Condition monitoring based on filter bank in the presence of data loss

Suzanne Lesecq, Sylviane Gentil, Cédric Berbra

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Suzanne Lesecq*, Sylviane Gentil and Cedric Berbra
GIPSA-Lab, Control Systems Dpt, Grenoble
BP 46, 38402 Saint Martin d'Hères Cedex, France
+33 (0)4 76 82 62 25
+33 (0)4 76 82 63 88
{suzanne.lesecq, sylviane.gentil, cedric.berbra}@gipsa-lab.inpg.fr
(* contact author)

Abstract

It is well known that Fault Detection and Isolation (FDI) can be performed using Signal Processing Techniques or Process Control Tools. In the first set of techniques, signals are directly analysed in order to detect changes in some quantities (mean, standard deviation, frequency contents, singularity appearance, etc.) related to a particular fault. In control theory, diagnostic methods are essentially based on models that are supposed to represent the behaviour of the process, either in the normal mode or in a particular faulty one. The model constitutes a prototype behaviour that is compared to the actual state, evaluated with data acquired online from the process. From the measurements and an analytical model, quantities called residuals are computed. Among all the tools used in the FDI community, observer (or filter) banks are very appealing. However, due to the introduction of networks between the sensors and the computational unit, the design of observers that can support data loss must be considered. This paper proposes an Extended Kalman Filter that takes into account the data loss that may appear during the data transfer from the sensor to the computational unit. The lost measurement is replaced with the previous available data, the corresponding variance being gradually increased. The proposed technique has been tested on real data acquired from an Inertial Measurement Unit composed of a tri-axis accelerometer, a tri-axis magnetometer and three rate gyros.

1. Introduction

Signal processing is a powerful tool to deal with fault diagnosis. It can be used to analyse directly the signals measured online. This approach avoids system modelling. It is based on the fact that a change in some quantity, e.g. the signal mean or the frequency contents, characterises a particular fault occurrence. Signals may be studied either with time-domain methods (including correlation, mean or standard deviation changes[1]), with frequency methods (e.g. Fast Fourier Transform), or with more sophisticated ones including time-frequency or time-scale methods (for instance references [2,3] and references therein).

Safety is an engineering area at the border of control engineering and process engineering. Its study is difficult, mainly due to the increasing complexity of industrial processes. Safety is critical not only for the process itself but also for its environment and for those working or living in proximity. It is justified also by economic reasons. Consequently, monitoring the health of the installation at each time instant in order to detect incipient faults and to isolate damaged components, known as FDI (on-line Fault Detection and Isolation), has gained increasing attention in order to enhance reliability of complex systems, with many potential industrial applications.

Many different diagnostic approaches have been developed among control scientists. The most common approaches rely on a deterministic analytical model of the process to be diagnosed[1,4,5,6]. The model, generally quantitative and dynamic, represents the behaviour of the process, either in the normal mode or in a particular faulty one. Usually, it is the normal process behaviour that is represented by the analytical equations, which avoids modelling fault modes. This is the case that will be considered in this paper. Diagnostic algorithms check the consistency between the *expected process behaviour*, as computed by the model, and the *real process behaviour* evaluated with measurements acquired on-line. This comparison is based on numerical quantities called residuals that are (approximately) null when there is no fault affecting the system or when none of the faults in a known set of faults is affecting the system. From these residuals, FDI algorithms have to provide decisions, such as “a fault is detected” or “fault *Fi* is isolated”. Fault detection is a two-stage process: residual generation and residual evaluation. If the detection is reliable, Fault Isolation follows naturally using a signature table.

Among the various techniques used for FDI among the control process community, *observer* (or filter) *banks*[7] are very appealing and this technique will be used in the sequel of this paper. The principle of observer banks is given in Figure 1. For each observer i, $i = 1 : N$, all the system outputs y but the measurement number i (y^i) are used to provide the state estimate $\hat{x}^i$. In this way, $\hat{x}^i$ is insensitive to any fault that may occur in the sensor S^i which provides the measurement y^i.

