Detection and Suppression of Power-Line Interference in Electrocardiogram Signals

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Abstract

A novel power-line interference (PLI) detection and suppression algorithm is proposed to pre-process real-time electrocardiogram (ECG) signals. This algorithm first compares the energy at the harmonic frequency against the energy at neighboring frequencies of the ECG power spectrum, and employs an optimal linear discriminant analysis (LDA) algorithm to determine whether PLI interference exists in the ECG signal. If the presence of PLI is detected, it then applies a recursive least square (RLS) adaptive notch filter to suppress the interference. Extensive simulation results indicate that the algorithm consistently exhibits superior performance in terms of less ECG distortion, faster convergence rate and numerical stability.

1. Introduction

Power-line interference (PLI) is a significant source of noise during bio-potential measurements [1]. For example, the presence of PLI would make it difficult to locate the specific positions of Q, S and T complexes in compromised electrocardiogram (ECG) signals.

PLI noise often consists of one or few harmonics whose frequencies may vary in time due to power line frequency jitters. Thus, some adaptive filtering algorithms have been proposed for ECG signal PLI suppression [2-5]. However, these existing PLI rejection adaptive filters are developed with an implicit assumption that the presence of PLI noise in the ECG signal has already been detected, perhaps by a human operator. For real time and on-line ECG processing applications, often it is not feasible to manually verify the presence of PLI noise over long duration. On the other hand, improper application of PLI suppression algorithms to clean ECG signals in the absence of PLI noise may distort the resulting ECG morphology, and cause performance degradation of subsequent ECG processing.

In this paper, we propose a fully automated PLI detection algorithm and a recursive least-squares based adaptive notch filtering algorithm for PLI suppression. The PLI detection algorithm will be applied to incoming ECG signal to assess the presence of PLI. The PLI suppression algorithm will be applied only after positive detection of the presence of PLI noise. As such, PLI suppression is judiciously applied to the ECG signal, and the resulting waveform would subject to less undesirable distortion. The averaged computation load may also be alleviated.

2. Methods

A block diagram of the proposed PLI detection and suppression technique is depicted in Figure 1. It consists of a PLI detection module and an adaptive filter module. The flow of ECG signal in Figure 1 depends on the outcome of PLI detection. In the absence of PLI noise, the ECG signal will by-pass the adaptive filter unchanged. Only during a positive PLI detection, the adaptive notch filter will be applied to suppress the PLI noise.

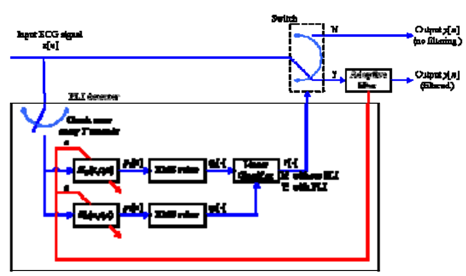

Figure 1 The block diagram of the proposed method.

2.1. PLI detection

The overall PLI detector structure is highlighted with the solid line labeled "PLI detector" in Figure 1. We assume that the presence of PLI needs to be verified once per T seconds (a decision period, T equals 1 in this study). For convenience, we will also assume there is only one fundamental frequency (nominally, 50 or 60 Hz) in the PLI. This structure can easily be generalized to situations with more than one fundamental frequency. The detection algorithm can further divided into two parts: feature extraction and pattern classification.

In the presences of PLI, the power spectrum of the corrupted ECG signal will have a narrow peak at the corresponding frequency that is much larger than power spectrum energy at surrounding frequencies. To exploit this characteristic feature of PLI, the observed signal $x[n]$ is filtered with two adaptive IIR bandpass filter, $H_N(z, \rho_N, a)$ and $H_W(z, \rho_W, a)$ in parallel. Both filters have the same transfer function formula with different values of the parameter ρ ($0 < \rho < 1$) which we will denote as ρ_N and ρ_W:

$$H(z,\rho,a) = \frac{1}{A}\cdot\frac{1-z^{-2}}{1+\rho\cdot a\cdot z^{-1}+\rho^2\cdot z^{-2}},$$

with $a = -2\cos(2\pi\cdot f_0/f_S)$.

Such a filter has a pair of poles located at $\rho\cdot\exp(\pm j2\pi\cdot f_0/f_S)$ and a pair of zeros at ±1. The symbol f_S denotes the sampling frequency and f_0 is the fundamental frequency of the PLI. The constant A is chosen so that $\|H(\exp(j2\pi\cdot f_0/f_S),\rho,a)\| = 1$. For $f_0 = 60$ Hz and $f_S = 360$ Hz, we choose ρN = 0.99 and ρW = 0.9 which yield a band-width of 1.1Hz and 12 Hz respectively. We compute the RMS values of the output of each BPF during each decision period to yield a 2-dimensional feature vector qk = [q1[k] q2[k]]T.

