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An adaptive Kalman filter technique for context-aware heart rate monitoring

Min Xu, Albert Goldfain, Jim DelloStritto, Satish Iyengar
Blue Highway Inc.
2-212 Center for Science and Technology, Syracuse, NY, 13244
Email: {mxu, agoldfain, jdellostritto}@blue-highway.com

***Abstract*—Traditional physiological monitoring systems convert a person's vital sign waveforms, such as heart rate, respiration rate and blood pressure, into meaningful information by comparing the instant reading with a preset threshold or a baseline without considering the contextual information of the person. It would be beneficial to incorporate the contextual data such as activity status of the person to the physiological data in order to obtain a more accurate representation of a person's physiological status. In this paper, we proposed an algorithm based on adaptive Kalman filter that describes the heart rate response with respect to different activity levels. It is towards our final goal of intelligent detection of any abnormality in the person's vital signs. Experimental results are provided to demonstrate the feasibility of the algorithm.**

I. Introduction

The recent advancements in sensing technologies, wireless communication and signal processing have enabled the development of telehealth and telemedicine. Ambulatory health monitoring has been an area of active research. The objective is to monitor a person's health status by remotely and continuously measuring various vital signs. Detecting abnormalities in vital signs before clinical signs are present allows timely treatment, earlier intervention, and prevention of advanced problems. How to accurately detect the onset of abnormalities in vital signs is a challenging problem.

It is becoming more apparent that contextual data captured along with physiologic data can be beneficial in helping to assess the health status of a patient. As a representative example, if a patient is wearing a mobile wireless health monitor for measuring heart rate and a monitoring system is looking to triage a range of patients with similar devices, a challenge will present itself. In one representative challenge an individual being monitored could in fact perform a strenuous activity, which will lead to an increased heart rate. When the heart rate is above a predefined heart rate limit simulating an adverse health condition, a subsequent false alarm is activated. Normally the goal of looking at a heart rate in a triage application is to look for measurement outside the normative. Physical activity is one way to increase this level and is not necessarily an indicator of a potential dangerous condition. Thus, it is necessary to incorporate contextual information such as activity level in order to reduce the false alarm of such physiological monitoring system.

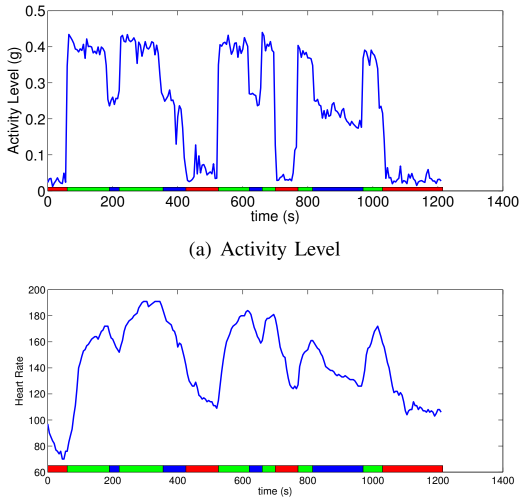
Many studies have attempted to explore the relationship between physical activity and health status. The use of motion data to provide context of the subject for physiological monitoring has been used in different applications such as assessment of energy expenditure[1], [2], computer-controlled treadmill system [3] and cardiac disease predictor. Heart rate is an important measurement related to a person's cardiac health status. Different linear and nonlinear models have been proposed to study and model the cardiac response during different type of activities [4], [5], [6], [7]. All these studies require a significant amount of training data to develop a model with fixed parameters to describe the heart rate function. In practice, it could work for a specific scenario. For example, in treadmill application, it is possible to use a fixed model to relate heart rate response with the running speed. However, the model has to be trained first for each individual and for each activity. A single model will not work for long term monitoring application, in which different type of activities could happen. That is to say, the model that is used for treadmill application can not be applied to resting scenario. Thus, long term monitoring application requires either multiple models corresponding to different activities or the model be adaptive. Thus, we have proposed to use an adaptive linear model to relate heart rate response with respect to the activity level. The advantage of it is that it does not require any training data and it avoids the classification step before triggering any model.

