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A NEW HAND-MOVEMENT-BASED AUTHENTICATION METHOD USING FEATURE IMPORTANCE SELECTION WITH THE HOTELLING'S STATISTIC

Rafal Doroz, Krzysztof Wrobel*, Piotr Porwik, and Tomasz Orczyk

Institute of Computer Science, Faculty of Science and Technology, University of Silesia, ul. Bedzinska 39, 41-200 Sosnowiec, Poland

E-mail: krzysztof.wrobel@us.edu.pl

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Abstract

The growing amount of collected and processed data means that there is a need to control access to these resources. Very often, this type of control is carried out on the basis of biometric analysis. The article proposes a new user authentication method based on a spatial analysis of the movement of the finger's position. This movement creates a sequence of data that is registered by a motion recording device. The presented approach combines spatial analysis of the position of all fingers at the time. The proposed method is able to use the specific, often different movements of fingers of each user. The experimental results confirm the effectiveness of the method in biometric applications. In this paper, we also introduce an effective method of feature selection, based on the Hotelling T^2 statistic. This approach allows selecting the best distinctive features of each object from a set of all objects in the database. It is possible thanks to the appropriate preparation of the input data.

Keywords: biometrics, person authentication, feature selection, Hotelling's statistic

1 Introduction

The constantly growing demand for remote and often anonymous data exchange and collection requires checking their credibility. Electronic authentication methods, including widely accepted biometric methods, are already used in banking, health care, police, courts, and government institutions.

Biometric authentication and verification methods [1, 2] are divided into contact and contactless methods. An example of a contact method is, among others, analysis of the user's fingerprint [3, 4]. The second group of methods uses non-contact techniques, in which there is no physical contact between a person and the recording device, e.g. voice recognition methods [5]. With the advent of the COVID-19 pandemic, contactless authentication has become especially important. Lack of contact with the recording equipment reduces the likelihood of virus transmission by a sick person and reduces the likelihood of infection.

The article presents a new method of dynamic verification of persons, based on the spatial analysis of fingers and hand movements. The sequence of movements is recorded in a non-contact mode with the use of a motion recorder, which records the spatial coordinates of the fingers. It should be noted that in the previous known solutions based on a spatial movement analysis, only a change of the position of one finger was registered and analyzed [6, 7, 8]. It means that proposed strategy is more comprehensive because movements of all fingerprints are observed. It allows to applied our method even with the limited mobility of a single finger. Additionally, it should be also noted that in proposed approach we focus on the contactless techniques in contrast to investigations where, for example, smartphone internal accelerator, gyroscope and gravity data are used [9]. Without a doubt, the contactless methods are more comfortable and hygienic for users. Other techniques are problematic due to the complicated methods of measuring biometric data [10], where electrodes based on electromyography signals have to be used. In practice, such contact methods are rather devoted to medicine or therapy and is very uncomfortable because human body has to be exposed. It should be also noted that mentioned in the last two works measurement protocols although use Hidden Markov Models, achieve worse results than presented in this article. In our method, we have chosen to continuously analyze the position of each finger in the sequence of movements. Finger movement analysis is performed in discrete time according to the sampling frequency of the motion recording device. This allows for better biometric recognition of individual users.

The novelty of the presented work is the use of position all fingers in the verification process, instead of just one finger as in most earlier works [11, 8]. In our approach, the movement of fingers is analyzed globally, where all fingers are observed during the sequence of movements. The person being verified performs a continuous movement of the hand representing various figures. This movement is recorded by the capture device connected to the user's terminal (e.g. PC). The proposed method does not require changes in the workplace and does not require special user training. The process of user enrollment consists of repeating the user's unique sequence of finger movements. The future verification of the user's identity requires a one-time repetition of the sequence of hand movements performed during the enrollment process. Due to the characteristics of the recording device, over 90 different spatial coordinates assigned to the individual elements of each finger can be registered and analyzed (position of the fingertips, finger joints, finger length, etc.). The advantages of this approach have been confirmed in the conducted experiments. To the best of our knowledge, such studies have not been performed before.

The proposed method takes into account the initial selection of the registered features. Thanks to this the verification of a given person is carried out only on the basis of the most distinctive (for this person) behavioral features. This accelerates the verification process. It is well known, that the features selection identifies the discriminant features in a given dataset of original features, thus reduces the complexity of the expert system. Selection of the best features subset is a key issue in obtaining a satisfactory accuracy of the recognition system. Nonetheless, the available data are not the same for all persons, hindering the inference of the classifier. For this reason, the most relevant individual biometric features should be disclosed and then selected.

In this paper, the initial features selection is based on Hotelling's statistics, and this has its justification. Reduction of data dimension can be performed by means of different methods, like LDA (Linear Discriminant Analysis), PCA (Principal Component Analysis) and Hotelling statistic, which are reviewed for example in the work [12]. In most data reduction strategies, we need to determine how many features have to be kept, versus how many have to be dropped, which is not always easy to predict. Additionally, in biometric tasks, the number of the best suitable features may vary from user to user, which makes it difficult to select the threshold for which the number of features is sufficient.

The described inconvenience can be overcome by using the Hotelling statistic, which does not require the initial determination of the reduction parameters [13]. The modified Hotelling features selection method will be presented in the Algorithm 1.

The work has been divided into 5 Sections. Section 2 provides an overview of the solution of a motion capture, including verification and identification of the individuals. Section 3 describes the scientific contribution of this article. Section 4 presents a new method of verifying people with a motion capture device. Section 5 presents the results of the conducted experiments. Last Section 6 presents the conclusions of the conducted measurements.

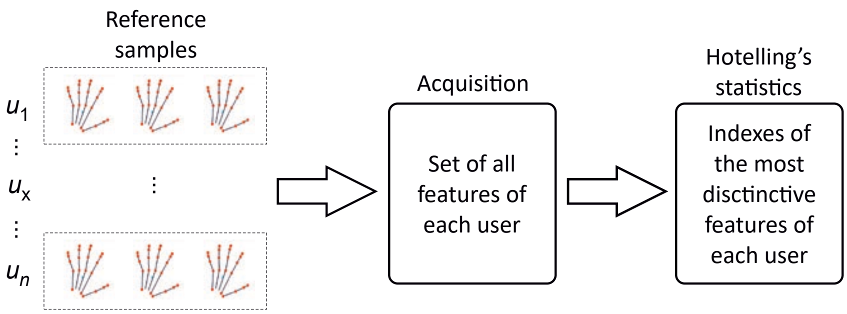


Figure 1. Block diagram of the first stage of the verification procedure.

