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신경망 ALE를 사용한 QRS complex의 증대

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Enhancement of QRS Complex using a Neural Network based ALE

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요 약 : 본 논문에서는 배경잡음이 섞여 있는 QRS 파의 증대를 위해 신경망에 근거한 적응라인증대기(ALE) 적용을 다루고 있다 Elman과 Jordan RNN 구조의 합성형태를 갖는 수정된 완전연결 리커런트 신경망이 ALE의 비선형 적응필터로 사용되고 있다. 신경망 노드사이의 연결계수와 이득, 기울기, 지연과 같은 노드 활성함수의 변수들이 기울기 강하 알고리즘을 사용하여 학습이 반복될 때마다 갱신된다 수정된 신경망은 먼저 미지의 선형과 비선형 시스템 identification을 수행함으로써 평가하였다 그리고 미약한 QRS를 증대시키기 위해서 적당한 크기의 잡음과 매우 심한 잡음이 포함된 실제의 ECG 신호를 비선형 신경망 적응필터를 사용하는 ALE에 입력하였다 수정된 신경망은 시스템 identification에 사용하기가 적합함을 확인하였으며, 시뮬레이션 결과에 의하면 신경망 ALE는 잡음 ECG 신호로부터 QRS 파를 증대를 잘 수행하였다.

Abstract : This paper describes the application of a neural network based adaptive line enhancer(ALE) for enhancement of the QRS complex corrupted with background noise Modified fully-connected recurrent neural network, which is the combined structure of Elman's and Jordan's RNNs, is used as a nonlinear adaptive filter in the ALE The connecting weights between network nodes as well as the parameters of the node activation function such as gain, slope, and delay are updated at each iteration using the gradient descent algorithm The modified network is firstly evaluated by performing the identification of unknown linear and nonlinear systems Then, the real ECG signal buried with moderate and severe background noise is applied to the ALE using a nonlinear neural network adaptive filter in order to enhance the weak QRS complex. It is verified that the modified network is suitable for use in system identification Simulation results also show that the neural network based ALE performs well the enhancement of the QRS complex from noisy ECG signals

Key words : QRS enhancement, Adaptive line enhancer, Noise modeling, Neural networks

Introduction

Detection of the QRS complex is one of the most important tasks in ECG signal analysis. After identifying the QRS beats, the heart rate calculation for modeling cardiac, the ST-segment examination for evidence of ischemia, or the waveform analysis for classifying normal or abnormal can be done[1]. For the ECG signal corrupted with noise, the preprocessing such as enhancement of the QRS complex and cancelation of background noise is required to improve the signal-to-noise ratio of the wanted wave embedded in noise like other signal processing applications[2,3].

A number of QRS detectors which work well in the presence of moderate noise have been designed[4,5]. The widely used method to detect the QRS wave includes bandpass filtering, squaring, averaging, and then thresholding. The ECG, however, is a nonlinear signal generated from a time-varying nonlinear system, i.e., human body Thus, we encounter with the following problems; the frequency band of the QRS complex may be different for

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different subjects and even for different beats of the same subject. The frequencies of the noise and the QRS complex partially overlaps each other In addition, under the improper environment the measured ECG signal accompanies severe background noise that has wideband frequency components.

Various adaptive filtering schemes have been used to achieve these tasks[6,7,8]. For examples in biosignal processing, they are applied to enhance EEG signals in the presence of ECG artifacts and to detect fetal ECG severely contaminated by the maternal cardiac signals. In these schemes, the coefficients of the adaptive filter are updated using adaptive algorithms such as the least mean square(LMS) or the recursive least square algorithms The LMS algorithm has been generally used because of simple structure and easy to implement These papers use the adaptive noise canceller (ANC) scheme in which an additional reference input is applied to the linear adaptive filter. However, this linear structure and adaptive algorithm is not suitable to process the signals of nonstationary or nonlinear characteristics, i.e., it may not appropriate to deal with the QRS complex embedded in wideband random noise

