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An adaptive denoising approach to powerline interference reduction in ECG recording

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The objective of this paper is to develop an adaptive denoising algorithm for the reduction of powerline interference (PLI) in electrocardiogram (ECG) recording. The problem of mode mixing and inability to deal with non-stationary characteristics have the major drawbacks posed by existing PLI removal techniques. The technique used in the proposed work has been combined with the concept of synchrosqueezing transform with an adaptive filter to overcome such limitations. The synchrosqueezing transform has facilitated as a mode decomposition tool to disintegrate the signal into a set of intrinsic mode functions and then applying adaptive filter on decomposition results to estimate PLI so as to recover noise free ECG. The performance assessment of the proposed techniques have been carried out with several established ECG database available in physio net and its adaptability to powerline frequency drift has also been studied. A comparative analysis has been conducted to validate the proposed techniques. Experimental results have suggested that the proposed SST based PLI reduction approaches provide better denoising effect than state of the art methods.

Keywords: Synchrosqueezing transform, Adaptive filter, Intrinsic mode function, Powerline interference, Modified discrete cosine transform

1 Introduction

Electrocardiogram (ECG) is a non-invasive tool to record the electrical activity of heart muscle by placing electrodes at appropriate position on the surface of the human body[1]. During recording and transmission process, ECG signal is corrupted by various kind of corrupted by various kind of noises and artifacts coming from unwanted sources[2,3]. Among these noises, Powerline Interference (PLI) is a major source of interference affecting the quality of the ECG recorded. PLI is introduced into ECG recording as a result of cross coupling between the cable carrying power to recording unit and electrodes. It is high frequency additive noise that contains fundamental frequency at 50 Hz along with higher order harmonics. This interference completely masks the important features of the ECG signal making signal interpretation is more complicated. Thus for proper interpretation of ECG recording, it is important to de-noise ECG signal. Filtering PLI without affecting the underlying ECG signal is a challenging one since spectral overlapping of signal with noise. Several studies are reported in literature addresses PLI estimation through different techniques such as digital filtering[4,5], notch filtering[6,7], adaptive notch filtering[8-12], wavelet transform[13-16], non-linear wavelet packet transform[17-19], fast ICA method[20], adaptive noise cancellation techniques[21,22]. Though they were designed to mitigate PLI, but they were incapable to eliminate them completely. Huang *et al.* developed data adaptive approach empirical mode decomposition to address the non-stationary issue[23]. With EMD, several ECG enhancement procedures[24-27] have developed to overcome limitations posed by conventional denoising techniques. The problem of Mode mixing and interpolator selection limits the efficiency of EMD based denoising approach. To solve mode mixing issues, Ensemble empirical mode decomposition[28,29] was introduced. It had the issue of increased iteration and gaussian noise to be added for each iteration causing more difficulties in practical implementation. Hence there is a need for a suitable method to deal with non-stationary, mode mixing. Ingrid Daubechies *et al.* developed an adaptable algorithm named Synchrosqueezing Transform found to be a suitable tool to analyze and reconstruct non-linear, non-stationary components more accurately[30]. Fixed wavelet basis, less computation and capability

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to solve mode mixing are the prime advantages of SST. In this proposed work, SST is used as the mode decomposition tool to disintegrate a noisy ECG signal into a set of intrinsic mode functions and, then adaptive filter is applied on the decomposition result for estimating the PLI so as to create an interference-free ECG. The layout of this paper is organized as follows: Section 2 presents background on Synchrosqueezing Transform and adaptive filter. Section 3 describes the proposed method. The experimental results are discussed in Section 4. Finally, conclusions are drawn in section 5.

2 Introduction to synchrosqueezing transform and adaptive filter

2.1 Synchrosqueezing transform

Synchrosqueezing transform (SST) is an effective tool to obtain a higher resolution time frequency analysis. It is a data-adaptive method[30] in which analysis of any kind of non-linear, non-stationary signal can be carried out. SST is developed by combining continuous wavelet transform with reassignment technique. The continuous wavelet transform (CWT) uses wavelet of different scales to localize component of signal and represents them by non-zero wavelet coefficient. Due to spectral bandwidth overlap, the wavelet energy corresponding to a scale of information is smeared into neighboring scale. For further improving time frequency representation (TFR) of the signal, these distributed energies within localized region must be concentrated. Hence, the reassignment operation is applied in the time frequency plane to squeeze CWT coefficients in accordance with local maxima to obtain better time frequency localization. This SST allows to create sharper time frequency representation of signal so that it is possible to accurately identify, reconstruct components exhibiting slow variation in amplitude and smooth changes in frequency. In general, the SST computation is organized in three steps:

1. Compute CWT of a signal to be analyzed
2. Extract Instantaneous Frequency (IF) from CWT coefficient
3. Combine CWT coefficient with IF through reassignment procedure

Consider a multi-component signal $f(t) \in L^2(R)$ and its relationship with CWT can be expressed as:

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t)a^{-1/2}\,\Psi_{a,b}^{*}(t)dt \qquad \text{... (1)}$$

where, $\psi_{a,b}^{*}(t)$ denotes complex conjugate of mother wavelet $\psi_{a,b}(t)$ and ***a*** is the scale factor that shifts wavelet to capture oscillatory feature across different scales.

The CWT transforms signal into wavelet coefficients and the value of coefficient can be either zero or non-zero. The non-zero wavelet coefficient represents the presence of signal component. For deriving individual spectral component of function from CWT coefficient, it is required the instantaneous frequency (IF). IF is measured by taking first order derivative with respect to translation parameter ***b***. This IF measure helps in reassigning the wavelet coefficient so that the component of function $f(t)$ is concentrated in the time scale domain.

$$w_f(a,b) = \frac{-i}{W_f(a,b)}\frac{\partial}{\partial b}W_f(a,b) \qquad \text{... (2)}$$

Having calculated IF, the next step is to apply the reassignment operation in the time scale domain. As a result of reassignment operation, every point (a, b) is assigned to another point $(w_f(a,b), b)$.The scales closer to IF are identified and the wavelet coefficient belonging to them are mapped to IF. This operation is called as Synchrosqueezing $T_f(w,b)$.

$$T_f(w,b) = (\Delta w)^{-1} \int_{\{a: w_f(a,b)\epsilon w\}} W_f(a,b)a^{-3/2}da \qquad \text{... (3)}$$

The preceding discussion demonstrates that SST compensates the spreading effect stemming from CWT. The SST based time-frequency representation offers better time frequency localization. The desired goal is not to create TFR, but to reconstruct individual modes from it. To facilitate SST as a mode decomposition tool, it is necessary to identify ridges followed by reconstructing along ridges to get individual modes. This proposed work has adopted the ridge extraction procedure[31] for detecting ridges and retrieval of individual modes. The ridge extraction and component retrieval procedure transforms SST into a mode decomposition tool.

2.2 Adaptive filter

The process of estimating a signal from corrupted one is to pass it through a filter which suppresses noise and keeps the signal characteristics unaffected[12].