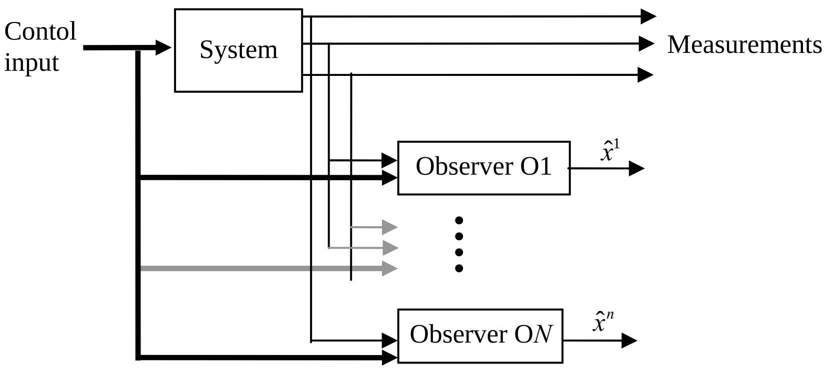

Figure 1: Observer bank principle.

One of the most significant challenges for control scientist today is that systems have been enlarged from single physical systems to large-scale complex systems that also include *networks* to both control and supervise these complex systems. At the same time, sensors are getting smaller, cheaper, pervasive and more powerful. Thus, everything is getting “sensed”. The possibilities created by all these sensors are extraordinary: they allow real-time monitoring of large-scale systems and hardware

redundancy can be considered with small extra-cost.
However, these *sensors may be faulty* and they have to be diagnosed in order to provide reliable information on the process functioning. Moreover, the network induces drawbacks such as *delays* and *packet losses* that may influence the FDI algorithms, especially when they implement observer banks. Notice that the network protocol implemented greatly influences the performances of the network controlled system(7) and of the diagnostic algorithms.

When estimation over a network is considered, two schemes can be run. The first one supposes that a centralised computation unit is implemented. The second scheme makes use of sensor nodes with enough computation capabilities to estimate locally the state.
Shi, *et al.*(9) consider both schemes, respectively centralised estimation and distributed estimation. They give a qualitative and quantitative analysis of the trade-off between estimation qualities and the communication and computation capabilities of each network node. They show that if the computation capabilities at each sensor node are limited and without packet drops, the transmission of raw data (scheme one) always provides a better estimation (measured with the state covariance matrix) than the transmission of distributed estimates (scheme two). However, in the presence of packet drops, they show that scheme one is not always better.
Actually, the implementation of a filter bank can be performed with one of these two schemes. In the first case, all the raw data are transmitted to a unique computational unit, leading to a centralised observer bank. In the second case, the observers are distributed over the system. Each observer can make use only of local data or data exchanges may be necessary. When data are transmitted (first scheme, or second case of the second scheme), they can be delayed or even lost. The observer must therefore take into account this problem.

Observer implementation (and especially Kalman Filter one) under certain information constraints has become of great interest especially since Systems (NCS) are controlled through a network (NCS). In this latter context, some authors suppose that the system state is fully measured and transmitted to the controller through the network(10). Actually, this might be obtained by considering that the observer is implemented right at the sensor node. Therefore, it supposes computational capabilities at the sensor node. Kalman filtering over lossy networks is considered for instance in (11) and (12). All these works suppose that the data loss can be modelled either by a Bernoulli binary random sequence or with a discrete-time binary Markov model.

The aim of the present paper is to consider the Kalman Filter implementation when measurements are transmitted through a network. Previous works (for instance (11, 12, 13, 14, 15, 16)) supposed that the entire output vector y_k is sent in a unique packet that may be lost. Therefore, when a packet is dropt, all the measurements at time k are lost. However, depending on the topology of the system, on the protocol used etc., measurements can be sent independently (or at least in several sets) across the network. Therefore, each output y_k^i (or set of outputs) is likely to be lost. In this paper, each measurement y_k^i is sent independently and the Kalman Filter is modified in order to deal with data loss. Note that the case of Filter Banks is straightforward and is not explained here.