Neural networks have been successfully applied to more complex signal processing Since the neural networks consist of distributed neurons to process nonlinearity and have the ability to learn from its environment, neural network-based filtering methods are potentially useful for time-varying signals with inherent nonlinearity The ECG signal generated from nonlinear system is difficult to adapt to a linear model In other words, it cannot be whitened much by a linear adaptive filter Lately the periodic or quasi-periodic signals with an additive noise are detected or enhanced using the filter structure of neural networks[9,10] The QRS beats is considered as a quasi periodic signal

This paper presents an off-line method for enhancing the QRS complex buried in background noise using the ALE scheme with a neural network adaptive filter The ALE is a special form of the ANC that is designed to suppress the wideband noise components of the input, while passing the narrow-band signal components with little attenuation. The objective of this paper is to enhance the weak QRS beats under the presence of moderate or severe background noise It assumes, however, that only a signal including both the QRS complex and background noise is available.

In this paper, we used the modified recurrent neural networks(MRNN) as a nonlinear adaptive filter The fully connected MRNN is the combined structure of both the Elman's and the Jordan's RNNs with one-to-many variable connections[11-13] Jordan developed a network model capable of displaying temporal variations and temporal context dependence In Elman networks, rather than the outputs of the network being fed into the input units as in Jordan's model, the activation results of the hidden units are fed into the input units While the Jordan's RNN has appeared in a variety of control applications, the Elman's RNN has been often applied to the problem of symbolic sequence prediction

The connecting weights as well as the gain and slope of the node activation function are updated with the error backpropagation algorithm An adaptively tuned multilayer neural network is used to model the nonlinear, time-varying background noise. We expect in the QRS enhancement that the neural network model predicts non-QRS portions of the signal better than the QRS complex itself. In other words, the neural network based nonlinear adaptive filter can recognize the quasi-periodic characteristics of the ECG activity by attenuating white background noise. To improve the possibility of the QRS enhancement of normal heart beats with severe background noise, the highpass filter, if necessary, can be used as a preprocessing stage in order to reduce the effect of the neural networks due to the low frequency components.

For the evaluation of the modified network, we compared the MRNN with a conventional RNN by performing linear and nonlinear system identification with the test signal of the artificially generated Gaussian random noise. In the experiment of the QRS enhancement, we used the real ECG signals with background noise Simulation results indicate that the modified MRNN is more suitable for the system identification than the RNN It also shows that the MRNN based ALE enhances well the weak QRS complex under the presence of moderate or severe background noise in real ECG data.

Neural network based ALE

Fig. 1 shows the structure of the ALE that can be used to enhance quasi-period QRS beats buried in wideband background noise The ALE has only a primary input $x(l)$ unlike the ANC in which two inputs of primary and reference signals are used. Instead of being derived separately, the reference input $x(l-M)$ to the adaptive filter is obtained from the primary input by inserting a delay such that the required decorrelation of noise components is achieved. This delay called decorrelation delay plays a role to remove the correlation between the noise of the primary input and one of the reference input.

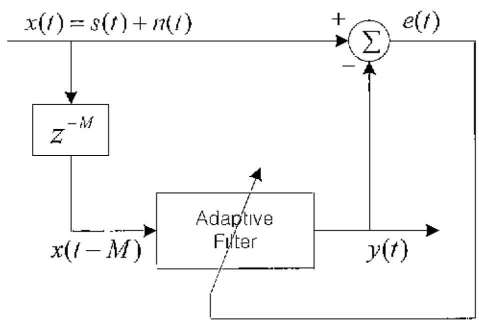


Fig. 1. Adaptive line enhancer

The objective of the ALE is to enhance a wanted signal $s(t)$ in the measured signal $x(t)$ that is contaminated with additive noise $n(t)$.

$$x(t)=s(t)+n(t) \tag{1}$$

For the detection of ECG beats, the signal $s(t)$ represents the QRS complex, and the noise $n(t)$ represents all other components of the ECG signal including the P and T waves, additive instrument noise, power interference, and electromyographic noise. These time-varying noise components are often correlated, i.e. they are colored noise.

