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Adaptive Spectral Estimation of Non-stationary Biomedical Signals Based on Autoregressive Modeling and Kalman Filtering

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Abstract

In this paper, we present an adaptive spectrum estimation method for non-stationary Biomedical Signals. The algorithm is based on time-varying autoregressive (TVAR) modeling where the time varying parameters are estimated by Kalman filtering. The algorithm generates adaptively an estimate of the power spectral density (PSD) at each time instant. A comparison was made with the recursive least squares (RLS) method, the main feature of the proposed approach is the capability of the Kalman filter that enables tracking smooth and sharp changes in the time varying process parameters. Furthermore, it provides better time-frequency resolution and gives a good spectral peak matching. Simulation studies and applications on real EEG data show that the proposed algorithm can provide important transient information on the inherent dynamics of non-stationary biomedical processes.

Keywords

Brain-Computer Interface (BCI), Motor Imagery, Kalman Filtering, Autoregressive Model,
Event Related Desynchronization (ERD)

1. Introduction

Power spectral density (PSD) estimation is widely used in the analysis of biomedical signals [1]–[2]. There are two general frameworks of PSD estimation: nonparametric and parametric methods [3]–[5]. Nonparametric methods such as the periodogram and its improvements (i.e., Barlett's, Welch's, and Blackman-Tukey's methodologies) [6]–[8] are based on the idea of estimating the autocorrelation sequence of a random process from measured data, and then taking the FFT to obtain an estimate of the power spectrum. The main two advantages of these techniques are their computational efficiency, due to the numerical efficiency of the FFT algorithm, and that they do not make any assumptions about the process except its stationarity. However, these techniques have some limitations. In fact, they require stationarity of the studied segments and they have a limited time frequency resolution.

Time-frequency resolution can be improved by using parametric methods of PSD estimation. The parametric approach is based on modeling the signal under analysis as a realization of a particular stochastic process and estimating the model parameters. In the absence of a priori knowledge about how the process is generated, parametric PSD is generally performed assuming an autoregressive (AR) model [9].

The above-mentioned methods assume that the signal under analysis is stationary and its statistics such as mean, variance, and autocorrelation do not change with time. However, most biomedical signals, such as HRV and EEG signals considered in this work are inherently non-stationary processes with complex dynamics; they contain numerous non-stationary or transient characteristics such as drifts, trends, abrupt changes, and beginnings and ends of clinical events. To understand the time-frequency properties of such non-stationary signals, several time-varying PSD estimation methods have been developed based on nonparametric spectrum estimation such as the spectrogram, scalogram [10]–[11]. Similarly, parametric spectrum estimation algorithms have been proposed using a Time varying autoregressive model [12]. It has been shown that parametric PSD estimation methods may result in higher time-frequency resolutions than nonparametric PSD estimations [13]–[14].

Many approaches have been proposed to identify time-varying autoregressive TVAR models. While traditional adaptive parameter estimation algorithms, for example the recursive least squares (RLS) and least mean squares (LMS) can be applied to track time-varying trends [15]–[16], these algorithms can often produce lagged tracking of time varying parameters. Fast transversal recursive instrumental variable (FTRIV) and generalized least mean squares (GLMS) [17], are proposed for the estimation of AR non Gaussian processes. The algorithms are seen to have better performance in terms of convergence speed and adjustment even in low SNR.

Another method for TV system identification is to expand the TV parameters onto a linear or nonlinear combination of a set of basis functions. A good choice of the basis functions should allow abruptly or rapidly changing parameters to be tracked. However, there is no guideline on how to choose the appropriate basis functions for a specific modeling problem. Conventionally, the basis functions have been chosen to be polynomials (including Chebyshev and Legendre types), prolate spheroidal sequences which are the best approximation to bandlimited functions [18]–[22] and wavelets that have a distinctive property of multi-resolution in both the time and frequency domains [23]–[24]. In fact, each family of basis functions has its own properties of accuracy and tractability, for example, Walsh functions can work well for tracking most abrupt changes while Chebyshev polynomials perform well for smoothly and slowly varying coefficients. Basis function expansion methods have been widely applied to solve various engineering problems. For example, a TVAR model can be expanded over a Fourier–Bessel (FB) series to constitute a feature vector for segmentation of the EEG signal, and then to find a simple model for the parametric representation of EEG signals [25].

The fundamental problem in the Kalman filtering is how to choose the optimal parameters that control the filter and update the estimates. Generally, we are forced to some simplifications of the model in order to reduce the number of parameters which must be tuned by manual setting. In almost all studies, the estimates are updated only by the value of the state noise variance whose large values produce speed convergence but with large variance of the estimates, on the other hand small values produce smooth estimates with slow convergence. In fact, there is a bias/variance tradeoff that must be handled according to the problem. We assume that accurate estimates without lag can produce smooth PSD and the time-frequency resolution will be much better.

