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[1]D. P. Kucherov,
[2]V. G. Tkachenko,
[3]I.-F. F. Kashkevych,
[4]A. O. Androshchuk,
[5]S. O. Perepelitsyn

RECOGNITION OF TEXT PHRASES DISTORTED BY INTERFERENCE BY BACK PROPAGATION NEURAL NETWORK

[1,2,3,4]Department of Computerized Control Systems, National Aviation University, Kyiv, Ukraine
[5]Institute of NetCentric LLC of Ukraine, Kyiv, Ukraine
E-mails: [1]d_kucherov@ukr.net, [2]tkachenkvg@gmail.com, [3]ikashkevich@gmail.com, [4]anastasiandroshchuk@gmail.com, [5]sergpsa@inbox.lv

Abstract—*The paper takes into consideration risk systems that can use not only in nuclear reactions but other plants with frequent risks for people's life, such as mining, and other. Such facilities apply information systems in which take place exchange text messages through free space. The main problem of information radio reception is an increasing number of emitting means that equal the increase of noise level receiving set. As an additional means of processing distorted textual information, it is proposed to use a neural network, which must be pre-configured. For analysis, the back propagation neural network was selected. The adjustment is carried out by an algorithm assuming a double differentiation of the error function, which ensures a high network convergence rate. Learning is stopped according to the total criterion for the deviation of the output signal from the reference. The paper formulates the conditions of quadratic convergence of the back propagation network with one new tuning procedure, and also offers examples of the construction of a neural network for recognizing a text message in various reception conditions. The fed to the neural network is sequence of the letters of English alphabet. A feature of the structure of the neural network that provides correct recognition is the use of completely nonlinear neurons. Comparison of options for the structure of the neural network when recognizing text phrases is carried out according to indicators of the probability of recognition, error, and training time. The established properties of the neural network are useful in the design of efficient information system.*

Index Terms—Back propagation neural network; text recognition; recognition probability.

I. INTRODUCTION

The application of the risk-informed design is so popular for the engineering of nuclear reactors and many authors analyzing and taking into account the different risks, for example, [1], [2]. So, in [1], the main focus of the study is on multicomponent risks, their assessments studied along with well-known reliability, risk, and optimization metrics.

The second example [2] presented a method for adjusting the interval of periodic inspections of nuclear power plants based on risk (RI). To find the testing interval, they used a self-diagnosis, which is then confirmed by a risk assessment method.

The next type of plants by the high risks are mine, and paper [3] shows the mine accidents only of 2018, where they are analyzing in the areas of the occurrence of accidents, time of occurrence, and type of accidents. Countermeasures and suggestions based on the causes of accidents are including also using new information systems. Text messaging is part of these systems.

We should note that text messaging for various purposes is very popular nowadays. Text messages come asynchronously, which does not distract the person from the main work, on there do not need to give an immediate answer, which makes it possible to analyze the received information in a calm environment and work out the right solution for it. Also, text messages can be generated to inform the consumer about the current state of the device or one reading, which is useful in tasks of remote monitoring of the state of the observed object.

In some cases, the information system has a radio network, then text messages sent in free space or over the radio network. The main problems of the exchange are observed when receiving messages from the air, where the growth of emitting devices is manifested and the mutual influence, causing certain difficulties in decoding message symbols. The mutual influence is complicated by the propagation conditions of radio waves, when there is repeated re-reflection from buildings, rein-forced concrete structures, the underlying surface and emergence of the impossibility of decoding or confusing characters [4].

To eliminate mutual influence, multichannel reception is used, synchronization of reception and transmission is provided, special signal processing is introduced, for example, message analysis by the method of extracting the main components, decision trees, and some other methods are used. Multichannel reception requires the creation of a complex structure with several antennas and receivers located in space and possibly polarized, respectively, which is not always possible, for example, in spatially limited places. Effective synchronization is carried out in the presence of a stable external reference synchronizing generator, which also requires the presence of additional external devices.

Text recognition refers to the classification of images, however, the problem under consideration differs from image recognition by the absence of computer vision systems, there is no need to use a graphic format, classification of many image classes, it is possible to present text in binary format as well.

