Fault Detection Architecture for Proprioceptive Sensors based on a Multi Model Approach and Fuzzy Logic Decisions

Nicolas Pous[1], Dominique Gruyer[2] and Denis Gingras[1]
[1]LIV (Laboratory of Intelligent Vehicles), in the Electrical and Computer Engineering Department of Sherbrooke University, Sherbrooke, Qc J1K 2R1, Canada
[2]IFSTTAR- IM - LIVIC, 14 route de la minière, bat. 824, 78000 Versailles-Satory, France

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Abstract: In this paper a new fault detection architecture will be presented. Inspired by multi-model data fusion algorithms and fuzzy logic decisions, it consists in the comparison between the estimation of a dynamic mode using each sensor independently. This method is used to deal with important non-linearity and strong interaction with the environment usually encountered in the domain of the intelligent vehicles localization. The concept of analytic redundancy is also used to ignore model uncertainties.

1 INTRODUCTION

More and more, our society is evolving to be partially automatized. In this context, the automotive industry is contributing by focusing on autonomous vehicles. As a step between this technology and the previous one, vehicular companies are developing a large series of tools helping drivers and improving both safety and comfort. These tools, when used to improve driving safety, are generally named ADAS (Advance Driver Assistance System) (Andreas Riener, 2009). ADAS are generally composed of a large amount of tools permitting, for example, to reduce stopping distance, or improve the car position determination. In that case precisely, a large set of exteroceptive and proprioceptive sensors are used to obtain a better knowledge of the vehicle environment and attitude, in order to reduce the localization uncertainties via data fusion algorithms. Some of them are using only proprioceptive sensors (Cai Bai-gen et al., 2009), others are using both (Kim, S.-B et al., 2011 and Adrien Bak et al., 2012). Communication and map matching can also be used to reinforce the precision of the measurement (Rohani et al., 2013 and Rohani et al., 2014).

In both cases, a faulty data source can lead to a catastrophic error in the position determination. That's why, in order to properly improve safety, we need to detect faults and identify the associated sources before using faulty data in the fusion algorithm. One of the most used detection method is based on the comparison between the normal behavior model and the recording of the real behavior from the sensors. This method supposed that the system behavior is perfectly known and can be modeled (Patton, R. J. et al., 1989).

But, the important non-linearity of our system (The vehicle) behavior and the strong impact of environmental perturbation will improve the complexity of our task. Others methods based on analytical redundancy are also used to avoid the model issues, as described in (Sun and Cannon, 1998), where a Kalman filter is used to obtain estimations of a same metric in order to compare the values obtained from different sensors.

In this paper an alternative approach based on the determination of the dynamic comportment of the vehicle using analytical redundancy is developed in order to treat with the non-linearity of the system. The nominal comportment was divided in 4 sub-systems defined by the direction changes and longitudinal accelerations as describe in table 1.

Table 1: Dynamic modes definition.

Straight line	H1	H3
Speed change	H2	H4

Based on the sensors information, we will use fuzzy logic and calculate the weight corresponding to the membership degree of each dynamic mode in every time, and use these values from each sensor to determine the presence of a faulty data source.

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In part 2 a traditional approach for the fault detection will be studied and our context will be presented. Then, in part 3, the proposed method based on the dynamic mode determination will be presented. Section four will then present some simulation results and a performance analysis before treating in the fifth section of the ongoing developments and conclude in section six.

2 CONTEXT AND TRADITIONAL APPROACH

2.1 Context

As we focused on the ego-localization of an intelligent vehicle, we decided to focus on proprioceptive sensors related to the vehicle comportment determination.

2.1.1 Odometer

The odometer is based on an electric sensor detecting marks equally disposed on a wheel. As the odometer is a counting device, the output will be a discrete value representing both the integrated travelled distance and the speed during a sampling time.

2.1.2 INS

The INS is usually composed with 3 accelerometers and 3 gyroscopes which respectively provide information about linear accelerations and angular speed on the 3 axes.

