BP-Neural Network based- characterization of Electrographic Magnetohydrodynamic Signals in MR

Yurong Xu[1], Zhifeng Wang[1], Fillia S. Makedon[1], Justin D. Pearlman[1+2]
[1]Department of Computer Science, Dartmouth College, Hanover, NH, USA
[2] Dartmouth Hitchcook Medical Center, Lebanon, NH, USA

Abstract—**Electrocardiographic (ECG) signal collected during magnetic resonance (MR) imaging is affected by signal artifact because magnetic fields produce competing signals, from moving conductors in the large vessels. That is called the magnetohydrodynamic effect, which makes it difficult to recognize ST-T changes from ECG signal collected in a magnetic field (MRI). Resolving that problem is important both for accurate triggering (elimination of false triggers from tall peaked T waves) and for monitoring (identifying if or when patient develops ischemia or myocardial injury). This paper describes an algorithm based on neural network that is designed to cancel this artifact for ECG signal acquired during MR imaging.**

Keywords—**Neural Network, ECG, magnetohydrodynamic effect, aorta model, Source separation**

I. INTRODUCTION

It is important in cardiac monitoring to collect accurate electrocardiogram (ECG) signal, but this is difficult in the presence of magnetic fields, e.g., during magnetic resonance (MR) imaging. A normal ECG signal can be separated into several components, which are called the P, QRS and T waves, and into segments (intervals), with special interest in the S-T segment (end of QRS to beginning of T) because it shifts vertically when the heart is ischemic (has inadequate blood supply). The magnetohydrodynamic effect consists of competing electric signals produced due to blood flow (mainly in the aorta and vena cava) in a strong magnetic field; the character of the ECG, especially the S-T segment and T wave, is modified by these artifacts.

There are a number of related problems: for example artifact corrections for stress ECG signals [1][2][3], but the magnetohydrodynamic problem (MHP) has distinct challenges and opportunities for solution.

Therefore, we examine a method to redress MHP based on Back-propagation (BP) neural network algorithm to characterize the electrograph signals collected during MR imaging. With a neural network algorithm, a training processing is required, but after training, applying the networks is computationally simple and fast.

II. MODEL OF ECG SIGNALS IN MAGNETIC FIELD

The MHP is produced primarily from competing electric signals produced by protons moving through the magnetic field in blood plasma [4]. Assuming that the strength of the magnetic field in MR is stable, this effect will depend on the speed of fluid, and also on the placement of the pair of electrodes whose potential difference produces ECG recordings.

Given a steady magnetic field $\vec{B}$, and a steady flow velocity $\vec{v}$, we can give a simple equation for the effect as following:

$$E = \left(\vec{v} \cdot \vec{B}\right) d$$

Where d is the distance between two reference electrodes, v is the velocity of blood flow in the great vessels, B is the strength of magnetism).

This can be rewritten as $\frac{\partial E}{\partial d} = \vec{v} \cdot \vec{B}$. The potential is proportional to both $\vec{v}$ and $\vec{B}$.

Our approach to minimizing this artifact is to isolate it by comparing different lead-pair ECG signals with distinct impact of MHP. Since the dominant blood flow occurs in the aorta and vena cava, which have orientation parallel to the spine, if we pick up ECG signals from the two positions on a human torso shown in Fig.1, we can get a pair of ECG signals, one with a large signal contribution from the aorta and the other with a very small contribution. By determining the effects induced in the former that are not present in the latter, we can arrive at a model for the artifact we wish to remove.

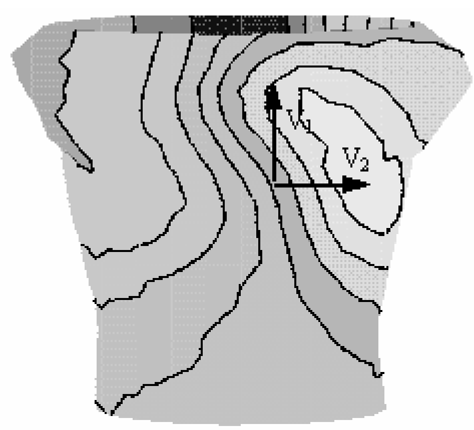

Fig.1 ECG data collection points and resulting sampling vectors (V_1 and V_2) on a human torso. One of these (V_1) is parallel to the direction of aortic blood flow, and the other (V_2) is orthogonal.

