RECOGNITION OF VARIOUS EVENTS FROM 3-D HEART MODEL

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Abstract: This paper presents a new way to solve the inverse problem of electrocardiography in terms of heart model parameters. The developed event estimation and recognition method is based on an optimization system of heart model parameters. An ANN-based preliminary ECG analyser system has been created to reduce the searching space of the optimization algorithm. The optimal model parameters were determined by minimizing the objective functions, as relations of the observed and model-generated body surface ECGs. The final evaluation results, validated by physicians were about 86% correct. Starting from the fact that input ECGs contained various malfunction cases, such as Wolff-Parkinson-White (WPW) syndrome, atrial and ventricular fibrillation, these results suggest that this approach provides a robust inverse solution, circumventing most of the difficulties of the ECG inverse problem.

Keywords: Medical applications, Real-time systems, Neural network, Signal processing, Heart wall motions, Models.

1. INTRODUCTION

The most important health problem affecting large groups of people is related to the malfunction of the heart, usually caused by heart attack, rhythm disturbances and pathological degenerations. One of the main goals of health study is to predict these kind of tragic events, and by identifying the patients situated in the most dangerous states, it is possible to apply a preventing therapy.

Computerized ECG analysing systems, most of which are based on recognition and clustering algorithms, have to recognize any potentially dangerous arrhythmia with at most a few seconds delay. Recent signal processing techniques apply the mixture of time-frequency analysis (Fourier, wavelet, cosine transforms), sample-based (neural networks) and parameter estimation (regressive models).

The application of large databases can cause the improvement of the precision, but the following disadvantages are still held:
1. It is impossible to store all possible wave forms;
2. If the size of the database grows, the clustering algorithm becomes more and more complicated, it will be hard to develop and maintain;
3. Real-time learning is impossible during the clinical practice at the moment (PC's are still too slow). The algorithm might take wrong decisions in case of unknown waveforms.

These disadvantages lead to the idea, that the development of a heart-model-based system is necessary.

Creating a heart model is basically practical, (Thaker, *et al.*, 1998) because the computer, when applying traditional signal processing algorithms, recognizes lots of waves, but it does not really "understand" what is happening. This can be avoided only if the computer knows the origin, the formation of the ECG signal (MacLeod and Brooks, 1998). During the signal processing, if the traditional algorithm finds an unrecognisable waveform, the model-based approach is activated, which tries to estimate the causes of the encountered phenomenon (e.g. quick recognition of ventricular fibrillation) (Szilágyi, 1998).

The main goal of the inverse problem of ECG is to characterize and reconstruct cardiac electrical events from measurements. In contrast to the forward problem of the electrocardiography, the inverse problem does not possess a mathematically unique solution. Another not easily by-passable problem is its ill-posed nature whereby the desired inverse solution is unstable and may oscillate widely with the slightest perturbation.

Several approaches have been explored to handle the problem of multiple solutions by using equivalent cardiac generators (such as equivalent dipole and multi-pole), heart surface isochrones (Cuppen, *et al*., 1984), or epicardial potential (Guanglin, *et al*., 2001). The high sensitivity of solutions to the different disturbances forced the investigators to explore regularization techniques (Shahidi, *et al*., 1994). These methods allow a significant progress, but the different uncertainty elements of the processing hinder the potentially beneficial ECG inverse solutions from becoming a routine clinical tool at present.

Body surface potential mapping (BSPM) was developed to allow an almost complete data acquisition from the body surface. BSPM may have a great advantage over the standard 12-lead system in different situations due to deeper accessible information. Mirvis has shown some cases of BSPM recordings that clearly demonstrate the inadequacies of the standard ECG lead sets in a variety of pathologies (Mirvis, 1988). As we know more about the depolarization – repolarization mechanism, we can understand in a better way the internal function of the heart.

This paper presents an event recognition study performed with ECG signal analysis and 3D heart model. The main purpose is to evaluate the strength and weakness of each method, and to analyze the cooperation efficiency in malfunction diagnosis.

2. MATERIALS AND METHODS

2.1. Study records

The first signal resource was a 32-electrode measurement (BSPM) database (sampled at 1000 Hz with 12-bit resolution) obtained from the Research Institute for Technical Physics and Materials Science (MTA-MFA) of Budapest. These registrations contain various malfunction cases as WPW syndrome, atrial and ventricular fibrillation, flutter. These measurements were collected using Lux-32a (Lux, *et al*., 1978) electrode placement, as presented in Fig. 1.

