ON FAULT TOLERANT ESTIMATION IN SENSOR NETWORKS

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Abstract

This paper addresses the fault tolerant estimation problem. Fault tolerance is defined with respect to a given estimation objective, namely a given functional of the system state should remain observable when sensor failures occur. Three criteria, which evaluate the system fault tolerance with respect to sensor failures when a reconfiguration strategy is used, are introduced, and it is shown that they can be used to define maintenance policies. A ship boiler example is used for illustration.

1 Introduction

Control and monitoring of complex systems require the time evolution of many variables to be known. Direct measures are not always necessary, since some variables can be estimated using analytical redundancy or observers. Given a set of variables to be estimated, the problem of defining the subset of variables to be measured is known as the sensor network design problem, and it has been addressed by many authors, e.g. for a non exhaustive list [1], [2], [3], [4], [5], [6], [10], [12], [13], [14], [15], [16], [17], [21], [23].

The design of sensor networks can be based on different criteria : observability [23], estimation accuracy [13], cost [15]. The perspectives of fault detection and isolation [5], [6], reliability and fault tolerance, have been recently increasingly considered [22], [14], [20]. In fact, sensors faults may be avoided (up to a certain degree) by the design of ad-hoc maintenance policy, or they may be taken into account by means of fault tolerant estimation. This paper presents the fault accomodation and sensor reconfiguration strategies, which can be used to achieve fault tolerant estimation. Using reconfiguration, only a subset of the original sensor set is available at a given time : according to the way this subset allows to estimate the state functional of interest (if it does), the notions of minimal and redundant sensor subsets are introduced and used to evaluate the fault tolerance of the system with respect to sensor failures. Based on the fault tolerance evaluation, maintenance policies can be designed.

The paper is organized as follows. Section 2 sets the fault tolerant estimation problem. Minimality and redundancy properties are defined with reference to the observability of a functional of the state in Section 3. In Section 4, the fault tolerance effectiveness of the sensor network is evaluated using deterministic and probabilistic criteria. Section 5 discusses the relations between fault tolerant sensor network design and the design of condition based or systematic maintenance policies. A short example is provided in Section 6.

2 Problem setting

Consider the continuous time deterministic system given by :

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) && (1) \\ y(t) &= g(x(t)) && (2) \\ z(t) &= h(x(t)) && (3) \end{aligned}$$

where $x \in R^n$ is the state vector, $u \in R^m$ is the control input, $y \in R^p$ is the measurement vector, and $z \in R^q$ is some functional of the state, which is to be estimated. f, g, h are smooth vector fields.

Although sensors always introduce measurement noises, and the system model might include some stochastic behaviour, the deterministic model (1) and (2) is used, because only structural properties, which are necessary conditions for the estimation to be possibly performed, are considered. In fact, there is no loss of generality because considering *admissibility* (related with the estimation quality) instead of *possibility* would lead exactly the same considerations.

2.1 The estimation problem

The estimation problem is as follows : using the outputs of the sensor network defined by (2), estimate the functional of the state defined by (3). It can be solved using algebraic or observer based approaches. Observer based approaches [11] proceed by designing a dynamic system

$$\begin{aligned} \dot{\zeta}(t) &= \varphi(\zeta(t), y(t), u(t)) && (4) \\ \hat{z}(t) &= \gamma(\zeta(t), y(t), u(t)) \end{aligned}$$

such that, for any initial condition $\zeta(0)$, one has

$$\lim_{t \to \infty} (z(t) - \hat{z}(t)) = 0 \quad (5)$$

Algebraic approaches first perform successive derivations of $y(t)$ in (2), and use (1) to obtain the equations

$$\bar{y}(t) = G(x(t), \bar{u}(t)) \quad (6)$$

where, for any vector $v(t)$, $\bar{v}(t) \triangleq (v^\tau(t), \dot{v}^\tau(t), \ddot{v}^\tau(t), ...)^\tau$ up to some order of derivation (which needs not to be specified here), and τ stands for transposition. By different mechanisms [8], [9], these equations are transformed into a system

$$\Psi(\bar{y}(t)) = \Gamma(z(t), \bar{u}(t)) \qquad (7)$$

Therefore, z is observable using the measurements y if an observer (4) with property (5) can be built, or if the set of equations (7), can be solved for z.

