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Multidimensional mutual ordering of patterns using a set of pre-trained artificial neural networks

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Abstract. The article shows that large artificial neural networks can be used for mutual ordering of a set of multi-dimensional patterns of the same nature (handwritten text, voice, smells, taste). Each neural network must be pre-trained to recognize one of the patterns. As a measure of ordering one can use the entropy of patterns "Strangers" that are input to a neural network trained to recognize only examples of the pattern "familiar". The neural network after training reduces the entropy of the examples of the pattern "Familiar" and increases the entropy of examples of pattern "Stranger." It is shown that the entropy measure of the ordering always has two global minima. The first minimum corresponds to the pattern "Familiar", the second to the inversion of the pattern "Familiar". It is also shown that the Hamming distance between the patterns belonging to two different groups (groups of the two global minima) is always as large as possible.

1. General biometrics, generalizations prospects

The process of informatization of society is rapidly developing. Each of us is forced to remember numerous passwords to access various information resources. At the same, time people are good at remembering and recognizing patterns, but are poor at remembering passwords consisting of a set of random characters. This has led many countries to develop biometrics. The main task of biometrics is to create artificial intelligence capable of accurately recognizing a biometric pattern of its master. Various technologies can be used for recognition of people: fingerprint analysis [1], [2] the analysis of the iris pattern of the eye, the analysis of the dynamics of handwriting [3], the analysis of the subcutaneous blood vessels [4]. The United States, Canada and the European Union are developing the technology of so-called "fuzzy extractors" [5-8]. Russia and Kazahstan are using the technology of learning artificial neural networks [9]. It can be shown that these technologies complement each other, but the technology of large artificial neural networks is more common, and produces the best results with respect to all the indicators [10]. Unlike an expert, a neural network of artificial intelligence provides not only an assessment of the situation (the rating of the object), but also provides the user with an estimate of the probability of errors of the first and second order of his decision. [10] Potential evaluation of expert opinions is a very promising direction of the development of the technology of modern neural networks.

2. Neuronetwork emulators quadratic forms

If one assumes the normal distribution of human biometric patterns and remains within the apparatus of linear algebra, then one will have to use quadratic forms:

$$e^2 = (\overline{E}(v) - \overline{v})^T \cdot [R_n]^{-1} \cdot (\overline{E}(v) - \overline{v}) \tag{1}$$

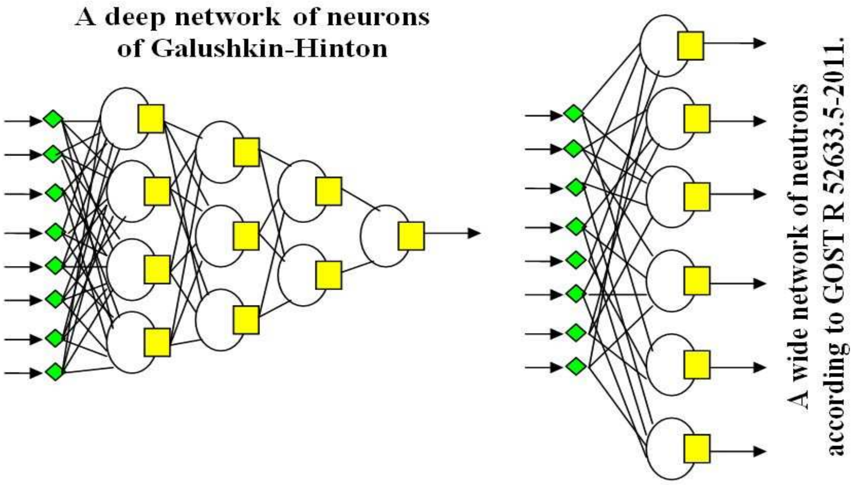
where $\overline{E}(v)$ is the vector of expectations of several hundreds of parameters of the pattern, $\overline{v}$ is the vector of the parameters of test image $\overline{\sigma}(v) = \overline{1}$ normalized by the standard deviation, $[R_n]^{-1}$ is the inverse correlation matrix of several hundreds (thousands) of controlled parameters of the recognizable pattern.

If we consider the quadratic form (1) with respect to the recognition of the pattern of the image of the iris [2, 8], the dimension of the reversible correlation matrix will be 2048x2048. To calculate the correlation matrix of such a high dimension is technically quite possible, but to calculate its inverse is not. This has to do with the bad-conditioning problem of handling high-dimensional matrices.

Networks of artificial neurons have been actively used for recognition since the middle of the last century. Neural Galushkin-Hinton networks [11,12] are currently used everywhere. For example, they are embedded in each digital camera to search the field of view for human faces. Google extensively uses "deep" neural networks to classify images on the Internet.

