Power Line Interference Suppression for ECG Signal Recovery

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ABSTRACT

The electrocardiogram (ECG) recovery is very important for clinical diagnosis, especially in the presence of power line interference (PLI). In this work, to suppress the PLI, it is modeled as a linear combination of sinusoidal signals that have a sparse representation in the frequency domain. To accurately reconstruct the ECG, the time domain as a sparse domain for ECG signal is exploited. Based on the sparse representations, a joint optimization estimation problem is developed that allows one to simultaneously perform the ECG recovery and PLI suppression. In order to solve the optimization problem, two efficient schemes based on the greedy algorithms such as orthogonal matching pursuit (OMP) and compressive sampling matching pursuit (CoSaMP) are utilized. Finally, numerical studies demonstrate that the JCoSaMP estimation algorithm outperforms the state-of-the-art approaches.

KEYWORDS

ECG recovery, PLI suppression, transform domain, sparsity, joint estimation

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1 INTRODUCTION

The electrocardiogram (ECG) signal is a useful means in the clinical diagnosis because it provides critical information for patients [15]. In practice, the power line interference (PLI) is a common source of interference during the process of recording the ECG. To recover the ECG signal for further diagnosis, PLI suppression is required and thus attracts intensive research interests [3, 7, 13, 14].

Generally speaking, PLI suppression approaches are divided into two groups, namely, nonadaptive filters and adaptive filters. For the nonadaptive filters, the famous one is the notch filter [13], which devises a bandstop filter to suppress the interference that occupies the certain frequency band. Unfortunately, the spectrum of ECG signal in the same band will be suppressed as well as an interference, thereby degrading the quality of the ECG signal drastically. It is also obvious that to achieve high suppression ratio and less useful signal distortion, the suppression band of the notch filter should be as narrow and deep as possible. This fact leads, however, to the need of high order of the filter, which is not pratical for portable devices, especially the wearable health devices.

In the second group, the adaptive interference cancellation concept is utilized to remove the PLI. To successfully perform cancellation, the reference input must be correlated to the interference that is intended to be removed. For the PLI suppression, the reference input can be a sinusoid of 50Hz frequency if the PLI consists of only the fundamental frequency. To suppress the harmonics, the prior information on the number of harmonics are required for adaptive cancellation to work. If we have the reference input, the error function is minimized under different cost functions, for example, least squares and minimum mean square error criteria. As a consequence, the error function produces the estimate of the ECG signal. The authors in [3], [14] show that adaptive filters, for example, least mean square(LMS) and recursive least square(RLS) can also be utilized to minimize the error function. It has already been shown in [7] that after the convergence of adaptive filters, these adaptive filters and the notch filter are equivalent.

Recently, in [5, 6, 12], the compressed sensing (CS) algorithm is applied to perform ECG compression, where basis pursuit (BP) and greedy algorithms including orthogonal matching pursuit (OMP), compressive sampling matching pursuit (CoSaMP), regularized orthogonal least squares and normalized iterative hard thresholding are utilized to perform the ECG recovery. By exploring transform domain, the CS concept has been successfully applied to perform more accurate reconstruction. However, the idea of utilizing the CS is mostly restricted to perform compression. In [4], a detailed review of the CS algorithm that applied to different biosignals is provided.

The main motivation of this work is to utilize the sparsity of the signals to perform PLI suppression and to recover the ECG signals. To achieve this end, in this work, the PLI is represented as the linear superposition of the multiple sinusoids with unknown amplitudes and frequencies. To sparsely represent the PLI, the frequency domain is utilized in which the sinusoids have sparse representations. For the ECG signal, the time domain is utilized to reveal the sparse representation. Therefore, using the coefficients in the transform domain, a joint approach is proposed under an optimization framework to recover the ECG and to suppress the PLI simultaneously. To solve the proposed optimization problem, two greedy algorithms based on OMP and CoSaMP are utilized. According to the results of experiments, the approach based on CoSaMP appears to be a promising candidate for ECG recovery and PLI suppression when provided the sparsity of the signals.