Filter used for the above purpose can be either fixed or adaptive. The design of the fixed filter requires prior knowledge of both signal and noise. In most of the biomedical applications, the bio-signal appears to be non-stationary and processing them with fixed filter is inappropriate. Hence, it is needed to design a filter in a way that it is adaptable to the nature of the signal. An Adaptive filter is a filter that can adjust its own impulse response automatically. For the proper functioning of the adaptive filter, it requires error signal $e(n)$ which is a difference between filter output and desired signal. The error signal is feedback to the adaptive filter and adjusts filter coefficient according to the LMS algorithm. Adaptation process[32] continues until the error is minimized (adaptive filter output equal to desired signal). At each iteration filter coefficient updated according to the weight update equation:

$$W_{n+1}(k) = W_n(k) + \mu e(n)x(n) \qquad \text{... (4)}$$

where, $W_n = [W_n(0), W_n(1), \ldots\ldots\ldots W_n(p)]^T$ denotes the vector of filter coefficient at time n $x(n) = [x(n), x(n-1), \ldots, x(n-p)]^T$ represents input signal vector, p refers to filter order.

The parameter μ is a step size that affects the performance of LMS algorithm. For a small value of μ the adaptive filter takes a longer duration to converge. As the value of μ increases, the filter becomes unstable and ends up with divergence. Let a desired process $d(n)$ be corrupted to form noisy observation. The design of pth order FIR adaptive filter with impulse response $W(n)$ allows to recover desired process $\hat{d}(n)$ and the relationship between the recovered processwith filter impulse response is expressed as follows:

$$\hat{d}(n) = W_n^T x(n) \qquad \text{... (5)}$$

3 Powerline interference reduction method using sst based filtering

Two SST based filtering methods for suppressing of PLI (50Hz) noise were developed and investigated. Both methods incorporates SST analysis applied to corrupted ECG signal. This SST transforms any kind of signal into sum of well separated amplitude modulated, frequency modulated components. It also has ability to reduce the spectral leakage between components and to deal with non-stationary component. For our application, the time varying characteristics and in-band nature of PLI[8] introduces difficulty in removing interference without affecting the underlying ECG signal. But this SST helps to localize and retrieve non-stationary PLI accurately. The objective of the proposed work is to suppress interference without affecting ECG frequencies. By analyzing non-stationary characteristics, PLI is modeled as $A(n)\exp(j2\pi f_{PLI} n + \Phi)$ then, ECG recording with such interference can be written as

$$x(n) = d(n) + A(n)\exp(j2\pi f_{PLI} n + \Phi) \qquad \text{... (6)}$$

The goal of PLI elimination is to estimate the desired signal $d(n)$ from corrupted recording without any distortion. Hence the recovered signal $\bar{d}(n)$ after estimation of interference is of the form:

$$\bar{d}(n) = x(n) - \bar{A}(n)\exp(j2\pi f_{PLI} n + \bar{\varphi}) \qquad \text{... (7)}$$

where, $d(n), x(n)$ refers to the desired and corrupted ECG signal. In this proposed approach, we apply SST principles in two possible ways to estimate PLI component. Once PLI estimated, then the desired ECG signal is recovered by simply subtracting it from corrupted recording.

3.1 Synchrosqueezing transform based filtering by retrieval of PLI using indirect subtraction method (Technique A)

Synchrosqueezing transform represents a multicomponent signal as set of concentrated curves in the time frequency domain[31]. Being invertible transform, the retrieval of any component can be done through the integration of wavelet coefficients around curve (ridge). Likewise, the original ECG signal corrupted by PLI is transformed into a set of ridges where each ridge specifies its instantaneous component. For effective ECG denoising, it is necessary to estimate PLI component. As mentioned above, the PLI is modeled as a component with time varying frequency and amplitude. Hence, the retrieval of PLI through SST filtering requires identification of a band that accommodates ridge belonging to the PLI, followed by applying SST inverse over that band to reconstruct PLI. The filter structure used for the PLI estimation is shown in Fig. 1. Considering frequency variation of PLI around nominal frequency of 50 Hz, the frequency band selected for the estimation of interference is 47-53 Hz. Finally, The Noise free ECG signal is reconstructed by simply subtracting estimated PLI from the corrupted ECG signal.

3.2 Synchrosqueezing transform based adaptive filtering by extracting PLI through modified reference (Technique B)

The effectiveness of ECG denoising is highly decided by PLI estimate and its estimation in SST is accomplished through reconstructing ridges holding them. The previously described method of PLI estimation seems to be ineffective since the ridges are carrying part of signal (QRS peak) besides interference. Hence, the direct subtraction of the PLI estimate from the corrupted ECG recording ends up the desired ECG signal with reduced peak. In some way, the peak information must be recovered for effective denoising. In these circumstances, adaptive filtering with a modified reference method is a suitable procedure to deal with accurate estimation of interference. The proposed SST based adaptive filtering structure for PLI elimination is shown in Fig. 2. For the proper functioning of an adaptive filter, selection of reference input must be correlated with interference component, and be uncorrelated with signal component. If the reference input to adaptive filter[12] contains a part of signal in addition to interference, the presence of this signal component enables the filter to cancel out some primary input which resulted in the distorted output. To reduce the risk of signal distortion, one possible way is to modify reference input so that it contains correlated interference alone. In the proposed Technique B, adaptive filtering is applied after SST decomposition of PLI corrupted ECG signal. As a result of SST, noisy ECG signal transformed into a set of intrinsic mode function. Let the mode carrying interference be treated as noisy mode. The higher order modes other than noise mode carries more information about QRS than noisy mode, but the noisy mode contains a mixture of PLI with part of QRS.

Selecting noisy mode as a reference input for adaptive filter limits the accuracy of PLI estimate. Hence noisy mode before being applied to adaptive filter is processed so that it keeps interference alone. Processing noisy mode begins with segmentation. This segmentation is accomplished by multiplying noisy mode with adaptive window. The adaptive window is constructed through Hilbert Transformation of higher order modes. Now the windowed noisy mode becomes interference alone except its windowed part. The windowed region needs to be filled up and the necessary condition for filling it up is to compromise frequency of time series on either side of the window. In the proposed work, Modified Discrete Cosine Transform (MDCT)[33] is applied to interpolate windowed portion to obtain reference input. The detailed steps involved in filtering of Noisy ECG are explained as follow:

1. Perform SST decomposition on noisy ECG signal into a set of intrinsic mode functions

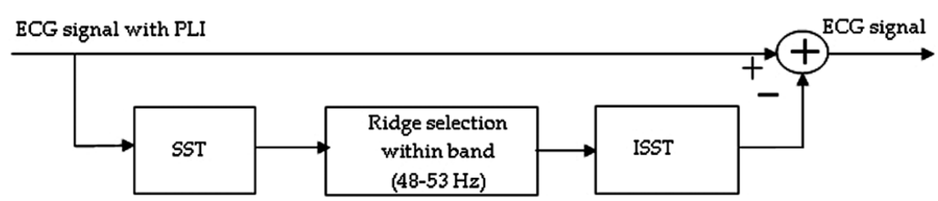

Fig. 1 — Synchrosqueezing transform based filtering by retrieval of PLI using indirect subtraction method (Technique A).

