MODELS OF GENERATION OF INPUT DATA OF TRAINING OF NEURAL NETWORK MODULES FOR DIAGNOSTIC OF DISEASES IN UROLOGY

The subject of the research presented in the article is neural network modules (NNMs), which are used to solve problems in the practice of diagnosing diseases in urology. This work aims to develop a mathematical model for generating a multitude of uroflowmetric parameters, in particular, graphs of uroflowgrams of the required volume, used as input data for NNM training. Objective: to develop a mathematical model for the formation of uroflowmetric parameters using a probabilistic approach based on a uniform "white noise". To develop an effective algorithm for the procedure for generating new parameter values and tools for its implementation. Methods used: NNM training methods, mathematical modeling methods, digital signal processing methods, tools for generating and processing random numerical sequences, digital data filtering methods. The following results were obtained: when creating and implementing a mathematical model for generating a large amount of training data, the requirements of randomness are taken into account when obtaining new values of uroflowmetric parameters. And at the same time, the obtained noise values are filtered to values of a given range, which are percentage-wise comparable to the amplitude value of the uroflowmetric parameter. Conclusions. The scientific novelty of the results is as follows: the NNM training method for recognizing diseases in urology has been improved by developing a mathematical model to generate uroflowmetric parameters for NNM training. The presented model allows you to create the necessary amount of data for training neural network modules in the course of experimental research on the recognition of diseases. The generation of uroflowmetric parameters is based on adding noise to the parameter values. This allows you to change the input data of the NNM training in a given range. This ensures the creation of the required input volume of the NNM training procedure. In the future, this contributes to the testing process of trained neural network modules with reliable information on the diagnosis of diseases in urology.

Keywords: uroflowmetric parameters; graph of the uroflowrogram; normal noise; neural network modules; training of neural network modules; diagnosis of diseases.

Introduction

Modern medicine has been long using computer diagnosing of diseases. The procedures for collecting and processing diagnostic information (in particular, the results of radiography, electrocardiogram, ultrasound, mammography, tomography, uroflowmetry, etc.) have been automated, in real time as well by means of telemonitoring [1-3]. Another factor influencing the systems of diagnosing diseases is the implementation of intelligent information technologies for solving medical issues. In particular, the neuronet approaches to diagnosing diseases have been widespread in various fields of medicine, such as cardiology, urology, diseases of the lungs, infectious and other diseases [4-6].

A current task with such an approach is to obtain the necessary amount of data sufficient for training, and further correct recognition of diagnosed diseases. In addition, neuronet modules should have a high level of generalizing abilities to identify diseases, taking into account the individual characteristics of patients and the possible influence of regional factors on the diagnostic parameters associated with the state of the environment or natural changes. In this regard, the current task is to provide a sufficient amount of training data to assure the reliability of the diagnosis of diseases in urology.

Objective of the paper is to develop a model for the formation of uroflowmetric parameters using a probabilistic approach based on a uniform "white noise".

Network training issues

Network generic capabilities can be improved by increasing the amount and updating of training data. The study of the neuronet is performed with the help of additional learning pairs. The purpose of this approach is to provide a network that allows one to identify the incoming data that is slightly modified and has variations in values within the given permissible limits. In other words, when processing incoming signals the network should produce adequate output signals, so it should be insensitive to the variations in input data within a given range. Even when it was tested, the input signals were not included in the training set. There is a mathematical
substantiation for such a requirement. Let the vector of test set be \( x_v \). The task of network training is to minimize the target function [7-9]:

\[
L = \frac{1}{2} \sum_{j=1}^{N} \left\| p_j - f(x_l) \right\|^2 ,
\]

(1)

where \( p_j \) is the type of disease, \( f(x_l) \) is the output value of the net, \( N \) is the volume of training sample. However, this does not guarantee that the trained network will accurately recognize the input vector \( x_v \) from the test set \( X_V = \{ (x_v_k) \}_{k=1}^{Z} \), where \( Z \) is volume of test set. Further research is based on the assumption that the test vector is \( x_v \) slightly different from the vector \( x_l \). Define this difference in the form:

\[
x_v_k = x_l + r ,
\]

(2)

where \( r = [r_1, r_2, ..., r_M]^T \) is a noise vector which is a random variable with small values of the amplitude, \( M \)– is the number of input neurons.