2 PROBLEM FORMULATION

The ECG signal that is corrupted by the PLI is modeled by [16], [8]

$$\begin{aligned} y(n) &= x(n) + i(n) \\ &= x(n) + \sum_{k=1}^{K} A_k \sin(\omega_l n), n = 1, 2, \cdots, N, \end{aligned} \tag{1}$$

where $x(n)$ is the clean ECG signal to be recovered, $i(n)$ is the PLI to be suppressed, and n is the time index. When $K = 1$, this is the case corresponding to the PLI with only the fundamental frequency (50Hz or 60Hz), and when $K \geq 1$, the PLI contains harmonic frequencies. To achieve simultaneous suppression of the PLI and restoration of the ECG, transform domains are utilized in which the ECG and PLI are sparsely formulated. In what follows, time transform domain is introduced, where the ECG signal has sparse representations, and the frequency domain [11], [9] is utilized to explore its sparse representation for the PLI.

2.1 Time domain for ECG

A simulation of the ECG signal is provided in Figure 1, where three heartbeats are simulated. From the figure, it is obvious that the ECG signal contains large amplitudes when the heartbeat is active and small/zero amplitudes when the heart is at rest. This phenomenon suggests that the ECG is a sparse signal itself in the time domain. In the matrix form, the representation is denoted by $\boldsymbol{\alpha}_{time} = \boldsymbol{\Phi}_{time}\mathbf{x}$, where $\boldsymbol{\Phi}_{time} = \mathbf{I}$ is the sparse domain and the coefficient $\boldsymbol{\alpha}_{time}$ is sparse. This is the property that will be exploited when the ECG signal recovery approach is developed.

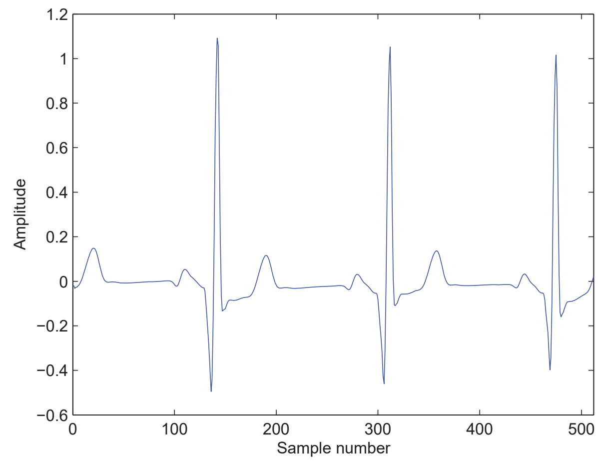


Figure 1: Clean ECG signal

2.2 Frequency domain for PLI

From the signal model in (1), the PLI is a linear combination of sinusoidal signals and using the matrix representation, the PLI is

$$\mathbf{i} = \Theta\mathbf{a}, \tag{2}$$

where $\mathbf{i} = [i_1, \cdots, i_N]^{\mathrm{T}}, \mathbf{a} = [A_1, \cdots, A_K]^{\mathrm{T}}$, and Θ has the form

$$\boldsymbol{\Theta} = \begin{bmatrix} \sin(\omega_1) & \sin(\omega_2) & \cdots & \sin(\omega_K) \\ \sin(2\omega_1) & \sin(2\omega_2) & \cdots & \sin(2\omega_K) \\ \vdots & \vdots & \vdots & \vdots \\ \sin(N\omega_1) & \sin(N\omega_2) & \cdots & \sin(N\omega_K) \end{bmatrix}_{N\times K} \tag{3}$$

To see the sparse property of the PLI, the whole frequency range of interest is uniformly discretized, denoted by a vector $[f_0 : df : f_e]$, where f_0 and f_e are the initial and final frequency, respectively, and df is the discretization step. With this discretization, a dictionary similar to (3) is constructed by considering all the frequency components in the vector. That is,

$$\boldsymbol{\Omega} = \begin{bmatrix} \sin(f_0) & \sin((f_0 + df)) & \cdots & \sin(f_e) \\ \sin(2f_0) & \sin(2(f_0 + df)) & \cdots & \sin(2f_e) \\ \vdots & \vdots & \vdots & \vdots \\ \sin(Nf_0) & \sin(N(f_0 + df)) & \cdots & \sin(Nf_e) \end{bmatrix}_{N\times M} \tag{4}$$