The objective of this study is thus twofold: (i) to develop a time-varying modeling framework that exploits the improved tracking capability of the Kalman filter so that the resultant time-varying models can track rigorously non-stationary processes with sharp and smooth changes in the system parameters; and (ii) to apply the time-varying modeling algorithm to ERS/ERD analysis where the proposed algorithm can provide almost smooth spectrum and the resultant time–frequency resolution produced by the identified model is extremely high; this is usually very important for feature extraction from EEG signals in both the time and frequency domains.

2. Methodology

2.1. Time Varying Autoregressive Model

Time varying autoregressive (TVAR) methods have been used in a number of studies to model EEG data by representing the signal at each channel as a linear combination of the signal at previous time points.

Based on time varying autoregressive or all-pole model of the EEG signal, an EEG signal dataset can be characterized as an output of a causal, stable, linear time-variant AR (P^{th} order) system given by

$$y(\mathrm{n}) = -\sum_{i=1}^{\mathrm{p}} a_i(n)\, y(n-i) + e(n) \tag{1}$$

where ($a_i(n)$) are the TV coefficients to be determined in the model, and $e(n)$, is assumed to be white Gaussian noise excitation with zero mean and variance σ^2.

AR models provide a compact, computationally efficient representation of EEG signals. Furthermore, AR model parameters are invariant to scaling changes in the data that can arise from inter-subject variations, such as scalp and skull thickness. Due to these properties, AR modeling has been extensively used in EEG for different analyses such as feature extraction, classification tasks, and PSD estimation.

2.2. Kalman Filtering

In order to use the Kalman filtering, we must represent the signal model in state-space form as:

$$x(n+1) = \Phi(n)x(n) + w(n) \tag{2}$$

$$y(n) = H(n)x(n) + v(n) \tag{3}$$

where $x(n) = (\, a_1(\mathrm{n}), \dots,\, a_p(\mathrm{n}))^T$ is the state of the system, $\Phi(n)$ is the transition matrix, $H(n)$ is the observation matrix, $y(n)$ are the observation at time n, $w(n)$ is the state noise with zero mean and covariance matrix Q, $v(n)$ is the observation noise with zero mean and covariance matrix R.

In the above model the matrices Φ and H are assumed to be known, as well as the covariance matrices Q and R. However, in reality we are not able to know exactly the above matrices. In that case some assumptions are considered for the model. In almost all studies they assume that the evolution of the parameters is a random walk procedure [26], i.e. $\Phi = I$, where I is the identity matrix. The adaptation speed of the kalman filter is controlled only by the state noise covariance matrix Q. There is a tradeoff between high adaptation speed (fast tracking) and variance of the estimates.

3. Results

The performance of the new method to estimate the TV parameters, then the time varying spectrum and the Instantaneous Frequency (IF) of a non-stationary system is evaluated, using both simulation examples and an application of the method to experimental data.

3.1. Simulations Results

We consider a 6 order TV AR model:

$$y(n) = -\sum_{i=1}^{6} a_i(n)y(n-i) + e(n) \quad (4)$$

where $[a_1(n), a_2(n), a_3(n), a_4(n), a_5(n), a_6(n)]$ is equal to [-.71,.82,-.49,.61,-.4,.26] for the first 1000 samples and changes to [-2.06,1.84,-.98,.8,-.97,.58] for the next 1000 samples successively, an example is shown in Fig.1.

The simulation procedure involves the generation of N=100 realizations using the same parameters with different random process e(n). To illustrate the effectiveness of the proposed method, the synthetic signals are designed to contain sudden changes of AR parameters.

