HEALTH WORKER MONITORING: KALMAN-BASED SOFTWARE DESIGN FOR FAULT ISOLATION IN HUMAN BREATHING

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ABSTRACT

Breathing is an involuntary action by the human body, and irregularities in breathing suggest possible respiratory disorders. This paper proposes a signal-noise separation algorithm for estimating the Oxygen partial pressure pression, an important respiratory parameter, by means of Kalman filtering. This technique is considered a powerful method to detect and isolate signal noise and it represents one of the most significant approach for multisensory data fusion measurements. Our results show that this technique can effectively filter out sensor noise.

Keywords: computer science, software design, sensor information, sensors

NOMENCLATURE

$\mathbf{x}$ is the state vector;
$\mathbf{u}$ is the input vector;
$\mathbf{w}$ is system noise (representing model inaccuracies), with zero mean, and known covariance Q;
$y \in \mathrm{R}$ is the system output;
$\nu \in \mathrm{R}$ is measurement noise with zero mean and covariance R.
$\boldsymbol{y}_i$ is the i-th sensor measure;
$\boldsymbol{R}_i$ is the i-th measurement noise covariance ;
$\boldsymbol{C}_i$ is the i-th measurement matrix.

1. INTRODUCTION

In the recent years different fusion schemes are introduced in many applications such as communication networks, sensor networks, automotive, aerospace as well as energy systems (Fiengo, Santini, and Glielmo 2008; Carotenuto, Iannelli, Manfredi, and Santini 2005; Brancati, Montanaro, Rocca, Santini, and Timpone 2013; Sarghini, de Felice, and Santini 2003; Manfredi 2014; Manfredi 2014; Valente, Montanaro, Tufo, Salvi, and Santini, 2014; Manfredi, Pagano, and Raimo 2012; Manfredi 2010).

One of the simplest and most intuitive general methods of measurement fusion is to take a weighted average of redundant information provided by multiple sensors and use this as the fused value (Qiang and Harris 2001; Willsky, Bello, Castanon, Levy, and Verghese 1982; Sderstrm, Mossberg, and Hong 2009; Lee 2003). More complex approaches to measurement fusion uses sensors information as well as model information for on line estimation. There are various multi-sensor data fusion approaches of which Kalman filtering is the most significant (Anderson and Moore 2006). Kalman filter is predominantly preferred because it results in estimate for the fused data that are optimal in a statistical sense (Simon 2006).

1.1. Medical application of method

Breathing is an involuntary action by the human body, and irregularities in breathing suggest possible respiratory disorders. Oxygen partial pressure pression is an important parameter for breath analysis and determines how much oxygen can be delivered from the lungs to the blood. This paper proposes a signal-noise separation algorithm for estimating the real Oxygen partial pressure pression.

The main limitations in the existing oxygen measurement methods suffer from either low sensitivity or low spatial or temporal resolution, or are invasive by nature.

In order to obtain more precise measurement of the parameter and to recognize and isolate the noise from the examined signal, this paper proposes the Kalman filtering as a powerful method to facilitate the estimation of the respiratory parameter. This filter estimates explicitly account for process and measurement noise inherent in clinical data making these estimates more informative than raw observation alone.

The Kalman filter has been recently used in different medical application. Charleston and Azimi-Sadjadi (1996) suggest the implementation of the Kalman filter to solve the problem of the cancellation of the heart sounds in respiratory signals. Sameni, Shamsollahi, Jutten, and Babaie-Zadeh (2005) proposed the extended version of the Kalman filter for filtering noisy ECG signals and they succeeded in extracting fetal cardiac signals from maternal abdominal signals. In order to eliminate the motion artifact in InfraRed spectroscopy measurement Izzetoglu, Chitrapi, Bunce, and Onaral (2010) developed a Kalman filter algorithm used in its discrete version.

Moreover, Kalman filtering is one of the most significant approach for multisensory data fusion measurements, which has several biomedical applications with especially regard to critical care monitoring and medical images. Tobergte, Pomarlan, and Hirzinger (200), for example, presented a sensor fusion for pose estimation using optical and inertial data based on extended Kalman filter.

2. PROBLEM STATEMENT

Given a generic nonlinear discrete-time process of the form:

$$\begin{cases} \mathbf{x}(k+1) = f(\mathbf{x}(k), \mathbf{u}(k), \mathbf{w}(k)) \\ y(k) = h(\mathbf{x}(k), \nu(k)) \end{cases} \quad (1)$$

where:

$\mathbf{x} =\in \mathrm{R}^n$ is the state vector;

$\mathbf{u} =\in \mathrm{R}^m$ is the input vector;

$\mathbf{w} =\in \mathrm{R}^n$ is system noise (representing model inaccuracies), with zero mean, and known covariance Q;

$y \in \mathrm{R}$ is the system output;

$\nu \in \mathrm{R}$ is measurement noise with zero mean and covariance R.

