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Original Research Article

A segment-wise reconstruction method based on bidirectional long short term memory for Power Line Interference suppression

Yue Qiu, Kejie Huang *, Feng Xiao, Haibin Shen

Institute of VLSI Design, Zhejiang University, 38 Zheda Road, Hangzhou, Zhejiang Province, PR China

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ABSTRACT

The overlap between the signal components of Power Line Interference (PLI) and biomedical signals in the frequency domain makes the filtered results prone to severe distortion. Electrocardiogram (ECG) is a type of biomedical electronic signal used for cardiac diagnosis. The objective of this work is to suppress the PLI components from biomedical signals with minimal distortion, and the object of study is mainly the ECG signals. In this study, we propose a novel segment-wise reconstruction method to suppress the PLI in biomedical signals based on the Bidirectional Recurrent Neural Networks with Long Short Term Memory (Bi-LSTM). Experiments are conducted on both synthetic and real signals, and quantitative comparisons are made with a traditional IIR notch filter and two state-of-the-art methods in the literature. The results show that by our method, the output Signal-to-Noise Ratio (SNR) is improved by more than 7 dB and the settling time for step response is reduced to 0.09 s on average. The results also demonstrate that our method has enough generalization ability for unforeseen signals without retraining.

1. Introduction

Power Line Interference (PLI) is one of the main noises in biomedical signals. The elimination of PLI is usually the first step of preprocessing the biomedical signals acquired by sensors. However, the overlap components in the frequency domain can introduce significant distortion in the filtering process. Thus, it is intractable to suppress the PLI resided in the biomedical signals without corrupting the useful components, and the amplitude and frequency deviations of PLI always make the problem more challenging.

In this study we focus on the task of PLI suppression in Electrocardiogram (ECG) signals, which is a classic problem in the literature for years. The difficulty of this problem is the filtering distortion in the scope of QRS complex, where the ECG signal components overlap the PLI in the frequency domain.

Numerous works have been done for the PLI suppression. The classical methods are based on notch filters [1], which is dependent on the analysis of the signals in the frequency

* *Corresponding author at*: Institute of VLSI Design, Zhejiang University, 38 Zheda Road, Hangzhou, Zhejiang Province, 310027, PR China
E-mail addresses: yueq235@zju.edu.cn (Y. Qiu), huangkejie@zju.edu.cn (K. Huang), xiao_feng@zju.edu.cn (F. Xiao), shen_hb@zju.edu.cn (H. Shen).

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domain. Wavelet transform [2] and empirical mode decomposition [3] are also popular methods, which decompose the signal into multiple independent components to distinguish the PLI components with the others. Adaptive filters [4,5] are also good solutions for this problem, despite that each sample needs an external reference signal for gradually convergence, which is unavailable in some situations. Methods based on artificial neural network has also been attempted to solve the problem from a different perspective [6]. Moreover, advanced signal processing algorithms, like Kalman filter and its variants, are also applied [7].

To further minimize the distortion caused by the process of filtering PLI, we propose a novel segment-wise reconstruction method based on Bidirectional Recurrent Neural Networks with Long Short Term Memory (Bi-LSTM) [8,9] to suppress the PLI. The Bi-LSTM model serves as the kernel of the proposed algorithm to extract the coefficients of the PLI components from the input signals, which are then used for the reconstruction of PLI. The technique of Bi-LSTM has been proved to be a powerful method for sequential and nonlinear dynamic analysis in the field of machine learning. It has been widely applied to numerous problems involving sequential data analysis and nonlinear modeling, such as speech recognition and handwriting recognition, and remarkable performance has been achieved [10,11]. The bidirectional architecture of the Bi-LSTM can take full advantage of the historical information across the processed points, leading to improved capability of nonlinear approximation.

We compared our method with a traditional IIR notch filter and two state-of-the-art algorithms in the literature: the fixed-lag Kalman smoother in [7] and the ensemble empirical mode decomposition-based algorithm in [3], from different respects. Experiments are mainly conducted on ECG signals for comparability. The results demonstrate that by our proposed method, the output Signal-to-Noise Ratio (SNR) is improved by more than 7 dB and the settling time for step response is reduced to 0.09 s on average. Furthermore, the experiment results show that our method has enough generalization ability for unforeseen input signals without retraining and can be directly applied to other kinds of biomedical signals. We provide the examples of Electroencephalography (EEG) and abdominal Fetal Electrocardiogram (FECG).

The rest of this paper is organized as follows. Section 2 describes our proposed method in detail and Section 3 provides the data acquisition and settings of our experiments. Sections 4 and 5 provide the experiment results and the discussion. Finally, the conclusion is drawn in Section 6.

2. Method

2.1. *Bidirectional Recurrent Neural Networks with Long Short Term Memory (Bi-LSTM)*

Bidirectional Recurrent Neural Networks with Long Short Term Memory units (Bi-LSTM) is a popular technique in the field of deep learning. The Recurrent Neural Networks (RNN) is famous for solving sequential nonlinear problems in recent years. The recurrent connections between neurons provide the network the inherent recurrent and causal architecture, which enables the model to transform the acquired historical information into expected results. Soon afterwards, researchers found that the bidirectional version of the RNN can provide accumulated information both before and after the processed points, which brings big improvements for the problems involving contextual relationship [8]. The unrolled structure of Bidirectional RNN is shown in Fig. 1 and the formulas are as follows:

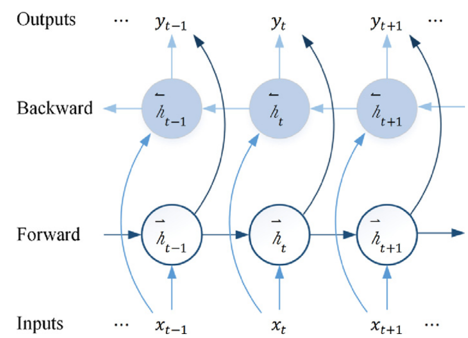

Fig. 1 – The unrolled structure of Bidirectional RNN.

$$\vec{h}_t = H(W_{x\vec{h}} x_t + W_{\vec{h}\vec{h}} \vec{h}_{t-1} + b_{\vec{h}}) \tag{1}$$

$$\overleftarrow{h}_t = H(W_{x\overleftarrow{h}} x_t + W_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h}_{t+1} + b_{\overleftarrow{h}}) \tag{2}$$

$$y_t = W_{\vec{h}y} \vec{h}_t + W_{\overleftarrow{h}y} \overleftarrow{h}_t + b_y \tag{3}$$

where the W terms denote weight matrices (e.g. $W_{x\vec{h}}$ is the input-forward-hidden weight matrix), the b terms denote bias vectors (e.g. $b_{\vec{h}}$ is the forward hidden bias vector) and H is the activation function of hidden layers.

As depicted above, the Bidirectional RNN consists of two independent RNN layers that process the input signals forward and backward, respectively. The outputs of these two layers are both employed to yield the final outputs. H is usually an element-wise nonlinear function. However, RNN with simple cells usually brings poor performance, which is caused by the vanishing gradient problem [12]. To solve this problem, LSTM was proposed by researchers as a special kind of architecture of RNN cells that maintains a more constant error to allow to learn over many time steps, thereby opening a channel to link causes and effects remotely [9]. The architecture of LSTM is shown in Fig. 2, and the formulas of LSTM are described in the following composite functions:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$