Detection of Abnormal Sensor Behaviour using TBM

Bruno Marhic[1], Laurent Delahoche[1], Clément Soleau[2], Anne-Marie Jolly-Desodt[3] and David Menga[2]

[1]Laboratoire des Technologies Innovantes, University Picardy Jules Verne
University Institute of Technology, 80025 Amiens, France
Email: bruno.marhic@u-picardie.fr
[2]EDF, Research and Development, 92140 Clamart, France
[3]PRISME Institute, University Orléans
Polytech Orléans, 45072 Orléans, France

Abstract— **This paper illustrates how we detect abnormal behaviour using evidential analysis of the conflict signal produced by Transferable Belief Model (TBM) fusion. With our paradigm, we focus on the problem of sensor dysfunction whilst taking the sensor output into account. In order to describe normal sensor output, the prediction phase is run using a Markov Chain Model. The abnormal sensor output is detected by merging the monitored and the predicted mass functions using the TBM. We implement two techniques: the first one employs a probabilistic Markov Chain and the second one employs an evidential approach. The experimental results are subsequently used to evaluate our diagnostic method and to show the superiority of the generalised evidential framework**

Keywords: TBM, Fusion, Abnormal behaviour, Evidential prediction, Conflict analysis.

I. INTRODUCTION

Our research is anchored in the TBM [7] framework and targets information fusion in smart homes. A smart home is a habitat in which heterogeneous sensors are integrated. Owing to this model, the uncertain nature of the information sensors, and specifically the potential conflict between sources, are taken into account. Our work is not situated at the signal level but at the symbolic level and its objective is to detect behavioural drifts of a particular sensor amongst others. In order to detect abnormal behaviour, we first need to establish what is considered to be normal behaviour. In our project, a sensor possesses different symbolic states through which it can progress. Different techniques have been put forward to detect sensor anomalies. The most common ones can be classified as:

1) The sensor is perfectly modelled and the provided values are constrained. If the values exceed the boundaries, we can conclude that there is a malfunction.

2) Several sensors produce redundant data on the same variable. By comparing the sensors, the anomaly between two sources can be determined [6].

3) A prediction-verification algorithm permits to detect the change of state. An evidential approach [2] or a Kalman filtering approach [1] can be used to manage fault detection in sensor information.

With the first method the integrity of data can be verified, but not their coherence. As we only use one sensor, the second method is not applicable in our case. This means that we will focus on the third method. As we have chosen a predictive approach, we have opted for a sensor modelling by a Markov Chain [8]. Such a model can predict the future by using the present without knowing the past. Many recent works propose an evidential alternative. E. Ramasso and M. Rombaut were the first to introduce the principle of behavioural modelling with an HMM in order to detect the changes of states in a video [2]. E. Ramasso in [5] deals with the problem of fault diagnosis with an extension of HMM: the evHMM. D. Mercier and T. Denoeux address the problem of modelling of sensor reliability with contextual discounting [10]. A proposition to build a predictive belief function from statistical data is made in [11] and could be used in this context. More generally, the use of evidential classification processing [12] would be particularly well adapted to this problem of sensor diagnosis.

Paper organisation: in this paper we will first present a brief outline of the TBM and then how we model a sensor with a Markov Chain. We will then go on to detail the detection of abnormal behaviour of a single sensor. Next, we will propose a solution based on a predictive evidential matrix not correlated to Markov Chain processing. This is in fact the major difference with the preceding works exposed in [5]. Finally, we will validate the model with experimental results and we will compare a Markov Chain approach and a generalised evidential approach.

