Fault detection and identification for proprioceptive sensors using analytical redundancy and road signature determination.

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Abstract—A fault detection and identification architecture is presented using analytical redundancy in order to detect faulty comportment from proprioceptive sensors. The three dimensional comportment analysis is then studied in order to create a road signature. This signature is then studied in order to discriminate sensors faults from environmental perturbation. Finally, some strategies are developed to verify the faulty comportment origin, and so ensure the decision process.

Keywords—sensor fault detection and identification; analytical redundancy; localization; intelligent vehicles.

I. INTRODUCTION

Intelligent vehicles need a high level of knowledge of their environment and behavior to operate safely. This information is generally obtained from the use of embedded sensors which will inform about position, speed, near environment, etc. In this paper, we will focus on proprioceptive sensors generally embedded in a vehicle, and more particularly odometers and INS (Inertial Navigation System), often used in the vehicle localization through data fusion algorithms [1-3] in order to a more precise position determination. However, data fusion algorithms suffer from reliability issues. As only one failure, on one sensor can lead to a significant error on the position estimation, the need for a fault detection and identification scheme is inevitable in order to quickly detect and isolate the corrupted information from the faulty source.

Model based methods are generally used to make the fault detection and identification [4]. The system with its FDI (Fault Detector and Identification) are frequently represented by figure 1. However, these methods generally need a perfect knowledge of the system (in our case, the vehicle) behavior, and also make strong assumptions concerning the fault occurrence, considering faults on only one part of the global system [5]. Some solution permit to deal with system non-linearity [6], but considering our system important non-linearity coupled with significant interactions with its environment will not allow to take the system behavior as a reference in the fault detection process. Some other methods use analytical redundancy which allow to compare the estimation of a chosen metric from sensors of different natures in order to distinguish deviant comportment [7].

![Figure 1: Representation of a system and its model based FDI.](image)

This paper’s objectives are to present a sensor fault detection based on analytical redundancy, which allows, in a first time to determinate the faulty sensors assuming the system working nominally, and in a second time to find a way to reject false alarms due to environmental interactions, using the three dimensional behavior analysis to create a road signature. The concept of road signature has already been studied in [11] and [12] using proprioceptive sensors in the purpose of analyzing driver comfort in urbanized areas.

This paper is structured as follows: the second section will present the fault detector architecture followed in the third section by some simulation results concerning the fault detection. The fourth part will focus on the road signature determination using the three dimensional behavior analysis in order to improve fault identification, and the fifth section will be dedicated to further investigations in that purpose and strategies studied. We conclude this paper in the fifth section.
II. FAULT DETECTION AND IDENTIFICATION ARCHITECTURE

The proposed fault detection and identification (FDI) architecture is inspired by data fusion algorithms like [8], which implies to determine a dynamic mode according to longitudinal acceleration and yaw rate using proprioceptive sensors (in this case, INS and odometers on each wheel). The determination of these two metrics will then allow to evaluate the chosen vehicle dynamic mode as depicted in Table 1.

<table>
<thead>
<tr>
<th>Table 1: Dynamic mode description</th>
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<tr>
<td>Constant speed</td>
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<tr>
<td>Speed change</td>
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The FDI architecture presented in figure 2 consists of the calculation of the membership degree corresponding to the presence of one of the two metrics described earlier. The presence is determined using the selected metric value recorded by every sensor, in a fuzzy logic decision process, as described by (1) and figure 3 for the case of the longitudinal acceleration measured by the INS.

\[
P(\text{Acc|INS}) = 1 - \left[ \frac{1}{\sqrt{0.4 \times (2\pi)^{0.5}}} \right] \exp^{-0.5 \times \text{Acc}_{\text{INS}} / \sigma^2} \]  \tag{1}

Here the \(\sigma\) value corresponds to the sensitivity of the corresponding detector. According to the membership degree equation and the architecture depicted in figure 2, the metrics has to be determined using every sensor. Using this analytical redundancy, will determine faulty comportments from the embedded sensors by comparison of the different membership degrees computed for each sensor independently, and an instantaneous mean value. These mean values calculated taking into account the membership degrees of each sensor for one metric as depicted in (2).

\[
\bar{p}(\text{Acc} | S_1, S_2, ..., S_N) = \frac{1}{N} \sum_{i=1}^{N} C_i p(\text{Acc} | S_i) \]  \tag{2}

Here, \(S_i\) is the \(i^{th}\) sensor, and \(N\) the total number of sensors. The \(C_i\) binary value corresponds to the decision from the fault detector, computed by comparison between the residual absolute value and a threshold fixed analytically, which permits to reject a sensor for the mean value calculation if the algorithm determines the presence of a faulty comportment from this sensor.