II. Related works

Text recognition was carried out by various researchers, some of the results achieved are presented in [5] – [15]. One of the classifiers trained by the Random Forest method is presented in [5]. The recognition accuracy of the classifier did not exceed 80%.

In article [5], a mechanism for recognizing text with a background presented on signboards and the shape of which has a curvature is presented. The main limitation of the proposed method is a limited set of data for training, texts with a curved shape, a variety of fonts and background may be recognized incorrectly.

The processing of pixel information in a recurrent neural network is presented in [6]. The complexity of the approach is determined by the recognition of the color of the pixels of a two-dimensional image, which required the creation of a 12-layer network to recognize a limited set of images. Recognition for an unlimited data set remains a problematic issue, also, there is no evaluation of the processing efficiency of distorted images and in noise.

In article [7], the features of the multilevel propagation algorithm are explained taking into account the forecasting operator, which helps to assess the relevance of input data based on the topology of the studied model itself.

Various deep learning techniques are presented in [8] – [12]. Extensive reviews of the emergence and current state of deep machine learning technology are presented in [8], [9]. In these works, the importance of the developed algorithms for image recognition is noted. The use of deep neural networks for recognition of image classes is presented in [10]. The neural network used did not allow the authors to determine the recognition accuracy, although they recognize that the accuracy of the class is high. Comparing the networks AlexNet and ImageNet, the authors note that the latter produced classes recognition for the selected image databases (ImageNet and Caltech-101) with errors.

In article [11], a fast learning algorithm for learning digital recognition by a network with associative memory is presented, which has three hidden layers. The algorithm works correctly if the expected distribution of the input data matches the true posterior distribution. However, in the interest of learning speed, the authors resort to contrast divergence and achieve a positive result by studying the behavior of additional layers. Unfortunately, no rigorous proof of the convergence of the proposed method is presented.

The authors of [12] assumed that a deep neural network uses textual information to decrypt a recognizable color image, thus it is realizing its multimodality. Unfortunately, no other use of deep neural networks for the recognition of textual information was found in the available literature.

Current work is based on research [13], [14], based on the results of processing alphabetic information in the Matlab environment. The proposed studies are aimed at exploring the possibility of constructing a compact neural network capable of recognizing text messages transmitted to radio networks where noise distortions that cannot be eliminated by correlation-filter processing or obtained due to multiple reflections.

The author [15] described of the Levenberg-Marquardt algorithm and software in the Matlab environment for solving nonlinear least square curve-fitting problems.

The Levenberg-Marquardt algorithm is iterative, but there is a problem of convergence and reliability of the given initial data. Therefore, [16] proposes methods for improving the algorithm by updating the approximation step by geodesic correction and when moving uphill, as well as some method for updating the Jacobi matrix.

The identification of a linear system with one input and one output with is presented in [17], based on the neural network ADaptive LINear – ADALINE (by Widrow), trained by the Levenberg–Marquardt method. In order to accelerate the convergence of training and, thus, expand the capabilities of tracking time-varying system parameters, authors added an impulse to the weight adjustment.

In article [18] developed a model for predicting the bending force of a hot rolling mill based on a back propagation (BP) 3-layer neural network. To prevent the tuning parameters from entering the local minimum, the LM algorithm is used.

The article [19] presents an extension of the Levenberg–Marquardt algorithm based on parallel computing, which allows to increase the performance of the algorithm in training large neural networks.

Since the text is a limited set of alphabetic, digital, and auxiliary characters, the work explores the possibilities of processing a text message by a neural network, as well as determining the network structure, avoid local minimums at finding optimal parameters of the network, and evaluating the recognition accuracy when text information is transmitted by a flow.

III. PROBLEM STATEMENT

A text message considered, consisting of a limited set of alphabetic characters received at the input of the receiving set in a certain sequence. The sequence of characters can be separated by spaces and be distorted by noise, which is equivalent to the effect of the mutual influence of several signal sources. The message is presented in digital form, which is similar to the modern approach to the formation and processing of signals in the receiving set.