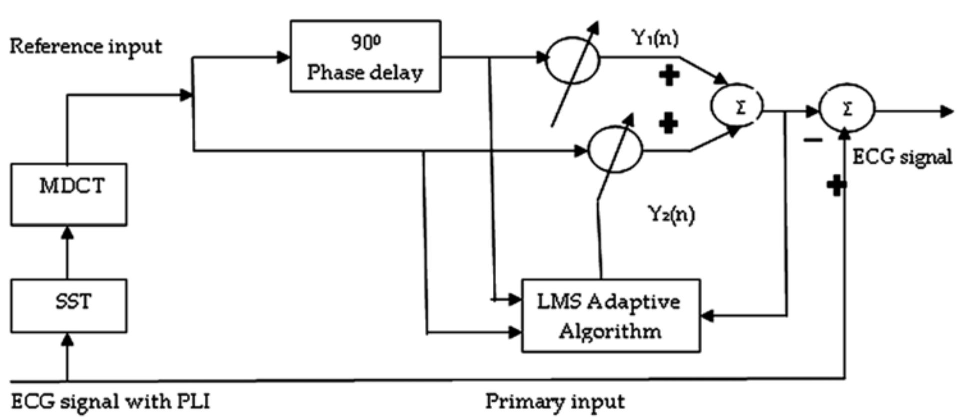

Fig. 2 — Synchrosqueezing transform based adaptive filtering of ECG signal through modified reference method (Technique B).

$$x(n) \xrightarrow{SST} \sum_{i=1}^{N} IMF_i(n) \quad \text{... (8)}$$

2. Categorize modes into two group signal mode, noisy mode

$$\sum_{i=1}^{N} IMF_i(n) \rightarrow S_{imf}(n) + N_{imf}(n) \quad \text{... (9)}$$

3. Estimate adaptive window from higher order modes through Hilbert transform

$$H(n) = HT\{S_{imf}(n)\} \quad \text{... (10)}$$

$$W(n) = abs(H(n)) \quad \text{... (11)}$$

4. Multiply adaptive window with noisy mode to get windowed noisy mode

$$S(n) \leftarrow W(n) * N_{imf}(n) \quad \text{... (12)}$$

5. Apply MDCT to time series on either side of window to interpolate time series within window.

Hakki Gokhan*et al.*[33] developed MDCT to carry out interpolation of time series. It involves two stage processing such as DCT computation, followed by linear interpolation. Let $S_{left}[k]$& S_{right}[k] be the DCT coefficient of time series outside the window. Then, DCT coefficient for the time series within window is calculated by linear interpolation as follows

$$S_{int}[k] = S_{left}[k]\left(1 - \frac{n}{T}\right) + S_{right}[k]\left(\frac{n}{T}\right),$$
$$n = 0,1, \ldots \ldots . T - 1 \forall k \quad \text{... (13)}$$

Once interpolated, inverse modified discrete cosine transform (IMDCT) is applied to interpolated DCT coefficient to reconstruct time series in the time domain. Hence, the accurate reference input for adaptive filter is formed.

$$S(n) = \sum_{k=0}^{N-1} f_k\, u^k S_{int}[k] cos\left[\frac{(2n+1)k\pi}{2N}\right] \quad \text{... (14)}$$

Primary input: PLI corrupted ECG signal

Reference input: $S(n)$

The adaptive filter produces PLI corrected ECG signal by minimizing mean squared error between a primary input and reference input. In this work, a modified form of noisy data is given as a reference and corrupted signal as primary input to adaptive filter. The proposed SST based adaptive filtering approach is fully adaptable and is capable to deal with both stationary and non- stationary PLI characteristics. In addition, it is insensitive to the variation of PLI frequency and preserves the morphology of ECG.

4 Results and Discussion

SST provides a higher resolution time frequency representation when applied to any kind of signals. The better component localization and well separation of modes by the SST is studied and tested with a sample multi-component signal $S(t)$ that consists of stationary and non-stationary components. The signal $S(t)$ and its equivalent SST representation is as shown in Fig.3.

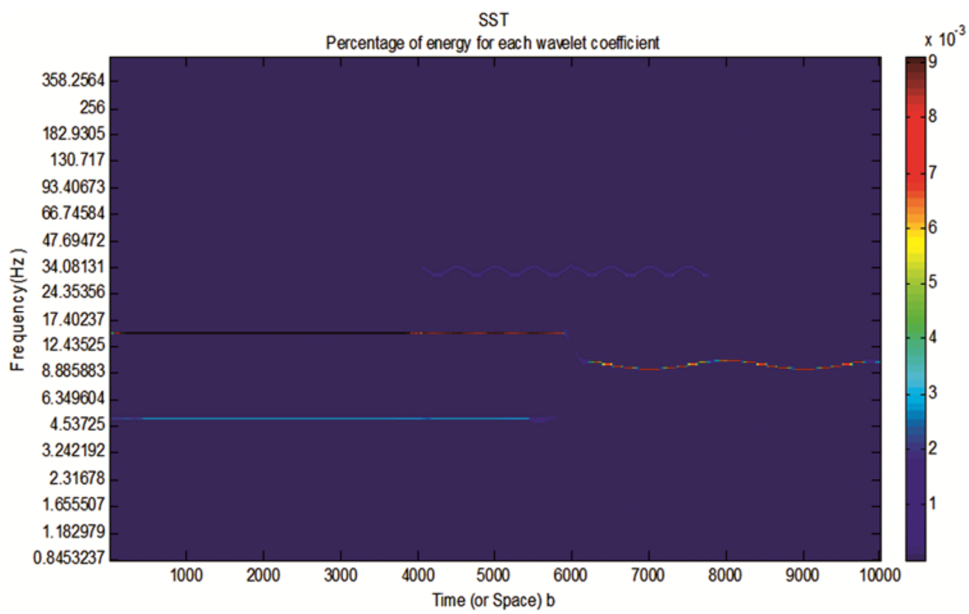

Fig. 3 — SST representation of multicomponent signal $S(t)$.

$$S(t) = \begin{cases} 0.5\cos(10\pi t) & 0 < t < 6 \\ 08\cos(30\pi t) & 0 < t < 10 \\ 0.7\cos(20\pi t + sin(\pi t)) & 6 < t < 10 \\ 0.6\cos(66\pi t + sin(4\pi t)) & 4 < t < 7.8 \end{cases} \quad \ldots (15)$$

It is evident that the SST tool provides an accurate description of the component of signal and the representation of components by them appears as in the form of ridges. Hence, ridge detection and extraction procedure[31] is applied to extract components. The extracted individual mode of multicomponent signal through ridge extraction procedure is shown in Fig. 4. The mode reconstructed through SST is identical to the ideal mode and there is no mode mixing involved in the mode reconstruction. From the analysis of mode reconstruction, it is understood that SST can disintegrate any kind of multicomponent signal into its component. In this proposed work, SST is utilized a as decomposition tool to disintegrate the corrupted ECG signal.