Assume that system (1) is observable in absence of disturbances w and ν. In what follows we propose an adaptive measurement fusion strategy, based on Kalman filter, that, on the basis of residuals, adaptively estimates noise covariance of each sensor thus providing a simple fault tolerant data fusion algorithm. The proposed approach is able to cope with sudden and significative faults, like abrupt bias or jump, as well as with sensors slow derives. Further enahcement of the proposed approch will rely on more innovative and sopfisticated adaptive mechanisms.

3. ADAPTIVE MEASUREMENT FUSION SCHEME

To solve the above mentioned problem we follow a fusion scheme by exploiting the idea of covariance-matching (Manfredi and Santini 2013), where EKF is Extended Kalman filter given by the following coupled difference equations (Anderson and Moore 1979):

$$\hat{\mathbf{x}}_{k+1|k} = f(\hat{\mathbf{x}}_{k|k}, \mathbf{u}_k, 0) \quad (2a)$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{\mathbf{k|k}} \mathbf{A}_{\mathbf{k}}^{\mathbf{T}} + \mathbf{W}_{\mathbf{k}} \mathbf{Q}_{\mathbf{k}} \mathbf{W}_{\mathbf{k}}^{\mathbf{T}} \quad (2b)$$

beeing

$$\hat{\mathbf{x}}_{\mathbf{k|k}} = \hat{\mathbf{x}}_{\mathbf{k|k-1}} + \mathbf{K}_{\mathbf{k}} \left(y_k - h(\hat{\mathbf{x}}_{k|k-1}, 0) \right)$$

(3a) $\mathbf{K}_{\mathbf{k}} = \mathbf{P}_{\mathbf{k|k-1}} \mathbf{H}_{\mathbf{k}}^{\mathbf{T}} \mathbf{\Omega}_{\mathbf{k}}^{-1}$

(3b)

$$\mathbf{\Omega}_{\mathbf{k}} = \mathbf{H}_{\mathbf{k}} \mathbf{P}_{\mathbf{k|k-1}} \mathbf{H}_{\mathbf{k}}^{\mathbf{T}} + \mathbf{V}_{\mathbf{k}} \mathbf{R}_{\mathbf{k}} \mathbf{V}_{\mathbf{k}}^{\mathbf{T}}$$

(3c) $\mathbf{P}_{\mathbf{k}} = (\mathbf{I} - \mathbf{K}_{\mathbf{k}} \mathbf{H}_{\mathbf{k}}) \mathbf{P}_{\mathbf{k|k-1}}$

(3d)

Where

$$\begin{cases} \mathbf{A}_k = \left. \dfrac{\partial f}{\partial x} \right|_{\substack{x = \hat{x}_{k|k} \\ u = u_k}} \\ \mathbf{W}_k = \left. \dfrac{\partial f}{\partial w} \right|_{\substack{x = \hat{x}_{k|k} \\ u = u_k}} \\ \mathbf{H}_k = \left. \dfrac{\partial h}{\partial x} \right|_{x = \hat{x}_{k|k-1}} \\ \mathbf{V}_k = \left. \dfrac{\partial h}{\partial \nu} \right|_{x = \hat{x}_{k|k-1}} \end{cases} \quad (4)$$

Let now y_i be the *i-th* sensor measure; R_i: i-th measurement noise covariance and C_i be the *i-th* measurement matrix. The Measurement Fusion block in Figure 1 provides the fused measurement information *y* as [1]:

$$y(k) = \left[\sum_{j=1}^{N} \mathbf{R}_j^{-1}(k) \right]^{-1} \sum_{j=1}^{N} \mathbf{R}_j^{-1}(k) y_j(k), \quad (5a)$$

$$\mathbf{C}(k) = \left[\sum_{j=1}^{N} \mathbf{R}_j^{-1}(k) \right]^{-1} \sum_{j=1}^{N} \mathbf{R}_j^{-1}(k) \mathbf{C}_j(k), \quad (5b)$$

$$\mathbf{R}(k) = \left[\sum_{j=1}^{N} \mathbf{R}_j^{-1}(k) \right]^{-1}. \quad (5c)$$

Equations (5) have a clear physical meaning: the information of higher measurement noise covariance sensors (R_i) are weighted less than those of the lower measurement noise covariance sensors. Note that if all the N sensors have the same measurement noise covariance, equations (5) simply reduce to an arithmetic mean.

Measurement fusion works very well if noise statistics of each sensor are exactly known. Poor "a priori" information about noise statistics may degrade the Kalman filter performance. Moreover, even if we carefully know the noise statistics of each sensor, one of them could suddenly fault (wrong calibration, sudden jump, bias). Measurement fusion schemes, as in Fig.1, is not able to cope with these situations, while an adaptive scheme could recognize and recovery the fault. To this aim a considerable amount of research has been carried out in the adaptive Kalman filtering area (Simon 2006; Mehra 1970; Lee 2003), but in practice an "ad hoc" adaptive scheme has to be developed considering the specific problem characteristics.