Processing of radio signals in the receiving system based on frequency filtering, isolating the signal from the background of noise by threshold processing, and performing character-by-symbol decoding of the received information. It is assumed that the reception of radio signals occurs under conditions of interfering noise, i.e.

$$y_j(t) = d_j(t) + n_j(t)\,, \tag{1}$$

where $y_j(t)$ and $d_j(t)$ are the signals that associated with the received and generated symbols of message and $n_j(t)$ is the noise signal, $1 \le j \le N$, N is the number of symbols in the message.

The nature of the noise is unknown, however, it makes sense to assume that the noise has a Gaussian distribution with a zero mean. The level of interfering noise is such that the result of decoding is the incorrect identification of characters, and we have unreadable information.

A possible solution in the context of the problem under consideration is the processing of noisy information by a neural network that has the properties of parallelizing information processing and obtaining a reasonable result by self-learning.

The recognition quality achieved by minimizing recognition errors over the entire training interval i = 1 ... M, and can be represented by a quadratic function

$$e = \sum_{j=1}^{N}\sum_{i=1}^{M}\left[d_i - y_i(w_j)\right]^2\,, \tag{2}$$

In equation (2) w is the parameter of neural network learning.

Self-learning is key to solving complex problems that cannot be solved in the usual way. The problem of building such a network is the choice of invariant features that describe the input information so that differences are caused only by random factors, for example, noise. In this case, the informative features will be considered a vector representation of the characters on which the noise component superimposed. It is assumed that an indicator of the quality of identification is the probability of correct identification of characters, measured as the number of identifiable characters, i.e.

$$P = \frac{N_c}{N}\,, \tag{3}$$

where N_c is the number of symbols correctly recognized.

IV. SOLUTION METHOD

Among the many types of neural networks including deep learning, the structure of the BP neural network is widely used, because it has the properties of self-tuning and the recognizing is computationally effective. Each neuron of the network includes an adaptive adder, a solver, and a feedback mechanism. The adaptive adder sums the input signals x_i of a neuron with a certain weight w_i [13].

$$v = \sum_{j=1}^{N} x_j w_j\,, \tag{4}$$

Here v is the output of the adaptive adder. The correction of the scales is carried out following the algorithm

$$w_j(n+1) = w_j(n) + \Delta w_j(n)\,, \tag{5}$$

where w_j is the weight coefficient of the jth neuron, n is the sequence number of the correction iteration w_j, and Δw_j is the correction calculated as

$$\Delta w_j(n) = k e_j(n)\,, \tag{6}$$

where k is the coefficient that determines the network-tuning speed, $e(n)$ is the correction error signal acting at the input of the neuron and defined as follows

$$e_j(n) = d_j(n) - x_j(n) w_j(n)\,, \tag{7}$$

where $d_j(n), x_j(n)$ is the desired output and input of the jth neuron at the nth iteration of the setup.

Since the task of recognizing a sequence of characters is not trivial and cannot be solved by a simple perceptron, it is appropriate to choose the structure of a multilayer perceptron containing one or more hidden layers of neurons. A distinctive feature of the multilayer structure is the presence of a solver with a smooth (differentiable) function, in contrast to the rigid threshold function used in the Rosenblatt perceptron. The differentiability property can be satisfied by several types of decision functions, however, the sigmoidal form is most often used

$$y_j(n) = (1 + e^{-v_j(n)})^{-1}, \tag{8}$$

There are two main approaches to ensure the global convergence of the tuning algorithm. The first is based on controlling the coefficient k, on which the value of the correction step depends, while in the zone far from the optimal solution $k < 1$, in the zone approaching the optimal setting, set $k = 1$.

The second is the application of the Levenberg–Marquardt algorithm, where the correction is determined as follows [20, 21]

$$\Delta w_j = (J^T J + \mu E)^{-1} J^T e_j, \tag{9}$$

In the last expression, J is the Jacobian of the matrix of weight coefficients calculated at the point w. These matrices assume double differentiation of the function of $e(w)$ [20]. The introduction of the identity matrix E in (9) with the regularization parameter $\mu > 0$ allows us to ensure the requirement of positive definiteness of the $J^T J$. If μ is large, the algorithm has properties of gradient setting, when μ is small, the algorithm acts similarly to the Gauss–Newton method.