II. BRIEF OUTLINE OF THE TBM THEORY

In this paper, we use the TBM, Transferable Belief Model, a variant of Dempster-Shafer Theory [7]. This framework lets us model and combine evidence in order to make a decision. The TBM supposes a frame of discernment (FoD) Θ which contains symbolic hypotheses representing the exclusive and exhaustive solutions to the problem. $\Theta = \{Hi,\ i = 1..n\}$, where $Hi \cap Hj = \varnothing\ \forall i, \forall j$ with $i \neq j$. Therefore we can define the power set 2^Θ which contains the Singletons hypotheses and all the disjunctions of hypotheses $2^\Theta = \{A / A \subseteq \Theta\} = \{\varnothing, H_1, H_2, .. H_n, H_1 \cup H_2, ..., \Theta\}$. This prior power set 2^Θ defines the frame of definition for the belief functions; hence the BBA's ("basic belief assignments") are built. Finally a collection of BBA's is called "a source of evidence" or "a mass function". It is a map m from 2^Θ to

[0,1] defined by: $\sum_{A\subseteq 2^\Theta} m(A)=1$, where m(A) represents the evidence that corresponds to the proposition A (independently of the evidence on the hypothesis composing A in the case of A being a disjunction).

Therefore, and that is its main interest, the TBM can model the doubt and the total ignorance. It is the major advantage contrary to the probability theory. The total ignorance is defined by a BBA named the vacuous BBA: $m(\Theta)=1$, and $m(A)=0 \forall A\neq 2^\Theta$.

In the case where several experts examine the data, several sources of evidence appear. We have to combine the opinion of the different experts before making any decision. The combination process is achieved by the application of operators on all the sources of evidence. The TBM model is particularly well adapted to isolate the resulting conflict from a data fusion. The Smets operator (*i.e.* conjunctive operator, "$\cap$") is then used. Given two distinct BBAs, ms1(A) and ms2(B), defined on the same FoD, the combination is: $m(C)=\sum_{A\cap B=C} ms_1(A).ms_2(B)$

The modelling of evidence and combination of sources constitute the first phase named "Credal Level". The next stage (the pignistic level) is in charge of the decision making. It consists of computing the probability named "pignistic probability" from the BBA resulting from the combination process.

Pignistic probability (BetP)

$$\forall Hi \in \Theta \quad BetP(Hi)=\sum_{A\in 2^\Theta, Hi\subset A} \frac{1}{|A|} m(A)\cdot$$

Then the decision is made by selecting the hypothesis with the maximal pignistic probability.

TBM decision

$$Hj = \arg\max_{Hi\in\Theta} [BetP(Hi)]$$

III. Behaviour modelling with a stochastic process

Our diagnostic method to detect abnormal sensor behaviour implies that we first need to model normal sensor behaviour. A Markov Chain in discrete time is a sequence X_0, X_1, X_2, ... with random variables. The set of values is called the state space with the value X_n being the process state at the time *n*. If the conditional probability distribution of X_{n+1} of the passed states is a function of only X_n, then:

$P(X_{n+1}=x \mid X_0, X_1, X_2,\ldots, X_n)=P(X_{n+1}=x \mid X_n)$, Where *x* is any given state in the process. This probability distribution can be represented by a transition matrix T. This transition probability matrix represents the evolution of a process in time. An example will be given, based on a sensor with three known states X_0, X_1, and X_2. There is a transition probability $P_{ij}\in[0,1]$ allowing the passage of state X_i to X_j.

Normal output of a sensor is correlated to its actual state and its previous state. If the sensor correctly follows the evolution of the Markov Chain, (*i.e.* a transition probability is non void for the passage of one state to the next), then its output will be considered to be normal. However, if the sensor transits from one state to the next with a void transition probability, then its output is considered to be abnormal. In this paper we suggest a comprehensive formalism with which these supposedly impossible (relative to our knowledge) transits can be detected.

IV. Anomaly detection by merging predictions/observations

A. Proposed synopsis

Inspired by the different filtering methods discussed above, we have developed a dynamic fusion process that provides a prediction based on one or several observations. In the figure below, we distinguish four main stages in order to detect behavioural anomalies (Figure 1).The proposed method based on a Markov-Chain, requires that the system (analogical for instance) is digitized into distinct states. Two approaches for the prediction stage are proposed: (1) one obtained from a Markov Chain (§IV-B), (2) one obtained with an evidential transition matrix (§IV-C). The point discussed in §IV-B, is one of the main contributions of this paper. The results are compared in the section V.

