

PAPER • OPEN ACCESS

Biometric pattern recognition using wide networks of gravity proximity measures

To cite this article: A E Sulavko and S S Zhumazhanova 2018 *J. Phys.: Conf. Ser.* **1050** 012082

View the [article online](#) for updates and enhancements.

You may also like

- [A CT image feature space \(CTIS\) loss for restoration with deep learning-based methods](#)
Ao Zheng, Kaichao Liang, Li Zhang et al.
- [Faster variational quantum algorithms with quantum kernel-based surrogate models](#)
Alistair W R Smith, A J Paige and M S Kim
- [A data-driven spike sorting feature map for resolving spike overlap in the feature space](#)
J Wouters, F Kloosterman and A Bertrand



ECS
The
Electrochemical
Society
Advancing solid state &
electrochemical science & technology

DISCOVER
how sustainability
intersects with
electrochemistry & solid
state science research

Biometric pattern recognition using wide networks of gravity proximity measures

A E Sulavko, S S Zhumazhanova

Omsk State Technical University, 11, Mira, ave., 644050, Omsk, Russia

E-mail: sulavich@mail.ru

Abstract. In this article a new interpretation of the pattern recognition problem is proposed, in accordance with the problem the own domain of pattern (image) classes are gravitational fields generated by immovable objects (classes of patterns) that propagate in the feature space. A measure of proximity is proposed for calculating the ‘attractive force’ of the pattern to existing templates in the feature space, which can work with both strongly dependent features and with independent ones. A network of gravitational proximity measures was configured to recognize a person by the characteristics of voice and handwritten passwords reproducing. Comparatively low error rates are obtained.

Keywords. Quadratic forms, attraction of a pattern, curvature of feature space, correlation dependence of dynamic biometric parameters.

1. Introduction

The problem of confidential information and computer resources protection from unauthorized access becomes more actual than ever. Mechatronic, computer, and robotic systems have to be protected. The classic way to solve the problem is to protect the data with encryption and authentication based on passwords and hardware keys. However, these authenticators are alienated from their owner, the protected information (system) can be compromised in the case it getting to third parties.

This problem is being solved with the help of key and passwords binding to the biometric parameters of a person. In Russia within the national technology initiative (NTI) program, a ‘road map’ concept is being projected for the development of the SafeNet safe and protected computer technologies market. Key segments of the market, as well as current scientific and technical tasks and pilot projects have already been identified. They include: the introduction for the first time in the world of a national biometric authentication platform, an electronic signature with biometric activation, multimodal biometrics for a personal data management system, etc.

Most of the current commercial products for biometric protection are based on static biometric patterns (three-dimensional models of face and skull, fingerprints, iris patterns, etc.). The fundamental problem lying in the use of open biometric patterns is that they are not secret and can be falsified (by creating a fake finger, using high-quality photography, etc.).

To date, active studies of dynamic biometric features [1] are being conducted to solve similar problems (authentication by handwriting and keystroke dynamics, voice). Dynamic biometric patterns can be secret, however, as many studies have shown, these patterns consist mainly of low informative and interdependent features (biometric parameters, quantity characterizing subjects). This circumstance makes it very difficult to develop procedures for highly reliable authentication in the



space of dynamic biometric features. The present study is aimed at finding effective proximity measures for pattern recognition in feature space with different mutual correlation dependencies.

2. Problem statement

The classical statement of the pattern recognition problem (its geometric interpretation) leads to the construction of separating hyperplanes in hyperspace. Each dimension of this space is a range of values of a certain feature. If the pattern classes are considered inseparable in the original feature space, then it is necessary to go to a space of higher dimension for the construction of hyperplanes. In this case, the derived (derivatived) hyperspace is sometimes called rectifying.

In the process of learning the recognition system by learning examples of the pattern, the example's template is being created (we introduce this term, replacing the notion of the pattern class). For the purpose, each presented example of the pattern is transformed into a vector of features, i.e. to a point with coordinates equal to the values of the corresponding features. The template is a cluster of such points. Next, hyperplanes are constructed that separate their own domains (scope) of templates. At the stage of identification (or verification) of the pattern, a vector of values of similar features is assigned to the pattern and it is required to determine which new point belongs to its own domain. The existing variety of methods and approaches to pattern recognition allows to solve this problem in some ways with some error.

If the feature space is 'plane', i.e. n -dimensional Euclidean space, then the shortest path from the pattern to the center of the template can be found using the Euclidean measure (1). If the ranges of values of particular features vary significantly in scale, the space ceases to be 'ideally plane', but it can be normalized by calculating distances with the help of the Pearson's measure (2) [2].

$$e = \sqrt{\sum_{j=1}^N (m_j - a_j)^2}, \quad (1)$$

$$\Pi = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}, \quad (2)$$

where a_j is the value of the j -th feature, N is the number of features processed by the functional (the dimension of the functional), m_j and σ_j are the mathematical expectation and the standard deviation of the j -th feature values calculated from the training sample data. In the problems of biometric authentication (identification), such an idealized case is rare one, because most of the features are correlated differently. Correlation 'bends' the features space in the neighborhood of patterns templates. The force of 'bending' in each spatial dimension can be different, as in the template neighborhood (Figure 1). This is explained by the different nature of the correlation dependence between the biometric features of each person. In order to take into account the heterogeneity of the curvature/bending of the feature space in the theory a quadratic form of (3), also called the Mahalanobis measure, can be used.

$$y = (\bar{m} - \bar{a})^T \cdot [R]^{-1} \cdot (\bar{m} - \bar{a}), \quad (3)$$

where $\bar{a}$ is the vector of features values in the normalized coordinate system, $[R]$ is the matrix of pair correlation coefficients between the features. The use of this quadratic form is complicated by the fact that it is required to perform the inversion of the correlation matrix $[R]$, which is not possible in practice. The point is that this operation is ill-conditioned and performed with significant errors [3]. An attempt of such treatment leads to a problem called the 'dimensional curse' [4], at least in the problems of dynamic biometric patterns recognition on training samples in dozens of examples.