We choose the Fisher's linear discriminant analysis (LDA) in this study for its simplicity and computational efficiency. The LDA classifier is briefly described as follows [6].

Given a feature vector q, a linear classifier computes a weighted linear combination of the feature vector q as follows.

$$r = w^{T}q + w_0, \tag{1}$$

where, $\boldsymbol{w}$ is a weight vector and w_0 is an offset scalar.

The optimal LDA classifier is derived to maximize the Fisher's linear discriminant function

$$J(\boldsymbol{w}) = \frac{\boldsymbol{w}^{T}\boldsymbol{S_B}\boldsymbol{w}}{\boldsymbol{w}^{T}\boldsymbol{S_W}\boldsymbol{w}} \tag{2}$$

where the between-cluster scatter matrix S_B and the within-cluster scatter matrix S_W are defined as

$$\boldsymbol{S_B} = (\boldsymbol{m_1}-\boldsymbol{m_2})(\boldsymbol{m_1}-\boldsymbol{m_2})^{T} \tag{3}$$

and

$$\mathbf{S}_{W} = \frac{1}{N_1+N_2}\sum_{i=1}^{2}\sum_{q_k\in\text{class }i} N_i\cdot(\mathbf{q}_k-\mathbf{m}_i)(\mathbf{q}_k-\mathbf{m}_i)^{T}\,. \tag{4}$$

The symbol m_i denotes the sample mean of class i and N_i is the number of feature vectors in class i. The solution of w that maximizes $J(w)$ can be found as

$$\boldsymbol{w} = \boldsymbol{S}_{\boldsymbol{W}}^{-1}(\boldsymbol{m}_1-\boldsymbol{m}_2)\,. \tag{5}$$

and the offset w_0 in equation (1) can be found as

$$\boldsymbol{w_0} = -\,\boldsymbol{w}^{T}(N_1\boldsymbol{m}_1 + N_2\boldsymbol{m}_2)/(N_1+N_2). \tag{6}$$

2.2. PLI suppression filter

The PLI suppression filter we proposed is an adaptive IIR notch filter of which the harmonic frequency jitter is tracked using a recursive least-squares (RLS) updating algorithm. The block diagram of the filter structure is shown in Figure 2. We assume that $x[n]$ consists of the clean ECG signal $s[n]$ and PLI noise $p[n]$, and $e[n]$, as the output of the narrow band-pass filter is an estimate of the PLI noise. Thus,

$$y[n] = x[n]-e[n] = s[n]+p[n]-e[n] \tag{7}$$

is an estimate of the clean ECG signal $s[n]$. Assume that $s[n]$ and

$$r[n] = p[n] - e[n] \tag{8}$$

are uncorrelated, and that $r[n]$ is zero mean, one has

$$E\{|y[n]|^2\} = E\{|s[n]|^2\} + E\{|r[n]|^2\}. \tag{9}$$

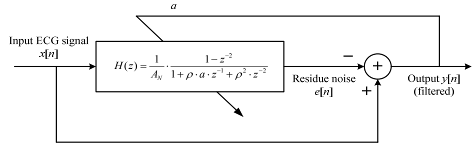

Figure 2 The block diagram of the proposed adaptive filter.

If one modifies the value of a in the band-pass filter, it is possible to reduce the term $E\{|r[n]|^2\}$, but not the terms $E\{|s[n]|^2\}$ which does not consists of any energy in that particular frequency. As such, minimizing $E\{|y[n]|^2\}$ will have the equivalent effect of minimizing $E\{|r[n]|^2\}$.

To achieve this goal, note that

$$y[n] = x[n] + a[n]\cdot\rho\cdot e[n-1] + \rho^2\cdot e[n-2] - \frac{1}{A_N}\{x[n]-x[n-2]\} \tag{10}$$

where we labeled the parameter "a" as $a[n]$ to emphasize the fact that it will be updated at each step n.