The rest of this paper is organised as follows. The problem under investigation is formulated in section 2. The Kalman Filter with loss of a subset of the measurements is proposed in section 3. This Kalman Filter is exemplified in section 4: it is applied to the attitude estimation problem when measurements are issued from an Inertial Measurement Unit (IMU) connected to the processor through a network. Finally, some conclusions are drawn in section 5.

2. Problem formulation

Consider the linear discrete-time varying stochastic system:

$$\begin{aligned} x_{k+1} &= F_k x_k + w_k \\ y_k &= C_k x_k + v_k \end{aligned} \tag{1}$$

where $F_k \in \Re^{n\times n}$, $C_k \in \Re^{m\times n}$, x_k is the system state and $y_k \in \Re^m$ is the output (measurement) at time k. $\left\{w_k,\, k \geq 0\right\}$ and $\left\{v_k,\, k \geq 0\right\}$ are two mutually independent sequences of independent and identically distributed (i.i.d.) Gaussian white noises with covariance matrices Q and R respectively. Moreover, the pair $\left[A_k, C_k\right]$ is supposed to be observable and the pair $\left[A_k, Q_k^{1/2}\right]$ controllable.

The estimation problem with “missing observations” has been previously studied for instance in (9, 10, 11, 13) for discrete-time linear systems. In these papers, the output vector y is set in a unique packet. In the present work, each measurement y_k^i is likely to be lost.
In the literature(11, 13), the packet loss process is assumed to be an i.i.d. Bernoulli binary random sequence. This choice is clearly an idealisation that is chosen by the authors for mathematical tractability. In this way, the stability of the Kalman Filter may be studied(13) by a Modified Algebraic Riccati Equation (MARE). Other authors (e.g. (10, 14)) propose the use of a discrete-time binary Markov model. Contrarily to the i.i.d. model, the Markov chain allows to capture the temporal correlation of the channel variation. With this packet loss modelling, stability results for the Kalman Filter can also be achieved(14). The choice of the data loss model is not discussed in this paper, and the Bernoulli process is considered.

In both contexts, the Kalman Filter equations become:

$$\left| \begin{aligned} \hat{x}_{k+1/k} &= F_k \hat{x}_k \\ P_{k+1/k} &= F_k P_{k/k} F_k^T + Q_k \end{aligned} \right. \tag{2}$$

$$\left| \begin{aligned} \hat{x}_{k+1/k+1} &= \hat{x}_{k+1/k} + \gamma_{k+1} K_{k+1} (y_k - C_k \hat{x}_{k+1/k}) \\ P_{k+1/k+1} &= P_{k+1/k} - \gamma_{k+1} K_{k+1} C_{k+1} P_{k+1/k} \end{aligned} \right. \tag{3}$$

where A^T is the transpose of matrix A. $\gamma_{k+1} \in \left\{0,1\right\}$ indicates if the measurement vector y_{k+1} has been received. $K_{k+1} = P_{k+1/k} C_{k+1}^T \left[C_{k+1} P_{k+1/k} C_{k+1}^T + R_{k+1} \right]^{-1}$ is the Kalman gain

matrix. Note that (2) corresponds to the prediction step while (3) is the correction step that is performed only if the measurements have been received. Note that the covariance matrix P is now a random variable, because of the randomness of γ.
As stated above, some stability properties can be achieved (see for instance [13, 14, 16] and references therein).
The case where only a subset of the components of y has been received for the update stage is now presented. This gives rise to a new Kalman Filter with partial data loss.