**Influence of noise on uroflowmetric parameters**

When forming the training data for learning the neuronet, the author has used the values of the uroflowmetric parameters and their respective diseases. An increase in the amount of training pairs has been carried out by generating a quantity of values of the uroflowmetric parameters.

This is done by adding the noise as indicated in formula (2) to the uroflowmetric parameters, which with 100 % confidence correspond to the disease.

The studies were conducted to analyze the network's response to changes in training data over several stages. In particular, in the first phase of training there were 100 training pairs.

After completing the training, an analysis of quantitative and qualitative indicators of the network operation was carried out.

The network has been trained to diagnose of two classes of diseases: a slight bladder outlet obstruction (class 1), detrusor-sphincter dyssynergia (class 2) [10]. The analysis of the influence of noise on changes of the uroflowmetric parameters was investigated in the graphs of uroflowograms. Figure 1 shows a typical graph of the uroflowrogram for disease in class 1. Noise formation is based on the following condition white noise is a random value ranging from 0 to \( a \times x_l \), where \( a \) is a constant (threshold value of change in amplitude of noise)), \( x_l \) is a vector of the values of the uroflowmetric parameter (in particular, of the uroflowrogram) involved in the training, \( M \) is a number of vector values of the uroflowmetric parameter (number of input neurons). It should be noted that the value of the constant \( a \) is determined experimentally, depending on the value of the reliability of the results obtained by the identifying the uroflowmetric parameter.

Subsequently, an analysis was made of the effect of noise on changes in the values of uroflowmetric parameters. In particular on the graphs of uroflowograms for a disease of class 1. Figure 1 shows a typical graph of uroflowograms for this disease.

![Fig. 1. Uroflowrogram for disease in class 1](image-url)
To prepare the parameters for learning the network, their values are normalized by the formula

$$x_l^j = \frac{x_l^j}{x_l^{\text{max}}}$$

where $x_l^{\text{max}}$ is the maximum value quantity of uroflowmetric parameters, $x_l^j$ is the current vector value. Figure 2 shows the graphs of the uroflowrogram after normalization for two classes.

Then the normalized values of the uroflowrogram change under the influence of noise in the same way as in expression 2:

$$x_l^j = x_l^j + r_j,$$

where $r_j$ is the noise value corresponding to each value of the vector of the uroflowmetric parameter. MATLAB generates noise sequentially; one random number is generated in the range from 0 to 1 using the function $\text{rand}(1,1)$ which is called even white noise.

Figure 3 shows a graph of generated noise for a set of 125 values of a uroflowrogram.

At the initial stage of the constant $a$ has value 0.15. In other words, the noise threshold is 15% of each current value of the vector of uroflowmetric parameter. After that, the noise value is filtered in the range from 0 to $a = 0.15$. Figure 4 shows the filtered noise graph for class 1 uroflowrogram. Further network learning included 100 training pairs for two diseases of class 1.
and 2. In Figure 5 shows one of the variants of the uroflowrogram of the first class of the disease (distorted and undistorted), which took part in the learning process.

Figure 6 presents a variant of distorted uroflowrogram of two classes of diseases involved in the training.

Figure 7 shows the graphical results of training a neural network module in the volume of 100 training pairs for two classes of diseases with distorted input vectors.

