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**TRAINING A NEURAL NETWORK TO IDENTIFY OBJECTS BY PARAMETERS IN NON-OVERLAPPING SPACES**

**Abstract**. The present moment is characterised by the active use of digital information processing technologies in electronic communications systems. An important task in this case is to develop methods and algorithms for deciding whether a certain object $O$ belongs to one or another m-th class: $O_m, m=1,2,...M, M \geq 2$ – number of classes. This task can be solved with the use of neural networks that implement the processing of $k$ conditional estimates of physical parameters $\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m}$ objects, $k=1,2,\ldots,K,$ $K$ – is the maximum number of training steps, n is the current physical parameter that characterises the object and is an input to the neural network), $N$ – is the number of such physical parameters, $N \geq 2$.

Contingent valuations $\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m}$ are random, depend on the energy characteristics of the impacts and dynamically change over time, and the decision to determine whether an object $O$ belongs to one or another $m$-th class involves the use of neural networks, which have the properties of learning and self-learning.

Suppose that, from the energy point of view, the input influences are powerful enough to assign the object $O$ to one or another $m$-th class $O_m$. Thanks to the expert's ability to accurately determine the $m$-th class after receiving the $k$-th conditional vector of physical parameter estimates $\frac{x_k}{m}$, the neural network will be trained by refining the lower and upper limits of displacements in the first layers of perceptrons for each $m$-th class $Q_{1m \min}$ and $Q_{1m \max}$, after the next estimates of physical parameters are received and the expert provides the real value of the object $O$ belonging to class $m$ .

The article solves the inverse problem of finding, $Q_{m \min}, Q_{m \max}$, which ensure the specified quality indicators in neural network training for the minimum number of steps $K$. The article considers the implementation of a three-layer neural network trained by an experienced expert to solve the problem of object identification by several parameters. The solution to the problem of object identification by classes is presented for known distributions of conditional estimates of physical parameters. The problem of object identification by classes at infinite signal-to-noise ratios in the process of estimating physical parameters is solved. The expressions that determine the perceptron displacement for the problem of object identification by classes when the spaces of true values of input parameters do not intersect are found.

**Keywords:** neural network training, quality criteria for object distinction, errors of the first and second kind of decision theory, indicators of quality.

**Formulation of the problem in general terms.** The modern development of digital information processing technologies is associated with decision-making processes regarding the object $O$'s belonging to one of the $m$-th classes: $O_m, m=1,2,...,M, M \geq 2$ – number of classes that need to be processed $k$-th conditional estimates of physical parameters

$$\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m},\ k = 1, 2, \ldots, K,$$

where $K$ – maximum number of learning steps;
$n$ – current physical parameter (influence on the neural network);
$N$ – the number of physical parameters, $N \geq 2$.

Contingent valuations $\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m}$ are random, depend primarily on the energy characteristics of the impacts, and change dynamically with time, and the decision on the object's $O$ belonging to one of the $m$ classes involves the use of neural networks, which have the properties of learning [1]–[3] and self-learning [4]. It will not consider here the synthesis of optimal algorithms that will process the input influences and provide better estimates of physical parameters (estimates of influences on the neural network). Assume that, from the energy point of view, the input influences are sufficiently powerful to assign the object $O$ to one of the $m$-th classes: $O_m$ it is clear that more powerful input influences should train the neural network in fewer steps $K$ [5].

Let the neural network be trained by an experienced expert [6], who, each time after receiving $k$-th vector of conditional estimates of physical parameters accurately determines the class $m$, to which the object belongs $O : O_m$ vector of conditional estimates of physical parameters $\frac{x_k}{m} = \left( \frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m} \right)$ is the $k$-th input influence on the neural network, which depends on the class of the object $m$ and the energy conditions of the influence, summarised in $k$-th always a positive vector of true input influences $x_k = \left( \frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m} \right) > 0$ so, that $\forall k = 1, 2, \ldots, K$ $x_k \in X_1 \cup X_2 \cup \ldots X_m \cup \ldots \cup X_M$, where the areas of true input influences for the enrolment of the $m$object are continuous

$$X_m \in \left[ X_{m\ \min}, X_{m\ \max} \right], \tag{1}$$

where $X_{m\ \min}, X_{m\ \max}$ – $N$-measurable fixed lower and upper bounds of the true values of input influences for the object's enrolment $O$ to $m$-th class:

$$X_{m\ \min} = (X_{m1\,\min}, X_{m2\,\min}, \ldots, X_{mn\ \min}, \ldots, X_{mN\ \min}),$$
$$X_{m\ \max} = (X_{m1\,\max}, X_{m2\,\max}, \ldots, X_{mn\ \max}, \ldots, X_{mN\ \max}).$$

