Survey on Multi-domain Physiological Activity Recognition System

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Abstract
Main objective of this survey paper is to discuss method to convenient monitoring of detailed ambulatory movements in daily life, by use of wearable Electro-cardiogram (W-ECG) sensor employing ECG signals. Here, novel physiological Activity (PA) Recognition System based on both temporal and Cepstral information is surveyed. Two different methods are discussed here. First in time domain the cardiac activity mean and motion artifact noise of ECG are modeled by Principle Component Analysis (PCA) and Hermite Polynomial Expansion (HPE), respectively. Then Cepstral feature extraction of ECG signal is done by Frame Level Analysis. For supervised classification purpose support vector Machine and Gaussian Mixture Model are used for Time domain System and Cepstral Domain System, respectively. Finally, fusion of both time and Cepstral information has been done to improve the overall performance of resulting system.

Keywords: - *Electrocardiogram, Multi-domain Physiological Activity Recognition System, Time domain System, Cepstral Domain System*

I. Introduction
A striking increase in the number of people with Metabolic Syndrome associated with cardiovascular disease has taken place. Although the metabolic syndrome appears to be more common in people who are genetically suspect able, acquired underlying risk factors-being over-weight or obese, physical inactivity and an atherogenic diet. Current guidelines recommend practical, regular, and moderate regiments of physical activity. A practical and reliable method to investigate individual's daily physical activity allows better assessment for medical innervations. Information such as intensity of exercise, types of activities is also necessary to appropriately formulate safe and beneficial exercise program on individual basis [1, 2].
Ambulatory movement is most accessible type exercise easy to perform that does not require any special equipment; therefore reliable assessment of ambulatory movements in daily life such as standing, walking, ascending stairs, running is essential for exercise prescription in clinics as well as in health promotion program [3].

Varieties of methods are available to quantify levels of habitual physical activity during daily life using heart rate. These all methods are employing many bio-signals for analyzing purpose. So, we are considering ECG signal for analyzing PA recognition ECG signal and ECG feature extraction play significant role in diagnostic of cardiac disease [4]. We can design wearable Cardiogram (W-ECG) sensor having ability of ECG signal feature extraction from heart rate. Physiological Activity Recognition System with wearable sensor can help to get reliable assessment of ambulatory movement in daily life. Also wearable sensor system with fusion of ECG feature Extraction system improves the average accuracy of proposed system compared with wearable system with single extraction method.
Main theme of this paper is to have discussion about Wearable sensor system with Multi-domain (temporal and Cepstral) for physiological Activity Recognition employing ECG signal.

II. Material

A Feature Extraction
A feature is characteristic measurement, transform or structural mapping extraction from input data to represent important patterns of desired phenomena. In our paper, we are taking Physical Activity (PA) as phenomena. Mean of the continuous heart rate via ECG is good candidate for physical activity feature. It is always beneficial if we fuse outcomes of systems of different methods; it always results in good performance rather than having single method system. It increases average accuracy of result.

B ECG signal
The ECG records the electrical activity of heart, where each heart rate beat is displayed as series of electrical waves characterized by peaks and valleys. Normally the frequency range of ECG signal is of 0.05 to 100Hz and its dynamic range of 1-10mV. Peaks and valleys of ECG signal are labeled by letter P, Q, R, S, and T. The performance of ECG analysis system depends on mainly accurate and reliable

detection of the QRS complex as well as P wave. The P wave represents the activation of the chamber of the heart, the atria, while the QRS complex and T wave, represents the excitation of ventricles of the lower chamber of the heart. The detection of the QRS complex is most important task in automatic ECG signal. Once QRS complex has been identified more detailed examination of ECG signal including heart rate, ST segment detection can be performed easily. Following figure 1 shows basic components of an ECG signal.

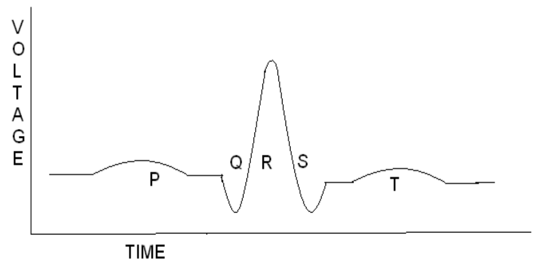

Fig. 1 Components of ECG signal

P –Wave →Depolarization of artria in response to SA node triggering
PR –Interval →Delay of AV node to allow filling of ventricles
QRS- Complex→Depolarization of ventricles, triggers main pumping contractions
ST-Segment→Beginning of ventricle repolarization, should be flat
T-Wave →Ventricular repolarization