In the second stage of the study we used 12-lead ECG registrations from our database. These signals were sampled at 500-1000 Hz with 12-bit resolution.

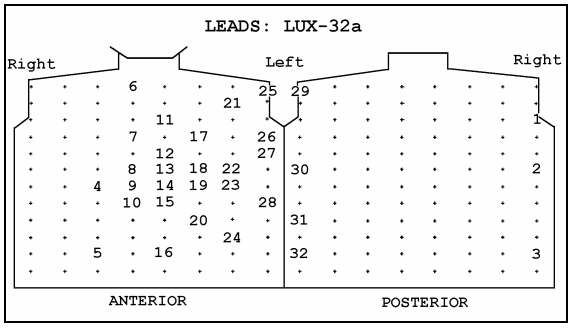

Fig. 1. Lux-32a electrode placement.

2.2. The approach of ECG inverse problem

In contrast to methods that directly solve the matrix equation linking electrical sources with electrical potential fields to estimate ECG inverse solution, our approach indirectly obtains the solvent in terms of heart model parameters. The schematic diagram of the method is presented in Fig. 2.

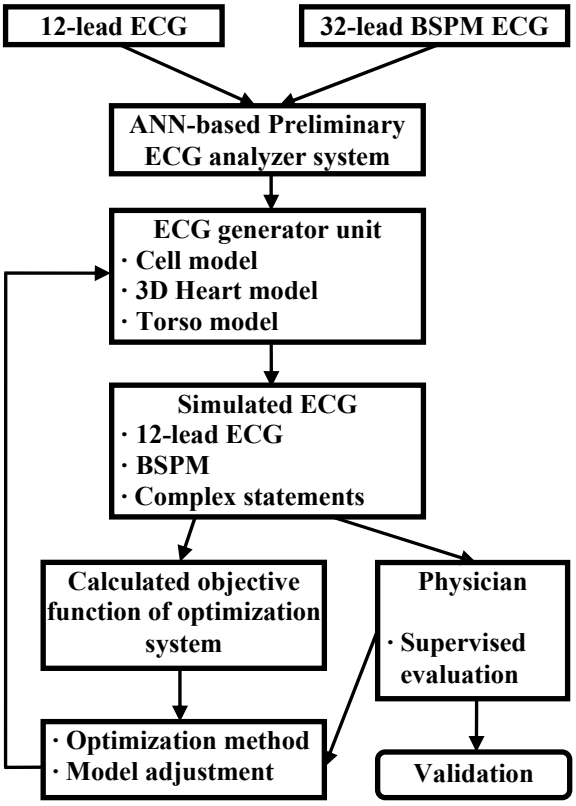

Fig. 2. The schematic diagram of the heart-model-based ECG analyzer method.

The preliminary ECG analyzer system (PAS) is based on detailed human anatomical and functional a priori knowledge, developed using an ANN, tested and validated by physicians in clinical environment. In this study the PAS was used to obtain initial information on the site of origin of cardiac activation. The output of the ANN provides the initial heart model parameters. Then the BSPMs or 12-lead ECGs were simulated by the ECG generator unit, and the objective functions that assess the similarity between the measured and simulated signals were determined.

The heart model parameters are adjusted with the aid of optimization algorithms or eventually physicians. The simulation procedure is performed until the objective functions satisfy the given convergence criteria. Finally the parameters are validated.

2.3. ANN-based preliminary ECG analyzer system

Application of a priori knowledge to reduce the searching space of heart model parameters is quite important. The PAS was developed to determine roughly the cardiac status and state, which was than used to initialize the model parameters and decrease the searching space for the optimization system.

2.4. The structure of the combined heart model

Based on a simulation and a measured ECG signal, the estimation of the internal state of the human body is a considerably complicated task, requires the solution of several theoretical and practical problems. Theoretically the model should contain all those factors that should be handled considerately during implementation, but that is practically impossible. If the required information is not available, the values of the unknown parameters should be determined empirically. As the amount of available information grows, the model can become more and more sophisticated. The theoretical model determines the internal structure of the human body on three levels.

Level of the myocardial cell. The ion channels (Na+, K+, Ca++, Mg++, etc.), pumps, and transporters are included in this model-layer as they determine the function of each cell. Unfortunately, the precise mechanism of these units is not known (Thaker, *et al.*, 1998). When we study the behaviour of a simple myocardial cell, it is likely to consider the character of the currents, which appear during depolarisation.

