Model-based sensor fusion of multimodal cardiorespiratory signals using an unscented Kalman filter

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Based on a model of three coupled oscillators describing the influence of respiration, namely respiratory sinus arrhythmia (RSA), and so-called Mayer waves on the heart rate, an unscented Kalman filter (UKF) is designed to perform sensor fusion of multimodal cardiorespiratory sensor signals. The aim is to implicitly use redundancy between the sensor signals to improve the estimated heart rate while utilizing model knowledge. The effectiveness of the approach is shown by estimations of heart rate variability on synthesized data as well as multimodal patient data, which provide different numbers of sensor channels.

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I. Introduction

Heart rate variability (HRV), i.e. the variation in beat to beat intervals, earned prominence by its correlation with heart diseases such as myocardial infarction. It was shown that a low low-frequency to high-frequency ratio in terms of spectral power can be associated with an increased mortality after myocardial infarction [2]. Recently it was also discovered that HRV can be used to classify different mental and physical states [8]. While most approaches use frequency-based methods or differences in the beat to beat interval [2,3,8], this paper introduces a model-based approach to utilize prior knowledge about the influences on the heart rate to make a more robust estimation. The effectivity of an unscented Kalman filter was shown in [7] while estimating the respiratory sinus arrhythmia (RSA). This paper is divided as follows. First, the conjugated unscented transformation (CUT) [1] as an improvement for the unscented transformation (UT) of the unscented Kalman filter (UKF) [6] is revised. Second, the model describing the coupling of heart rate by RSA and Mayer waves is introduced which was first postulated in [4]. Fourth, the UKF approach is presented followed by a presentation and discussion of the results.

I.I. The conjugated unscented transformation

The unscented Kalman filter was first introduced by Julier et al. [6] to overcome the degradation of the Kalman filter estimate when dealing with nonlinear systems. The unscented Kalman filter makes use of the UT which uses *2n* carefully chosen sample points propagated by the nonlinear system function to approximate the new distribution of the state vector *x* of dimension *n*. In this paper, an extension of the UT is used to tackle the degradation of the central weight of the UT for dimensions higher than three, namely the conjugated unscented transformation (CUT) [1]. The CUT propagates additional 2^n sample points symmetrically distributed on axes constructed from linear combinations of the principle axes of the current distribution to approximate the new distribution after the nonlinear transform capturing higher order moments [1]. The UKF equations remain unchanged (see [1]).

I.II. Model for cardiorespiratory coupling

First introduced by Hoog Antink et al. [4] the influence of respiration and Mayer waves on the heart rate can be described by means of three coupled oscillators described by

$$\begin{aligned}[\dot{x}_1, \dot{x}_2, \dot{x}_3, \dot{x}_4, \dot{x}_5, \dot{x}_6]^T = \\ [-2\pi f_{\mathrm{LF}} x_2,\ 2\pi f_{\mathrm{LF}} x_1,\ -2\pi f_{\mathrm{HF}} x_4,\ -2\pi f_{\mathrm{HF}} x_4,\ 2\pi f_{\mathrm{HF}} x_3, \\ -2\pi[f_{\mathrm{HR}} + k_{\mathrm{LF}} g_1(x_1,x_2) + k_{\mathrm{HF}}\, g_2(x_3,x_4)]x_6, \\ 2\pi[f_{\mathrm{HR}} + k_{\mathrm{LF}} g_1(x_1,x_2) + k_{\mathrm{HF}}\, g_2(x_3,x_4)]x_5]^T,\end{aligned}$$

with $f_{\mathrm{LF}}, f_{\mathrm{HF}}$ and f_{HR} being the mean frequencies of the Mayer waves, the respiration rate and the heart rate respectively, and k_{LF} and k_{HF} being coupling constants. If g_1 and g_2 are assumed to be cosine functions dependent on the phase of the respective oscillator given by

$$\varphi = \mathrm{atan2}(x_{i+1}, x_i),$$

then g_1 and g_2 can be assumed to be x_1 and x_3 respectively (see [4]).

Using the phase information of these oscillators, a sensor signal output can be generated by means of template functions obtained from real sensor signals (see [4]). These templates are divided into a ‘cardiac’, an ‘additive respiratory’ and ‘modulating respiratory’ template which together give a modality dependent sensor output

$$\begin{aligned}h(x) = T_{\mathrm{card}}(\varphi_{\mathrm{card}}) \cdot [1 + T_{\mathrm{resp,mod}}(\varphi_{\mathrm{resp}})] \\ + T_{\mathrm{resp,add}}(\varphi_{\mathrm{resp}}),\end{aligned}$$

with φ_{card} and φ_{resp} being the phase signal of heart and respiration. The templates mimic the coupling effects being observed on real sensor signals (see [4]).