III. System Overview

In this paper, multi-domain (Time and Cepstral) physiological Activity recognition system employing ECG signal is proposed. In time domain, first ECG signal has to be preprocessed. Then Hermite Polynomial Expansion (HPE) has to be used for capturing the ECG shape characteristics [5]. For classification, support vector Machine is to be adopted [6]. Hermite Polynomial Expansions are classical orthogonal polynomial sequence which have been success fully used to describe ECG signal and thus can be employed to model the morphological differences for each heart beat.
However noise and motion artifacts can affect the ECG signal. So Principal Component Analysis (PCA) based classification approach helps to detect and reduce motion artifacts in single lead wearable ECG signal induced by body movement [5]. So ECG signal contain additional discriminative information about PA with heart rate details. Here we are going to combine instant heart rate variability (Mean/ Variance) and heart-beat shape variability with HPE and PCA co-efficient to generate set of ECG temporal feature. Support Vector Machine is used to model this temporal feature from ECG signal for supervised classification purpose.
We are employing Generalized Linear Discriminative Sequence (GLDS) kernel. GLDS has good classification performance and low computational complexity. GLDS kernel metric is simply an inner product between averaged feature vector and model vector, which is computationally efficient with small size. This concept can be used for designing mobile device application.
Recently it is shown that Cepstral features of stethoscope collected heart sound can be used for proposing biometric system [7]. So, we can use concept of Cepstral domain ECG feature to design PA recognition system. We can employ Cepstral features extracted from single ECG signal combined with GMM.
One advantage of this my system is that it avoid pre-processing stage. If we consider time domain system, the unit for modeling is each normalized heartbeat, thus peak detection heartbeat segmentation and normalization are required as pre-processing step due to its inherent variability. If the preprocessing step is not accurate or robust, this front end error can accumulate to influence the feature and modeling step; moreover, the computational cost of this preprocessing is also high. So ECG Cepstral feature calculation doesn't require heartbeat segmentation and normalization. We can Gaussian Mixture Model to model Cepstral domain ECG feature for PA recognition system.

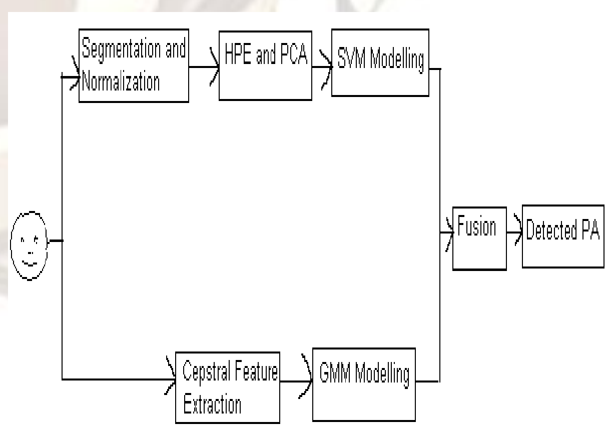

Fig. 2 System Overview

At the end, outcomes of temporal and Cepstral domain system can be fussed to increase average accuracy of PA recognition system [8]. The figure 2 shows overview of proposed system.

IV. SVM based Time domain System

A. Feature Extraction

The four features sets are comprised of features that describe the discriminative activity information for the ECG signals. 1) The mean and variance of the instantaneous heart-rate 2) The principal component analysis (PCA) error vector, for body movement activity recognition, 3) The Hermite polynomial expansion (HPE) coefficients, and 4) The standard deviation of multiple normalized beats. These features result from more complexes processing of the ECG signal. These techniques model the underlying signals, and the resultant model parameters are the features.

B. Preprocessing of the ECG Signal

If there are M Hypothesized activities, for the ***j***th heartbeat observation under the *i*th activity, the continuous-time recorded ECG signal, $r_{ij}(t)$ is modeled as [5]

$$r_{ij}(t) = \theta_i(t) + \chi_{ij}(t) + \eta_{ij}(t)$$

where $\theta_i(t)$ is the cardiac activity mean (CAM) which is the normal heart signal, $\chi_{ij}(t)$ is an additive motion artifact noise (MAN) due to *i*th class of activities, and $\eta_{ij}(t)$ is the sensor noise present in the ECG signal.

Fig. 3 shows the mean and standard deviation of the normalized ECG signal for different activities.

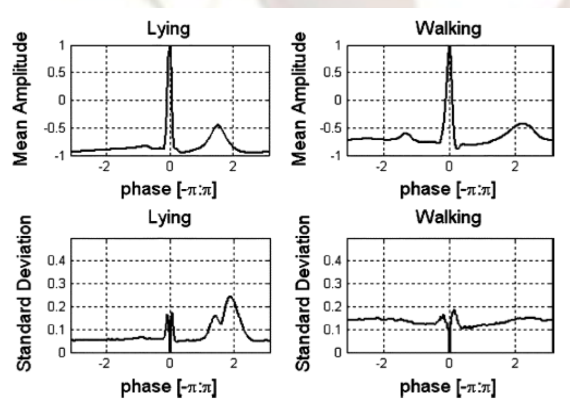

Fig. 3 Mean and standard deviation of normalized ECG Signal.