2.1.3 Compass

The compass, usually integrated on the INS chip, will inform us about the absolute orientation of our mobile.

2.1.4 GNSS

This device provide the absolute position of the vehicle on the earth.

2.2 Traditional Approach

Traditionally, a system and the associated FDI (Fault Detector and Identification) are represented as followed. In this representation, we can distinguish three parts which can present faults. The actuators, the system itself and the sensors which give information about the system comportment.

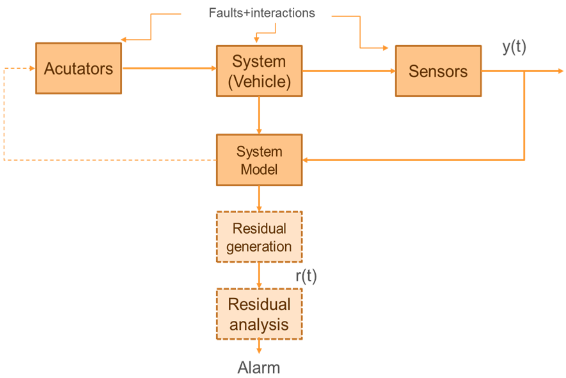

Figure 1: Classical structure of an FDI model based.

(Qi et al., 2013) present a description of the different eligible faults on the actuators, the system and the sensors. According to these description, we can elaborate tests to detect every kind of fault, for every part of the complete data flow (Actuators, System, in our case, the vehicle and Sensors) as describe in figure 1. Here, as we focus in this publication on the sensors faults, actuators and system failures and uncertainties will not described.

Four types of faults are depicted by Qi et al. for the sensors.

- Total failure
- Constant bias failure
- Constant gain failure
- Outlier failure

Knowing these failures nature, we can elaborate tests to detect the presence of each kind of failure. Usually, model-based fault detector assume that at least one part of the global system (representing the system with its actuators and sensors) is working efficiently. In this paper we will discuss about new techniques to detect and identify faults without any assumptions on any part of the global system. In that purpose, we developed a detection method based on the information redundancy and determination of the system comportment.

3 DYNAMIC MODE DETERMINATION

Inspired by the IMM fusion algorithm presented in (Gruyer et al., 2010), we developed a multi-model approach to detect faulty behavior on sensors used in the determination of a mobile position. The multi-model implementation consists in separating the operating space into linear sub-spaces where we can identify some simple maneuvers. This sub-space, also called dynamic mode, has then to be determined only

using the sensors data. The determinations from different sensors will so diverges if one of them present a faulty comportment.
The global structure of our fault detection and identification architecture is depicted in figure 2.

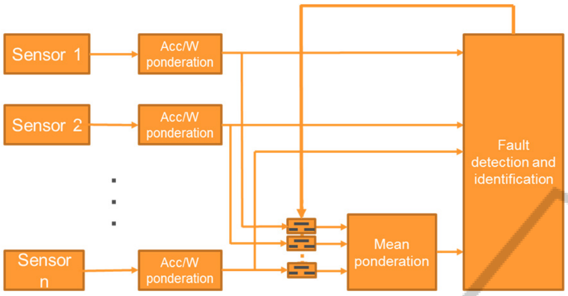

Figure 2: Proposed FDI structure.

The dynamic modes are defined by the longitudinal acceleration and the angular velocity of the mobile (representing the two possible maneuvers for the user), and we so can separate the operating space into four principle dynamic modes as seen in Table 1.

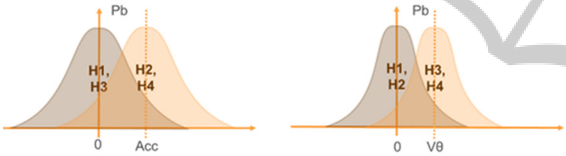

Figure 3: Acceleration and angular speed distribution for the four dynamic modes.

According to the dynamic mode description, the two needed metrics are the acceleration and the angular speed of the vehicle.

