Sensors fault detection architecture in a strongly uncertain environment

Nicolas Pous¹, Dominique Gruyer², Denis Gingras¹

1. Liv, Sherbrooke University, Canada, nicolas.pous@usherbrooke.ca, denis.gingras@usherbrooke.ca
2. IFSTTAR- IM – LIVIC, Versailles-Satory, France, dominique.gruyer@ifsttar.fr

Abstract: Most of the solutions proposed in fault detection focusing on one part of the analyzed system (Actuators, System, Sensors) supposing other parts in a nominal and well known state. In this paper a new method aiming to complete a sensor fault detection without any assumptions made on the comportment of the rest of the complete system is proposed. For that, a faults identification will be proposed in order to reject defaults due to environmental perturbations or failure in the system or the actuators, as we focus in this paper on sensor fault detection.

Keywords: Fault detection and identification, intelligent vehicle, Localization.

I Introduction

Autonomous or partially automatized vehicles need a perfect knowledge of their environment and attitude, especially about their ego localization to operate safely. To ensure that, the use of GPS receiver is necessary, however if we wish to refine the position estimation without having to use more accurate, but also more expensive GPS receiver (RTK-GPS, DGPS), it’s possible to combine classical GPS data with proprioceptive (Odometers, INS…) and exteroceptive (Lidar, Radar, etc.) sensors using data fusion algorithms to provide a more precise position estimation [1-3]. Cooperative approach has also been studied to improve the estimation result [4-5].

However, the use of data fusion algorithms suffers from reliability issues. Indeed, those algorithms are sensitive to sensor failure as only one failure can lead to a significant error on the position estimation. Since error sources increase by the number of used sensors in the system, the need for a fault detection and identification scheme in order to quickly detect and isolate the corrupted information from the faulty source is inevitable.

In contrast to frequently used model based methods [6], we propose a new FDI (Fault Detector and Identification) architecture which doesn’t need a perfect knowledge of the system behaviour. Others solutions deal with the non-linearity of the system [7]. But, considering both its important non-linearity and the significant interaction with the environment (road condition, weather, etc.) the
Sensors fault detection architecture in a strongly uncertain environment

System behaviour study cannot be taken as a reference for fault detection. Moreover, previously published methods generally assume that, in order to make a proper sensor fault detection, all the other parts of the system are presenting a nominal behaviour [8]. However, system failure (Engine issues, flat tire, etc.) can also, just as the environmental interaction, impact the measurement and be registered by the sensors. Identifying the failure source may be tricky.

This paper’s objectives are to present a sensor fault detection and identification architecture which permit distinction between sensors faults and faults due to other sources. The proposed architecture is inspired by multi-model data fusion algorithm as found in [9] that uses fuzzy decision laws with analytic information redundancy to realize the detection of sensors faults. It consists in finding the current vehicle dynamic mode by computing weights which correspond to the membership degree of a given vehicle dynamic mode regarding the information coming from each sensor independently. Then, a comparison between each weight and a mean value weight calculated instantaneously for all sensors allow to observe behaviour divergence.

In order to insure the distinction between error sources (sensors/system/environmental, etc.), a three dimensional analysis of the vehicle behaviour is also performed.

This paper is structured as follows: the second section will present the fault detector architecture and the primary idea. In the third part, the three dimensional vehicle behaviour will be analysed in order to help for the fault source discrimination. Some simulations results will be presented in section four, with a first part concerning the study of detection algorithm and next simulation about the error source distinction. We conclude this paper in the fifth section.

II fault detector algorithm

As presented in the introduction, our proposed fault detection algorithm was originally inspired by multi-model data fusion approaches. We separate the vehicle behavior in different dynamic modes using a Markov chain model. The dynamic modes will be characterized by the acceleration and the yaw rate (heading change) of the vehicle, as presented in figure 1 and table 1.