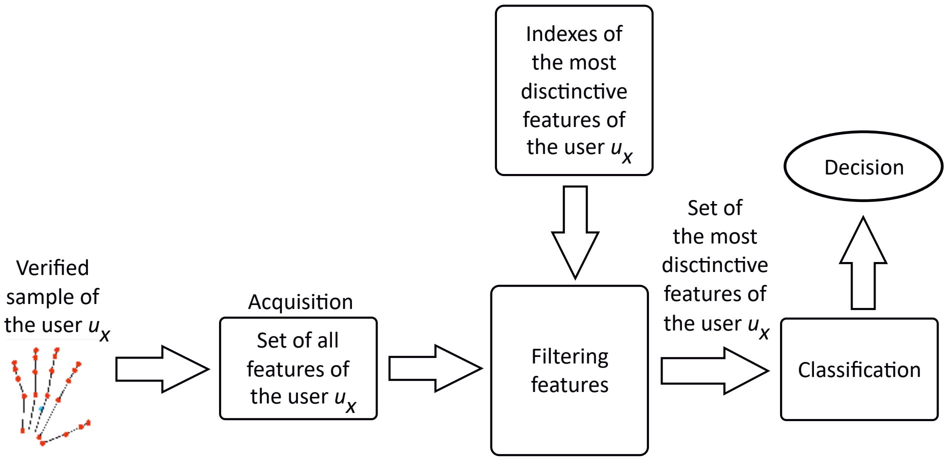
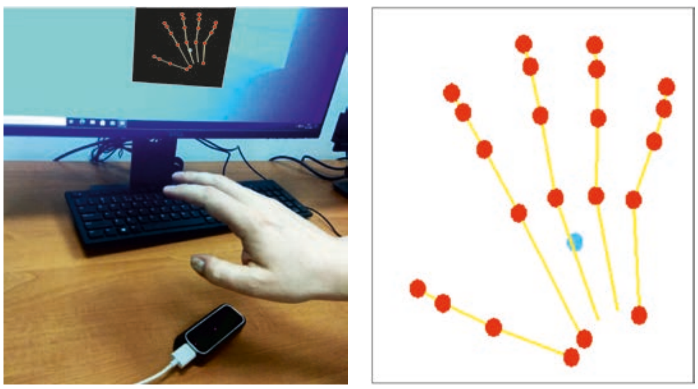


Figure 2. Block diagram of the second stage of the verification procedure.



(a) (b)

Figure 3. (a) Interface for generating virtual hand using LMC, (b) the virtual hand skeleton with the spatial measurement points.

2 Related work

In recent years, there has been a growing interest in biometric analysis methods [9, 10]. This applies both to the control of devices using the spatial analysis of hand and finger movements, as well as for known methods of analyzing fingerprints, signatures, voice, etc. In this article a spatial analysis of the features recorded during the movement of the hands and fingers will be employed. Similar investigations have been presented in works [11, 14, 15] but in those approaches movements of only one finger were tracked, whereas in our solution, a more complex movements of all fingers are taken into account. In the second group of methods, hand and fingers registration heavily depend on the background and lighting conditions, so hand and fingers areas are simplified using markers [16], what additionally complicate the method.

In [17], the Microsoft Kinect controller [18] was used to register the hand movements. The hand movement was made by the user in a circular manner. This strategy allows a recognition rate of approximately 90% for a database of 20 people. Identification of people based on the analysis of simple raising or shaking a hand, is presented in [19]. The Nintendo WiiMote controller was used in the process of hand movement. The effectiveness of the method was tested using a database containing features of 10 people. In the work [20], it was proposed to use a low-cost micro controller to register movements. However, research was limited to drawing simple shapes in the air, such as a predetermined square or circle. Another approach was to use a three-axis accelerometer for user verification [21]. In this approach, only four simple hand movements were recorded and analyzed: the right arm opening and closing horizontally, the rotation of the wrist, a gesture similar to answering a phone, and a gesture consisting of touching the left shoulder. The database used in the study contained data of 10 users. This method is not a fully contactless method as the accelerometer must be attached to the hand. In the above-mentioned methods, the recorded data were analyzed using the k-NN classifiers, PCA or DTW (Dynamic Time Warping) methods.

Another popular device used in non-contact authorization methods is the Leap Motion Controller (LMC). This device owes its popularity to the possibility of spatial registration of hand and finger movements in a limited area. LMC has been widely used in many areas of life, such as medicine, music, and biometrics [22, 23, 24, 25].

The use of the LMC for registration and analysis of the 3D signatures was proposed in works [6, 7, 8]. In the study [6], the authors used an approach based on the neural networks, achieving 97.1% efficiency, while in the study [7] accuracy of 92.2% was achieved using distance measurements and statistical analysis. In the work [8], the classification of a 3D signature was done by a Least Square Support Vector Machine, and the equal error rate (EER) was about 1%.

Another method using the LMC is described in the paper [26]. This research methodology is similar to ours. In this work, the approach called ”Leap Password” was proposed. In this strategy, the LMC was used to allow the user to enter a password consisting of six movements performed using one finger. In this work instead of the FRR, the GAR coefficient has been used. Because GAR=100-FRR=81.17% we assume that approximately FRR=18.83%. The Levenshtein distance was used to compare feature sets registered from different users.

The identification system using LMC to register the geometric features of the hand is presented in the paper [27]. The data for the tests was collected from 21 people. For each user, the length and width of fingers, the distance between fingers, and the center of the hand and wrist were recorded. Popular classifiers such as k-NN, SVM, Multilayer Perceptron, and Logistic Regression were used for classification. The classification efficacy was higher than 90%. However, the researches were conducted without taking into account the behavioral features, i.e. the analysis of hand movement.

The possibility of logging in and continuous authentication with the LMC has been tested at work [28]. Data for testing were gathered from users when using LMC to read and navigate Wikipedia pages. Using the presented method, 98% efficacy was achieved for 10 users. The method is only intended for simple, predetermined gestures, such as moving the cursor with one finger, pressing a key, or moving your finger in a circle.

However, the LMC device can be used much more widely than is shown in the works described above. It will be presented in details in the next part of the paper.

3 Proposed innovation

In the proposed method, we use an optical module (LMC) that records hand movements. In our strategy, we perform a spatial analysis of fingers movements based on the data stored in the hand and fingers skeleton model. A user's hand fingers parameters are detected in mid-air and converted to three-dimensional (x,y,z,t), where x,y,z are spatial coordinates and t is a time stamp build on the device's sampling time. The novelty of the solution is the analysis of the movement of all fingers and the reduction of biometric data by selecting the most important features on the basis of Hotelling statistics.

In the paper we analyze the finger coordinates from the spatial motion of the hand and treating them as behavioral features. Hand movement analysis is performed continuously (taking into account the sampling frequency of the device). Moving the hand and fingers can be treated as performing a specific biometric characteristic of a given person. This characteristic comprises of spatial parameters and time stamp. The results of experimental studies clearly show the advantages and possibilities of continuous hand tracking for any positioning of the hand, both in the case of clearly raised fingers, and when the fingers are bent. Additionally, we use an approach, where discriminatory features are determined for each user. It is done by the use of the Hotelling statistic. This means that each person may have different characteristics that will be used in verification process. This strategy reduces the number of features that must be stored in the database. All contribution elements will be confirmed by the performed experiments.

4 Method description

In the proposed method, the verification of the person consists of the two main stages. In the first stage, the hand movement features are recorded. This process is conducted for all users who in the future can be verified. In the acquisition process, the set of features f_i, $i = 1,\ldots,94$ of all users u_j, $j = 1,\ldots,n$ is formed (see Table 1). On the basis of this set, the Hotelling T^2 statistic selects the most distinctive features of each user. Features are selected independently for each user, thus for each person, different features can be chosen. The feature selection is made using a set of reference hand and finger movements previously created by the verified person. This process has been depicted in Figure 1. It should be noted that the data for the Hotelling best features selection have to be prepared in the right way, what will be in details presented later.

Dynamic movements are analyzed as the sequences of spatial parameters of fingers. According to the device sampling frequency, each hand and finger movement is registered as a set of specific features f_i (Table 1). It means that instead of one finger as so far [29], verification is performed by analyzing position of all fingers in the three-dimensional space. As a result, sequence of finger movements $(f_1,\ldots,f_p)^{t_1},(f_1,\ldots,f_p)^{t_2}$, ... is described by $p = 94$ features, measured at each time stamp t, determined by the device sampling process.

In this stage, the automatic selection of the best discriminant features is realized. Features are selected independently for each user by means of the Hotelling's statistic, thus for each person, different features can be chosen. The feature selection is made using a set of reference hand and finger movements previously created by the verified person.