The methods for networks configuration of quadratic forms (3) with perceptron training algorithms [5] do not solve the problem of processing highly dependent features.

For these reasons, proximity measures, which are quadratic forms, are focused on processing only independent and weakly dependent data.

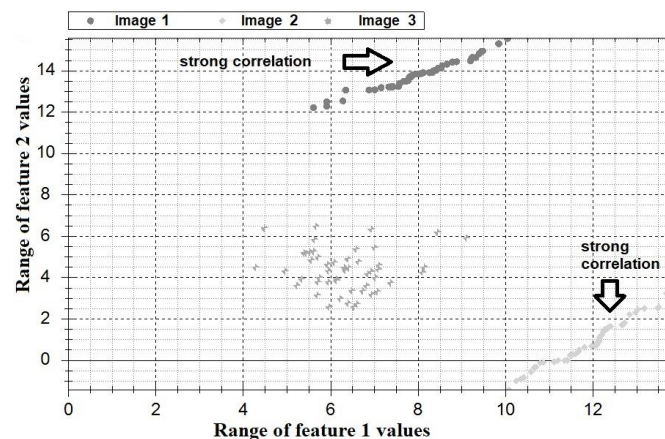


Figure 1. ‘Bending’ of the two feature space under influence of correlation.

A fundamental scientific problem is the search for effective methods for assessing the closeness of patterns to templates in the space of features, curved by the correlation between them.

3. Theory

A. Proximity measures oriented to processing of dependent features

The results of recent studies indicate that there are functionals (proximity measures) that can take fewer wrong decisions if the correlation between the features is high. The first group of such proximity measures was called multidimensional Bayesian functionals [3, 6, 7, 8]. They evaluate not only the proximity of the pattern to the template, but also the dependence of a certain feature of the pattern on several other features. Besides functionals of the greatest likelihood (Bayesian formulas) there are multidimensional correlation [6], difference [3], Bayesian hyperbolic functionals [7]). The greater value of N and higher the coefficient of equal correlation of features, the more effectively the Bayesian functional works [8].

After the multidimensional Bayesian functionals were proposed, it became clear that the strength and direction of the correlation relationship between the features is a special kind of information about the pattern. Later, other groups of functionals were proposed that could work with dependent data. However, all of them are ineffective working with independent data. Therefore, they should be combined into a network consisting of various measures of proximity, including from quadratic forms.

B. Wide hybrid neural networks

In biometric applications, various methods and approaches to pattern recognition are used: fuzzy extractors [9], artificial neural networks (ANN) [10], artificial immune systems (AIS), methods of mathematical statistics and probability theory [11], k-nearest neighbors method [12], support vector machine [12], and etc. Each of them operates with certain computational elements (CE) and is a variant of generalization of a number of methods, defining the principle of operation and interaction of CE, as well as the general structure of the pattern recognition method. For example, different algorithms of noise-immune coding can be used in fuzzy extractors, in ANN - neurons with different activation functions, in AIS - lymphocytes and antibodies, in the methods of statistics, probability theory and k-nearest neighbors, various measures (proximity metrics) are used to calculate distances in space features (Euclid, Pearson, Mahalanobis, etc.). All approaches have advantages and disadvantages. However, the authors of this article adhere to the ideology of configuration of the so-called ‘wide’ ANN [13] with a small number of layers based on neurons, which are based on various functionals (analogues of proximity measures). This approach is used in applications where the volume of the training sample is substantially limited. In practice, it is usually required that the biometric authentication system is guaranteed to be trained on 10-20 examples of the user's pattern.

The training of the ‘wide’ ANN is layer-by-layer and is carried out without using the backpropagation method (the input of the next layer receives the data of the training sample enriched with the previous layer after its preliminary configuration). Each neuron is trained independently of the rest, weights (or other parameters of the neurons) are calculated determinately, based on the distribution parameters of the characteristic values. Rejection of iterative training procedures allows to remove many disadvantages inherent in multi-layer (‘deep’) ANN, the most significant of which for biometric applications are the following:

1. to learn ANN classical algorithms in the presence of several layers requires a large training sample (hundreds and thousands of examples).
2. Iterative learning algorithms lose stability when the ANN structure becomes more complex. In particular, it is not possible to configure neurons with a large number of inputs (the ‘blindness’ effect of the training automaton occurs) [14].
3. The process of learning a multilayer network by an iterative algorithm can be unlimitedly long.
4. The classic ANN configuration algorithms are characterized by the problem of ‘retraining’.

It is also has to be noted that the backpropagation method has an exponential computational complexity that does not allow it to be implemented on a weak processor without remote connection to the server. A secret biometric pattern should not be sent over the network, thus it is possible to violate the requirement of Russian standard GOST R 52633.0 not to compromise the biometric template.

All these problems do not apply to ‘wide’ ANN.

The structure of the artificial neuron of the ‘wide’ network of this type generally corresponds to the prevailing ideas about their construction. First, the data processes the neuron's functional, then its value is sent to the activation function. However, each neuron can contain several functionals and activation functions and, accordingly, have several outputs (Figure 2). For comparison, in the classical perceptron there is one activation function and one functional, performing a weighted summation of features values. These functionals lose stability processing highly dependent features.