In the sequel, only structural properties are considered, namely the permanence of the observability of z when sensors fail. Therefore, it is assumed that some condition exists, which allow to decide whether the functional of the state z is, or is not, observable using the set of sensors $I \triangleq \{1, ...p\}$ or a given subset of sensors $J \subseteq I$. For example, for linear systems defined by

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) & (8)\\ y(t) &= Cx(t) & (9)\\ z(t) &= Hx(t) & (10) \end{aligned}$$

this condition writes [20]:

$$\mathrm{Im}H \subseteq \Omega(J) \qquad (11)$$

where

$$\Omega(J) = \oplus_{i \in J}\Omega(i)$$

is the space covered by the subset of sensors, $J \subseteq I$, and $\oplus$ is the direct sum of the subspaces $\Omega(i)$, which are defined by

$$\Omega(i) = span\left\{c_i, c_iA, ...c_iA^{\nu_i - 1}\right\}$$

where $c_i, i \in I$ is the i^{th} row of C, and ν_i is the individual observability index of sensor i, given by :

$$\nu_i = \dim span\left\{c_i, c_iA, ...c_iA^{n-1}\right\}$$

2.2 Fault tolerant estimation

Let $I = \{1, ...p\}$ be the sensors available in the nominal system, leading to the measurement equation (2), and assume that the functional z is observable by I. Suppose now that sensor failure(s) occur(s) at time t_f, so that the set of sensors I can be decomposed into the normal and the faulty ones: $I = I_n \cup I_f$. Therefore, the measurement equations (2) can be written

$$\begin{aligned} y_n(t) &= g_n(x(t)) & (12)\\ y_f(t) &= g_f(x(t)) & (13) \end{aligned}$$

where y_n (resp. y_f) represent the normal (resp. the faulty) outputs of the sensors I and g_n (resp. g_f) are the normal (resp. the faulty) measurement equations. Fault tolerance can be seeked following two different strategies, namely fault accomodation or system reconfiguration [19].

In fault accomodation, it is assumed that the FDI algorithms are able to detect the fault (hence it is known that I contains faulty sensors), to isolate it (hence the decomposition of I into I_n and I_f is known) and also to identify the vector field $y_f = g_f(x(t))$ (hence the new measurement equations are known). The estimation of the functional z is still possible provided the system (1), (12), (13), (3) is observable. This strategy deserves two remarks :

1. It cannot be used if the FDI algorithm is not able to identify the new vector field $y_f = g_f(x(t))$ with good accuracy,

2. According to the form of the vector field $y_f = g_f(x(t))$ the solution may or may not exist, and therefore no structural conclusion (which would hold whatever the faults on the sensors of J_f) can be drawn.

The second strategy is system reconfiguration, where the faulty sensors I_f are switched off. The problem is to assess the possibility of estimating z by using only the remaining sensors I_n, which is indeed true, provided that system (1), (12), (3) is observable. Note that the reconfiguration strategy only needs fault detection and isolation : the associated fault tolerance property is a structural one, since it only depends on the triple (1), (12), (3) and not on the kind of fault which affects the sensors I_f. In the sequel, only the reconfiguration strategy is considered.

3 Minimality and redundancy

3.1 Definitions

Let $J \subseteq I$ be a subset of sensors. Introduce the notation $P(z/J) = 1$ if z is observable using J, and $P(z/J) = 0$ otherwise. Let 2^I be the set of all subsets of I, then $P(z/J)$ induces a two-class partition

$$2^I = 2^{I+} \cup 2^{I-}$$

where 2^{I+} contains all the subsets of sensors by which z is observable. From the partial order associated with set-inclusion, minimal elements can be defined on 2^{I+}.