In the second stage, a confirmation of person identity is performed. In this process a classification algorithm is used, which works on the the reduced feature set. Indexes of the most informative features for each user have been established in the first stage, using the Hotelling procedure. In the second stage, features with appropriate indexes are selected. It was schematically depicted in Figure 2.

The innovation of the classification process is based on the use of only those features that were previously selected as the most characteristic for the verified person based on the analysis of the features of all people in the database. Achieving this effect requires appropriate data preparation and interpretation. This will be shown later in the article.

4.1 Registration of hand and finger motion

As already stated, to register the spatial hand movement parameters, the LMC device was employed. The LMC device includes the 3D sensors. The module is equipped with several cameras with a field of view of approximately 150 degrees, and an infrared optical sensor. The device tracks the movements of both hands and 10 fingers with high precision and speed. The features of this device allowed for the development of person verification method based on the analysis of hand motion using the human-computer interaction method.

The hand and finger movements are captured by a specialized motion capture device, connected to the user terminal (e.g. PC). There are no special requirements for the workplace, nor it requires any special training for the user. The user enrollment process consists of repeating a custom gesture by the user in front of a motion capture device. Further identity verification, requires a single repetition of the custom gesture shown by the user in the enrollment process. As of software version v2, the device receives and interprets data from sensors and compares this data with the internal model of a human hand to determine the exact orientation of the user's hand in space (Figure 3(a)). The human hand has many degrees of freedom but in the device, only points shown in the Figure 3(b) are recognized in the space where the coordinates (x, y, z, t) of the hand elements are assigned. It should be noticed that the middle part of the hand, along with the wrist, is devoid of points with recorded data from optical sensors of the device. For this reason, it is difficult to precisely define the shape of this body part. This part of the hand is not suitable for biometric recognition.

The movement registration process is fully automated and consists of three basic steps:

1. *Initiation of registration*: the user holds his hand over the sensors.

2. *Registration time*: when the sensor detects motion, it starts recording data.

3. *Completion of registration*: when the system detects no motion for at least 0.2s, the device stops collecting data.

The hand and fingers movements consist of making a sequence of hand motions, e.g. turning your hand, clenching your fist, bending any finger, etc. The specified hand movement can be performed at different distances from the sensor and with any speed.

As previously stated, the LMC records 94 features such as position, dimensions, speed, direction of individual fingers, etc. The registered features are gathered in Table 1. All registered features form a set of features $O = \{f_1, \ldots, f_{94}\}$.

Table 1. Features registered by the LMC.

Feature	Description
f_1	Measurement time in microseconds.
f_2	Hand identifier.
f_3, f_4, f_5	Position of center (x_p, y_p, z_p) of the palm.
f_6, f_7, f_8	Direction. A vector $(pitch, roll, yaw)$ pointing from the center of the palm toward the fingers.
f_9	Velocity of palm.
f_{10}, f_{11}	Width and height of Thumb.
f_{12}, f_{13}, f_{14}	Joint 1 of Thumb (x_1, y_1, z_1) coordinates.
...	...
f_{24}, f_{25}, f_{26}	Joint 5 of Thumb (x_5, y_5, z_5) coordinates.
f_{27}, f_{28}	Width and height of Index finger.
f_{29}, f_{30}, f_{31}	Joint 1 of Index finger (x_1, y_1, z_1) coordinates.
...	...
f_{41}, f_{42}, f_{43}	Joint 5 of Index finger (x_5, y_5, z_5) coordinates.
f_{44}, f_{45}	Width and height of Middle finger.
f_{46}, f_{47}, f_{48}	Joint 1 of Middle finger (x_1, y_1, z_1) coordinates.
...	...
f_{58}, f_{59}, f_{60}	Joint 5 of Middle finger (x_5, y_5, z_5) coordinates.
f_{61}, f_{62}	Width and height of Ring finger.
f_{63}, f_{64}, f_{65}	Joint 1 of Ring finger (x_1, y_1, z_1) coordinates.
...	...
f_{75}, f_{76}, f_{77}	Joint 5 of Ring finger (x_5, y_5, z_5) coordinates.
f_{78}, f_{79}	Width and height of Pinky finger.
f_{80}, f_{81}, f_{82}	Joint 1 of Pinky finger (x_1, y_1, z_1) coordinates.
...	...
f_{92}, f_{93}, f_{94}	Joint 5 of Pinky finger (x_5, y_5, z_5) coordinates.

During registration, the LMC device samples data with a maximum frequency of 200 Hz. It means that any attainable feature f_i, $i = 1, \ldots, 94$

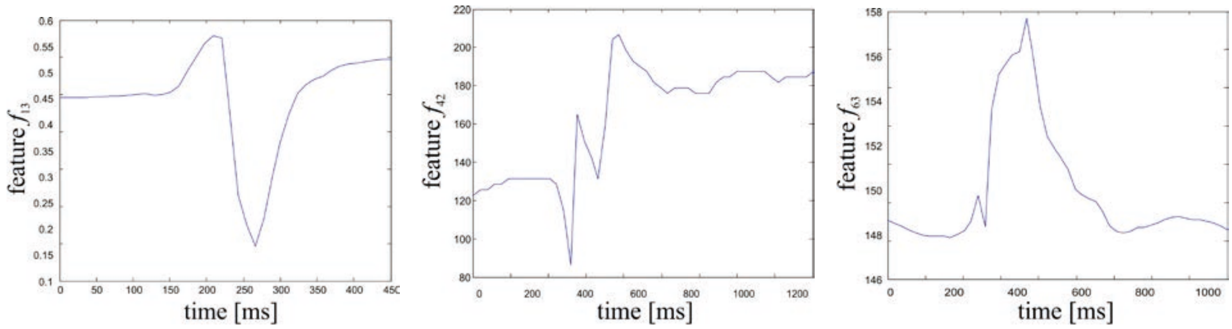
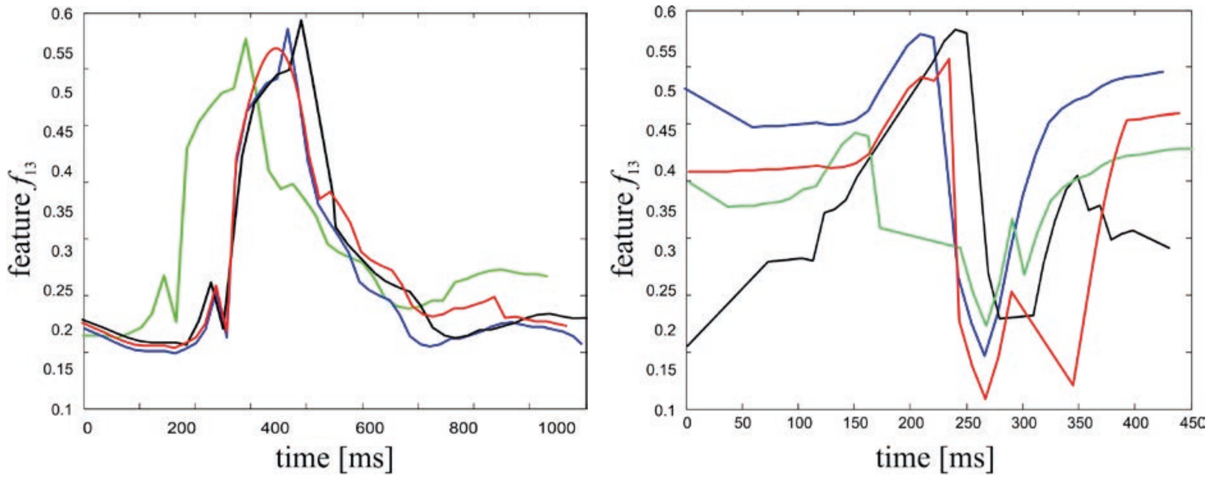


Figure 4. Feature samples grabbed over time and registered by the LMC.