![Figure 1 - dynamic mode represented by a Markov chain](image-url)
STRAIGHT       CURVE

<table>
<thead>
<tr>
<th>CONSTANT SPEED</th>
<th>H1</th>
<th>H3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPEED CHANGE</td>
<td>H2</td>
<td>H4</td>
</tr>
</tbody>
</table>

Table 1 – Dynamic modes definition

The Markov chain is designed to constrain the dynamic modes evolution according to Newtonian laws (we can go from reverse gear to forward without stopping the vehicle for example), However in this paper we focus on the four principle dynamic modes, H1 to H4 as described in Table 1.

According to the description of the vehicle dynamic modes, we need both the angular speed and the linear acceleration of the vehicle to determine the current dynamic mode. We will so determine these values with the information of the proprioceptive sensors embedded in the vehicle.

Concerning the INS, these two values will be directly given by the sensor. For the odometer, it is necessary to calculate (derivatives) these values since this sensor provides displacement and wheel angular speed data only. We first compute the vehicle mean speed as follow,

\[ V_{e - S}(t) = \frac{RW_{- S}(t) + LW_{- S}(t)}{2} \] \hspace{1cm} (1)

where \( RW_{- S} \) and \( LW_{- S} \) are the right and left wheel speeds respectively. The acceleration value can be obtained by computing the derivation of the previous equation.

\[ Acc_{od}(t) = \frac{D(V_{e - S})}{Dt} = \frac{V_{e - S}(t) - V_{e - S}(t-1)}{T} \] \hspace{1cm} (2)

Concerning the angular speed of the vehicle, it’s possible to deduce it by computing the differential speed from the two wheel speeds,

\[ Dif_{- S_{od}}(t) = RW_{- S}(t) - LW_{- S}(t) \] \hspace{1cm} (3)

On the other hand, the compass, can provide us with heading and angular speed only, the latter being computed by derivation of the heading \( \theta(t) \).

\[ An_{- Sp_{compass}}(t) = \frac{\Delta \theta(t)}{\Delta t} \] \hspace{1cm} (4)

These equations allow us to determine the two metrics used for the determination of the current vehicle dynamic mode. As not all the sensors can provide information on the two of them (for example, compass, not studied here, will only give information about orientation), the fault detection will be based on them independently, which means that the metrics will be analyzed separately, in order to determine the presence of an acceleration/rotation.

The presence of an acceleration and a rotation will respectively be represented by the variable \( Acc \) and \( V\theta \).
Sensors fault detection architecture in a strongly uncertain environment

Hence the four dynamic modes can be characterized by the four following equations.

\[
\begin{align*}
H1 &= \overline{Acc} \cdot \overline{V\theta} \\
H2 &= Acc \cdot V\theta \\
H3 &= \overline{Acc} \cdot V\theta \\
H4 &= Acc \cdot V\theta
\end{align*}
\] (5)

Instead of performing a standard multi-hypothesis test giving a binary output value for each hypothesis by comparing the sensor data to a fixed threshold, we will instead compute for each hypothesis a weighted value corresponding to a function of the membership degree of its acceleration and its rotation. This is realized as described in figure 2, using a Gaussian membership function to determine the weight.

![Figure 2 - weight determination using a Gaussian threshold](image)

The weight is calculated as follow (example for the INS linear acceleration), with the \(\sigma\) coefficient value allowing to adjust the sensitivity of the detector.

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

The complete fault detection architecture is presented in figure 3. The global hypothesis weight computation is the instantaneous mean value of the weight for each metric (linear acceleration and yaw rate) independently taking into account the weight from every sensor. It is calculated for the \(Acc\) weight value in (7).
Sensors fault detection architecture in a strongly uncertain environment

![Fault detection architecture diagram](image)

**Figure 1 - Fault detection architecture**

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

(7)

Here, $\overline{Po}(Acc|S_1,S_2,...S_N)$ and $\overline{Po}(Acc|S_j)$ are respectively the mean weight for every sensor concerning the acceleration and weight for the sensor $j$, and $C_j$ is the corresponding decision. This decision is represented in the fault detection architecture by the switch before the mean calculation step, which will be controlled by the fault detection algorithm itself. It consists in the rejection of a faulty sensor in the mean ponderation value determination.