Define $w[n] = -\rho\cdot a[n]$, $u[n] = e[n-1]$, and

$$x_t[n] \equiv x[n] + \rho^2\cdot e[n-2] - \frac{1}{A_N}\{x[n]-x[n-2]\}, \tag{11}$$

then $y[n]$ can be expressed as a single tap adaptive filter

$$y[n] = x_t[n] - w[n]\cdot u[n] \tag{12}$$

Define an instantaneous cost function $\xi(n)$ at iteration n as

$$\xi(n) \equiv \sum_{i=1}^{n}\lambda^{n-i}\cdot\|y[i]\|^2, \tag{13}$$

where λ ($0 < \lambda < 1$) is a forgetting factor which is usually chosen to be very close to unity. The optimal solution w can be found by setting the gradient of $\xi(n)$ with respect to w to 0. This leads to

$$w[n]\cdot\sum_{i=1}^{n}\lambda^{n-i}\cdot u^2[i] = \sum_{i=1}^{n}\lambda^{n-i}\cdot x_t[i]\cdot u[i]\,. \tag{14}$$

Now define two scalar quantities

$$z[n] = \sum_{i=1}^{n}\lambda^{n-i}\cdot x_t[i]\cdot u[i] = \lambda\cdot z[n-1] + x_t[i]\cdot u[i] \tag{15}$$

and

$$\varphi[n] = \sum_{i=1}^{n}\lambda^{n-i}\cdot u^2[i]\,. \tag{16}$$

Then the optimal tap weight of the filter can be found as

$$\hat{w}[n] = z[n]/\varphi[n] \qquad \varphi[n] \neq 0 \tag{17}$$

A recursive update formula for inverse of $\varphi[n]$ can also be derived by applying the matrix inversion lemma [7]:

$$\varphi^{-1}[n] = \lambda^{-1} \cdot \varphi^{-1}[n-1] - \frac{\lambda^{-2} \cdot \varphi^{-2}[n-1] \cdot u^2[n]}{1 + \lambda^{-1} \cdot \varphi^{-1}[n-1] \cdot u^2[n]}. \tag{18}$$

This expression can further be simplified as:

$$p[n] = \lambda^{-1} \cdot p[n-1] - \lambda^{-1} \cdot k[n] \cdot u[n] \cdot p[n-1]. \tag{19}$$

where $p[n] = \varphi^{-1}[n]$, and

$$k[n] = \frac{\lambda^{-1} \cdot p[n-1] \cdot u[n]}{1 + \lambda^{-1} \cdot p[n-1] \cdot u^2[n]}. \tag{20}$$

Substitute above into equation (17), the optimal tap weight can be expressed as follows

$$\hat{w}[n] = \hat{w}[n-1] - k[n] \cdot \{x_t[n] - \hat{w}[n-1] \cdot u[n]\}. \tag{21}$$

3. Results

We evaluate the effectiveness of the PLI detection algorithm using MIT-BIH ECG database, and compare the performance of the proposed RLS PLI suppression filter with existing adaptive PLI suppression filters.

3.1. Performance evaluation of the PLI detection

The MIT-BIH arrhythmia database is the most widely used ECG signal database in public domain [8]. In general, ECG signals in this database are considered very clean in terms of PLI noise. However, as noted in [9], there is indeed evidence of tiny PLI noise in some of the data record. We have manually examined the power spectrum of the ECG signal in the entire MIT-BIH arrhythmia database over individual short segments, and label each record with one of two labels: ″with 60-Hz PLI″ and ″without 60-Hz PLI″.

We apply the LDA-based PLI detector to make a decision once per second. Thirty-minute length for each record in the database is adopted for analysis, it thus yields 1800 2×1 feature vectors for each record. The scatter plot of the total feature vectors is demonstrated in Figure 3 with ″+″ sign representing the features extracted from the records deemed corrupted by PLI, whereas the ″×″ sign indicating those from clean records. The LDA-based PLI detector yield a linear decision boundary as illustrated in Figure 3 in the form of a straight line. We then project each of the feature vectors into the subspace orthogonal to the decision boundary to compare the values of r.

Given a particular threshold, we can compute the number of false negative and false positive detections as well as true positive and true negative detections. These statistics can then be converted into two commonly used performance criteria, *specificity* and *sensitivity*. Using different thresholds, different values of specificity and sensitivity can be computed. By connecting these pairs of values, the receiver operating characteristic (ROC) curve can thus be derived and is demonstrated in Figure 4. It is highly desirable that the ROC curve is as close to the upper left corner as possible. The scale of the Y-axis (sensitivity) is enlarged to emphasize the specificity remains at unity with a sensitivity value exceeding 99.8%, and this proves the PLI detector can attain our requirement even in ECG signal with only tiny PLI.

