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Elimination of Heart Signal Baseline Wandering by Neural Network

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ABSTRACT : *In this paper, we propose artificial neural network approach for elimination of Electro Cardio Gram (ECG) baseline wandering. This technique uses self-organization feature map (SOM) technique without any disorder in important parameters such as ST-segment. Proposed technique not only eliminates base line divergence better than classic methods but also have lower disorder in ST-segment.*

Keywords: *ECG, SOM, neural network, baseline noise, ST-Segment.*

I. INTRODUCTION

In Cardiac Care Unit (CCU) nurse should pay attention to vital signals (heart, brain, etc.) of several patient continuously. Certainly supervising of them and quick decision-making will be difficult. Therefore it is necessary that an intelligent system contribute to human in decision-making. Noises in heart signals could be recognized by experienced doctors and they could analyze ECG signal without any problem. However, noise is so much important in correct diagnosis of disease with assistant machine. To recognize the heart function, it is essential that we know facts of heart physical activity which is possible by receiving of heart electrical signals which come to body surface [1]. Our object in this research is elimination of ECG baseline to better analyze of this critical wave.

This pre-processing is necessary for other essential processing to work correctly. These algorithm are such as ECG signal compression[2, 3], QRS complex detection[4, 5], heart rate Variability[6], ST segment analysis[7], arrhythmia diagnosing[8] and even arrhythmic elimination (by pace makers), Morphological Characteristics of P-Waves[9], Tele monitoring[10, 11], could be available by time analyses method, neural network method[12, 13], syntactic method[14], and Hidden Markov model[15]. Therefore, noises should be cleared from signal.

In this article, our contribution is decreasing of ECG baseline and comparison to classical techniques. This paper is organized as follows. In section II, two important types of noise in biomedical measuring and appraise current methods of baseline elimination are introduced. General reviewing of self-organization feature map is in section III. In section IV proposed algorithm are described. Experimental results of proposed method are shown in section V and conclusion is in section VI.

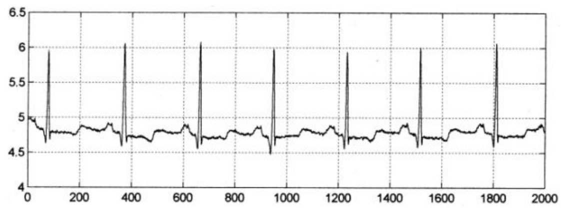
II. BASE LINE WANDERING NOISE AND ELIMINATION METHODS

A. Different types of noises

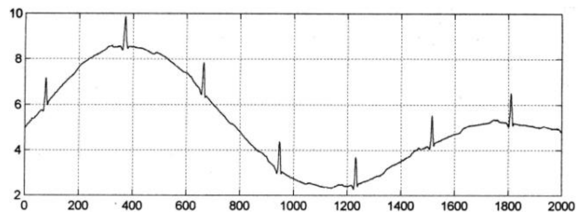
Noises in heart signal are divided into two groups in frequency.

- Disorders which have higher frequency compare with ECG signal. Disorder source alters signal by undesirable pulses which are called impulsive.
- Disorders which have lower frequency and could make slow changes in signal. This group of noises are called baseline wandering.

To eliminate of these kinds of noises, there are different methods such as time-based method [16], frequency-based method, neural network methods and so on. Fig. 1 shows a Normal ECG and a base line noisy signal.



(a) Normal ECG



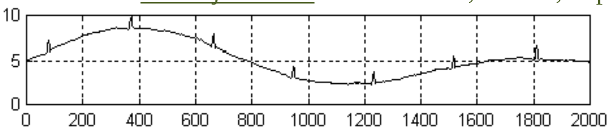
(b) ECG wave with base wandering noise

Fig. 1. Normal and base line wandering noise

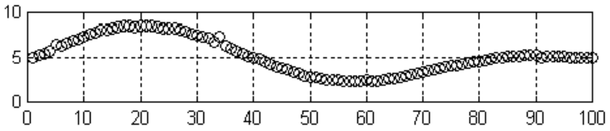
A. Base line elimination methods

Using of a low pass filter and a filter which could eliminate AC power frequency, remove of high frequency noise is not problematic. But for elimination of base line wandering, which has alternative and partial low frequency and unpredictable extent, find of an effective solution is necessary. Available base line wandering elimination methods include:

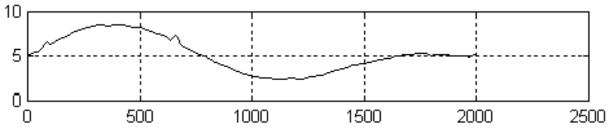
- Method I: getting of low rate samples from the wave and pass a curve (e.g. spline curve) through these points. The curve makes base line of wave, which by subtraction of ECG wave noise free ECG wave will be made. Figure 2(a) depicts an ECG wave with 2000 points. Low rate sampling, getting 100 points (5%), is shown in Fig. 2(b) and Fig 2(c) is predicting of base line. Figure 2(d) shows this method is not efficient. Because, some sample point are get from local picks of wave and it can not makes a noise free wave.



