A New Approach for Hand-Palm Recognition

KHALID SAEED[1], MARCIN WERDONI[2]
Faculty of Computer Science, Bialystok University of Technology,
Wiejska 45A, 15 – 351 Bialystok, Poland,
http://aragorn.pb.bialystok.pl/~zspinfo/
e-mail: [1]aidabt@ii.pb.bialystok.pl [2]mwerd@tlen.pl

Abstract: A new algorithm for human recognition by hand-palm images is presented in this paper. The suggested approach is based on characteristics of the minimal eigenvalues obtained from Toeplitz matrices for image description. The recognition steps in the algorithm use both classical and new approaches. The achieved results are promising although of not very high rate of classification. The effectiveness of the recognition has achieved 100% in small classes and about 70% in large classes using the new trend of minimal eigenvalues. It reaches, however, a 100% rate of classification following the classical methods of comparison and classification for even bigger classes.

Key words: Hand-Geometry, Human Identification, Classification, Toeplitz, Biometrics

1. INTRODUCTION

Methods and algorithms for different biometric identification techniques have their own advantages and disadvantages. Among these techniques, hand geometry possesses the least disadvantages from the authors' point of view [1].

The general systems for hand geometry identification work in two phases: an enrollment phase and a comparative one. In the enrollment phase, several photographs are taken of the user. These photographs are then preprocessed to enter the feature extraction block, where a set of measurements is performed. With the features extracted, the user's pattern is computed and stored in a database. In the verification phase, a single photograph is taken, preprocessed, and entered in the feature extraction block. This single set of features is compared with the template previously stored, obtaining a ratio of likeliness to determine who the user is whose hand had been photographed.

The comparative block was configured as a classifier, where the extracted features are compared with all of the users' templates to determine which the examined person's palm is.

All the different blocks of the designed hand-geometry identification system are given throughout the following minimal-eigenvalue-based algorithm. The algorithm is introduced in two stages, feature extract and classification.

2. FEATURE EXTRACT

The aim of this first block is to capture a sample of the user's hand geometry from palm side, process it extracting a set of feature points. To achieve this, three tasks are performed.

2.1 Image Capturing

The sample signal is obtained with a HP 4400c scanner. The hand is placed onto a platform (Fig.1a) designed to properly formulate the hand-palm geometry and location. This platform has been modified (Fig.1b) to allow more flexibility of feature capturing. The platform works as the data acquisition device for the hand-palm identifying system.

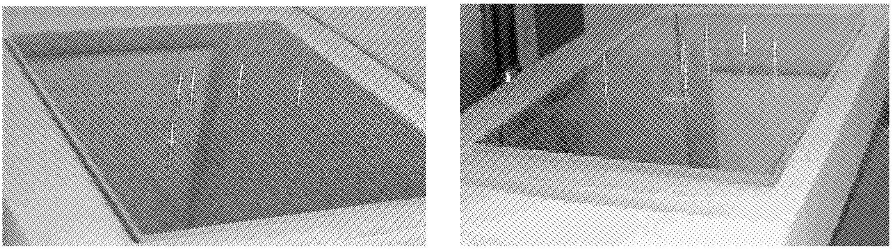


Fig. 1. The used-in-work platform, the original (a) and the modified one (b).

The hand-palm is scanned in grayscale with resolution of 72 dpi to BMP format. The image is captured and saved for data acquisition and processing.

2.2 Preprocessing

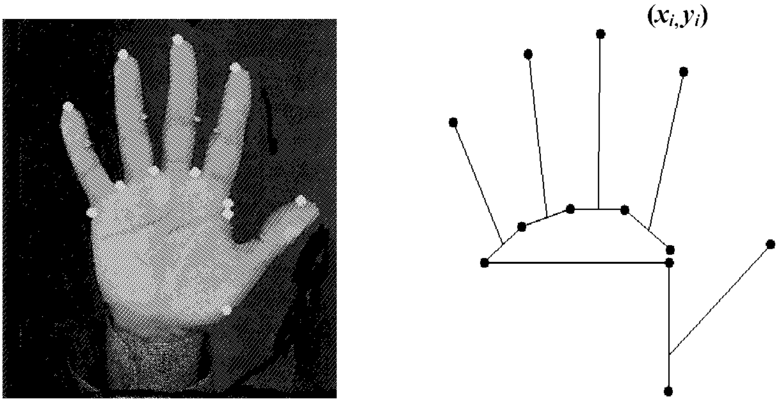
After the image is captured, preprocessing is performed. The first step in the preprocessing block is to transform the grayscale image into a black and white one.