"Deep" neural networks used today (Fig. 1) may have several tens of layers of neurons combined into multiple parallel processing branches. There are, however, problems with the training of such deep networks. They are trained by back-propagation of errors of "deep" layers of neurons [11] and with the use of the Boltzmann machine to train the first (surface) layers of neurons [12]. Unfortunately, the learning algorithm has an exponential computational complexity and requires a very large number of examples. The learning process of a neural network consisting of 12 layers requires 10000 examples and recognizable patterns, and on a standard PC lasts for up to 40 days. However, over the past 60 years, significant progress has been made in the learning process of neural networks, through which high-dimensional pattern recognition problems with the use of "deep" neural networks have become technically solvable [14].

Neural networks using converters built on "broad" single-layer and double-layer neural networks are standardized in Russia (Fig. 1).



a) b)

Figure 1. Two types of architecture of neural networks: a) "deep" network; b) "wide" network

The mathematical meaning of the standardized learning algorithm is to ensure that every pair of controlled biometric data distribution image of "Familiar" will look like an ellipse (Fig. 2).

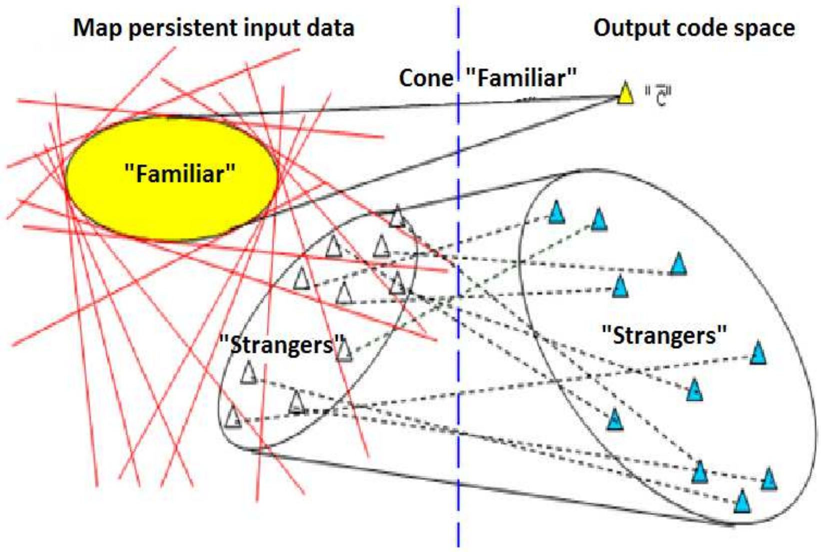


Figure 2. Operation of the neural-network converter pre-trained to convert the biometric pattern of "Familiar" into the key code and hash (mix) the data of the pattern "Stranger."

Each artificial neuronal network will break the plane with a straight line. The idea of the learning algorithm GOST R 52633.5 is that no dividing line should cross these ellipses "Familiar". In this case, all the examples of the pattern "Familiar" of the output of the neural network drive will have the same output code. Any neural-network converter for the pattern "Familiar" should reduce the natural entropy of the output code of the biometric data to the nearly zero level:

$$H("c_1, c_2, ..., c_{256}") \approx 0 \tag{2}$$

On the contrary, the entropy of the output code of the pattern "Stranger" should be as high as possible:

$$\frac{256}{10} \approx 26 < H("x_1, x_2, ..., x_{256}") < 256 \tag{3}$$

Referring to Figure 2, the secants divide the ellipse of the distribution pattern "Stranger" into fragments. Each fragment will give its own output code. This is what provides hashing (mixing) of the data of the biometric pattern "Stranger." The principal feature of the Russian standardized training algorithm [9] is that it has a linear computational complexity. This fact allows training neural networks with 20 examples of the pattern "Familiar" on conventional machines. This property of the algorithm distinguishes it from many other large training algorithms of artificial neural networks.

The special feature of domestic neural-network converters of biometric data into code is that they all have 256 outputs. This is due to the orientation of biometric standards on Russian cryptographic algorithms of information protection using cryptographic keys 256 bits long for encryption, as well as for generating digital signatures. In other words, we can say that any standardized neural-network converter of biometric data into code is a neural-network emulator quadratic form in the Hamming space of distances:

$$h = \sum_{i=1}^{256} ("c_i") \oplus ("x_i") \tag{4}$$

The Hamming distance is zero for all the examples of the pattern "Familiar". It is greater than 1 for the pattern "Stranger". Besides, the entropy of the codes (2) are significantly different. As a result, in order to discern the recognizable pattern codes, the Hamming distance and the entropy of the output codes must be controlled.