3.1 Metrics Determination

So we need to determine these two characteristics using each sensor independently. Concerning the INS, these two values will be directly given by the sensor. Concerning the odometer, it is necessary to recalculate the value according to the nature of the information given by the sensor. As we have the speed of each wheel from the odometer, we can approximate the speed of the vehicle (VE_S) by computing the mean value of the right and left wheels speed.

$$Ve\_S(t) = \frac{RW\_S(t) + LW\_S(t)}{2} \quad (1)$$

Where *RW_S* and *LW_S* are the right and left wheel speeds respectively. It is now possible to determine the acceleration by deriving the speed value.

$$Acc_{Odo}(t) = \frac{D(VE\_S(t))}{Dt} = \frac{VE\_S(t) - VE\_S(t-1)}{T} \quad (2)$$

Having the acceleration, we need now to determine the angular speed of the vehicle. In order to determine if we are in a straight line or in a curve, we analyze the differential speed between the 2 wheels given by (3).

$$Dif\_S_{Odo}(t) = RW\_S(t) - LW\_S(t) \quad (3)$$

Concerning the compass, it can only inform us about the angular speed, by derivation of the orientation $\theta(t)$.

$$An\_Sp_{Compass}(t) = \frac{\Delta\theta(t)}{\Delta t} \quad (4)$$

3.2 Weight and Residual Determination

Knowing acceleration and angular speed values, it is now possible to determine the dynamic mode. Let's call *Acc* the presence of an acceleration, and $V\theta$ the presence of a rotation, so the 4 dynamic modes will be defined as follow.

$$\begin{aligned} H1 &= \overline{Acc} \bullet \overline{V\theta} \\ H2 &= Acc \bullet \overline{V\theta} \\ H3 &= \overline{Acc} \bullet V\theta \\ H4 &= Acc \bullet V\theta \end{aligned} \quad (5)$$

Instead of a classic determination using a simple threshold, a fuzzy logic decisions permit to determine a weight corresponding to the presence of an acceleration/rotation, as represented in figure 4 for an acceleration. The event probability is currently determine using a Gaussian threshold as depicted in equation 6 for the presence of an acceleration, where the σ coefficient value permit adjust the sensitivity if the detector.

$$P_{Acc} = 1 - \left[\left(\frac{1}{(0.4*(2*pi)^{0.5}} \right) * exp^{-0.5*(Acc_{INS}/\sigma)^2} \right] \quad (6)$$

$$\begin{aligned} P_{H1} &= (1 - P_{Acc}) * (1 - P_{V\theta}) \\ P_{H2} &= P_{Acc} * (1 - P_{V\theta}) \\ P_{H3} &= (1 - P_{Acc}) * P_{V\theta} \\ P_{H4} &= P_{Acc} * P_{V\theta} \end{aligned} \quad (7)$$

Then, the dynamic mode membership degree can be determined as followed, where *Px* is the weight corresponding to the event *x*.

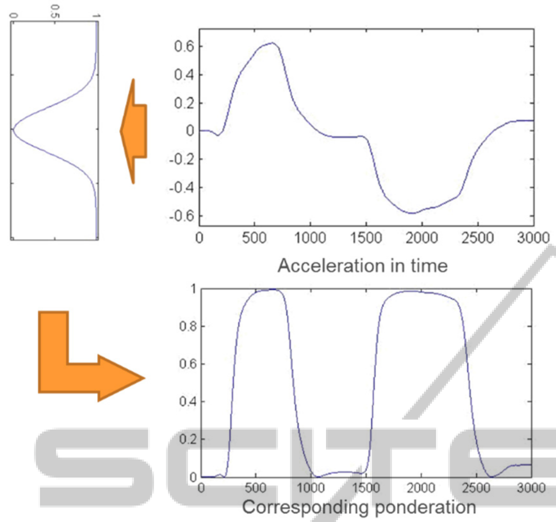

Figure 4: Acc Weight's determination according to the acceleration value.