The ability to change the functional of a neuron increases the potential of the ANN in terms of the reliability of the decisions made and generates new benefits. One of them is the ability to process data with varying level of correlations. Commonly, dependent features are tried to be eliminated, and the dimensionality of the feature space is reduced (applying the principal component method, etc.). However, the hybrid ‘wide’ ANNs is focused on processing all available features, regardless of degree of their mutual correlations. Neurons can consist of different functionals, each of which can give the wrong decision in some cases, but these errors are low-correlated, so their collective solution will be much more powerful. Together they form an effective tool for data enrichment, compensating for the lack of information on the pattern using many ways to process it. The functionals and the number of neuron inputs, as well as the synapses, are selected automatically at the learning stage, depending on mutual correlation and features’ informativeness (each neuron must process features that have a comparable amount of information about patterns [10]). Evaluation of information and correlation between the signs is based on the training sample, the volume of which is very limited. At the same time, the increase in the number of features and neurons does not lead to an increase in the required volume of the training sample.

In the simplest case, only one layer of neurons can be configured. This is often enough for most pattern recognition tasks. The increase of the layers number requires justification. A reasonable explanation in this case may be the use of another principle of enriching the data entering the next layer of the network, to take into account additional information about the pattern.

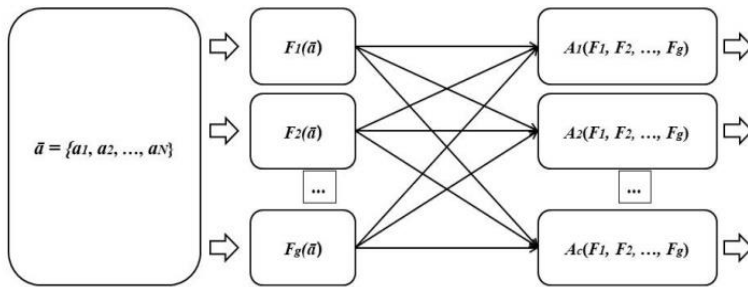


Figure 2. Configuration of a neuron with several functionals and activation functions in the ‘wide’ ANN.

Thus, the ‘wide’ ANN considered by the authors are flexible and refer to hybrid neural network algorithms. Each neuron processes the values of those features of the pattern that are best suited for its functionality.

However, this ANN class has its own problems. One of them is the low accuracy of calculating the correlation coefficients and estimates of the features informativeness on small training samples. This makes it difficult to configure many neurons (although it does not reduce the possibility of their training to none).

For the development of ‘wide’ ANN, it is very important to search for universal functionals that are able to work efficiently both with highly dependent data, and with independent ones, as well as with data of any informativeness. This will make it possible to abandon the assessment of information content and the correlation of features at the training stage.

C. The ‘attraction’ method of recognizable patterns

The curvature of the feature space by means of a correlation between them seems to be how the real space-time is curved under the influence of gravity. The deformation of space, connected with the presence of mass-energy, was described in the general theory of relativity, proposed by Einstein in 1915. We will not describe the theory in details, but merely note that when patterns are recognized, the effect of the feature space squeezing in the neighborhood of the pattern template is also observed, if the features are dependent. However, in this case, the space is compressed perpendicularly with respect to the direction of the features dependence, i.e. the feature space ‘contracts on the sides’ (Figure 3), while the gravitational forces cause space-time in the real world to be curved ‘around’ an object that has a mass (Figure 4).

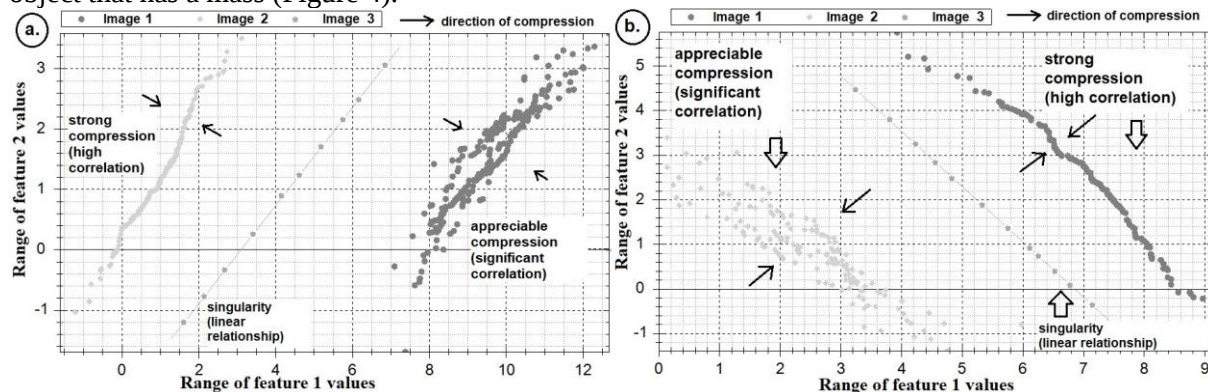


Figure 3. The direction of the space squeezing of two generated features: (a) if there is a positive correlation between them, (b) if there is a negative correlation between them.

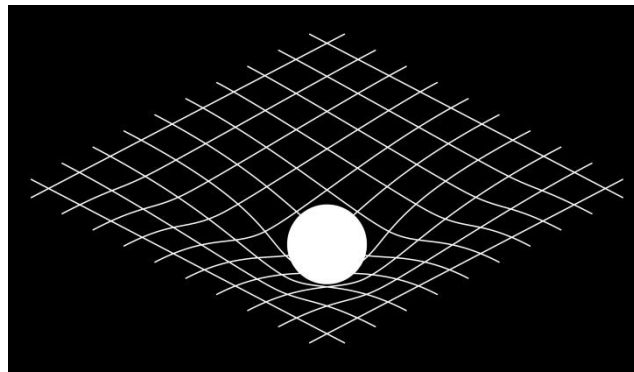


Figure 4. The curvature of the real world space by an object that has mass.