3. Kalman Filter with partial data loss

The estimation problem is reformulated as follows. In the present paper, the lost measurement is replaced with a null measurement, the standard deviation of the noise being arbitrarily large. Consider matrix $M_k \in \Re^{m\times m}$ defined as follows:

$$\begin{aligned} M_k(i,j) &= 0 && \text{if } i \neq j \\ M_k(i,i) &= 1 && \text{if the measurement is present} \\ M_k(i,i) &= \lambda_i >> 1 && \text{if the measurement is absent} \end{aligned} \tag{4}$$

The absence of measurement i (i.e. y_k^i has not been received at time k) corresponds to $\lambda_1 \to +\infty$. Let $\overline{R}_k$ denote the covariance matrix of the measurement noise when some measurements are missing, written as:

$$\overline{R}_k = M_k R_k M_k \tag{5}$$

As stated above, the missing data variance becomes arbitrarily large $\overline{\sigma}_i^2 = \lambda_i^2 \sigma_i^2$.The EKF formulation is now summarized. The Kalman Filter proposed here is implemented with the traditional “prediction step” and “correction step”. Note that the structure of the Kalman filter is unchanged, contrarily to the work in [17] where the lines in matrix C corresponding to lost data are removed.

- *Initialization*

initial state $\hat{x}_0$, initial covariance matrix $P_0 = \lambda I,\ \lambda >> 1$.

- *Prediction step*

$$\begin{aligned} \hat{x}_{k+1/k} &= F_{Gk}\hat{x}_k \\ P_{k+1/k} &= F_{Gk}P_{k/k}F_{Gk}^T + Q_k \end{aligned} \tag{6}$$

- *Computation of the gain matrix*

$$\overline{K}_{k+1} = P_{k+1/k}C_{k+1}^T\left[C_{k+1}P_{k+1/k}C_{k+1}^T + \overline{R}_{k+1}\right]^{-1} \tag{7}$$

- *Correction Step*

$$\begin{aligned} \hat{x}_{k+1/k+1} &= \hat{x}_{k+1/k} + \bar{K}_{k+1}(y_k - C_{k+1}\hat{x}_{k+1/k})) \\ P_{k+1/k+1} &= P_{k+1/k} - \bar{K}_{k+1}C_{k+1}P_{k+1/k} \end{aligned} \tag{8}$$

Actually, equations (6) to (8) can also be formulated using matrix $\bar{C}_k = T_k C_k$ with $T_k = M_k^{-1}$. The modifications appear in the equations of matrices K and P:

$$\begin{aligned} \bar{K}_{k+1} &= K_{k+1}T_{k+1} \\ P_{k+1/k+1} &= P_{k+1/k} - P_{k+1/k}\bar{C}_{k+1}^T\left[\bar{C}_{k+1}P_{k+1/k}\bar{C}_{k+1}^T + R_k\right]^{-1}\bar{C}_{k+1}P_{k+1/k} \end{aligned} \tag{9}$$

4. Results

The Kalman filter proposed in this paper has been applied to the problem of attitude estimation of a rigid body. The filter bank that is implemented for sensor diagnosis makes use of the same ideas. The implementation of each Kalman Filter within the filter bank is straightforward and is not explained in details. Actually a set of N observer is implemented, each Kalman Filter having as measurement vector all the measurements but one. Then equations (6) to (8) with their modified version (9) are implemented for each Kalman Filter in the filter bank.
The low-cost light-weight Inertial Measurement unit (IMU) is made of nine MEMS (Micro Electro-Mechanical Systems) sensors, namely, three rate gyros mounted at right angles, a triaxis accelerometer and a triaxis magnetometer. Lost data are supposed to be issued from the magnetometers and/or from the accelerometers. The case when rate gyro measurements are lost has been studied in [(18)]. However, this latter work cannot be used here because the attitude dynamics of the system are not known.
In the present application, sensors are situated at the same location. Therefore the concept of distributed sensors does not apply. Moreover, due to power and computational limitations at the sensor node, no high level computation can be done at the sensor node and the raw data must be transmitted through the network. Therefore, scheme one in [(9)] must be implemented. In this situation, the loss of raw data might occur.
The IMU model is first proposed. Then its discrete time version is derived. The Kalman Filter with partial data loss is then applied to the attitude estimation problem. Filter banks are classical tools in FDI. Therefore, its implementation is not explained in this paper and will be described during the oral presentation. Results for different scenarios of data loss are given at the end of this section.