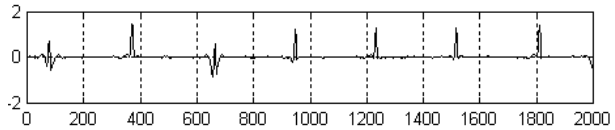
(a) Normal ECG signal with baseline noise



(b) Low sampling (5%)



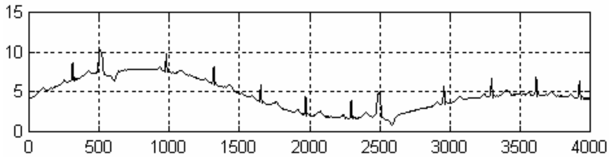
(c) Baseline estimation curve



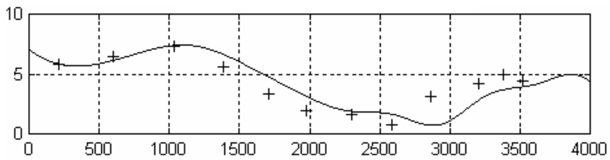
(d) Removing of baseline

Fig. 2. Baseline noise damping, Method I

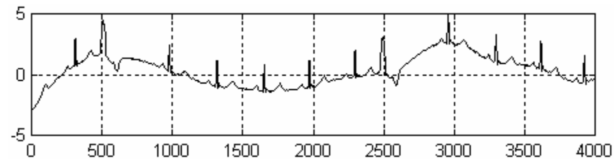
- Method II: This technique find beginning point of QRS complexes and then passes a curve (e.g. spline curve) through the obtained points. Other processing is similar to method I. Fig. 3(a) to 3(c) depict process of this technique. Figures show that this technique for abnormal wave, such as PVC wave, is not efficient.



(a) Arrhythmic ECG signal with baseline noise



(b) Detection of ECG beat's position and plotting of baseline estimation curve



(c) Removing of baseline

Fig. 3. Base line noise damping, Method II

III. ARTIFICIAL NEURAL NETWORK METHODS [17]

In recent years, many kinds of information processing have not any classic solution and could not be solved easily. One of these modern and experience based methods is Artificial Neural Networks (ANN) which transfer hide knowledge and rule of data to network structure by processing of experimental data. These intelligent systems learn general rules based on calculation of numeral data or examples and after training they could decide to solve a new problem and also they have very strong pattern recognition.

Competitive neural network as dependent detector of signal density

With random selection of inputs and apply them in network, after every repetition, winner cell weight vector moves towards input vector. Finally, each weight vector directs towards cluster point of some input vectors. In this competitive method, reference pattern is not available and weight vector of a cell is changed, in other words a row of weight matrix which is nearest to input vector tends to input vector. Therefore, each cell is represents a group of applied inputs.

Self-Organization Feature Map (SOM)

A. Introduction

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discredited representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighbourhood function to preserve the topological properties of the input space.

B. Learning algorithm

The training utilizes competitive learning. When a training example is fed to the network, its Euclidean distance to all weight vectors is computed. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU.

1. Randomize the map's nodes' weight vectors
2. Grab an input vector
3. Traverse each node in the map
   a. Use Euclidean distance formula to find similarity between the input vector and the map's node's weight vector
   b. Track the node that produces the smallest distance (this node is the best matching unit, BMU)
4. Update the nodes around BMU by pulling them closer to the input vector according to following by (1):

$$Wv(t + 1) = Wv(t) + \Theta(t)\alpha(t)(D(t) - Wv(t)) \qquad (1)$$

Where, t denotes current iteration, Wv is the current weight vector, D is the target input, Θ(t) is restraint due to distance from BMU, usually called the neighbourhood function, and α is learning restraint due to time.

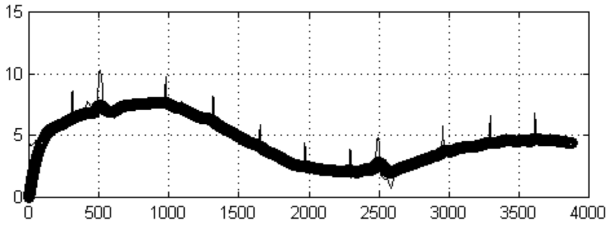
5. Increase t and repeat from 2 while $t < \lambda$

Where, λ is the limit on time iteration.