For the enhancement of weak QRS waves in severely contaminated background noise, a noise removal filter is required to reduce the correlation components in the noise. Among many other noise removal filters, a linear adaptive autoregressive modeling technique is very suitable for real-time processing of ECG signals. In this model, it assumes that the sampled data $n(t)$ from the colored noise process of background signal at time t can be predicted by a linear combination of previous q data samples $\{n(t-i)\,|\,i=1,\cdots,q\}$.

$$n(t)=\sum_{i=1}^{q} w(i)n(t-i)+\varepsilon(t) \tag{2}$$

where $\{w(i)\,|\,i=1,\cdots,q\}$ is the set of filter parameters, and $\varepsilon(t)$ is the modeling error which gradually approximated white noise if the model is correct. It is observed that the QRS complex waveform consists of relatively high frequency components. Hence, by selecting the proper length q, the filter can be adjusted so that it does not predict the QRS complex $s(t)$. Therefore, when the signal $x(t)$ is applied to the filter, a large prediction error signals the presence of a desired QRS complex. After the delayed signal of $x(t)$ is applied to the filter, the output is

$$\begin{aligned} y(t) &= \sum_{i=1}^{q} w(i)x(t-i) \\ &= \sum_{i=1}^{q} w(i)s(t-i)+\sum_{i=1}^{q} w(i)n(t-i) \\ &= \hat{s}(t)+n(t)-\varepsilon(t) \end{aligned} \tag{3}$$

where $\hat{s}(t)$ is the distorted QRS complex after passing through the filter. As long as the observation window length q is kept small enough so that the high frequency components in $s(t)$ are not modeled by the set of filter parameters $w(i)$, the $\hat{s}(t)$ is equivalent to the $s(t)$ since the background noise $n(t)$ is well predicted from the previous noise $n(t-i)$. If the background noise consists of white noise, i.e., $n(t)=\varepsilon(t)$, the $\hat{s}(t)$ is almost same as $s(t)$.

In order to cope with the time varying nature of the background noise in QRS enhancement, the adaptive LMS algorithm has been used to compute filter coefficients. Due to the nonlinearity inherent in the background noise processes, the effectiveness of such a linear model to perform the QRS complex enhancement may still be very limited. What is needed is to choose a method to accurately model the nonlinear relationship that exists among the samples of the background noise processes. Thus, our approach for dealing with the inherent nonlinearity of the ECG signal is to replace the linear adaptive filter with a neural-network-based nonlinear adaptive filter.

Recently, a number of neural networks have been studied and implemented for signal processing, including noise cancellation. Neural networks can be classified into static and dynamic networks based on their structures and input-output presentation. For the higher degree of signal processing, dynamic neural networks such as time-delay neural networks and recurrent neural networks are adequate models. They use feedback loops or delayed elements as memories in order to process temporal information, thus can perform well the more complex signal processing. The neural network used as an adaptive filter in this paper is the combined structure of both the Elman's and the Jordan's RNNs.

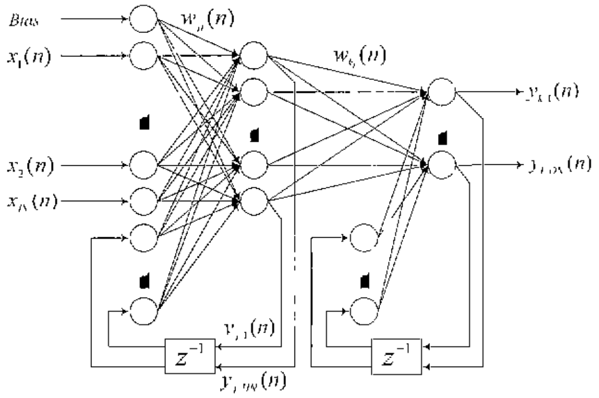


Fig. 2. Modified recurrent neural networks

Fig. 2 shows the modified fully connected MRNN. It consists of three layers. All the units in a layer are connected to all the units in the following layers In the input layer, it has external inputs and additional inputs that are fed from all neurons of the hidden layer. In the hidden layer, it has nodes connected to the input layer, and additional nodes that are fed from all neurons of the output layer. These additional inputs are also fully connected to every other node in the next layer of the network, i.e they are one-to-many variable connecting weights These recurrent connections improve the dynamics of the neural networks in order to efficiently process temporal characteristic of the signal.