Definition. $J \in 2^{I+}$ is a minimal sensor set (MSS), iff $\forall K \subset J \quad K \notin 2^{I+}$. It is a redundant sensor set (RSS), iff it is not minimal.

Let I be a sensor network, which (hopefully) includes some MSS (or RSS). The set of the MSS (resp. of the RSS) included in I is noted as $MSS(I)$ (resp. $RSS(I)$).

Assume that at time t, the system is operating with a subset of sensors $J \in MSS(I)$. By the definition, z is no longer observable by the remaining ones if any sensor of J fails. On the contrary, if the system is operating with a RSS subset of sensors, there exists subsets of sensors which can be lost without destroying the observability of z, and the estimation procedure (whatever the actual algorithm which is used) can be reconfigured so as to still provide the functional estimate using only the remaining sensors. Note that the definition of RSS just states that such subsets exist, and does not give any detail about their number or their size.

3.2 The different versions of the estimation service

Consider a RSS J such that $|MSS(J)| = 1$, and let J^* be that MSS. Then, the failure of any subset of $J \backslash J^*$ can be tolerated, since z is still observable using the sensor set J^*. On the contrary, any sensor of J^* is a *critical resource* : the estimation of z cannot be performed any more when it is lost. It follows that the design of an estimation algorithm can be based on any super-set of J^*, thus providing possibly as many different estimators as the number of super-sets of J^* which exist in J (namely, $2^{|J \backslash J^*|}$). Intelligent sensors use these different estimators, which are called the different *versions* of the *estimation service* [18]. The different versions which result from the sensors of $J \backslash J^*$ do not increase the fault tolerance of the estimation service with respect to J^* (since any failure in J^* is fatal), but they might be justified in applications, because they might increase the estimation performances. Therefore, failures in the sensors of $J \backslash J^*$ would result in the running of versions which are still able to provide the estimation service (z is still observable), but with degraded performances (smaller super-sets are used).

For a RSS J such that $|MSS(J)| > 1$, the situation is analyzed similarly. Let $J_k^* \in MSS(J)$, $k = 1, ... |MSS(J)|$. Then, any super-set of J_k^* can be used for estimating z (thus providing a number of different versions), but the fault tolerance of the estimation is improved since failures of sensors in J_k^* can now possibly be tolerated. Indeed, as long as $|MSS(J_n)| \geq 1$, where $J_n \subset J$ is the set of the remaining sensors, there is still at least one set which allows to estimate z. *Critical sensor subsets* are those whose simultaneous unavailability result in $|MSS(J_n)| = 0$.

4 Evaluating the fault tolerance capability

Let $J \subseteq I$ be the subset of sensors available at time t. (J, t) characterizes the state of the sensor network, and z can be estimated as long as the set

$$E(z, t) \triangleq MSS(J) \cup RSS(J)$$

is not empty. Therefore, evaluating the fault tolerance capability of the sensor network at any time t rests on evaluating the size of the set $E(z, t)$, which can be done using two different approaches.

1) Weak (resp. strong) redundancy degrees are associated with the maximum (resp. the minimum) number of sensors which can be lost before $E(z, t) = \emptyset$. Their evaluation needs no model of the sensor losses. 2) When sensor reliabilities are known, the "size" of $E(z, t)$ can be evaluated by the time which will (in probability) elapse untill it becomes empty. In that case, significant measures are the sensor network reliability, or the mean time to non observability.