The current study focuses on implementing the proposed denoising technique on ECG data. To do so, The ECG data were gathered from two different sources. The artificial ECG data were collected using ECGSYN software which is designed to simulate all standard lead configuration. The real ECG data is obtained from MIT-BIH database. This database contains a total of 32 noise free ECG records of duration of a 35 min each and each record sampled at a rate of 360 sample per second. Powerline interference is introduced into ECG data by adding simulated interference to generate degraded ECG for testing and analysis of proposed method. For the analysis of data, SST makes use of either Morlet or bump type wavelet. It is known that Morlet wavelet offers the best trade-off between temporal and frequency resolution than the bump wavelet. For the event related changes, Morlet wavelet is more sensitive than other wavelet. Hence in this paper, Morlet wavelet is chosen for SST analysis of ECG signal. As previously mentioned, the SST uses the phase information in CWT to sharpen time frequency analysis of signal. Like wavelet transform, SST has its own inverse SST which transforms signal back into their respective domain. The component localization and ridge analysis in SST allows to reconstruct modes which is impossible to obtain it with conventional filtering methods. On applying SST, The corrupted ECG signal is decomposed and the result of decomposition is shown in Fig. 5. Inspection of decomposition results reveals that a high-frequency

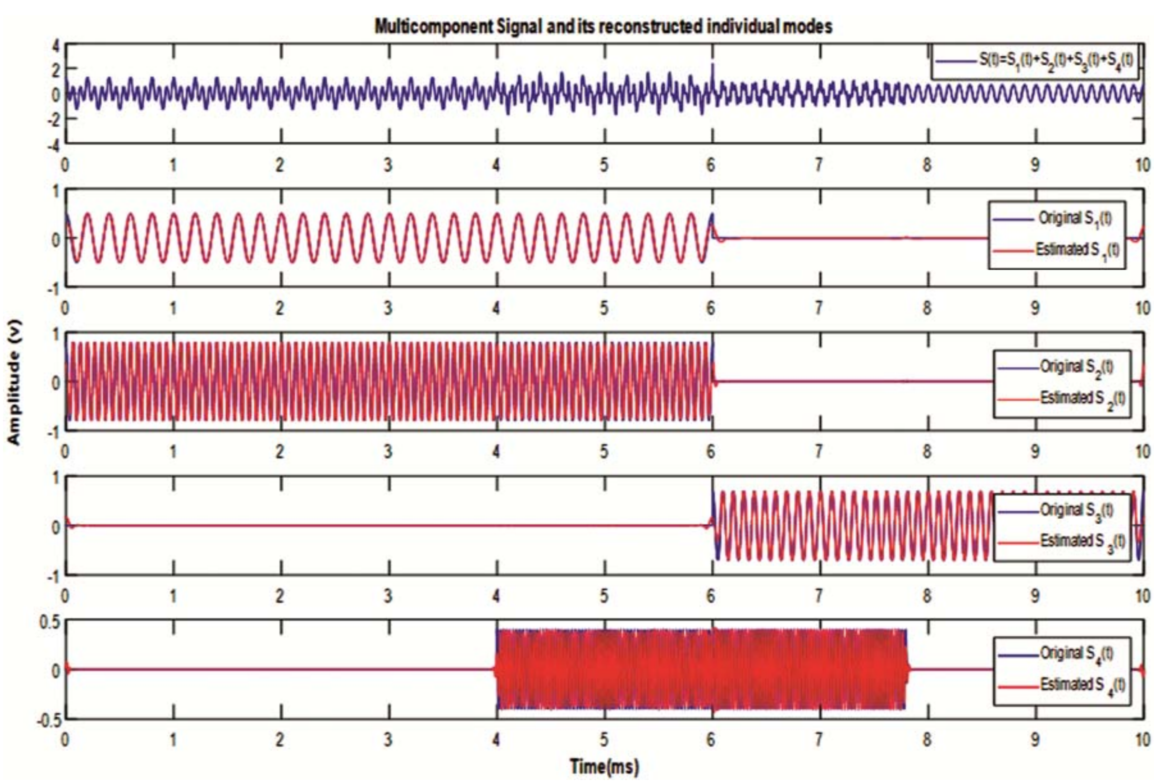

Fig. 4 — Reconstruction of individual modes through SST decomposition.

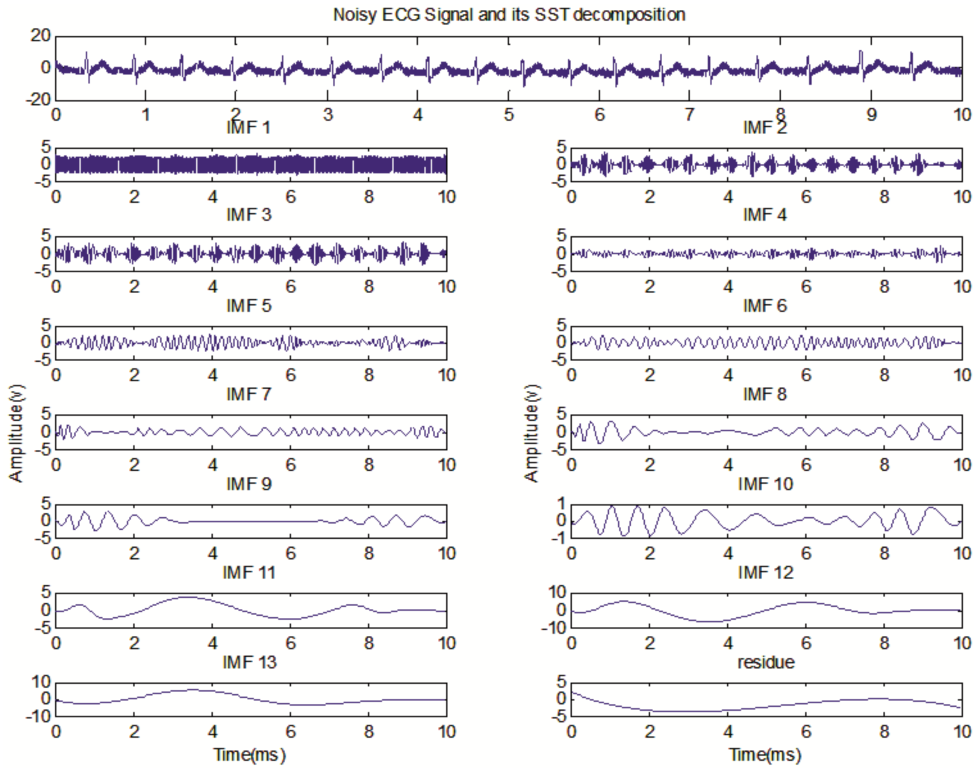

Fig. 5 — Noisy ECG signal and its SST decomposition.

mode is ranked on top and low-frequency mode is at bottom of decomposition. As a high frequency component, PLI would be incorporated into one of lower order modes. For understanding the mode that carries the interference, the spectrum obtained for the first four modes is shown in Fig. 6. It is evident that the presence of interference found in the lower order mode IMF_1.