II. Data Collection and Processing

Most heart rate monitors in the market can only be used when the subject is at rest and gives motion artifact when the subject is moving. We chose a Garmin belt containing ECG electrodes to collect heart rate data continuously because this Garmin heart rate monitor is designed for fitness application and can measure the heart rate accurately when the subject is moving. The sampling rate of the heart rate monitor is 0.2HZ.

Due to the advantage of small power consumption and small size, we used an accelerometer as a tool to measure activity level for our application. A Freescale triaxis accelerometer mounted in custom made casing is attached to the chest to measure the acceleration of the body. The accelerometer is positioned such that the sensor plane is parallel to the torso and Y axis is along the gravity line when the subject stand upright. The sampling rate of accelerometer sensor is 30 HZ.

It is not necessary to process all the three axes of acceleration. Therefore, The Z axis of the acceleration data, which



(a) Activity Level

(b) Heart Rate

Fig. 1. Example of heart rate data and activity level data (red: sitting; blue: walking; green: running)

represent the acceleration of the subject moving forward, is used to calculate the activity status of the subject. As one sample of heart rate data corresponds to 150 samples of acceleration data, we calculate the standard deviation of 150 samples from the acceleration data to measure the activity level over a time window of one second. This activity level provides an estimate of the average energy the person spent over a short period of time.

Figure 1 displays one example of the heart rate data and corresponding acceleration data from one subject performing different levels of activities. From the two plots, it is observed that the heart rate signal is highly correlated with the activity level. When the subject started running, the heart rate of the subject increased immediately. When the subject was walking after running, the heart rate decreased gradually and remained quite stable when the subject finally sat. In addition, we also observed that the behavior of heart rate signal varied when walking at different time. When the subject walked right after a long run, a dramatic decrease in heart rate was observed while the heart rate decreased slowly when the subject walked after a short run. It implies that even for the same activity, it is difficult to characterize the heart rate response using a fixed model.

III. Adaptive Kalman filtering algorithm for abnormal heart rate detector

A. Problem Formulation

The basic idea is to use history of the heart rate and activity level measured by acceleration data to predict the future heart rate. When the new measurement of heart rate is received, it will be compared with the predicted heart rate. The prediction error will stay within tolerance if the system converges and the person is healthy. If the subject has a sudden adverse health condition resulting in abnormal heart rate change, the system is not able to predict the heart rate accurately and the prediction error will be quite large. Thus, the onset of adverse health event is detected by comparing the instant prediction error of the subject's heart rate with a predetermined or adaptive threshold.

The first important step is to build a model that can describe the relationship between the future heart rate and the history of heart rate together with activity level. The heart rate data is calculated from ECG signals coming from electrodes in the Garmin belt. The ECG signals' quality degrades especially when the subject is not in stationary condition as various types of noise such that that due to sweating, muscle movement or electrode movement are in coupled in dynamic environment. Some of the signal-to-noise ratio (SNR) and artifact problems that arise during these recordings can be suppressed by simple, frequency-selective filtering techniques [8]. However, due to the partial overlap of signal and noise bandwidths, this frequency-selective filtering can only help to some extent [8]. Also, simple filtering techniques such as median filtering and low pass filtering could suppress the physiological dynamics of the ECG signals, and therefore, failed to detect the physiologically relevant changes. Hence, we developed an adaptive Kalman filter to dynamically detect unanticipated physiological abnormality.

B. Kalman Filter Model

We consider that the heart rate signal is a random process and attempts to predict the future signal based on the previous signals. Under such assumption, the heart rate signal x_n at the time stamp t_n is modeled by a p^{th} autoregressive process with exogenous term (ARX), which is given by

$$x_n = a^1 x_{n-1} + ... + a^p x_{n-p} + b u_n + w_n \tag{1}$$

where, a^i and b are the coefficient parameter in the model, the exogenous term u_n is the acceleration signal that provides the contextual information of the subject and w_n is the process noise which is assumed to have multivariate Gaussian noise with zero mean and covariance Q.