1. Observation Stage
   The observation is the initial mass function at the time *n*, provided by the sensor that needs to be diagnosed.
2. Prediction stage
   The prediction is the operation with which we estimate the state of the sensor at time *n+1*.
3. Fusion stage
   The fusion is the operation with which we combine the new observations and the predictions.
4. Verification/Detection Stage
   The verification is the operation by which we validate the result of the fusion by examining the conflict signal. We also detect the discrepancy between the observation and the prediction.

Figure 1: Synopsis of the proposed method.

Observation Stage, Stage 1: The observation can be the output of a single sensor but it can also be the output of a dynamic or static fusion process. Generally speaking, the observation (sensor output) provides a mass function $m_{observation}$ on the FoD Θ composed by the possible Xi states of the sensor.

Prediction Stage, Stage 2: (see our two propositions detailed in §IV-B and §IV-C). Once this observation is attained, the predicted mass function $m_{prediction}$ can be calculated from an evolution model [8]. In our case, this model is the Markov Chain that represents the sequence of the possible states and that enables us to establish a Markovian prediction.

Fusion Stage, Stage3: To merge the prediction mass function $m_{prediction}$ and the observation mass function $m_{observation}$, we use the conjunctive Smets operator "$\cap$" to isolate the conflict in the FoD Θ resulting from the fusion according to: $m_{fusion} = m_{prediction} \cap m_{observation}$

Verification/ Detection Stage, Stage4: With the above formula, we compute and isolate the conflict value so that we can analyse its temporal evolution and detect a behavioural anomaly. This stage is detailed in §IV-D.

B. The Markovian prediction, (Stage 2)

The prediction input is a probabilistic observation $V_{observation}$ vector that corresponds to the state of the sensor at time *n*. We obtain the computation of the Markovian prediction from the transition matrix T, which is a $V_{prediction}$ vector of the same size as the $V_{observation}$ vector, by:

$$V_{prediction} = V_{observation} \times T \quad (1)$$

If we take a transition matrix T (X_0, X_1, X_2) empirically defined as:

$$T = \begin{bmatrix} 0.5 & 0.5 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 0.5 & 0.5 \end{bmatrix}$$

and an observation vector $V_{observation}$ = (1 0 0) , *i.e.* the process is in state A0 at time *n*, then we compute the prediction vector $V_{prediction} = V_{observation} \times T$ = (0.5 0.5 0). This predicts that when the process is in state A0 with a probability of 1, it will be in state A0 or A1 at the next point in time. This shows that the Markovian prediction uses a probability set as input and renders a probability set as output, in other words a predicted probability set. As the entry of our system is a sensor that renders an observation mass function $m_{observation}$ (result of an evidential fusion), we need to proceed to a pignistic conversion phase (first conversion, Evidential ⇒ Probabilist). This allows the Markovian prediction to be computed from a single observation mass function. Equation (2) presents the method (conversion) to compute the pignistic probability (see §II):

$$V_{observation}(Xi) = BetP(Xi) = \sum_{\substack{A \in 2^{\Theta} \\ Hi \subset A}} \frac{1}{|A|} m_{observation}(A) \quad (2)$$

The Markovian prediction of the probability set can then be obtained. This probability set then has to be converted into a prediction mass function to allow us to merge the prediction and the observation (second conversion, Probabilist ⇒ Evidential), *i.e.* the stage 3, *Fusion Stage*.

Evidential conversion:

Remark: The predicted set of probabilities we obtain can be considered as a pignistic distribution. Consequently, there are numerous mass functions that correspond to this pignistic. In a general setting, the choice of the mass function must respect the MIP (minimum information principle). [4] This means that the least specific function needs to be chosen. This solution was not retained as the MIP function would compute fewer conflicts in ulterior fusion operations; *i.e.* it would be contradictory to our strategy of analysing the conflict signal variations in order to detect anomalies.