Using the determination of both individual and global membership degree, it is now possible to determinate the residual value for one sensor and a given metric, by computing the difference between these two values as depicted by (3).

\[
R(\text{Acc} | S_i) = \bar{p}(\text{Acc} | S_1, S_2, ..., S_N) - p(\text{Acc} | S_i) \]  \tag{3}

Assuming an uncorrelated perturbation \(\Delta P\) on one of the sensors, the residual of the faulty and a non-faulty sensors will then be affected as described by (4) and (5), where \(p(\text{Acc} | S_f)\) and \(p(\text{Acc} | S_{NF})\) are respectively a faulty and a non-faulty membership degree computation.

\[
R(\text{Acc} | S_f) = p(\text{Acc} | S_f) - p(\text{Acc} | S_1, S_2, ..., S_N) \]  \tag{4}

\[
R(\text{Acc} | S_{NF}) = p(\text{Acc} | S_{NF}) + \Delta P - p(\text{Acc} | S_1, S_2, ..., S_N) \]  \tag{5}

The resulting perturbation impact will so depend of the previous decision state. If this is a first detection, then all the fault detection decision will be wrong (No detection, \(C_i \forall (1 \leq i < N) = 1\) ) and the resulting perturbation on the residual will be described by (6) and (7).
\[
\Delta R_F = \frac{N - 1}{N} \Delta P \\
\Delta R_{NF} = \frac{-1}{N} \Delta P
\]

Once a decision is made and the faulty source is discarded in the global membership degree computation, a non-faulty residual will correspond to a zero-mean process and the faulty one will present a perturbation bias equals to the perturbation on the membership degree, \(\Delta P\).

### III. Fault Detection Simulation

All the simulation were realized on Pro-Sivic simulator, which permits to simulate the dynamic behavior of a vehicle, and the real reaction registered by the sensors. It allows configuring vehicle’s trajectory and speed. It will return all the other components of the mobile state like position, acceleration, angular speed, etc.

Few scenarios have been run to bring out fault detector reaction to sensors failures.

First, we consider a gain on the speed measurement of the left front wheel odometer. 100 seconds after the beginning of the simulation, the failure is injected, illustrated by the red line on figure 4, representing the computed residuals for the three sensors sets chosen (INS, front odometers couple, back odometers couple). In order to eliminate punctual perturbations, the results presented here are mean values computed on 100 samples.

As predicted, the non-faulty residuals remain around zero while the front odometers will increase.

In a second time, a set of simulations has been realized to demonstrate the impact of the detector sensitivity, the importance of the failure and the noise level presented by the sensor information.

First, we varied both the offset value and the detector sensitivity \(\sigma\). Figure 5 present the results of the fault detection, with detection represented by red areas and missed detection represented by blue areas.

Reducing the \(\sigma\) value allows smaller faults detection, but reducing it will also make the detector more sensitive to noise. A simulation, increasing noise level, has been realized in order to study this sensitivity to noise. Keeping a failure value at 0.5 m/s\(^2\), we then vary the sensitivity to observe the noise impact on the detection. According to figure 5, an offset of 0.5 m/s\(^2\) needs a \(\sigma\) lower to 0.5 to observe a detection. We so expect detection for the lower \(\sigma\) values (left side of the graph), and missed detection on the right part (Right side of the graph). A white noise have then been injected on the INS measurement with an RMS value varying from 0.01 to 0.2 m/s\(^2\) to analyze its impact on the detection (figure 6).

As expected, we can observe a left side with a detection and a right side with missed detection, but globally it is difficult to discuss about the noise impact on the detection. So, a last set of simulations has been realized, keeping the same noise levels and varying \(\sigma\) but removing the failure. The results are presented in figure 7, and represent the false alarm generated simply by noise injection.
It is now possible to observe that the lowest $\sigma$ values can be perturbed by noise. A compromise is then necessary to ensure detection of low failure values but keeping it above 0.2 to limit false alarm risks due to noise.