4.1 IMU model

Attitude estimation is necessary for various applications ranging for instance from human motion tracking to satellite control and Unmanned submarine or aerial vehicle control where the knowledge of the actual attitude is a prerequisite for attitude control. Two frames are considered to describe the dynamic equations of a rigid body in movement: the inertial frame $N(x_n, y_n, z_n)$ and the body frame $B(x_b, y_b, z_b)$ attached to the

Rigid Body (RB) with its origin at the centre of mass of RB. The RB orientation can be parameterized by three rotation angles with respect to frame *N:* yaw (ψ), pitch (θ) and roll (Φ). $\omega \in \Re^3$ is the angular velocity of the RB relative to *N* expressed in *B*.

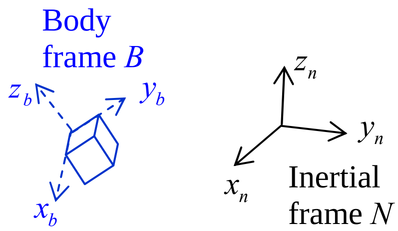

Figure 2: Inertial frame *N* and Body frame *B* definition.

Actually, the attitude can be modelled using various representations such as Euler angles, Cardan angles, etc.. Another appealing representation makes use of unitary quaternion(19) $q = \begin{bmatrix} q_0 & \vec{q}^T \end{bmatrix}^T \in \Re^4$, $\|q\|_2 = 1$. From (unit-)quaternion algebra, the rotation operator can be re-defined. If vector $\vec{r}$ is expressed in *N*, its coordinates in *B* are:

$$\vec{b} = R(q)\vec{r} \quad \text{or} \quad b = q^{-1} \otimes r \otimes q \tag{10}$$

where $\otimes$ is the quaternion product, $r = (0, \vec{r}^T)^T$, $b = (0, \vec{b}^T)^T$ and *R(q)* is the rotation matrix defined as:

$$R(q) = (q_0^2 - \vec{q}^T\vec{q})I + 2(\vec{q}\vec{q}^T - q_0\left[q^\times\right]) \tag{11}$$

The kinematics equation can be expressed with *q*:

$$\dot{q} = (1/2)\,\Omega(\omega)q = (1/2)\,\Xi(q)\omega \tag{12}$$

$$\Xi(q) = \begin{bmatrix} -q^T \\ q_0 I + \left[\vec{q}^\times\right] \end{bmatrix}, \ \Omega(\omega) = \begin{bmatrix} 0 & -\omega^T \\ \omega & -\left[\omega^\times\right] \end{bmatrix}, \ \left[\omega^\times\right] = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix} \tag{13}$$

An IMU (MEMS technology) is embedded in the RB. It consists of a triaxis accelerometer, a triaxis magnetometer and three rate gyros mounted at right angle. The motion is supposed quasi-static so that the linear acceleration of the RB is neglected. The sensor measurements (expressed in frame *B*) are modelled as:

$$\text{rate gyro:} \quad \vec{\omega}_G = \vec{\omega} - \eta_G \quad \in \Re^3 \tag{14}$$

$$\text{accelerometers (normalized):} \quad \vec{b}_A = R(q)\vec{g} + \eta_A \quad \in \Re^3 \tag{15}$$

$$\text{magnetometers (normalized):} \quad \vec{b}_M = R(q)\vec{h}_M + \eta_M \quad \in \Re^3 \tag{16}$$

η_i, $i = \{G, A, M\}$ are assumed to be independent Gaussian white noises of appropriate dimension and covariance matrices R_i. $\vec{g}$ is the normalized gravity vector measured in *N*. $\vec{h}_M = \left[h_{Mx}, 0, h_{Mz}\right]$ represents the normalized magnetic field measured in frame *N* at the location of the experiment. Note that (15)-(16) are static nonlinear equations. Therefore an Extended Kalman Filter (EKF) will be implemented.