(a) (b)

Figure 5. The course of the exemplary feature f_{13} registered in four measurement of (a) person 1, (b) person 2.

is also sampled with the same frequency. Let k be a number of samples of a feature f_i recorded over a given time, then each feature f_i can be presented as a vector $\mathbf{F}_i = [f_i^{t_1}, f_i^{t_2}, \ldots, f_i^{t_k}]$ of discrete samples. An example of the exemplary features f_{13}, f_{42} and f_{63} is depicted in Figure4.

The solution proposed in the article assumes, that each user individually defines the sequence of hand movements and their duration. It should be noted, that the longer movements are performed, the number of elements in the vector $\mathbf{F}_i$ also increases.

The classifiers used in the verification process require the compared data to have the same number of elements. In our case, this condition is not fulfilled. To remove this inconvenience, we use a scaling method called Fixed Number of Points (FNP) to equalize the length of each vector $\mathbf{F}_i$. This method was described in detail in [30]. The selection of the number of elements in vector will be described in the part where experiments are presented.

All the features $\mathbf{F}_i$ of the hand and fingers movement of a given person, can be presented in a compact, matrix form, where the $\mathbf{G}$ matrix consists of rows with the values of the appropriate features, gathered at the time of the motion registration:

$$\mathbf{G} = \begin{bmatrix} \mathbf{F}_1 \\ \mathbf{F}_2 \\ \vdots \\ \mathbf{F}_{94} \end{bmatrix} = \begin{bmatrix} f_1^{t_1} & f_1^{t_2} & \cdots & f_1^{t_k} \\ f_2^{t_1} & f_2^{t_2} & \cdots & f_2^{k} \\ \vdots & \vdots & \vdots & \vdots \\ f_p^{t_1} & f_p^{t_2} & \cdots & f_p^{t_k} \end{bmatrix}, \tag{1}$$

where $p = 94$, f_i^j denotes the $j'th$ value of $i'th$ feature, and $t_1, \ldots, t_k$ are successively registered multidimensional data samples according to the device sampling time.

4.2 Features selection

In the biometric systems, the decision-making process is based on the result of comparison of the test sample and the reference sample. In order to achieve the highest effectiveness of the verification, samples being compared (taken from the same person) should be as similar as possible. The above assumption is very desirable, but unfortunately in reality biometric samples taken even from the same person can differ from each other. It is obvious that it hinders their correct verification.

An additional complication is the fact that the lack of repeatability can concern only certain features. Decision which features are repeatable, depends on the individual behavior of the user. The lack of repeatability of a specific feature, recorded in several samples, can be easily illustrated by overlapping these features one above the other. Figure 5(a) shows the changes of an exemplary feature (f_{13}), repeated four times by the same person, whereas Figure 5(b) shows the superimposition of the same feature, but now it shows finger and hand motion coming from another person. The more the graphs of the compared features overlap, the more repeatable this feature is.

Analyzing Figure 5, it can be seen that the first person has satisfactory repeatability of the analyzed feature, which cannot be said for the second person.

The above comparison shows that use the some features may reduce the effectiveness of the verification process. Moreover, for each person being verified, the set of such features may be quite different. That is why it becomes such an important task to select and classify only those features of a given person for which the effectiveness of verification is the greatest. In order to achieve this goal, a method has been developed which independently for each person, determines a set containing only repeatable features. Such selected features will be used in the verification process.

In the proposed algorithm, selection of features is performed by means of the Sequential Backward Selection (SBS) [31] mode, using two-class linear discrimination, based on the Hotelling T^2 statistic [32, 33]. This strategy minimizes the within-group variability, which leaves the repetitive features, while maximizing the between-group variability, making the selected features are more distinctive. Hotelling's algorithm is executed in several steps and data should be appropriately prepared, what will be shown below.

The process of the feature selection begins with the creation of the two sets for each person. A set π_1 contains m reference hand and finger movements $\mathbf{G}$ made by person being verified:

$$\pi_1 = \{\mathbf{G}_1, \mathbf{G}_2, ..., \mathbf{G}_m\}. \tag{2}$$

The set π_2 consists n reference movements $\mathbf{G}^{\Delta}$, made by other people, randomly selected from the database:

$$\pi_2 = \{\mathbf{G}_1^{\Delta}, \mathbf{G}_2^{\Delta}, ..., \mathbf{G}_n^{\Delta}\}. \tag{3}$$

Next, similarities between movements contained in the created sets are determined.

The result of the comparison are the two matrices $\mathbf{X}$ and $\mathbf{Y}$. The $\mathbf{X}$ matrix contains values of similarities Φ between consecutive pairs of movements from the π_1 set.

The structure of the matrix $\mathbf{X}$ is presented by formula (4):

$$\mathbf{X} = \begin{bmatrix} \Phi(\mathbf{G}_1,\mathbf{G}_2)^{f_1}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_m)^{f_1}, & \ldots \\ \Phi(\mathbf{G}_1,\mathbf{G}_2)^{f_2}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_m)^{f_2}, & \ldots \\ \vdots & \vdots & \vdots & \\ \Phi(\mathbf{G}_1,\mathbf{G}_2)^{f_p}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_m)^{f_p}, & \ldots \end{bmatrix}$$

$$\begin{bmatrix} \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_3)^{f_1}, & \ldots, & \Phi(\mathbf{G}_{m-1},\mathbf{G}_m)^{f_1} \\ \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_3)^{f_2}, & \ldots, & \Phi(\mathbf{G}_{m-1},\mathbf{G}_m)^{f_2} \\ & \vdots & \vdots & \vdots \\ \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_3)^{f_p}, & \ldots, & \Phi(\mathbf{G}_{m-1},\mathbf{G}_m)^{f_p} \end{bmatrix}_{p\times\binom{m}{2}} =$$

$$= [\mathbf{x}_1, \ldots, \mathbf{x}_{\binom{m}{2}}], \tag{4}$$

where: $\Phi(\mathbf{G}_1,\mathbf{G}_2)^{f_i}$ denotes similarity value of the feature f_i of the movements $\mathbf{G}_1, \mathbf{G}_2 \in \pi_1$, calculated with the use of Euclidean distance measure.

Let $[g_i^{t_1}, g_i^{t_2}, \ldots, g_i^{t_k}] \in \mathbf{G}_1$ and $[h_i^{t_1}, h_i^{t_2}, \ldots, h_i^{t_k}] \in \mathbf{G}_2$, then similarity between of the two movements $\mathbf{G}_1, \mathbf{G}_2$ can be computed:

$$\Phi(\mathbf{G}_1,\mathbf{G}_2)^{f_i} = (\sum_{j=1}^{k} |g_i^{t_j} - h_i^{t_j}|^2)^{1/2}, i = 1, ..., p, \tag{5}$$

where k is number of samples, values g_i^j and h_i^j represent the same feature f_i measured for $\mathbf{G}_1$ and $\mathbf{G}_2$ movements, respectively.

The second matrix $\mathbf{Y}$ is created on the basis of the sets π_1 and π_2 and consists of data from hand and finger motion of a given person and motion of other users.

