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Robust Sleep Apnea Monitoring using Heart Rate Variability and Extended Kalman Classification based on Single Lead ECG

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Abstract— **Sleep apnea diagnosis requires analysis of long term polysomnographic signal during one period of night sleep. Limited access to sleep laboratories, various required devices and dedicated assistants made the diagnosis of sleep apnea underestimated and not easily accessible to the general population. In this work, a classification method based on modified Kalman filter which uses heart rate variability (HRV) wavelet signal obtained from a single electrocardiogram (ECG) lead is proposed. A pre-filtering was performed on wavelet transform to improve the correlation of extracted features. Sample entropy was used to enhance the convergence rate and accuracy of classification. The performance of the proposed method was evaluated in terms of accuracy, sensitivity and specificity. The classifier overcomes these methods by 5.3% to 7.2% improvements in accuracy.**

I. INTRODUCTION

Sleep apnea is one of the sleep disorders known by the repetitive breath ceasing during sleep duration. Physicians and intelligent software analyzers usually divide this disorder into three levels: 1) obstructive sleep apnea (OSA), 2) central sleep apnea (CSA), and 3) mixed form. OSA is the most common form with 84% and CSA is the least common form with 0.4% prevalence and mixed sleep apnea constitutes 15% of general population [1]. OSA is caused by a collapse in the upper airways that leads to interruption of the airflow to the lungs. All types of sleep apnea lead to a reductions in blood oxygen saturation and arousal events. The most common symptoms of sleep apnea are impaired concentration during day work, tiredness, sleepiness, and lack of comprehension [2]. The resultant effects produce serious damages in the works that need high precision and adequacy. Furthermore, severe types of apnea result to continual hypertension and cardiovascular malfunctioning may lead to death if it is not cured or well diagnosed.

Sleep apnea diagnosis requires analysis of polysomnography signal recorded during one period of night sleep in a sleep laboratory. Limited number of sleep laboratories with required devices and dedicated assistants made the diagnosis of sleep apnea underestimated and not easily accessible to the general population despite the fact that 4 to 9 percent of middle-aged men and 2 to 4 percent of middle-aged women suffer sleep apnea [3]. These difficulties motivate new efforts aimed at obtaining simpler and more accessible ways of evaluating sleep apnea.

The aim of this paper is to propose a feature extraction approach based on dynamic autoregressive and sample entropy and a classification method based on Extended Kalman Filter (EKF) model to improve the system performance by enhancing the accuracy while keeping the number of leads and computational cost steady. The extended Kalman filter linearizes the state space model to predict the nonlinear system behavior. This procedure provides a local estimate using Riccati equation. In this work the structusre of the extended Kalman filter is retained and robustness is achieved by modification of Riccati equation. This structure is appropriate for application on nonlinear systems. To achieve the desired objective, three aspects are taken into account: 1) feature extraction based on the physiological knowledge of sleep apnea events to better describe the inherent mechanisms of phenomenon; 2) implementation of dynamic classifier which could deal with nonlinear and non-stationary behavior of signals during sleep apnea; 3) use of adaptive methods that could handle the variable characteristics of the system. Also, different classification methods were examined on the same feature sets to clarify the influence of the classification methodology on the results.

II. MATERIALS AND METHODS

A. Protocol

The database used in the present research composed of two sets, 1) the data come from the Physionet Apnea-ECG database [4] and 2) the data obtained from clinical recordings. Complete polysomnographic signal is recorded during night sleep including bipolar two lead EEG C_3-A_2 and C_4-A_1, single modified lead ECG V_2, SPO_2, thorax movements, nasal flow, snoring sound, and body position for both sets. The aim of this research is to reduce the number of signal recording while keeping the accuracy of detection. The complete signal recording is used by experts for accurate labeling of apnea events. The Physionet database includes apnea labels which were used without further modifications. The clinical databases labeled by experts were based on polysomnographic data including ECG, respiration, blood oxygen saturation, snoring sound and

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thorax movements. Three labels assigned to sampled data: apnea, hypopnea and normal. Deviated recording and corrupted data were omitted based on statistical methods. Apnea label assignment was performed by the experts according to the standard clinical criteria [5]. First set consists of 21 males and 4 females. The subject age for the first set in the dataset ranged between 28 and 68 years. Second set consists of 28 males and 12 females. For the second dataset the subject age ranged between 25 and 72 years. The recordings for both datasets are classified into three classes defined as 1) apnea (class A), 2) marginal apnea (class M), and 3) normal (class N). Apnea is assigned for subjects with more than 100 minutes in apnea, marginal apnea is defined for subjects with apnea duration between 5 and 99 minutes, and normal is assigned to the subjects with less than 5 minutes in apnea in a total of 8 hour sleep recording.