As our probability set is complete, ($\sum V_{prediction}(Xi) = 1$) and considering the previous remark, it can be directly converted into a mass function. The probabilities of the hypothetical Singletons are then directly placed on the mass sets of the corresponding hypothetical Singletons through:

$$m_{prediction}(Xi) = V_{prediction}(Xi) \quad (3)$$

The focal elements of our mass function are only singleton hypotheses and ours is clearly a Bayesian mass function. Hence, the masses of the non Singleton hypotheses are void.

C. The Markovian prediction in an evidential sense, (Stage 2); second proposition

As discussed above, in a Markovian prediction framework, we don't work directly with a mass function but with a probabilities set, necessitating a pignistic conversion process. The process of converting masses to probabilities engenders a loss of information on the representation of symbolic data. The notion of doubt is absorbed and the advantages related to the belief functions are lost. We have therefore endeavoured to unite the formalisms used in our perception architecture and we offer a transformation of the transition matrix in an evidential sense. This transformation works directly with mass functions. We convert the probabilistic Markov Chain transition matrix into an evidential Markov Chain transition matrix. This conversion consists in modelling the hypotheses' disjunctions directly into the matrix.

For an FoD Θ, we obtain a transition matrix named evidential T_{Cred} sized $(2^{\Theta}-1)\times(2^{\Theta}-1)$:

$$T_{Cred} = [X_0, X_1, X_2, X_0 \cup X_1, X_0 \cup X_2, X_1 \cup X_2, \Theta] \times [X_0, X_1, X_2, X_0 \cup X_1, X_0 \cup X_2, X_1 \cup X_2, \Theta]$$

This evidential Markov Chain is given for a sensor with the three states X_0, X_1, X_2. This evidential transition matrix redistributes the transition probabilities on the hypotheses and on the hypotheses' disjunctions. For each state or disjunction of states, we obtain a probability $P_{ij} \in [0,1]$ allowing the passage of state X_i to X_j with $i,j \in 2^{\Theta}$. This manipulation implies that we consider the disjunction of states as states in their own right and they represent an intermediate state. The passage from one state to the next is rendered smoother as a result of the passage via an intermediate state.

The evidential Markov Chain renders the prediction process more reliable because the two stages of pignistic mass conversion to probabilities and vice versa are no longer. It suffices to use an evidential observation vector $V_{observation}$ that is consistent with the sensor's state at time *n*. The computation of the evidential Markovian prediction from the evidential transition matrix T_{Cred} is obtained in the same manner:

$$V_{prediction} = V_{observation} \times T_{Cred} \quad (4)$$

D. Detection of an anomaly, (Stage 4)

To detect abnormal behaviour of the sensor, we use the Smets operator to observe the temporal conflict evolution $m_{fusion}(\varnothing)$ that emanates from the fusion between the observation mass function $m_{observation}$ and the prediction $m_{prediction}$. Our experimental results show that abnormal behaviour can be characterised by a significant increase of conflict. The conflict value analysed here is the sum of the auto-conflict and conflict produced by the combination. As a matter of fact, when the prediction and the observation are in discord, the fusion of the mass functions $m_{obervation}$ and $m_{prediction}$ provokes an increase in conflict $m_{fusion}(\varnothing)$. Our experimental results also show that the conflict is subject to an abrupt increase when there is an anomaly and then recovers a stable value once the prediction is stabilised, regardless if this is done with the transition matrix T or T_{Cred}.

Consequently, an anomaly is characterised by an increase in conflict during a short lapse of time, in other words a conflict peak. To automatically detect a conflict peak, we use a new system of symbolic fusion between experts. This system is in charge of signal peak detection and is formed by three experts (Ei, i=1,..3) that render an opinion on the conflict which issues from the prediction and observation fusion. The FoD of the three experts is: $\Theta_{behaviour} = \{Ok, NotOk\}$. The hypothesis "Ok" means "the behaviour of the sensor is normal" and the hypothesis "NotOk" means "the behaviour of the sensor is abnormal".