The simplest segmentation process is the gray level thresholding [2]. The algorithm searches all the pixels of the image. An image element at the segmented image is an object pixel, if $f(x,y) \geq T$, and is a background pixel otherwise. x and y are the coordinates of the pixels, T is the captured image threshold.

In the next step the algorithm separates the object pixels from the background ones. In this way the feature points are selected and registered. The following section shows the way this is done according to the method used in this work for image input data necessary to work with in the proposed analysis method.

2.3 Characteristic Features

After preprocessing, the image is analyzed and the feature points are selected (Fig.2). The selection of these points is based on the choice of points describing the palm parameters [3], that is, finger width and length, palm width and length, and so forth as shown in Fig.2b. Thirteen different characteristic points are selected for the sake of classification.



(a) (b)

Fig. 2. Feature points localization.

3. CLASSIFICATION

Here, in the classification stage, the image of Fig.2b is put on the x-y plane to determine the coordinates of the feature points extracted from the captured image. These points are the input data to the classifying algorithm and its adjacent recognizing system both described in details in [4]. Instead of matching the hand image points one-to-one to a reference image, this work proposes to use an algorithm based on the minimal eigenvalues of Toeplitz matrices. These matrices are evaluated from the transfer function whose coefficients are determined from the characteristic points of the hand geometry. The algorithm proceeds in a similar manner of the classification used in some previous work of the first author [5,6]. For convenience the classifying criterion is given below.

Read the values of x_i and y_i coordinates of all n points (x_i, y_i), $i = 0,1, 2, ..., n$, from Fig. 2b.

Form the following rational function:

$$H(z) = \frac{P(z)}{Q(z)} = \frac{x_0 + x_1 z + x_2 z^2 + ... + x_n z^n}{y_0 + y_1 z + y_2 z^2 + ... + y_n z^n} \tag{1}$$

in which the coefficients in the polynomials $P(z)$ and $Q(z)$ are respectively the x and y co-ordinates of the points (x_i, y_i), i=0, 1, 2, ..., n.

For the rational function of $H(z)$ in *Eq.*(1) find Taylor series:

$$\mathrm{T(z)} = c_0 + c_1 z + c_2 z^2 + ... + c_n z^n + ... \tag{2}$$

The coefficients c_i, i = 0, 1, 2, ... n, are expressed by the coordinates of x_i and y_i of the points as follows:

$$c_0 = \frac{x_0}{y_0},\ c_1 = \frac{1}{y_0^2}\begin{vmatrix} x_1 & y_1 \\ x_0 & y_0 \end{vmatrix},\ c_2 = \frac{1}{y_0^3}\begin{vmatrix} x_2 & y_1 & y_2 \\ x_1 & y_0 & y_1 \\ x_0 & 0 & y_0 \end{vmatrix}, \dots \tag{3}$$

From these coefficients the determinants of Toeplitz matrices are evaluated as follows:

$$D_0 = c_0 = \frac{x_0}{y_0},\ D_1 = \begin{vmatrix} c_0 & c_1 \\ c_1 & c_0 \end{vmatrix},\ D_2 = \begin{vmatrix} c_0 & c_1 & c_2 \\ c_1 & c_0 & c_1 \\ c_2 & c_1 & c_0 \end{vmatrix}, \dots \tag{4}$$

Once the determinants have been calculated, determine their eigenvalues and evaluate the lowest (minimal) eigenvalue for each determinant. For the i^{th} determinant D_i, the lowest eigenvalue is $\lambda_{\min_i}$, designated simply by λ_i :

$$\lambda_{\min}\ \{D_i\} = \lambda_{\min_i} = \lambda_i,\ i = 0,\ ...,\ n. \tag{5}$$