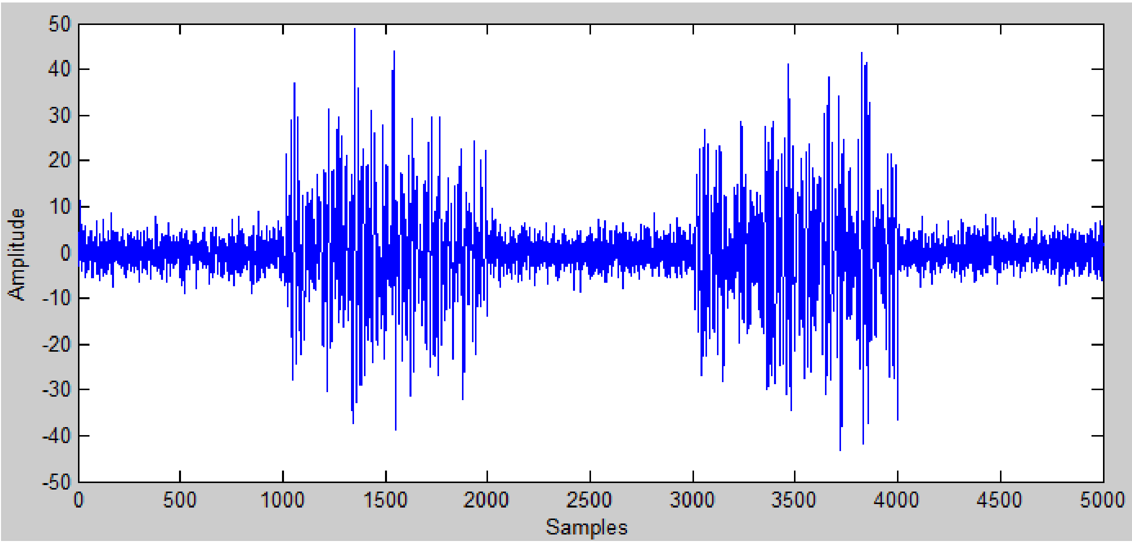

Fig. 1. *Time varying autoregressive signal of order 6.*

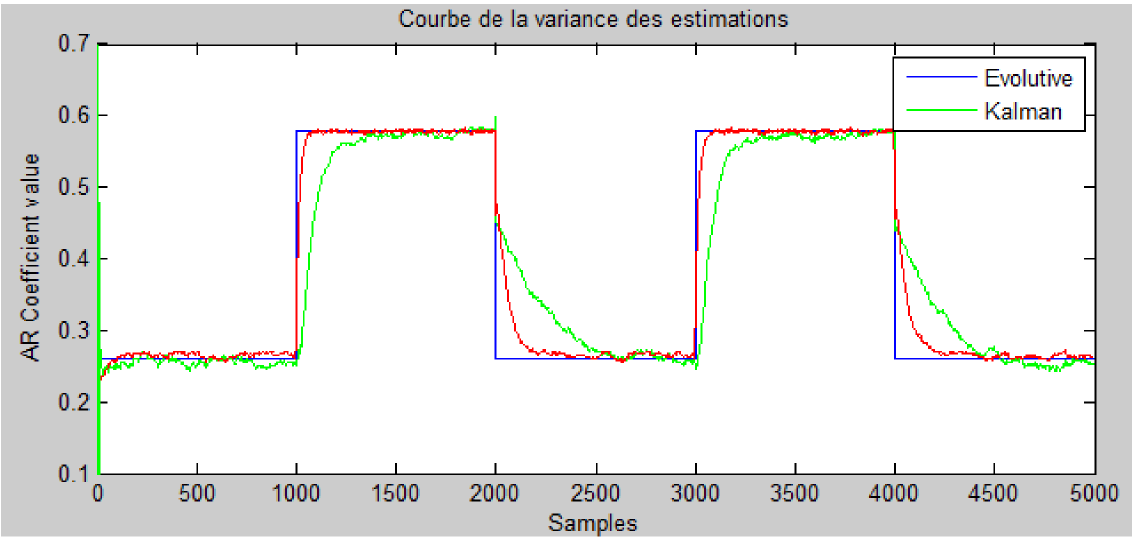

Fig. 2. *Time varying parameter estimation ($a_6(n)$), blue line: true value, green line: RLS method, red line: Kalman filter.*

Figure 2 shows that the proposed method improves the convergence speed of the algorithm and both the variance and the bias of the estimates are significantly reduced, the produced estimates are more accurate.

Figures 3 and 4 confirm the improvement in the variance and the bias of the estimates, the adaptation of the Kalman filter is more rapid which enable tracking rapid changes in TV parameters.

We expect that this improvement in TV parameters estimation accuracy and speed will produce smooth spectrum and high time-frequency resolution when we will apply the proposed method in ERS/ERD analysis in the next section.

3.2. EEG Signal and ERS/ERD Analysis

The electroencephalogram is the sum of the extracellular current flows in a large group of neurons. It can be acquired using either intracranial electrodes inside the brain or scalp electrodes on the surface of the head.

The EEG is a continuous measure over time and can be used to study ongoing activity in the brain while subjects perform long-lasting and/or various tasks. The alpha rhythm of the EEG is predominantly observed over the posterior cortex. This rhythm correlates with relaxation, and for this reason it has been interpreted as a sign of inhibition of activity in the areas over which it has been recorded. Activation of the cortex causes a desynchronization of the alpha band, i.e. its amplitude decreases, while alpha synchronization denotes the increase of alpha activity. When alpha desynchronization or synchronization is related to an internally or externally paced event, it is called as event related desynchronization (ERD) or event-related synchronization (ERS), respectively. ERD has been observed e.g. during complex auditory stimulation, during cognitive and attentional tasks, and during voluntary movement tasks.