In the learning of the network, the connecting weights as well as the gain, slope, and delay of the node activation function are updated with the error backpropagation algorithm. All processing neurons in the hidden and output layers use a sigmoid transfer function as the activation function. The output of the node k is defined as

$$y_k(n) = f(net_k) = \frac{g(n)}{1+e^{-s(n)(net_k - v'(n))}} \tag{4}$$

where net_k is the internal state of a neuron and $g(n)$, $s(n)$, and $v'(n)$ represent the gain, slope, and delay of the activation function, respectively They are considered as time-varying parameters in this network. The inputs ($z_i(n)$ and $z_j(n)$) and outputs ($y_j(n)$ and $y_k(n)$) of the hidden and output layers of the network are

$$z_i(n) = \{bias, x_1(n), \cdots, x_{IN}(n), y_{j,1}(n-1), \cdots, y_{j,HN}(n-1)\} \tag{5}$$

$$z_j(n) = \{y_{j,1}(n), \cdots, y_{j,HN}(n), y_{k,1}(n-1), \cdots, y_{k,ON}(n-1)\} \tag{6}$$

$$y_j(n) = f(v_j(n)) = f\Big(\sum_{i=1}^{K_1} w_{ji}(n)\, z_i(n)\Big), \quad K_1 = IN - HN + 1 \tag{7}$$

$$y_k(n) = f(v_k(n)) = f\Big(\sum_{j=1}^{K_2} w_{kj}(n)\, z_j(n)\Big), \quad K_2 = HN + ON \tag{8}$$

where $v_j(n)$ and $v_k(n)$ represent the internal states of neurons of the hidden and output layers, IN, HN, and ON are numbers of neurons of input, hidden and output layers.

The error of the network is as follows

$$E(n) = \frac{1}{2}\sum_k e_k^2(n) = \frac{1}{2}\sum_k (d_k(n) - y_k(n))^2 \tag{9}$$

The purpose of the training algorithm is to reduce the error, $E(n)$ by adaptively adjusting weights $w_{ji}(n)$, $w_{kj}(n)$ and parameters $g(n)$, $s(n)$, and $v'(n)$ The changes of the weights and parameters are defined and obtained as follows

$$\Delta w(n) = -\eta_w \frac{\partial E(n)}{\partial w(n)} = \eta_w \delta(n) y(n) \tag{10}$$

$$\Delta g(n) = -\eta_g \frac{\partial E(n)}{\partial g(n)} = \eta_g e_k(n) \frac{\partial f(v(n))}{\partial g(n)} \tag{11}$$

$$\Delta s(n) = -\eta_s \frac{\partial E(n)}{\partial s(n)} = \eta_s e_k(n) \frac{\partial f(v(n))}{\partial s(n)} \tag{12}$$

$$\Delta v'(n) = -\eta_{v'} \frac{\partial E(n)}{\partial v'(n)} = \eta_{v'} e_k(n) \frac{\partial f(v(n))}{\partial v'(n)} \tag{13}$$

$$\delta(n) = -\frac{\partial E(n)}{\partial v(n)} = e_k(n) \frac{\partial f(v(n))}{\partial v(n)} \tag{14}$$

Above equations shows the incremental weights and parameters of the output layer The weights and parameters of the hidden layer can be derived the same way as those of the output layer. The η (η_w, η_g, η_s, $\eta_{v'}$) represents the update rate for each parameter The momentum term is added to change only the connecting weights to speed up the learning. The incremental connecting weights $\Delta w(n)$($\Delta w_{kj}(n)$, $\Delta w_{ji}(n)$) and the parameters ($\Delta g_k(n)$, $\Delta g_j(n)$, $\Delta s_k(n)$, $\Delta s_j(n)$, $\Delta v'_k(n)$, $\Delta v'_j(n)$) of the activation function are updated at every iteration in the training process

The conventional RNN used for the relative comparison in this paper has only feedbacks from nodes of the hidden layer to the input layer and its training algorithm updates the connecting weights, not the parameters of neurons.