The three experts provide an opinion, *i.e.* m_{expert_i}(i=1,2,3) on a particular characteristic of conflict signal $m_{fusion}(\varnothing)$. The first expert refers to the sign of the derivative of the conflict signal in order to detect a rising peak. The second expert refers to the amplitude of the peaks and the third refers to the duration of the peaks. The three experts together detect the rise of high peaks that have a short duration. The fusion of the three experts (Dempster's rule of combination) allows the identification of the conflict peaks that correspond to an impossible transition of states, and thus the sensor functioning:

$$m_{fonct} = m_{expert1} \cap m_{expert2} \cap m_{expert3} \quad (5)$$

m_{fonct} furnishes a mass function for each of the conflict signal points and indicates whether these points correspond to an anomaly or not. Therefore, the opinions provided by the three experts are combined in turn (first we combine expert 1 with expert 2 and the resulting BBA with expert 3) using the Dempster rule of combination:

$$m_{expert12}(A) = \frac{1}{1-K} \sum_{A \subseteq \Theta : B \cap C = A \neq \phi} m_{expert1}(B) * m_{expert2}(C)$$

$$K = \sum_{B \cap C = \phi} m_{expert1}(B) * m_{expert2}(C)$$

In the same way: $m_{fonct} = m_{expert12} \cap m_{expert3}$. When conflict appears, this is due to a disaccord between the experts which are then normalised. However, if at least one expert's opinion does not indicate that the situation is abnormal, then we consider that to all intent and purposes the situation is indeed not abnormal and hence it is considered as normal.

The pignistic decision on the mass set m_{Fonct} makes it possible to detect a behavioural anomaly. A behavioural problem is settled when $P_{Fonct}(NotOk) > P_{Fonct}(Ok)$.

V. EXPERIMENTAL RESULTS

In this paper, data are simulated, and therefore the Markovian transition matrix setting is empirical. Concerning, the evidential one, we are now working on "learning methods" to set the evidential transition matrix automatically.

Thus in this paper both settings are empirical. We have defined T_{cred} from the Matrix T (§IV-B) as:

T_{Cred} =

	X_0	X_1	X_2	$X_0 \cup X_1$	$X_0 \cup X_2$	$X_1 \cup X_2$	Θ
X_0	1/3	1/3	0	1/3	0	0	0
X_1	0	0	0	0	0	0	1
X_2	0	1/3	1/3	0	0	1/3	0
$X_0 \cup X_1$	1/3	1/3	0	1/3	0	0	0
$X_0 \cup X_2$	0	0	0	0	0	0	0
$X_1 \cup X_2$	0	1/3	1/3	0	0	1/3	0
Θ	1/7	1/7	1/7	1/7	1/7	1/7	1/7

This simulation consists in using a symbolic expert at the input of the system, providing a mass function $m_{observation}$ on the discernment frame $\Theta = \{X_0, X_1, X_2\}$.

The probabilistic transition matrix has been defined in section IV-B. It prohibits the passage of state X0 to X2 and vice versa.

The temporal evolution of the states consists of seven phases (Graph 1 of Figure 2).

Figure 2 shows the apparition of two abnormal phases. At t=36 the sensor passes from state X0 to X2, which is theoretically impossible according to the transition matrix T. At t=48, the sensor passes from state X2 to X0, which is also theoretically impossible.

The temporal evolution of the mass function $m_{observation}$ is presented in Figure 2 (line & +).

Figure 2 also shows the evolution of the probabilistic Markovian prediction (in brown, dash-dot line), *i.e.* only the Singletons hypotheses.