The successive eigenvalues λ_i for i = 0, 1, 2, ..., n form a monotonically nonincreasing series, i.e.,

$$\lambda_0 \geq ... \geq \lambda_i \geq ... \geq \lambda_n,\quad i = 1, ..., n\text{-}1 \tag{6}$$

The final result given in *Eq.*(6) is used as the main tool for describing and classifying input and output data. The series of minimal eigenvalues of each image is then saved, sketched and compared with the data base images. The method used for this purpose is the absolute deviation [4] in testing for the minimal difference between the unknown image Ψ and the reference one Φ :

$$g(a,b) = \sum_{i=1}^{n} |\Psi - \Phi| \tag{7}$$

with $\Psi = y_i$ and $\Phi = ax_i + b$, the approximating line. After similarity process has been done, the output is given either as a graph representation of the image or as a written output on the screen.

4. EXPERIMENTS AND RESULTS

Now, to show how this theory works, consider the following experiments. The experiments start with the creation of hand-palm database of a number of people to compare with the under identification person. The under-test database has been changed several times for better checking of the system. The most recent data is composed of 45 scanned images taken from 15 people, 3 from each person.

The experiments were conducted applying *Eq.*(1) as the reference for data collection. Also, some modifications were applied to enter the *x-y* values of the numerator and denominator as polar coordinates, but this is not within the topics of this paper and is left for future work and applications. The number of input elements as system input data, that is the number of minimal eigenvalues considered in our experiments, was varying from a minimum of 10 to a maximum of 60 showing a large difference in the rate recognition. Therefore, the optimal number for better recognizing rate for the under testing class was 60 minimal eigenvalues as shown in Table 1. Thus, considering larger number of eigenvalues would increase the effectiveness rate to more than 90% definitely, but of course increasing the computation size to a double or triple one of that in the original algorithm. Notice that the results are worse than those in [1] but still the classical application is approaching almost 100% following the data extract method given above and the classical method in comparison for similarity. It is this result that makes us continue modifying the method of eigenvalues to replace the classical approach for the same preprocessing and describing data. Table 1, however, shows the low effectiveness of using the algorithm for both description and recognition. Although the system of minimal eigenvalues has proved its success in image description [3,4] for both small and large classes of images, it still needs more modification to use similarity comparison.

The results of classification experiments are given in Fig.3, 4, 5 and 6. The hand-palms of Iza, Marcin and Radek are scanned three times each, described and classified for recognition. Figures 3, 4 and 5 show the graphs of the minimal eigenvalues series obtained for their images with Fig.6 to show them together for comparison. Although the graphs furnish similar shapes for the individual examined hands (Fig.3, 4, 5), they show quite different behavior when put on the same plane with the same scale assuring that they are identified as graph representing images of different sources.

Number of Minimal Eigenvalues	Algorithm of Effectiveness
10	40 %
20	60 %
30	53.3 %
40	53.3 %
50	53.3 %
60	**66.7 %**

Tab. 1. Results of recognition rate experiments.

The three lines of Iza's hand in Fig.3, for example, are similar to one another (with about 99% recognition rate). From classifying and comparison point of view this comes from the fact that all the lines of the three graphs furnish similar behavior. This, in turn, means that the series of the minimal eigenvalues are of the same values. Hence, the points yielding them through Taylor series represent the same reference in the data base giving the indication that they belong to the same hand-palm image.

