Adaptive and Reconfigurable Data Fusion Architectures in Vehicle Positioning Navigation Systems

Guopei Liu  
Department of Electrical and Computer Engineering  
Université de Sherbrooke  
Sherbrooke (Québec) Canada J1K 2R1  
guopei.liu@yahoo.com

Denis Gingras  
Department of Electrical and Computer Engineering  
Université de Sherbrooke  
Sherbrooke (Québec) Canada J1K 2R1  
denis.gingras@usherbrooke.ca

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ABSTRACT

In positioning navigation systems, at any time, any of the sensors can break down or stop sending information, temporarily or permanently. To ensure a practical solution for use in guidance and navigation systems, faulty sensors must be detected and isolated such that their erroneous data will not corrupt the global position estimates. It is well known that Kalman filter is usually being used for data fusion applications. An interesting novel alternative is to use it for fault detection architecture as well. This paper describes the research conducted to evaluate the potential of combining fault detection and data fusion into a single architecture to make a robust positioning navigation system.

INTRODUCTION

Either from a user’s point of view or a designer’s perspective, any automotive navigation systems should be fully reliable and prevent faults or failures. In all but the most trivial cases the existence of a fault may lead to situations with safety, health, environmental, financial or legal implications. Although good design practice tries to minimize the occurrence of faults and failures, it is recognized that such events do occur. In such cases, faulty sensors must be detected and the system must be able to reconfigure itself so as to overcome the deficiency caused by the fault. In brief, a navigation system must be robust and adaptive.

As mentioned previously, faults can cause the loss of the overall performance of a system, which may present hazards to personnel or lead to unacceptable economic loss. In order to minimize the impact, fault detection schemes must be developed. Actually, many fruitful research efforts in the field of fault detection and filter based adaptive architectures, combining fault detection and data fusion, is proposed to improve the reliability and adaptability of various control systems [Reference]. However, little has been published in the area of automotive navigation systems.

FAULT DETECTION ARCHITECTURE

A fault is usually defined as an undesired change in system estimated parameters that degrade partial or overall performance. Fault detection is a binary decision making process. Either the system is functioning properly, or there is a fault present.

Generally speaking, fault detection consists of two processes: residual generation and decision making, as shown in Figure 1 [4].
Residual Generation

Residuals are defined as the resulting differences between analytically redundant quantities in the system model. These are similar to innovations generated by a Kalman filter, which are the differences between the measured and estimated outputs. Under normal conditions, residuals are small or zero mean; while the occurrence of a fault causes the residuals to go to non-zero or unusually large values.

Decision Making

The decision making process, which acts as an arbitrator, involves assessing the residuals and identifying when and where any abnormalities occur. This is done through threshold testing both static and dynamic residual behaviors, and various statistical tests, where the thresholds are typically based on signal/residual variance.

![Fault Detection Architecture](image)

**SENSOR FAULTY MODELS**

To be useful, systems must interact with their environment. To achieve this objective, in positioning navigation system, various sensors are used. Generally speaking, a sensor is a device that responds to or detects a physical quantity and transmits the resulting signal to a controller. Position sensors can be designed to detect various parameters (coordinate, distance, direction, or angular velocity) of the position of vehicular mechanical systems. The detail relationship between the position and sensors is shown in Table 1.

Table 1. Relationship of Vehicle Position and Sensor Outputs

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Output</th>
<th>Relation to position</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>Rover position</td>
<td>Directly output position coordinates</td>
</tr>
<tr>
<td>IMU</td>
<td>Accelerations and angular rate</td>
<td>Outputs can be integrated by an INS to obtain the vehicle position</td>
</tr>
<tr>
<td>Odometer</td>
<td>Distance or increment of distance</td>
<td>Position coordinates are determined by dead reckoning from the distance and direction relative to a known location</td>
</tr>
<tr>
<td>Inclinometer</td>
<td>Inclination</td>
<td></td>
</tr>
</tbody>
</table>

So far, although the precision and reliability of sensors are improved significantly with the development of the technology, various sensor faults driven by different situations do exist. In the following, several faulty scenarios of sensors are investigated and discussed.

GLOBAL POSITIONING SYSTEM (GPS) FAULTY MODEL

A low-cost GPS receiver can output the vehicle position and driving speed. However, the measurement is likely to be corrupted by time-correlated noise and the GPS signal is susceptible to jamming. However, the position and velocity measurements do not drift over long periods of time.

A GPS faulty model can be based on four particular parts: typical error budget, environmental interferences, signal lost, and hardware malfunction.