The effect that superdense matter has on space-time (the so-called ‘black hole’) is widely known. Under the influence of ‘black holes’, space and time converge to one point, called a singularity. At this point, the usual laws of physics are violated, the space-time dimensions cease to exist (they ‘fold’ to zero size).

The analogue of the singularity in the two-dimensional feature space is the eigenvalue of the object's template, for which both characteristics are linearly dependent (Figure 3). In fact, in this case, two characteristics turn into one (a singular feature), and the two-dimensional space is transformed into a one-dimensional one. In a multidimensional space for a template, several independent singular signs, each of which can be formed from several linearly dependent features, can exist. For example, in three-dimensional space with two linearly dependent features the template's own scope is converted into a plane, if there are three ones - in a line (in this case one singular feature). Thus, a singularity in feature space can extend to separate dimension and curvature of space under influence of the correlation between variables is heterogeneous and uneven.

Naturally, the described analogy is very conditional, but it makes us to reconsider the classical formulation of the pattern recognition problem. It can be said that the correlation links between the characteristics of templates impart some additional density to it (they increase the template's mass). Suppose that the accumulation of points belonging to the template's own scope is a gravitational field that is generated by a stationary object and propagates in the feature space unevenly in all directions. Then the task of identifying the pattern given by a point in space is reduced to calculating the trajectory of its continuous motion until it reaches the center of one of the templates. We call this approach to pattern recognition by the ‘attraction’ method.

The idea of using gravity theories in pattern recognition issues is not new. In [15], an edge detector method based on the law of universal gravity is proposed. To construct an edge detector it is assumed that each point of the pattern is a celestial body that has some connection with other points of the pattern within its neighborhood with the help of gravitational forces. For points outside the specified region, all gravitational forces are assumed to be zero. For each point of the pattern, the magnitude and direction of the vector sum of all the gravitational forces that the point exerts on its neighborhood, transmit important information about the edge structure, including magnitude and direction. The algorithm proposed in [15] consists of three stages:

1. The gravitational forces of a pixel exert on every other pixels around it are computed using the law of universal gravity.
2. The vector sum of all gravitational forces is calculated.
3. The magnitude and direction of the vector are used to detect pattern edges.

Gravity not only can distort space-time, but can also be used for data clustering. Samples in each training set can be considered as particles, and if each particle is assigned a mass value, it is possible to form a new equation of attraction. Based on the results of the studies, the edge detector based on the

universal gravity theory proved to be more resistant to noise than the methods of Sobel, LOG and Canny [15].

Gravitational search algorithm (GSA) is applied in optimization problems [16]. GSA is a heuristic optimization method. It is proved that this algorithm has a good ability to search for the global optimum, but at the last iteration has a low speed. To address this disadvantage, a hybrid optimization method based on the Particle Swarm Optimization method and GSA was proposed in [17], which was used to configure Feedforward Neural Networks.

In [18] using GSA the search was made to optimize the architecture of the modular neural network (the number of modules, layers and ANN's nodes). Further, ANN, configured using GSA, was used to recognize medical patterns of echocardiograms in order to identify healthy patients. In [19] the advantages of using fuzzy gravitational search in optimization of modular neural networks are shown. The proposed approach provides high reliability of echocardiogram recognition (the number of erroneous decisions was 0.51%).

Algorithm for data clustering (pattern recognition without a teacher), based on Newton's law of gravity is provided in [20]. In the proposed method, the points (samples, patterns) of data and the centers of clusters (templates) are considered fixed and mobile celestial objects, respectively. Fixed objects apply gravity to movable objects and change their position in feature space, and therefore the best positions of cluster centers are determined by applying the law of gravity. To evaluate the effectiveness of the proposed algorithm, a comparative experimental study is performed with some known clustering algorithms using three visual data sets. The experimental results confirm the effectiveness of the proposed algorithm.

In the present work, the described idea is formulated for the first time taking into account the influence of the correlation between features on the properties of the own scope of the template and, thus, an attempt is made to take into account information on the correlation of features for pattern recognition.

D. Gravitational measure of intimacy

Nature has always been an inspiration source for researchers. A large number of methods and algorithms for solving intellectual problems are suggested trying to copy processes from nature: ANN, AIS, genetic algorithms, etc. As a rule, these methods have a number of significant simplifications that, as a result, have little in common between them and the natural prototype. The method of 'attraction' isn't exception. Modeling the process of pattern 'attraction' to the templates can be resource-intensive. Therefore, within the work of this paper, we simplify the problem: assume that the pattern is attracted instantly. Also in the real world, the gravitational attraction is directed in all directions (i.e., in the direction of curvature), in the feature space, the attraction will be stronger in the direction opposite to compression.