As the heart rate signal is corrupted to some extent by noise and artifacts, we model the denoised consecutive heart rate signal as the state of Kalman filter. In a simplified form, both the relationship between consecutive heart rate readings and collected heart rate signal contaminated by noise can be described by a state-space model, which are written by,

$$\begin{aligned} X_n &= A_{n-1} X_{n-1} + B_{n-1} u_n + C w_n \\ y_n &= H X_n + v_n \end{aligned} \tag{2}$$

where, $X_{n-1} = [x_{n-1} \dots x_{n-p}]^T$ represents the system state at time $n-1$;

$A_{n-1} = \begin{bmatrix} a^1_{n-1} & a^2_{n-1} & \dots & a^{p-1}_{n-1} & a^p_{n-1} \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}$ represents the state transition matrix updated at time $n-1$ that describes the evolution of state over time;

$B_{n-1} = \begin{bmatrix} b_{n-1} & 0 & \dots & 0 \end{bmatrix}^T$ is the control vector updated at time $n-1$ that represents the contribution of input signal u_n to the state;

$C = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix}^T$ is the coefficient that is applied to process noise;

$H = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix}$ is the observation model that maps the system state to the measured signal;

v_n is the measurement noise which is assumed to be Gaussian distributed with zero mean and variance R.

These state-space models describe a linear dynamic system from the measured heart rate signal and can be used to predict future heart rate and refine the estimation by the Kalman filter theory. According to the well-known Kalman filter theory [9], the prediction step for state estimate and covariance matrix of state estimate error is given by,

$$\begin{aligned} \hat{X}_{n|n-1} &= A_{n-1}X_{n-1|n-1} + B_{n-1}u_n \\ P_{n|n-1} &= A_{n-1}P_{n-1|n-1}A_{n-1}^T + CQC^T \end{aligned} \tag{3}$$

With the new measured signal y_n, the updated state estimate is given by

$$\hat{X}_{n|n} = \hat{X}_{n|n-1} + K_n\left(y_n - H\hat{X}_{n|n-1}\right) \tag{4}$$

where, K_n is the Kalman gain given by,

$$K_n = P_{n|n-1}H^T\left(HP_{n|n-1}H^T + R\right)^{-1} \tag{5}$$

The updated covariance matrix of state estimate error is calculated as,

$$P_{n|n} = \left(I - K_nHP_{n|n-1}\right) \tag{6}$$

The prediction error of heart rate signal at time n is

$$Pr_n = \hat{X}_{n|n} - \hat{X}_{n|n-1} = K_n\left(y_n - H\hat{X}_{n|n-1}\right). \tag{7}$$

Thus, if the prediction error is larger than a baseline, it implies that the ARX model is not well fitted in the heart rate data and therefore, an event of abnormality is detected and an abnormal alarm is triggered.

C. Adaptive ARX model update

In the traditional Kalman filter state model, the ARX parameters a_n and b_n are fixed. As the ARX model illustrates the changes of heart rate corresponding to different activity level, it is not possible to use a single model to describe such phenomenon during the whole stage of activities. For example, the change of heart rate when someone rests immediately after a long run is different from the change of heart rate when someone rests for a while. In addition, such relationship usually changes gradually in normal case. Thus, we build the ARX model adaptively by updating the model gradually during the different stage of activities. The structure of adaptive Kalman filter is illustrated in Fig. 2. The enhanced signal at the output of Kalman filter is fed to the adaptive filtering subsystem to update the ARX model parameters. At the beginning, the noisy signal is used for ARX parameter estimation. After the system converges, the denoised signal is used to update the ARX model. The ARX model is updated on a per sample basis using a recursive least squares algorithm [10].