4.2 IMU model discretisation

Consider the discrete time version of the quaternion attitude kinematics equation (12):

$$q_{k+1} = F_k q_k \tag{17}$$

where $F_k = \exp\left(\tfrac{1}{2}\Omega(\vec{\omega}_k)h\right)$ is obtained by assuming that $\vec{\omega}_k$ is constant over a sampling period h. $\vec{\omega}_k$ is expressed with (14). Thus matrix F_k becomes

$$F_k = F_{Gk} + \Delta F_k, \quad F_{Gk} = \exp\left(\tfrac{1}{2}\Omega(\vec{\omega}_{G_k})h\right) \tag{18}$$

The error matrix ΔF_k can be expressed as a matrix power series. However, when the noise η_{Gk} and the sampling time h are small enough, ΔF_k is approximated by:

$$\Delta F_k = \tfrac{1}{2}\Omega(\eta_{G_k})h \tag{19}$$

Therefore, the state equation in (1) is rewritten as:

$$q_{k+1} = F_{Gk} q_k + \eta_{qk}, \; \eta_{qk} = \tfrac{h}{2}\Sigma\left(q_k\right)\eta_{G_k} = G_k \eta_{G_k} \tag{20}$$

The state noise is given by [20]:

$$Q_k = \frac{h^2}{4}\Sigma\left(\hat{q}_k\right)R_{Gk}\left(\Sigma\left(\hat{q}_k\right)\right)^T + \frac{h^2}{4}\Upsilon\left[R_{Gk}\otimes P_k\right]\Upsilon^T \tag{21}$$

where $\otimes$ is the Kronecker product, Υ = $[\Omega(\vec{e}_1)\ \Omega(\vec{e}_2)\ \Omega(\vec{e}_3)]$, Ω is defined in (13) and $(\vec{e}_1\ \vec{e}_2\ \vec{e}_3)$ is the orthonormal basis of $\Re^3$. The measurement equation $y_k \in \Re^6$ is built from (15) and (16)

$$\left[\vec{b}_{A_k}^T, \vec{b}_{M_k}^T\right]^T = g(q_k) + \eta_k = \begin{bmatrix} C(q_k) & 0 \\ 0 & C(q_k) \end{bmatrix}\begin{bmatrix} \vec{g} \\ \vec{h} \end{bmatrix} + \eta_k \tag{22}$$

with $\eta_k^T = \left[\eta_{A_k}^T, \eta_{M_k}^T\right]^T$. The measurement noise covariance matrix is:

$$R_k = E\left[\eta_k \eta_k^T\right]^T = \begin{bmatrix} R_{Ak} & 0 \\ 0 & R_{Mk} \end{bmatrix}^T \tag{23}$$

4.3 Results

The experiment reported in the present paper considers 30% of data loss for all the measurements from the accelerometers and magnetometers. The losses are supposed independent for each sensor axes, even if this hypothesis does not take into account the natural congestion that may appear in the network. Note that the attitude is given in the roll-pitch-yaw representation for the sake of clarity. The initial attitude of the Rigid Body is (-25;-30;-10) (*deg*) and the final one is (10;4;15) (*deg*). The attitude estimation filter is initialized with (-9;5;57) (*deg*). Moreover, a change in the attitude reference occurs at time $t=3s$ and the new reference is (0;0;0). The real (top) and estimated (bottom) attitudes are shown in Fig. 3. Fig. 4 gives the attitude error and the data loss indicator for the accelerometer acc_x: 0 means that the measurement is present for the estimation while 1 stands for "acc_x has not been received". As can been seen in Fig. 3 to 4, even in the presence of 30% of independent data loss, the attitude of the RB does not exhibits strong errors (see Fig. 4 where the error is less than 10 deg). Note that for other scenarios with various loss rate and lost data, the maximum error observed on the estimated angles depends on the movements and on the lost data that are considered.