To reduce the calculations when calculating the matrix J, the following computational procedure is proposed

$$J_j = J_{j-1} + \lambda \frac{\Delta e_j - J_{j-1}\Delta w_j}{|\Delta w_j|^2} \Delta w_j^{\mathrm{T}}. \tag{10}$$

This procedure differs from [16] enter the coefficient $\lambda > 0$ that provided smooth convergence of calculating process.

We assume that learning has reached the goal when the training error does not exceed some small value $\varepsilon > 0$ satisfying the system designer, i.e.

$$|e(w)| \le \varepsilon, \tag{11}$$

Proposition 1. A multilayer neural network (4) – (10) with a certain input vector x, given an initial nonzero weight vector $w(0)$ and the introduced stopping criterion converges in a finite number of steps with a quadratic convergence rate.

Proposition 2. A character recognition error satisfies the stop criterion (11).

Statement 1 follows from the structure of the neural network and the convergence of the algorithms used [20].

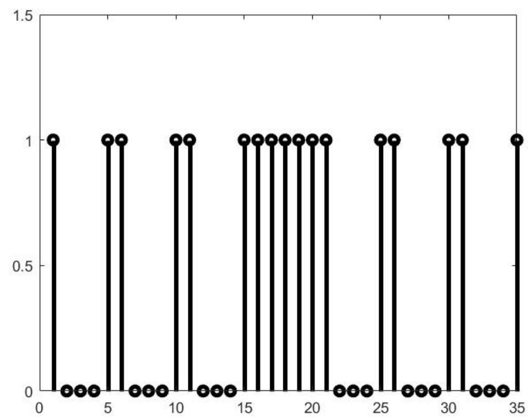
V. Simulation

The English alphabet, consisting of 26 characters and space, is considered. The vector representation of the 35 dots symbol in the Matlab programming environment has the form

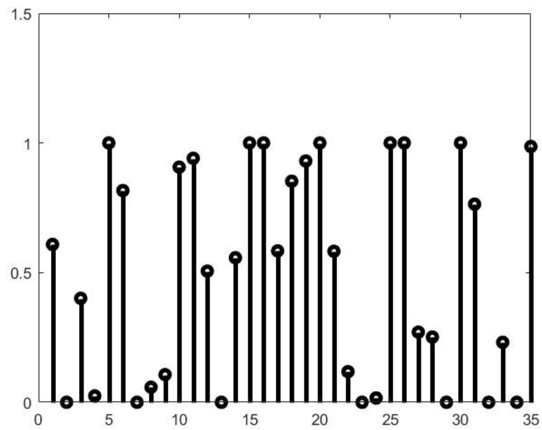
letterH = [1 0 0 0 1 1 0 0 0 1 1 0 0 0 1 1 1 1 1 1 1
0 0 0 1 1 0 0 0 1 1 0 0 0 1]'.

A graphic representation equivalent to it can be obtained as a lettering element is represented by a crossed-out square, this the same symbol, distorted by noise, is shown in Fig. 1.

Next, we determine the BP neural network with three layers. The initial structure has two layers, the number of neurons in the first layer is 33 and in the second is 27 as corresponds to the number of network outputs, we train according to the algorithm (5) – (7), (9).



a)



b)

Fig. 1. Letter H character representation without (a) and with noise (b) (its relative level 0.75)

To eliminate the problem of retraining the network, when the network remembers the input signals and is well trained on them, due to the noise present in the input signals, the network loses the property of correctly classifying input characters, it is proposed to divide the input set into three different non-intersecting parts, namely: training, test and valid subsets. As a rule, the input data set is divided to 0.7: 0.15: 0.15, where the large number corresponds to the training set, and the test and test are divided into equal shares between the remaining elements. The selection of elements in each subset is performed randomly. The maximum number of epochs for learning and the error at which learning ends are also established; these values are chosen equal to M = 555000 and $\varepsilon = 3 \cdot 10^{-5}$, respectively. The learning outcomes are presented in Figs 2 and 3.