where $M = (f_e - f_0)/df + 1$ is the total number of frequencies in which $M \gg K$ is commonly used to construct a fine dictionary. Let $\boldsymbol{\sigma} = [\sigma_1, \cdots, \sigma_M]^{\mathrm{T}}$ be a vector to represent the corresponding amplitude for each virtual frequency created in (4). One can imagine if $\boldsymbol{\Omega}$ were used to represent the PLI, then many elements in $\boldsymbol{\sigma}$ would be zero because $\sigma_i = a_i$ if, and only if $\omega_i = f_0 + i * df$, otherwise $\sigma_i = 0$. In other words, the PLI has a sparse representation in the frequency domain because it contains only finite number of sinusoidal signals. In a matrix form, $\mathbf{i} = \boldsymbol{\Omega}\boldsymbol{\sigma}$ where $\boldsymbol{\sigma}$ is sparse and this property will be explored to develop the PLI suppression algorithm.

3 JOINT ECG RECOVERY AND PLI SUPPRESSION ALGORITHMS

From the analysis conducted in Section 2, it is concluded that the ECG has a sparse representation in the time domain, and the PLI has a sparse representation in the frequency domain. The received signal now can be expressed using the sparse domains as

$$\boldsymbol{y} = \boldsymbol{\Phi}'_{time}\boldsymbol{\alpha} + \boldsymbol{\Omega}\boldsymbol{\sigma} \tag{5}$$

where $\boldsymbol{y} = [y_1, \cdots, y_N]^{\mathrm{T}}$ and $\boldsymbol{\Phi}'_{time}$ indicates the corresponding inverse transform. From (5), the $\boldsymbol{\alpha}$ and $\boldsymbol{\sigma}$ are sparse, hence, by utilizing this property, the following joint estimation is developed to perform the ECG recovery and the PLI suppression. That is,

$$\begin{aligned} &\text{minimize } \|\boldsymbol{\alpha}\|_0 + \lambda\|\boldsymbol{\sigma}\|_0 \\ &\text{subject to } \|\mathbf{y} - \Phi'_{\mathrm{time}}\boldsymbol{\alpha} - \Omega\boldsymbol{\sigma}\|_2 < \epsilon, \end{aligned} \tag{6}$$

with variables $\boldsymbol{\alpha}$ and $\boldsymbol{\sigma}$, $\|\cdot\|_2$ is the ℓ_2-norm that measures the data fidelity, $\|\cdot\|_0$ is the ℓ_0-norm that promotes the sparse solutions, see [2], and λ and ϵ are the regularization and precision constant, respectively. To solve this optimization problem in (6), two greedy algorithms, namely JOMP and JCoSaMP [10], are utilized.

The basic concept behind two joint algorithms is the alternating minimization. To be accurate, the entire algorithm essentially contains two steps, where in the first step the PLI is estimated and in the second step the ECG is restored. In the each step, the OMP/CoSaMP algorithm is applied to perform estimation and two steps are iterated until certain stopping rule is satisfied. For completeness, the JCoSaMP and JOMP algorithms are provided in Tables 1 and 2 , respectively. For more details, the interested readers are referred to [10].

4 SIMULATIONS

In this section, the results of simulations are presented to demonstrate the performance of the proposed joint estimation method. For comparison purposes, the results from the LMS filter are also provided. In the simulations, the parameters of $T = 500$ and $\delta = 10^{-5}$ for JCoSaMP are chosen, and also, $\delta = 10^{-5}$ is selected for JOMP. Two performance evaluation indexes are employed to provide accurate accessions on the proposed approaches, given by

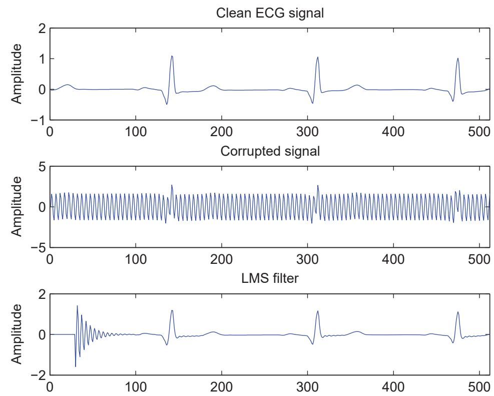
$$\text{suppression ratio:} \quad \gamma = 10\log_{10}\left\{\frac{\sum|x(n)|^2}{\sum|\widehat{x}(n)|^2}\right\}, \tag{7}$$

$$\text{distortion ratio:} \quad \beta = 10\log_{10}\left\{\frac{\sum|x_0(n) - \widehat{x}(n)|^2}{\sum|x_0(n)|^2}\right\}, \tag{8}$$