Let I_m be the sum of the currents that flow through the cell membrane of unitary surface. Then

$$I_m = I_{cap} + I_{ion} + I_{ext} = C_m \cdot dV_m / dt + \sum (I_{ch} + I_{transp} + I_{pump}) + \sum I_{env} \quad (1),$$

where I_{cap} is the capacitive (due to potential difference from the cell membrane surfaces), I_{ion} the ionic (sum of currents generated by channels, pumps and transporters), and I_{ext} the current coming from the external environment. C_m is the electrical capacity of a cell membrane with unitary surface, V_m is the potential difference between the two sides of the membrane (Huiskamp, 1998; Quan, *et al.*, 1998).

Anatomy of the heart and torso. There are many possible different heart structures (Quan, *et al.*, 1998). To describe various representative cases we studied our breast MRI records (42 examples) and some CT images. These samples allowed us to construct a morphological heart structure for simulation.

The geometry model of the heart and torso was constructed by tetra meshes. The torso, lung, endo- and epicardial surfaces were divided into 2344, 3834, 7780 and 8942 tetrahedrons. The heart model could have a spatial resolution of 0.5 mm that means more than one million individual compartments at highest decomposition. For a better simulation result we choose a time-slice between 0.1ms and 2ms over the whole ventricular excitation cycle.

Position of the surface electrodes. The structure of the chest, its position in space, the relative position and distance of the compartments with respect to the electrodes, and the electrical behaviour of the chest's contents must be known (Ramon, *et al.*, 1998).

As the model has to take in consideration extremely numerous parameter values, the problem cannot be solved in a deterministical way (we have much more unknown values then known equations). That is why a stochastical method (genetic algorithm, adaptive neural networks and fuzzy systems) should be applied to determine the values of the parameters (Szilágyi, 1998).

2.5. Mathematical description of the model

Let us consider that the basic element of the structure of the heart is the compartment that according to the model is the largest homogenous unit. We considered each compartment having the same type of connections with adjacent units. The type of cells determines the electrical propagation properties, but no additional considerations were taken in, such as tissue fiber torsion and so on.

Each compartment was considered homogenous, constructed by only one type of tissue with well-defined properties, such as: cell type, cell state, cell activation potential (AP) function. The environmental parameters such as 4D position (*x, y, z* spatial coordinates and time), conduction speed of stimulus, weight and connection with neighbor structures, localize each unit.

The heart behavior was characterized by the following parameters:
a. Type of cells: *T.* The main possible categories are: sinoatrial node, Bachmann's bundle, atrial muscle, atrio-ventricular node, bundles of His, Purkinje fibers, ventricular muscle;
b. State (time varying): *S.* Possible cell states are: normal function, ischemia, lesion, necrosis, ectopic node, etc.
c. Function of activation potential variation: AP(T,S,t), it depends on the type and the state. Different activation potential functions were assigned to different states of all cell types. The shapes of those functions vary according to the values of the main parameters of the cell model. Although the ion

concentrations determine the AP function shape, we had no realistic concentration data for all cases, so we had to use various empirical approximations. This fact can seriously disturb the simulation results;

d. Space position in time: $\mathrm{Pos_K}(x,y,z,t)$, the geometrical position in time of the gravity center of the compartment. Unfortunately these values are valid only for a static object, however the heart moves all the time. Often the time parameters approve essential to deal with some situations;

e. Conduction speed of the stimulus: CS(T,S), it mainly depends on the cell type and state;

f. Weight of the contents of the compartment: M;

g. Connections with other compartments: according to the cubic model, each compartment can be directly connected to its 26 neighbors;

h. The position of the electrode: $\mathrm{Pos_E}(x,y,z,t)$. The problem of heart and torso motion was introduced in point d);

i. The relative resistance of the electrode: $R_{E,K}(Pos_K, Pos_E)$.

Because the main ion channels situated inside the cells have a quite complicated behavior (with lot of unknown parameters), the activation potential function of the compartment was considered as basic input parameter (we determine an AP function with static shape for each cell type and state). Due to contractions of the heart, respiration, and other disturbing phenomena, the position of compartments was considered time-varying. The following mathematical expressions that describe compartment behavior will vary in time.