The fault detection algorithm will process the residual generated from each sensor, by subtracting its own weight value to the mean residual value coming from all sensors, as described in equation (8).

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

(8)

Assuming that a faulty sensor, uncorrelated with the other sensors output, introduces a perturbation $\Delta Po$ in the weight computation, the residual of a faulty and a non-faulty sensors will then be affected as described by equations (9) and (10), where $Po(Acc|S_f)$ and $Po(Acc|S_{nf})$ are a faulty and a non-faulty sensor weight respectively.

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

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

(9)

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

(10)

According to these equations, we can determine the impact of a perturbation on the residual before the decision ($C\forall(1 \leq i < N) = 1$).

$$\Delta R_f = \frac{N-1}{N} \Delta Po$$

$$\Delta R_{nf} = \frac{-1}{N} \Delta Po$$

(11)

(12)

Once a decision is made and the faulty source is discarded in the mean weight computation, a non-faulty
Sensors fault detection architecture in a strongly uncertain environment

residual will correspond to a zero-mean process and the faulty one will present a perturbation bias equals to the perturbation on the weight, $\Delta P_0$. This behavior will be investigated and illustrated with simulations in section IV.

III Three dimensional behavior analysis

In the introduction, the problem of strong interactions with the environment was discussed. Indeed it appears that a faulty behavior may arise from environmental perturbations, such as deteriorated roads or climate changes, but also from other vehicular malfunctions, like a flat tire for example, which will affect the vehicle dynamic states. As these perturbations will impact the residuals behavior, a three dimensional analysis of the vehicle dynamic will help in the fault detection and identification process.

At first, we analyze the nominal 3D comportment for each of the four principle dynamic modes (H1 to H4). As we know the longitudinal acceleration and the yaw rate defined around the Z-axe (figure 4), constitute the two metrics for the determination of the vehicle dynamic mode.

![Figure 2: Vehicle centered coordinate system](image)

In the following representations (figure 5 to 8), it is possible to observe the theoretical distribution of both acceleration and angular speed for each dynamic mode which can be registered during a scenario. Green distributions are representing the longitudinal acceleration and the Z-axe angular speed, which result of driver maneuvers (acceleration or direction change), will define the different dynamic modes. The others non-zero centered distributions are due to the different forces applied to the vehicle during the driving, as described in [10].

![Figure 3: H1 accelerations (right) and angular speeds (left) distributions](image)
Sensors fault detection architecture in a strongly uncertain environment

Figure 4: H2 accelerations (right) and angular speeds (left) distributions

Figure 5: H3 accelerations (right) and angular speeds (left) distributions

Figure 6: H4 accelerations (right) and angular speeds (left) distributions
To verify these behaviors, Simulations have been run using the vehicle simulator ProSivic (software from Civitec, France), which permit to simulate the dynamic behavior of a vehicle, and the output data generated by the sensors. As it is possible to adjust speed and direction during the simulation, we built a scenario which involves all the four dynamic modes considered in this study. All the dynamic modes have been tested and their behavior validated correspond to the theoretical distributions we use as model. The H4 dynamic mode is presented here in Figure 9 to illustrate the simulation results.

It can be observed in the figure that the angular speed on the X and Y axis alone are not sufficient to be relevant (they remain zero-centered even with a longitudinal acceleration), and the acceleration on the Z-axis is centered on the gravity value (9.82 m/s²) instead of 0, but this component is present on every simulation.

Once the vehicle behavior has been validated for every dynamic mode, it is now possible to use these information in the fault identification algorithm.

IV Simulations

A- Sensor fault detection algorithm

In this section, we will examine the fault detection algorithm performance, assuming that the vehicle present a normal behavior. Once again, we use the ProSivic Simulator software from Civitec to realize the simulation.