B. *Feature Extraction*

Complete polysomnographic recordings were used for labeling the apnea events by expert. Total signal was also used for verification of the proposed method. QRS complex peaks and RR intervals extracted from the recording using Hilbert transform and noise reduction methods [6] and [7] for both data sets. The features extracted from these recordings through time and frequency analysis will be used for event detection at the next level. HRV signals exist in Physionet database which are used in this research without further modifications. The method proposed by Penzel et al. [2] was used for HRV extraction of clinical data. Long-term recording of signals increases the probability of misaligned or omitted QRS peaks series. An interpolation method is used to fix a maximum of three consequent misaligned beats [8]. A total of 30 random samples, each with a length of 60 seconds labeled by one expert and verified by another one. The results showed that there is 98% time accuracy for the method compared to the results obtained by experts. The method mentioned above reduces subjective errors and per case inaccuracies compared to the conventional HRV extraction techniques [9].

C. *Wavelet Analysis of HRV*

RR interval for the ith QRS complex derived from RR sequence is defined as T_i. Heart rate is defined as $1/T_i$ for each segment and time difference of heart rate is defined as HRV. Mean value is subtracted from resulting time series to eliminate the bias and wavelet time–frequency representation is used to decompose the frequency elements of HRV at each time. The HRV indexes could be defined as total power (PT) at 0.0033-0.5 Hz, very low frequency power (PVLF) at 0.0033-0.04 Hz, low frequency power (PLF) at 0.04-0.15 Hz, and high frequency power (PHF) at 0.15-0.5 Hz. Wavelet decomposition of HRV signal can be written as [10]

$$HRV_l(m) = \sum_{j=0}^{l-1} \sum_{n \in I_j} d_{j,n} \psi_{nj}(m) + \sum_{n \in I_0} a_{0,n} \varphi(m-n) \quad (1)$$

in which $\psi_{nj}(m)$ is mother wavelet and corresponding

$$\varphi_n(m) \triangleq \varphi(m-n). \quad (2)$$

with index set

$$I_j = 2^j n + m, \quad n \in \mathbb{Z} \; and \; m \in \mathbb{Z}. \quad (3)$$

Dilation equation for Daubechies wavelet transform is written as

$$\varphi_j(m) = \sqrt{2} \sum_{i=0}^{2N-1} h_j(i) \varphi_k(2m-i) \quad (4)$$

where $\varphi(x)$ is Daubechies kernel function, $x(t)$ is the analytic signal, and N is the order of Daubechies transform. Rectangle integral approximation leads to following filter coefficients:

$$h_j(n) = 2^{-k/2} \sum_{l \epsilon \mathbb{Z}} W\big(2^{-n}(m_0 + l)\big) \overline{\tilde{\varphi}_{n,J}(m_0 + l - k)} \quad (5)$$

This pre-filter also reduces spurious components known as cross terms and disturbances of the energy signal interpretation in the time–frequency plane.

D. *Proposed Extended Kalman Classifier*

A revision of Kalman filter is proposed in this work which is used for hybrid classification of HRV wavelet and entropy. Combined time-frequency observation matrix with M rows and L columns was considered as

$$o_n = o_n(t, f). \quad (6)$$

where M is selected as the number of VLF coefficients of wavelet transform and L should be selected big enough to include at least one period of HRV signal. A nonlinear discrete system is defined as:

$$\begin{cases} s_{n+1} = f(\hat{s}_n, \hat{n}_n, k) + A_n(s_n - \hat{s}_n) + B_n(r_n - \hat{r}_n) \\ o_{n+1} = g(\hat{s}_n, \hat{e}_n, k) + C_n(s_n - \hat{s}_n) + D_n(e_n - \hat{e}_n) \end{cases} \quad (7)$$

where s_n is state vector, o_n is observation matrix, r_n process noise and e_n is measurement noise and

$$A_n = \left. \frac{\partial f(s, \hat{n}_n, n)}{\partial s} \right|_{s=\hat{s}_n}$$
$$B_n = \left. \frac{\partial f(\hat{s}_n, r, n)}{\partial r} \right|_{r=\hat{r}_n} \quad (8)$$