Decision on the belonging of the object $O$ to $O$ class is adopted when $\forall k = 1, 2, \ldots, K$ an event takes place:

$$\begin{gathered} \frac{x_{k1}}{m} \in \left[ X_{m1\,\min}, X_{m1\,\max} \right] \cap \frac{x_{k2}}{m} \in \\ \in \left[ X_{m2\,\min}, X_{m2\,\max} \right] \cap \ldots \cap \frac{x_{kN}}{m} \in \left[ X_{mN\ \min}, X_{mN\ \max} \right] \end{gathered}, \tag{2}$$

Suppose that after receiving the $k$-th conditional vector of estimates of physical parameters $\frac{x_k}{m}$, every $n$-th random effects are initially processed in two layers of perceptrons (see Fig. 1).

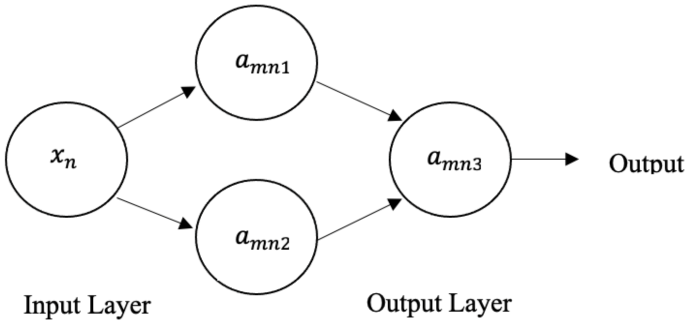


Figure 1 – The first two layers of a learning neural network

The first layer of perceptrons generates output signals (reactions of the output layers) in the form of expressions:

$$a_{mn1} = 1\left(\frac{x_n}{m} - Q_{mn\ \min}\right),$$
$$a_{mn2} = 1\left(\frac{x_n}{m} - Q_{mn\ \max}\right) \quad (1)$$

where $Q_{mn\min}$ – minimum value (lower limit of perceptron displacement) $n$-th impact for the object to be included in the $m$ class;

$Q_{mn\max}$ – maximum value (upper limit of the perceptron displacement) $n$-th impact for the object to be included in the $m$-th class;

$1(x)$ – unit function (Heaviside function).

The second layer generates the signal defined by the expression:

$$a_{mn3} = a_{mn1} - a_{mn2}, \quad (4)$$

The expert's ability to accurately identify $m$-th class after receiving $k$-th conditional vector of estimates of physical parameters $x_k / m$, training of the neural network will take place by specifying the lower and upper limits of displacements in the first layers of perceptrons for each $m$-th class:

$$Q_{m\ \min} = \left(Q_{m1\ \min}, Q_{m2\ \min}, \dots, Q_{mn\ \min}, \dots, Q_{mN\ \min}\right)$$
$$Q_{m\ \max} = \left(Q_{m1\ \max}, Q_{m2\ \max}, \dots, Q_{mn\ \max}, \dots, Q_{mN\ \max}\right). \quad (5)$$

After the next estimates of physical parameters are received and the expert provides the real value of the object $O$ belonging to class $m$.

If we denote by vectors $Q_{km\ \min}$ and $Q_{km\ \max}$ displacement (6) on $k$-th learning step, the displacements to be generated after processing $k$-th conditional vector of physical parameter $\frac{x_k}{m}$ estimates can be represented by functions:

$$Q_{(k+1)m\ \min} = L\left(Q_{km\ \min}, \frac{x_k}{m}\right)$$
$$Q_{(k+1)m\ \max} = H\left(Q_{km\ \max}, \frac{x_k}{m}\right). \quad (6)$$

It is clear that the functionalities should approximate the displacement of the perceptrons with each $k$-th training step, $k = 1, 2, ..., K$ to certain, fixed quality indicators, whatever the initial deviations $Q_{1m\ \min}$ and $Q_{1m\ \max}$. Ideally, it is advisable not to train the neural network at all $(K = 1)$ and whatever $\frac{x_k}{m}$ is, assign it displacement vectors $Q_{m\ \min} = Q_{1m\ \min} = Q_{2m\ \min}$ and $Q_{m\ \max} = Q_{1m\ \max} = Q_{2m\ \max}$.

