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Rapid Trend Detection for an Ambulatory Monitoring System

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Abstract -- An algorithm for rapid trend detection of physiological parameter is introduced for ambulatory monitoring applications. Kalman prediction error of monitored parameter is used to estimate the physiological status and detect rapid change. With this algorithm, rapid trend during ambulatory monitoring can be found to predict disease exacerbation; and it is also applied to identify outliers of measurement due to poor signal quality to avoid false alarms.

1. Introduction

Ambulatory monitoring provides physiological information while the subject is moving around. It extends healthcare services from hospital to the patient's daily life. Because of the nature of continuous monitoring, it provides richer information for diagnose and disease status assessment; and it can makes rapid prediction of disease status to help patients avoid exacerbation. It is particular useful manage chronic disease and help senior people to live independently [1, 2].

To further use the rich information within the ambulatory monitoring data (i.e. heart rate, respiration rate, ECG, blood pressure), trend analysis is very important. Traditional clinician decision is primarily based on snapshot of physiological parameters. With body sensor network systems for ambulatory monitoring, trend analysis of those parameters become possible for diagnose and disease status assessment [3]. Principle component analysis (PCA) or independent component analysis (ICA) has been applied to long term trend analysis [4]. However rapid trend in short term (less than 10 minutes) is also crucial for patients and caregivers to take actions to avoid exacerbation but no much research has been focused on this area.

Ambulatory monitoring data is not as accurate as the ones in hospital. Usually Less expensive equipments are used (sometimes they are disposable). On the other hand, the monitoring subjects may be with noisy environment and high activity level. Inaccurate results due to poor signal may lead wrong decisions to the patient such as false alarm or missing of important event. With redundant monitoring data, it would be possible to identify the inaccurate data point and remove them from analysis.

In this paper, we present an algorithm to analyze the ambulatory monitoring data and detect rapid trend of physiological parameters. We use heart rate as examples.

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Based on contextual monitoring data analysis, rapid trend in short term is identified which could be an indicator of patient health/disease status change. The algorithm also identifies the "most unlikely happen" changes of physiological parameters due to poor signal quality and eliminate them as inaccurate results.

2. Method

A. Signal Acquisition and Analysis

Five healthy subjects were used to collect physiological signals in this experiment during daily activities. Each subject was asked to wear an acoustic sensor on the trachea location. Body sound was acquired which contains respiration sound and heart sound; the acquired signal is transferred through a wireless body area network to a smart device; signal processing algorithm is applied to the body sound to extract heart rate and respiration rate. The subjects' activity level was also recorded using an accelerometer. The details about the acoustic sensing, wireless network system and signal processing algorithm have been discussed in previous paper [5] and [6].

As the subjects were all healthy, none of the disease relative events were involved during the data collection; the primary reason of physiological parameters rapid changes was due to subject's activity level change, which can be verified with an accelerometer in the system.

The data collection period for each subject varied from 8 to 15 hours. During the data collocation, all kinds of daily activities within working environment, commute and home were expected such as sitting in the chair, walking, running, driving and etc. Speech and surround noise were also expected. Signal processing algorithm was applied to detect and suppress the noise, process the acoustic signal, extract heart rate and respiration rate. Heart rate results are used as an example in this study for rapid change detection as an example.

One group of derived heart rate results are plotted as Fig. 1 as an example. The heart rate is calculated in every 15 seconds window without overlap. In Fig. 1, three groups of one hour heart rate for the same subject are shown. Fig. 1A is totally still and quiet status; Fig. 1B shows the subject results with some low level activities in the office such as walking; in Fig. 1C, the subject was doing exercises including running (started from ~ 10 min and stopped at ~ 35 min in that hour).

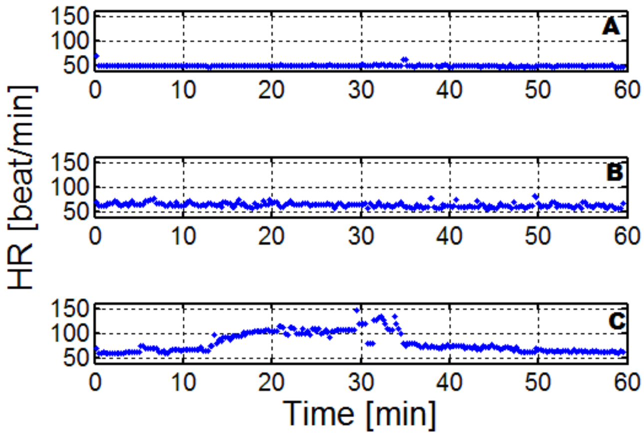

Fig. 1. Example heart rate results from data collection, A: subject is in still status in office; B: subject has low activity such as walking in office; C: subject has exercises such as running.