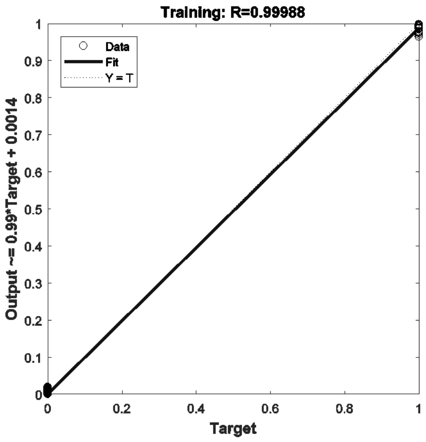


Fig. 2. Regression line

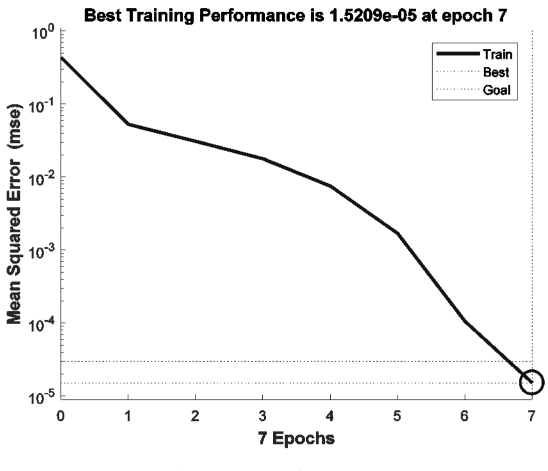


Fig. 3. Learning error

The network training function used allows you to evaluate the quality of network-tuning by constructing a regression line in which the proportionality coefficient allows you to determine the degree of correlation between input and output data. In the case under consideration, there is a high degree of correlation between input and output data, R = 0.999 (Fig. 2). The training in this example ends for an error of $1.48 \cdot 10^{-5}$, which is explained by the complexity of the source data. For training, it took only 8 epochs (Fig. 3).

Consider also the example of recognizing a phrase by a configured network. As a reference, the phrase "ALARM" is used, which is presented in the graphic window for displaying information by a sequence of characters in Fig. 4. The same phrase, distorted by noise, is presented in Fig. 5, and incorrect recognition is shown in Fig. 6.

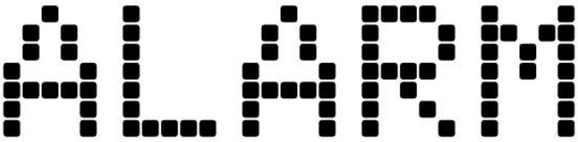


Fig. 4. A reference phrase for recognition by a configured network

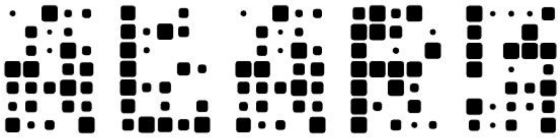


Fig. 5. A reference phrase distorted by noise level 0.5

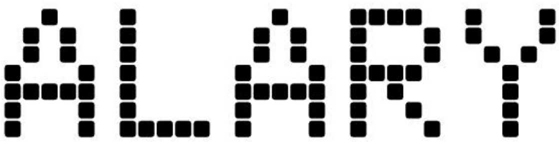


Fig. 6. An example of a phrase recognized with errors

The influence of the number of neurons in the hidden layer, the noise level, and the number of layers on the probability of correct recognition, error, and training time was also analyzed. The results of this analysis are presented in Tables I–III, from which it is seen that the greater the manifold of input signals, the more neurons should be in a hidden layer, an increase in the number of layers leads to an increase in recognition quality under noise conditions, while the stronger the interference, the more layers must be included to ensure high-quality recognition, but at the same time, the learning time is growing.

Of course, a complete analysis of a neural network in a limited study is quite difficult, but this analysis showed that the neural network works effectively if the activation functions of all layers are non-linear and the learning process has convergence with minimal error (main result). As expected, the more neurons in the hidden layer, the better the recognition under interference conditions. The level of interference generally affects the time and probability of recognition, which is confirmed by studies.