**Typical Error Budget**

The main error sources in GPS are listed in Table 2. These errors can be divided into two categories [1]: common and non common. Common errors are approximately the same for receivers operating within a limited geographic region. Non common errors are unique to each receiver and depend on the receiver type and multipath mitigation technique being used (if any). The point of this classification is that DGPS can effectively remove the common errors.

Table 2. GPS Error Sources and their Approximate Deviation [2]

<table>
<thead>
<tr>
<th>Source</th>
<th>Standard deviation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ionosphere</td>
<td>7.0</td>
</tr>
<tr>
<td>Clock and ephemeris</td>
<td>3.6</td>
</tr>
<tr>
<td>Troposphere</td>
<td>0.7</td>
</tr>
<tr>
<td>Non common</td>
<td></td>
</tr>
<tr>
<td>Receiver noise</td>
<td>0.1~0.7</td>
</tr>
<tr>
<td>Multipath</td>
<td>0.1~5.0</td>
</tr>
</tbody>
</table>

**Environmental Interferences**

GPS satellite signals, as with any other radio signals, are subject to some form of interference and jamming. It is known that GPS satellite currently transmit position information in the 1,500-MHz frequency band with a typical accuracy under 100 meters to anyone in the world who has a simple receiver costing as little as $100. Any electronic systems generating radio signals in
this frequency band, main lobe or side lobe, will tend to be a source of inference to the GPS receiver. With the popularization of personal radio and Wi-Fi devices, electromagnetic interferences, intentional or unintentional, are more and more serious. As an example, the proliferation of ultra-wideband (UWB) devices intended to be mass-marketed to the public could cause harmful interference to GPS.

Signal Lost

GPS is a line-of-sight sensor, and therefore GPS measurements are subject to signal outages. If it cannot “see” four satellites, then it will not produce the expected output. This case is called signal lost. It may include the following scenarios:

- Urban environments with all buildings (the so-called urban canyons).
- Inside parking structures.
- In a long tunnel without any relay station.
- Under heavy foliage.
- Under bridges.

Hardware Malfunction

A GPS receiver hardware malfunction can be caused by any abnormality of its components, such as antenna, amplifier, reference oscillator, frequency synthesizer, wire disconnection, and power lost, resulting to no output, or provide an unstable or incorrect signal.

Normally, the probability of the hardware malfunction of the GPS receiver is very low, so it is not taken into account in this simulation.

Sum up all above, the GPS faulty model can be described as in Figure 2.

**INERTIAL MEASUREMENT UNIT (IMU) FAULTY MODEL**

A low-cost IMU can output the vehicle accelerations and angular rate which can then be integrated by an Inertial Navigation System (INS) to obtain the vehicle position, velocity, and attitude. The advantage of an INS is low sensitivity to high-frequency noise and external conditions. But the measurement error of INS will accumulate if it is not calibrated on-line. The scenarios driving the IMU to a faulty state are discussed in the following:

**IMU Error Sources and Faulty Scenarios**

1. Bias due to bearing torques (for momentum wheel types), drive excitation feedthrough, electronics offsets and environmental temperature fluctuations. Intuitively, bias is any nonzero sensor output when the input is zero.
2. Scale factor error, often resulting from aging or manufacturing tolerances.
3. Alignment errors: Most stand-alone IMU implementations include an initial transient period for alignment of the gimbals (for gimbaled systems) or attitude direction cosines (for strapdown systems) with respect to the navigation axes. Errors remaining at the end of this period are the alignment errors. These include tilts and azimuth reference errors. Tilt errors introduce acceleration errors through the miscalculation of gravitational acceleration, and these propagate primarily as Schuler oscillations plus a non-zero-mean position error approximately equal to the tilt error in radians times the radius from the earth center. Initial azimuth errors primarily rotate the system trajectory about the starting point, but there are secondary effects due to Coriolis accelerations and excitation of Schuler oscillations.
5. Quantization error, which is inherent in all digitized systems.
6. Fault due to one or multiple of the moving parts wear out or jam, or gimbals lock.

**ODOMETER FAULTY MODEL**

An odometer is one of the most common devices used for tracking and relative positioning of vehicles. In the transmission-based odometer, the distance to be determined is based on the number of counts for the wheel and calibration constants which are proportional to the radius of the tire. Thus any potential trends that change the radius and the number of counts can drive the odometer to a faulty output.