The aim of the proposed approaches is to suppress the PLI without discarding ECG frequencies where PLI occurs. To accurately estimate PLI, the frequency band is set in the range of 47-53 for the proposed technique A. Two tapped Adaptive filter with a convergence step size of 0.0125 is employed for the implementation of proposed Technique B. Several simulations were performed to investigate the effectiveness of proposed filtering methods and the entire simulation was carried out in MATLAB environment. For the simulation, ECG recordings 215,115,106,100,101 from MIT-BIH database were taken. The de-noised ECG signal is qualitatively assessed for both the proposed and other existing methods. Figure 7 shows de-noised ECG signal of 215 recording for SST based filtering method (Technique A), the SST representation of Noisy ECG signal reveals the presence of interference as well as its instantaneous frequency component and the de-noised ECG signal resembles the original ECG signal.

Figure 8 shows the result of reference input generated for adaptive filter and de-noised ECG signal of SST based Adaptive filtering with modified reference approach (Technique B). With this approach, the pattern of enhanced ECG signal resembles the original ECG signal. From the obtained de-noised results, it is evident that the two SST based method has significantly attenuated PLI in the ECG recording. Both methods worked better on real and artificial ECG data and preserved the morphology of ECG signal. The effectiveness of the proposed filtering methods are compared with existing denoising methods such as adaptive notch filtering, wavelet denoising, EMD-wavelet and EMD-Adaptive filtering. The adaptive notch filtering[12] is designed with a notch at frequency of 50 Hz and its convergence factor value is set to 0.00125 for slow convergence. In the case of wavelet based ECG denoising, Symlet family of wavelet is more preferable since the shapes of it resembles the ECG features. Therefore wavelet denoising using symlet provides better denoising result than other type of wavelets.

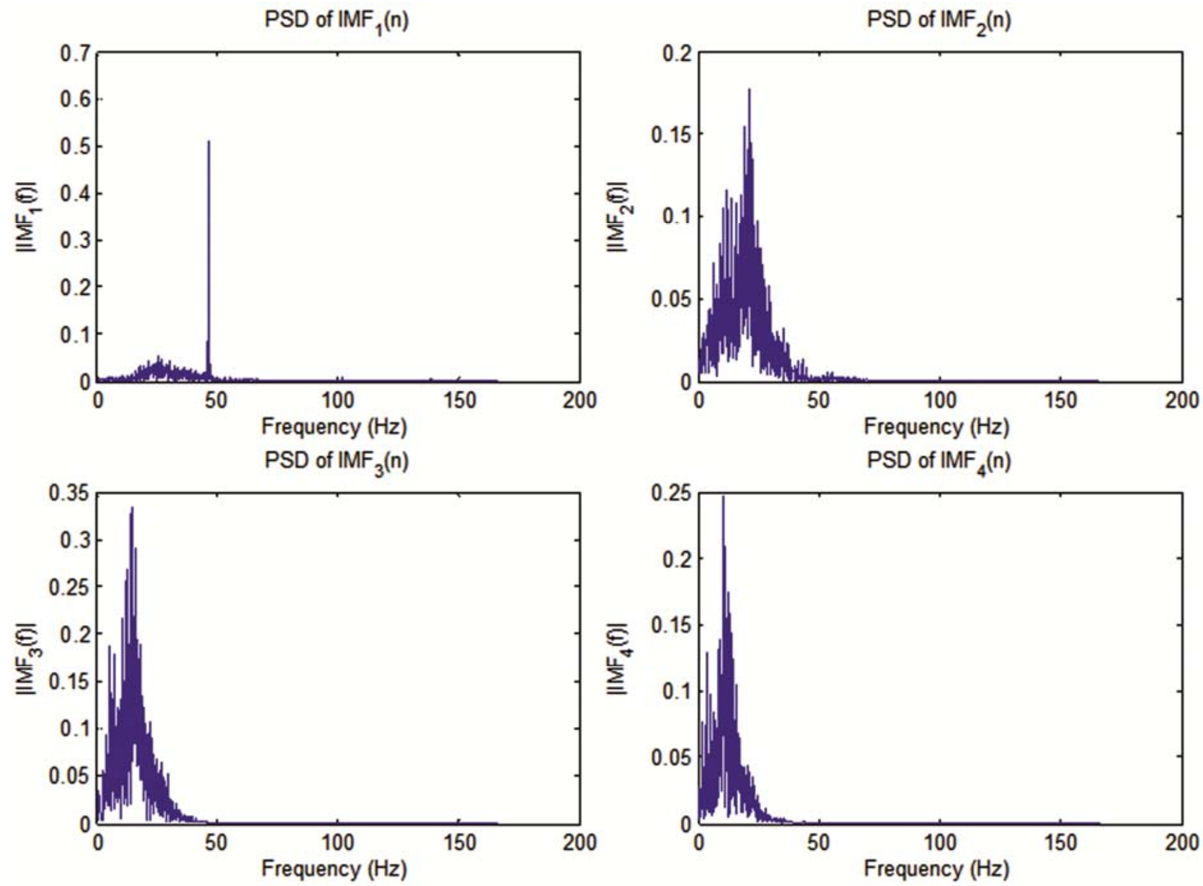

Fig. 6 — Power spectrum obtained for first four lower order modes of decomposition (IMF_{1-4}).

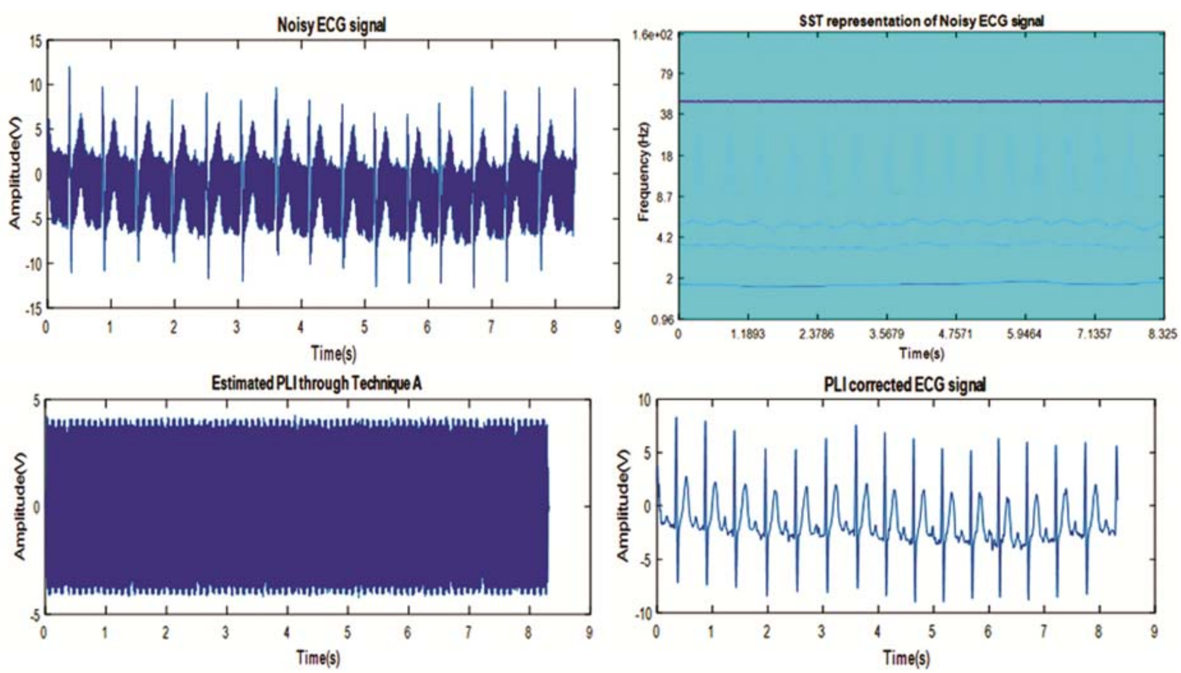

Fig. 7 — PLI corrected ECG signal by SST based filtering (Technique A).

