Iterative Models of Bioimpedance in Intelligent Systems for Early Diagnosis of Infectious Diseases

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Abstract. As a result of the study, fundamentally new results have been obtained, which make it possible to create intelligent decision support systems for the diagnosis of infectious diseases. A bioimpedance analysis model has been created, based on multifrequency bioimpedance measurement, which allows decomposition of biomaterial impedance into structural elements. On the basis of the proposed model, descriptors were formed, intended for classifiers executed on trained neural networks. To obtain descriptors, multifrequency sounding of the biomaterial was carried out, on the basis of which Cole's graphs were constructed. Using iterative algorithms and these graphs, Voight models of the biomaterial impedance were obtained. The parameters of these models are used as descriptors for the trained classifiers.

Keywords: Infectious Diseases, Bioimpedance Model, Multifrequency Sensing, Trainable Classifier, Iterative Algorithm, Training Set.

1 Introduction

The disease of infectious diseases is systemic in nature. For its diagnosis, in particular, early diagnosis, requires the search for new markers and the creation of new intelligent technologies [1-4]. The use of instrumental and laboratory research methods takes a significant amount of time and is associated with the influence of harmful factors on the body, which does not allow their use with high frequency and greatly complicates the study of the pathological process in dynamics. This is due to the introduction into practice of a number of innovative diagnostic technologies. However, the accuracy of identifying the risk of infectious diseases using these methods does not meet the requirements of modern medicine.

2 Materials and methods

The method of classification of biological objects is based on a method based on bioimpedance analysis, in which, to classify a segment of a biological object, its model is built in the form of a passive two-terminal, electrodes are applied to the selected segment of the biomaterial, and multifrequency sounding is carried out at as many frequencies as is required to determine the parameters of the model of a passive two-pole model. The classification of a biological object is carried out according to the obtained parameters of a two-port network [5-10]. As a model of a biomaterial segment, Voight's recursive model [11] is used, shown in Figure 1.

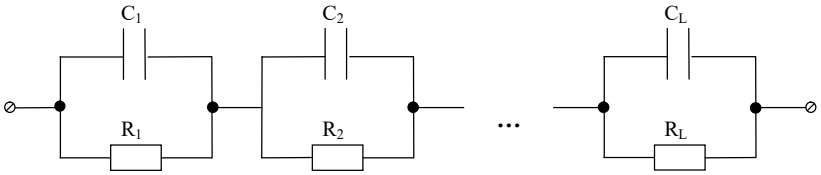

Fig. 1. The structure of the Voight model.

The impedance of the model in Figure 1 is determined by the formula

$$Z_{VOIT}(\omega) = \sum_{\ell=1}^{L} \left(R_\ell^{-1} + j\omega C_\ell \right)^{-1} \tag{1}$$

Where ω is the frequency of the probing current, at which the impedance of the model is determined, R_ℓ and C_ℓ are the parameters of the model, L is the number of RC - two-poles in the Voight model.

Considering that the impedance is a complex quantity, equation (1) can be represented as a system of two real equations

$$\left.\begin{aligned} a(\omega) &= \sum_{\ell=1}^{L} \frac{R_\ell}{1+\omega^2 R_\ell^2 C_\ell^2} \\ b(\omega) &= \sum_{\ell=1}^{L} \frac{-\omega R_\ell^2 C_\ell}{1+\omega^2 R_\ell^2 C_\ell^2} \end{aligned}\right\} \tag{2}$$

Where $Z_{VOIT} = a(\omega) + jb(\omega)$.

Bioimpedance can be measured at a variety of frequencies $\{\omega_i\}$, $i = \overline{1,N}$. Substituting these results into the left-hand sides of equation (2) and solving the corresponding system of equations, we can determine a set $\{R_\ell, C_\ell\}$ that can be used as descriptors for classifiers of the risk of infectious diseases.

To construct the Voigt model, the graph of the dependence of the impedance of the biomaterial under the corresponding electrodes on the frequency in the frequency

range from Ω_{min} to Ω_{max} is experimentally determined. An example of such a graph is shown in Figure 2. Each abscissa in this graph gives the values of two components of bioimpedance. Thus, each frequency value in this graph allows us to write two equations (2) with $2L$ unknowns. Therefore, to build a Voight model with L links, it is necessary to determine the impedance of the biomaterial at least at L frequencies, that is, $N > L$.