**Tire radius change**

The major sources of tire radius variation are listed in the following reference [5]:

**Figure 3. IMU Faulty Model**
1. Tire radius tends to increase as vehicle velocity increases because of increasing centrifugal force on the tire.
2. Tire radius tends to increase as air pressure within the tire increases due to increased tire temperature or other factors.
3. Tire radius tends to increase as tread is worn off during the lifetime of the tire.

**Road Situation**

This kind of error sources depend on the road situation, including:

- Running over objects on the road, slips or skids involving one or more wheels when the vehicle accelerates or decelerates too rapidly or travels on a snowy, icy, or wet road.
- In sharp turns, the contact point between each wheel and the road can change, so that the actual distance between the left and right wheels will be different from the one used to derive the heading.

**Gears Tooth Lost**

An odometer can operate by counting the pass of teeth or tabs of the ferrous wheel mounted on the rotating shaft of the vehicle. If one or more teeth are lost, then the value will abate \( n/t \), where \( n \) is the number of the lost teeth, \( t \) is the total teeth of the wheel. In the real situation, the occurrences of losing three or more teeth are so puny that they can be omitted.

In brief, the wear out of the tire, the pressure of the tire, the velocity of the vehicle, the slippage of the tire, and the gear teeth lost will contribute to the odometer fault.

**INCLINOMETER FAULTY MODEL**

The error sources of the inclinometer may consist of:

1. Error caused by thermal expansion or temperature changes. A normally distribution band-limited white noise is used to demonstrate the thermal noise.
2. Drift, calibration error or quantization error due to analog to digital converter resolution.
3. Electromagnetic interference (the major component of the inclinometer faulty model). It can be a uniform or a Gaussian distribution, or a combination of them. The variance and amplitude depend on the traveling environment.
4. Power lost or hardware malfunction: A permanent fault, but since it is only in a very low possibility, it is omitted in this simulation.

**MAGNETIC COMPASS FAULTY MODEL (FLUXGATE COMPASS)**

A magnetic compass is an inexpensive absolute direction sensor. The main drawback with this device is that the quantity measured, i.e. the intensity and direction of the magnetic field, can be distorted in the presence of metals and other electrical or magnetic fields, such as power lines, transformers and cars’ powertrain system.

Our simulated compass operations include the following error sources:

1. Hilly road error [6]: When the vehicle is traveling over a hilly road, the compass plan will not be parallel to the plane of the Earth surface. The compass measures only the projection of the vector components. This is a short-term magnetic anomaly.
2. Random noise error [6]: a) In the situation of traveling nearby power lines, big trucks, steel structures (such as freeway underpasses and tunnels), reinforced concrete buildings, or bridges (short-term magnetic anomalies); b) In an environment of electrical or magnetic noise, or magnetization of the vehicle body (long-term magnetic anomalies).
3. Calibration error: Misalignment of the compass with respect to the vehicle frame simply results in a constant error. This type of error can also be attributed to an inaccurate estimation of the current declination.
4. Permanent fault: power lost or interface cable disconnected (very low possibility, they are being omitted in the simulation).

## ADAPTIVE DATA FUSION ARCHITECTURE

In positioning navigation system, high precision and reliability with low cost are always pursued. Actually, for road navigation, the benefits of the information obtained by the fusion process make it possible to use multiple less powerful, lower cost sensors to achieve as good a performance as those much more expensive ones. Kalman filter and its derivatives, the most popular data fusion methods, have been used extensively in autonomous or assisted navigation system for several years. But almost all of these applications are based on the assumption that all sensed data are complete and reliable. If one or more sensors are faulty, then the fusion filters will tend to choke. In order to ensure a reliable positioning estimate in the case of faulty sensors, an adaptive approach is proposed as in Figure 4.

![Adaptive Sensor Fusion System](image-url)
vehicle as accurate and reliable as possible. Sensors (GPS, IMU, odometer, inclinometer and compass) data which are used to compute the position and attitude of the vehicle, often involve sources of uncertainties. Meanwhile, a state space model can be constructed from the vehicle dynamic to perform the function of sensor fusion. Both their outputs (measurements and estimates) can be combined together through a particular function so as to generate a residual signal. Passing this signal through a detection process, a decision is made: either the system is running properly, or there is a fault occurring, which leads to the fusion process rerunning to optimize the position estimates.

**PERFORMANCE ANALYSIS**

As mentioned previously, all position sensors have the risk of fault or failure. However, in the practical road driving environment, GPS signal lost, due to line-of-sight, is the most common and frequent event of sensor fault. So in this section, the cases of with and without GPS signal lost, will be considered respectively.