**Analysis of recent research and publications.** A considerable amount of fundamental and applied research has been devoted to modelling the processes of neural networks, the results of which are reflected in numerous publications [1]–[5]. For example, in [1]–[4], methods for optimising the training of neural networks using adaptive algorithms are considered. General approaches to the design and modelling of neural networks are covered in detail in [2], [3], where special attention is paid to forecasting results and analysing time series. Research papers [4]–[8] analyse the features of machine learning neural networks, including ethical aspects and energy efficiency, and propose various approaches to managing such systems. Publications [3]–[5], [10] describe deep learning methods, investigate their functionality, and propose ways to assess the quality of these processes in neural networks, in particular through binary models and integration with neuroscience [9]–[11]. However, the task of training a neural network to identify objects by parameters in non-overlapping spaces has not been fully solved and requires scientific research.

**The purpose of the article is to** solve the inverse problem of finding displacements $Q_{1m\ \min}$ and $Q_{1m\ \max}$, that will bring us closer to the desired fixed quality indicators in neural network training in the least number of steps $K$.

**Summary of the main research material.** It will solve the problem in a simple case when for $\forall m = 1, 2, \ldots, M \neq i$,

$$X_m \cap X_i = \varnothing . \tag{7}$$

**Justification of the third layer of the neural network.** The representation in the form of (4) makes it possible to use the De Morgan's law [7] and present the conjunction on $N$ parameters (2) as a response to input influences for the third layer of a neural network of a particular $m$-th class:

$$a_m = 1\left(\sum\nolimits_{n=1}^{N} a_{mn3} - N + \varepsilon\right), \tag{8}$$

where $\varepsilon$ – a non-zero small positive mixing of the perceptron in the third layer of the neural network.

The substitution in (8), taking into account (3) and (4), allows us to obtain a calculated expression for the third layer of the neural network – a random discrete value that is a function of $N$ random conditional estimates of continuous physical parameters:

$$a_m = 1\left( \sum\nolimits_{n=1}^{N \sum\left(\frac{x_n}{m} - Q_{mn\ \max}\right)} 1\left(\frac{x_n}{m} - Q_{mn\ \min}\right) \right), \tag{9}$$

whose value is "0" or "1".

The distribution of the discrete quantity (9) is easy to find when for the discrete quantity (9) is easy to find when for $\forall m = 1, 2, \ldots, M$, $N$ – dimensional probability densities of the conditional estimates are known $\frac{x_k}{m} - w_m\left(\frac{x_k}{m}\right)$. In this case, $\forall m = 1, 2, \ldots, M$:

$$P\left\{a_m = 1 \mid Q_{i_{\min}}, Q_{i_{\max}}\right\} = \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} w_m\left(\frac{x_k}{m}\right) d\,\frac{x_1}{m}\, d\,\frac{x_2}{m} \cdots d\,\frac{x_N}{m}, \tag{10}$$

$$P\left\{a_m = 0 \mid Q_{i_{\min}}, Q_{i_{\max}}\right\} = 1 - \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} w_m\left(\frac{x_k}{m}\right) d\frac{x_1}{m} d\frac{x_2}{m} \cdots d\frac{x_N}{m}, \quad (11)$$

**Quality indicators and the criterion of the best neural network training.** Let us take the probabilities of first- and second-order errors of the theory of $M$ -alternative decision-making as indicators of the quality of neural network training [6].

Errors of the first kind are considered to be the adoption of erroneous decisions to assign an object to the $m$ -th class to which it does not actually belong. The probability of this event, taking into account (10), is equal to:

$$a_m = \sum_{\substack{i=1 \\ i \neq m}}^{M} P(i) \cdot P\left\{a_i = 1 \mid Q_{i_{\min}}, Q_{i_{\max}}\right\} =$$
$$= \sum_{\substack{i=1 \\ i \neq m}}^{M} P(i) \cdot \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} w_m\left(\frac{x_k}{m}\right) d\frac{x_1}{m} d\frac{x_2}{m} \cdots d\frac{x_N}{m}, \quad (12)$$

where $P(m)$ – classification of objects into classes.