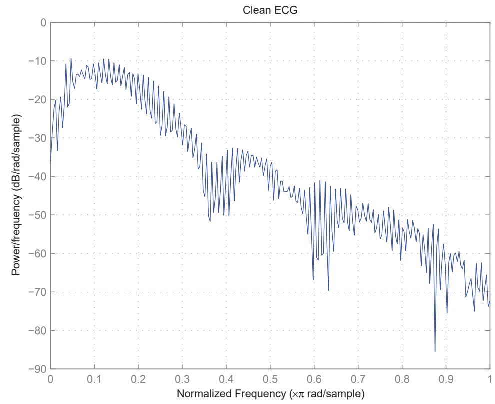
where $x(n)$ and $\widehat{x}(n)$ represent the signal before and after interference suppression, respectively, and $x_0(n)$ is the clean signal. For a desired suppression method, the suppression ratio γ should be high since the interference should be removed as much as possible. Meanwhile, the distortion ratio β should be low because the recovered signal should be close to the clean signal, which indicates that the reconstruction error is small.

The ECG signal is generated by $FECGSYN$ function [1] and then it is corrupted by the PLI to produce the received signal. In the first experiment, the ECG is contaminated by 50Hz PLI at signal-to-interference ratio (SIR)=-20dB, which is depicted in Figure 2a, and it is seen that the clean ECG is completely overwhelmed by the strong PLI. The result from LMS filter is provided in the same figure. Although LMS filter removes the PLI to certain extent, the residual interference is still noticeable in the recovered ECG, which is also observed in Figure 2d from the recovered spectrum. The JOMP and JCoSaMP algorithms are now applied and the results are demonstrated in Figure 3. It is now seen that the PLI is removed and ECG is clean. In addition, the spectrum of the recovered ECG is also free of interference, shown in Figures 3b-3c. The suppression and distortion ratios versus SIR are depicted in Figure 4. From Figure 4a, one observes that JOMP and JCoSaMP produce almost the same suppression ratios, which suggests that they are good at suppressing the interference. As expected, the suppression ratio decreases as the SIR grows. When the SIR is low, for example, SIR= -30dB, the suppression is 27dB, which indicates the excellent suppression capacity. For the distortion ratio, the JOMP and JCoSaMP outperform the LMS by almost 50dB, and produce nearly the same distortion ratios regardless of the SIR of the PLI. This indicates that the JOMP and JCoSaMP preserve the useful signal well. Therefore, both the JOMP and JCoSaMP are promising candidates in suppressing the interference and recovering the ECG signal.

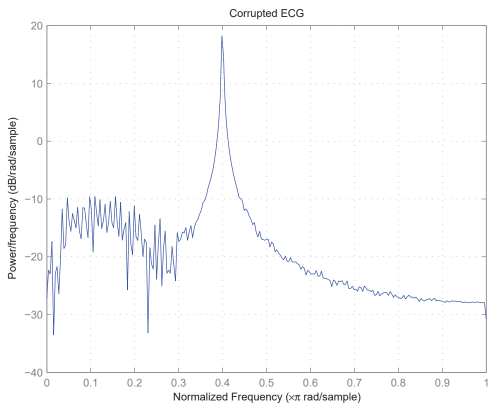
In the second experiment, the ECG is corrupted by a 50Hz PLI and its first harmonic at SIR= -20dB, depicted in Figure 5a, and the reconstructed result of LMS filter is also provided. From Figure 5a, for the LMS filter, even the known PLI is utilized as the reference input, there is still an convergence issue at the beginning. The LMS filter is able to form two stopbands in the frequency domain, but the ECG is also suppressed in the same bands. On the other hand, the JOMP and JCoSaMP approach are able to recover the ECG signal and to suppress the interferences simultaneously, and provide good recovery results, demonstrated in Figure 6. The recovered signals in both time and frequency domains