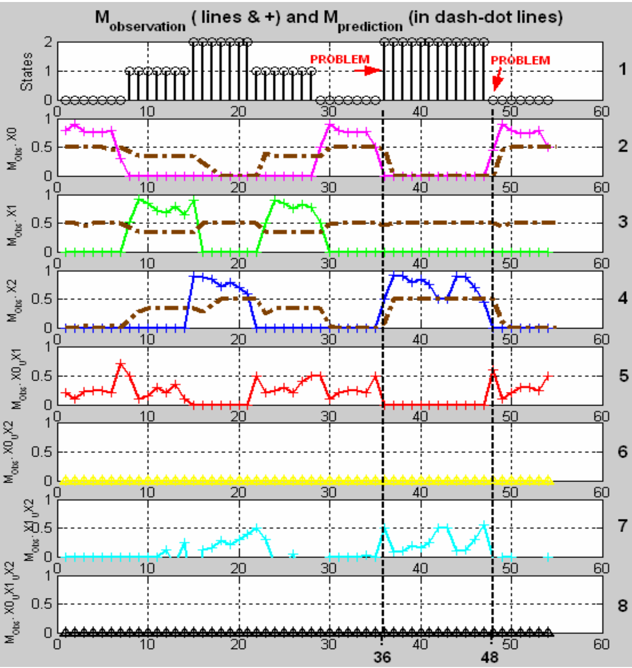

Figure 2: Probabilistic case. The temporal evolution of the mass functions $m_{observation}$ and $m_{prediction}$.

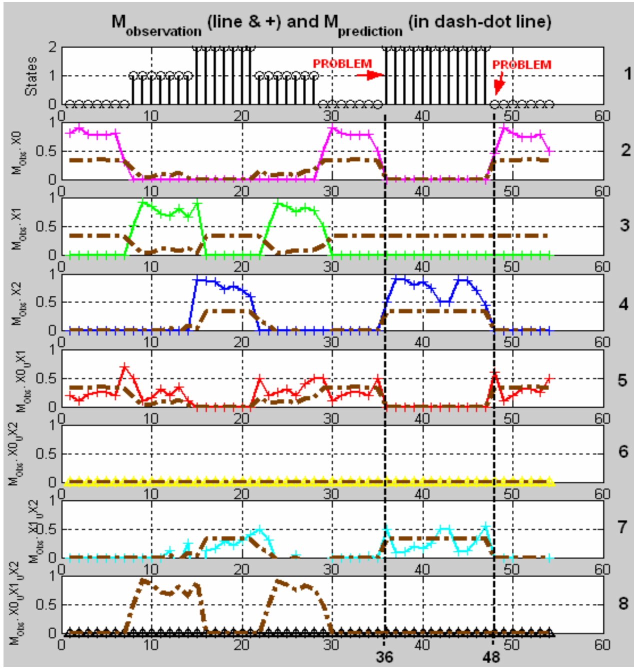

Figure 3: Evidential case. The temporal evolution of the mass functions $m_{observation}$ and $m_{prediction}$.

At t=36, the Markovian prediction, based the transition matrix T, shows with a firm belief that the state will be X0 ($m_{prediction}$(X0)=0.46) or X1 ($m_{prediction}$(X1)=0.46) but certainly not X2 ($m_{prediction}$(X2)=0.08). The observation shows with a firm belief that the state is X2 ($m_{observation}$(X2)=0.50). There is thus a conflict between the prediction and observation at this time.

Similarly, at t=48, the Markovian prediction shows with a firm belief, that the state will be X2 ($m_{prediction}$(X2)=0.45), or X1 ($m_{prediction}$(X1)=0.45) but certainly not X0 ($m_{prediction}$(X0)=0.10). The observation proves with a firm belief that the state is X0 ($m_{observation}$(X0)=0.40). This shows that there is again a conflict between prediction and observation at this level.

Figure 3 shows the evolution of the evidential Markovian prediction (in brown, dash-dot line).As expected, predictions on the disjunctions of the hypotheses appear, which indicates a possible transitory state between two established states. The masses on the disjunctions weaken the ones on the singletons, and consequently the residual conflict diminishes (Figures 4 & 5). This diminution of conflict is a result of an improved mass repartition during the prediction. In fact, this prediction is more precise and therefore the difference between observation and prediction is less. This means that when there is no anomaly; the conflict between observation and prediction is vastly reduced. We also note a rise of the total ignorance when we observe the state X1. In fact, when the sensor is in state X1, all the potential transitions are possible (by definition), and this means that we can not ascertain a particular hypotheses.

