International Journal of Engineering Research and Development
ISSN: 2278-067X, Volume 1, Issue 7 (June 2012), PP.38-41
www.ijerd.com

A Survey on Ambulatory ECG and Identification of Motion Artifact

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Abstract—*Ambulatory ECG monitoring (AECG) is increasingly for the patients suffering from cardiac disorders. Ambulatory monitoring has an advantage over the indoor monitoring that the patients can perform their daily routine activities. The major difficulty with ambulatory ECG monitoring is that the ECG signals are contaminated by motion artifact introduced due to physical activity (PA) of the patient. The AECG during commonplace PA is presumed to be an additive mix of signals due to cardiac activities, motion artifacts. Based on this fact, AECG is analysed to yield some information regarding the PA. This can be used for accurate interpretation of the AECG and hence can increase the utility of ambulatory cardiac monitoring. Here in this paper a brief introduction to the recent research activities for detecting and recognizing the PA related information from analysis of the ambulatory ECG signals is presented.*

Keywords*— AECG,* ***physical activity (PA), Wearable Device (WD), Motion Artifact, QRS, wavelet transform (WT)*

I. INTRODUCTION

Cardiovascular disease is the leading cause of death in many regions. Considering the fact that a majority of such deaths due to cardiac arrest occur before the patient can get the needed medical care, the patient should be continuously monitored for real time detection of the events of cardiac arrest. In recent years ambulatory ECG monitoring (AECG) devices become popular for long term cardiac monitoring because they are convenient to use and serve as an option to the hospitalization.

A surface ECG is a time-series cardiac signal of the heart that is easily recorded from the skin surface of the chest using Ag-Cl electrodes. ECG signal has the following important segments: P-wave, QRS-complex and T- wave occurring in a sequence as depicted in Fig. 1. The ECG-waves represents the following cardiac activities of the heart: P wave - atrial depolarization (contraction), QRS-complex - ventricular depolarization and T wave – ventricular repolarization (relaxation). For a normal heart the cardiac cycle repeats continuously in the same ordered manner and time of repetition of the cardiac cycle determines the heart-rate, which is variable due to many different physiological aspects. A medical expert visually investigates the abnormalities in the ECG signal for primary diagnosis of cardiac disease.

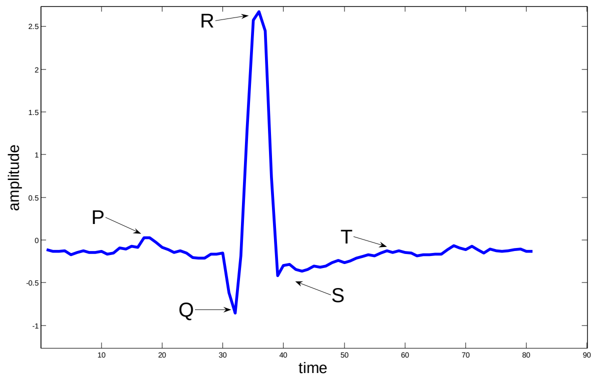

Fig. 1 A cardiac beat of ECG signal recorded in ambulatory conditions. The signal is contaminated by motion artifacts due to the patient's physical activity.

With an AECG device the ECG signal can be recorded or monitored in ambulatory conditions where the patient can perform all the routine activity. However, the effectiveness of AECG can be significantly impaired by motion artifacts which contaminates the signal and that can lead to errors in estimation of cardiac parameters and trigger false alarms. Skin stretching due to body or limb movement or physical activity (PA) is a main cause of motion artifacts in AECG signals. The motion artifact induced due PA has a spectral overlap with ECG signal in 1-10 Hz [16]. Many important cardiac features of ECG signal like P and T wave has significant energy content in this overlapping band of 1-10Hz. So it is very difficult to separate or eliminate motion artifact completely without affecting these cardiac features in AECG [16]. Therefore researchers have developed various techniques to provide PA information for AECG to prevent their wrong interpretation in presence of PA [16, 13, and 14]