4.1 Redundancy degrees

Let $K \in MSS(J)$. The quantity $|J \backslash K|$ is the maximal number of sensors which can be lost s.t. z can still be estimated by K. In the "best" situation, as many losses as $|J| - \min_{K \in MSS(J)} |K|$ can be accepted, which is the definition of the weak redundancy degree $WRD(J, t)$:

$$WRD(J, t) = |J| - \min_{K \in MSS(J)} |K| \qquad (14)$$

From the definition of $WRD(J, t)$ it follows that

$$\exists J' \subset J \text{ such that } |J'| = WRD(J, t) \text{ and } J \backslash J' \in MSS(J) \qquad (15)$$

Of course, in many cases, z will no longer be observable after less than $WRD(J, t)$ sensor losses. The strong redundancy degree $SRD(J, t)$ evaluates the maximal number of sensors which can be lost while keeping z observable *for sure* (i.e. considering the worst case situation). This means that the following statement is true

$$\forall J' \subset J \text{ such that } |J'| = SRD(J, t) \text{ then } J \backslash J' \in RSS(J) \qquad (16)$$

or, in other terms,

$$SRD(J, t) = |J| - \max_{J^* \in RSS(J)} |J \backslash J^*| - 1 \qquad (17)$$

Comparing WRD and SRD obviously gives

$$\begin{aligned} \forall J \quad \subseteq \quad I, \quad & SRD(J, t) \leq WRD(J, t) \\ SRD(J, t) \quad = \quad & WRD(J, t) = 0 \text{ iff } J \in MSS(I) \end{aligned}$$

4.2 Reliability of the estimation service

Sensor losses are events whose probability can be evaluated. Assume such data are available, then :

- $R(J_0, t_0, t)$, is the probability for the estimation of z to be possible during the time interval $[t_0, t[$, given the sensor network initial state (J_0, t_0),

- $MTTNO(J_0, t_0)$, is the mean time to fail in the estimation of z, i.e. the mean time to non observability, starting with the state (J_0, t_0).

These two evaluations can be easily computed as follows. Let $K \subseteq J_0$ be any subset of sensors. The probability for the estimation of z to be possible during the time interval $[t_0, t[$ using K is given by :

$$R(K, t_0, t) = P(z/K) r(K, t_0, t) \qquad (18)$$

where $P(z/K) = 1$ if K is a MSS or a RSS and $P(z/K) = 0$ otherwise, and $r(K, t_0, t)$ is the reliability of the set of sensors K, which is defined as the probability that no sensor of K fails during the interval $[t_0, t[$. If sensor failures are independent one has :

$$r(K, t_0, t) = \Pi_{k \in K} r_k(t_0, t) \Pi_{k \notin K} (1 - r_k(t_0, t)) \qquad (19)$$

where $r_k(t_0, t)$ is sensor k reliability, which is often modelled using the Poisson distribution:

$$r_k(t_0, t) = e^{-\lambda_k (t - t_0)} \qquad (20)$$

where λ_k is sensor k failure rate, supposed to be constant.

Now, considering the whole set J_0,

$$R(J_0, t_0, t) = \sum_{K \subseteq J_0} R(K, t_0, t) \quad (21)$$

follows from the fact that all its subsets K are exclusive. Finally, the mean time to non observability asociated with the initial sensor network state (J_0, t_0) is defined by :

$$MTTNO(J_0, t_0) = \int_0^\infty R(J_0, t_0, t)dt \quad (22)$$

5 Sensor network and maintenance design

The result of a design algorithm is a set of sensors I, with specific properties (state - or functional of the state - observability, faults detectability and isolability, reliability, minimum cost, etc., see e.g. [1], [2], [3], [4], [5], [6], [10], [12], [13], [14], [15], [16], [17], [21], [23]). When fault tolerance is considered, the produced sensor network I must fulfill one or more of the following design requirements (T is a given time - $[t_0, T]$ is, for example, the duration of the system mission - and S_1^*, S_2^*, R^*, M^* are given design parameters) :

$$SRD(I, t_0) \geq S_1^* \quad (23)$$
$$WRD(I, t_0) \geq S_2^* \quad (24)$$
$$R(I, t_0, T) \geq R^* \quad (25)$$
$$MTTNO(I, t_0) \geq M^* \quad (26)$$

Algorithms which take such requirements into account have already been presented (see e.g. [12]), and will not be discussed here. However, the influence of a more general setting of the problem, including maintenance, will be considered. Indeed, the previous discussion addresses the fault tolerant estimation problem by analyzing a sensor set, initially in the state (I, t_0), in which sensors are lost as time increases. Maintenance operations, by which sensors are restored to an operational state were not considered, thus limiting the scope of the results to sensor networks of embedded autonomous systems, where maintenance operations cannot take place at all (e.g. satellites) or embedded systems where maintenance cannot take place during the time of a given mission (e.g. transportation systems). Let us now include maintenance considerations.