The second kind of error is considered to be the false failure to assign an object to the $m$ -th class, the probability of which, taking into account (11), can be represented by the expression:

$$\beta_m = 1 - \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} w_m\left(\frac{x_k}{m}\right) d\frac{x_1}{m} d\frac{x_2}{m} \cdots d\frac{x_N}{m}. \quad (13)$$

To decide whether an object $O$ belongs to the $m$ -th class, we will choose a rigid criterion [8], according to which the results of neural network training in the current training step are considered better if (12) is uniformly minimal:

$$\sum_{m=1}^{M} a_m \to \min,$$
$$-\sum_{m=1}^{M} a_m \cdot \log(a_m) + \sum_{m=1}^{M} a_m \cdot \log\left(\sum_{m=1}^{M} a_m\right) \to \max \quad (14)$$

for fixed $\beta_1 = \beta_2 = \ldots = \beta_M = \beta = \text{const}$.

**Training a neural network for object classification at infinite signal-to-noise ratios in the process of estimating physical parameters with known non-overlapping true value spaces**.

In the case of such powerful energy characteristics of input influences that $\frac{x_k}{m} \to x_k$ the distribution of conditional estimates in (10) and (11) degenerates:

$$w_m\left(\frac{x_{kn}}{m}\right) = \prod_{n=1}^{N} \delta\left(\frac{x_{kn}}{m} - x_{kn}\right), \quad (15)$$

where $\delta(x)$ – delta function, and for any $X_m \in \left[Q_{m\ \min}, Q_{m\ \max}\right]$ taking into account (13):

$$\beta_m = 1 - \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} \prod_{n=1}^{N} \delta\left(\frac{x_{kn}}{m} - x_{kn}\right) d\frac{x_1}{m} d\frac{x_2}{m} \cdots d\frac{x_N}{m},$$

taking into account (12):

$$a_m = \sum_{\substack{i=1 \\ i \neq m}}^{M} P(i) \cdot \int_{Q_{1\min}}^{Q_{1\max}} \int_{Q_{2\min}}^{Q_{2\max}} \cdots \int_{Q_{N\min}}^{Q_{N\max}} \prod_{n=1}^{N} \delta\left(\frac{x_{kn}}{m} - x_{kn}\right) d\frac{x_1}{m} d\frac{x_2}{m} \cdots d\frac{x_N}{m} = 0$$

whatever the distribution of $P(i)$ is, and for (14) we get the best result:

$$\begin{cases} \min\{\sum_{m=1}^{M} a_m\} = 0 \\ \max\{\log\left(\sum_{m=1}^{M} a_m\right)\sum_{m=1}^{M} a_m \cdot \log\left(a_m\right)\} = \log\left(M\right) \end{cases}. \quad (16)$$

According to (16), the maximum value of entropy (the second equation of the system) corresponds to a random variable evenly distributed over $M$ classes, and the neural network will not require further training even when the area of true input influences expands to the maximum:

$$Q_{m\ \min} = X_{m\ \min}, Q_{m\ \max} = X_{m\ \max}, \quad (17)$$

Taking into account (7), the assignment of offsets for the first layers of perceptrons in accordance with (17) allows for any $k$-th vector of conditional estimates $\frac{x_k}{m} \to x_k$ to achieve an unambiguous response of the third layer of the neural network (9): $a_m = 0$ , if $O \notin O_m$ and $a_m = 1$, if $O \notin O_m$.

**Training a neural network to identify objects by class, in the case of spaces of true values of input parameters that are adjacent to each other.**

The training results of the network (17) are valid only when each vector of current estimates $\frac{x_k}{m} \to x_k$. For example, for any $k$-th estimate that is not powerful from the energy point of view $\frac{x_k}{m} \notin X_m$, there will be a region for which the neural network will not make any decision on whether the $O$-th object belongs to the $m$-th class: $O_m$ which may be perceived as the network's "lack of training" to perform the task correctly. However, the neural network will not require further training if the regions of the true values of the input parameters have $n\left(M-1\right)$ common points in the $M \times N$ – dimensional space of true input influences defined in (1):

$$\begin{matrix} X_{11_{\max}} = X_{12_{\min}} \cdot X_{12_{\max}} = X_{13_{\min}} \cdots X_{1(N-1)_{\max}} = X_{1N_{\min}} \\ X_{22_{\max}} = X_{22_{\min}} \cdot X_{22_{\max}} = X_{23_{\min}} \cdots X_{2(N-1)_{\max}} = X_{2N_{\min}} \\ \vdots \qquad \vdots \qquad \vdots \\ X_{(M-1)1_{\max}} = X_{(M-1)2_{\min}} \cdot X_{(M-1)2_{\max}} = X_{(M-1)3_{\min}} \cdots X_{(M-1)(N-1)_{\max}} = X_{(M-1)N_{\min}} \end{matrix}, \quad (18)$$

Even when $\frac{x_k}{m} \neq x_k$ is estimated, the rule for assigning displacements to the first layers of perceptrons (17), when (18) is fulfilled, allows solving the problem of identifying objects by classes with certain indicators that depend only on the energy characteristics of the input influences.