IV. ROAD SIGNATURE ANALYSIS

The road signature concept has been inspired by the three dimensional analysis which allows to determine vehicle behavior according to his dynamic mode [9]. In a nominal function, acceleration and angular speed on the 3 axes can be described by figures 8, 9 and 10.

Road conditions modification can appear during the drive, which will bring some vehicle behavior modifications. The main idea here is to determine a road signature using these modifications to help during the faults identification. The appearance of perturbations on the accelerations or angular speed can so be induced by either a sensor faulty comportment or environmental perturbations.

Simulations have been run in order to analyze the vehicle comportment with the appearance of environment change (degrade road quality by injecting altitude fluctuation, simulation 2). As the remaining modifications can be neglected, only the X-axis acceleration is shown here. The resulting X-axis accelerations are presented in figure 11, compared with the nominal behavior (simulation 1).

As the wheel angular speed is not affected by the introduction of environmental perturbation according to our simulations, the odometers will not register any faulty comportment, and the residual value will so be affected as depicted in the previous section. The distinction between a sensor failure and an environmental perturbation has so to be effected using other parameters.

The Z-axis acceleration is then studied to evaluate the difference between sensor and environmental faults. Considering a non-correlated fault on the INS (fault on only one component of the INS), the Z-axis acceleration will remain as the nominal function, while in the case of an environmental perturbation, it will present an higher energy, as depicted in figure 12.
The energy computation over 100 samples gives the results presented figure 13, with the red curve representing the “noisy road” simulation, and the blue one is the nominal function.

![Figure 13: Energy computed on the Z-Axis acceleration for the two simulation setups](image)

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 dynamic modes presenting an acceleration is higher), this aspect requires further investigation.

**V. FAULT ORIGIN DETERMINATION STRATEGIES**

According to faults description proposed in [10], sensors can present faulty comportment which can be similar to the compartment observed in the previous study (figure (11) and (12)). It means that it is still necessary to determine the fault origin by using others techniques.

We propose here, three different strategies in order to make distinction between environmental perturbations and sensor failure.

1. Machine learning can be used to make path recognition and gather experience. As it can be used in this way, it can also attach the road signature to each road segment. Assuming that road signature is not supposed to present brutal changes in time, knowing the previous signature encountered and comparing it to the current one could allow to distinguish the two different fault origins. Here the problem is when a same path is not used twice in a short time. In that case, signature modification can appear and the determination will be more difficult.

2. As the road signature is connected to the environment, it will be common with all vehicles in the same environment. Using a collaborative approach could also be interesting. If vehicles from a same environment can share their road signature determination, a comparison between the two of them will also allow the source distinction. Also, as the comparison is made instantaneously, it permits to deal with signature modification in time. This method needs the presence of other vehicles in the same area to work efficiently.

3. Finally, the last proposition is to use fixed references, which will stock road signature information. This solution permits to deal with problems encountered with the two others proposed solutions, but it will be more expensive as it needs more infrastructure investments.

These three methods are currently studied, and experiment to characterize road signature are run in order to extend this study.

**VI. CONCLUSION**

We presented in this paper a new FDI architecture based on analytical redundancy, inspired by multi-modal data fusion algorithms. This method consisting in the computation of weights corresponding to membership degree of metrics defining the vehicle dynamic mode. Then the difference between a single and a global weight will allow the sensor faulty comportment detection.

The proposed method has been studied in simulation in section three through two different faults cases. The first one allowed to verify theories about the fault detector which have been developed during the section two. The second case permitted the study of both the sensitivity impact on the detector results, and the injection of noise on the sensor information. This second case allowed to establish that a compromise is necessary on the sensitivity level to detect low perturbations values but keeping the sensitivity higher than the values which will allow false alarm due to noise.

In section four, we then discussed about three dimensional vehicle comportment, used in the fault identification by analyzing the 3D accelerations comportments. We introduce in this section, the notion of road signature, developed in the last part. This section presented few strategies currently into study to determine fault origin distinguishing environmental perturbations from sensors faulty comportment.

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