Classification of movements based on wearable device data in biometric authentication

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Abstract. The paper proposes a neural network algorithm for classifying human movements according to the accelerometer data, which is located in a mobile device. Intelligent algorithms for classifying movement types (single step, walking, walking on stairs, running) are considered on 9 types of different movements that a person performs in everyday life. The developed algorithm is proposed to be used in biometric authentication systems based on mobile phone data.

1. Introduction
The development of intelligent technologies is reflected in the field of processing, analysis and forecasting and it is in more and more aspects of human life. The correct choice of the neural network structure and its training algorithm allows you to approach the object of research more flexibly and find optimal solutions. In information systems the introduction of intelligent technologies opens a new stage of development of information systems. In particular, a promising direction are automated information systems that collect and process biometric information, including access control and management systems, the banking and medical sectors [1-3]. The desire to obtain biometric data, remote biometrics and the development of wearable devices require the development of new algorithms for collecting and analyzing biometric data. There are many ways to register human parameters [4-8]. Currently, the most common method of obtaining biometric data is using a video camera and a microphone [9-11]. In addition, other methods of collecting biometric indicators are actively developing. These methods are based on sensors built into personal portable devices, such as a mobile phone or a smart bracelet [12]. The purpose of this work is to develop technologies for collecting and analyzing biometric data in automated information systems to improve the quality of user identification and authentication procedures, increase the effectiveness of personalized health monitoring by identifying differences and changes in human movement parameters based on the accelerometer data of a wearable device.

2. Features of motion recognition
The task of recognizing human movements (both recognizing movements in one person and movements in different people – recognizing people) is reduced to their clustering and further classification. During recognition, the received data about objects is divided into subsets. Within each subset, the data samples should have the maximum similarity, and the data belonging to different classes should have the maximum differences. Subsequently, the new data is evaluated as belonging to one of the classes (subsets). The partitioning takes place on the basis of features. The input data can be: a set of features, a distance matrix, time series [13]. The main methods of data classification are: decision tree, Bayesian
classifier, nearest neighbor method, support vector machine method, random forest method, gradient
descent and booting, logistic regression, tobit and probit [14].

The classification of human movements according to the data of one sensor is incorrect, because the
resulting sets overlap very much with each other. The solution of the problem makes sense under the
condition of classification of a limited number of movements. In this work, the classification uses signs
determining the features of a person's gait in various conditions and indirectly include the parameters
of individual limb movements. That is, when moving, a large number of muscles, ligaments and joints
are involved in the work [15, 16]. In addition, the accuracy of the classification is affected by the features
of the method of registering movements, which are associated with changes in the registration process
of the location and orientation in the space of the sensor itself (which can be performed without walking),
the design and metrological features of the mobile device (the location and type of the accelerometric
sensor), the transformation of the projection of the acceleration of free fall into motion parameters.

To obtain a set of signs on the basis of which it is possible to classify movements, studies were
conducted on a group of people aged from 15 to 67 years. In total, 32 male and female people with
different physiological characteristics (height, weight, posture) participated in the research. For the
experiment, the subjects were divided into subgroups (according to similar physiological characteristics)
of 4 people in order to analyze the quality of distinguishing the subjects and their exercises from each
other on the basis of the developed classifier. The volume of the training sample was formed from
movements that were performed under various conditions: the form of clothing (loose and tight, different
types of shoes), the location of the phone (front and back pockets of pants, near the ear). The volume of
the training sample within each subgroup ranged from 2000 to 3000 movements. The main motor
patterns for classification were the movements performed when walking in a straight line and stairs with
a load (a bag with a laptop weighing 3.5 kg) and without it. Thus, the main movements performed in a
person's daily life were included in the training sample.

As a result of the conducted research, it was found that the most informative parameters are: duration,
standard deviation, composition of the frequency spectrum, signal shape (the value of the correlation
coefficient).

3. Classification of movements

The classification algorithm with preliminary data processing is shown in figure 1.

For each user, movement patterns are selected and a neural network classifier is trained. The duration
of the maximum time of the template is taken as the value of the time window. All patterns are
normalized in amplitude and supplemented with zeros up to the duration of the maximum pattern (time
normalization). Further, during the operation, the data read from the phone's accelerometer is processed
within the time window. Each component (axis) of the accelerometer is processed separately. This
makes it possible to bring the dependence of the data on the sensor orientation to zero.

The read data located within the time window is normalized. The average value and the standard
deviation of the time window data are estimated. After that, the correlation value of the time window
data and each of the templates is evaluated. If the correlation value exceeds the set threshold, the neural
network classifier is launched. During the research, it was found that the optimal threshold for the
correlation coefficient is a value from 0.75 to 0.8. Conducting a preliminary correlation analysis allows
you to discard some of the noise signals and improve the quality of the classifier. An example of the
structure of a neural network for distinguishing subjects within a group is shown in figure 2.

The direct propagation network is chosen as the basic structure for the neural network. The number
of inputs is 260, of which 256 belong to the analyzed time window with a dimension of 256 of the
reference, the following parameters are fed to the remaining inputs: the correlation coefficient, the
average value, the standard deviation of the template and the data of the time window.
Figure 1. Motion classification algorithm.

The neural network has 260 input neurons, 100 neurons in one hidden layer, and 4 neurons in the output layer. When training the neural network, the gradient reverse descent function was used. The entire sample was divided into a training sample, a sample for verification and testing in the following ratio: 70%, 15%, 15%. Cross-entropy was used as an optimization criterion. The activation function of the hidden layer was a sigmoid, and the output layer was a normalized exponential function.

As an example, the results of training a neural network are presented in figure 3, and the results of the proposed algorithm for classifying one of the subgroups of subjects for all types of movement are presented in figure 4.

Thus, as a result of the conducted research, it was found that even in the worst-case scenario, in which the subjects were in loose clothing and sneakers (which adds more noise components to the accelerometer signal and smoothest individual gait features by softening the step), the presented algorithm allows to distinguish the subjects when performing various movements in more than 90% of cases. This also applies to the most monotonous movements – going down and up the stairs and when walking with a mobile phone near your ear. The distinction of the subject's own movements is 100%.
4. Conclusion
In the course of the research, it was found that the use of a single accelerometric sensor of a mobile phone makes it possible to distinguish between individual movements of a person and movements made by different people. It should be noted that the proposed algorithm for distinguishing movements allows you to separate one movement from another under different conditions, which are characterized by the degree of fit of clothing to the body, the complexity of the path. To improve the quality of distinguishing movements and people, the neural network can be additionally trained in the process of functioning. However, for further development, it is necessary to conduct a larger number of subjects with different physiological characteristics and include a larger number of different interfering factors in the experimental methodology. Nevertheless, the implementation and development of the proposed
algorithm in practice will increase the functionality of automated information systems of the medical, law enforcement and banking sectors.

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