When we refer to ERS/ERD, it is necessary to specify the frequency band. In our experiments this frequency band is (8 10Hz), which corresponds to the mu rhythm band. The ERS/ERD phenomena are related to frequency changes, which can be detected by frequency analysis. The TVAR model is used here to produce the time varying spectrum and the Instantaneous Frequency (IF), which are helpful in the analysis of the ERS/ERD.

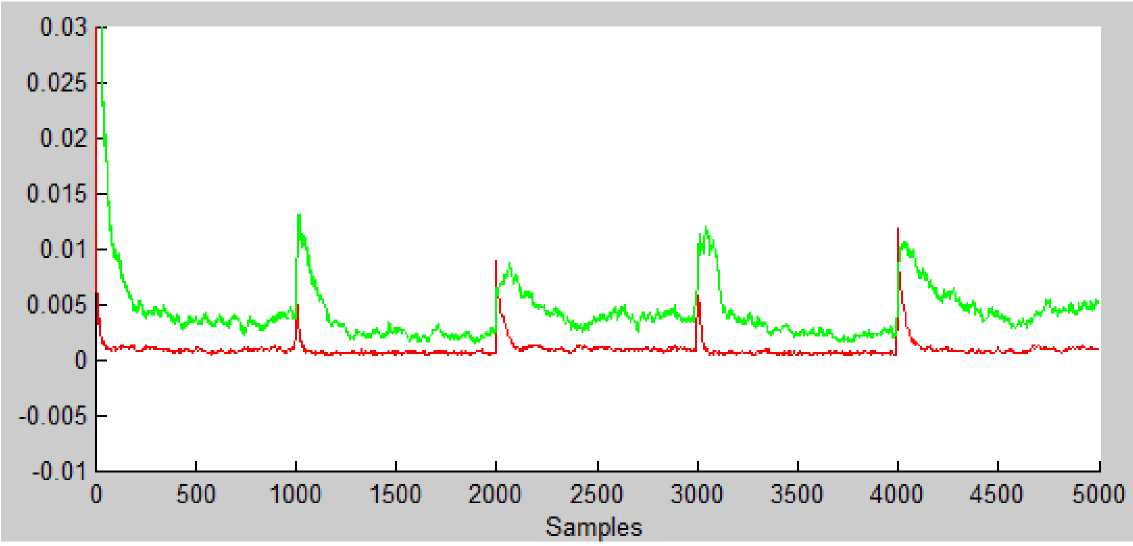

Fig. 3. *Variance of the estimates, green line: RLS method, red line: Kalman filter.*

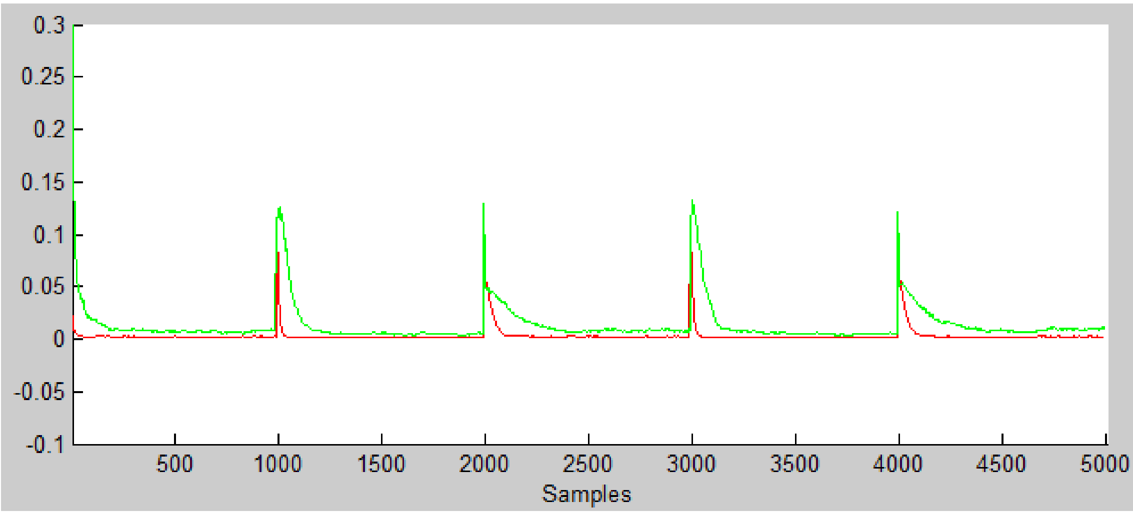

Fig. 4. *Bias of the estimates, green line: RLS method, red line: Kalman filter.*