II. ADDITIVE MODEL OF ECG SIGNAL WITH MOTION ARTIFACT

As explained in the previous section the major difficulty in AECG is that due to presence of motion artifacts in the recorded signal. The AECG signal is not just the cardiac signal but contaminated by motion artifact. The AECG is superposition of two independent events: the cardiac signal (ECG) and the motion artifact induced due to the PA. Since Electronics circuits in AECG devices may themselves add sensor noise in the acquired electrical signal from the electrodes, the AECG signal sample r(n) in digital form can be modelled as sample-wise addition of three different signal components at n^{th} instance of time as

$$r(n) = q(n) + s(n) + \alpha(n), \qquad (1)$$

Where q(n), s(n) and α(n) are samples of cardiac signal, motion artifact signal and sensor noise, respectively. Since the dc bias has been removed, it is assumed that the noise component have zero mean. The care has been taken to keep the sensor noise has much less power level than the other signal components in the AECG signal, r(n). The mathematical model in (1) used for representing the AECG has been proposed in [13-14].

III. AUTOMATED MOTION ARTIFACT DETECTION ALGORITHMS

The detection of QRS complex is an important task in automated analysis of ECG signals for localization of cardiac waves in ECG. In [1] author has used modified derivative based approach computationally simple and accurate. In [2] wavelet transform were used to optimize the detection of QRS complex and remove noise like motion artifact using continuous wavelet transform (CWT) and discrete wavelet transform (DWT), CWT is used to maximize energy scale from QRS complex while DWT is used to decompose 8-levels and to reconstruct detailed coefficient with the frequency of QRS complex. The result showed that CWT detected better in wearable ECG recorder.

The wavelet based methods are extensively used in pre-processing, denoising and analysis of ECG signals. In [3] DWT method is used to extract ECG parameters in a three-step processes: first, the low frequency components are removed using DWT transformation, second the noise in the signal is suppressed using the DWT based denoising techniques and finally ECG parameter are extracted. In [4] the morphology of ECG is used for classification of the ECG beats. To extract the shape related features from the ECG signal, three-level Daubechies-1 DWT is used after noise suppression in the ECG signal through a digital filter. After that principal component analysis and support vector machines are trained to formulate a classifier. In [7] undecimated wavelet transform was used for denoising ECG. In [8] spatial correlation filtering and stationary wavelet transform is proposed to eliminate the noise in ECG signal. The spatial correlation filtering is applied to shrink the wavelet coefficient, and the stationary wavelet transform used to decompose the noisy signal. In [9] stationary wavelet transform used to optimal denoise ECG signal in which signal to noise ratio is adjusted from 1 to 10 dB and result is evaluated by visual inspection then conclude using symlet4,decomposition at level5 and hard shrinkage function with empirical bayesian threshold can get superior denoise performance. In [12] an integrated electrocardiogram (ECG) signal processing scheme is proposed. Using a systematic wavelet transform (WT) algorithm, this signal processing scheme can realize multiple functions in real-time, including baseline drift removal, noise suppression, QRS detection, heart beat rate (HBR) prediction & classification, and clean ECG reconstruction. In [20] wavelet-based denoising technique is investigated for suppressing EMG noise and motion artifact in ambulatory ECG. EMG noise is reduced by thresholding the wavelet coefficients using an improved thresholding function combining the features of hard and soft thresholding. Motion artifact is reduced by limiting the wavelet coefficients. Thresholds for both the denoising steps are estimated using the statistics of the noisy signal. Denoising of simulated noisy ECG signals resulted in an average SNR improvement of 11.4 dB, and its application on ambulatory ECG recordings resulted in L2 norm and max-min based improvement indices close to one. It significantly improved R-peak detection in both the cases.

Adaptive filter based methods are also in use for ECG signal processing. In [5] a simple and efficient normalized LMS algorithm is proposed for removal of noise from ECG signal that is suitable for application requiring large signal to noise ratio with less computationally complexity using simple addition and shift operation and achieves considerably speed-up over other LMS based realization. In [6] block LMS algorithm is used to remove artifact preserving low frequency component of ECG.

In [19] the problem of noise cancellation from ECG signal using error normalization-based adaptive filters, their block-based versions are proposed and tested on real signals with different artifacts obtained from the MIT-BIH database. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. Among the six algorithms, the BB-ENSRLMS performs better than the other. From the simulated results, it is clear that these algorithms remove the artifacts efficiently present in the ECG signal
In [18] An Adaptive Kalman Filter for ECG Signal Enhancement used, filter operates by sequentially estimating the measurement and process noise covariance and uses these covariance to estimate the Kalman gain and update the estimated ECG complexes.