Experimental results

The MRNN is tested for system identification to evaluate its performance by comparing with conventional Elman type RNN. Then, the real ECG signal corrupted with moderate and severe background noise is applied to the ALE using MRNN based adaptive filter in order to enhance the weak QRS complex.

1. System Identification

The performance of the neural networks in the system identification is checked by the linear and nonlinear unknown system models. The suggested approach for the purpose of this discussion is shown in Fig. 3. In this figure, the artificially generated random input sequence to the unknown system is taken to be zero mean value and is also supplied to the neural networks. The training procedure allows the network to settle with the estimated optimum weights using input and output signal pairs such as $\{(d_k), (s_k, s_{k-1}, \cdots, s_{k-N})\}$, $k=1,2,\cdots,L$ where L is the length of training data. In the training procedure, $d_k(n)$ is used as a target signal, and input signal vector $s_k(n)$ and recurrent connections from the hidden layer are used as input signals. This approach can be applied to identify both linear and nonlinear time invariant systems without any change in the architecture because the network is capable of synthesizing nonlinear mappings as well as linear ones.

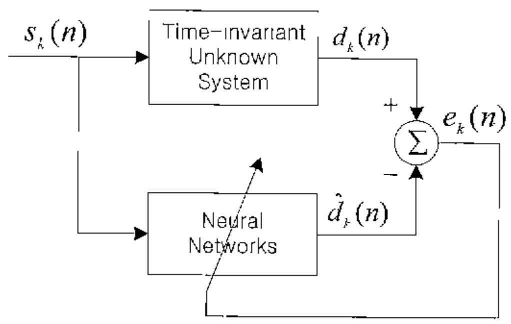


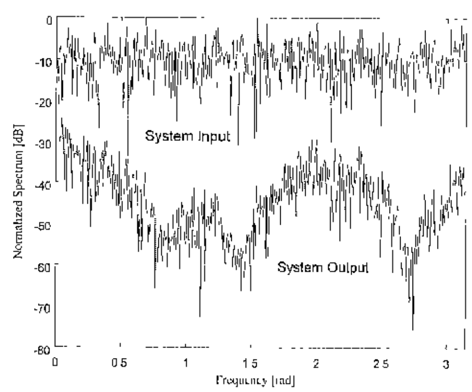
Fig. 3. System identification using neural networks

As an example of linear system identification, we used the following time invariant system such as a filter.

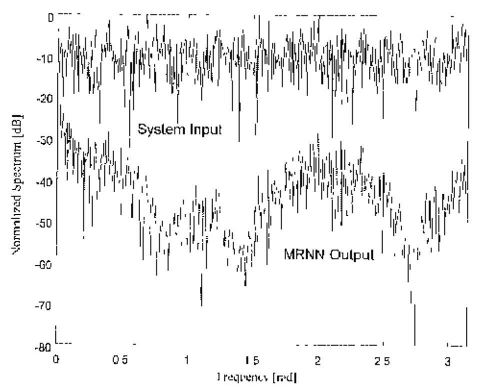
$$d_k(n) = 0.921 s_k(n) + 0.107 s_{k-1}(n) + 0.336 s_{k-2}(n) + s_{k-3}(n) + 0.336 s_{k-4}(n) + 0.107 s_{k-5}(n) + 0.921 s_{k-6}(n) \quad (15)$$

The input signal $s_k(n)$ to this unknown system is a white Gaussian random signal which has zero mean and a standard deviation of 1.0. In the training procedure, 2500 and 2000 iterations of 1000 samples of input/output pairs were performed to reach stable convergence for the RNN and the MRNN, respectively. The learning and the momentum rates of 0.7 were used for both networks and the gain and slope rates of 0.4 were used for the MRNN. Since the delay parameter of the activation function does not affect much the performance, it is not updated in the network.