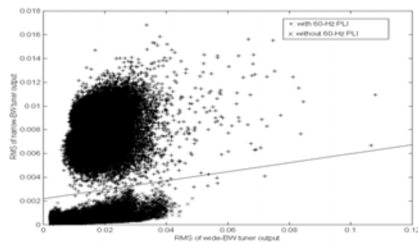

Figure 3 The scatter diagram for the feature vectors

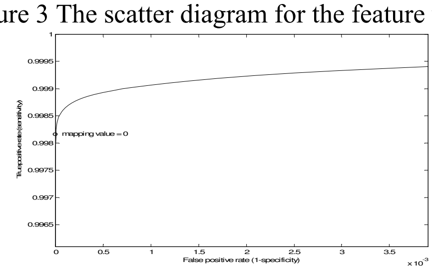

Figure 4 The ROC curve from the projection distribution.

3.2. Performance test of the RLS adaptive filter

Although some adaptive filtering techniques have been proposed for removing PLI in ECG signals [3-5], most of them used artificially corrupted ECG for the simulation purpose. Few studies have been evaluated by using practically PLI-corrupted ECG signal. In this study, a lead-II ECG signal is measured by a physiological signal acquisition system (MP30, BioPac System Inc.) at a sampling frequency of 500 Hz from a 23-year-old male subject in supine status with the power mains across him parallel at a distance of 110 cm.

The filtering results in time- and frequency-domain are gathered and shown in Figure 5. The illustrations from top to bottom in each subfigure are the results of Pei and Tseng′s method [3], So′s method [4], Ziarani and Konrad′s method [5] and the proposed method, respectively. In this experiment, the parameters for existing methods are selected according to the values suggested in the original paper, whereas those for the proposed adaptive filter are $\rho = 0.985$ and $\lambda = 0.995$. It is obvious the proposed adaptive filter, whose results are demonstrated at the bottom in each subfigure, can offer a competitive filtering performance and a faster numerical convergence than the existing methods with the selected parameters.

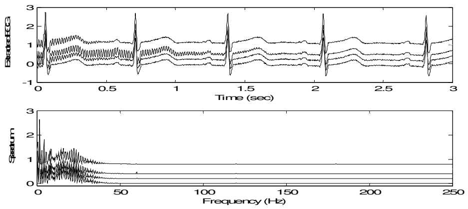

Figure 5 Filtered results in time- and frequency-domain.

4. Discussion and conclusions

PLI is a major interference of bio-potential measurement. There have been many studies devoted to the elimination of PLI in ECG signal processing; however, it is still a challenging problem due to its time-varying characteristics.

Adaptive filtering technique is a potential method to remove the PLI contaminated in ECG signals. The prime deficiency for existing methods is the filtering function will act even when the input signal is not contaminated by PLI. To surmount this deficiency, a novel structure contains a LDA-based PLI detector and an adaptive filter is presented in this study. Both the theoretic analysis and the computer simulation are given for the proposed structure. The statistical characteristics which are necessary for the LDA-based PLI detector is derived with the aid of MIT-BIH arrhythmia database, and it is verified that the PLI detector has a high sensitivity and high specificity even in slightly PLI contaminated signals such as those in MIT-BIH arrhythmia database. The PLI detector is designed to check PLI once per second, and the filtering function will delay one second after the PLI is detected. Practically corrupted ECG signal has been used in computer simulation to verify the feasibility of the presented method. From the simulation results, the proposed adaptive filter can support the task of eliminating PLI with fast numerical convergence; this filter is computationally efficient and has a competitive filtering performance compared with existing methods as PLI being detected in the ECG signal. For the proposed structure, there will be no filtering action as no PLI is detected, and this is what existing methods being deficient.

The elimination of sinusoidal interference in an observed signal is an important issue in many areas. PLI may be one kind of such interference that appears most popularly. PLI in practical case may consist of the fundamental component and its harmonics. This study focuses on the elimination of the fundamental component. The proposed structure shown in Figure 1 may be modified with the blocks for filtering harmonics being included in parallel to serve the purpose of eliminating severe PLI where harmonics may be present. The RLS algorithm has been demonstrated to have better performance than traditional LMS algorithm with faster convergence [7]. However, this improvement in performance is acquired at the expense of increased computational complexity [7]. But, the iteration processes included in the proposed RLS adaptive filter contains only simple multiplication/division and addition/subtraction. The total computational complexity is as simple as that of traditional LMS algorithm. For these properties, the proposed structure has the potential to eliminate the other kind of sinusoidal interference in different areas, e.g., the cases of interference with multiple sinusoids and sinusoidal interferences with fast changing characteristics.

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