TABLE I. THE EFFECT OF THE NUMBER OF NEURONS IN THE LAYER

Number of neurons	6	13	26
The probability of correct recognition,%	37.5	87.5	100
Recognition error $\times 10^{-5}$	0.06	2.67	0.28
Training time, s	1	2	4
Number of neurons	**33**	**52**	
The probability of correct recognition,%	100	100	
Recognition error $\times 10^{-5}$	1.45	1.74	
Training time, s	8	35	

TABLE II. THE EFFECT OF NOISE ON RECOGNITION QUALITY

Number of neurons	26		
Noise level	0.25	0.5	0.75
The probability of correct recognition,%	100	75	37.5
Recognition error $\times 10^{-5}$	0.28	1.75	1.72
Training time, s	4	9	5
Number of neurons	**33**		
Noise level	0.25	0.5	0.75
The probability of correct recognition,%	100	62.5	37.5
Recognition error $\times 10^{-5}$	1.45	0.07	2.73
Training time, s	8	8	7
Number of neurons	**52**		
Noise level	0.25	0.5	0.75
The probability of correct recognition,%	100	75	75
Recognition error $\times 10^{-5}$	1.74	0.5	0.05
Training time, s	35	23	65

TABLE III. THE INFLUENCE OF THE NUMBER OF LAYERS ON THE QUALITY OF RECOGNITION

Number of neurons	2	3	4
The probability of correct recognition,%	100	100	100
Recognition error $\times 10^{-5}$	2.36	0.5	0.05
Training time, s	9	27	65

VI. CONCLUSIONS

Information systems play an important role in reducing the risks of loss of working capacity of workers the biggest companies such as coal-mine production, metallurgical enterprises, for example. Very often, information systems use radio channels for transmitting information, which can lead to loss or distortion of received information. To correct the information, neural networks with self-tuning algorithms are useful. The self-tuning algorithm of the multilayer BP neural network is considered the most popular among supervised algorithms. In fact, it is an iterative gradient method for finding the best settings in the given conditions, characterized by the simplicity of the classification task in terms of "input-output" and the reliability of the work. All neurons of this network are non-linear due to the use of a non-linear activation function. The article presents a study of 2, 3, and 4-layer networks in the presence of interference. High convergence obtained due to the use of a new iterative procedure of calculating matrix Jacobian. This result can succeed in the application in the education process in examining neural networks. Network setup is a rather complicated procedure; the quality of the network is higher if all activation functions are non-linear. Despite the high degree of correspondence of the input to the output data established due to the regression function, the learning result may turn out to be incorrect due to the retraining of the system due to the accepted low level of learning errors. Further research is planned to be directed to the introduction of a neural network into a real receiving device.

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Dmytro Kucherov. orcid.org/0000-0002-4334-4175. Doctor of Engineering Science. Senior Research Fellow.
Department of Computerized Control Systems, National Aviation University, Kyiv, Ukraine.
Education: Kiev Higher Engineering Radio Technical School of Air Defense Troops, Kyiv, Ukraine, (1986).
Research area: automatic and adaptive control, signal and image recognition.
Publications: over 200.
E-mails: d_kucherov@ukr.net

Valerii Tkachenko. orcid.org/0000-0002-1759-7269. Candidate of Science (Engineering). Associate Professor.
Department of Computerized Control Systems, National Aviation University, Kyiv, Ukraine.
Education: Kiev Technology Institute of Food Industry, Kyiv, Ukraine, (1977).
Research area: automatic technology.
Publications: 40.
E-mail: tkachenkvg@gmail.com

Ivan-Farkhod Kashkevych. orcid.org/0000-0003-3135-0751. Post-graduate Student.
Department of Computerized Control Systems, National Aviation University, Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (2015).
Research area: avionics, optoelectronics, information technology.

Publications: 13.
E-mail: ikashkevich@gmail.com

Anastasia Androshchuk. orcid.org/0000-0002-0156-9691. Student.
National Aviation University, Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (from 2018).
Research area: information technology.
E-mail: anastasiandroshchuk@gmail.com

Serhii Perepelitsyn. orcid.org/000-0002-8435-2729 Head of Research Institution.
Institute of Netcentric LLC, Kyiv, Ukraine.
Education: Kiev Higher Engineering Radio Technical School of Air Defense Troops, Kyiv, Ukraine, (1982).
Research area: information analysis and protection systems, unmanned aerial vehicles and laser systems.
Publications: 5.
E-mail: sergpsa@inbox.lv