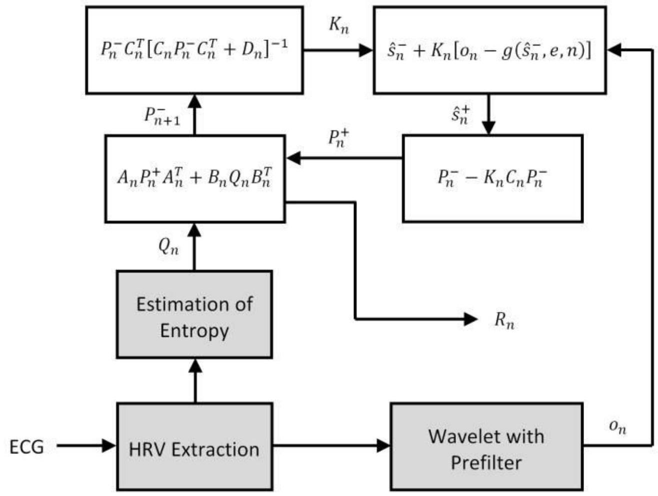

Fig. 1. Block diagram of modified Kalman filter classifier.

$$C_n = \left.\frac{\partial g(s, \hat{e}_n, n)}{\partial s}\right|_{s=\hat{s}_n}$$

$$D_n = \left.\frac{\partial g(\hat{s}_n, e, n)}{\partial e}\right|_{e=\hat{e}_n}. \quad (9)$$

Time propagation and measurement propagation of extended Kalman filter (EKF) are obtained as follows [11]:

1. Selection of initial values for *a posteriori* estimate of the state vector $\hat{s}_n^+$ and covariance matrix P_n^+.
2. Forward projection for estimation of a prior state vector $\hat{s}_{n+1}^-$:
3. $\hat{s}_{n+1}^- = f(\hat{s}_n^+, w, n)|_{w=0}$
4. Projection of error to the a prior covariance estimate matrix P_{n+1}^-:
5. $P_{n+1}^- = A_n P_n^+ A_n^T + B_n Q_n B_n^T$
6. Updating the estimation with measurement o_n:
7. $\hat{s}_n^+ = \hat{s}_n^- + K_n[o_n - g(\hat{s}_n^-, e, n)|_{e=0}]$
8. Computing the gain of Kalman filter:
9. $K_n = P_n^- C_n^T [C_n P_n^- C_n^T + D_n]^{-1}$
10. Updating the covariance of error:
11. $P_n^+ = P_n^- - K_n C_n P_n^-$

$\|R_n\|$ is a measure of classification for observation vector o_n. Two EKFs are trained for normal and OSA conditions. The dominant state is the state with smaller $\|R_n\|$ value. The block diagram description of the EKF classifier is presented in Figure 1. The most important feature of the Kalman filter is that the error covariance is independent of the observations. Therefore, P_n^- can be computed initially and the accuracy of the filter achieved before the observations are made.

III. Results and Discussions

Two databases combined together for all examinations and a validation test for data are discussed later in this section. All the experiments performed by MATLAB 2010 on a personal computer. Classification results for modified Kalman filter combined with Daubichies wavelets number 2 to 14 are depicted in Fig. 2 with L and M equal to 128 and 150, respectively. It was done on 20 random selected members of database for evaluation of wavelet transform. It can be seen that Daubichies 4 leads to accuracy of 93.6% and no significant improvement of accuracy occurs for other degrees. Daubichies 4 was selected to minimize the complexity of computations and also to maintain the optimum accuracy. The method was also evaluated for various levels wavelet coefficients L. Accuracy of this classifier for different values of window sizes is depicted in Figure 3 for different values of L with M equals to 1500. It can be seen that values of L greater than 128 do not lead to much higher values of accuracy. These results indicate that selection of this value for L is an optimal selection to provide high accuracy with minimum computational cost possible. The results depends on the size of processing segments and are not satisfactory for small values of M. Fig. 3 also shows that values of M greater than 1500 do not lead to great change on accuracy rate. The values of L and M are selected as 128 and 1500 on the reminding of the text.

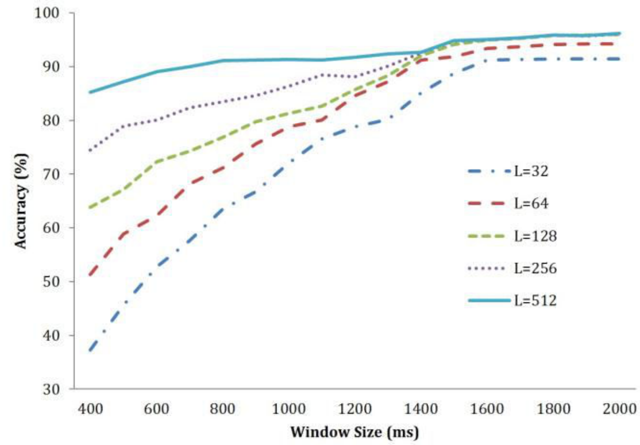

Fig. 2. Accuracy of modified Kalman filter for various values of wavelet levels L versus window size.