The matrix $\mathbf{Y}$ is built as follows:

$$\mathbf{Y} = \begin{bmatrix} \Phi(\mathbf{G}_1,\mathbf{G}_1^{\Delta})^{f_1}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_n^{\Delta})^{f_1}, & \ldots \\ \Phi(\mathbf{G}_1,\mathbf{G}_1^{\Delta})^{f_2}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_n^{\Delta})^{f_2}, & \ldots \\ \vdots & \vdots & \vdots & \\ \Phi(\mathbf{G}_1,\mathbf{G}_1^{\Delta})^{f_p}, & \ldots, & \Phi(\mathbf{G}_1,\mathbf{G}_n^{\Delta})^{f_p}, & \ldots \end{bmatrix}$$

$$\begin{bmatrix} \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_1^{\Delta})^{f_1}, & \ldots, & \Phi(\mathbf{G}_m,\mathbf{G}_n^{\Delta})^{f_1} \\ \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_1^{\Delta})^{f_2}, & \ldots, & \Phi(\mathbf{G}_m,\mathbf{G}_n^{\Delta})^{f_2} \\ & \vdots & \vdots & \vdots \\ \ldots & \Phi(\mathbf{G}_2,\mathbf{G}_1^{\Delta})^{f_p}, & \ldots, & \Phi(\mathbf{G}_m,\mathbf{G}_n^{\Delta})^{f_p} \end{bmatrix}_{p\times(m\cdot n)} =$$

$$= [\mathbf{y}_1, \ldots, \mathbf{y}_{m\cdot n}], \tag{6}$$

where: $\mathbf{G}_i \in \pi_1$ is the parametrized hand movement of a person being verified and the $\mathbf{G}_j^{\Delta} \in \pi_2$ is the hand movement of other person from database.

It should be noted that in our method number of elements in the sets π_1 and π_2 may be different, what follows from the formulas (2) and (3). The number n of elements in the set π_2 should be estimated by the equation $n = round\left(\binom{m}{2}/m\right)$, for the assumed value m.

It makes that the matrices $\mathbf{X}$ and $\mathbf{Y}$ will have the same number of columns. It guarantees that, in the subsequent procedures, there is no need to implement techniques dedicated to imbalanced data. In multivariate Hotelling's procedure, the variance-covariance matrix is estimated by unbiased estimators [34]. Let the matrix $\mathbf{X}$ (4) forms the columnar vectors $\mathbf{x}_i$ and the matrix $\mathbf{Y}$ (6) forms the columnar vectors $\mathbf{y}_i$.

Additionally, the mean vectors are formed:
$\bar{\mathbf{x}} = [\bar{x}_1, \bar{x}_2, ..., \bar{x}_p]^T$ and $\bar{\mathbf{y}} = [\bar{y}_1, \bar{y}_2, ..., \bar{y}_p]^T$.

For equation simplification let $\binom{m}{2} = A$ and $m \cdot n = B$, then covariances can be expressed as:

$$\begin{aligned} S_1 &= \frac{1}{A-1}\sum_i (\mathbf{x_i} - \bar{\mathbf{x}})(\mathbf{x_i} - \bar{\mathbf{x}})^{\mathbf{T}}, \\ S_2 &= \frac{1}{B-1}\sum_i (\mathbf{y_i} - \bar{\mathbf{y}})(\mathbf{y_i} - \bar{\mathbf{y}})^{\mathbf{T}}. \end{aligned} \tag{7}$$

For binary classification, the polled common variance-covariance matrix will be formed as a maximum likelihood estimator:

$$\mathbf{V}_1 = \frac{S_1(A-1) + S_2(B-1)}{A+B-2}, \mathbf{V}_2 = \frac{S_1}{A} + \frac{S_2}{B}. \tag{8}$$

For such an assumption a two-sample Hotelling's T^2 statistic is defined as follows:

$$T^2 = (\bar{\mathbf{x}} - \bar{\mathbf{y}})^T \mathbf{V}_i^{-1} (\bar{\mathbf{x}} - \bar{\mathbf{y}}), \quad i = \{1, 2\}. \tag{9}$$

In our case we have rather a small number of samples, and thus the Hotelling statistics $\tilde{F}$ are asymptotically F-distributed [32]:

$$\tilde{F} = \frac{A + B - p - 1}{p(A + B - 2)} T^2, \tag{10}$$

where p is the number of features.

The Hotelling's T^2 statistics can be approximated well by means of Snedecor's distribution F:

$$\tilde{F} \sim F_{p, A+B-p-1, \alpha}, \tag{11}$$

where $\alpha = 0.05$ denotes an established significance level.

Hotelling's feature reduction procedure is performed step by step for every feature and is presented by Algorithm 1.

The selection of features using Algorithm 1 is carried out independently for each user. The result of the feature selection process is a set O^* which contains the most distinctive features of a given person. For example, in the database of 50 users, the frequency of selecting a given feature using the Hotelling's method is shown in Figure 6.

The presented visualizations show that the distinctive features of each user are different and there are no clear relationships between them. This shows that there are no common characteristics for all users.

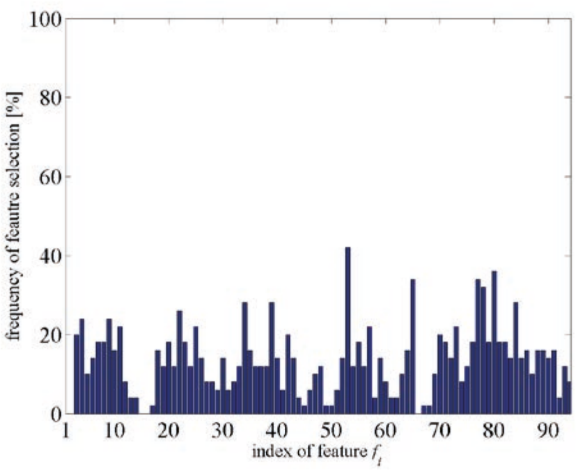


Figure 6. Percentage of use of particular features in the verification process.

The next chart shows the features selected by the Hotelling method for one of the 50 users. It was depicted in Figure 7.

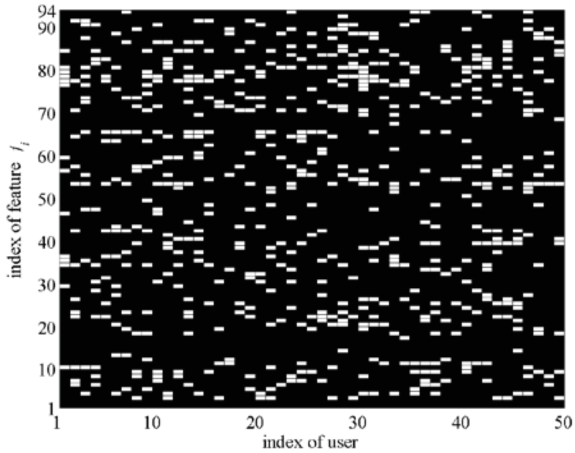


Figure 7. Distribution of features (white colour) selected for each user.

4.3 Movements verification

The hand and fingers movements verification consists of two major phases - training and classification. The aim of the training phase is to prepare a machine learning algorithm to train the classifier. This process requires the preparation of a training set. In classification phase, the machine learning model is used for making a decision about hand and fingers movement being verified. For each user, the classifier training process is performed independently. The training set contains matrices $\mathbf{X}$ and $\mathbf{Y}$ created for a verified user. Each column vector of the matrix $\mathbf{X}$ represents the positive class label ($c = +1$), whereas each column vector of the matrix $\mathbf{Y}$ belongs to the negative class label ($c = -1$).

The assumption of the proposed method is to use only the most distinctive features of each person in the classification process. For this reason, the values (rows) of useless features are removed from the matrices $\mathbf{X}$ and $\mathbf{Y}$. It was done by predefined for each person set O^*, created in Algorithm 1.