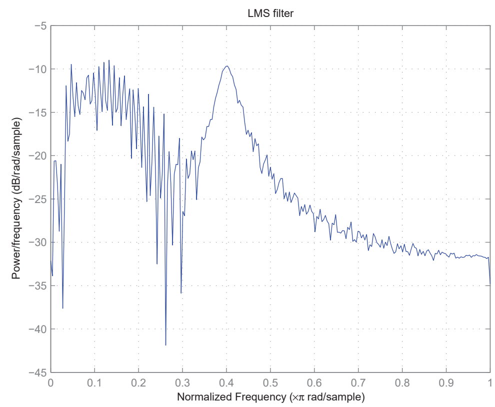
(a) Reconstructed signal



(b) Spectrum of Clean ECG

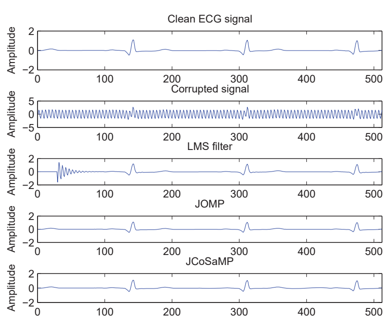


(c) The spectrum of corrupted ECG

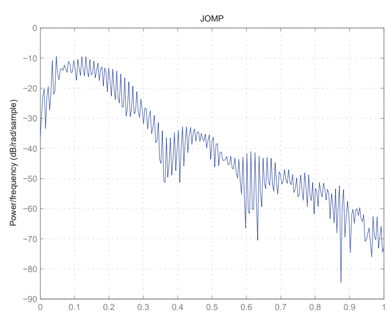


(d) The reconstructed spectrum

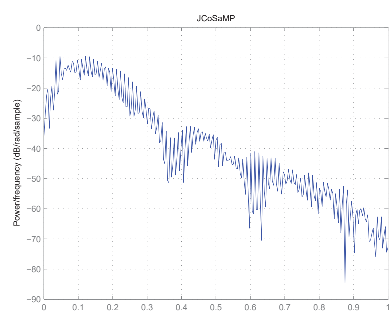
Figure 2: Reconstructed signal by the LMS filter



(a) Reconstructed signal



(b) The reconstructed spectrum by JOMP



(c) The reconstructed spectrum by J-CoSaMP

Figure 3: Reconstructed signal by JOMP and JCoSaMP

Table 1: JCoSaMP Algorithm.

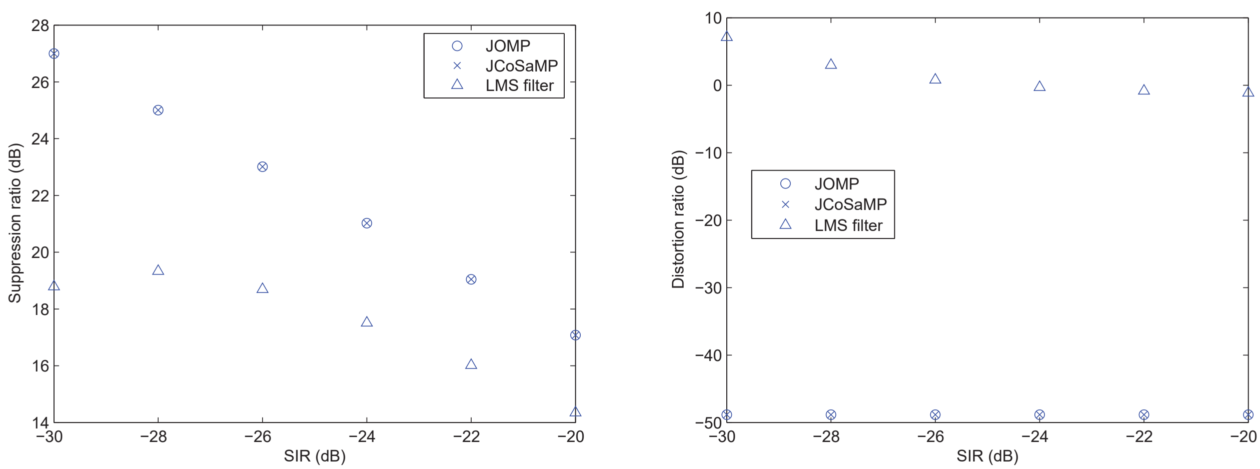
Objective function: minimize $\|\boldsymbol{\alpha}\|_0 + \lambda\|\boldsymbol{\sigma}\|_0$ subject to $\|\mathbf{y} - \boldsymbol{\Phi}'\boldsymbol{\alpha} - \boldsymbol{\Omega}\boldsymbol{\sigma}\|_2 < \epsilon$
Inputs: $\mathbf{y}$, $\boldsymbol{\Phi}$, $\boldsymbol{\Omega}$, K_1 {sparsity level for $\boldsymbol{\sigma}$}, K_2 {sparsity level for $\boldsymbol{\alpha}$}
Outputs: Estimates of $\boldsymbol{\sigma}$ and $\boldsymbol{\alpha}$