Based on experiments, it is verified that both networks identify well the linear system. Fig. 4 shows the normalized power density spectra of the input signal, linear system output, and MRNN output. Since the RNN output, not drawn in the figure, shows similar result to the MRNN output, it cannot be distinguishable visually the overall difference between both networks. Fig. 5 shows the enlargement of frequency spectra of RNN and MRNN outputs from 1.225[rad] to 1.508[rad] frequencies. From this figure, we can identify the qualitative difference between networks. The performance of the MRNN is better than the RNN since the MRNN output is more close to the linear system output.

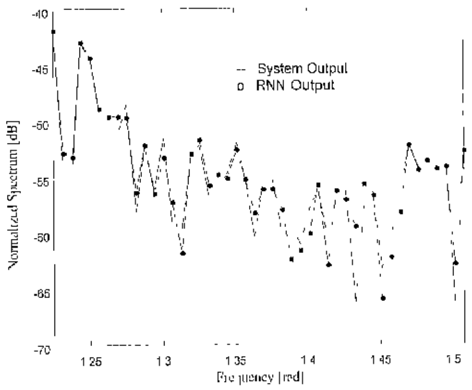


(a) System input and linear system output

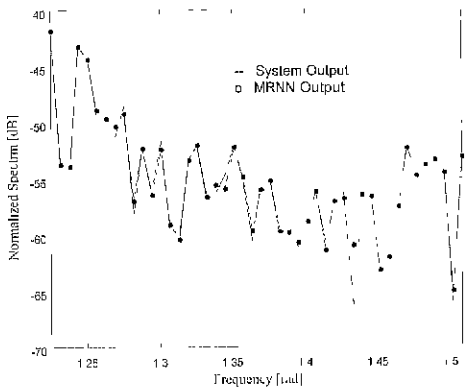


(b) System input and MRNN output

Fig. 4. Normalized power spectrum density of linear system output and MRNN output



(a) RNN



(b) MRNN

Fig. 5. Enlarged power spectrum density between 1.2 [rad] and 1.5[rad]

For the quantitative comparison, we calculate errors in time and frequency domains using the following equations

$$t\_err = \sum_k |d_k(n) - \hat{d}_k(n)| \quad (16)$$

$$f\_err = \sum_k |\,|fft(d_k(n))| - |fft(\hat{d}_k(n))|\,| \quad (17)$$

where $d_k(n)$ and $\hat{d}_k(n)$ are outputs of the system and the neural network, respectively. The average of 5-times trials for the RNN and the MRNN is t_err=1.5323, f_err=30.2952 and t_err=0.9200, f_err=17.0792. The system identification using the MRNN improves 1.6655 times in time domain and 1.7738 times in frequency domain better than ones using the RNN.

As an example of nonlinear system identification, we used the system with the following difference equation.

$$d_{k+1}(n) = 0.15d_k(n) + 0.3d_{k-1}(n) + 0.6s_k^3(n) + 0.18s_k^2(n) - 0.24s_k(n) \quad (18)$$

The learning, momentum, gain, and slope rates are 0.8, 0.8, 0.4, and 0.4, respectively. The number of iterations is 6000 for the RNN and 3000 for the MRNN. Using eqs. 16 and 17, we get the following results, t_err=0.4000, f_err=10.2842 for the MRNN, t_err=0.5807, f_err=19.2721 for the RNN. The MRNN performs 1.4518 times in time domain and 1.8740 times in frequency domain better than the RNN. The performance of nonlinear system identification between the RNN and the MRNN is almost same as the case of linear system identification. These results indicate that the modified neural network is more suitable for use in both linear and nonlinear system identification.

2. Enhancement of QRS complex

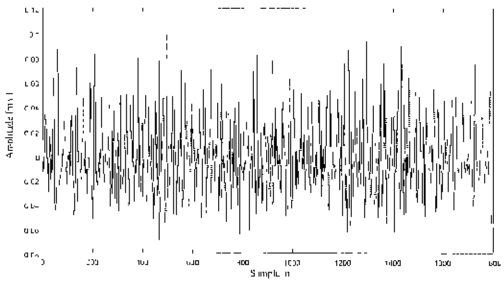
We used the real ECG data, which had been collected at HST (Health Sciences and Technology) division of the Harvard-MIT[14]. All ECG data was measured using the CH2000 (Cambridge Heart Inc.) system with the sampling rate of 300[Hz]. This system is capable of performing on line analysis for microvolt level T wave alternans.