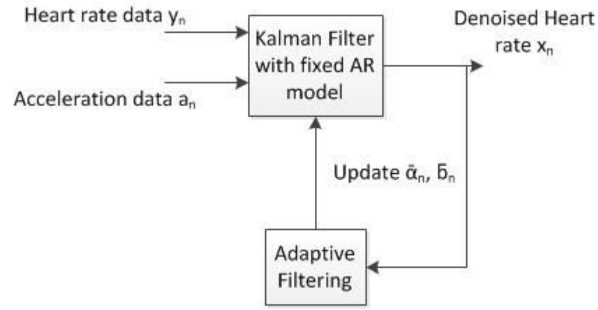


Fig. 2. Block Diagram of Adaptive Kalman Filtering System

The whole procedure is described as follows,

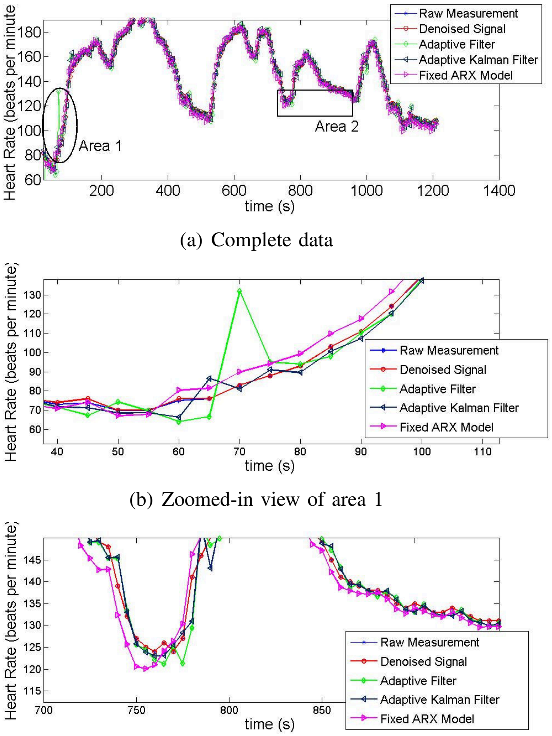
1) Predict the state (denoised heart rate signal) $\hat{X}_{n|n-1}$ and its covariance $P_{n|n-1}$ using Eq. 3
2) With the new measurement Y_n, calculate Kalman gain K_n using Eq. 7
3) Calculate prediction error Pr_n using Eq. 7
4) Update the state and covariance matrix using Eq. 4 and 6
5) With the updated state, update the ARX model a_n and b_n.

IV. Experimental Results and Discussions

In this experiment, to evaluate our proposed algorithm, we also implemented adaptive filter based algorithm and ARX algorithm with fixed parameters. Different from our proposed algorithm in which we create ARX model using the denoised heart rate (states in Kalman filter), adaptive filter based algorithm adaptively updates the ARX parameters using the measured heart rate data. In the ARX algorithm with fixed parameters, we used half of data as training data to build the ARX model and the other half of data as testing data to evaluate the model performance.

We have collected data from the accelerometer sensor and heart rate monitor from three healthy subjects aging from 20 to 30. Each subject is asked to perform three tasks during 20 minutes, sitting, running at different speeds, and walking. Three algorithms are implemented.

Figure 3 shows the raw heart rate data, denoised heart rate data by Kalman filtering, predicted heart rate using our proposed algorithm (adaptive Kalman filter), predicted heart rate using adaptive filter based algorithm and predicted heart rate using fixed ARX model based algorithm. Figure 3(a) displays the result of the complete data set and (b) and (c) display the zoomed-in view of two areas. In the first area, the subject started running from sitting and a dramatic increase of heart rate is observed. In the second area, the subject sat for a short time during a run and a transition between a decrease of heart rate and an increase of heart rate is observed. Compared with adaptive filter based algorithm and fixed ARX based algorithm, which produces relatively larger error, our proposed



(a) Complete data

(b) Zoomed-in view of area 1

(c) Zoomed-in view of area 2

Fig. 3. Predicted, denoised and raw heart rate data ((a) shows the results of the complete data; (b) and (c) are the zoomed-in view of area 1 and 2.)

algorithm can predict the heart rate closer to the measured and denoised heart rate. In particular, our proposed algorithm can adapt the model when the subject changes his physical activity status, and therefore, can be suitable for the application of long term monitoring.