Let V_K be the potential of an arbitrary compartment K: $V_K(t) = AP(T,S,t-\tau_K)$, where τ_K is the time the stimulus needs to reach the compartment K. The activation potential function that varies from cell type T and state S, has a short delay τ_K due to activation propagation until compartment K. These AP potentials for normal functioning cells are presented in Fig. 3.

If we study the measured potential E_j, generated by compartment K_i then:

$$E_{j,K_i}(t) = V_{K_i}(t) * R_{E_j,K_i}(t) - E_{GND,K_i}(t) \qquad (2),$$

where, $R_{E,K_i}(t)$ represents in time the resistance from compartment K_i to electrode E_j. Using bipolar electrodes, the value measured on the reference electrode E_{GND} will be subtracted. As all compartments have an accession to the measured potential on each electrode, the measured voltage on electrode E_j will become the sum of each $E_{E,K_i}(t)$ generated by compartment K_i:

$$E_j(t) = \sum_{i=0}^{N-1} \left[V_{K_i}(t) * R_{E_j,K_i}(t) - E_{GND,K_i}(t) \right] \qquad (3),$$

where N is the number of compartments.

These equations determine the measured electrical potentials and the inner mechanism in the heart. During the simulation, these voltages were determined for each compartment and electrode for every time-slice (especially between 0.1ms and 2ms). In the following it is presented, how simulations were antagonized from different environmental factors (muscle fiber elasticity, distortion, different structural abnormalities, etc.). Although these disturbing factors limit the overall performance of the simulation, with pragmatic algorithm organization these effects could be minimized.

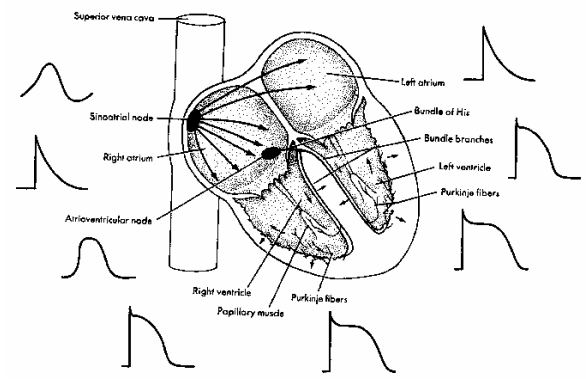

Fig. 3. The AP shapes of different cell types for normal case

2.6. Applied tools and mathematical methods

At the moment, testing the theoretical model is possible only if the values of unknown variables are determined empirically. This compromise must be taken in all cases, where the estimation error is greater then the statistical error occurring when the empirically determined values are applied.

The cell motions caused by the motion of the heart are neglected, so the transfer functions of the compartment-electrode ensemble is not time varying. The simulation program performs a genetic algorithm to determine the values of the unknown parameters. As the estimation of the parameters of this simplified model still requires an adaptive regressive model of 1500 terms, the simulation is extremely slow.

The algorithm was accelerated by coding the main cycle in machine code using MMX, SSE2 (multimedia instruction set with single instruction multiple data structure for processors Intel Pentium3, 4 and AMD Athlon processor family).

3. RESULTS

During the simulation, a parameter classification algorithm was applied to distinguish the normal QRS complexes from the abnormal ones, in order to

determine the specific differences between the normal and abnormal parameter values.

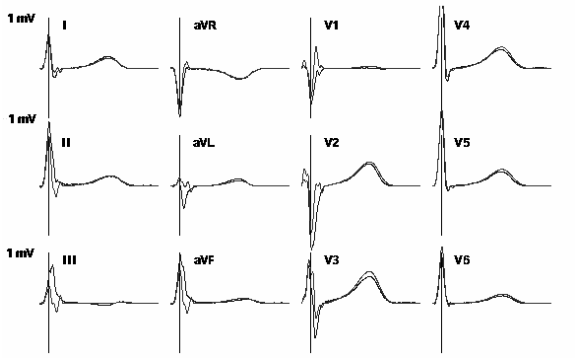

Fig. 4. The simulated ECG signal in normal and abnormal case

For normal cases the detection ratio is practically 100%. During the simulation by using the initial parameter set for a normal and abnormal situation, we obtained the signals presented in Fig. 4.