A measure (4), that calculates the force of attraction to the template acting on the recognizable pattern, is proposed. Name (4) as the gravitational measure of proximity. The measure does not take into account the gravitational constant and the mass (or attraction force) of the recognized pattern, in this case they are constants that do not affect the recognition result.

$$G_{trig}^2 = \frac{\sum_{j=2}^N \left[\sum_{t=1}^{j-1} \left(trig(j,t) = \begin{cases} \cos(\bar{a}, \bar{v}_{j,t}) \cdot r_{j,t}, & \text{if } r_{j,t} > 0 \\ -\sin(\bar{a}, \hat{v}_{j,t}) \cdot r_{j,t}, & \text{if } r_{j,t} < 0 \end{cases} \right)^2 \right]}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}}, \quad (4)$$

where $\bar{a}$ is a vector of features' values, $\bar{v}_{j,t}$ is a vector with coordinates under the numbers j and t , equal to 1, and the remaining coordinates equal to 0, $r_{j,t}$ is the correlation coefficient between the indices j and t , calculated from the training sample data, $trig(j, t)$ is the evaluation functional of the attractive force of the template in 2 spatial dimensions (the order of G is 2). The physical meaning of the functional $trig(j,t)$ is to increase the attraction more, the closer the location of the recognized pattern to the 'compression line' of space. In fact, this functional takes into account additional information about the position of the pattern and the correlation between the features. The total attraction force is equal

to the ratio of the sum of the squares of the component forces in all two-dimensional subspaces of the original feature space to the value of the Pearson's measure. The Pearson's measure plays the role of distance in a normalized coordinate system. Based on a series of computational experiments on pattern recognition, the following empirical formulas for calculating gravitational metrics are also proposed:

$$G_1^2 = \frac{\sum_{j=2}^N \left(\sum_{t=1}^{j-1} \cos(\bar{a}, \bar{v}_{j,t}) \right)}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}}, r_{j,t} > 0 \quad (5)$$

$$G_2^2 = \frac{\sum_{j=2}^N \left(\sum_{t=1}^{j-1} \cos(\bar{a}, \bar{v}_{j,t})^2 \right)}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}}, r_{j,t} > 0 \quad (6)$$

$$G_3^2 = \frac{\sum_{j=2}^N \left(\sum_{t=1}^{j-1} (1 + \cos(\bar{a}, \bar{v}_{j,t})) \cdot (1 - \sin(\bar{a}, \bar{v}_{j,t})) \right)}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}} \quad (7)$$

$$G_4^2 = \frac{\sum_{j=2}^N \left(\sum_{t=1}^{j-1} |\cos(\bar{a}, \bar{v}_{j,t})| \cdot |\sin(\bar{a}, \bar{v}_{j,t})| \right)}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}} \quad (8)$$

$$G_5^2 = \frac{\sum_{j=2}^N \left(\sum_{t=1}^{j-1} (|\cos(\bar{a}, \bar{v}_{j,t})| \cdot |\sin(\bar{a}, \bar{v}_{j,t})|)^2 \right)}{\Pi(N) = \sqrt{\sum_{j=1}^N \frac{(m_j - a_j)^2}{\sigma_j^2}}} \quad (9)$$

As seen, the above formulas (5) - (9) do not contain computational operations related to the correlation coefficients. The attraction force of the pattern and template is reduced in proportion to the distance, rather than the square of the distance between them (as the law of universal gravity says). Normalizing the force with respect to the square of the distance produces lower results. Newton's law (and other theories of gravitation) help to find an analogy with the problem being solved, but they do not hold for objects which the theory of pattern recognition deals with.

4. Experimental results

An experiment was carried out to recognize patterns in the space of dependent and independent features with different informativeness. Informativeness is the main indicator of the quality of a feature, which is numerically estimated through the intersection area of the feature's probability density function characterizing the recognizable patterns. The informativeness of feature I can be measured in bits or using a relative scale from 0 to 1 (the smaller the I , the more informative the feature). More details on the evaluation of features' informativeness can be found in one of the papers [10, 21, 22]. Patterns and features were generated using the Monte Carlo method for the parameters of the normal distribution law (the most common case for dynamic biometric features). The parameters for generation were chosen so that features were of low-informative ($0.6 < I < 0.8$). The features values were generated as independent values, then for correlated features a dependence was created, for this value of each feature for each pattern ranged in ascending order (the order of values for each feature varied from the lowest to the highest one). The normal distribution law is the most common for dynamic biometric features.

The reliability of the pattern recognition procedure (as for any biometric authentication) is determined by the probability (or percentage) of errors of the 1st and 2nd kind - False Rejection Rate (FRR) and False Acceptance Rate (FAR), respectively.

In Figure 5, it's shown a comparative evaluation of the effectiveness of the Pearson's measure application (2) and the functional (4) for recognizing the generated patterns in the feature space.

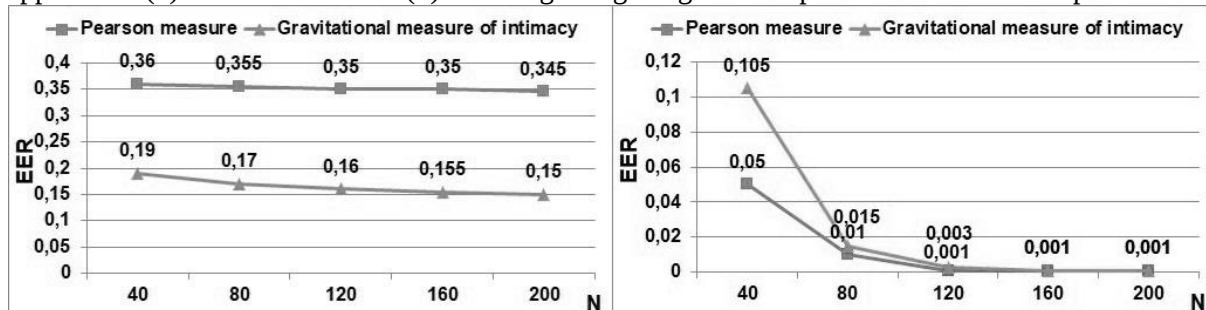


Figure 5. Probability of pattern recognition errors in the space of dependent (above) and independent (below) low-informative features (for $I \approx 0.7$).