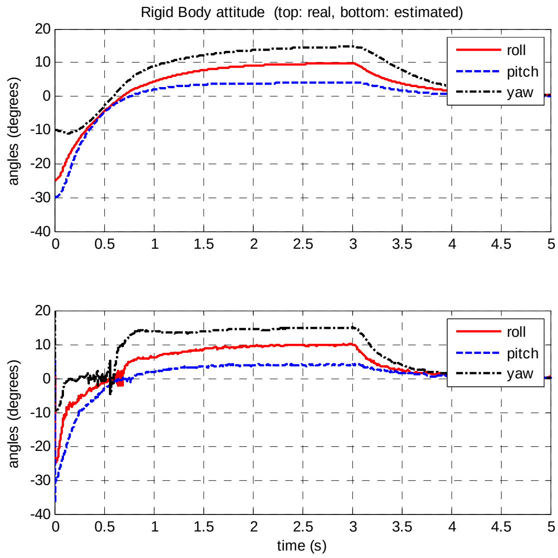

Figure 3: Attitude error and data loss indicator.

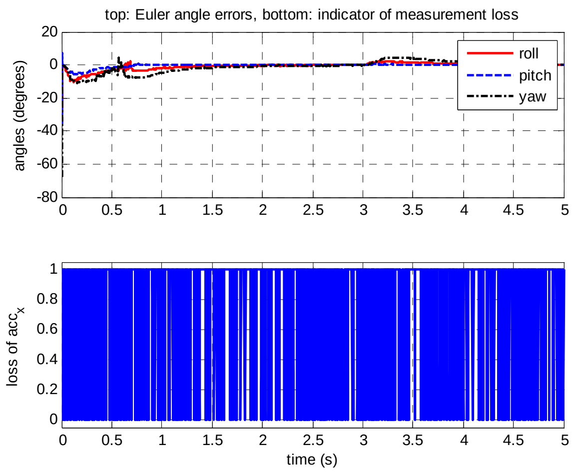

Figure 4: Attitude error and data loss indicator (zoom)

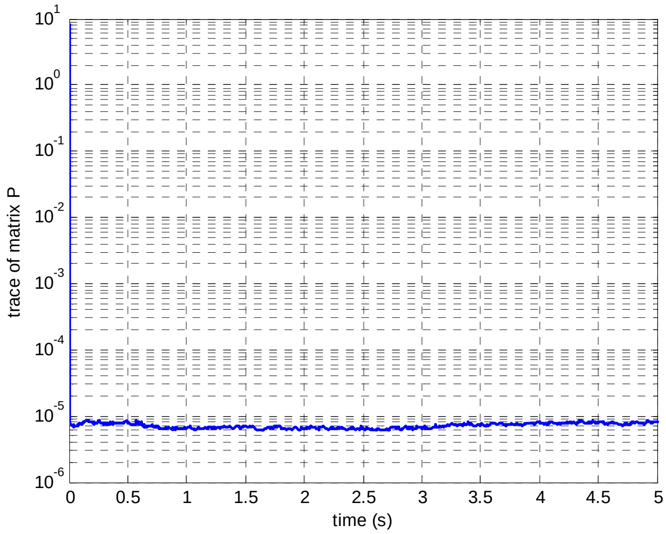

Figure 5: Trace of matrix *P*.

Fig. 5 exhibits the trace of matrix $P_{k/k}$. It shows that the confidence in the estimate $\hat{q}$ does not drastically decreases even in the intermittent data scenario.

5. Conclusions

This paper has proposed a Kalman Filter that aim at dealing with partial packet losses, i.e. a subset of the measurements have been received at the computational unit. The technique proposed is derived from the Kalman Filter previously published in Sinopoli *et al*(11). In the present work the lost data is replaced with 0 while its covariance becomes arbitrarily large. The Kalman Filter proposed here is exemplified on an attitude estimation problem. In this application data acquired from an Inertial Measurement Unit are sent to the computational unit through a network. Experiments show that the estimated attitude error does not drastically increase even in the presence of 30% of data loss, which is quite high for wired network, but which can exist in wireless network such as Zigbee one. The implementation of a filter bank in order to perform sensor fault detection and isolation (FDI) is straightforward: it will be presented during the oral presentation. Ongoing work tries to obtain stability conditions for the Kalman Filter with partial data loss. The stability conditions will depend on the model that is supposed for the data loss.