To simulate a sensor failure, 100 seconds after the beginning of the simulation, a gain is injected on the front left wheel speed measurement, which physically correspond to a tick lost on the corresponding odometer. The figure 10 shows the residual behavior with the moment of the failure introduction marked by a red line. The graphs are respectively representing INS, front and back odometers residuals. The failure introduction increases the residuals variations for, and it also appears that the faulty sensor will present a
Sensors fault detection architecture in a strongly uncertain environment

residual opposite to others and about twice their values (equations (11) and (12)).

It remains difficult to ensure a detection when the vehicle behavior presents strong accelerations or
direction changes. Indeed, each faulty behavior will affect differently the dynamic mode determination
(apparance of a dynamic change, missed detection of an event…). For example, the appearance of a sensor
failure may induce the detection of a vehicle rotation even if the real dynamic is describing a straight line.
But if the vehicle remains in a rotation, the detection cannot be done.

Figure 10: Comportment of residuals with the introduction of a faulty behavior on one of the
sensors (front odometer)

A better way to ensure the occurrence of each dynamic mode is to analyze the mean values of all the
residual during a long time period involving the occurrence of all the dynamic mode in order to realize the
detection. The decision process is also add to the detection algorithm to reduce non-faulty residuals around
zero and increase the faulty residual value. The mean value is so calculated for 1000 samples, and the result
is presented in figure 11.

Figure 8: Residual mean value taking into account the decision procedure
Sensors fault detection architecture in a strongly uncertain environment

A failure corresponding to an offset appearing on the acceleration given by the INS has also been simulated. In these simulations we varied both the offset values injected on the INS acceleration, and the threshold sensitivity $\sigma$ to study their impact on the fault detection. Results of the fault detection according to $\sigma$ and the offset value are presented in figure 12.

![Figure 12: Fault detection according to sigma and offset value.](image)

The red areas correspond to detection, and the blue correspond to a missed detection. It appears that reducing the $\sigma$ value permit the detection of smaller faults. But, a compromise has to be done to limit the sensitivity to noise of our algorithm.

Increasing the noise level before the injection of the INS failure, some false alarm can appear for the lowest sigma values (figure 13).

![Figure 13: false alarm due to noise when sigma value is too low.](image)

For this set of simulations, the offset value is set at 0.5 m/s$^2$. It means that the minimum sigma value needed for the detection will be around 0.5. It seems logical to expect a detection for the sigma values under the needed value while there will be no detection for the upper values. This expected behavior of the detector has been confirmed in this simulation (figure 14).
A compromise is necessary to make a detector as sensitive as possible without introducing false alarm due to noise present at the sensor output. It could be interesting to use filters to reduce noise impact, but this can mask some faults which are supposed to be detected. This will be part of future investigations.

The proposed architecture is efficient for almost all kinds of failure, assuming that the faulty signal presents a level higher than the programmed sensitivity. This study is still in progress to permit the configuration of the smallest sensitivity possible.

**B- Identification of other sources of failure**

Except from sensors, faults can result from environmental perturbations, vehicle malfunctions or vehicle states changes (process deviations). In order to simulate these sources of malfunctions, three simulations have been realized with the same trajectory but varying some road/vehicle parameters to simulate concrete faults cases, which can generate dynamic changes.

- The first simulation corresponds to a nominal behavior, it will be used as a reference, and it will also be possible to add faults on the sensors data to simulate a sensor fault.

- In the second one, the track parameters have been modified to integrate some perturbations on the road altitude, corresponding to degradations of the surface (holes, undulation…).

- The last simulation represents a flat tire, appearing during a lapse of time and disappearing after that. This is realized by modifying the wheel radius and shock absorber parameters.

To illustrate the behavior of each case, let us first compare the longitudinal acceleration for the same trajectory.
It clearly appears that introducing a road perturbation or a vehicle malfunction will generate a signal perturbation looking like an oscillation on the sensors data. The perturbation noted in simulation 3 presents an oscillation with a period of 30 ms. The oscillation period doesn’t change during all the perturbation time. Concerning simulation 2, the oscillation period seems to depend on the vehicle speed (figure 16).