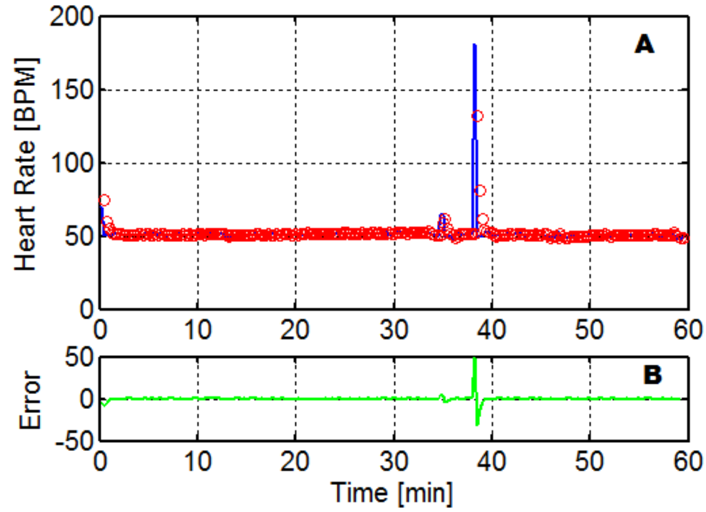

Fig. 2. Kalman prediction for heart rate A: Blue curve is heart rate result from signal processing algorithm, red circles: Kalman prediction results. B: errors of prediction.

B. Kalman Prediction and Error Analysis

To identify the rapid change of heart rate during monitoring, Kalman prediction error is used. Kalman filter has been widely applied for system identification and estimation. [5, 6] In this study, physiological system is estimated with Kalman filter using heart rate. Eq. 1 and 2 are general expressions of Kalman filter.

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (1)$$

$$z_k = Hx_k + v_k \quad (2)$$

In these equations, x_k is the heart rate prediction for window k; A is the difference equation transfer from last window k-1 to the current window k; B relates to the optional control input u_k which is not applicable in this case. w_k is the procedure noise of each window. H relates to the measurement z_k with estimation x_k. v_k is the measurement noise. More details about Kalman filter can be found in [8].

After several recursive loops, the prediction error of each window will become minor and stable. If the prediction error significantly increases, it indicates physiological system change or inaccuracy of measurement and the previous estimated system could not predict it. Fig. 2 shows an example of heart rate measurement using the wearable sensor and the Kalman prediction. The prediction error is also presented in Fig 2B. Each data point corresponds to 15 seconds window without overlap.

As shown in Fig. 2B, the error of Kalman prediction becomes close to 0 after a few recursions and stays very small. If there is change of heart rate but it's not rapid (i.e. ~35 min in Fig. 2), the prediction error is still quite low; however at ~38 min, as there is a rapid jump of heart rate, the prediction error increases significantly.

C. Classifier for short term change

The Kalman prediction error varies for stable status, rapid physiological change (i.e. activity change, disease status change and etc.) and outliers result due to poor signal quality. To find the classifier boundaries to differentiate those three cases based on the Kalman prediction error, training set data with reference data is collected.

A healthy subject continuously wore the acoustics sensing system for about 12 hours with daily activity including sitting, walking, driving, talking, doing exercises and etc. Heart rate was derived in every 15 seconds from the recorded signal. None disease relevant event was expected during the data collection. Rapid change of heart rate was primarily due to activity level change which was verified with an accelerometer in the system.

Kalman prediction algorithm is applied to the 12 hours heart rate results and prediction error is calculated. The histogram of prediction error is show as Fig. 3. Fig. 3B is a zoom in of Fig 3A to show the details of rapid changes cases and outlier cases. To identify a rapid change due to activity, accelerometer data is used and those cases are marked as green bars in Fig. 3. Outlier points are automatically detected and manually verified to ensure the accuracy; outlier points are marked as red in Fig. 3. Dash lines in Fig. 3B are the classifiers to differentiate those three cases.