Here the sensor fusion based on an adaptive Kalman filter is enhanced by using the covariance matching approach and employing the forgetting factor technique. In Kalman filtering theory, the difference between the current measurement and the predicted one is called innovation sequence, and it is, for an optimal filter, a Gaussian white noise sequence. For analogy with the linear case, residuals

$$c_i(k) = y_i(k) - h(\hat{x}(k \mid k-1), 0), \; i = 1,...,3$$

are called the innovation process and are assumed to be well described by a white sequence $N(0, C_i(k))$. The innovation sequence plays an important role in the adaptive algorithm design and represents a flag of the actual estimation errors. The monitoring of the innovation process of each sensor can be utilized for fault detection.

The idea of covariance-matching techniques is to make the innovation samples consistent with their theoretical covariance. The theoretical covariance of the innovation sequence is (Simon 2006):

$$\mathbf{C}_i(k) = E\left[c_i(k)c_i(k)^T\right] = \mathbf{H} \cdot \mathbf{P}(k \mid k-1) \cdot \mathbf{H}^T + \mathbf{R}_i \quad (6)$$

where the index *i* is referred to *i-th* sensor.

The actual covariance of $c_i(k)$ can be approximated by its sampled covariance as:

$$\hat{\mathbf{C}}_i(k) = \frac{1}{k}\sum_{j=1}^{k}\mathbf{c}_i(j)\mathbf{c}_i(j)^T = \\ = \frac{k-1}{k}\hat{\mathbf{C}}_i(k-1) + \frac{1}{k}\mathbf{c}_i(k)\mathbf{c}_i(k)^T \quad (7)$$

Assuming that (7) would be a good approximation of (6), we could estimate on line noise covariance by (6):

$$\hat{\mathbf{R}}_i(k) = \hat{\mathbf{C}}_i(k) - \mathbf{H} \cdot \mathbf{P}(k \mid k-1) \cdot \mathbf{H}^T \quad (8)$$

We now use $\hat{\mathbf{R}}_\mathbf{i}$ estimation (8) to compute equations (5), thus achieving the following advantages:

1. sensor noise covariances has not to be "*a priori*" known;
2. if one of the sensors give wrong information it is less weighted in the measurement fusion since its noise covariance estimation is high.

To cope with slowly changing bias we further introduce a forgetting factor in the adaptive scheme. Indeed, estimation in (7) get worse with time k, thus not allowing the fault detection for slowly sensor faults. To overcome this drawback we introduce the forgetting factor μ as:

$$\hat{\mathbf{C}}_i(k) = \frac{1}{k}\sum_{j=1}^{k}\mu^{k-j}\mathbf{c}_i(j)\mathbf{c}_i(j)^T = \\ = \mu\frac{k-1}{k}\hat{\mathbf{C}}_i(k-1) + \frac{1}{k}\mathbf{c}_i(k)\mathbf{c}_i(k)^T \quad (9)$$

4. VALIDATION OF THE APPROACH

The most common failure mode for sensors is failing to achieve the proper output for a given input signal, resulting in a lower than true reading. Some sensors fail suddenly, stopping all current production, while others give off a burst of energy before ceasing output. The most serious for safe-critical medical applications is the nonlinear sensor saturation to produce the exhact output above a given level. This failure taken to extreme results is a sensor generating a fixed high-level output regardless of the physical value of the monitored variable. To avoid this problem we consider different measurements that are fused together to realize a more accurate estimation of oxygen partial pressure. In particular the considered scenario refer to three identical oxygen sensors for measure redundancy.

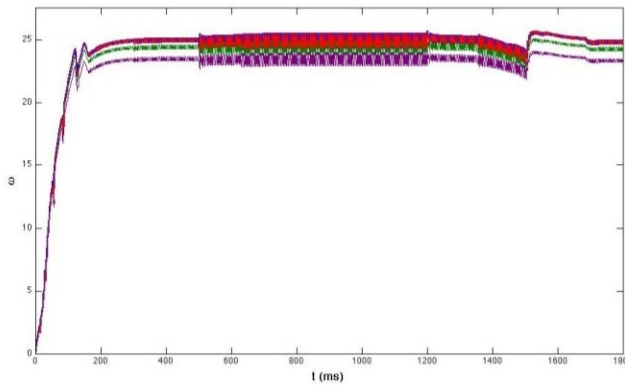

Figure 1: Multiple faults scenario. Oxygen partial pressure pression (red line) against actual value (blue line). sensor 1 (purple line); sensor 2 (dashed green line); sensor 3 (black line).

Figure 1 shows how the estimated variable (red line) is in perfect agreement with the actual oxygen level (blue line) despite the presence of nonliear saturated sensors measurements (sensor 1 (purple line) and 2 (black line)).

5. CONCLUSIONS

In this paper a Kalman filter based approach has been used to obtain more accurate estimation of oxygen partial pressure, due to its ability to precisely assess system states in the presence of substantial sensor noise. Our results show that this technique can effectively filter out sensor noise.

Because of the lack of a shared method for signal-noise separation in medical applications, along with the few works present in literature inspecting breath monitoring, it is difficult to compare the method presented in this paper with other techniques. Further studies, after accurate bibliographic researches, will aim to find the best procedure among those proposed in literature.

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