An experiment was performed comparing functionals of wide networks of neurons formed on considered proximity measures, in the problem of recognizing subjects by the peculiarities of reproduction of handwritten and voice passwords. In the experiment, 90 people took part, each of which during a month entered a secret handwritten pattern using a Wacom graphic tablet (the pen's coordinates and the force of pressing the pen on the tablet were registered) and a voice pattern using a Sony F-V120 microphone. Each week, the subject made at least 20 attempts to introduce each handwritten and voice pattern. As a result, more than 100 biometric samples of voice and handwritten passwords were received from each subject. All samples were subjected to statistical processing to extract the features from them. The methods from [9] were used for analysis of handwritten patterns and for voice patterns – from [22].

After calculating the vectors of features' values from each entered pattern, the formation and training of the ANN on the basis of Pearson's measures and gravitational metrics was carried out. For each subject, a unique network was formed, consisting of two segments (subnets): based on the Pearson's functional and gravitational metrics (Figure 6). The first subnet treated only combinations of weakly dependent or independent features, the second one - combinations of features, the correlation coefficient between which exceeded 0.3. Independent features were divided into categories of informativeness ($0 < I < 0.9$ for $\Delta I = 0.1$, total 9 categories), the less informative the features are, the more inputs were created for the neuron that processed them. At $I < 0.1$, there were 3 inputs of the neuron ($N_1 = 3$), for $0.1 < I < 0.2$ - $N_2 = 4$, at $0.2 < I < 0.3$ - $N_3 = 6$ inputs, and so on. Going to a category with more informative features, the number of neuron's inputs increased ΔN times. It is empirically established that for the types of patterns used, Pearson's network shows good results at $\Delta N = 1.5$. These optimal parameters (N_1 , ΔN) were chosen empirically in the process of the experiment.

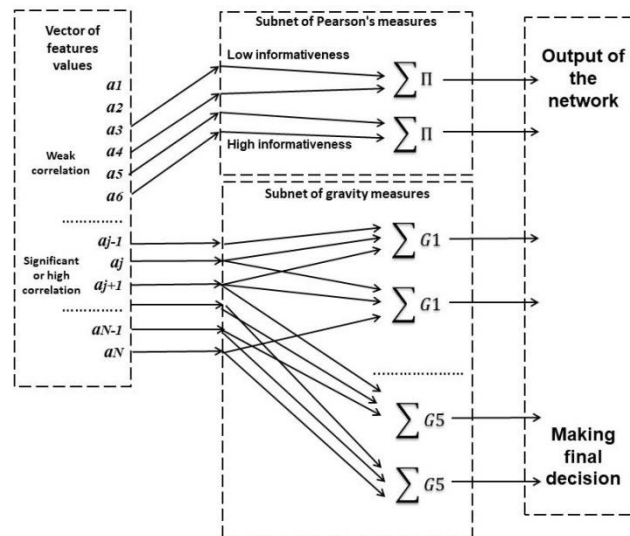


Figure 6. Scheme of a single-layer hybrid 'wide' network based on the Pearson's measure and gravitational metrics.

The subnetwork of gravity proximity measures was formed for processing only those combinations of features, the correlation dependence between which is essential (more than 0.5). In this case, the dimension of the functionals was fixed without considering the informativeness, since dependent features have close informativeness value. The optimal number of inputs of the 'gravitational neuron' ($N=20$) was chosen empirically in the process of the experiment.

Learning is understood as the computation of mathematical expectations and standard deviations of each feature's value of the subject. 20 biometric samples of the subject were used for training. The remaining samples were used to assess the reliability of subject recognition. As a result (Figure 7), the probabilities of recognition errors of subjects according to the peculiarities of handwritten and voice patterns reproduction were as follows:

- Pearson's subnet: voice – EER=10.2%, handwriting – EER=8%;
- subnet of gravity proximity measures: voice – EER=9,5%, handwriting – EER=6,9%;
- hybrid INS: voice – EER=7.1%, handwriting – EER=6.8%.