3.2.1. Data Set

The data set was provided by the department of medical informatics, institute for biomedical engineering, university of technology Graz [27]. It was recorded from a normal subject (female, 25y) during a feedback session. The subject sat in a relaxing chair with armrests. The subject was asked to control a feedback bar by means of imagery left or right hand movements after a cue was indicated. The order of left and right cues was random. The experiment consists of 7 runs with 40 trials each. In the available data set there are 280 trials. As shown in Fig. 5, each trial lasts 9 seconds, in which the first 2 seconds was quiet. At t=2s an acoustic stimulus indicates the beginning of the trial, with a cross “+” displayed for 1s. At t=3s, an arrow (left or right) was displayed as a cue, and at the same time the subject was asked to do motor imagery along the direction of the cue. Three bipolar EEG channels (anterior ‘+’, posterior ‘-‘) were measured over C3, Cz, and C4. The EEG was sampled with 128Hz and was filtered between 0.5

and 30Hz.

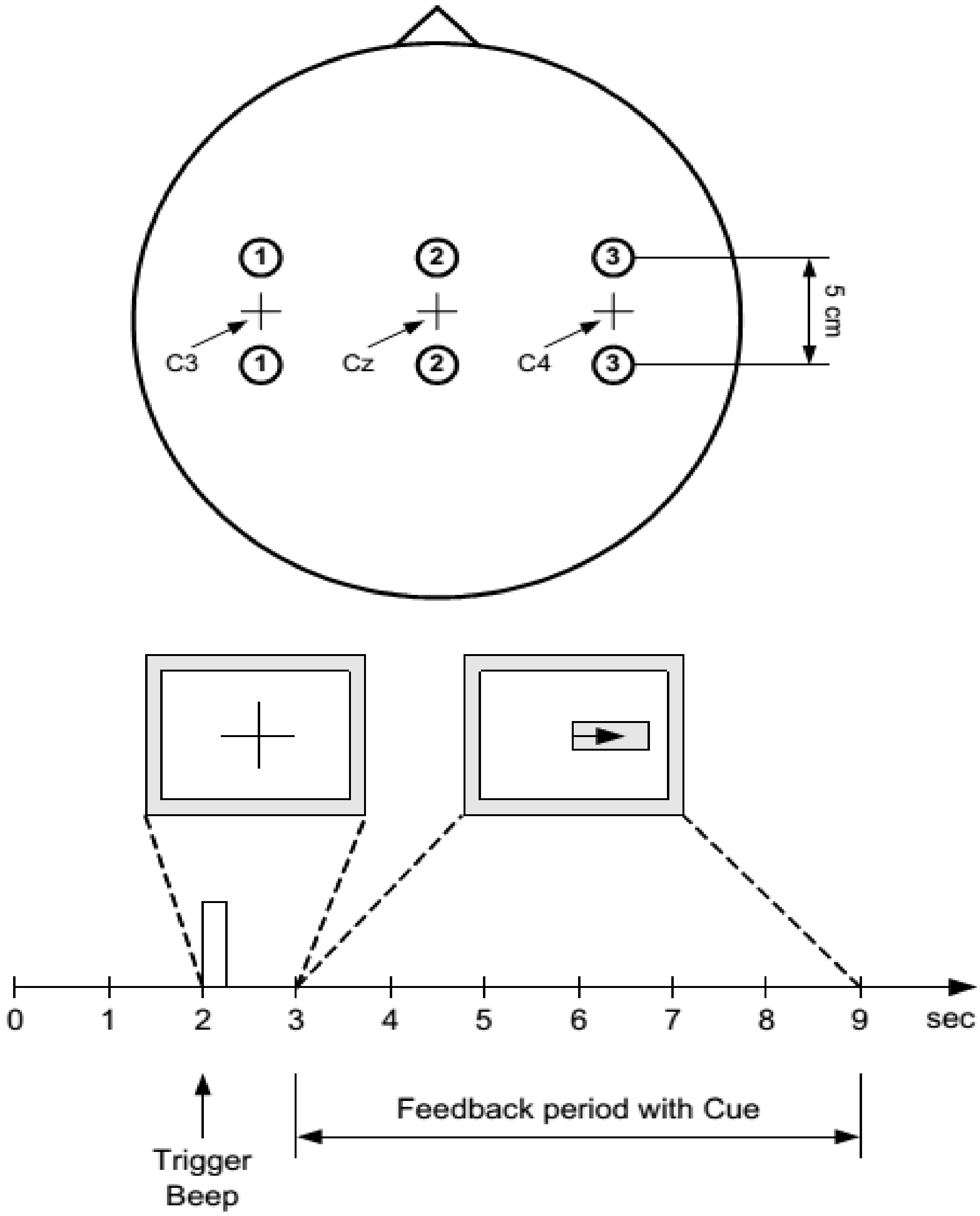

Fig. 5. *Electrode positions (top) and timing scheme (bottom) for recording the Graz BCI data set.*

3.2.2. ERS/ERD Analysis Results

The TVAR model has been applied to these trials using the Kalman filter only and the Kalman filter together with the parameters expansion and filter parameters estimation algorithm. The model order for both methods has been set equal to 6. The initial state and covariance was set to zero and identity matrix, respectively.