Figure 4 shows the prediction error of three algorithms using the data from one subject. It is observed that our proposed algorithm produces smaller error than the other two algorithms throughout the experiment. The root mean square error (RMSE) of predicted heart rate during the complete 20 minutes is calculated for all the three algorithms and shown in Table I. Our proposed algorithm produced the smallest error on the data from all the three subjects. The prediction error can be caused by several reasons. First, it is based on the model that the future heart rate is a linear function of historical heart rate. The model fitting error is the major cause for the prediction error. Second, the measured heart rate contains non-Gaussian noise from ECG device due to power-line interference and electrode contact, which also leads to the prediction error. We assume that the amount of such prediction error under normal condition is much smaller than the error caused by a sudden adverse event such as heart attack, which is to be validated in our future experiments using data from patients with cardiac diseases.

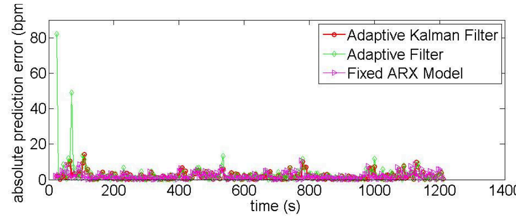


Fig. 4. Prediction error of three algorithms

TABLE I
RMSE OF PREDICTION ERROR OF THREE ALGORITHMS

Suject	1	2	3
Adaptive Kalman Filter	2.72	3.17	1.47
Adaptive Filter	3.55	3.58	1.70
Fixed ARX model	4.07	3.95	1.90

V. CONCLUSIONS

In this paper, we proposed an adaptive Kalman filter based algorithm to predict the heart rate signal with the acceleration data and the history of heart rate. Our proposed algorithm builds an ARX model of heart rate response with adaptive parameters that could be used in different activity contexts without any training data. Experimental results have demonstrated that the use of an adaptive model provides a better description than the model with fixed parameters. In particular, our proposed algorithm works better during the transition stage when the subject changes their activities.

REFERENCES

[1] G. A. Meijer, K. R. Websterp, H. Koper, and F. ten Hoor, "Assessment of energy expenditure by recording heart rate and body acceleration," in *Medicine and Science in Sports and Exercise*, vol. 21, 1989, pp. 343 –347.

[2] D. Kim, J. Cho, H. Oh, Y. Chee, and I. Kim, "The estimation method of physical activity energy expenditure considering heart rate variability," in *Computers in Cardiology*, sept. 2009, pp. 413 –416.

[3] T. Cheng, A. Savkin, B. Celler, S. Su, and L. Wang, "Nonlinear modeling and control of human heart rate response during exercise with various work load intensities," *Biomedical Engineering, IEEE Transactions on*, 2008.

[4] M. Yuchi and J. Jo, "Heart rate prediction based on physical activity using feedforwad neural network," in *International Conference on Convergence and Hybrid Information Technology*, aug. 2008, pp. 344 –350.

[5] G. Velikic, J. Modayil, M. Thomsen, M. Bocko, and A. Pentland, "Predicting heart rate from activity using linear and non-linear models," in *IEEE 13th International Conference on e-Health Networking, Applications and Services*, 2011.

[6] J. Lefever, F. Jansen, J.-M. Aerts, and D. Berckmans, "Real-time monitoring of the heart rate response to power output for cyclists," in *2010 International Conference on Body Sensor Networks*.

[7] D.-e.-Z. Baig, H. Su, T. Cheng, A. Savkin, S. Su, and B. Celler.

[8] R. Vullings, B. de Vries, and J. Bergmans, "An adaptive kalman filter for ecg signal enhancement," *Biomedical Engineering, IEEE Transactions on*, vol. 58, no. 4, pp. 1094 –1103, 2011.

[9] S. M. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*. Prentice Hall, 1997.

[10] A. H. Sayed, *Adaptive Filters*. Wiley-IEEE Press, 2008.