Д. П. Кучеров, В. Г. Ткаченко, І.-Ф. Ф. Кашкевич, А. О. Андрощук, С. А. Перепеліцин. Розпізнавання текстових фраз, спотворених перешкодами, нейронною мережею зворотного розповсюдження помилки

У статті розглядаються системи, які можуть використовуватися на установках, що використовуються в умовах ризику для життя людей, наприклад, в гірській, ядерній промисловості, ін. Інформаційні системи здатні попереджувати про небезпеку передаванням текстових повідомлень через вільний простір. Основною проблемою радіоприймання інформації в сучасних умовах є збільшення кількості випромінюючих засобів, що еквівалентно збільшенню рівня шуму на вході приймального пристрою. Як додатковий засіб обробки викривленої текстової інформації пропонується використовувати попередньо налаштовану нейронну мережу. Для аналізу було вибрано нейтральну мережу зворотного розповсюдження помилки. Налаштування мережі здійснюється алгоритмом, що передбачає подвійне диференціювання функції помилок, що забезпечує високу швидкість збіжності мережі. Вивчення припиняється за критерієм відхилення вихідного сигналу від еталонного. У статті сформульовані умови квадратичної збіжності мережі, що використовує одну нову процедуру настройки, а також пропонуються приклади побудови нейронної мережі для розпізнавання текстового повідомлення в різних умовах прийому. Вхідними даними для нейронної мережі є англійський алфавіт, представлений двійковим сигналом. Особливістю структури нейронної мережі, що забезпечує правильне розпізнавання, є використання абсолютно нелінійних нейронів. Порівняння варіантів структури нейронної мережі при розпізнаванні текстових фраз здійснюється за показниками ймовірності розпізнавання, помилки і часу навчання. Встановлені властивості нейронної мережі корисні при розробці ефективних інформаційних систем.
Ключові слова: нейронна мережа зворотного розповсюдження помилки; розпізнавання тексту; ймовірність розпізнавання.

Дмитро Павлович Кучеров. orcid.org/0000-0002-4334-4175. Доктор технічних наук. Старший науковий співробітник.
Кафедра комп’ютеризованих систем управління, Національний авіаційний університет, Київ, Україна.
Освіта: Київське вище інженерне радіотехнічне училище протиповітряної оборони імені маршала авіації О. І. Покришкіна, Київ, Україна, (1986).
Напрямок наукової діяльності: автоматичне та адаптивне керування, розпізнавання сигналів та систем.
Кількість публікацій: понад 200.
E-mail: d_kucherov@ukr.net

Валерій Гаврилович Ткаченко. orcid.org/0000-0002-1759-7269. Кандидат технічних наук. Доцент.
Кафедра комп’ютеризованих систем управління, Національний авіаційний університет, Київ, Україна.
Освіта: Київський технологічний інститут харчової промисловості, Київ, Україна, (1977).
Напрямок наукової діяльності: автоматизація технологій.
Публікації: 40.
E-mail: tkachenkvg@gmail.com

Іван-Фарход Фуркатович Кашкевич. orcid.org/0000-0003-3135-0751. Старший викладач.
Кафедра комп’ютеризованих систем управління, Національний авіаційний університет, Київ, Україна.
Освіта: Національний авіаційний університет, Київ, Україна, (2015).
Напрямок наукової діяльності: авіоніка, оптоелектроніка, інформаційні технології.
Кількість публікацій: 12.
E-mail: ikashkevich@gmail.com

Анастасія Олександрівна Андрощук. orcid.org/0000-0002-0156-9691. Студент.
Кафедра комп’ютеризованих систем управління, Національний авіаційний університет, Київ, Україна.
Освіта: Національний авіаційний університет, Київ, Україна, (2018).
Напрямок наукової діяльності: інформаційні технології.
E-mail: anastasiandroshchuk@gmail.com.