In [10] in the time domain the cardiac activity mean and the motion artifact noise of the ECG signal are modeled by Hermite polynomial expansion and principal component analysis, a set of time domain accelerometer feature is also extracted. A support vector machine is employed for supervised classification using these time domain feature, motivated by their potential for convolution noise, cepstral features extracted from ECG and accelerometer signals based on frame level analysis are modeled using Gaussian mixture models (GMM). To reduce dimension of tri-axial accelerometer cepstral features which are concatenated and fused at the feature level hetroscaedastic linear discrimination analysis is performed.

Finally to improve overall recognition performance, fusion of the multi modal and multi domain subsystem at the score level is performed.

Neural networks are also used for detection of events and pattern classifications in ECG signal analysis. In [11] an adaptive neuro-fuzzy filtering which is basically a nonlinear system structure presented here for the noise cancellation of biomedical signals (like ECG, PPG etc) measured by ubiquitous wearable sensor node (USN node). In this paper non-linear adaptive filter which uses fuzzy neural network (FNN) to treat with the unknown noise and artifacts present in biomedical signals. The presented work based on ANFF (Adaptive Neuro Fuzzy Filter), where adaptation process includes neural network learning ability and fuzzy if-then rules with the optimal weight setting ability. ANFF is basically a fuzzy filtering implemented in the framework of adaptive neural networks environment. ANFF setting parameters such as the training epochs, number of MFs for each input and output, type of MFs for each input and output, learning algorithm etc.

The AECG is analysed beat-by-beat using a recursive principal component analysis (RPCA) based method in [16]. The RPCA based method can follow the slow changes in cardiac cycle, while detecting abrupt changes in motion artifact signal due to the transition to a different type of PA. The RPCA algorithm is useful for temporal segmentation of ECG beats with respect to the type of PA. In [13], [14], [15] the separability of motion artifacts due to different types of PA is tested by classifying them automatically based on the nature of PA. A principal component analysis (PCA) based method is used for supervised learning of the classifiers for the same purpose. It has also been observed in [17] that different pace levels of the PA have different impact on the generation of motion artifact in AECG. The RPCA based error signal is derived from AECG as an index of motion artifacts and also as a measure of impact of different pace levels on AECG, simply referred as an impact signal [17].

IV. CONCLUSION

In this paper a brief introduction to AECG and related automated algorithms available in the literature is presented. The motion artifact due to PA is considered a great challenge for AECG monitoring. On the other hand, we have seen here that the motion artifact can be treated as a useful source of information regarding PA of the patient.

REFERENCES

[1]. D. Vala,T. Pawar, ,Rahul kher, and V.K.Thakar. "Implementation of Derivative Based QRS Complex Detection Methods" in 3rd International Conference on BioMedical Engineering and Informatics (BMEI 2010), Yantai, China,.pp 927 - 931,Oct. 2010.

[2]. Uk-jin, In-seop Hwang, and Yeon-Sik Noh. "Comparision of CWT for detecting QRS complex on wearable ECG recorder." In International Conference on Wavelet Analysis and Pattern Recognition, Qingdao, July , 2010.

[3]. Abdulrhman Elbuni ,Salah Kanoun, Dr. Mohamed Elbuni, and Dr. Nasser Ali. "ECG parameter extraction algorithm using DWTAE algorithm." In International Conference on computer Technology and Development ,Cairo, Egypt pp. 315 – 320, Dec. 2009.

[4]. Dusit Thanapatay1, Chaiwat Suwansaroj,Chusak Thanawattano. "ECGbeat classification method for ECG printout with Principle Components Analysisand Support Vector Machines" in international conference on electronics and information engineering, Kyoto,pp. V1-72 V1-75, Aug. 2010.

[5]. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik, D V Rama Koti Reddy. "Noise Cancellation in ECG Signals using Normalized Sign-Sign LMS Algorithm". In international symposium on Signal Processing and information Technology in Ajman, United Arab Emirates,pp 288 – 292, Dec. 2009.