Using these weights from each sensor, it is possible to determine an instantaneous mean value of the corresponding metric weight by using equation (8) taking into account every sensors independently. Instead of calculating dynamic mode weights, we dissociate the 2 metrics weights (Po(Acc) and Po(Vθ)) which will be more useful.

$$\overline{Po}(Acc|S_1,S_2...S_N)=\frac{1}{\sum_{i=1}^{N}C_i}\sum_{j=1}^{N}C_jPo(Acc|S_j) \qquad (8)$$

Where $\overline{Po}(Acc|S_1,S_2...S_N)$ is the mean value taking all the sensors, $Po(Acc|S_i)$ is the acceleration weight for the sensor *i*, and C_i corresponding to the decision of the fault detection device.

Using both the mean weight value and individual ones, we can calculate a residual value for each sensor equal to the difference between the two of them (9). A residual variable will then be calculated for each sensor and each metric used (acceleration and angular speed).

$$R(Acc,S_i)=\overline{Po}(Acc|S_1,S_2...S_N)-Po(Acc|S_i) \qquad (9)$$

The calculated residual has to be stationary to make the detection easier. In our case, for a normal behavior, the residual variable will have a zero mean value. In order to illustrate it, we simulate the drive of a vehicle with the appearance of the 4 dynamic modes, with only the use of four odometers (one on each wheel, simulated by the recording of the wheel speed), and an inertial system with accelerometers and gyroscopes on the three axes. The figure 5 represents the mean weight calculated with information of all the sensors, and figure 6 is the residual variable for both acceleration and angular speed for the inertial sensor.

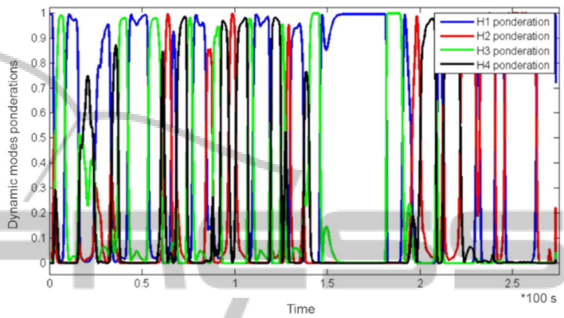

Figure 5: Dynamic modes weights evolution in time.

These results were obtained by calculating the differential weight between the mean weight values and the INS ones. As the sensors information was noisy, we decided in a first time to apply a Butterworth low pass filter to eliminate the high frequencies component of signals.

The residual value is still not perfect, and some adjustment are still needed, but it remains possible to use these results for the detection algorithm. Actually, what is primordial is to observe modification of the residual values, so, it's possible to imagine calibration procedure to determinate a standard residual profile before beginning the analysis.

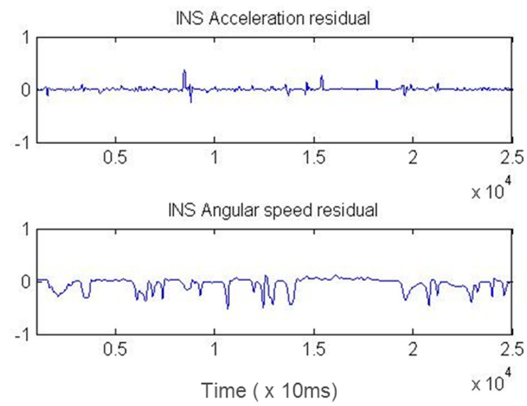

Figure 6: Acceleration and angular speed residual for the INS sensor.

3.3 Fault Detection

In this section, faulty data will be introduce in sensors information, according with what was described in section 2-c, regarding the sensors faults. We so simulated each kind of fault and analyzed the residual values in order to establish some detection rules. Just as we did previously in this section, we will focus on two kind of sensors, odometers (one on each wheel) and inertial system.

