feature based methods. These algorithms can also be classified according to the transformation model, used to relate the reference image space with the target image space [5], i.e. linear and non-rigid. Most of the existing fingerprint recognition and verification techniques are based on minutiae (ridge bifurcation and ending) features. Extracting minutiae from fingerprint images is one of the most important steps in automatic fingerprint identification systems [5]. These systems at first detect minutiae in a fingerprint and then match the input minutiae set with the stored template [9].

In order to deal with low quality fingerprint images, optimal global transformation with fitness function was designed and proposed in [12] to improve the chances of identification between two fingerprint images.

In [13], a modified and improved BioGINA algorithm for biometric recognition was presented and application tested with BioGINA database of 1200 fingerprints from 12 and database from 2000, 2002, 2004 Fingerprint Verification Contests. Application showed 40% relative improvement of

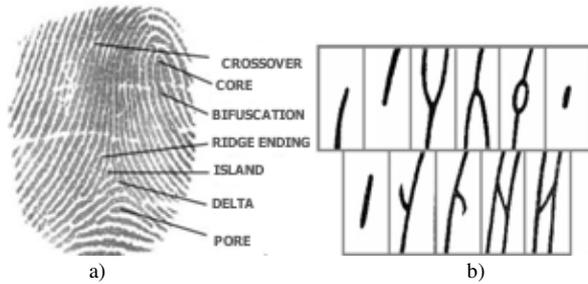the equal error rate at the best case with 2000 Fingerprint Verification Contests database 1.

Fig. 1. Fingerprint sample with minutiae marked (a)[10]; minutiae types (b) [11].

There were also other methods proposed for fingerprint verification technique improvement during years like Kohonen self-organizing neural network, embedded with genetic algorithms for fingerprint recognition in [14] that showed improved learning performance and accuracy of the neural network etc. Aforementioned methods are used for fingerprints classification, in [15] described a new method for fingerprint matching, based on lines extraction and graph matching principles. The method adopts a hybrid scheme which consists of genetic algorithm phase and a local search phase [15].

One more application of genetic algorithms is their adoption for fingerprint database generation. Fingerprint databases are used for testing biometric authentication systems. While constructing a fingerprint database, it is important to have in mind the performance of automatic recognition systems. In practice, constructing of such database would be too costly, unrealistic or incomplete [16]. In [17] a method that generates fingerprint images automatically from a few training samples by using genetic algorithms was presented. Generated fingerprint images (Fig. 2) include similar characteristics to those collected from a real environment. The proposed method constructs a set of filters that modifies an original image.
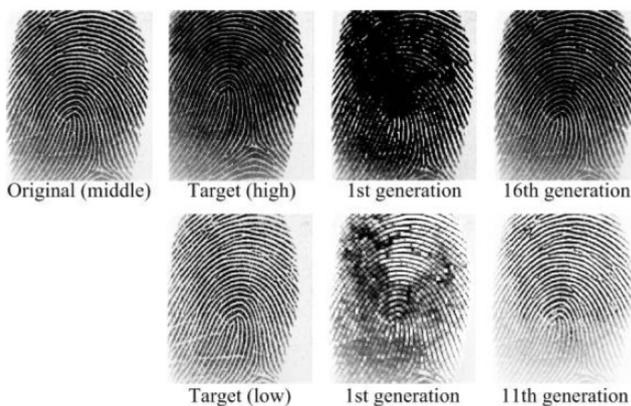

Fig. 2. Fingerprints generated by GA-based method [17].

A set of filters is found by the genetic algorithm – fitness evaluation is conducted using various statistics of fingerprints to measure the similarity. In the initialization step, it sets basic parameters such as maximum number of generations, population size, selection rate and so on. Only a few samples are required to calculate several statistics for

the target environment to evaluate a chromosome. The usability of the proposed method was verified by comparing the fingerprints collected from real environments with generated ones. Besides, the proposed method has the applicability to the fingerprint image enhancement by modifying the fitness evaluation module (Fig. 2).