A trial from the dataset with the extracted IF of the ongoing activity of the brain using the RLS method and the proposed method are shown in figures 6 and 7.

It is clear that both methods track well the frequency evolution. However, the proposed method produces smoother estimates.

For each trial the time varying spectrum has been calculated using the TVAR coefficients. Then the Instantaneous Frequency (IF) has been extracted from the time varying spectrum.

The mean spectrum of trials for the left hand movement, using both methods, is presented in figures 8 and 9. The extracted Instantaneous Frequency is presented in figures 10 and 11.

We can observe that the RLS method gives noisy estimates of the time varying spectrum and Instantaneous frequency. In contrast, the proposed method produces smooth estimates of the time varying spectrum and Instantaneous Frequency; furthermore the time-frequency resolution is much better.

From figure 11 we can observe that the frequency of the ongoing activity is constant and equal to 10 Hz over the trial time (3-9s) which mean that there is no activation in the left primary sensory motor cortex area during imaginary left hand movement. These results confirm the hemispherical asymmetry of the brain; they show clearly the contralateral dominance of the mu ERD. Similar conclusions can be extracted for the right hand movement.

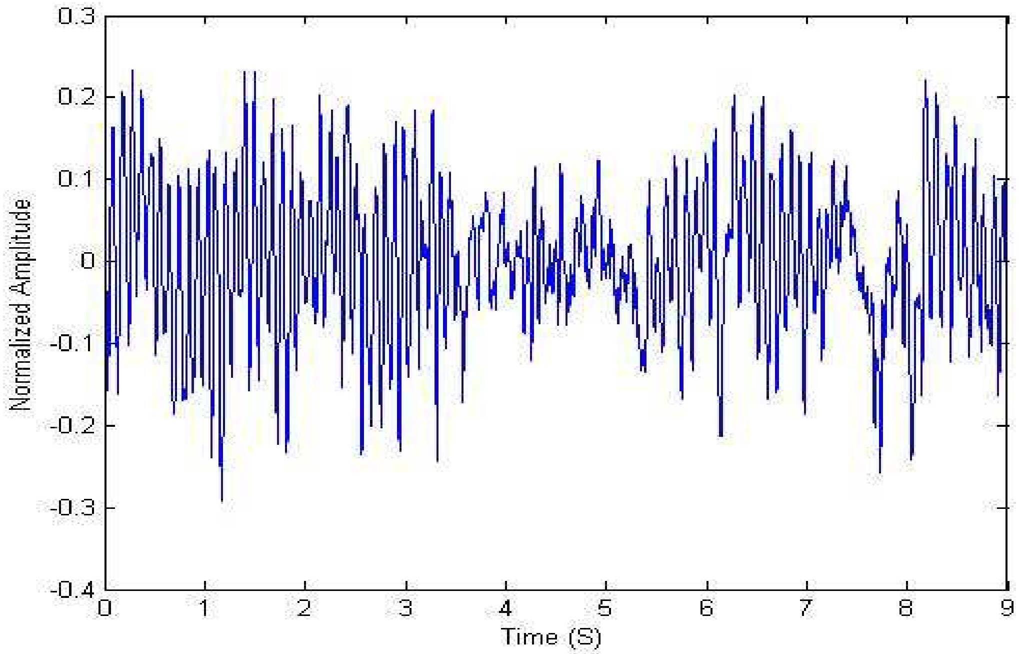

Fig. 6. *Trial data from the dataset.*

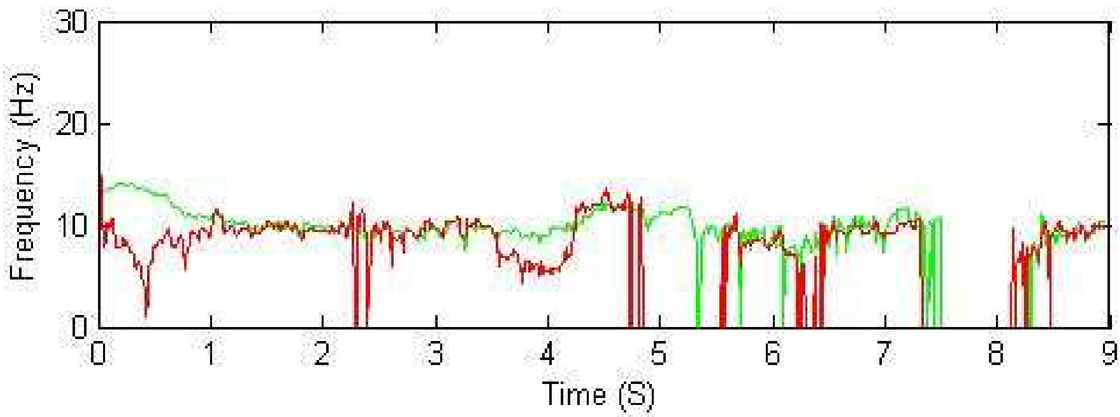

Fig. 7. *Instantaneous Frequency using the proposed method (green line) and the RLS method (red line).*

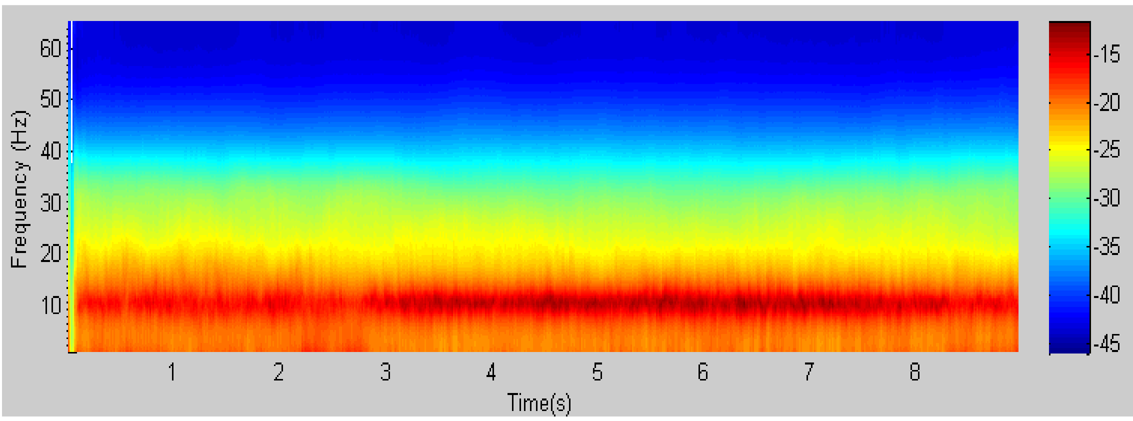

Fig. 8. *Mean time varying PSD for channel C3 in left hand movement using RLS method.*

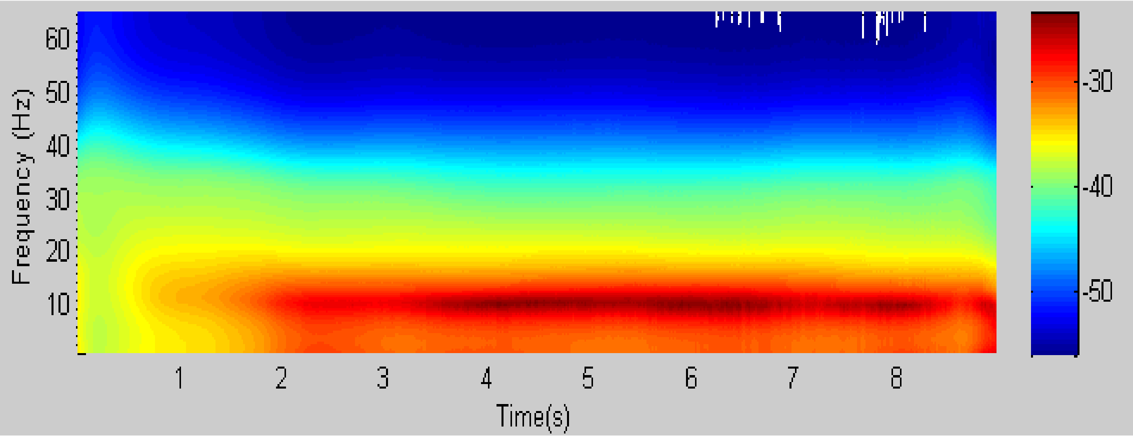

Fig. 9. *Mean time varying PSD for channel C3 in left hand movement using the proposed method.*