After creation of the training set, a user provides a hand and fingers motion G^* to be verified. This hand and finger movement is compared with m reference movements $G \in \pi_1$ for the person having the claimed identity. Each time, when the verified movement G^* is compared with another reference movement from the database, the additional vectors

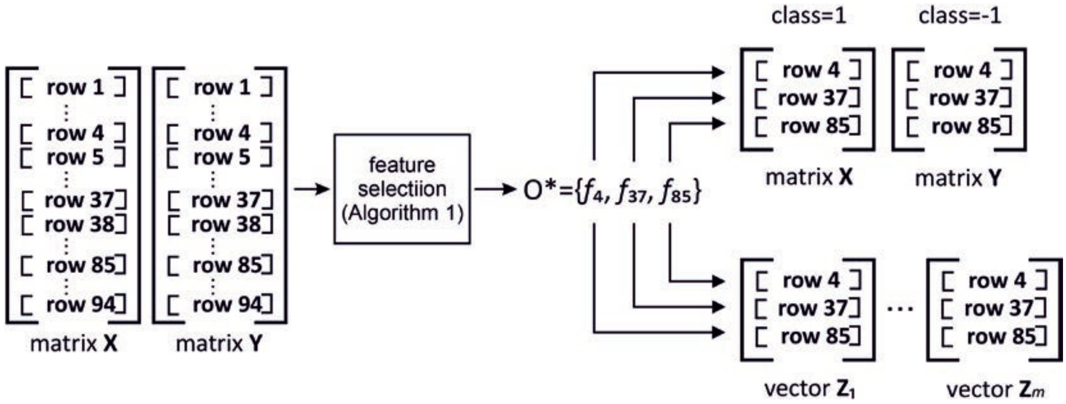


Figure 8. The principle of elimination of rows in the full populated **X** and **Y** matrices. Features after selection create a set O^*. The vectors **Z** are reduced on the basis of the same set O^*.

$\mathbf{Z}_i$ are created:

$$\begin{aligned}
\mathbf{Z}_1 &= \left[\Phi(\mathbf{G}_1,\mathbf{G}^*)^{f_1},\Phi(\mathbf{G}_1,\mathbf{G}^*)^{f_2},\ldots,\Phi(\mathbf{G}_1,\mathbf{G}^*)^{f_{94}}\right]^T,\\
\mathbf{Z}_2 &= \left[\Phi(\mathbf{G}_2,\mathbf{G}^*)^{f_1},\Phi(\mathbf{G}_2,\mathbf{G}^*)^{f_2},\ldots,\Phi(\mathbf{G}_2,\mathbf{G}^*)^{f_{94}}\right]^T,\\
&\vdots\\
\mathbf{Z}_m &= \left[\Phi(\mathbf{G}_m,\mathbf{G}^*)^{f_1},\Phi(\mathbf{G}_m,\mathbf{G}^*)^{f_2},\ldots,\Phi(\mathbf{G}_m,\mathbf{G}^*)^{f_{94}}\right]^T.
\end{aligned} \tag{12}$$

In the next stage, dimension of the vectors $\mathbf{Z}_i$ is also reduced, basing on the following formula:

$$\mathbf{Z}_i^* = \{f_i \in \mathbf{Z}_i : f_i \in O^*\}. \tag{13}$$

For a better understanding of this process, the general rule of rows reduction in both **X**, **Y** matrices and vectors $\mathbf{Z}_i$ is shown in Figure 8.

Next, each vector $\mathbf{Z}_i^*$ is evaluated by the classifier Ψ according to its class label $c \in \{+1,-1\}$:

$$\Psi : \mathbf{Z}_i^* \to c \in \{+1,-1\}. \tag{14}$$

Finally, the predicted class label for the verified movement G^* is established via a majority voting:

$$\overline{\Psi} = sign\left[\sum_{i=1}^{m} \Psi : \mathbf{Z}_i^*\right]. \tag{15}$$

The sign of the $\overline{\Psi}$ classifier output determines to which class the verified hand and finger movement G^* belongs. If the classifier's sign is +1, then it is a genuine hand motion, otherwise it is recognized as forged:

$$G^* = \begin{cases} \text{genuine} & \text{if} \quad \overline{\Psi} = \text{"}+\text{"} \\ \text{forged} & \text{if} \quad \overline{\Psi} = \text{"}-\text{"} \end{cases}. \tag{16}$$

5 Experiments and results

In this Section, the experimental framework is described. Details are provided on the dataset, accuracy measures, and classification algorithms.

5.1 Dataset

The database was created by the authors and consists of 750 hand and finger movements M_i registered from 50 people; 10 genuine, and 5 forged hand movements were registered for each person. To hand motion registration Leap Motion controller type LM-C01-US was used. Everyone was allowed to invent their own movements, and participants were informed, that position or all their fingers will be registered. As a result, the registered hand motions lasted from 1.17s to 7.22s. Additionally, the hand movements of each person was falsified by 5 randomly selected people, each person performed one skilled forgery. To perform this type of counterfeit, the counterfeiter could observe from a distance of about 1 meter the person making their hand motion. The created database is publicly available at `http://biometrics.us.edu.pl/resources/downloads` .

5.2 Evaluation metrics

Evaluation of the proposed method was carried out using various measures and characteristics: *FAR* (False Acceptance Rate), *FRR* (False Rejection Rate), *ACC* (Overall Accuracy), and *AER* (Average Error Rate), where:

$$FAR = \frac{\text{number of forgeries accepted}}{\text{number of forgeries tested}} \cdot 100\%, \quad (17)$$

$$FRR = \frac{\text{number of genuine gestures rejected}}{\text{number of genuine gestures tested}} \cdot 100\%, \quad (18)$$

$$ACC = \frac{\text{number of gestures correctly recognized}}{\text{number of gestures tested}} \cdot 100\%, \quad (19)$$

$$AER = \frac{FRR + FAR_{random} + FAR_{skilled}}{3} \cdot 100\%. \quad (20)$$

5.3 Experiment 1

In the first experiment, the overall effectiveness of the proposed method of verifying users was determined. During the research, a training set was created for each person as described in Section 4.2. All experiments were carried out in the ten-fold cross validation procedure. The measure FAR_{random} was determined for randomly selected hand movements of other users used as a forgery. These forgeries had not been used previously in the training set. The use of only skilled forgeries allowed to designate $FAR_{skilled}$. Ten popular classifiers, built in Weka package [35], were used to classify the verified gesture. Table 2 shows the algorithms that were employed and their parameter settings.

The classifiers used, together with achieved classification results are shown in Table 3. As can be seen in Table 3 the efficacy of the proposed method is greater than 90% for all tested classifiers. The highest efficacy was obtained for IBk classifier, which achieved $ACC = 99.88\%$. It should be noted that proposed strategy of features registration and selection allow to obtain high biometric factors also for other classifiers, what is ensured by analysis of Table 3.

5.4 Experiment 2

The aim of the second experiment was to determine how the lack of feature selection influences the effectiveness of the method. As in Experiment 1, the same classifiers were used. The results are presented in Table 4.