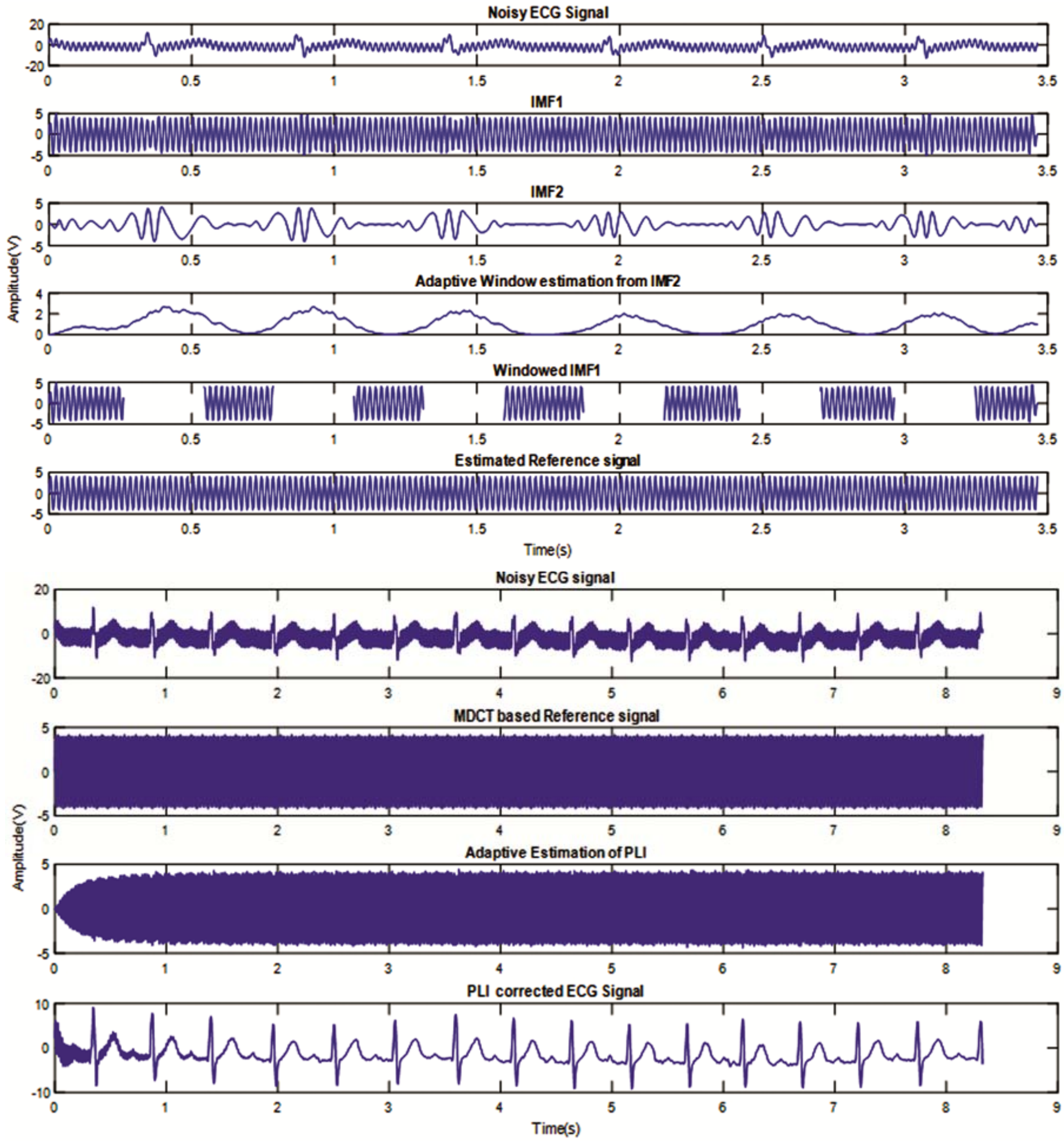

Fig. 8 — PLI suppression by Synchrosqueezing based adaptive filter with modified reference approach (Technique B).

For the EMD-Adaptive filtering[27], reference input for the adaptive filter is obtained by band pass filtering (BPF) the intrinsic mode function (IMF_1). The BPF is designed with a pass band ranging from 48 to 51 to isolate interference components. The result of each filtering method is presented in Fig. 9 after applying corrupted ECG signal to the method mentioned above. It is found from the enhanced ECG results that there are some distortions present in the case of other methods. The enhanced ECG signal obtained by the proposed methods offer better enhancement in comparison to other methods.

Now, a quantitative comparison of the proposed denoising approaches is carried out by performing signal to noise ratio (SNR) test, mean squared error (MSE) test and percentage root mean squared difference (PRD) test. For this case, The SNR, MSE, and PRD is defined as follows:

$$SNR_{imp}[dB] = 10log_{10}\left[\frac{\sum_{i=1}^{L}\left|\overline{x(l)} - d(l)\right|^2}{\sum_{i=1}^{L}|x(l) - d(l)|^2}\right] \quad \ldots (16)$$