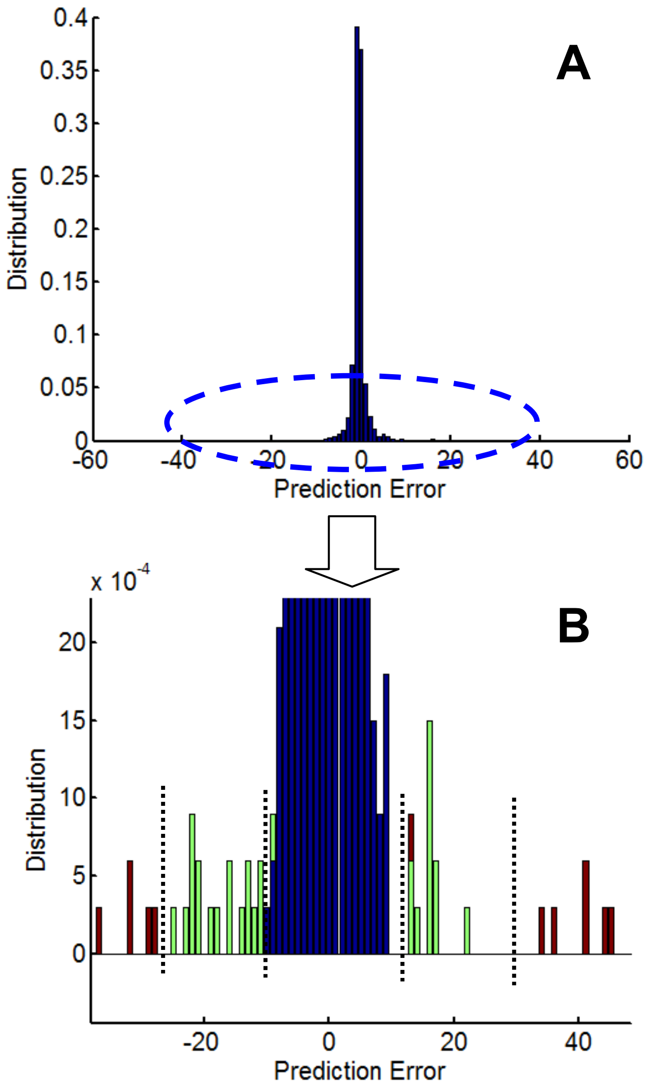

Fig. 3. Kalman prediction error of heart rate: X is prediction error in BPM, Y is normalized distribution probability. Fig. 3B is a zoom in of Fig. 3A. Blue bars are stable cases, green bars are rapid changes cases and red bars are outlier cases. Dashed lines in Fig. 3B are the classifiers.

Fig. 4 shows three typical cases (i.e. stable, rapid change and outlier) using the classifiers in Fig. 3. Red circles are heart rate measurement for every 15 seconds and blue curve is the Kalman prediction. If the prediction value is within green region, the case will be identified as stable (as Fig. 4A); if the prediction value is within pink region, the case will be identified as rapid change (as Fig. 4B); if the prediction value is out of green and pink region, it will be identified as outliers (as Fig. 4C).

Within a chronic disease management system, rapid change detection event will be sent to expert system and further analysis for disease status estimation, along with other physiological measurement. Outlier data points will be eliminate from further analysis to avoid false alarms.

