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A neural model for the heart muscle

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Abstract

An electric model of the heart muscle, using neural networks (NN), is proposed, the heart distributed electrical resistance being modelled by weights of a NN. It is argued that the suggested model is more credible than the existing ones.

1 Introduction

The electrical behavior of the heart basically consists in the dynamic depolarization/repolarization of the myocard. The heart electrical activity is known to be dependent on two main elements:

i) the heart muscle (myocard) distributed conductances, which determine the current distributed path,

ii) the internal pacemaker (atrial node and afferent system).

The current distributed path is dependent on the distributed conductivity of the heart muscle. The information one clinically gets on the muscle state is only indirect: this information is registered at the surface of the body, as electrical signals. the electrical signal so registered is named electrocardiogram (EKG).

The EKG is known to carry global, indirect, hidden information (about the diseases for example) of the heart. The global information about the muscle conductivity is available only as transformed by the human body distributed conductivity.

In many heart diseases, such in an infarct development, the muscle state plays a major part. The determination of muscle areas with low conductivities is very important, as decreased conductivity indicates ill muscle areas, e.g. necroses.

To determine the electric component of the heart muscle, and also to generate in a logic way the knowledge needed by an expert diagnosis system, one possibility is to use an electric (more or less simplified) model. This way was recently used by many research groups, by using different modeling principles and techniques. There are three basic models:

i) analytic, continuous i.e. the description by analytic equations of the electric muscle behavior;

ii) finite elements models;

iii) network-type models.

To exactly describe the electric fields inside the conducting bodies with complex shapes, analytic models use complicated equations. These equations are sometime impossible to analytically solve, or their solutions are very difficult to find. So, it is necessary to approximate the solution, using the finite element method for example, or other time - consuming techniques, and this is a major disadvantage for these models [1], [2], [3] and [4].

Different ways to model electrical conductors in the human body are listed bellow. Oostendorp [2] uses the boundary element technique in the computation of the electric potential distribution into isotropic inhomogeneous volume conductors of arbitrary shape. Mitchell [3] uses for model of the ventricular conduction a discrete elements neighborhood (cellular automaton), using 2500 (50x50) element rectangular grid. Hatsell [4] uses an analytical model of the bulk conductor for measuring the impedance in plethysmografy.

Another model, based on neural networks (NN), was introduced in [5]. In the present paper are developed the ideas formulated in [5], namely, the heart muscle is simulated using a NN. The model presents an important advantage because of the computation simplicity offered by NNs. Indeed, for a NN, the training is based on a well established algorithm, with exact steps, which are repeated for a number of iterations. The computer automatically rules this algorithm until the iterations are finished. On the other hand, the use of NNs is nearest to the biological modeled object, because the NN has as model the biological neurons with their connections - a good enough approximation of the muscle cells.On the other hand, one can simulate the inhomogeneous bodies (layered bodies) using neurons with different functions of activation, to simulate homogeneous layers with different properties.

2 Principle of the models

2.1 The principles

A way for developing the models based on NN for the heart muscle was first presented in [5].In this model, one divides the heart into concentric volumes, ordered by the surfaces of electric potential that limit these thickness. Each layer is modeled by a layer of neurons in a layered NN.

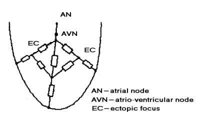

Figure 1:Schematics of the electrical model of the myocard.

The neurons are representing points into the heart muscle. On the surface modeled by a layer of neurons, the same distance separates two adjacent neurons.

We are modeling the heart by a set of interconnected, nonlinear resistances. The linear part of the resistances are modeled by the weights of the NN, while the nonlinearity is introduced by the characteristic function of the neurons.

The stimulus, generated by the pacemaker situated in the atrial node (AN), travels through the His bundle to the atrioventricular node (AVN) and then is propagating through the Purkinje fibers, to and through the muscle (Fig. 1)

It is known that the normal activity of the muscle is equivalent to high electrical conductance and a malfunction with a low conductance.