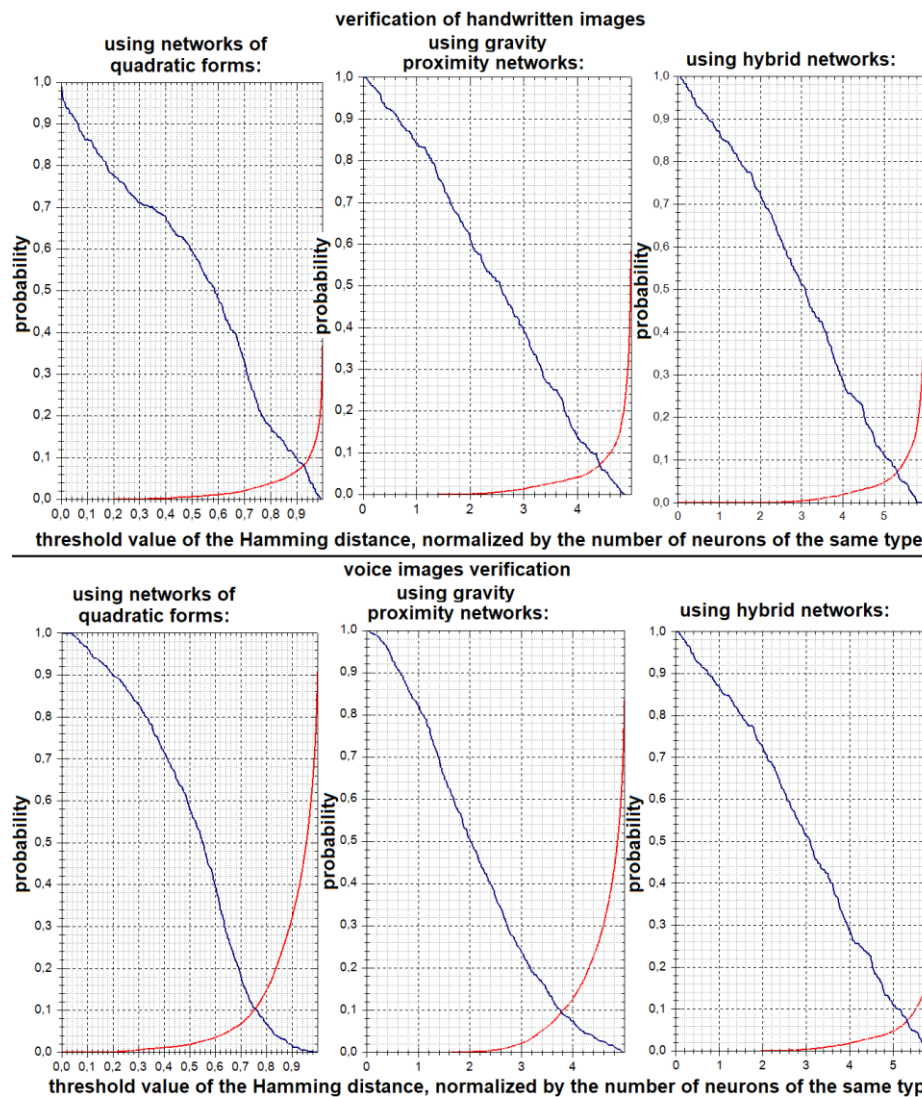


Figure 7. Probabilities of errors of the 1st and 2nd kind of recognition of subjects by handwritten images and voice messages, depending on the threshold value of the Hamming measure from the code generated by the network to the correct one

The positive effect of the integration of quadratic forms with gravitational metrics is most noticeable when recognizing voice images (Figure 7).

5. Discussion of results

As seen from Figure 5, the proximity measure (4) shows similar results with the Pearson's measure (2), if the features are independent, but only for high dimensionality of N . A similar case is observed with respect to the other proposed gravitational metrics. All the proposed proximity measures (4) - (9) give similar indicators of EER in the presence of a positive correlation between the features. However, their error decisions are not strongly correlated, which indicates the possibility of their joint use. When recognizing patterns in the space of correlated features, the proposed gravitational proximity measure shows better results than the Pearson's measure (and Euclid's one respectively).

It is established that the distribution law of the calculated values of the functionals (4)-(9) with received 'Own' input data (corresponding to the subject to whom the template belongs) have a distribution close to lognormal. In the case of the 'Stranger' input data (data from unregistered entities), the values of the functionals (4)-(9) can be described by a normal law (with some reservations). The hypothesis of the distribution law for these quantities was verified by the Chi-square method. Thus, the probability density of the values of gravitational functionals can be used as additional information in the recognition of the pattern. Further enrichment of the input data can be performed by neurons of subsequent layers.

6. Conclusion

A new interpretation of the problem of pattern recognition is proposed, according to which the own scopes of the pattern classes are gravitational fields that are generated by a stationary object and propagate in the feature space unevenly in all directions. Identification of the pattern given by a point in space is reduced to calculating the trajectory of its continuous motion until it reaches the center of one of the templates (classes of patterns).

The measures of proximity are proposed to calculate the 'attractive force' of the pattern to the existing templates in the feature space. These measures of closeness show similar results with measures that are oriented toward the absence of correlation between the features (providing the availability of a large number of processed features), but surpass them when recognizing patterns in the space of correlated features.

Different 'gravitational' functionals can be a big variety, and they can complement each other since their solutions are not completely correlated (at least, it is observed for the proposed metrics). On the basis of each such functional, neurons can be configured for a 'wide' ANN. An important property of 'gravitational' functionals is that they work quite efficiently both in the space of independent features and with strongly correlated ones. In the provided work, one of the possible variants of configuration of hybrid networks of such functionals to solve problems of subjects recognition of by voice and handwritten passwords is proposed. As a result, it was possible to achieve the following indicators of error decisions: voice – EER=7.1%, handwriting – EER=6.8%. These indicators are much lower (by 10-30%), if the system configure individually for each user (estimates of Figure 7 are obtained when setting up networks for the "average user").

References

- [1] Boriev Z, Sokolov S, Nyrkov A, Nekrasova A 2016 Mathematical and information maintenance of biometric systems *IOP Conference Series: Materials Science and Engineering* (Saint-Petersburg, Russia) pp 1–4
- [2] Sulavko A E, Fedotov A A, Eremenko A V 2017 Users' identification through keystroke dynamics based on vibration parameters and keyboard pressure *Proc. of XI Int. IEEE Scientific and Technical Conf. 'Dynamics of Systems, Mechanisms and Machines' (Dynamics)* (Omsk, Russia, 14–16 Nov. 2017) pp 1–7
- [3] Ivanov A I, Lozhnikov P S, Serikova Yu I 2016 Reducing the Size of a Sample Sufficient for Learning Due to the Symmetrization of Correlation Relationships Between Biometric Data *Cybernetics and Systems Analysis* vol 52(3) pp 379–385
- [4] Ivanov A I, Lozhnikov P S, Kachajkin E I 2015 Identifikatsiya podlinnosti rukopisnykh avtografov setyami Bayyesa-Khemminga i setyami kvadraticnykh form [Identification of the authenticity of hand-written autographs by Bayes-Hamming networks and networks of quadratic forms] (in Russian) *Voprosy zashchity informatsii* **2** pp 28–34
- [5] Lozhnikov P S, Sulavko A E 2017 Usage of quadratic form networks for users' recognition by dynamic biometric patterns *Proc. of XI Int. IEEE Scientific and Technical Conf. 'Dynamics of Systems, Mechanisms and Machines' (Dynamics)* (Omsk, Russia, 14–16 Nov. 2017) pp 1–6
- [6] Ivanov A I, Kachajkin E I, Lozhnikov P S 2016 A Complete Statistical Model of a Handwritten Signature as an Object of Biometric Identification *Proc. of 2016 Int. Siberian Conf. on Control and Communications (SIBCON 2016)* (Moscow, Russia, 12–14 May 2016) pp 1–5
- [7] Ivanov A I, Lozhnikov P S, Vyatchanin S E 2017 Comparable Estimation of Network Power for Chisquared Pearson Functional Networks and Bayes Hyperbolic Functional Networks while Processing Biometric Data *Proc. of Int. Siberian Conf. on Control and Communications (SIBCON)* (Astana, Kazakhstan, 29–30 June 2017) pp 1–3. DOI: 10.1109/SIBCON.2017.7998435
- [8] Ivanov A I, Lozhnikov P S, Sulavko A E 2017 Evaluation of signature verification reliability based on artificial neural networks, Bayesian multivariate functional and quadratic forms *Computer Optics* **5** pp 765–774
- [9] Lozhnikov P S, Sulavko A E, Eremenko A V, Volkov D A 2016 Methods of Generating Key Sequences based on Parameters of Handwritten Passwords and Signatures *Information* **7(4)** p 59