Performance of proposed modified Kalman filter was compared to the methods presented by other researchers. Parametric model Time Varying Autoregressive Model (TVAM) is proposed for feature extraction with two classification methods: K-nearest neighbor (KNN) and neural network (NN) [12]. The TVAM+NN and TVAM+KNN are according to [4], TVAM+SVM method is according to [7] and SampEn method is according to [2]. SampEn is used for studying the heart rate and HRV and it is used in this work also to evaluate it as a feature extraction method combined with Kalman filter. It should be noted that in this method the SampEn is the only feature used for classification despite the proposed model in which the entropy is an inherent part of classifier. Support vector machine (SVM) classification was used for OSA/CSA recognition based on wavelet features. Ordinary EKF was

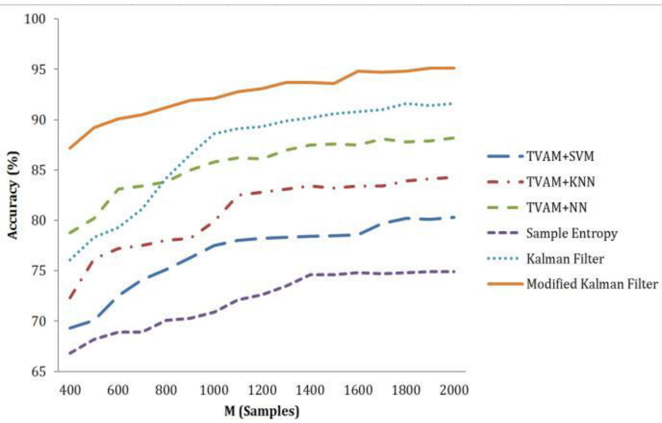

Fig. 3. Accuracy of various classifications methods versus M.

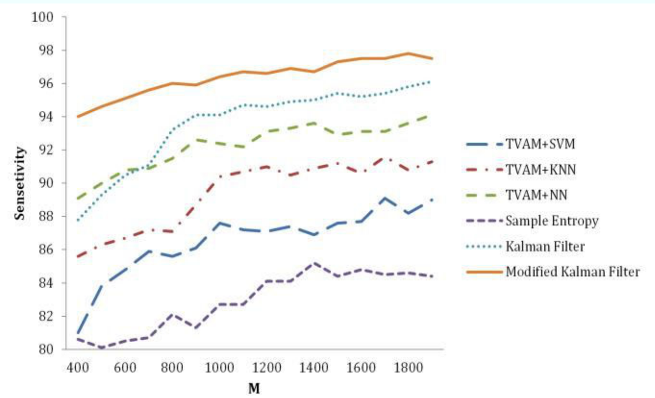

Fig. 4. Sensitivity of various classifications methods versus M.

also evaluated to be compared to the proposed modified EKF. In this method, the observation method achieves by inherent Kalman equations not using sample entropy estimation. As it could be seen the computation cost increases in this method. However, the classification method could preserve the accuracy in the low sampling rates and lack of data. Another deficiency of system could be the uncertainty of convergence of Ricatti equations. The system performance could be unknown in complex situations.

Accuracy rate of these methods are presented in Fig. 4 for various values of M. Apnea assignment rate has the best accuracy of 94.8% for modified Kalman filter with M equals to 1600. The lowest value obtained for sample entropy method equals to 74.9% with M equals to 1400. Kalman filter has the most variance in accuracy versus changes of window size but for large values of M has the second best accuracy among all methods. Kalman filter has a degradation of 3.6% respect to the modified Kalman filter at the best condition. Using SampEn and by applying pre-filtering which separates the hyperspace created by the dependent parameters of Kalman filter hyper-planes, the separation of sleep stages was performed the best. The assignments of apnea type based on Kalman filter without pre-filter and SampEn resulted in 91.6% which increased to 95.1% when entropy estimation was also included.

IV. Conclusions

Modified Kalman filtering proposed in this work is capable of detecting the periodic changes of entropy. Due to the nature of this method which is a model based filtering using state space estimation, short term errors are neglected and time wrapping does not affect the classification. Furthermore, the pre-filtering of wavelets leads to reduction of misaligned peak R detection, increase of the accuracy of HRV and specificity of apnea assignment. In this study, we confirmed that modified Kalman filter is a robust tool for assignment of apneas during sleep. Modifications on wavelet coefficients based on the variation of HRV signal provide more adequate state space estimation. The results overcome the previous proposed methods and show that highly accurate apnea monitoring is possible using only single lead ECG.

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