III. Methodology and Material

In order to characterize the ECG signal differences that occur in MR, we apply a neural network model. We have implemented a standard three-layer neural network with training *via* a back-propagation algorithm. There are three layers, including the input layer, output layer and hidden layer, as shown in Fig.2 (the middle layer is referred to as "hidden" because it does not directly connect to either the inputs or outputs of the system, which are shown graphically as the leftmost and rightmost columns of nodes)

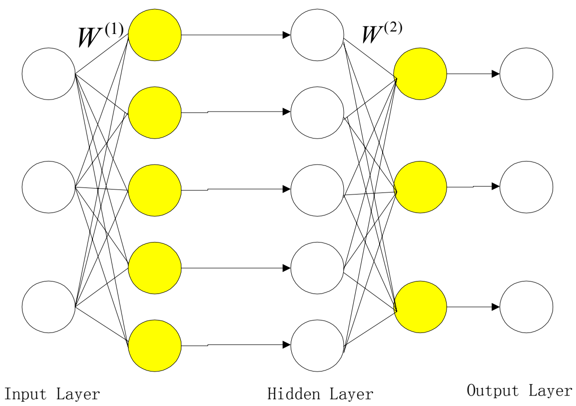

Fig.2 Neural Networks with Hidden Layer
Inputs (leftmost column) drive an input layer, which in turn causes propagation of information through weighted links ($W^{(1)}$), to a hidden layer; this layer then influences an output layer with additional weighted links ($W^{(2)}$), ultimately driving a set of outputs (rightmost column of nodes)

Given input node x_k, hidden node h_k and output node y_k, we can calculate the values of each of the latter two of these based on the earlier ones plus sets of weights, $w^{(1)}$ and $w^{(2)}$, between layers:

$$h_k = F^{(1)}[\sum_j w^{(1)}_{ij} \bullet x_i]$$

$$y_k = F^{(2)}[\sum_j w^{(2)}_{jk} \bullet h_k]$$

Given training set $\{x_n\}$ and desired target outputs $\{t_n\}$, to find $w^{(1)}$ and $w^{(2)}$ we minimize Networks Error, defined by

$$E = \sum_n |y(x_n) - t_n|^2$$

We use a standard back propagation algorithm to train this neural network. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as outputs are known. This algorithm is a generalization of the least mean squares approach, and modifies network weights to minimize the mean squared error between the desired and actual outputs of the network. The calculation of $w^{(2)}$ proceeds as follows:

$$\frac{\partial E}{\partial w^{(2)}_{jk}} = \frac{\partial E}{\partial y} \bullet \frac{\partial y}{\partial \sum} \bullet \frac{\partial(\sum_j w^{(2)}_{jk} \cdot h_j)}{\partial w^{(2)}_{jk}} = 2(|y-t|) \cdot F^{(2)}[\sum] \cdot h_j$$

$$w^{(2)}_{jk} = w^{(2)}_{jk} - a \bullet \frac{\partial E}{\partial w^{(2)}_{jk}} \quad \text{(here, } a \text{ is learning rate)}$$

A similar procedure is used to calculate $w^{(1)}$. Once trained, the network weights are identified as fixed values to be used to compute output values for new input samples.

The ECG signal reports voltage over time, periodically repeated. Different time delays within the cardiac cycle (known as cardiac phase) are not equivalent and should not be treated as random samples. If we train the neural networks directly with ECG signal this information would be lost.

In order to track cardiac phase, we add time sequence values to the training set as explicit values, as shown in Fig.3. Our training process uses both ECG signals obtained during MR imaging and a time sequence curve as input, with the desired output set to an ECG signals with substantive elimination of MHP.

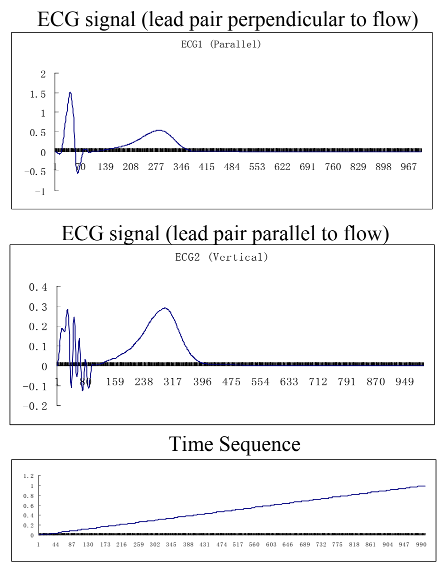

Fig. 3 Training data is constructed from ECG data with time-sequence information added

IV. Experiments and Results

As with any neural network implementation, one must decide how many nodes to include in the hidden layer is optimal, Fig.4 shows the relationship between the hidden node number and error, and Fig.5 shows the relationship between the hidden node number and training time.

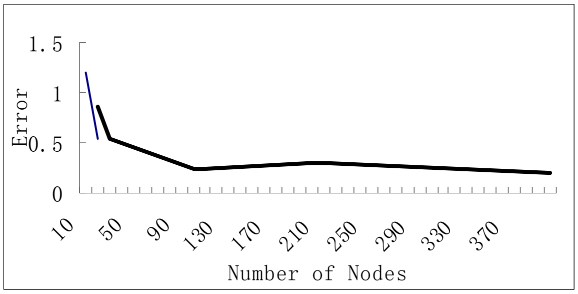

Fig.4 Network Error *vs*. number of hidden nodes.
The network error drops considerably when the ten first hidden nodes are added, further through first 100 nodes, then levels off. This indicates that n=100 works well for resolving MHP, and higher node number has no significant advantage

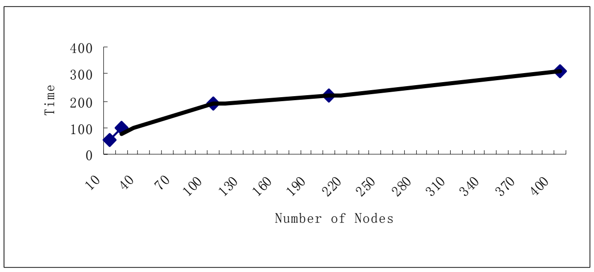

Fig.5 Training time *vs*. number of hidden nodes.
Increasing amounts of computation time are required when additional hidden nodes are added.