5.1 Condition based maintenance

Consider a given sensor network (I, t_0). Since the FDI algorithms detect and isolate the sensor faults, the state (J, t) of the sensor network is known at all times. Therefore, performing the on-line evaluation of the fault tolerance capability associated with this state provides indicators for condition based maintenance. Let s^*, r^*, m^* be design parameters. Then maintenance should take place when one or several of the three following conditions become true.

1) $SRD(J, t) \leq s^*$ means that without maintenance, the sensor network state is such that it will tolerate no more than s^* extra sensor failures (for example, if $s^* = 0$, maintenance is decided when the sensor network state becomes a MSS, i.e. the next failure is fatal).

2) $R(J, t_0, T) \leq r^*$ means that, without maintenance, the probability that the estimation will remain possible untill time T becomes too low. Computing the threshold r^* is obviously the main problem to be solved in that case.

3) $MTTNO(J, t) \leq m^*$ can be interpreted in the same way : without maintenance, the requirement (26) cannot be satisfied. Note that this means $m^* \leq M^* - t$, but computing the threshold should take more complex features into account, for example the mean time to repair.

5.2 Systematic maintenance

Considering not only failure rates, but also repair / replacement rates in the computation of the reliability or the mean time to non observability, allows to design systematic maintenance policies which insure the desired requirements. Indeed, defining a given rate for systematic maintenance can be modelled by a repair/replacement rate μ which will "compensate" the degradation rate λ, thus leading to perform all the above evaluations using the modified Poisson law

$$r_k(t_0, t) = e^{-(\lambda_k - \mu_k)(t - t_0)}$$

instead of (20). Note that this case is not really concerned with *fault tolerance*, but merely with *fault avoidance*. It may require complex tradeoffs, since the same result (e.g. a given mean time to non observability, or a given probability that the mission will be successfully achieved) can be obtained in two ways :

1) by using more redundancy, namely by designing a redundant sensor network whose sensors are not individually reliable, but where the estimation service exists under many versions,

2) by using more maintenance, which results in less sensors, but individually more available, as the result of more repair / replacement.

6 Application example

Consider the fourteenth-order model of a ship boiler described by [7]. Figure 1 shows the process, which implements a thermodynamic cycle in which the hot water tank is supplied with pre-heated water from the condenser by means of a turbo pomp, the produced steam is overheated before it supplies the group of high and low pressure turbines, and the relaxed steam is cooled in the condenser.

The main controls are Q_{EA} (the water flow), Q_C (the fuel flow), and Q_{ED} (the flow of overheating water). Q_V is the steam flow at the output of the superheater. In [7], a linear model is used around an operating point, and the measured variables are N_B (the water level in the hot water tank), P_S (the steam pressure at the output of the superheater), T_S (the

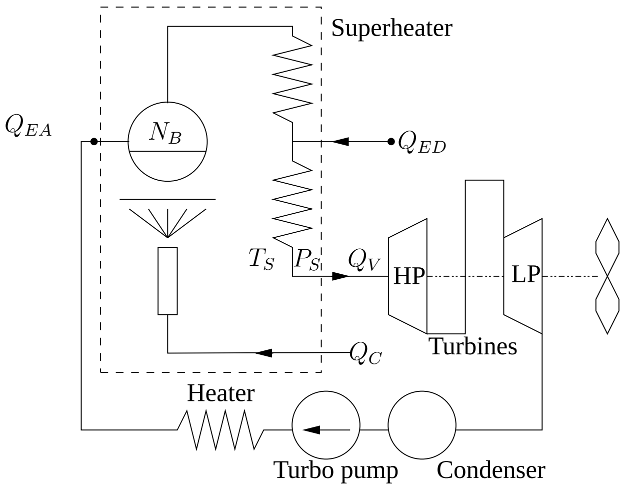

Figure 1: The ship boiler

steam temperature at the output of the superheater).