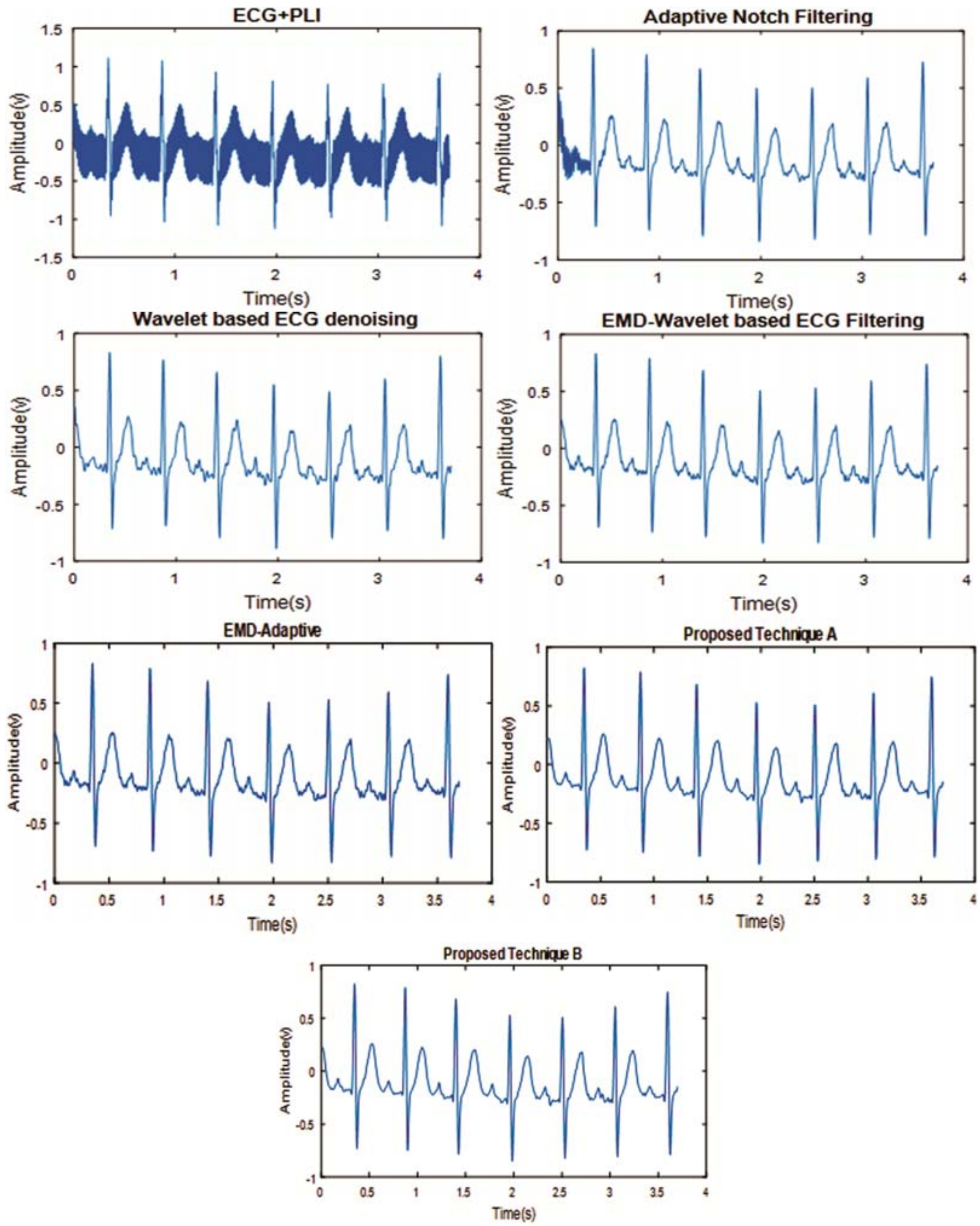

Fig. 9 — Qualitative analysis of ECG enhancement by various denoising methods.

$$MSE = \frac{1}{L}\sum_{l=1}^{L}\left[d(l) - \overline{x(l)}\right]^2 \quad \text{... (17)}$$

$$PRD = \sqrt{\frac{\sum_{l=1}^{L}\left[d(l) - \overline{x(l)}\right]^2}{\sum_{l=1}^{L} d^2(l)}} * 100 \quad \text{... (18)}$$

where, $d(l), x(l)$ denote the original and noisy ECG signal and $\bar{x}(l)$ refers to enhanced ECG signal. L is the total number of samples.

A better denoising method would results in improved SNR, smaller MSE and PRD values. Figure 10 shows the result of SNR_{imp} for different ECG enhancement schemes over a range of input SNR levels (-5 dB to 55 dB). This figure reveals that the highest SNR_{imp} is obtained for our proposed methods over the different level of input SNR while other methods offering lower SNR_{imp}. Synchrosqueezing based adaptive filter with modified reference approach achieves higher SNR_{imp} even at lower input SNR.

Figure 11 shows MSE values obtained for different denoising schemes at various input SNR levels. As input SNR varies from low to high, synchrosqueezing based adaptive filter with modified reference approach maintains lowest MSE than other methods. Figure 12 shows the comparison of PRD results obtained for different PLI removal techniques at various levels of input SNR. It is more evident that Synchrosqueezing based adaptive filtering with modified reference approach (Technique B) yields lowest PRD value at all the levels of input SNR while other methods results in higher PRD values.

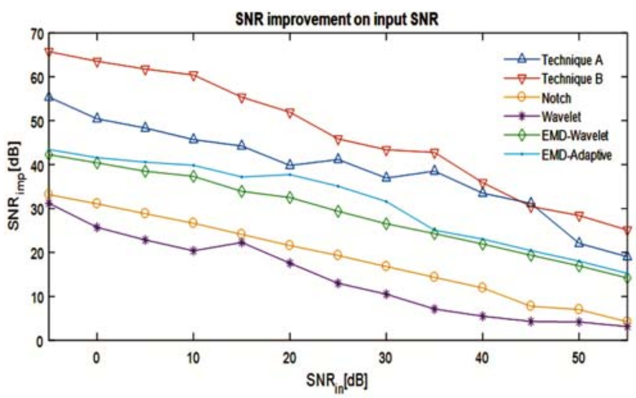

Fig. 10 — Comparison of SNR $_{imp}$ for different denoising methods at different input SNR level.

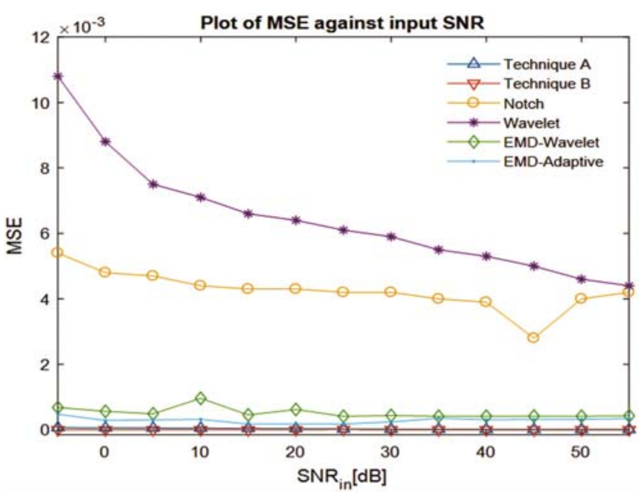

Fig. 11 — Comparison of MSE obtained for different ECG enhancement at various input SNR level.

To evaluate the efficiency of proposed methods over ECG beats of different cardiac conditions such as myocardial infaraction, Bundle of Block, Premature Ventricular contraction, the ECG recordings with such conditions from Staff III database, PTB diagnostic database and St. Peterburg 12 lead arrhythmia database were used to test the different PLI suppression techniques. Table (1-3) present the results of SNR$_{imp}$ test, MSE test, PRD test for ECG signal of different cardiac condition. From this tables, it is observed that Synchrosqueezing based adaptive filtering with a modified approach (Technique B) maintains higher SNR$_{imp}$, Lower MSE and PRD value when compared to other denoising methods.

To show the proposed methods sensitive to variations of PLI frequency, we assumed that PLI has highest local maxima in the frequency band between 47 to 53 Hz of TFR. The drifting of PLI frequency is done by shifting 0.5 Hz to the left or to the right about 50 Hz. The denoising capability of the proposed methods are tested with its adaptability to PLI frequency drift. At each frequency drift, quantitative assessment is performed and tabulated

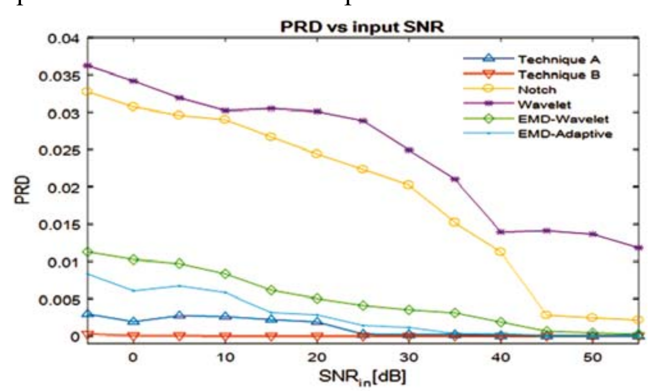

Fig. 12 — PRD value obtained for different ECG enhancement procedures at various SNR level.