References and footnotes

1. M. Basseville, I. Nikiforov, *Detection of abrupt changes*, Prentice Hall Ed., 1993.
2. S.Lesecq, A. Barraud, “Arcing fault detection using wavelet transform”, *IFAC Symposium on Fault Detection, Supervision and Safety of Technical Process, Safeprocess 2003*, Washington D.C., USA, 2003.

3. Z.K.Peng, F.L. Chu, “Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography”, *Mechanical Systems and Signal Processing*, Vol. 18, pp. 199-221, 2004.
4. R. Patton, J. Chen, ‘Observer-based fault detection and isolation: robustness and application’, *Control Engineering Practice*, Vol. 5(5), pp 671-682, 1997.
5. M. Kinnaert, ‘Fault Diagnosis Based on analytical models for linear and nonlinear Systems-A tutorial’, *IFAC Symposium on Fault Detection, Supervision and Safety of Technical Process Safeprocess 2003*, Washington D.C., USA, 2003.
6. R. Isermann , *Fault diagnosis systems*, Springer Verlag Berlin Heidelberg, 2006.
7. P. Frank, “Analytical and qualitative model-based fault diagnosis, a survey and some new results”. *European Journal of Control*, Vol. 1(2), pp 6-28, 1996.
8. J.R. Moyne, D.M. Tilbury, “The emergence of industrial control networks for manufacturing control, diagnostics and safety data”, *Proceeding of the IEEE*, Vol. 91(1), pp. 29-47, 2007.
9. L. Shi, K.H. Johansson, R.M. Murray, “Estimation over wireless sensor networks: Tradeoff between communication, computation and estimation qualities”, *17th IFAC World Congress*, Seoul, Korea, 2008
10. L. Xie, L. Xie, “Stabilizing sampled-data linear systems with Markovian Packet losses and random sampling”, *17th IFAC World Congress*, Seoul, Korea, 2008.
11. B. Sinopoli, L. Schenato, M. Franceschetti, K. Poolla, M.I. Jordan, S.S. Sastry, “Kalman filtering with intermittent observations”, *IEEE Transactions on Automatic Control*, Vol. 49(9), pp. 1453-1464, 2004.
12. J. Hespanha, P. Naghshtabrizi, Y. Xu, “Networked control systems: analysis and design”, *IEEE Network controlled systems*, 2007.
13. L. Schenato, B. Sinopoli, M. Franceschetti, K. Poolla, S.S. Sastri, “ Fundations of Control and estimation over lossy networks”, *Proceeedings of the IEEE*, Vol. 95(1), pp. 163-187, 2007.
14. M. Huang, S. Dey, “Stability of Kalman filtering with Markovian packet losses”, *Automatica*, Vol. 43, pp. 589-607, 2007.
15. S. Sun, L. Xie, W. Xiao, Y.C. Soh, “Optimal linear estimation for systems with multiple packet drpouts”, Automatica, Vol. 44, pp. 1333-1342, 2008.
16. M. Epstein, L. Shi, A. Tiwari, R. Murray, „ Probabilistic performances of state estimation across a lossy network, *Automatica*, Vol. 44, pp. 3046-3053, 2008.
17. X. Cao, J. Chen, C. Gao, Y. Sun, “An optimal control method for applications using wireless sensor/actuators networks”, *Computer and Electrical Engineering*, in Press, 2009.
18. M.A. Peck, “Attitude propagation with intermittent gyro measurements and single-vector observations”, *American Institute of Aeronautics and Astronautics*, pp. 331-338, 2000.
19. J. Chou, “Quaternion kinematics and dynamic differential equations”, *IEEE Transactions on Robotics and Automation*, Vol. 8, pp. 53–64, 1992.
20. S. Lesecq, S. Gentil, Daraoui N., “Quadrotor attitude estimation with data losses”, *accepted for publication in ECC 09*, 2009.