3. Estimate of a multidimensional entropy of long codes with dependent digits

One problem of the use of neural-network converters is their testing. Based on the algorithm for calculating the Shannon entropy, the evaluation of the second-kind error probability (assuming the image of "Stranger" for the image of "Familiar") requires a base consisting of at least 226 images of "Stranger" (see. (3)). To create such a large base of patterns of "Stranger" is technically difficult. However, using a standard [13] to assess the probability of the second-kind error, one can use only 32 patterns "Stranger". The test standard is based on the normal distribution of the Hamming distance between compared codes. With this hypothesis, the probability of the second-kind error of the elementary statistical moments can be estimated with the following relationship:

$$P_2 = \frac{1}{\sigma(h)\sqrt{2\pi}} \int_{-\infty}^{1} \exp\left\{\frac{-(E(h)-u)^2}{2(\sigma(h))^2}\right\} \cdot du \qquad (5)$$

where E (h) is the expectation of the Hamming distance between the code "Familiar" and the code "Stranger", $\sigma(h)$ is the standard deviation of the Hamming distance.

One can easily go from the probability of the second-kind errors to the entropy of "Strangers" codes:

$$H(" x_1, x_2, ..., x_{256} ") \approx -\log_2(P_2) \qquad (6)$$

If we abandon the Shannon principle of the expectation of rare events and go to the prediction of the probability of their occurrence using (5), we should be able to estimate the entropy of the code that is 256 bits long using a small sample of 32 examples of pattern "Stranger".

The fast method of calculating the entropy allows ordering multidimensional images of the same nature. An example of such mutual ordering is shown in Figure 3.

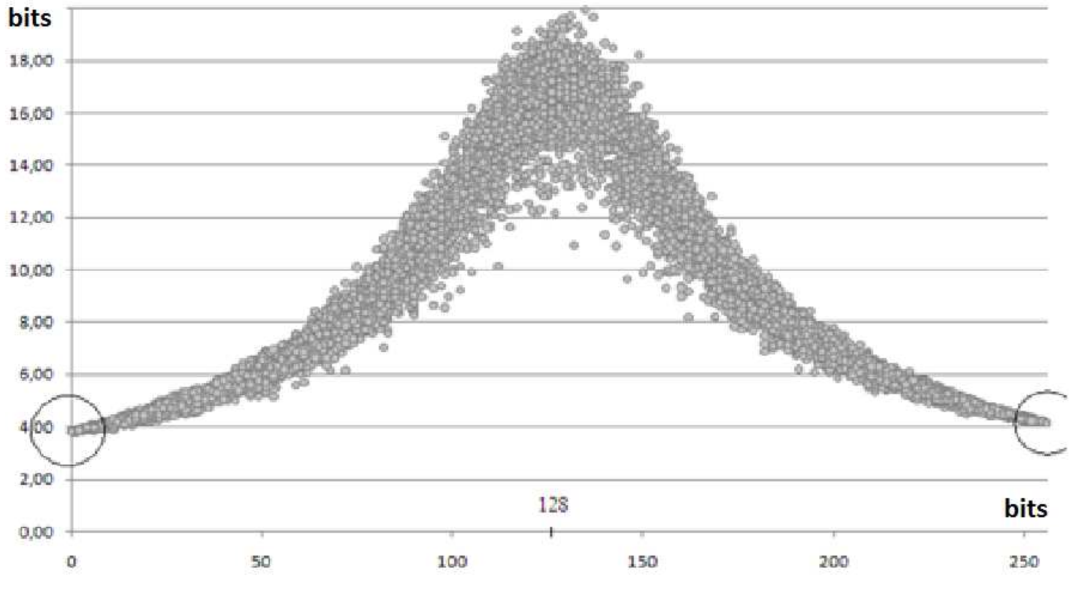


Figure 3. Examples of reciprocal ordering of handwritten biometric patterns according to their entropy calculated from the output codes of neural networks trained to recognize the pattern "Familiar".

Figure 3 shows that the relative entropy ordering necessarily leads to the discovery of a group close to the pattern "Familiar" with an entropy of about 4 bits and is very close to the patterns of distant inverse pattern "Familiar" (the inverse of the pattern "Familiar"). Both these groups are marked by circles in Figure 3.

4. Conclusion

In this paper we propose a method of comparing and ordering multiple multi-dimensional images of the same nature with the use of "broad" neural networks. The method has significant prospects for further development and wide use. One advantage of the method is the absence of practical limitations on the number of parameters being compared. This makes it possible to assess complex objects and systems without the use of integral parameters, which to some extent lose information during the computation. Another important advantage is the simplicity of the method of forming the coordinate system and the initial reference point. Experts need only agree on a single multi-dimensional pattern "standard" that allows continuing to carry out ratings of objects regardless of the peer reviews. A third advantage of the proposed method is the possibility of training neural networks with small samples, which opens up additional possibilities for the use of the proposed method in real time.

Naturally, all the above needs to be verified, but such multi-dimensional comparisons have been conducted on the biometric data, which gives one hope for a positive result. The special tools that have been created are successfully working for "fuzzy addressing" arbitrarily large databases of handwritten patterns, repeatedly accelerating search for patterns closest to a single copy of the manuscript pattern.

We hope that similar results will be achieved for ordering multi-dimensional images of a different nature (in other subject areas) using a plurality of pre-trained artificial neural networks. The problems of mutual ordering of the images and their "fuzzy addressing" are close to each other.

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