IV. GENETIC ALGORITHM BASED FACE RECOGNITION METHODS

Face recognition is a biometric authentication method that is becoming more significant and popular in recent years. It plays an important role in law enforcement forensic investigation [18], security access control systems [19] and other applied and security systems. Generally there are three categories of approaches for recognition, namely global facial feature, local facial feature and hybrid feature [20]. In [21] authors present an optimization approach that creates and improves Hausdorff Distance-Based Face Localization model using genetic algorithms. In [22] authors discuss human head movement and real-time processing and using genetic algorithms for template matching in order to solve these problems. Though generally genetic algorithms are not suitable for real-time processing, authors state that in simulations the 97,9% eye tracking accuracy and an average processing time of 28 milliseconds per frame was achieved.

In [23] authors present an automatic facial feature extraction method using genetic algorithms. They are applied when searching for the best ellipse in the image and when extracting facial features. The general processing scheme is shown in Fig. 3.
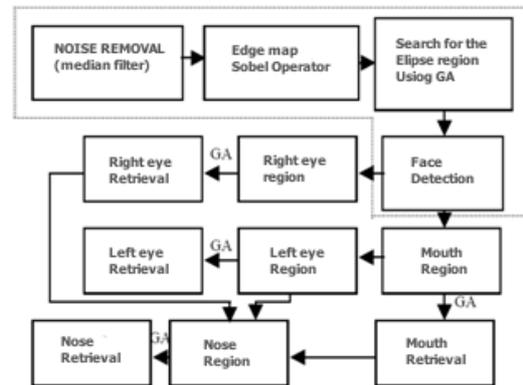

Fig. 3. Block diagram of the facial feature extraction method [23].

The fitness function is defined by the number of edge pixels in the ellipse like face to the actual number of pixels in the actual ellipse. In the feature extraction stage, genetic algorithm is used to search for the global maximum point when the template best matches the feature. The fitness is evaluated in terms of density of the template and the best one is selected when fitness is maximized. The proposed method was validated with a large number of images, containing one and more persons. Genetic algorithm was able to search effectively and reduce computational complexity and the search time. In [24] authors describe a method for 3D face recognition. Each model in the described method consists of 2953 vertices. In order to better characterize 3D features of the facial surface, each of these vertex on the individual model is labeled by one of eight

label types. A cubic approximation method is used to estimate the principal curvatures of each vertex of the model. Some non-feature labels could be noise, therefore a feature screening process for maximizing the difference between different subjects while minimizing the size of the feature space is applied. The face model is divided into 15 sub-regions in order to select optimal features and to remove irrelevant or redundant ones that may degrade the performance. Genetic algorithm is used to address this type of problem. Method, based on it, selects features that contribute the most to the face recognition task. Procedure for selection consists of two parts: selecting vertices in each sub-region and integration of sub-regions. During the tests, correct recognition rate of 92% was reached.

V. GENETIC APPLICATIONS FOR OTHER BIOMETRIC INFORMATION PROCESSING

Other techniques of biometric information processing, using genetic algorithms might include speaker recognition (most works in the area of speech and speaker recognition focus on speech in noiseless environments, but in [25] Neuro-Genetic Hybrid algorithm with cepstral based features has been used to improve the performance of the speaker identification under noisy environment. Highest recognition rate of 94-95% was reached.), online biometric verification system (as presented in [26], such system, requiring no additional equipment, combining two distinct tests to ensure authenticity, showed the fraudulent access rate equal to 4.4% while authentic users could access the system with 99% rate.) and so on.

VI. PALM RECOGNITION METHOD

Aforementioned methods are more suitable for user recognition when the stream of people is small. They ensure high reliability of the system. But there are situations when express user authentication is needed for big stream of users. Authentication in concerts, stadiums, transport junctions and other mass meetings might serve as the examples when the speed of the system is more important and a particular number of system errors can be tolerable. Biometric information that assures such requirements could be palm recognition. Geometric characteristics of a person's palm have a sufficient level of uniqueness that makes this method suitable for authentication.