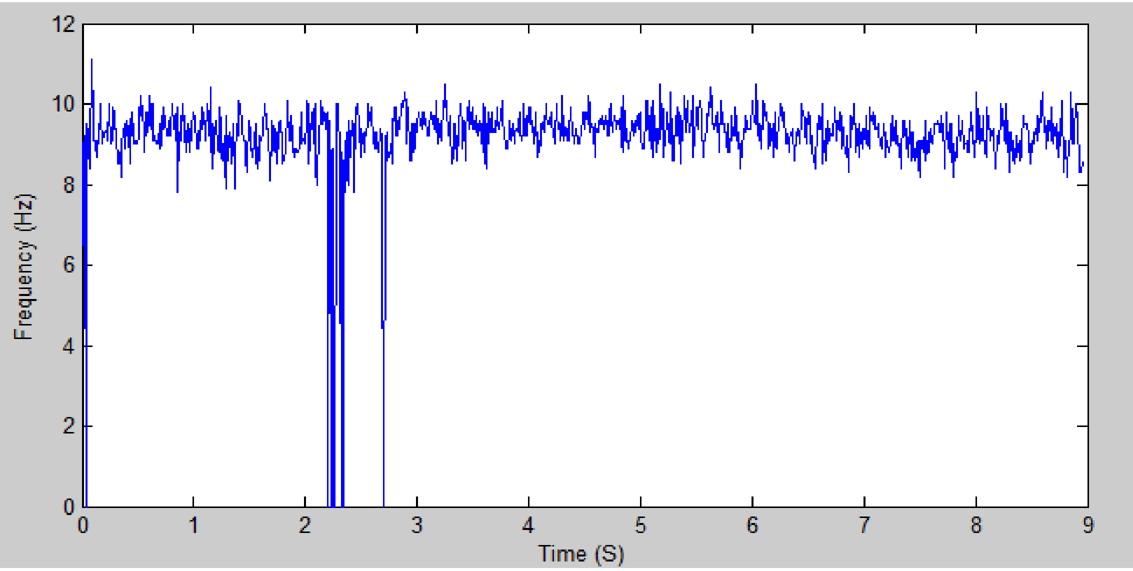

Fig. 10. *Mean time varying PSD for channel C3 in left hand movement using RLS method.*

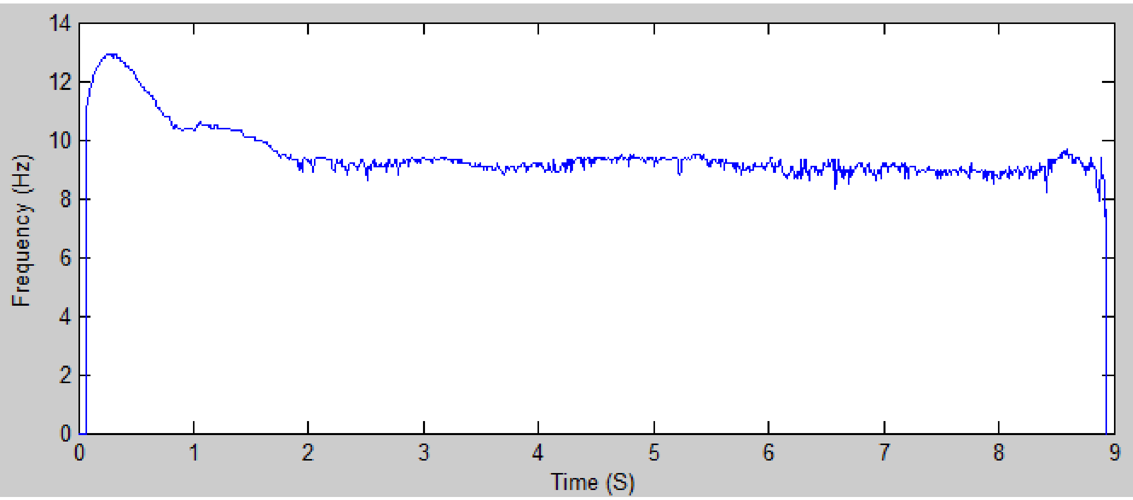

Fig. 11. *Mean time varying PSD for channel C3 in left hand movement using the proposed method.*

4. Conclusion

In this paper, we present a technique for parametric representation of the non-stationary biomedical signals by employing a six-order TVAR model. The TVAR coefficients were estimated by RLS method and then by the proposed method in which we used Kalman filter. The improvement in the TVAR estimation process has led to smoother spectrum and high time frequency resolution which are crucial for non-stationary biomedical signal spectral analysis. The time-dependent spectrum based on TVAR model can reflect the global frequency behavior of the signal and reveal the local variations of the signal along the time course. One advantage of the proposed model, compared with traditional time-invariant models, is that it can capture much more transient information of the inherent non-stationary dynamics of the associated processes.

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