

# Spatial Heart Simulation and Analysis Using Unified Neural Network

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## 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 kinds of tragic events, and by identifying the patients situated in the most dangerous states, to make it possible to apply a preventing therapy.

Creating a heart model is important (Thaker & Ferrero, 1998) as the computer, while applying traditional signal processing algorithms recognizes lots of waves, but it does not really “understand” what is happening. To overcome this, the computer needs to know the origin and the evolution process of the ECG signal (MacLeod & Brooks, 1998). During signal processing, if the traditional algorithm finds an unrecognizable 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 heart is a dynamic organ and places special demands on spatial techniques. To understand its physiology and pathophysiology, not only the electrical activity and spatial distribution of its structures is important, but also their movement during cardiac cycles. The measured ECG signal is influenced during repolarization by the mechanical movement of the heart.

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 electrocardiography, the inverse problem does not possess a mathematically unique solution and in order

to improve stability, it needs to adopt regularization techniques.

Several approaches have been explored to handle the problem of multiple solutions by using equivalent cardiac generators (such as equivalent dipole and multipole), heart surface isochrones (Cuppen & Oosterom, 1984), or epicardial potential (Guanglin & Bin, 2001). The high sensitivity of solutions to the different disturbances forced the investigators to explore regularization techniques (Shahidi, Savard, & Nadeau, 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 (Mirvis, 1988). BSPM may have a great advantage over the standard 12-lead system in different situations due to deeper accessible information. Mirvis (1988) has shown some cases of BSPM recordings that clearly demonstrate the inadequacies of the standard ECG lead sets in a variety of pathologies. As we know more about the depolarization-repolarization mechanism, we can understand better the internal function of the heart.

Many interesting biomedical applications of artificial neural networks are in the area of data processing (Minami, Nakajima, & Yoyoshima, 1999). The best known neural solutions involve multilayer perceptrons, Kohonen self-organizing networks, fuzzy or neuro-fuzzy systems, genetic algorithms, and the combination of various solutions within a hybrid system (Lagerholm, Peterson, Braccini, Edenbrandt, & Sornmo, 2000). A typical heart modeling system applies many neural networks and chooses the best one, while discarding

the rest. Most efficient approaches usually are based on the combination of many classifiers utilizing either different classifier network structures or different data preprocessing methods (Osowski & Hoai, 2001).

The support vector machine (SVM), pioneered by Vapnik (1998) assumed to solve the main drawbacks of conventional artificial neural networks (ANNs) such as:

- Modern biological problems are high-dimensional, and if the underlying mapping is not very smooth, the linear paradigm needs an exponentially increasing number of terms with an increasing dimensionality of the input space, which means an increase in the number of independent variables. This is known as “the curse of dimensionality.”
- The real-life data generation laws may typically be far from the normal distribution and a model-builder must handle this difference in order to construct an effective learning algorithm.
- The maximum likelihood estimator (and consequently the sum-of-error-squares cost function) should be replaced by a new induction paradigm that is uniformly better, in order to model properly non-Gaussian distributions.

The SVM classifiers became quite popular due to their robustness and stability (Osowski, Hoai, & Markiewicz, 2004). An SVM used in a heart modeling system is rigorously based on statistical learning theory and simultaneously minimizes the training and test errors. Apart from that, they produce a unique globally optimal solution and hence are extensively used in diverse applications including medical diagnosis (Smola & Cholkopf, 1998).

This article presents an event recognition study performed with ECG signal analysis and 3D heart model using unified neural networks (UNN). The main purpose is to evaluate the strength and weakness of each method and to analyze the cooperation efficiency in malfunction diagnosis.

## **MATERIALS AND METHODS**

### **Unified Neural Networks**

If we focus on the two-class classification case and consider linear discriminant functions, the respective

decision hypersurface in the  $n$ -dimensional feature space is a hyperplane that can be described as:

$$g(x) = w^T \cdot x + w_0 = 0 \tag{1}$$

where  $w = [w_1, \dots, w_n]^T$  is known as the weight vector and  $w_0$  as the threshold value. For a given vector  $x_d$ , if the function  $g(x_d) = 0$  than  $x_d$  situates on the decision hyperplane. The distance  $z$  of a vector  $x$  from the decision hyperplane can be represented as:  $z = \frac{|g(x)|}{|w|}$

$$, \text{ where } |w| = \sqrt{\sum_{i=1}^n w_i^2} .$$

In a classification problem, our purpose is the optimization of vector  $w$  in such a way, that the criteria function  $J(w)$  is minimized. Let  $\omega_1$  and  $\omega_2$  be the two classes that we have to separate. We assume that this task can be performed using a linear relation. This means

that there exists at least one such a  $w_{sol}$  hyperplane that fulfill the following relations:

$$\begin{aligned} w_{sol}^T \cdot x > 0 \text{ for } \forall x \in \omega_1 \\ w_{sol}^T \cdot x < 0 \text{ for } \forall x \in \omega_2. \end{aligned} \tag{2}$$

If we design a classifier, where the desired output is  $y_{des} = +1$  for  $\forall x \in \omega_1$  and  $y_{des} = -1$  for  $\forall x \in \omega_2$ , and try to modify weights in vector  $w$  in such a way that the criteria function  $J(w) = (y_{des} - x^T \cdot w)^2$  is minimized, than we have constructed a root mean square error based separator method.

A very popular classifier algorithm is based on SVM-s. The main concept incorporates the search for the “most robust solution” vector  $w_{sol}$  that gives the maximum possible margin. The margin is represented by the minimal distance:

$$z = \frac{|g(x)|}{\|w\|}$$

This means the minimization of  $\|w\|$ .

Although these methods deliver good results in a certain noise-free environment, in biomedical simulation such sterile conditions never occur. The main reason of this problem is caused by measurement errors and

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