Сергій Олександрович Перепеліцин. orcid.org/000-0002-8435-2729. Керівник науково-дослідної установи.
ТОВ Institute of Netcentric LLC, Київ, Україна.
Освіта: Київське вище інженерне радіотехнічне училище протиповітряної оборони, Київ, Україна, (1982).
Напрямок наукової діяльності: системи аналізу та захисту інформації, безпілотні літальні апарати та лазерні системи.
Публікації: 5.
E-mail: sergpsa@inbox.lv

Д. П. Кучеров, В. Г. Ткаченко, И.-Ф. Ф. Кашкевич, А. О. Андрощук, С. А Перепелицын. Распознавание текстовых фраз, искаженных помехами, нейронной сетью обратного распространения ошибки

В статье рассматриваются системы, которые могут использоваться на установках, используемых в условиях риска для жизни людей, например, в горной, ядерной промышленности, др. Информационные системы способны предупреждать об опасности передачей текстовых сообщений через свободное пространство. Основной проблемой радиоприема информации в современных условиях является увеличение количества излучающих средств, что эквивалентно увеличению уровня шума на входе приёмного устройства. В качестве дополнительного средства обработки искаженной текстовой информации предлагается использовать предварительно настроенную нейронную сеть. Для анализа выбрано нейтральную сеть обратного распространения ошибки. Настройка сети осуществляется алгоритмом, предусматривающим двойное дифференцирование функции ошибок, что обеспечивает высокую скорость сходимости сети. Изучение прекращается по критерию отклонения выходного сигнала от эталонного. В статье сформулированы условия квадратичной сходимости сети, использующей одну новую процедуру настройки, а также предлагаются примеры построения нейронной сети для распознавания текстового сообщения в различных условиях приема. Входными данными для нейронной сети является английский алфавит, представленный двоичным сигналом. Особенностью структуры нейронной сети, что обеспечивает правильное распознавание, является использование абсолютно нелинейных нейронов. Сравнение вариантов структуры нейронной сети при распознавании текстовых фраз осуществляется по показателям вероятности распознавания, ошибки и времени обучения. Установленные свойства нейронной сети полезны при разработке эффективных информационных систем.

Ключевые слова: нейронная сеть обратного распространения ошибки; распознавание текста; вероятность распознавания.

Дмитрий Павлович Кучеров. orcid.org/0000-0002-4334-4175. Доктор технических наук. Старший научный сотрудник.
Кафедра компьютеризированных систем управления, Национальный авиационный университет, Киев, Украина.
Образование: Киевское высшее инженерное радиотехническое училище ПВО имени маршала авиации А. И. Покрышкина, Киев, Украина, (1986).
Направление научной деятельности: автоматическое и адаптивное управление, распознавание сигналов и изображений.
Количество публикаций: более 200.
E-mail: d_kucherov@ukr.net

Валерий Гаврилович Ткаченко. orcid.org/0000-0002-1759-7269. Кандидат технических наук. Доцент.
Кафедра компьютеризированных систем управления, Национальный авиационный университет, Киев, Украина.
Образование: Киевский технологический институт пищевой промышленности, Киев, Украина, (1977).
Направление научной деятельности: автоматизация технологий.
Публикации: 7.
E-mail: tkachenkvg@gmail.com

Иван-Фарход Фуркатович Кашкевич. orcid.org/0000-0003-3135-0751. Аспирант.
Кафедра компьютеризированных систем управления, Национальный авиационный университет, Киев, Украина.
Образование: Национальный авиационный университет, Киев, Украина, (2015).
Направление научной деятельности: авионика, оптоэлектроника, информационные технологии.
Количество публикаций: 12.
E-mail: ikashkevich@gmail.com

Анастасия Александровна Андрощук. orcid.org/0000-0002-0156-9691. Студент.
Национальный авиационный университет, Киев, Украина.
Образование: Национальный авиационный университет, Киев, Украина, (2018).
Направление научной деятельности: информационные технологии.
Количество публикаций: 0.
E-mail: anastasiandroshchuk@gmail.com

Сергей Александрович Перепелицын. orcid.org/000-0002-8435-2729. Руководитель организации.
ООО Institute of Netcentric LLC, Киев, Украина.
Образование: Киевское высшее инженерное радиотехническое училище противовоздушной обороны, Киев, Украина, (1982).
Направление научной деятельности: системы анализа и защиты информации, беспилотные летальные аппараты и лазерные системы.
Количество публикаций: 5.
E-mail: sergpsa@inbox.lv