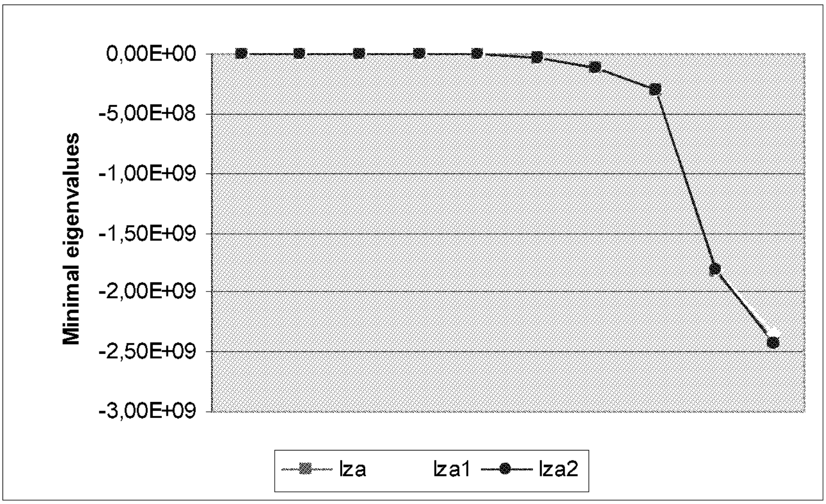


Fig. 3. The graph of minimal eigenvalues for Iza

The same discussion holds for Marcin's hand in Fig.4. Here the rate of recognition is a bit lower as the series of minimal eigenvalues, which the images yield, diverge when approaching their limits to show different values. This affects the values of the input data to both *Eqs* (6) and (7) leading to less efficiency of the algorithm. However, Marcin's hand was still identified as *his* in more than 85%. This point is considered as one of the important conclusions that have been reached. Simply, if the limit of the series is taken into consideration as an additional element in classification and hence description, the results of comparison may seem more reasonable. This leads to a higher rate of identification and recognition.

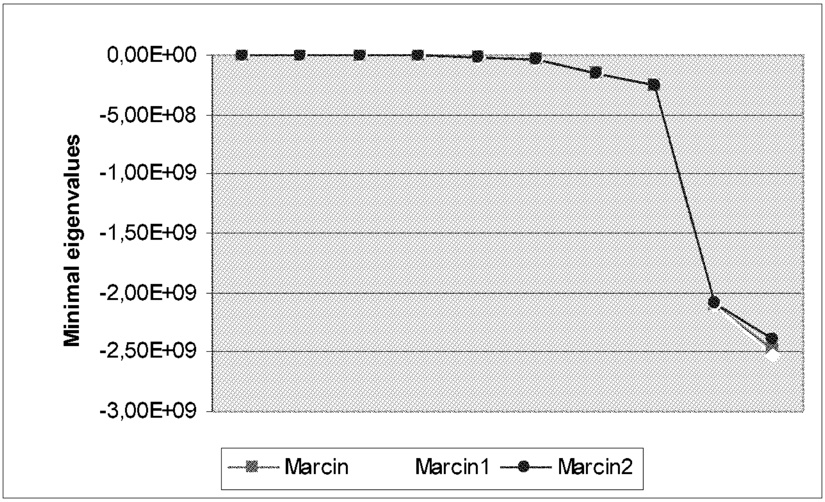


Fig. 4. The graph of minimal eigenvalues for Marcin

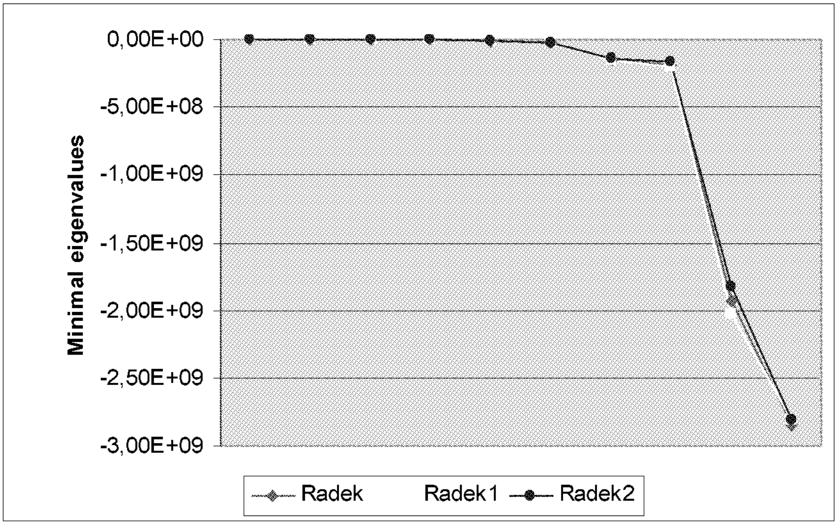


Fig. 5. The graph of minimal eigenvalues for Radek

Radek's hand processing results with rather another different behavior (Fig.5). The lines do not approach the limit of the series fast. They tend to follow different routes. However, the most important thing here is that they go through parallel paths and again showing almost the same character. They, therefore, belong to the same person, to Radek and differ from those of Iza's and Marcin's.