[6]. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik, D V Rama Koti Reddy. "Adaptive Noise Removal in the ECG using the Block LMS Algorithm"in 2nd International confserance on adaptive science and technogy, Accra,pp 380 – 383, Jan. 2009.

[7]. Naregalkar Akshay, Naga Ananda Vamsee Jonnabhotla, Nikita Sadam And Naga Deepthi Yeddanapudi. "ECG Noise Removal and QRS Complex Detection Using UWT" in International Conference on Electronics and formation Engineering Kyoto,pp. V2-438 - V2-442, September 2010.

[8]. Wentao Sui,Dan Zhang. "Noise Reduction of ECG using spatial Correlation Filtering and Stationary Wavelet Transform".In 5th International conference On Computer Science & Education, Hefei, China. August 2010.

[9]. Suyi Li , Jun Lin. **"**The optimal de-noising algorithm For CG usingstationary wavelet transform". In wri worldcongress on computer science and information engineering, LosAngeles, CA ,pp. 469 - 473 , March 31 2009- April 2009.

[10]. Ming Li, Viktor Rozgi´c ,Gautam Thatte, Sangwon Lee, Adar Emken, Murali Annavaram, Urbashi Mitra, Donna Spruijt-Metz, Shrikanth Narayanan. Multimodal Physical Activity Recognition by Fusing Temporal and Cepstral Information". In IEEE Transction on neural system and rehabilation engineering,vol 18,no. 4,pp. 369 – 380, August 2010.

[11]. Alka Gautam, Hoon Jae Lee and Wan-Young Chung. "Adaptive Neuro-Fuzzy Interference Cancellation for Ubiquitous Wearable ECG Sensor Node".In 11th conference on advance communication technology, Phoenix, Park, pp. 2321 - 2324, Feb. 2009.

[12]. Xin Liu, Yuanjin Zheng, Myint Wai Phyu, Bin Zhao, Minkyu Je, and Xiaojun Yuan. " Multiple Functional ECG Signal Processing for Wearable Applications of Long-Term Cardiac Monitoring", In IEEE transaction on biomedical engineering,pp. 380 – 389, Feb. 2011

[13]. T. Pawar, Subhasis Chaudhuri and Siddhartha P. Duttagupta. "Analysis of Ambulatory ECG Signal", In 28th international conference of the IEEE on engineering in medicine, New York, NY pp. 3094 –3097, Aug. 2006.

[14]. T. Pawar, S. Chaudhuri and S. P. Duttagupta. "Body Movement Activity Recognition for Ambulatory Cardiac Monitoring" in IEEE transaction on biomedical engineering. **,**Vol- 54,pp. 874 – 882, May 2007.

[15]. Rahul kher,Dipak Vala, T. Pawar and V.K.thakar. "Introduction to Ambulation Study of ECG in Wearable Devices". International Conference on Signals, Systems &Automation (ICSSA-2009), GCET, V V Nagar, pp.344-348, Dec 2009.

[16]. T. Pawar, S. Chaudhuri and S. P. Duttagupta "Ambulation Analysis in Wearable ECG". In Springer ISBN: 978-1-4419-0723-3, 2009.

[17]. T. Pawar, N. S. Ananthakrishanan, S. Chaudhuri and S. P. Duttagupta ,"Impact of Ambulation on ECG"., in journal annals of biomedical engineering, vol-36,pp.1547-1557, 2007.

[18]. Rik Vullings, Bert de Vries, and Jan W. M. Bergmans "an adaptive kalman filter for ecg signal enhancement" IEEE transactions on biomedical engineering, vol. 58, no. 4, april 2011

[19]. Muhammad Zia Ur Rahman, , Rafi Ahamed Shaik, and D. . Rama Koti Reddy "Efficient and Simplified Adaptive Noise Cancelers for ECG Sensor Based Remote Health Monitoring" ieee sensors journal, vol. 12, no.3, march 2012

[20]. P. Mithun, Prem C. Pandey, Toney Sebastian, Prashant Mishra, and Vinod K. Pandey "A Wavelet Based Technique for Suppression of EMG Noise and Motion Artifact in Ambulatory ECG " 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30 – September 3, 2011