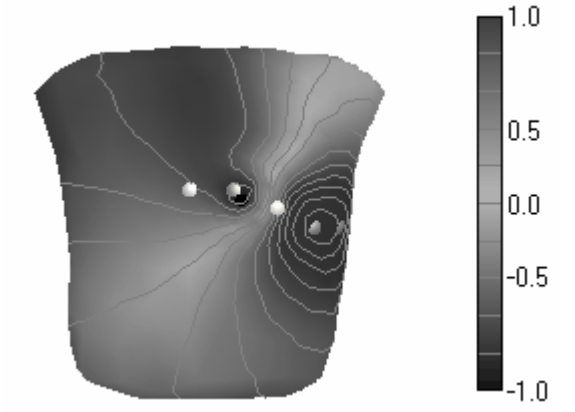

Fig. 5. The simulated surface potentials

Fig. 5. represents the simulated surface potentials t=41ms after the start moment of ventricular depolarization.

Table 1 Simulation performance for various pathological and normal cases

Pathological case	Decision number	Failed decisions	Perfor-mance
Normal	44	1	97.72%
Ectopic beat	21	4	80.95%
WPW syndrome	14	2	85.71%
Atrial flutter	22	2	90.90%
Atrial fibrillation	18	2	88.88%
Ventricular Fibrillation	19	1	94.73%
Re-entry mechanisms	19	3	84.21%
Triggered activity	36	5	86.11%
Aberrant ventri-cular conduction	21	3	85.71%

Table 1. shows the correctness of simulation for different cases. The evaluation of the simulated results was made by physicians. The performance was determined as the ratio of correct and total decisions.

4. DISCUSSION

As Table I. showed us, that the 3D heart simulation (Szilágyi, *et al*., 2003 a,b) could deal in most cases, such as WPW (Wolf Parkinson White) syndrome, pre-excitations, and tissue activation modeling. The cases of ectopic beats and triggered events represent the weak points of the simulation model. The application in practice of the model has several obstacles, which can be classified into the following groups:

- Effects of internal and external perturbations (such as environment, sympathetic and parasympathetic despondence);
- Lack of information on elements of the model;
- Lack of technical background.

4.1. The deficiencies of the model

- The processes performed inside the cells are not well known, the behaviour of the studied components cannot be determined with an acceptable precision;
- In critical cases, if a group of cells does not get the necessary food, it changes its behaviour. A model created to simulate the normal behaviour of the cell will not simulate it correctly in abnormal case;
- Because the structure of the heart differs from patient to patient, this structure is not known a priori, it has to be determined in real-time, based on the available information;
- The determination of the torso's structure introduces the same problem. It is hard to determine the electrical conductivity and precise position of its elements.

4.2. Perturbation phenomena

- It is known, that respiration makes the heart change its shape and position. Although the motion of the heart can be tracked, it is not possible to determine from the ECG the amplitude of the motion;
- The continuous motion and displacement involves very hard problems. Because the motion has an effect on the behaviour of all internal elements, the behaviour of the heart will also be modified. The model has to follow the changes of the cell properties. For example: a resting man suddenly jumps out of the bed. The controlling mechanisms start their adjustment, the values of model parameters will change;
- Fever and respiration frequency can also cause alterations;
- External events (the patient senses something annoying or pleasant) change the dependence between the previously measured signals, and the determined parameters. This is one of the causes why the perfect simulation of a human body is impossible. These factors strongly influence the behaviour of the

SA node. As the mechanism is not precisely known, the values of the model parameters cannot be determined in a deductive way.

4.3. Technical background

Nowadays, the performance of personal computers does not make possible the real-time determination of parameter values. The practical application is possible only in case of strongly parallel systems. The simplified model can be applied in real-time, but its efficiency is reduced because of the neglected parameters. The waveform of the simulated ECG (Szilágyi, 2000) in normal cases can be considered acceptable. The shape and duration of basic waves have realistic values. In case of abnormal cases the obtained waveform is not acceptable and more simulations are needed.

5. CONCLUSIONS

Regarding the fact, that computerized ECG (Szilágyi, *et al.,* 1996) diagnostics refer to several medical and technical problems, at the moment it cannot be applied as a standalone system. The short-term solution is the application of fuzzy systems and systems based on multi-agents that make possible, based on empirical information, to accomplish an adaptive advising system based on continuous transitions.

If a hybrid system (neuro-fuzzy and model-based approach, simultaneously) is built, it may become possible to learn the model via the knowledge of the traditional advising system, which, after a suitable learning process, will be able to replace gradually the old system (Benyó and Czinege, 1997).

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