A. Method description

Palm is a unique part of the human body [27]. This means that a person can be identified by his palm. There are two most common methods of palm recognition – hand geometry and palm print. Palm print is made of main lines and wrinkles. Main lines of a palm are unique and can be used to recognize a person. But it is a rather difficult task for computer systems to find these lines. Special methods are used. One of them is described in [27]. Traits of lines are found from a photo of normalized hand print, using four detectors. Every one of these filters detect lines that are arranged 0, 45, 90 and 135 degrees. Plot of the print is divided into smaller pieces and convolution with all filters is processed. The highest result corresponds to the direction of

the line. This way the directed print of the palm lines is made.

Hand geometry is also a unique characteristic of a human body. It is the most commonly used method to recognize the hands/palms. In order to recognize people using such method, particular parts of the hand are measured (Fig. 4)
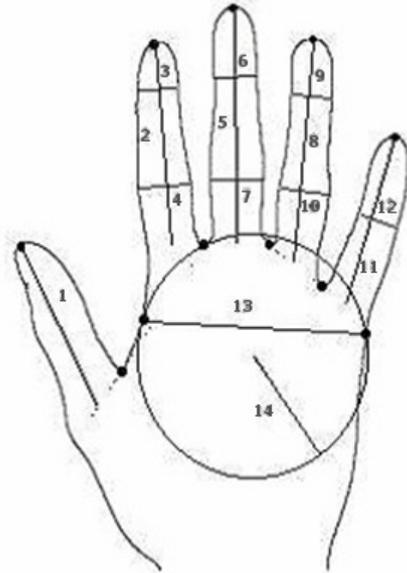

Fig. 4. Measuring hand traits [28].

The system must be taught to recognize a person. Several measures of a palm of a person are made. The number of measurements depends on precision required. When too many measurements are made, system will be more precise, but the right identity will be rejected more often. When there are too little measurements – the wrong person will be recognized as the correct one more often. After several measurements, results are written to vector that is saved in memory. It must be kept in mind that two prints are never fully homogenous. Limiting value that is determined via experiments is used. It shows how much two prints can differ [28]. This method has its weak points. One of the main problems is the change of form of human hand. This causes trouble for automatic recognition systems and comparing prints to the ones, saved in database. Yet another technical issue is insufficient reliability when recognizing a person. It recognizes the person when it shouldn't and vice versa.

In this article, a new method of palm recognition is proposed. In order to use this method, no highly precise scanners are needed and no special equipment is used. Biometric systems of this type are not widely used since geometry of a hand is comparatively new information in biometry and has specific applicable areas. The main principle of methods used in practice is to compare various parts of a hand and to look for equivalents. Fingers have the biggest amount of distinctive information thus the proposed method uses only fingers in order to minimize the quantity of information and to maximize the precision. Method that uses the whole finger should be more precise than systems using only parts of a finger or hand.

In the proposed method (Fig. 5) the image of the whole finger is compared to the ones existing in database. It is