To observe the impact of the two conflicts, we focus on the mass function m_{fusion} resulting from the fusion of $m_{observation}$ and $m_{prediction}$ as depicted in figure 4.

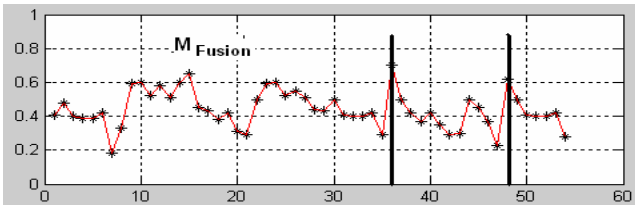

Figure 4: Conflict (∅) between prediction & obs° in framework of a *probabilistic* Markovian Chain (*cf* IV-B).

Two conflict peaks can be observed at t=36 and t=48, consistent with the abnormal functioning of the sensor. These conflict peaks are characterised by a strong positive amplitude of a short duration. However, it is difficult to analyse this signal automatically for two reasons: the first being that the average conflict is important (0.44) during the complete duration of the signal and the second being that the signal has no stable phase characterising a normal functioning of the sensor.

Figure 5 represents the results of the application of the evidential version of the Markov Chain (§IV-C). The results are practically identical to those presented in Figure 4 (two important conflict peaks at t=36 and t=48), but the conflict peaks for behavioural anomalies are of such a height that they are easier to distinguish and this facilitates automatic detection. The average conflict shifts from 0.44 to 0.16 and is stable during the normal performance of the sensor.

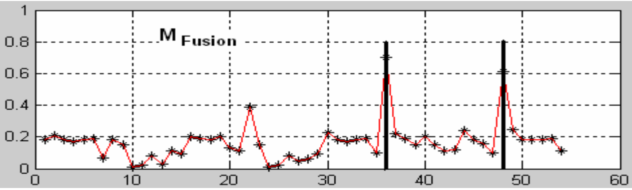

Figure 5: Conflict (∅) between prediction & observation in the *evidential* framework of a Markov chain (*cf* §IV-C).

Figure 6 presents a comparison of the two methods that we use, §IV-B and §IV-C. Graphs 1 and 3 represent the conflict signals which issue from the observation / prediction fusion relatively to methods §IV-B (probabilistic version) and §IV-C (evidential version) (see figure 5 & 6 for more details). Graphs 2 and 4 represent the pignistic probability on the hypothesis "NotOk". The final decision on abnormal behaviour is made when P_{fonct}(NotOk)>P_{Fonct}(Ok). In this case we can state that the sensor is not functioning correctly.

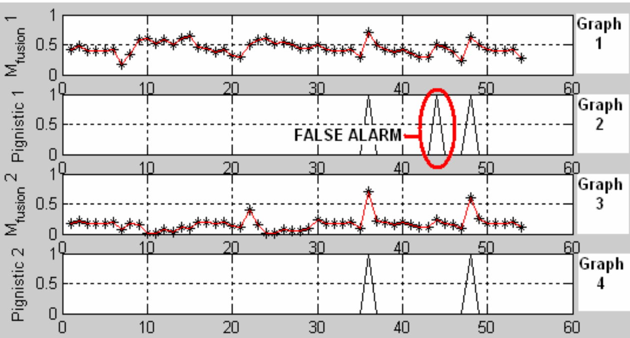

Figure 6: Conflict signals (from fusion pred. /obs.) of both methods: graph 1 - the probabilistic method and graph 3 - Evidential Markov Chains. Graphs 2 & 4 are pignistic decisions (peak detection), with a false alarm in graph 2.