Initialization: $t = 1$, $\mathbf{r} = \mathbf{y}$, $\boldsymbol{r_\sigma} = \mathbf{0}$ {residue for $\boldsymbol{\sigma}$}, $\boldsymbol{r_\alpha} = \mathbf{0}$ {residue for $\boldsymbol{\alpha}$}, $\boldsymbol{\sigma}_0$ and $\boldsymbol{\alpha}_0$
Repeat
t=t+1
Step 1: Estimate the $\boldsymbol{\sigma}$ as $(\boldsymbol{\sigma}^t, \boldsymbol{r}^t_{\boldsymbol{\sigma}}) \leftarrow$ CoSaMP($\mathbf{y}$,$\mathbf{r}$,$\boldsymbol{\Omega}$,K_1)
Step 2: Estimate the $\boldsymbol{\alpha}$ as $(\boldsymbol{\alpha}^t, \boldsymbol{r}^t_{\boldsymbol{\sigma}}) \leftarrow$ CoSaMP($\mathbf{y}$,$\mathbf{r}$,$\boldsymbol{\Phi}$,K_2)
Step 3: Update the global residue as $\mathbf{r} = \mathbf{y} - \boldsymbol{r}^t_{\boldsymbol{\sigma}} - \boldsymbol{r}^t_{\boldsymbol{\alpha}}$
Until $t > T$ {maximum iteration} or norm($\mathbf{r}$) $< \delta$ {predefined threshold}

Table 2: JOMP Algorithm.

Objective function: minimize $\|\boldsymbol{\alpha}\|_0 + \lambda\|\boldsymbol{\sigma}\|_0$ subject to $\|\mathbf{y} - \boldsymbol{\Phi}'\boldsymbol{\alpha} - \boldsymbol{\Omega}\boldsymbol{\sigma}\|_2 < \epsilon$
Inputs: $\mathbf{y}$, $\boldsymbol{\Phi}$, $\boldsymbol{\Omega}$
Outputs: Estimates of $\boldsymbol{\sigma}$ and $\boldsymbol{\alpha}$