accomplished by putting two imprints of finger one on another and comparing the coinciding pixels. Imprint of compared finger can be moved or turned thus user is not forced to keep his hand in particular position. The only requirement is that scanned fingers should not to be put close together. When the system gets the image of the whole hand, it singles out imprints of the fingers that are used for identification. To optimize the choice of the position of every finger genetic algorithms are used. Three parameters are optimized: coordinates of x and y and turning angle of imprint.
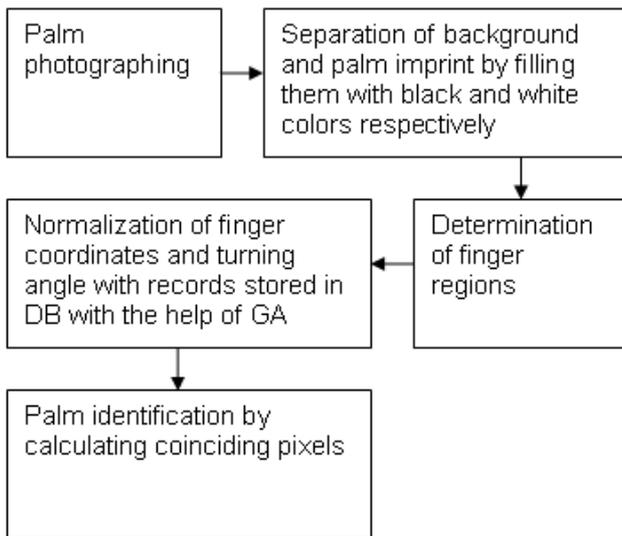

Fig. 5. Block diagram of the proposed GA-based palm recognition method.

After analyzing every pixel in the image submitted to the software, background is filled with black and the imprint of the hand with white colour. Differences between background and hand imprint is obtained by converting colours of the image and comparing differences between them.

Fingers are excluded by marking 4 points around their area. Later in the process only marked areas are compared. System precision and calculation time depends on the number of excluded finger areas. There are moments when the single finger is enough to recognize the whole hand, but probability of mistakes is higher. Database file with data of hand imprints is saved in XML format. The system can choose between two methods for calculation – to check every possible combination (full sorting) or to use a method based on genetic algorithms.

First of all finger imprints are prepared for comparing. Hand imprint is processed so that white pixels that do not fall under marked area of fingers are colored black. During calculation coinciding white pixels are counted. The correctly recognized hand will have the maximum number of coinciding pixels.

In case of full sorting moving an imprint is moved by one position on x and y axes at a time and/or turning it by one degree. In order to move and turn an imprint, recalculation of every pixel is needed. After new position of imprint is established, verification of white pixels is performed.

The general software interface developed for method tests is presented in Fig. 6.
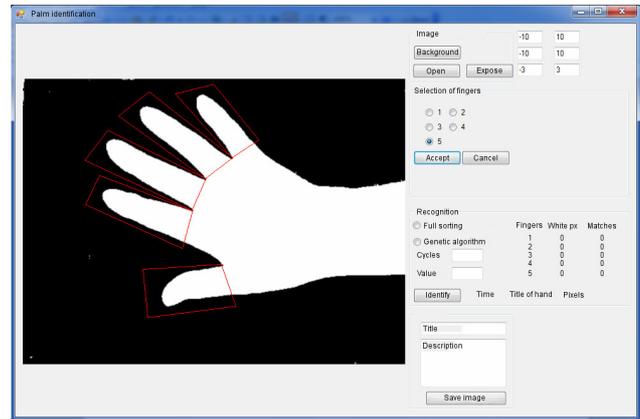

Fig. 6. Graphical user interface of an application developed.

Genetic algorithms are used to accelerate the sorting of turned fingers. Suitability of a candidate is defined by evaluating number of white pixels that matches in candidate and in standard. The used genetic algorithm parameters are as follows: initial population – random numbers. Chromosome (a member of population) is made of 3 parameters (Fig. 7): coordinates of imprint position (x and y) and the angle of position (α).

Fig. 7. Chromosome structure defining finger regions.

New chromosomes are generated every cycle. Their fitness is verified according to probability function that corresponds to coinciding white pixels. Depending on meaning of probability function, best and worse candidates of population are picked. Crossover is performed with 50% of the best candidates. Others are removed from population.

Mutation is performed on the worst candidates and the best ones become parents during crossover. Chromosomes are crossed over using crossover in one point. The point is chosen randomly. In one case the descendant receives coordinates, in another – angle of turning.

Mutation is performed with 20% of the worst candidates. During the mutation, parameter is chosen randomly and it is replaced with random meanings. Number of cycles is defined at program startup.