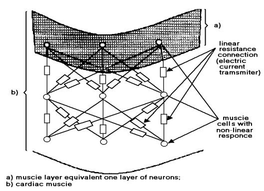

Figure 2:NN associated to myocard muscle.

The values of weights in the NN represent the strength of conductance between the couples of neurons (Fig.2). This is a basic principle for the use of NN to model the behavior of the myocard muscle.

The medium of propagation is considered to be homogeneous. This is a non-realist model, because the myocard muscle is an inhomogeneous medium. However, in the first approximation, the model in this form is satisfactory, and moreover, it is easy to simulate inhomogeneous, layered media by NN, taking different neurons on each layer.

It must be emphasized that NN-s based models allow the simulation of discontinuous propagation, by introducing delays between the layers.

In this paper, the propagation of the electric impulse into the myocard muscle is considered to be continuous.

Some modifications are used for the functions of activation of neurons, in comparison with standard sigmoid or linear function [5], [6]. These modifications, that have a biological support, are in accordance with the representation of waveforms to input or output,that may have negative value.

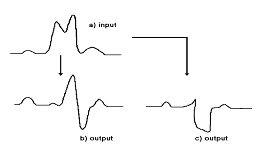

Figure 3:Standard static EKG waveform transformations.

Two kind of simplified models are considered in this paper, according to the possibilities regarding the available input and output data. A first possibility consist in :

i) as input data, only the spatial signal distribution at one moment of time is available (the distribution is considered on the inner part of the heart muscle);

ii) the corresponding spatial distribution at outer surface of the heart muscle is given (see Fig.3).

In the second model, the same output is considered, but the input consist in delayed excitations on the inner surface of the muscle (see Fig.4).

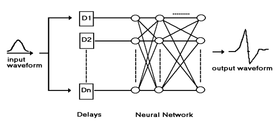

Figure 4:Delayed waveform transformation.

This dynamic behavior is suggested by delayed waveform which is presented at input and the standard delayed EKG waveform at output (Fig.5). We use that for to model the transformation the time-domain in the space-domain.

Again, we remember that the waveforms at input and output are considered to be know, although, at our best knowledge, the corresponding waveforms are not yet actually known by physiologists.

2.2 The models

2.2.1 The model 1

A classic three layer perceptron type NN [6] is used. The only modification of NN is the absence of the weighted inputs for the first layer

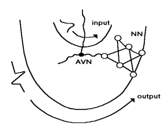

Figure 5:Heart muscle and delayed waveforms.

(input layer) for both models. Each layer has the same number of neurons (Fig. 6). The function of activation is:

$$f(x) = x \tag{1}$$

If the neuron is on the first, or on the last layer, and the sigmoidal function, without threshold, for the neurons on the hidden layer:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The learning method is back-propagation, modified according to E. de Doncker [6].

We use the notation:

a_j^k – the output(activation) of j-th neuron in the k-th layer;

w_{ij}^k – the connected weight between i-th neuron in the $k-1$ layer and the j-th neuron in the k layer.

For every neuron, the weighted input is given by:

$$s_j^k = \sum_i w_{ij}^k \cdot a_i^{k-1}, \quad k = 1, 2, \cdots, L \tag{3}$$

where L is the number of the layers in the NN. We define for $L = 0$:

$$s_j^0 = \text{input} \tag{4}$$

Also, we have for the input and output layers:

$$a_j^k = s_j^k, \qquad (\text{for} \;\; k = 0 \text{ or } \;\; k = L) \tag{5}$$

The output errors are given by:

$$e_j^k = t_j - a_j^L \tag{6}$$

where t_j are the target outputs. Now let the magnitude of the LMS errors (the cost for the errors) be:

$$J = 1/2 \sum_j (e_j^k)^2 = 1/2 \sum_j (t_j - a_j^L)^2 \tag{7}$$

We take as the objective the minimization of the total error:

$$J_{total} = \sum_p J_p \tag{8}$$

over this trajectory (over all p). We do this by a gradient descendent procedure, adjusting w_{ij}^k along the negative of the $\nabla_w \; J_total$,