**Conclusion**

The article presents a mathematical model for generating a sufficient volume of input data for training neural network modules for diagnosing diseases in urology. A solution to this problem is necessary for experiments to analyze the reliability of disease recognition results. The experiments were carried out on uroflowrogram, which are one of the most difficult to recognize uroflowmetric parameters. In the work, we
used graphs of uroflowograms with 100% certainty identifying the disease. The required number of graphs is generated by adding uniform “white noise” to the main uroflowrogram taking into account the limitation of its amplitude in a given range. This approach allows you to simulate the presence of patients with the same diseases.
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обу́чения НСМ. Задача: разраба́ть мате́матическую модель формирования множества урофлоуметрических па́раметров с использованием вероятностного подхода, основанного на равномерном «белом шуме»; разраба́ть эффе́ктивный алгоритм для процедуры генерации новых значений па́раметров и инструмента́ для его реализации. Используе́мые методы: методы обуче́ния НСМ, методы мате́матического моде́лирования, методы цифровой обработки сигналов, инструменты для генерации и обработки случайных числовых последовательностей, методы цифровой фильтрации данных. Были получе́ны следую́щие результаты: при создании и реализации мате́матической модели для генерации больших количества обучающих данных требования случайности учитываются при получении новых значений заданного диапазона, которые в процентах относи́тельно совпа́дают со значением амплитуды урофлоуметрического па́раметра. Выво́ды. Научная новизна получе́нных результатов заклю́чается в следую́щем: метод обуче́ния НСМ для распозна́зывания заболеваний в урологии был усовершенство́ван путем разрабо́тки мате́матической модели для генерации множества урофлоуметрических па́раметров для обуче́ния НСМ. Представле́нная модель позволяет создать необходимый объем данных для обуче́ния нейромережевых модулей в ходе экспериментальных исследований по распозна́зыванию заболеваний. Генерация множества урофлоуметрических па́раметров основа́на на добавлении шума к значени́ям па́раметров. Это позволяет измене́ть входные даные обуче́ния НСМ в заданном диапазо́не, что обеспе́чивает создание необхо́димого объема данных для процедуры обуче́ния НСМ. В дальнейше́м это способствует процессу тестиру́ння обуче́ния нейромережевых модулей с достове́рной инфома́цией по диагнози́ке заболеваний ура́ологи́и.

Ключевые слова: урофлоуметрические па́раметры; график урофлюо́рограммы; нормальны́ шум; нейромережевые модули; обучение нейромережевых модулей; диагностика заболеваний.

МОДЕЛІ ГЕНЕРАЦІЇ ВХІДНИХ ДАНИХ НАВЧАННЯ НЕЙРОМЕРЕЖЕВИХ МОДУЛІВ ДЛЯ ДІАГНОСТИКИ ХВОРОБ В УРОЛОГІЇ

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Предметом дослідження, представленим в статті, є нейромережеві модулі (НММ), які використовуються для вирішення проблем у практиці діагностики захворювань у урології. Метою даної роботи є розробка математичної моделі для формування множини урофлоуметричних па́раметрів, зокре́ма, графіків урофлюо́рограм необхідного обсягу, що використовуються в ході вхідних даних для навчання НММ. Задача: розробити математичну модель формування множини урофлоуметричних па́раметрів, використовуючи ймовірнісний підхід, заснований на рівномірному «білому шумі»; розробити еффе́ктивньй алгоритм процедури генерації нових значень па́раметрів та інструментів для його реалізації. Використовувані методи: методи навчання НММ, методи математичного моде́лирования, методи цифрової обробки сигналів, інструменти для генерації та обробки випадкових числових послідовностей, методи цифрової фільтрації даних. Отримани такі результати: при створенні та реалізації математичної моделі для формування великого обсягу навчальних даних, вимоги випадковості враховуються при отриманні нових значень урофлоуметричних па́раметрів. І в той же час отримані значення шуму фільтруються до значень заданого діапазона, які в відсотках порівня́ні з вали́чним значення́м амплітуди урофлоуметричного па́раметра. Висновки. Наукова новизна результатів полягає в тому: метод навчання НММ для еффе́ктивного формування множини урофлоуметричних па́раметрів для навчання НММ. Представле́нная модель дозволи́ть створити необхідні обсяги даных для навчання нейромережевих модулей у ході експериментальних дослідженнях з розпізнавання захворювань. Формування множини урофлоуметричних па́раметрів забезпечується на додаванні шуму, що забезпечує створення необхідного входного обсягу даних процедур навчання НММ. Надалі це сприяє процесу тестування навчених нейромережевих модулях з достові́рною інформа́цією по діагности́ці захворювань уурологі́ї.

Ключові слова: урофлоуметричні параметри; графік урофлюо́рограми; нормальний шум; нейромережеві модулі; навчання нейромережевих модулях; діагностика заболеваний.

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