As depicted in the previous section, the residual will be calculated by computing the difference between the mean weight value and the weight from the sensor under watching. But as a failure will induce some perturbation on the mean value calculation, it's important to determine how this perturbation will impact the failure detection. Considering a perturbation ΔPo on one sensor noted S_F, the mean weight value, before the decision can be represented by equation 10.

$$\overline{Po}(Acc|S_1,S_2...S_N)=\frac{1}{N}\left[\left(\sum_{j=1}^{N}C_jPo(Acc|S_j)\right)+\Delta Po\right] \quad (10)$$

The residual of a non-faulty sensor will so be impacted by a failure, and this impact will depend on the number N of sensors used in the detection algorithm. Residuals for both faulty and non-faulty sensors can so be calculated by (11) and (12), and the related perturbations can so be depicted by (13) and (14), where N is the number of sensors used in the mean value calculation.

$$\begin{aligned}
R(Acc|S_F)&=Po(Acc|S_F)-\overline{Po}(Acc|S_1,S_2...S_N)\\
R(Acc|S_F)&=Po(Acc|S_{NF})+\Delta Po-\overline{Po}(Acc|S_1,S_2...S_N)\\
R(Acc|S_F)&=\frac{N-1}{N}\Delta Po+\left[Po(Acc|S_{NF})-\frac{1}{N}\sum_{i=1}^{N}Po(Acc|S_i)\right]
\end{aligned} \quad (11)$$

$$R(Acc|S_{NF})=\frac{-1}{N}\Delta Po+\left[Po(Acc|S_{NF})-\frac{1}{N}\sum_{i=1}^{N}Po(Acc|S_i)\right] \quad (12)$$

$$\Delta R_F=\frac{N-1}{N}\Delta Po \quad (13)$$

$$\Delta R_{NF}=\frac{-1}{N}\Delta Po \quad (14)$$

The more sensors we use, the more important the difference between a non-faulty and a faulty residual will be. This also mean that it is important to distinguish by comparison, a perturbation on the residual due to another sensor fault.

4 SIMULATIONS AND PERFORMANCE ANALYSIS

All the simulation were realized with the help of the ProSivic simulator, which permit to simulate the dynamic behavior of a vehicle, and the real reaction registered by the sensors. This simulator allow us to determine the trajectory and the speed of a vehicle and will return us all the others component of the mobile state, like position, acceleration, angular speed…

In order to illustrate the response to a faulty comportment, a gain on the speed measurement of the left front wheel has been injected to simulate a failure, 100 seconds after the beginning of the simulation.

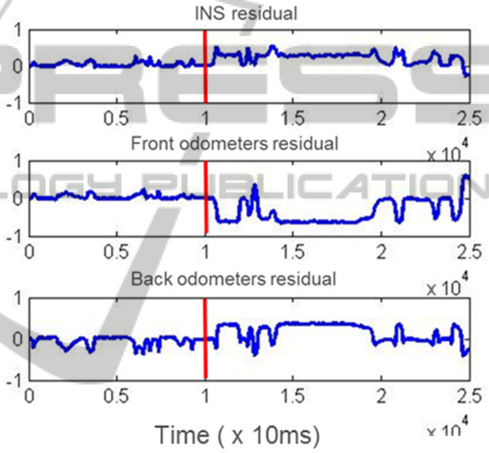

Figure 7: Comportment of residuals with the introduction of a faulty comportment on one of the sensors.

Figure 7 presents the residuals for respectively the INS, the front and the back odometers for the angular speed determination. As predicted, the amplitude of the residual value is increasing after the injection of a failure, and the most important raise coming from the affected sensor. It also appears that the residual of the faulty sensor is the opposite of the others sensors as prove equations (11) and (12). As the appearance of a failure will create an event different for each type (Detecting a rotation in a straight line mode, an acceleration in a constant speed mode) but will remain undetectable during some dynamic mode. It's so important to go through every dynamic mode to be sure to detect failures. For example, a failure on an odometer as presented previously will introduce a rotation even if the real dynamic mode is descripting a straight line. But if the vehicle remains in a rotation, the detection cannot be done. A better way is to analyze the mean values of all the residual on a long time period with the occurrence of all the dynamic mode in order to realize the detection.