In the case of a probabilistic Markov Chain, we observe a false detection (time=44) that is not apparent in the evidential case. Several experimental results demonstrate that the evidential approach presents fewer discordant cases as the conflict signal is more stable during the periods of normal behaviour. In fact, as the prediction is less specific, the observation and prediction differ far less (60% less on average). During periods of abnormal behaviour, the conflict undergoes an important increase and is easily detected by the three experts

VI. Conclusion

In this article, we developed a method to detect abnormal behaviour in a sensor within the TBM framework. Our method compares an observed state and a predicted state. The predicted state is based on the behavioural model of the sensor previously defined. Two mass functions ($m_{prediction}$ and $m_{observation}$) are obtained and merged. The conflict between the observed and predicted mass functions is analysed using three experts. In order to estimate the mass function, two approaches are proposed and compared. The first one uses a probabilistic behavioural model with the help of a Markov Chain. It has the inconvenience that it loses the advantages linked to belief functions because it passes through a process where mass function is converted to probabilities. The second approach resolves this problem and proposes a technique based on belief functions. We have empirically defined an evidential Markov Chain transition matrix, more adapted in an evidential fusion design. With this second approach we can obtain a more precise prediction of the expected behaviour. It facilitates the creation of the predicted mass function and the identification of the behavioural anomalies. In fact, as the prediction is closer to the observation, the conflict resulting from their fusion accurately characterises the correct functioning. If the prediction diverges from the observation, the conflict evolves in relation to this divergence and indicates abnormal behaviour that can be robustly identified by the three experts. To conclude, we are now working to automatically estimate the evidential transition matrix.

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References

[1] A. Okatana, C. Hajiyevb, U. Hajiyevaa, "Fault detection in sensor information fusion Kalman filter", AEU - International Journal of Electronics and Communications, Elsevier, Vol. 63, Issue 9, Sep. 2009, pp 762-768.
[2] E. Ramasso, M. Rombaut, and D. Pellerin, "State filtering and change detection using TBM conflict," IEEE Transaction on CSVT, vol. 17, pp. 944–949, 2007.
[3] Ph. Smets, "Analyzing the Combination of Conflicting Belief Functions", Information Fusion 8(4): 387-412, 2007
[4] P. Smets, The necessity of the pignistic transformation, Int. J. of Approximate reasoning, 38: 133-147, 2005
[5] E. Ramasso, "contribution of belief functions to hidden markov models with an application to fault diagnosis", IEEE Int. Workshop on Machine Learning for Signal Processing, MLSP'09, Grenoble, France (2009).
[6] Ricquebourg V.,Delafosse M., Delahoche L., Marhic B., Jolly A.M., Menga D., "Combinaison de sources de données pour la détection de dysfonctionnement capteur", LFA'07, Novembre 2007, Nîmes, France.
[7] Smets Ph., "The Transferable Belief Model for Quantified Belief Representation.", Handbook of Defeasible Reasoning and Uncertainty Management Systems, Kluwer Ed, pp 267-301, 1998.
[8] Zhang, Y., Augenbroe, G., Vidakovic B. « Uncertainty analysis in using markov chain model to predict roof life cycle performance » - ICDBMC 05, April 17-20 2005, Lyon, France.
[9] F. Delmotte, D. Gacquer, "Detection of defective sources with belief functions", IPMU'08, Malaga, Spain, juin 2008, pp 337-344.
[10] D. Mercier , B. Quost, T. Denoeux, "Refined modeling of sensor reliability in the belief function framework using contextual discounting", Information Fusion, pp 246-258, Vol. 9, No. 2, April, 2008.
[11] A. Aregui, T. Denœux, "Constructing consonant belief functions from sample data using confidence sets of pignistic probabilities", International Journal of Approximate Reasoning, Volume 49 , Issue 3 (November 2008) Pages 575-594.
[12] S. Fabre, A. Appriou and X. Briottet, "Presentation and Description of Two Classification Methods Using Data Fusion Based on Sensor Management", In Information Fusion, volume 2, pages 49-71, 2001.