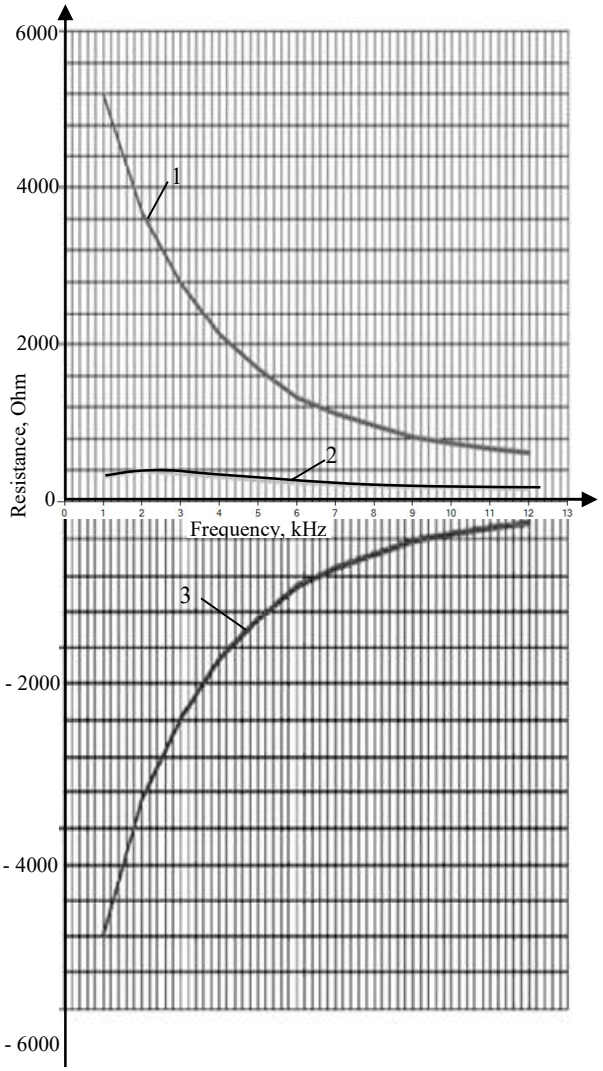

Fig. 2. A plots of the dependence of the impedance of a biomaterial on frequency: 1-modulus of complex resistance, 2-real part of complex resistance, 3-imaginary part of complex resistance.

For example, to represent the impedance of a biomaterial by the Voigt model in the form of a single link, equation (2) will take the form:

$$\left.\begin{aligned} a(\omega) &= \frac{R_1}{1+\omega^2 C_1^2 R_1^2}; \\ b(\omega) &= \frac{-\omega C_1 R_1^2}{1+\omega^2 C_1^2 R_1^2}. \end{aligned}\right\} \quad (3)$$

To solve (3), it is sufficient to measure the bioimpedance at only one frequency, for example, at ϖ. In this case, it is necessary to make sure that such a model is adequate, that is, the impedances of this model at frequencies different from ϖ are equal to the impedances obtained as a result of experimental studies.

For this purpose, a recursive procedure for solving systems of nonlinear equations (2) is performed to determine the parameters of the model, starting from the single-link Voight model and sequentially increasing the links in the Voight model. In each Voigt model, a set j is defined $\{C_i, R_i\}_j$, where *i* is the link number in the *j*-th iteration of the Voigt model. The iterative process is performed until the functional of the approximation error of the experimental data by the Voigt model reaches an acceptable value. The error is determined by comparing the simulation results according to (1) with the results of experimental studies presented in the form of a graph in Figure 2.

Voigt's models are constructed by solving a system of nonlinear equations obtained on the basis of the graphs shown in Figure 2. Voigt's model allows theoretically obtaining the amplitude-frequency characteristic (AFC) according to equation (1), with the set elements calculated from the system of equations (2) $\{R_\ell, C_\ell\}$. The AFC model is compared with the experimental AFC. The approximation error ε is determined, for example, by the Euclidean distance, and is compared with the allowable error ε_{add}. If the error is less than the allowable, then the iterative process of building the model ends. Otherwise, one more link is added to the model and Voight's model is rebuilt, that is, a new system of nonlinear equations (2) is solved with the addition of the next frequency - two values of the impedance parameters at the next frequency of the graphs Figure 2. Before incriminating the parameter *L*, it is checked for its output beyond the limit value. When this parameter goes beyond the limit value, the parameters of the Voight model are not redefined, but are displayed as a space of informative features.

3 Results

Voight's model for a two-link model uses two points in the graph in Figure 2 and has the form

$$\left.\begin{aligned} a_1(\omega_1) &= \frac{R_1}{1+\omega_1^2 C_1^2 R_1^2} + \frac{R_2}{1+\omega_1^2 C_2^2 R_2^2}; \\ a_2(\omega_2) &= \frac{R_1}{1+\omega_2^2 C_1^2 R_1^2} + \frac{R_2}{1+\omega_2^2 C_2^2 R_2^2}; \\ b_1(\omega_1) &= \frac{-\omega_1 C_1 R_1^2}{1+\omega_1^2 C_1^2 R_1^2} + \frac{-\omega_1 C_2 R_2^2}{1+\omega_1^2 C_2^2 R_2^2}; \\ b_2(\omega_2) &= \frac{-\omega_2 C_1 R_1^2}{1+\omega_2^2 C_1^2 R_1^2} + \frac{-\omega_2 C_2 R_2^2}{1+\omega_2^2 C_2^2 R_2^2}. \end{aligned}\right\} \quad (4)$$

After solving equation (4), we obtain new parameters of two-port networks in the Voigt model and repeat the procedures for solving system (4). If the approximation accuracy is not satisfactory, then we add two more equations to the system of equations (4), solve it and build the model (1) anew.