For our illustration, assume that there are six possible sensors, labelled $\{a, b, c, d, e, f\}$, such that

$$y^\tau = (x_1, x_3 - x_4, x_6 + x_7, x_{10}, x_{12}, x_{14})$$

while the functional of the state to be estimated is defined by

$$z^\tau = (x_2, x_3, x_4, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14})$$

It is also assumed that the reliability of each sensor $k \in \{a, b, c, d, e, f\}$ can be modeled using the Poisson distribution, by $r_k(t) = \exp -\lambda t$, and that the failure rates of the sensors are all equal to $\lambda = 0.4 \times 10^{-5} H^{-1}$ (for simplicity, $t_0 = 0$). The fault tolerant sensor network design problem is stated as follows : select a subset of sensors such that its strong redundancy degree is at least equal to 1 and its weak redundancy degree at least equal to 3 and the mean time before the observability of z is lost is at least equal to $3 \times 10^5 H$ (when no maintenance is done).

The sensor network design algorithm presented in [12] exhibits three minimal solutions which satisfy the requirements, namely $\{a, b, c, f\}, \{a, c, d, f\}$, and $\{b, c, d, f\}$. They all have the same performances, namely $WRD = 3$, $SRD = 1$, $R = e^{-\lambda t} + 2e^{-2\lambda t} - 3e^{-3\lambda t} + e^{-4\lambda t}$, $MTTNO = 3.13 \times 10^5 H$. The strong redundancy degree is 1 since z becomes unobservable when sensor f is lost. The weak redundancy degree is 3 since $\{a, b, c\}, \{a, c, d\}$, and $\{b, c, d\}$ can be lost without changing the observability status of z (in fact, z is observable through f alone).

Assume the sensor network that has been implemented is $\{a, b, c, f\}$ and that maintenance is decided on sensor network states (J, t) such that J is a MSS. Then maintenance should be undertaken (at latest) when the lost sensors are $\{a, b, c\}$ or $\{a, f\}$ or $\{b, f\}$, since the three MSS are $\{f\}$, $\{b, c\}$ and $\{a, c\}$.

7 Conclusion

Multisensor systems can accept sensor failures as long as their objective (estimate some functional of the system state) can still be achieved. In this paper, the fault tolerant estimation problem is addressed by means of the reconfiguration of the sensor network, a strategy by which only the subset of healthy sensors is used. Although it might seem quite drastic, the main interest of this strategy is that it needs neither fault models nor fault identification, and therefore it provides structural results and properties, i.e. fault tolerance properties which do not depend on the kind and size of the faults, but only on the subset of the faulty components.

Fault tolerant estimation first rests on the existence of different means by which the sensor network can provide the estimation service. It has been shown how different versions of this service can be obtained, provided the sensor network includes redundant sensor subsets. This provides a simple and efficient means of characterizing and evaluating the fault tolerance capability, either by using deterministic criteria such as the weak and strong redundancy degrees, or by using probabilistic ones, based on reliability considerations.

When maintenance operations are not considered, the results only apply to autonomous / embedded systems. However, including maintenance is possible, and can be done by performing on-line evaluation of the sensor network fault tolerance capability as sensor failures occur, thus providing indicators for condition based maintenance, or by considering not only failure rates, but also repair / replacement rates in order to design systematic maintenance policies which would ensure the specified requirements. This obviously introduces the necessity of a multicriteria evaluation of the sensor network since the improvement of the operation time can be obtained either by using a sensor network with higher fault tolerance, or by applying a higher cost maintenance policy.

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