A comparison of the results presented in Table 3 and Table 4 shows that strategy of data preparation and features selection (FS) increases effectiveness of the verification. This was further confirmed by the Bayesian character rank statistical tests, adapted in [36] to the graphic version. In the reported Bayesian test, the Authors introduce so-called *rope* concept – the ”Region of Practical Equivalence” for each two classifiers. If this parameter was set to 0.01, then the two classifiers are considered equivalent if the difference in their performance is smaller than *rope*. The test results in three possible out-comes: a) one method is better than the other, b) vice versa, or c) they are equivalent. In this method (see Figure 9), the bottom-left and bottom-right regions correspond to the case where one classification method (with FS) is better than the other (without FS) or vice versa. The top region represents the case where the equivalence between the methods is more probable. If all the points (here blue) fall inside one of the regions, we conclude that the hypothesis that one method is better than the other is true with probability ≈ 1 [36]. Examples of statistical test results obtained for tested classifiers are shown in Figure 9. In this experiment, our strategy was compared with the modified Hotelling's procedure of feature reduction, and methods where these modifications were not applied. It was done by means of the Bayesian Signed-Rank tests.

From the charts of Figure 9 we can conclude that proposed in this paper input data reduction gives always better results compared to not reduced (raw) data. This can be seen for all classifiers used in the experiments. In some cases differences are bigger whereas in other are smaller but these differences are always in favor of our method.

5.5 Experiment 3

An important stage of the proposed method is the necessity to scale the **F** vectors, registered by the LMC (Subsection 4.1). As a result of scaling, the length of each vector **F** is the same and equal to k - see also eq. (1). Selection of the value k is very important, because creating too long vectors does not improve the effectiveness of the method, but at the same time it has a negative impact on the extension of the time of the training phase.

On the other hand, reduction of too many elements of the vector **F** may lead to the degradation of information contained in this vector. In other words, we want to determine how many data samples are enough to collect to ensure the best classification efficiency. In this experiment, the influence

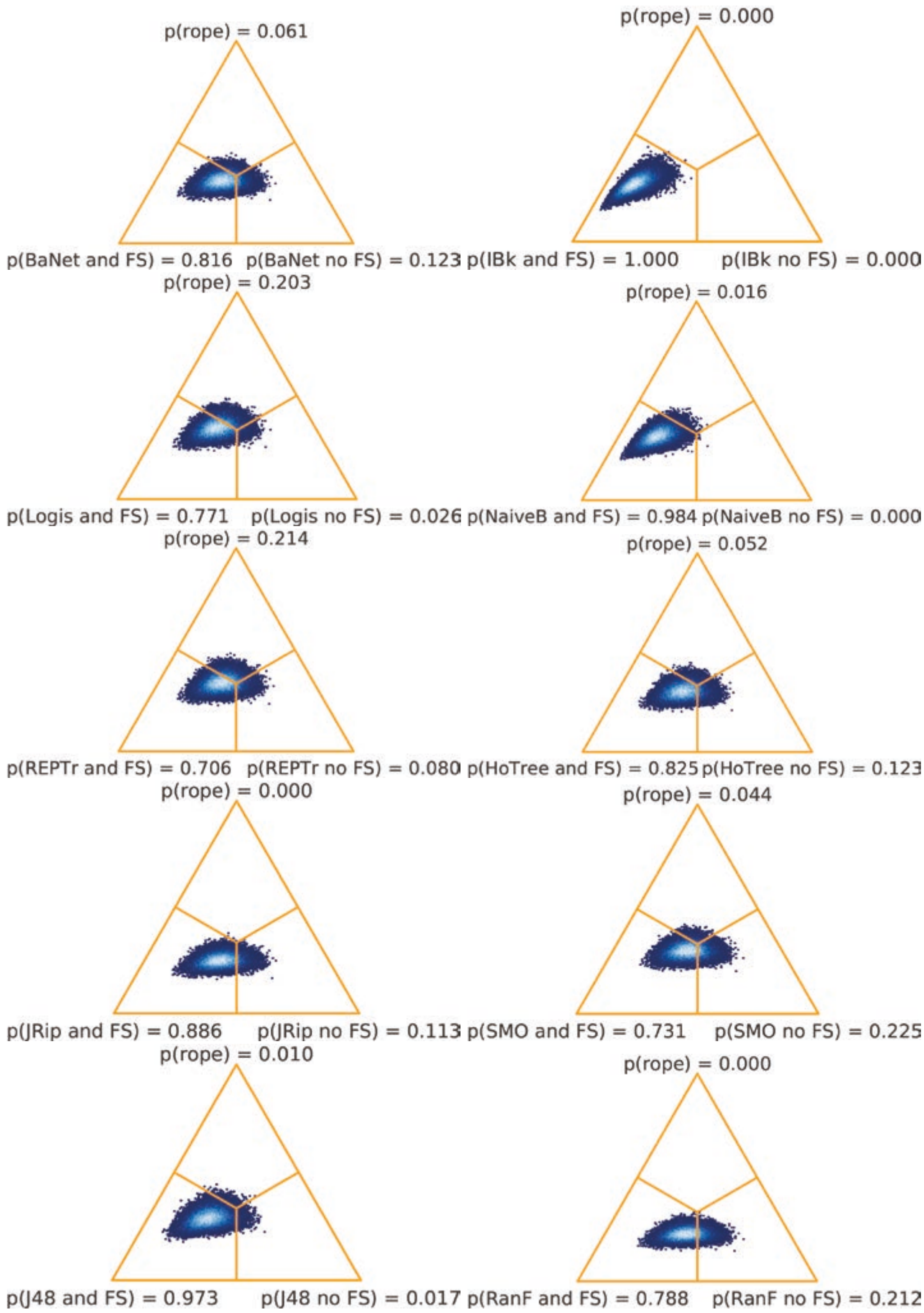


Figure 9. Posteriors for the Bayesian Signed-Rank tests for Accuracy measure (ACC) for various classification strategies.

of parameter k on the efficacy of classification was determined. The obtained results are presented in Table 5.

The experiment shows that it is enough to collect 110 consecutive data samples delivered by the LMC device. It was previously stated that for o equalize the length of the vectors **F**, we used a scaling method called Fixed Number of Points [30].

5.6 Experiment 4

The most important papers in the field of authorization of persons based on gestures was presented collectively in Table 6, where quality measure values obtained with the use of various methods are presented. These methods constitute a reference point for the results of the proposed method. However, it should be stressed that such a comparison is not fully reliable. This is because many authors use in experiments their own databases that are not publicly available. The database we have set up, on which the tests were conducted, has been made publicly available and can be downloaded from the website `http://biometrics.us.edu.pl/resources/downloads`.

Analyzing Table 6, we can see that the presented approach is competitive with existing solutions.

6 Conclusions

The article proposes a new method of biometric verification based on analysis of hand and finger movements using the LMC. The results of the experiments confirm that the proposed method allows obtaining high efficiency of biometric verification. The main advantages of the approach presented in the article are summarized below:

- An effective method of user authorization has been developed ($ACC = 99.88\%$), analyzing hand and fingers motion made with all fingers. It has been shown that this method is competitive with methods analyzing 3D movements, in which only one finger has been used.
- The usefulness of various classifiers in the proposed method was checked. Results were confirmed by statistical Bayesian Signed-Rank test.
- Thanks to the strategy of selecting features, number of important features is reduced, independently for each user, leaving only those that are relevant during the verification process.

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Algorithm 1: Feature selection using Hotelling's method.

Data:
$O = \{f_1, \ldots, f_{94}\}$ a set of all registered features by LMC devices for a given user;
X and **Y** are matrices with the Φ coefficients crated for person being verified (see eqs. 4 and 6);
$T2(f_1, \ldots, f_p)$ is Hotelling's statistics based on features $f_1, \ldots, f_p$.
Result:
O^* – the set with the most distinctive features determined for the person being verified.