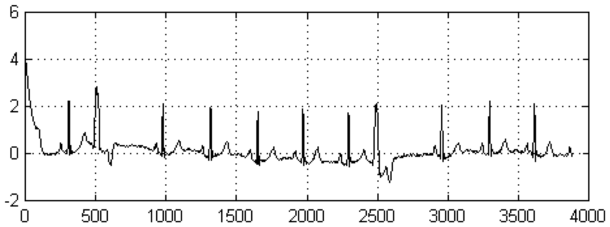
IV. DESCRIPTION OF PROPOSED METHOD

The main idea of this method is based on density of baseline, signal pause parts, which has more density than other part of ECG wave such as P, QRS complex and T waves. This means that quick and short time changes (such as QRS complex) could not allocate high quality of signal density. Therefore, after training by SOM algorithm, each neuron represents several near points of signal curve. Clearly, Fig. 4 depicts that, in a competitive system distribution of cells around the baseline is more than other part of wave.

This cells estimate baseline curve of ECG wave and by subtraction of noisy image from predicted baseline, elimination of baseline wandering without any damaging on other part of ECG wave, specially ST-segment, are attained. Figure 4 shows proposed noise elimination that its quality can be compared with other methods. For implementation of SOM, ratio of neurons number to wave vector dimension chose 1 to 40.



(a) Tracing of base line by neurons in SOM algorithm

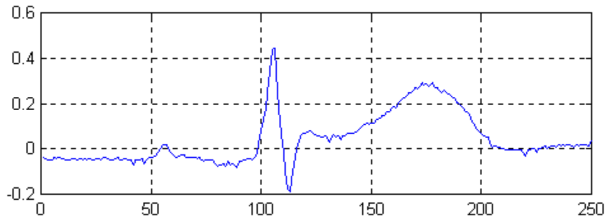


(b) Tracing of baseline by trained neurons in SOM and finding of base line curve

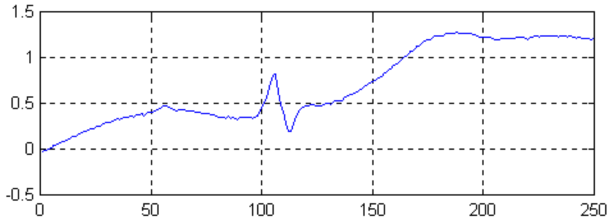
Fig. 4. Recovery of baseline by SOM method; proposed technique

V. Experimental Results

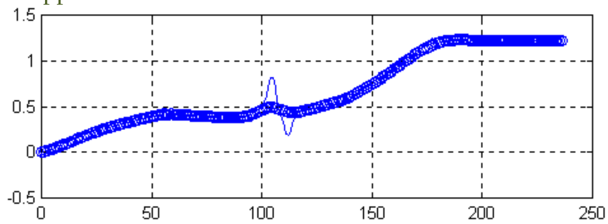
In order to show this method does not make any damaging on ST-segment, this technique was applied to one period of baseline wandered heart signal. Ratio of neurons was chose 1 to 10. Fig. 5(a) and 5(b) show normal and baseline noisy wave. Figure 5(c) depicts tracing of ECG wave baseline by neurons in SOM method. Finally, Fig. 5(d) depicts elimination of baseline wandering with least effect on ST segment according to other methods.



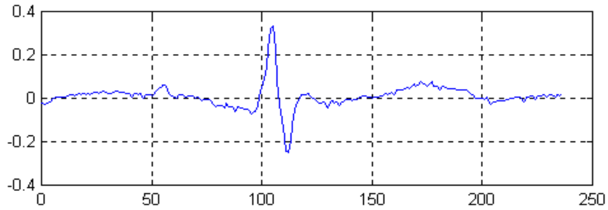
(a) One period normal ECG wave



(b) Base line noisy signal



(c) Tracing of baseline by trained neurons in SOM and finding of baseline curve



(d) Base line noise elimination with no damaged ST-segment

Fig. 5 Noise cancelation process in proposed method

VI. Conclusion

Method that we proposed in this paper is based on self-organization feature map (SOM) technique in neural network. Comparison with other methods it makes better removing of baseline wandering with least effect on ST segment. Furthermore, ratio 1:40 for neuron number to signal vector is enough for removing of baseline wandering.

VII. Acknowledgment

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