Table 1 — The SNR$_{imp}$ test results obtained by using different ECG denoising method for ECG signal of various cardiac disorder.

	SNR$_{imp}$(dB)					
ECG Signal	Adaptive notch[12]	Wavelet Filtering[14]	EMD Wavelet[26]	EMD Adaptive[27]	Proposed Technique A	Proposed Technique B
215^{m}	21.6142	17.2202	24.4892	25.3318	32.5371	35.6134
101^{s}	20.9432	16.8223	25.9378	26.5072	28.9889	31.5663
155^{s}	27.5985	24.2226	36.1603	35.6474	40.6897	42.0614
S0010re^{p}	15.8095	11.5628	14.2524	16.3438	17.8501	21.4052
S0017re^{p}	26.0287	24.6097	36.8410	39.0507	45.4552	48.7792

Table 2 — MSE test result obtained for the ECG signal of various cardiac abnormalities.

ECG Signal	MSE. Adaptive notch[12]	Wavelet Filtering[14]	EMD Wavelet[26]	EMD Adaptive[27]	Proposed Technique A	Proposed Technique B
215[m]	1.4207E-4	2.7776E-02	1.6107E-04	2.5161E-4	1.1487E-08	1.271E-8
101[s]	5.0163E-3	9.3500E-02	6.1046E-04	9.9821E-4	4.9867E-09	1.7280E-10
155[s]	2.7772E-4	6.4385E-03	3.5315E-04	6.4570E-5	2.1601E-07	2.4963E-10
S0010re[p]	2.4004E-3	6.4525E-02	2.640E-04	3.3640E-04	2.3781E-07	4.1755E-09
S0017re[p]	2.486E-3	2.9878E-02	3.7809E-03	3.5714E-04	2.5845E-05	4.78616E-7

Table 3 — PRD test result obtained for the ECG signal of various cardiac disorder.

ECG Signal	PRD Adaptive notch[12]	Wavelet Filtering[14]	EMD Wavelet[26]	EMD Adaptive[27]	Proposed Technique A	Proposed Technique B
215[m]	0.052395	0.61517	0.009640	0.004127	0.0027114	0.000416
101[s]	0.04072	0.051154	0.0021	0.01276	0.00245	0.000192
155[s]	0.06694	0.61499	0.04942	0.026519	0.006772	0.000405
S0010re[p]	0.0694	0.7353	0.05124	0.01174	0.00204	0.000570
S0017re[p]	0.05233	0.8819	0.07273	0.06272	0.003363	0.000296

[m]stands for MIT-BIH Arrhythmia database, [s]stands for St.Peterburg 12 lead arrhythmia database, [p]stands for PTB diagnostic database

Table 4 — Performance assessment of proposed ECG enhancement method over PLI frequency test.

	SNR_{in}= - 3dB					
	Proposed Technique A			Proposed Technique B		
Noise Frequency (Hz)	SNR_{imp}	MSE	PRD	SNR_{imp}	MSE	PRD
47	46.4131	0.00025415	7.004E-3	50.5962	0.00009836	3.752E-6
47.5	46.6191	0.00025415	6.829E-3	50.0266	0.000011489	3.89E-5
48	47.0413	0.00021995	6.516E-3	49.0722	0.000012952	4.413E-6
48.5	47.0683	0.00021645	6.342E-3	49.9674	0.000011013	3.964E-5
49	47.5883	0.00019394	6.118E-3	52.1161	0.000069043	3.028E-5
49.5	46.2818	0.00014658	4.212E-3	52.0806	0.000069747	3.192E-5
50	48.0423	0.0001747	5.807E-3	52.3349	0.000067006	3.077E-6
50.5	48.541	0.00016031	5.562E-3	53.2903	0.00005881	2.922E-5
51	48.3957	0.00016106	5.576E-3	52.0195	0.000053358	3.134E-6
51.5	48.6679	0.00015752	5.489E-3	52.8403	0.000011909	3.167E-5
52	48.6463	0.00015205	5.417E-3	49.7568	0.000011285	3.962E-6
52.5	48.7636	0.00014677	5.334E-3	50.2707	0.000010101	3.837E-5
53	48.8569	0.00014663	5.34E-3	49.6462	0.000019981	3.247E-6

in Table 4. In the case of PLI frequency shift, the proposed technique A removes part of signal component besides PLI which resulted in reduction of SNR_{imp} value. This is due to indirect subtraction of estimated interference so the estimated interference needs to be processed before it is subtracted. The proposed technique B improves SNR_{imp} and yields lower MSE while dealing with PLI frequency drift. It is evident from Table 4 that both SST based ECG enhancement methods are insensitive to variations in PLI frequency. It is evident from the comparison that the SST based Adaptive filtering with modified approach yields superior performance than the other methods.

5 Conclusions

Powerline interference is a major type of interference found in ECG recordings. The presence of such interference masks the features of ECG signals completely so that it makes the diagnosis process more complicated. For proper diagnosis and interpretation, it is necessary to filter such interference from ECG recordings. The existing ECG enhancement methods like WT, EMD, and EEMD have not been efficient due to mode mixing and inability to deal with variation of PLI frequency. Hence, the design of ECG enhancement technique that has self-adjusting capability to the variations of PLI frequency becomes an important objective for many researchers. Initially, SST was introduced for analyzing nonlinear and non-stationary signals and it is a modified form of TFR method that allows to represent time varying components more accurately. The components reconstruction property of SST allows to transform any type of signal into sum of well separated intrinsic mode functions. The mode decomposition of sample multicomponent signal using SST is demonstrated with its reconstructed mode more identical to ideal mode. This proves that SST tool is suitable to analyze non-linear and non-stationary signals. Some of the advantages of using SST for mode decomposition are fixed wavelet basis, well separated modes and less computation complexity.

In this paper, two ECG enhancement procedures based on SST were introduced for removal of PLI from ECG recordings. Both methods are aimed at obtaining reliable PLI estimate for the better reconstruction of noise free ECG signals. The first method is based on the reconstruction of PLI component from the selected band of SST, whereas the second method uses adaptive filtering of SST component to estimate PLI. Finally, Simulations are carried out to test the effectiveness of proposed methods. It is evident from the simulation results that the proposed methods can remove PLI of 50 Hz and its harmonics. The proposed techniques effectively removed PLI in both real and artificial ECG signals and to test its performance they are compared with state of the art methods. The SST based filtering methods outperformed other methods under the condition of PLI frequency variations. The experimental results also suggest that the SST based adaptive filtering with modified reference approach (Technique B) offers better PLI suppression than all other methods.

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