- [10] Ivanov A I 2016 Mnogomernaya neyrosetevaya obrabotka biometricheskikh dannykh sprogrammym vosproizvedeniem effektov kvantovoy superpozitsii [Multidimensional neural network processing of biometric data with program reproduction of quantum superposition effects] (in Russian) Penza: PNIEI 133 p
- [11] Vasilyev V I, Sulavko A E, Eremenko A V, Zhumazhanova S S 2016 Identification potential capacity of typical hardware for the purpose of hidden recognition of computer network users *Proc. of X Int. IEEE Scientific and Technical Conf. 'Dynamics of Systems, Mechanisms and Machines' (Dynamics)* (Omsk, Russia, 15–17 Nov. 2016) pp 1–5 DOI: 10.1109/Dynamics.2016.7819106
- [12] Pervushin E A 2011 Obzor osnovnykh metodov raspoznavaniya diktirov [Review of the main methods for speakers recognition] (in Russian) *Matematicheskie struktury i modelirovaniye* **24** pp 41–54
- [13] Akhmetov B S, Ivanov A I, Funtikov V A, Bezyaev A V, Malygina E A 2014 Tekhnologiya ispol'zovaniya bol'shikh neyronnykh setey dlya preobrazovaniya nechetkikh biometricheskikh dannykh v kod klyucha dostupa [The technology of using large neural networks to convert the fuzzy biometric data in the key code access] (in Russian) Kazakhstan, Almaty: LEM 144 p.
- [14] Ivanov A I 2012 Podsoznaniye iskusstvennogo intellekta: programmirovaniye avtomatov neyrosetevoy biometrii yazykom ikh obucheniya [Subconscious of artificial intelligence: programming of neural network biometrics automata by the language of their learning] (in Russian) Penza: PNIEI 125 p
- [15] Genyun Sun, Qinhua Liu,*, Qiang Liu, Changyuan Ji, Xiaowen Li 2007 A novel approach for edge detection based on the theory of universal gravity *Pattern Recognition* **40** pp 2766 – 2775.
- [16] Rashedi E, Nezamabadi-pour H, Saryazdi S 2009 GSA: a gravitational search algorithm *Information Science* **179** pp 2232–2248
- [17] SeyedAli Mirjalili, Siti Zaiton Mohd Hashim, Hossein Moradian Sardroudi 2012 Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm *Applied Mathematics and Computation* **218** (2012) pp 11125–11137
- [18] González B, Valdez F, Melin P, Prado-Arechiga G 2015 A Gravitational Search Algorithm for Optimization of Modular Neural Networks in Pattern Recognition In: *Castillo O., Melin P. (eds) Fuzzy Logic Augmentation of Nature-Inspired Optimization Metaheuristics. Studies in Computational Intelligence* vol 574. Springer, Cham
- [19] Beatriz González, Fevrier Valdez, Patricia Melin, German Prado-Arechiga 2015 Fuzzy logic in the gravitational search algorithm enhanced using fuzzy logic with dynamic alpha parameter value adaptation for the optimization of modular neural networks in echocardiogram recognition *Applied Soft Computing* vol 37 pp 245–254
- [20] Abbas Bahrololoum Hossein Nezamabadi-pour Saeid Saryazdi 2015 A data clustering approach based on universal gravity rule *Engineering Applications of Artificial Intelligence* vol 45 pp 415–428
- [21] Sulavko A E, Fedotov A A, Eremenko A V 2017 Users' identification through keystroke dynamics based on vibration parameters and keyboard pressure *Proc. of XI International IEEE Scientific and Technical Conference 'Dynamics of Systems, Mechanisms and Machines' (Dynamics)* (Omsk, Russia, 14–16 Nov. 2017) pp 1–7
- [22] Sulavko A E, Yermenko A V, Borisov R V, Inivatov D P 2017 Vliyaniye psikhofiziologicheskogo sostoyaniya diktora na parametry yego golosa i rezul'taty biometricheskoy autentifikatsii po rechevomu parolyu [Influence of speaker's psychophysiological state on the parameters of speaker's voice and the results of biometric authentication on the voice password] (in Russian) *Komp'yuternyye instrumenty v obrazovanii* **4** pp 29–47

Acknowledgments

The research was supported by the Russian Scientific Foundation (project №17-71-10094).