We can observe in figure 8 that the mean value of each residual is varying according to equation (13) and (14), but it's necessary now to determine decision laws to minimize the false alarms and missed detections rate. The optimization will be part of the future work. For now, we assume that the detection is decided by a threshold determined analytically at 0.4. In that case, after the detection the faulty data source will not be taken into account in the mean value computation, just as described in equation (9) where the corresponding decision coefficient *C* will be equal to 0. The residual of a non-faulty and a faulty sensor will so be as described respectively in equation (15) and (16).

$$R(Acc|S_{NF}) = Po(Acc|S_{NF}) - \overline{Po}(Acc|S_1, S_2 ... S_N) \quad (15)$$

$$R(Acc|S_F) = Po(Acc|S_{NF}) + \Delta Po - \overline{Po}(Acc|S_1, S_2 ... S_N) \quad (16)$$

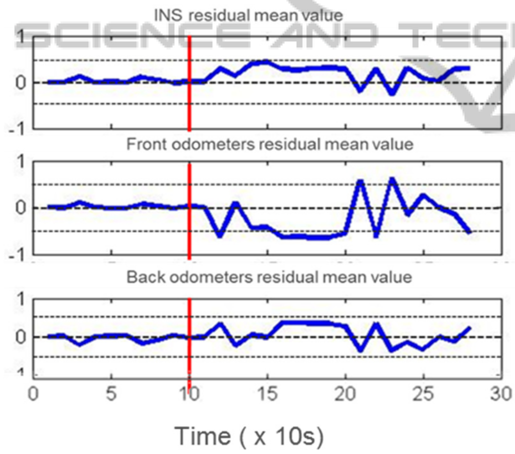

Figure 8: Residual mean value calculated every 10 seconds for each sensor.

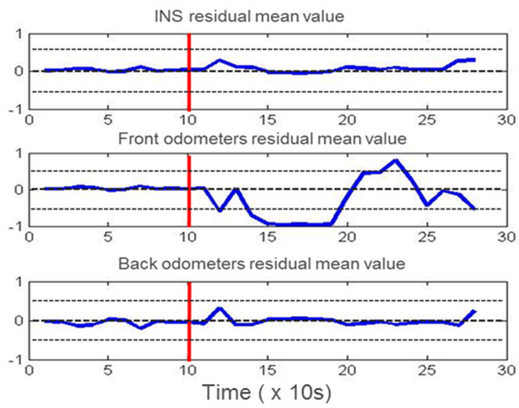

Figure 9: Residual mean value taking into account the decision procedure.

The perturbation for a non-faulty sensor will so be zero centered while the perturbation for a faulty one will correspond to the perturbation on the weight *ΔPo*.

As predicted, incorporating the decision process will keep the non-faulty residuals around zero and increase the faulty residual value.

A second set of simulations has been run in order to illustrate the detection of a failure corresponding to an offset appearing on the acceleration given by the INS. In these simulations we varied both the offset values and the threshold sensitivity σ to study their impact on the fault detection. Figure 10 present the results of the fault detection according to σ and the offset value.

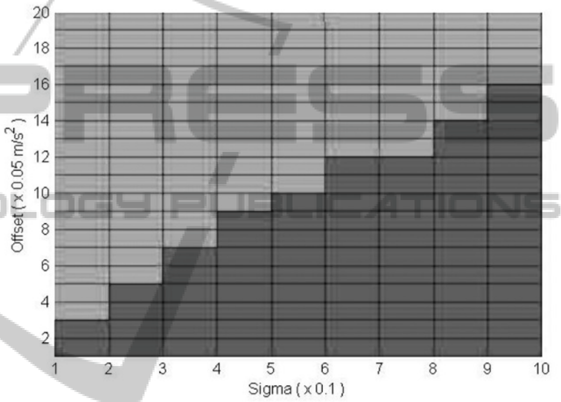

Figure 10: Fault detection according to sigma and offset value.