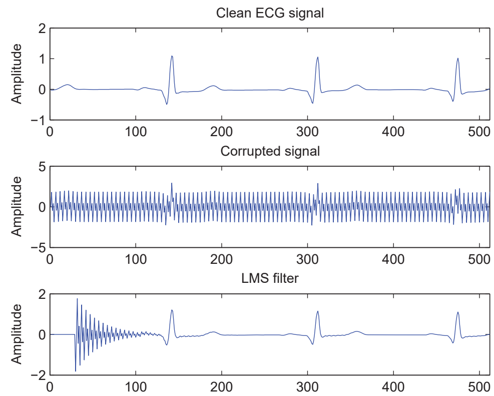
Initialization: $t = 1$, $\mathbf{r} = \mathbf{y}$, $\boldsymbol{r_\sigma} = \mathbf{0}$ {residue for $\boldsymbol{\sigma}$}, $\boldsymbol{r_\alpha} = \mathbf{0}$ {residue for $\boldsymbol{\alpha}$}, $\boldsymbol{\sigma}_0$ and $\boldsymbol{\alpha}_0$
Repeat
t=t+1
Step 1: Estimate the $\boldsymbol{\sigma}$ as $(\boldsymbol{\sigma}^t, \boldsymbol{r}^t_{\boldsymbol{\sigma}}) \leftarrow$ OMP($\mathbf{y}$,$\mathbf{r}$,$\boldsymbol{\Omega}$)
Step 2: Estimate the $\boldsymbol{\alpha}$ as $(\boldsymbol{\alpha}^t, \boldsymbol{r}^t_{\boldsymbol{\alpha}}) \leftarrow$ OMP($\mathbf{y}$,$\mathbf{r}$,$\boldsymbol{\Phi}$)
Step 3: Update the global residue as $\mathbf{r} = \mathbf{y} - \boldsymbol{r}^t_{\boldsymbol{\sigma}} - \boldsymbol{r}^t_{\boldsymbol{\alpha}}$
Until $t > T$ {maximum iteration} or norm($\mathbf{r}$) $< \delta$ {predefined threshold}



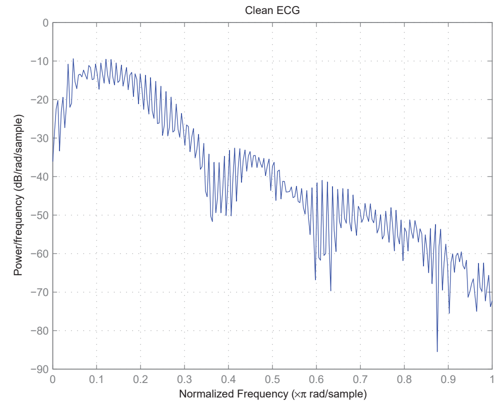
(a) Suppression ratios **(b) Distortion ratios**

Figure 4: Suppression ratios and distortion ratios obtained by JOMP, CoSaMP and LMS filter

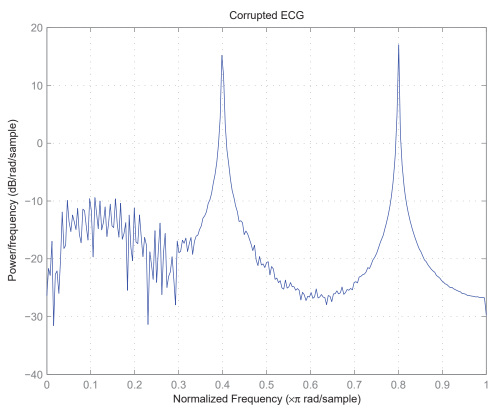
match the original ones well. In this case, the suppression and distortion ratios versus SIR are depicted in Figure 7. However for JOMP, its performance degrades occasionally in suppression, especially when the SIR is small, which is also observed in the distortion ratio. It is clear that JCoSaMP is a better choice for handling the ECG recovery and PLI suppression for its steady performance. It should be noted that the JCoSaMP based approach requires the prior knowledge on the sparsity of the signal and in this case, the sparse level is set to be two, namely $K_1 = 2$, since there are two PLI interferences.