Studying the oscillation period during stable vehicle speed laps of time permit us to note the values in table 2. As the noise on the road has a spatial frequency, it seems logical to observe such phenomena.

<table>
<thead>
<tr>
<th>VEHICLE SPEED</th>
<th>OSCILLATION PERIOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>22.5 m/s</td>
<td>90 ms</td>
</tr>
<tr>
<td>8.5 m/s</td>
<td>30 ms</td>
</tr>
</tbody>
</table>

Table 1 : Oscillation period according to the vehicle speed

The wheel speed is not affected by the two defaults simulated, so odometers will not suffer of these perturbations either.
Sensors fault detection architecture in a strongly uncertain environment

Observing the residual obtained for the acceleration (figure 17) it clearly appears that false alarm will be generated if the detector consider the residual value only.

Figure 17: Residual value for the acceleration on three sensors (simulation2)

According to the description made in section III, the Z-acceleration is supposed to be zero centered with a very low standard deviation for all the dynamic modes. Its simulated behavior is illustrated in Figure 18 for the simulation 1 and 2. As the simulation behavior of scenario 3 during the appearance of the flat tire is similar to the second simulation, we therefore focus on the results of the second simulation.

Figure 18: Z-Acceleration for the simulation 1 and 2

The two simulations exhibit a zero-mean acceleration, but the energy in the second case seems higher than the first one. Computing the energy over 100 simulations has allowed us to analyze the difference.
The red curve representing the energy for the second simulation is always higher than the blue one (first simulation).

Using this information, it is therefore possible to discriminate sensors failures from vehicle malfunctions or road perturbations due to the environment or system parameters variation. But as the energy of the residuals depends in theory on both the vehicle/environment perturbations and also on the dynamic mode considered (the residual energy for the modes presenting an acceleration is higher), this aspect requires further investigation but these results, showing two different energy levels is encouraging for the distinction between sensors and environment faulty behaviors.

V Conclusion

This paper present the FDI architecture permitting to detect proprioceptive sensor failures. Using the three dimensional comportment analysis, a discrimination between sensors faults and environmental perturbations or system parameters variation has been developed too. The detection algorithm is tested in section IV where two different fault cases are studied. The second case is also used to realize a short performance analyze of the detection algorithm, depending on the detector characteristics and noise. The discrimination process is then studied. Results allow us to observe differences between the behavior with and without perturbation, which can lead to a good discrimination. This study will be continued to ensure the sensor faults detection and identification, rejecting environmental or system perturbations. The improvement of detector performances will also been pursued in further researches.

Acknowledgement

This work is part of CooPerCom, a 3-year international research project (Canada-France). The authors would like to thank the National Science and Engineering Research Council (NSERC) of Canada and the Agence nationale de la recherche (ANR) in France for supporting the project STP 397739-10.

This work is done in the LIV research group (Laboratory of Intelligent Vehicles), in the Electrical and
Sensors fault detection architecture in a strongly uncertain environment

Computer Engineering Department of Sherbrooke University, (www.gel.usherbrooke.ca/LIV/public/), Authors want to thank the LIV group members for their cooperation.

References
3. Adrien Bak; Dominique Gruyer; Samia Bouchafa; Didier Aubert. (2012), Multi-Sensor Localization – Visual Odometry as a Low Cost Proprioceptive Sensor; ITSC proceedings.
4. 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.
7. Mr. Huangqi Sun; Dr. M. Elizabeth Cannon. (1998), Reliability analysis of an ITS navigation system; Department of Geomatics Engineering; The University of Calgary; Calgary, Alberta, Canada.
10. Sébastien Glaser. (2004), Modélisation et analyse d’un véhicule en trajectoires limites Application au développement de systèmes d’aide à la conduite; PhD thesis; Université d'Evry.