VII. RESULTS AND DISCUSSIONS

25 imprints of human hands were collected for testing of a new method. Parameters were defined (in experimental way) as described in Table I. Parameters, listed in Table I enable software to recognize hands with little change in position. The time of identification is directly proportional to number of hand imprints saved in the database.

TABLE I. GENETIC ALGORITHM PARAMETERS USED IN METHOD TESTS.

Boundaries of search on x axis (in pixels)	10
Boundaries of search on y axis (in pixels)	10
Boundaries of search for imprint turning (in pixels)	10
Number of generations	10
Size of population	10
Probability of crossover	0.8
Probability of mutation	0.2
Change of population in one generation (%)	70

Tests have shown that when there is a little change in position, imprint of one finger is sufficient to recognize the hand. This fact allows decreasing the time of identification almost 5 times. The proposed method was compared with full sorting in order to evaluate its effectiveness. The results are shown in Fig. 8.
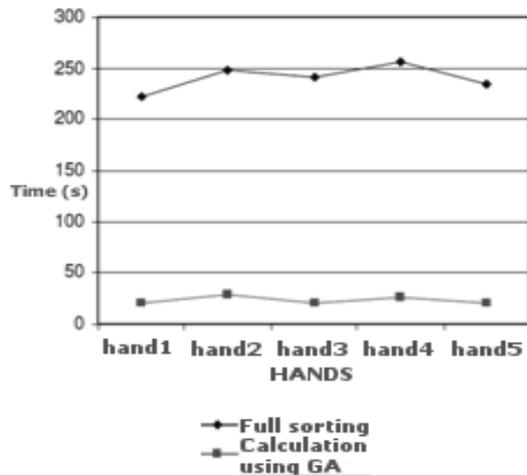

Fig. 8. Comparison of time needed to identify a person in case one finger is used for recognition.

Desktop computer with Intel Core 2Duo 2.33Ghz Processor and 2048 MB of RAM running on Windows XP Pro (SP3) was used for both developed method and full sorting tests. It was insured that there is a similar test system load level by other system processes during tests of both methods and that other system processes do not influence time consumption of the methods tested.

Average time of palm identification when using full sorting is about 220 seconds and identification using genetic algorithms didn't exceed 25 seconds i.e. the productivity was improved almost 10 times. But although calculation time is shorter, precision of the method does not suffer. Testing results have shown that when comparing 5 fingers of a hand, reliability of the method is 96% and when comparing 1 finger – 92%.

It is also worth mentioning that during the tests of the new method, parameters of genetic algorithms were not optimized. Attention was paid to demonstration of principal correctness of the method and to demonstration of the perceptiveness of usage of genetic algorithms.

The effectiveness of the proposed method was also compared with the method when software measures 18 parameters of a hand. 13 of them are calculated using finger imprints. Calculations are processed in precision of pixels. Final result is the sum of all measurements of a hand (Table II).

TABLE II. HAND RECOGNITION RATE BY MEASURING 18 HAND PARAMETERS

Difference between hands (in pixels)	Number of recognized hands			
	Hand1	Hand2	Hand3	Hand4
150	47	60	53	56
105	19	26	22	19
75	8	13	11	8
60	2	4	1	1
30	0	1	1	1

Performed tests have shown that the system using sum of

18 parameters of a hand is not as reliable as the method proposed and reaches only 75%. Test results, presented in Table II show that differences between hands are just 30 pixels. Average sum of measurements is 1780 pixels. Possible error of calculation is only 1.69%.

VIII. CONCLUSIONS

In this article the principle correctness and applicability of the newly proposed genetic algorithm based hand recognition method was proved.

The method tests have shown that application of genetic algorithms for handprint search and recognition decreases time consumption almost 10 times compared to full sorting method.

The achieved method reliability 92-96% is sufficient for express biometric authentication systems but detection rates achieved still need to be improved by optimizing genetic algorithm parameters.

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