The red zone correspond to a good fault detection, and the blue correspond to a missed detection. It's so possible to see that reducing the σ value permit the detection of smaller faults. But, reducing this value will also mean that the fault detector will be more sensitive to noise. A simulation with different noise levels has also been realized in order to study this sensitivity. A white noise was so injected on the INS measurement only, with an RMS value varying from 0.01 to 0.2 m/s2. A new set of simulation was run, keeping an offset of 0.5 m/s2 (100 seconds after the beginning of the simulation) and varying the sigma value from 0.1 to 1 (just like the previous simulation set).

During the first part of the simulation, when the fault has still not appeared, the presence of noise can create some false alarm when the sigma value is too low.

After the appearance of the offset, the algorithm is working efficiently. As the injected offset is set at 0.5 m/s2, the minimum sigma value needed for the detection will be around 0.5 (as shown by the previous study, figure 10). It seems logical to expect a detection for the sigma values below 0.5 while there will be no detection for the upper values. This is verified in this simulation (figure 12) where the detection is realized for the lower sigma values.

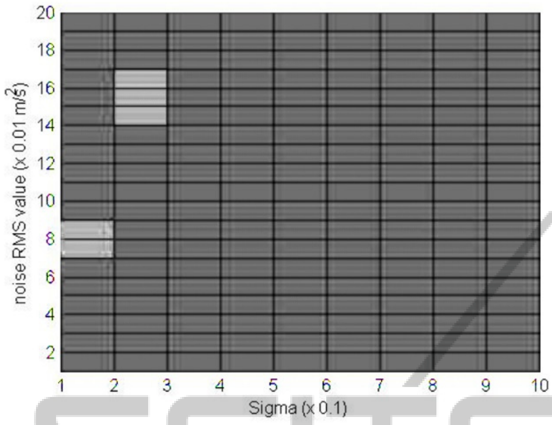

Figure 11: false alarm due to noise when sigma value is too low.

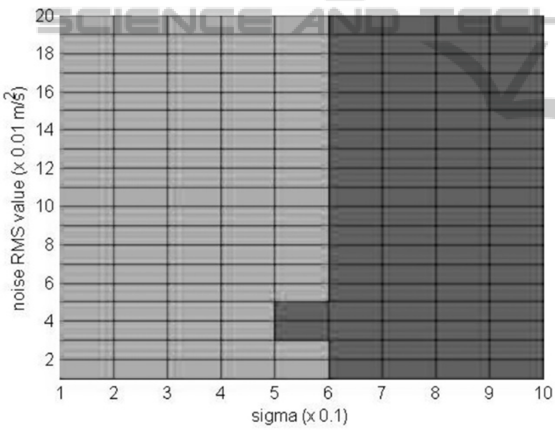

Figure 12: Offset detection with different sigma values varying noise level.

These results verify what has been said earlier, the detection is well done for a sigma value lower than 0.5, for every noise level injected.

For now, the residuals generated permit the distinction of most of the default presented in the section 2, but not all of them. It is still necessary to work on the residual analysis and on others residuals to be able to detect and identify all kind of faults.

5 FUTURE WORK

As it was said in the previous section, the analysis of residuals will lead to the failure detection, and the distinction of which sensor is faulty. But, in our problematic, it's also important to distinguish faults generated by sensors to other ones due to environment interferences or a system perturbation (flat wheel…). So, we need to develop strategies to establish the distinction between each kind of fault.

To bring out this strategy, let's discuss about a concrete case, and compare the results obtained for three different faults.