II. Method

Additional to the system described in the previous section, the interval estimator from [3] is used to adapt f_{HR} for having a reliable mean heart rate estimation. The frequency f_{LF} is modelled as a slow-changing process and is incorporated in the state vector similar to [7] such that $\boldsymbol{x} = [x_1, x_2, x_3, x_4, x_5, x_6, f_{\text{LF}}]^T$. For real data, templates for the cardiac signals are obtained from the first 120 seconds of the record. For respiration signals, mean templates obtained from a fraction of the dataset are used since they do not differ as much between individuals as the ones for cardiac signals. An UKF with CUT is used to estimate the states $\boldsymbol{x}$ with h modelling the output function. Due to the fact that the template extraction is performed in the first 120 seconds, the estimation is close to real time. The HRV is obtained by the derivative of the phase signal of the heart oscillator.

III. Results and discussion

First, the effectiveness of the UKF approach is tested on artificial data provided by the synthesizer of [4] having six channels. As visible in figure 1 the HRV can be accurately estimated even though only the Mayer frequency's mean is correctly estimated. Second, the approach is tested on real multimodal sensor data from the Fantasia dataset [5] and the Sleep Laboratory dataset [3]. The Fantasia dataset provides up to three channels (Electrocardiography (ECG), respiration and Photoplethysmography (PPG)) and the Sleep Laboratory six channels (Ballistocardiography, ECG, nasal flow, thoracic / abdominal stretch, and PPG). The HRV estimate for real data improves with an increasing number of channels due to the UKF's ability to implicitly use redundant information from all sensors, see Figure 2. This can be assumed to be an implicit sensor fusion. Even though the estimates for real data show promising results, improvements are necessary to become as accurate as frequency-based methods. This is due to the fact that the coupling of the heart rate, namely the functions g_1 and g_2, and the coupling factors need further research. As discussed in [4], the coupling factors are likely to be dependent on frequency and amplitude of respiration and thus should be adapted.

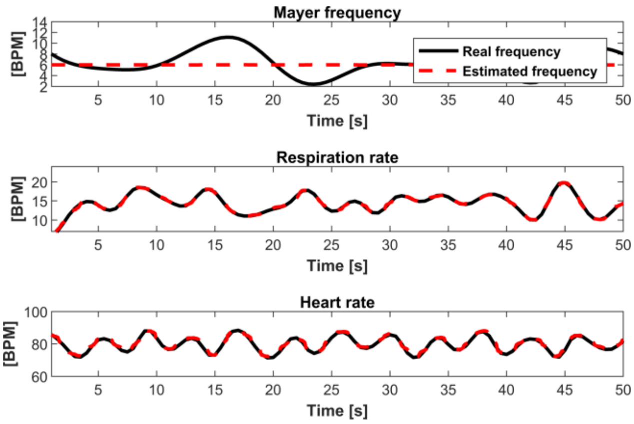

Figure 1 Estimated frequencies for synthesized data.

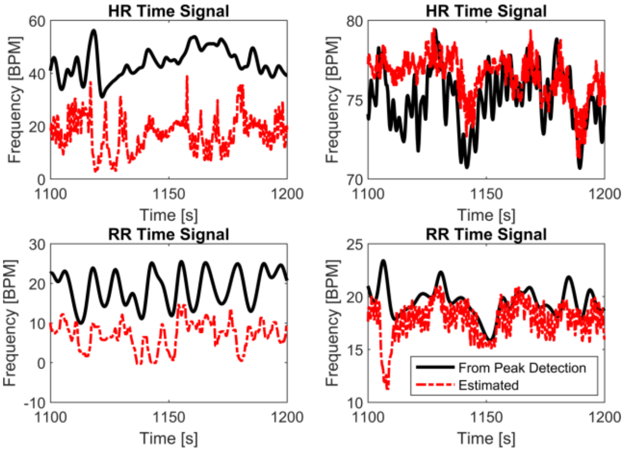

Figure 2 Record 'f1o09' (left, Fantasia, two channels) and 'BO_ZEA_14' (right, Sleep Lab., six channels).

IV. Conclusions

It was shown that a UKF approach is able to accurately estimate HRV in multi-sensor applications using redundancy from different channels to obtain more accurate estimations. While the estimation on synthesized data is nearly perfect, the estimation of real data is corrupted due to model errors and the faulty estimation of the Mayer waves. Therefore, to obtain further improvements, a deeper understanding of the coupling effects of the heart rate is needed.

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Author's statement

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