C. Principal component analysis

Principal component analysis (PCA) [5] is used for feature extraction from the MAN component. PCA method does not use the heart rate or other intra-beat statistical information, and focuses only on the normalized heartbeats only.

D. Hermite Polynomial Expansion

A Hermite polynomial expansion (HPE) is used to model the CAM component $\boldsymbol{\theta}_i$ of the sampled ECG signal [5], and the resulting coefficients serve as another feature set for classification. Rather than subtracting the activity mean to model the motion artifact noise, we average the normalized ECG signal to estimate the cardiac activity mean.

$$E = \left\| \acute{\theta}[n] - \sum_{l=0}^{L-1} c_l \psi_l(n, \delta) \right\|_2^2 = \left\| \acute{\boldsymbol{\theta}} - \mathbf{Bc} \right\|_2^2$$

$$\mathbf{c} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\acute{\boldsymbol{\theta}}.$$

The HPE coefficients **c** is employed as ECG temporal features.

E. Standard Deviation of Multiple Normalized Beats

The sum of standard deviations for all the normalized bins (D bins) in the window is also employed as a feature. The sum of standard deviations for all the normalized bins (D bins) in the window is also employed as a feature. By using multiple measurements, this temporal ECG feature vector covers both conventionally used heart rate information and novel morphological shape information.

F. SVM classification for Temporal Feature

By using kernel function, an SVM can be generalized to nonlinear classifiers by mapping the input features into high dimensional feature space [6].

V. GMM based Cepstral Domain System

A. Cepstral Feature Extraction

ECG signals have quasi-periodic characteristics resulting from the convolution between an excitation (heart rate or moving pace) and a corresponding system response (ECG waveform shapes) [7]. To filter out the effects of the different paths from the source signals to the sensors, using Cepstral features to model the frequency information of the native signal allows us to separate inherent convolutive effects by simple linear filtering.

The sensor signal has some frequencies at which motion artifacts or sensor noise dominate. Discrete cosine transform (DCT) of the M filter log-energy outputs is calculated to generate the Cepstral features

$$C[n] = \sum_{m=0}^{M-1} S[m] \cos(\pi n(m + 1/2)/M), 0 \leq n < M.$$

Cepstral mean subtraction (CMS) and Cepstral variance normalization (CVN) are adopted to mitigate convolutional filtering effects for ensuring robustness.

B. GMM modeling for Cepstral features

A GMM is used to model the Cepstral features of the ECG signals [7]. For subject-dependent PA identification using the Cepstral features of sensor signals, each activity performed by every subject is represented by a GMM and is referred to by its model λ_i. The UBM model is trained using all the training data including all the activities and all the subjects; then the subject-dependent activity model is derived using MAP adaptation from the UBM model with subject specific activity training data.

VI. Score Level Fusion

Multi-domain information can also be fused at the score level rather than the feature level [8]. The match score is a measure of similarity between the input sensor signals and the hypothesized activity. Let there be K input PA recognition subsystems, each acting on a specific sensor feature set, where the k_{th} subsystem outputs its own normalized log-likelihood vector $l_k(\boldsymbol{x}_t)$ for every trial. Then the fused log-likelihood vector is given by

$$\acute{l}(\boldsymbol{x}_t) = \sum_{k=1}^{K} \beta_k l_k(\boldsymbol{x}_t).$$

The weight B_k is determined by regression based on the training data.

VII. Discussion

It has already shown that performance of ECG based biometric system using fusion of temporal and Cepstral information can be improved over single domain based biometric system [9]. Experimental setup was done for testing its performance whether improved or not. So, we can say that experimental set up can be done to test and measure resulting system's performance. We can check results and performance for time domain system and Cepstral domain system separately and for system based on their fusion. We can compare both results to show whether performance improved or not.

VIII. Conclusion

In this work, a novel ECG Physiological Activity Recognition algorithm is proposed. In the time domain, HPE, PCA and SVM are used to efficiently model the intra-heartbeat patterns of different individuals with linear kernel. In the frequency domain, without the need of heartbeat segmentation and normalization, Cepstral feature extraction is combined with GMMs to directly model the short time characteristics of the ECG signal. And by fusing both temporal and Cepstral information together, the overall biometric system performance is improved. Future work would include validating the performance of test subjects, comparing/combining with other techniques, and investigating the robustness against a variety of physical and emotional state variability.

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