We imagined a scenario where a fault on one of the odometers appears. This fault is traduced by a gain on the distance measured as described in (17).

$$Dist_{Me} = Dist_{\mathrm{Re}al}(1 - 1/x) \qquad (17)$$

$Dist_{Me}$ is the measures distance, $Dist_{Real}$ is the real distance and x is the number of marks originally presented on the encoded wheel. This kind of fault is generally caused by a missing mark on the coded wheel. It's corresponding to a contact gain failure, as depicted in the second section concerning sensors failures. But, a flat tire could also have an equivalent impact, as the wheel diameter will be reduced, with a same angular speed, the travelled distance will be smaller.

$$Dist_{Me} = Dist_{\mathrm{Re}al}\left(\frac{D_{iF}}{D_{iN}}\right) \qquad (18)$$

Where D_{iF} and D_{iN} are respectively the flat tire and the normal wheel diameter. Mathematically these two errors lead to the same result, but it remains important to be able to distinguish the two of them. In the future work we will focus on this distinction by using a three dimensional model of our system.

6 CONCLUSIONS

This first paper is a presentation of the architecture and preliminary results on the fault detection method proposed.

In this paper a new fault detection architecture was presented, based on a multi-model approach. In a first time, our context was presented before introducing the developed method using both a multi –model approach and a fuzzy logic decision to generate residual variables allowing to distinguish faulty data. As explained in the section 3, the residual will permit to detect perturbation by computing the difference between weights of each sensor independently and a mean value computed with all the sensors. It also has been demonstrated that adding the decision result to the mean value computation will increase the difference between a faulty and a non-faulty residual, which permit a better discrimination between the two of them.

In the simulation results presented in the section four, two study cases have been presented. The first one corresponding to a gain on the odometer speed allowed us to illustrate the calculation proposed on the previous section, and so to verify the efficiency of the proposed FDI. Finally, a study on the sensitivity and robustness has been effected on the second case, presenting an offset on the INS acceleration. This study also permit to determine the importance of the detector parameters configuration according to the noise and the needed sensitivity.

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REFERENCES

Andreas Riener; 2009; *Sensor-Actuator Supported Implicit Interaction in Driver Assistance Systems*; Chapter 9; vieweg-teubner.

Cai Bai-gen; Wang Jian ; Yin Qin ; Liu Jiang, 2009, A GNSS Based Slide and Slip Detection Method for Train Positioning, *Asia-Pacific Conference on Information Processing*, *APCIP 2009*.

Kim, S.-B.; Bazin, J.-C.; Lee, H.-K.; Choi, K.-H.; Park, S.-Y.; 2011; Ground vehicle navigation in harsh urban conditions by integrating inertial navigation system, global positioning system, odometer and vision data; *Radar, Sonar & Navigation; Vol.5; pp 814 – 823.*

Adrien Bak; Dominique Gruyer; Samia Bouchafa; Didier Aubert; 2012; Multi-Sensor Localization – Visual Odometry as a Low Cost Proprioceptive Sensor; *ITSC.*

Rohani, M.; Gingras, D.; Vigneron, V.; Gruyer, D., 2013; A New Decentralized Bayesian Approach for Cooperative Vehicle Localization based on fusion of GPS and Inter-vehicle Distance Measurements; *ICCVE*.

M. Rohani; D. Gingras; D. Gruyer, 2014; Vehicular Cooperative Map Matching; *International Conference on Connected Vehicles and Expo (ICCVE).*

Patton, R.J; Frank, P.; Clark, R.; 1989; *Fault Diagnosis in Dynamic Systems, Theory and Application*; prentice hall.

Xin Qi; Didier Theilliol; Juntong Qi; Youmin Zhang; Jianda Han, 2013; A Literature Review on Fault Diagnosis Methods for Manned and Unmanned Helicopters; *International Conference on Unmanned Aircraft Systems; May 28-31.*

Gruyer, D.; Pechberti, S.; Gingras, D.; Dupin, F.; 2010, Robust positioning in safety applications for the CVIS project; *IEEE Intelligent Vehicles Symposium; pp 262 - 268.*

Mr. Huangqi Sun; Dr. M. Elizabeth Cannon, 1998; Relibaility analysis of an ITS navigation system; *Department of Geomatics Engineering; The University of Calgary; Calgary, Alberta, Canada.*