**Conclusions**. Thus, the analytical and theoretical research conducted allows us to draw the following conclusions:

1. The neural network for solving the problem of object identification by several parameters will not require training, in the case of known spaces of true values of physical parameters of influences that do not intersect and do not adjoin each other.

2. Further study of neural network training for object identification by several parameters should focus on the following $Q_{m\ \min}$ and $Q_{m\ \max}$ in case (18) is not fulfilled, taking into account (12)-(14).

3. The final solution of the problem of object identification by several parameters is possible only after the justification of the functionalities (6).

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ДМИТРО ЄВГРАФОВ,
СЕРГІЙ ШОЛОХОВ

## НАВЧАННЯ НЕЙРОМЕРЕЖІ ДЛЯ ІДЕНТИФІКАЦІЇ ОБ'ЄКТІВ ПО ПАРАМЕТРАХ У ПРОСТОРАХ, ЩО НЕ ПЕРЕТИНАЮТЬСЯ

**Анотація.** Дійсний момент часу характеризується активним застосуванням у системах електронних комунікацій цифрових технологій обробки інформації. Важливою задачею при цьому є розробка методів та алгоритмів прийняття рішення щодо належності певного об'єкту $O$ до того або іншого $m$ - го класу: $O_m, m=1,2,...,M, M \geq 2$, – кількість класів. Ця задача може бути вирішена із застосуванням нейронних мереж, які реалізують обробку $k$ -х умовних оцінок

фізичних параметрів $\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m}$ об'єктів, $k = 1, 2, \ldots, K$, $K$ – максимальна кількість кроків навчання, $n$ – поточний фізичний параметр, що характеризує об'єкт та є вхідним впливом для нейромережі, $N$ – кількість таких фізичних параметрів, $N \geq 2$.

Умовні оцінки $\frac{x_{k1}}{m}, \frac{x_{k2}}{m}, \ldots, \frac{x_{kn}}{m}, \ldots, \frac{x_{kN}}{m}$ мають випадковий характер, залежать від енергетичних характеристик впливів та динамічно змінюються у часі, а прийняття рішення про належність об'єкту $O$ до того або іншого $m$-го класу передбачає застосування нейромереж, яким притаманні властивості навчання та самонавчання.

Нехай, з енергетичної точки зору, вхідні впливи достатньо потужні для віднесення об'єкту $O$ до того, або іншого $m$-го класу $O_m$. Завдяки вмінню експерта безпомилково визначати $m$-й клас після отримання $k$-го умовного вектору оцінок фізичних параметрів $\frac{x_k}{m}$ навчання нейромережі відбуватиметься шляхом уточнення нижніх та верхніх границь зміщень у перших шарах перцептронів для кожного $m$-го класу $Q_{m\ \min}, Q_{m\ \mathrm{mi}ax}$ після надходження чергових оцінок фізичних параметрів та надання експертом реального значення належності об'єкту $O$ до класу $m$.

У статті розв'язана зворотна задача відшукання $Q_{1m\ \min}$ та $Q_{1m\ \max}$, які за найменшу кількість кроків $K$ забезпечують задані показники якості у навчанні нейромережі. Розглянуто реалізацію тришарової нейромережі, яка навчається досвідченим експертом для розв'язання задачі ідентифікації об'єктів за декількома параметрами. Поданий розв'язок задачі ідентифікації об'єктів по класах здійснений для відомих розподілень умовних оцінок фізичних параметрів. Розв'язано задачу ідентифікації об'єктів по класах при нескінченних співвідношеннях сигнал/шум у процесі оцінювання фізичних параметрів. Знайдено вирази, які визначають зміщення перцептронів для задачі ідентифікації об'єктів по класах, коли простори істинних значень вхідних параметрів не перетинаються.

**Ключові слова**: навчання нейронних мереж, критерії якості розрізнення об'єктів, помилки першого та другого роду теорії рішень, показники якості.

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