We selected 100 hidden nodes, based on the tradeoff of computing time and Error rate. Based on the above training set and neural networks, we got the result shown in Fig.6:

V. Conclusion

This demonstrates that a neural networks algorithm can resolve the MHP, to enable monitoring of the ST segment during MRI. The Neural network characterizes the relation between paraspinal to orthogonal ECG signals. We plan prospective testing for ability to identify myocardial ischemia severity in terms of ST segment displacement during MRI.

Acknowledgment

We thank Lynn H. Lee, Ling Gao, James Ford and the MRI technicians in DHMC for their assistance.

References

[1] Mary Anne D. Raya, Luis G. Sison, “Adaptive noise canceling of motion artifact in stress ECG signals Using Accelerometer”, Proceedings of the Seond Joint EMBS/BMES Confererence, Houston, TX, USA, Oct. 23-26,2002, pp1756-1757.

[2] N.V. Thakor and Y. Zhu, “Application of adaptive filtering to ECG analysis: noise Cancellation and arrhythmia detection”, IEEE Trans. Biomedical Engineering, Vol.38, Aug. 1991, pp785 -794.

[3] W.J.Tompkins and S.Luo, “Experimental study: brachial motion artifact reduction in the ECG”, IEEE Trans. Comouters in Cardiology, 1995, pp33-36.

4] Rosa, R. J. (1987). “Magnetohydrodynamic energy conversion”. Washington, Hemisphere Pub. Corp, 1987.

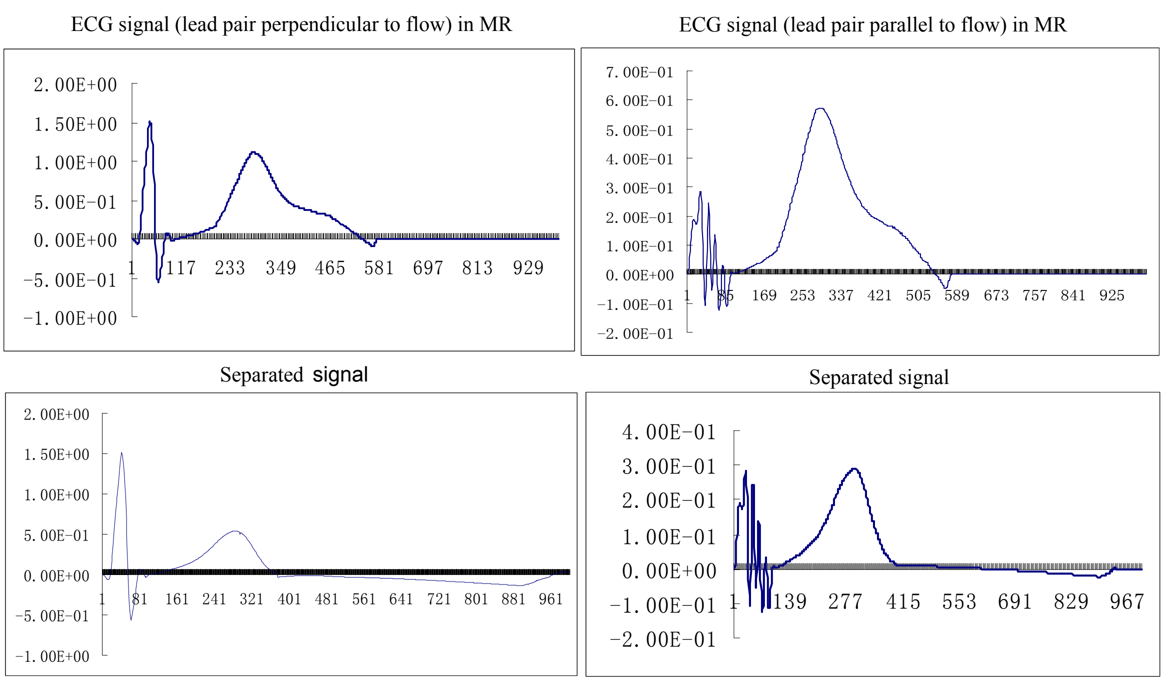

Fig.6 Results with neural network separation of artifact component from desired signal component.
In the above separated signals, it is clear that the artifacts are cancelled, though leaves some lower signal at the end range of it.