Fig. 6, however, shows the three hand-image average-graphs of Iza, Marcin and Radek all in one figure. As can easily be noticed they are different from each other showing that they belong to different hand-images.

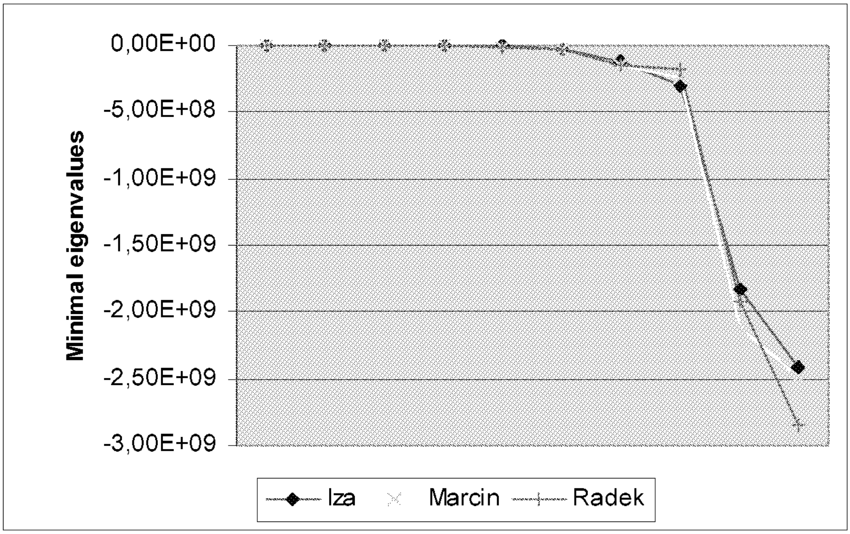


Fig. 6. The graph of minimal eigenvalues for Iza, Marcin and Radek

5. CONCLUSIONS AND FUTURE ASPECTS

The achieved results are encouraging. The recognition rate can approach 90% in the case of increasing the size of Toeplitz matrices. The time of recognition is about 1.5 second per image, working on processor Intel Celeron 633MHz. These results, therefore, show that the approach given in this work is developing. However, as the increasing in the rate of recognition associates with the increasing of the computing size, then the method so far used is costly for ideal results. It demands that the data matrix size becomes much larger than that made used of in classical methods. This is impractical. The classical methods of feature-to-feature comparison, from the other side, have shown almost ideal results of about 100% of correct recognition in most cases. Therefore, the best expected results would be obtained when decreasing the size of the equivalent to the Toeplitz ones and then considering eigenvalues-to-eigenvalue comparison instead of making the tedious feature-to-feature comparison. Obviously, the number of the computed minimal eigenvalues should be much less than the number of the extracted features in order to be able to speak about better system of classification and recognition.

The use of Toeplitz matrices theory has proved the possibility of applying the worked out previously algorithm on other biometric fields [5, 6, 7, 11, 12, 13], to this topic of human identification.

The current and future work will concern a number of other aspects. This would include the increasing of the database size and creating a hybrid system to identify a person by hand geometry recognition in parallel with another biometric technique, for example the recognition of person fingerprints, his iris or signature. Moreover, we are following some studies to consider the limit of the minimal eigenvalues series as a useful tool, too. This adds an additional element to better classification and would certainly result in more precise comparison and may give more precise decision leading to a higher rate of identification and recognition. This means that a two-feature-vector system is then used $\boldsymbol{U} = (V, W)$ where V is the vector whose elements are those obtained from eigenvalues series while W would carry the properties of the sequence limit. Moreover, the data extracted from the hand-palm would not be limited to the fingers and their dimensions and characteristics. The thickness of fingers, the palm-print and all other possible parameters that may increase the information data and hence decreasing the number of calculations more eigenvalues for more precise results, as the usual taking place situation.

The scanning platform used as data acquisition device is also of special importance and its improvement has really increased the effectiveness of the approach in both the classical and the eigenvalues methods raising the efficiency of the algorithm and increasing the rate of recognition.

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