The network structure and the value of update rates used in the experiment are as follows. For both cases of the moderate and severe noise, the numbers of neurons of input, hidden, and output layers are 5, 9, and 1, respectively. The delay M is set to 5. The learning rate of 0.7, the momentum rate of 0.7, the gain rate of 0.3, the slope rate of 0.3, and the iteration number of 2000 are used. Since the delay parameter does not affect the performance of the network, it is not used in the experiment. These structure and update rates are determined experimentally.

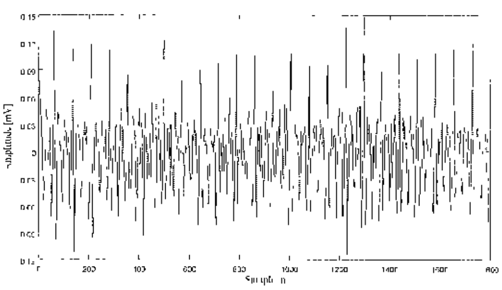
Fig. 6 shows the enhancement of the QRS complex from the ECG signal severely corrupted with background noise. We cannot identify the QRS complex from the original ECG signal (Fig. 6(a)). The output of the nonlinear adaptive filter is shown in Fig. 6(b). The QRS complex is clearly distinguished from background noise. This explains that the neural network based adaptive filter removes background noise fairly well. Since the frequency components of the QRS complex and background noise are overlapped, the QRS complex is somewhat affected while filtering. However, the signal to noise ratio is apparently increased. For the relative comparison of filtering performance, the same ECG signals is applied to the tapped-delay line(TDL) filter structure using LMS algorithm and its filtering result is shown in Fig. 6(c). The parameters such as $M=5$, number of taps=10 and step size=0.03 are used in linear filtering. The LMS algorithm is repeated 400 times on the same signal. The performance of noise rejection in the LMS algorithm does not improve any more after 300 iterations. From the figure, it is identified that the neural network based non-linear adaptive filter using error backpropagation algorithm outperforms the TDL linear adaptive filter using the LMS algorithm. The backpropagation algorithm can be considered as an extension of the LMS algorithm for nonlinear units, since both techniques use a gradient descent algorithm.

Fig. 7 shows the frequency spectra of the original ECG signal and the output of the MRNN based adaptive filter for the severely corrupted ECG signal of Fig. 6(a). Fig. 7(a) and 7(b) compare the spectra between 0.02 π and 0.2 π, between 0.2 π and π. The solid and dotted lines represent normalized frequency spectra of the original and MRNN filtered ECG signals, respectively. As shown in the figures, higher frequency components of the background noise are greatly reduced while the major components of the QRS complex are still keeping with reduced amplitude.

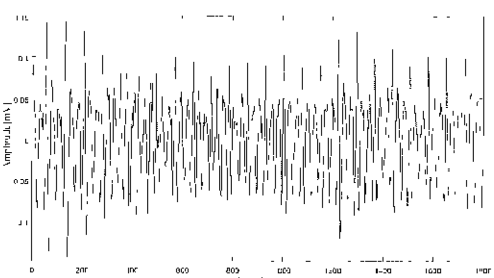
Fig. 8 shows the enhancement of the QRS complex from the ECG signal under moderate background noise. The ALE makes the QRS complex more apparent comparing with the original ECG signal, resulting in easy detection of the QRS complex. We also identified that the higher frequency components of the original ECG signal were reduced, similar to the case of severe background noise. These simulation results indicate that the MRNN based adaptive filter scheme in the ALE is effective filter structure to enhance the QRS complex by removing higher frequency components of the background noise.