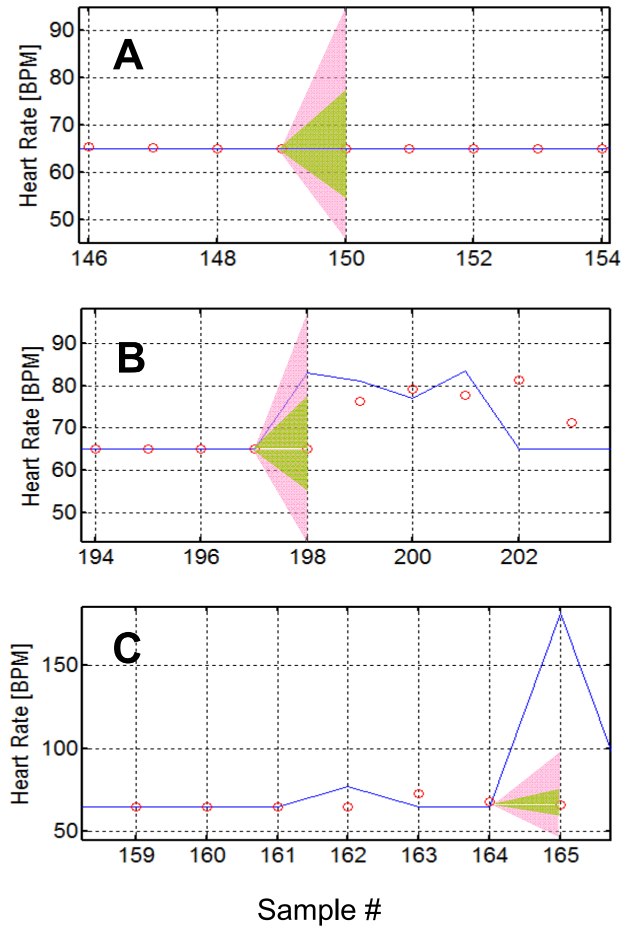

Fig. 4. Kalman detection cases: red circles are heart rate measurement and blue curves are Kalman prediction; Each sample corresponds to 15 seconds. A. stable status; B. rapid change detected; C: outlier detected

3. RESULTS

The classifier of Kalman prediction error is applied to collected signal derived heart rate which is described in the method section 2A. The heart rate data in Fig. 1 is used as an example to demonstrate the classification results as Fig. 5. In Fig. 5A, the subject was mostly in still and quite status, the only activity level change was caught at ~35 min and it is verified with accelerometer. There is always some higher error at the beginning of Kalman filter before convergence; these are also applicable to the other two cases within Fig. 5.

It will only happen at the beginning of continuously monitoring and can be easily identified. In Fig. 5B, more heart rate changes (due to activity change) are detected and they are consistent with accelerometer detection results. In Fig. 5c, the subject was doing exercises; the detected red circles are corresponding to activity level change, not high activities. These are consistent with accelerometer measurement. In this case, there are also two points (at ~29 min and 31 min) that heart rate results are detected as outliers due to poor signal quality.

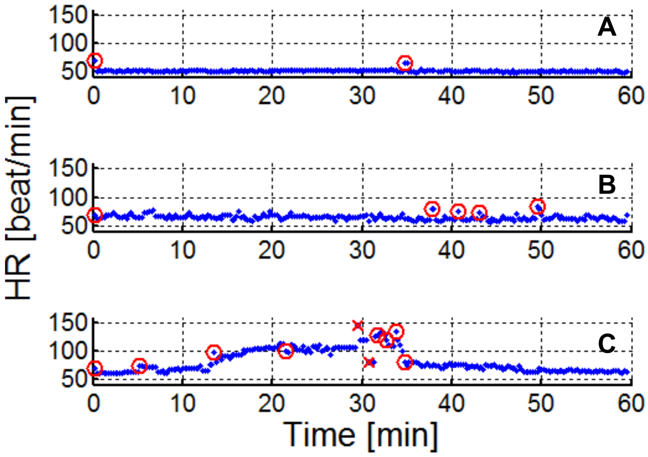

Fig. 4. Kalman detection cases: red circles are heart rate measurement and blue curves are Kalman prediction; Each sample corresponds to 15 seconds. A. stable status; B. rapid change detected; C: outlier detected

All heart rate results from five subjects are processed using Kalman prediction with classifications based on prediction error. The detected events are compared to accelerometer measurement and have about 90% accuracy.

4. Discussion

This paper presents an automatic event (disease status change) detection algorithm, which can identify rapid trend of physiological parameters in short term. Heart rate is used as an example; it is also applicable to respiration rate, blood pressure and etc. Rapid changes can be corresponding to disease status change, activity level change and possibly mood change. To further identify each case, other reference such as accelerometer can be used.

For an ambulatory disease management system, short term prediction of disease status based on physiological parameters rapid change is quite helpful. It provides valuable time to the patients to take medication, contact the caregiver to avoid the exacerbation of disease.

Collected signal from 5 healthy subjects shows that the classifier for physiological parameters based on Kalman prediction is subject independent. However, more data from specific disease patients are necessary to validate the classifier.

This algorithm also can detect outliers of measurement due to poor signal quality during ambulatory monitoring. Outliers will be eliminated from further analysis. This is crucial for chronic disease monitoring applications, since outliers could lead false alarms and improper guidance to the patient and caregiver. When outlier point is detected and removed, interpolation algorithm can be applied to recover the data points and keep the integration of the results. However we need to be more careful about inserting interpreted points to replace outliers since no new information is created.

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