The weights are adjusted by:

$$\Delta w_{ij}^k = -\alpha \cdot \frac{\partial J_p}{\partial w_{ij}^k} \tag{9}$$

and

$$\Delta w_{ij}^k = \alpha \cdot e_j^k \cdot \frac{\partial S_j^k}{\partial w_{ij}^k} \tag{10}$$

For $k = L$, are has

$$\frac{\partial S_j^k}{\partial w_{ij}^k} = a_j^{k-1} \tag{11}$$

The errors for $k = L-1, L-2, \ldots, 1$ are recursively computing. Obviously, we have in both models, for the sigmoidal functions:

$$e_j^k = -\frac{\partial J}{\partial S_j^k} \tag{12}$$

$$\begin{aligned} e_j^k &= -\sum_i \frac{\partial J}{\partial S_j^{k+1}} \cdot \frac{\partial S_i^{k+1}}{\partial a_j^k} \cdot \frac{\partial a_j^k}{\partial S_j^k} = \\ &= \sum_i e_i^{k+1} \cdot w_{ji}^k \cdot f'(S_j^k) \end{aligned} \tag{13}$$

$$f'(x) = f(x)(1.0 - f(x)) \tag{14}$$

and the weights are adjusted iteratively:

$$w_{ij}^k(t+1) = w_{ij}^k(t) + \Delta w_{ij}^k(t) \tag{15}$$

For each NN and so for each waveform presented at input, one trained the NN with a single output waveform (Fig.3). For each NN, a single input waveform, which corresponds to a single output waveform, is used.

2.2.2 The model 2

A three layer perceptron is also used in this model [6]. The function of activation is (for all neurons):

$$f(x) = \frac{1}{1+e^{-x}} - \frac{1}{2} \tag{16}$$

This shifted form is chosen to allow the processing of the pattern waveforms which have the positive and negative values.

Again, the NN (Fig.6) has the same number of neurons on each layer, and the method of training is back-propagation, according to [7]. A delayed pick is a stimulus at the input layer, and the correspondent delayed waveform is considered to be the target (output) of NN (fig.4).

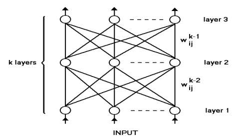

Figure 6:The multilayer NN.

Representation methods

The major problem after obtaining the value of the weights of NN, after the training process, is to present these results as in a convenient manner [5].

The major difficulty of the model, as reported in [5], is the compression of the results. In this paper this difficulty is surpassed by using appropriate data representation methods.

An attractive method is to represent the weights values, (after scaling between maximum and minimum over all weights values in the NN), by line styles. A line styles scale is used in the graphic representation of these values. This modality of representation is used for both models.

We are choosing two modes of representation of the weights:

i) by different line styles for different weight values (each line connects a couple of neurons - see Fig.7),

ii) by filled areas with different patterns around of this line connection.

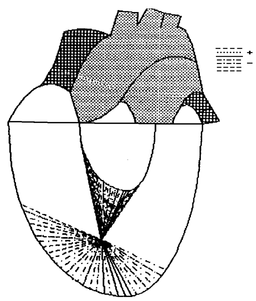

Figure 7:Electric conductivity for the first mode of representation.

An example of representation by the (ii) - mode is shown in appendix (only the area of interest).

Approximations used

Only preliminary results are reported here. In the tests, the used model has three layers of neurons. Obviously, this is a much simplified model for the heart muscle, and it cannot offer satisfactory results for the clinical use.

The model of the heart muscle using NN has a few approximations to determine easier its electrical behavior.

However in this stage of the research development the three layer NN is flexible enough to offer a realistic tour of experiments. Adding hidden layers to the NN, the development of this model is a simple question of technique.

The second limitation is due to the representation in the 2D plane, because for a realistic model, a spatial representation (three-dimensional) is necessary. (By the way,the model in [5] hat the same deficiency).