To construct a classifier for this space of informative features, we use trainable neural networks with a hierarchical structure [12-16]. The output of the neural network of the first hierarchical level shows confidence in the biomaterial belonging to the class of functional state for which the neural network was trained. The neural networks of the first hierarchical level are trained using the same training samples. The outputs of the neural networks range from zero to one. In this case, the classification is carried out in two classes "class of interest" and the class "everything else". At the second hierarchical level, there is only one neural network with one output and the number of inputs equal to the number of neural networks at the first hierarchical level.

As an example, a group of patients with pneumonia with a clearly defined diagnosis (radiography, X-ray tomography, laboratory analysis data) and a group of volunteers without pulmonary pathologies were taken. Diagnoses are coded with the characters "0" and "1". Control samples are formed from the obtained training sample by the rolling exam method. To obtain bioimpedance analysis data, an electrode belt is put on the patient's chest and impedance curves of the type shown in Figure 2. Each impedance curve corresponded to a certain combination of electrodes. The process of obtaining them is illustrated in Figure 3.

Indicators of the quality of diagnostics in the "pneumonia - no pneumonia" classes for one of the control samples are presented in Table 1.

Table 1. Indicators of the quality of forecasting on the control sample.

Surveyed	Bioimpedance studies			X-ray examinations		
	DS	DSp	DE	DS	DSp	DE
$n^1_{\omega_1} = 60$	75%	83%	79%	87%	66%	77%
$n^2_{\omega_1} = 60$	83%	75%		66%	87%	

The indicators of the quality of diagnostics of the proposed method were compared, as with the prototype, with the indicators of the quality of X-ray studies on the same control sample.

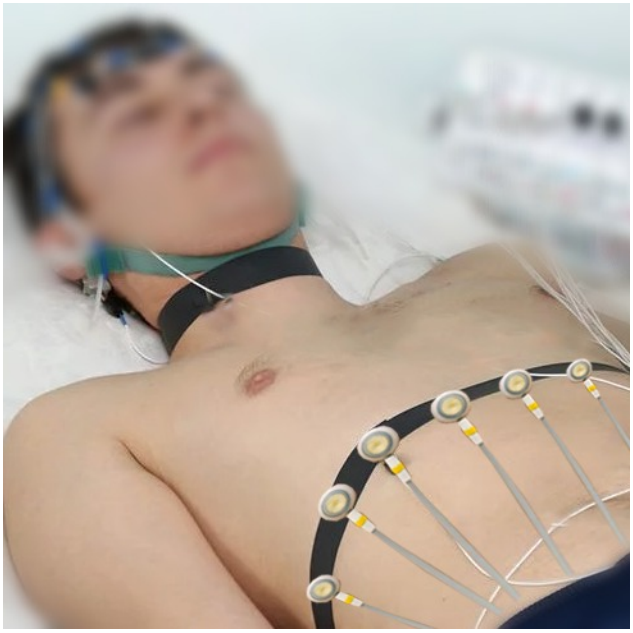

Fig. 3. Illustration of the process of classification of biomaterial in an in vivo experiment.

4 Discussion

Analyzing Table 1, we come to the conclusion that in this control sample both methods have practically the same diagnostic efficiency, but bioimpedance studies are superior to radiological studies in specificity and are somewhat inferior in sensitivity, which allows them to be recommended for clinical practice.

Thus, to classify a biomaterial for the presence of infectious diseases, descriptors are used, which are determined by representing the model of a biomaterial in the form of a multi-link bipole, the parameters of the links of which are determined on the basis of multipart sensing. The obtained multidimensional model of descriptors is used to train neural networks that perform the functions of a biomaterial classifier. As a result of the study, the results were obtained that allow the creation of intelligent decision support systems for the prediction and diagnosis of infectious diseases. The possibility of multifrequency sensing will make it possible to construct algorithms for differential control of tissue impedance and fluid impedance, which will make it possible to obtain new decisive rules for diagnosing pathological conditions of the body (cardiovascular, infectious and oncological diseases).

5 Conclusion

The scientific novelty of the study lies in the fact that descriptors are used to classify a biomaterial for the presence of infectious diseases, which are determined by representing the biomaterial model in the form of a multi-link bipole, the parameters of the links of which are determined on the basis of multipart sensing. The obtained multidimensional model of descriptors is used to train neural networks that perform the functions of binary classifier of biomaterial.

As a result of the study, the results were obtained that allow the creation of intelligent decision support systems for the prediction and diagnosis of infectious diseases. The possibility of multifrequency sensing and the use of iterative biomaterial models will allow the construction of algorithms for differential control of tissue impedance and fluid impedance by non-invasive methods in in vivo experiments. This will contribute to obtaining new decisive rules for the diagnosis of pathological conditions of the body (cardiovascular, infectious and oncological diseases).

6 Acknowledgments

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