(a) Original ECG, sample interval $\Delta n = 1/300$[sec]

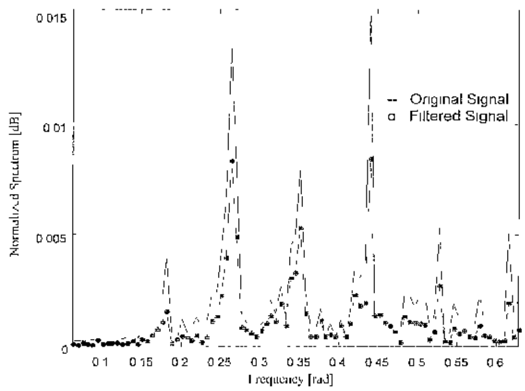


(b) MRNN filtered ECG, $\Delta n = 1/300$[sec]

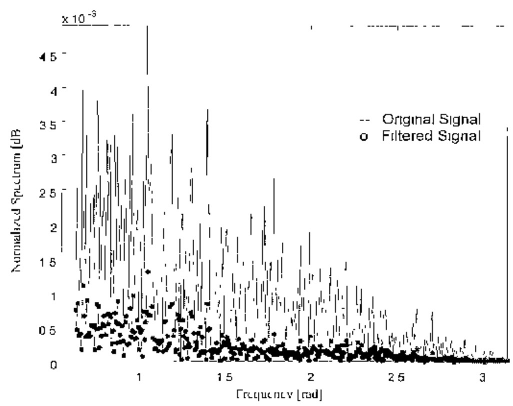


(c) LMS filtered ECG, $\Delta n = 1/300$[sec]

Fig. 6. QRS enhancement under severely corrupted noise

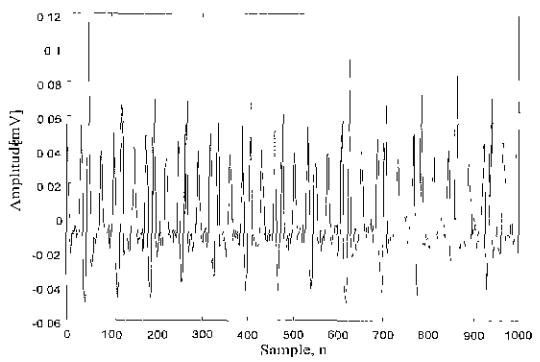


(a) Frequency range, $0.02\pi - 0.2\pi$[*rad*]

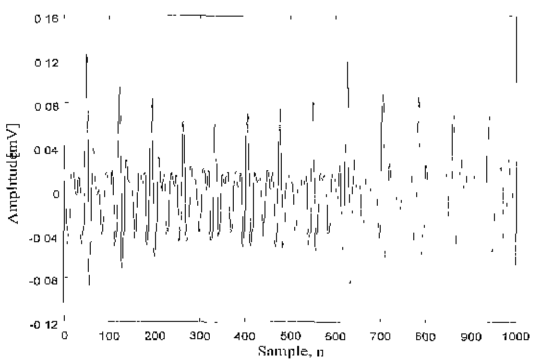


(b) Frequency range, $0.2\pi - \pi$[*rad*]

Fig. 7. Comparison of normalized spectrum density of original and filtered ECG signals under severely corrupted noise



(a) Original ECG, $\Delta n = 1/300$[sec]



(b) MRNN Filtered ECG, $\Delta n = 1/300$[sec]

Fig. 8. QRS enhancement under moderate corrupted noise

Conclusions

This paper describes the enhancement of the weak QRS complex from the ECG signal corrupted with background noise using the neural network based ALE. Firstly, the performance of the modified recurrent neural networks is evaluated by identifying the unknown linear and nonlinear systems. Then, the noisy ECG signals are applied to the ALE using the MRNN nonlinear adaptive filter in order to enhance the QRS complex. It is shown from the experimental results that the adaptively tuned MRNN models well the nonlinear and time-varying wideband random noise. Thus, the modified neural network based ALE has been proved to be effective structure to enhance the weak QRS complex by reducing background noise from the corrupted ECG signal. It is also verified that it consistently outperforms the conventional linear adaptive filtering approach.

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