Done:=FALSE;
$O^* := O$; $p := 94$;
repeat
    for i:=1 to p **do**
        /* calculate the necessity U_i of the $f_i \in O^*$ as a difference of two preceding Hotelling's statistics */
        $U_i = T^2(f_1, ..., f_p) - T^2(f_1, ..., f_{i-1}, f_{i+1}, ..., f_p)$;
    $j := \arg\min_i (U_i)$;
    $\tilde{F} := (n + m - p - 1) \cdot \frac{U_j}{1 + T^2(f_1, ..., f_p) - U_j}$;
    if $\tilde{F} < F_{1,n+m-p-1,\alpha}$ **then**
        Remove the j-th row of the matrices **X** and **Y**
        Remove the feature f_j from the set O^*
        $p := p - 1$;
    else
        Done:= TRUE;
until Done=TRUE;

Table 2. Algorithms used in the experiments and their parameters.

Algorithm	Model type	Parameter settings
Bayesian Network	Probabilistic	
IBk	*k*-NN	
Logistic regression	Regression	ridge = 0.00000001
Naive Bayes	Bayesian	
REP Tree	Decision Tree	
Hoeffding Tree	Decision Tree	
JRip	Rules	
Sequential Minimal Optimization (SMO)	SVM	Polynomial kernel
J48	Decision Tree	
RandomForest	Bagging	100 trees

Table 3. Results obtained using different classifiers (with features selection).

Classifier	FAR [%]		FRR [%]	AER [%]	ACC [%]
	random	*skilled*			
Bayesian Network	0.40	1.11	1.73	1.08	98.74
IBk	0.05	0.20	0.37	0.21	99.88
Logistic	1.65	2.18	2.87	2.23	99.02
Naive Bayes	0.97	1.93	3.13	2.01	98.72
REP Tree	1.87	3.52	2.90	2.76	97.54
Hoeffding Tree	1.19	2.36	2.89	2.15	98.52
JRip	1.89	2.91	2.55	2.45	97.87
SMO	0.66	0.94	1.57	1.06	99.13
J48	6.83	10.52	10.96	9.44	92.97
Random Forest	1.08	2.28	4.58	2.65	98.32

Table 4. Results obtained using different classifiers (without features selection).

Classifier	FAR [%]		FRR [%]	AER [%]	ACC [%]
	random	*skilled*			
Bayesian Network	0.55	0.69	1.88	1.04	98.59
IBk	2.92	3.65	3.24	3.27	97.01
Logistic	1.74	2.47	2.96	2.39	98.93
Naive Bayes	2.56	3.38	4.72	3.55	97.13
REP Tree	2.01	2.51	3.04	2.52	97.40
Hoeffding Tree	3.06	4.31	4.76	4.04	96.65
JRip	2.21	2.94	2.87	2.67	97.55
SMO	0.70	0.80	1.61	1.04	99.09
J48	8.21	11.90	12.34	10.82	91.59
Random Forest	1.24	1.91	4.74	2.63	98.16

Table 5. Influence of number of samples of feature f_i, $i = 1, \ldots, 94$ on the quality of verification.

	Number of the samples k in the vectors $\mathbf{F}_i = [f_i^{t_1}, \ldots, f_i^{t_k}]$											
	40	50	60	70	80	90	100	110	120	130	140	150
Bayesian Net.	38.00	54.70	69.70	83.90	88.50	98.40	98.70	98.74	98.40	98.20	98.50	98.40
IBk	51.10	57.30	65.60	75.50	84.00	95.00	97.80	99.88	99.80	99.80	99.50	99.90
Logistic	46.10	54.70	63.70	70.10	76.50	96.40	98.30	99.33	99.30	99.40	99.50	99.30
Naive Bayes	60.80	71.20	87.50	86.70	91.50	94.70	96.90	97.32	97.30	97.50	97.50	97.10
REP Tree	53.20	63.50	69.80	77.00	82.80	88.80	95.00	97.54	97.40	97.50	97.80	97.70
Hoeffding Tree	31.20	50.00	60.00	71.60	80.80	94.60	96.40	97.52	97.40	97.00	97.30	97.90
JRip	56.40	55.40	70.70	77.00	85.60	96.40	96.90	97.87	97.90	97.90	97.70	97.00
SMO	26.90	46.60	61.60	71.60	84.90	89.60	95.10	99.57	99.00	99.60	99.00	99.30
J48	45.60	54.90	65.40	73.20	85.80	92.30	91.00	92.97	92.50	92.50	92.00	92.50
Random Forest	18.20	38.10	39.20	45.10	45.20	58.90	87.40	98.32	98.50	98.40	98.00	97.80

Table 6. A comparison of our results with the most representative achievements from the literature.

Methods	**Evaluation metric**	**Database description**
Presented method	Accuracy 99.88% (IBk)	750 gestures from 50 users
Palm distance and finger length [26]	Acceptance rate (1% false positive): 75.78% (NB), 78.04% (RDF), 78.55% (NN)	1700 samples obtained from 150 users
Distance between gestures and DTW method [37]	Accuracy 86%–91%	13 users and two mid-air gestures
Hand model and circle gesture [28]	EER = 1% (for static gestures), EER = 2% (for dynamic gestures)	16 users (static gest.), 10 users (dynamic gest.)
Hand model values and different classifiers [38]	$\geq$90% correct classified instances	21 users and different number of features
Distance of fingertip to palm and different similarity metrics [39]	Accuracy with Cosine 90%, Euclidean 88.22%, Jaccard 86%, Dice 83.11%	10 different users
Least Square Support Vector Machine [8]	EER about 1%	100 users (10 genuine and 10 forgery samples)
Deep Convolutional Neural Network [40]	Accuracy 93%-98%	600 air signatures from 50 users
HMM, Bayes classifiers and DTW [11]	EER = 2.12% - 4.58%	Air signatures from 96 users
k-NN, DTW and HMM methods [6]	Accuracy 92%-97.1%	2000 air signatures from 100 users

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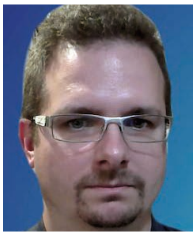
Rafal Doroz received his Ph.D. degree in computer science from the University of Silesia, Poland, in 2011. Currently, he is an assistant professor in the Institute of Computer Sciences, University of Silesia. He has also been a visiting professor at the University of Calgary, Canada. He main research interests are biometrics, image processing, classifiers, and machine learning. He has published more than 70 papers in internationals journals and conference materials.

Krzysztof Wrobel received his M.Sc. and Ph.D. degrees in computer science from the University of Silesia in 1999 and 2006, respectively. Currently, he works in the Institute of Computer Science, University of Silesia. His research interest areas are biometrics, machine learning, digital image processing and computer graphics. Dr Wrobel is an author more than 70 scientific papers, published in international journals and conference materials. He also been a visiting professor at the University of Calgary in Canada.

Prof. **Piotr Porwik** works at the Institute of informatics, University of Silesia, Poland. His research interests relate to applied spectral Boolean function analysis, machine learning, classifiers, pattern classification and biometrics. Prof. P. Porwik is a member of the Editorial Board of the International Journal of Biometrics and International Journal of Applied Mathematics and Computer Science and Mathematics. He presented invited papers, tutorials and keynotes in Japan, India, Czech Republic, Greece and Poland. He takes part in many national and international conferences where worked as a chairman or member of scientific and organizing committees. P. Porwik is also a reviewer in many prestigious international scientific journals.



Tomasz Orczyk has been a research and teaching worker at the Faculty of Science and Technology at the University of Silesia in Katowice since 2009. In 2018 he received a Ph.D. in Computer Science. He specializes in machine learning methods and their applications in medicine and biometrics. During his work at the university, he published more than 30 research papers and participated in numerous international scientific conferences. In addition to his scientific work, he teaches subjects like machine learning in biometry, computer networks, and digital electronics.