3 Simulation results

A three layer NN with 64 neurons on each layer is used for the first model. For this NN, 2x64x64 = 8192 weights carry the information about conductivity in the heart, and will be represented. The NN is trained with sampled waveforms (64 samples). The learning factor, experimentally determined for faster convergence, is equal to 0.001. After 9000 iterations, the standard deviation (SD) between the target waveform and the output waveform is less than 0.1%. The input and the output waveforms are shown in Fig.3.

For the second model, a three layer NN, with 32 neurons of each layer (2x32x32 = 2048 weights), is used. A number of 32 samples are used to represent the waveforms. The NN is trained with delayed waveforms (12 delays) at input, and with the corresponding delayed target waveforms (Figures 4 and 5). After 24000 iterations, with optimal learning factor equal to 0.35, the SD is less than 0.01%. For both models, the range of weights values is between [-12.0, +12.0].

For these two models we are using a 2D image of the heart. This image is located in the vertical position, and the center of coordinates is situated approximately in AVN (Fig. 5).

In these models, usually a neuron in the middle layer has more than 32 connections,and an extremity layer has more than 16 connections, so more information is available than in paper [3] where each cell has eight neighbors.

The image for the first mode is shown in Fig. 7. The color scale has seven colors. The image for the second mode is shown in **Appendix**. In this image only the area of interest is represented. The scale of the weights has the symbol "-" for the low conductance and the symbol "+" for the high conductance, The divisions of the scale intervals are equal.

4 Discussion and conclusions

The simplicity of this method, and the algorithm, proposed in this paper avoid the use of the method of finite elements, or of another complicated calculus, as in other papers [1], [2], [3], and [4].

The models which are proposed have a few approximations. First. the medium is considered homogeneous, the same that [1], [3], but different to [2], where the medium is considered inhomogeneous, and so more appropriated to reality.

A composed NN [7] may be used for modeling an inhomogeneous body. In such NN, for each layer we use different functions of activation.

The model has a major deficiency by using only 2D plane for representation and not 3D representation, as needed for modeling the real case. It is a common deficiency [3], and may be solved using Spatial Neural Networks. This model needs powerful resources or parallel computers.

For satisfactory results more layers are needed in the NN, and more neurons on each layer. For NN's algorithm, it is a simple question of

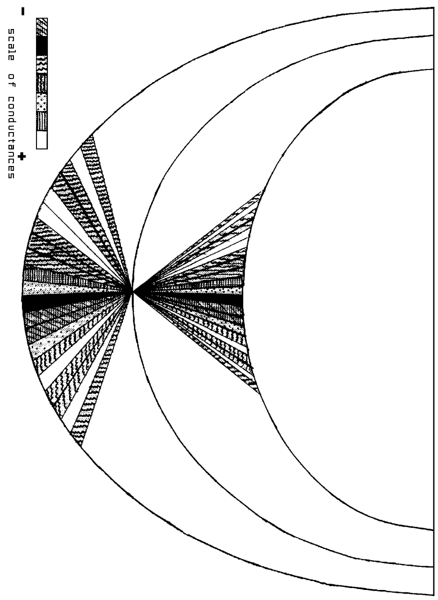

Figure 8:Appendix.

technique to increase the layers number.

It can be seen that the connections in the NN permit to link each neuron with more 16 neighbors neurons (16 weights), and we achieve a higher amount of information than the cellular model [3], who eight neighbors-model only.

The heart models based on NNs open a new way to deal with heart models and new directions of development.

Using more than three layers for NN, and many neurons for each layer, the model will be more realistic. One way in the realistic modeling of the myocard muscle is to use the composed NN, for modeling an inhomogeneous volume. Another way is due to [8]. The response of the heart muscle is not a “crisp” value. Almost sure, the response of the cell is fuzzy (a non-deterministic mode).

That suggest one way to use for modeling the heart muscle with fuzzy neurons, and appropriate method to describe the surfaces of electric field distributions.

The result of the models proposed in this paper may be used to create a complete model of the heart. The complete model uses the static character of myocard muscle with NN, proposed by this paper, and the oscillatory character. The oscillator characteristic may be implemented by using a Recurrent Neural Network.

After complete implementation of model, the result should be verified by medical conclusion.

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