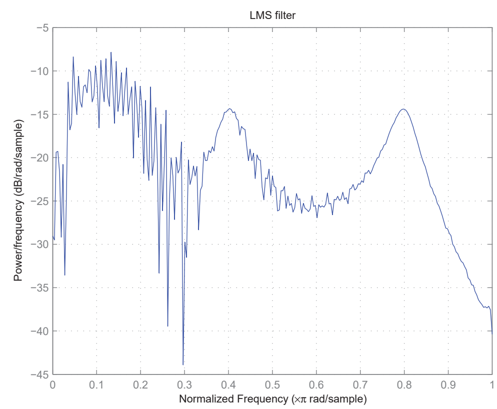
(a) Reconstructed signal



(b) Spectrum of Clean ECG

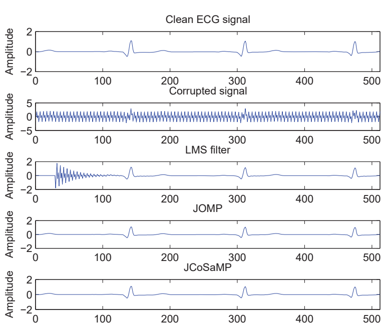


(c) The spectrum of corrupted ECG

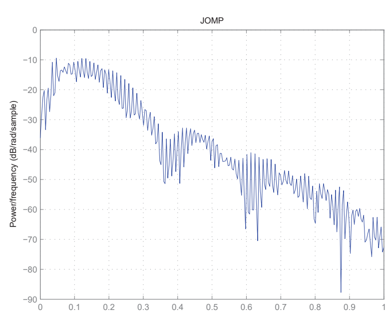


(d) The reconstructed spectrum

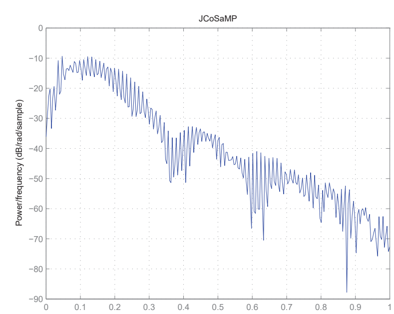
Figure 5: Reconstructed signal by the LMS filter in the presence of harmonic PLI



(a) Reconstructed signal

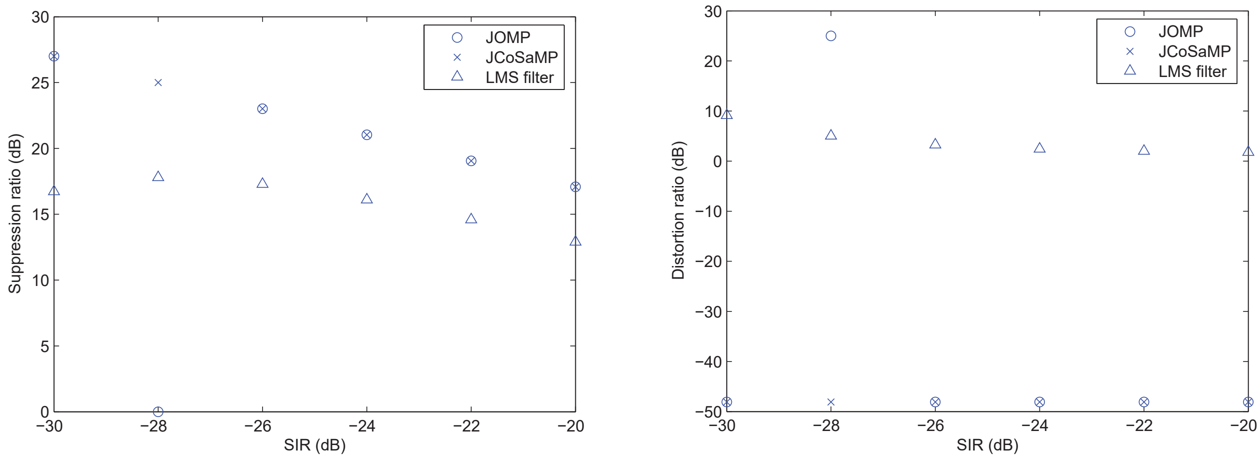


(b) The reconstructed spectrum by JOMP



(c) The reconstructed spectrum by JCoSaMP

Figure 6: Reconstructed signal by the JOMP and JCoSaMP in the presence of harmonic PLI



(a) Suppression ratios **(b) Distortion ratios**

Figure 7: Suppression ratios and distortion ratios obtained by JOMP and CoSaMP in the presence of harmonic PLI

5 CONCLUSION

In this work, a joint estimation approach of the ECG signal recover and PLI suppression based on JOMP and JCoSaMP is developed. To utilize the algorithms, the time domain is exploited as a sparse domain to represent the ECG signal. The PLI, on the other hand, is modeled as a linear combination of the sinusoidal signals, which can be sparsely represented in frequency domain. An optimization framework is developed to perform ECG restoration and PLI suppression simultaneously, and JOMP and JCoSaMP are applied to efficiently obtain the solutions. From the experiments conducted, the joint estimation approach offers great performance improvement over the state-of-the-art algorithms, especially for JCoSaMP.

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