First, suppose there is no GPS signal lost. So, as described in the section of Sensor Faulty Models, uncertainties of the imperfect sensors would be including:

- GPS: environmental interference and typical error source.
- IMU: alignment error, scale factor error, nonlinearity error, and quantization error.
- Odometer: tire radius change, wheel slippage, and gears tooth lost.
- Inclinometer: environmental noise, drift, and electromagnetic interference.
- Magnetic compass: environmental noise, hilly road error, and calibration error.

In order to see the benefit, data with uncertainties from different sensors are fused using a conventional Kalman filter (Figure 5 without shaded blocks) and with the proposed embedded fault detection (FD) module (Figure 5 shaded blocks). The results (trajectory estimates in shaded bold gray line) are printed out comparing with the real trajectory (fine black full line) in Figure 6, and the statistics of their errors are shown in Table 3.

![Adaptive Sensor Fusion Architecture Flow Chart](image-url)

**Figure 5. Adaptive Sensor Fusion Architecture Flow Chart**

From the diagram above, we can see how a residual signal generator and a fault detector are embedded into the conventional data fusion architecture. A Kalman filter approach is used, since it is simpler and more effective to attain the residual signal via state estimation. The key idea is to reconstruct the outputs of the process with the aid of Kalman filter and to use the estimation error, or some particular statistical functions of them to assess the residual signal. Then the faultiness can be detected by considering the residual properties against some threshold. If any information from the sensors is detected to be faulty (residual properties goes over a given threshold), then the corresponding measurements are discarded. In that case, the position estimate need to be re-updated. The detailed flow chart is shown in Figure 5. Note that the shaded blocks are part of the fault detection process.
Table 3. Statistics of Position Errors (no signal lost)

<table>
<thead>
<tr>
<th>Position</th>
<th>SNR (dB)</th>
<th>SNR Gain (%)</th>
<th>Mean (m)</th>
<th>Mean Gain (%)</th>
<th>Variance (m²)</th>
<th>Variance Gain (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>conventional</td>
<td>adaptive</td>
<td>conventional</td>
<td>adaptive</td>
<td>conventional</td>
<td>adaptive</td>
</tr>
<tr>
<td>latitude</td>
<td>11.613</td>
<td>34.470</td>
<td>-49.193</td>
<td>243</td>
<td>1.428×10⁵</td>
<td>1.270×10⁴</td>
</tr>
<tr>
<td>longitude</td>
<td>12.874</td>
<td>-42.881</td>
<td>122.850</td>
<td>386</td>
<td>1.725×10⁵</td>
<td>7.777×10⁴</td>
</tr>
<tr>
<td>altitude</td>
<td>-9.813</td>
<td>93.736</td>
<td>114.159</td>
<td>-22</td>
<td>652.783</td>
<td>315.600</td>
</tr>
</tbody>
</table>

\[ SNR = -10 \times \log \left( \sum_{i=1}^{n} S_i^2 \right) \sum_{i=1}^{n} N_i^2 \]

\[ Gain = \frac{V_{\text{conventional}} - V_{\text{adaptive}}}{V_{\text{conventional}}} \]

S_i and N_i are defined as the values of signal and noise at i-th sampling time.

Table 3 shows that there is at least 50% gain (91%, 54%, 51%) in error variance for the use of adaptive solution comparing to the conventional Kalman filter one.

Now suppose that all uncertainties described before are present at any time and also including a GPS signal lost. Similarly, the trajectories of this case are printed out in Figure 7 and error statistics are listed in Table 4.

Note that the ranges of coordinate for the trajectories (With and Without FD) are not the same. The loss of GPS signal has a huge impact and makes the real trajectory just look like a point in the figure without fault detection.

Table 4. Statistics of Position Errors

<table>
<thead>
<tr>
<th>Position</th>
<th>SNR (dB)</th>
<th>SNR Gain (%)</th>
<th>Mean (m)</th>
<th>Mean Gain (%)</th>
<th>Variance (m²)</th>
<th>Variance Gain (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>conventional</td>
<td>adaptive</td>
<td>conventional</td>
<td>adaptive</td>
<td>conventional</td>
<td>adaptive</td>
</tr>
<tr>
<td>latitude</td>
<td>-41.644</td>
<td>-1.265×10⁵</td>
<td>-47.176</td>
<td>99</td>
<td>2.214×10⁵</td>
<td>1.217×10⁵</td>
</tr>
<tr>
<td>longitude</td>
<td>-41.187</td>
<td>1.624×10⁵</td>
<td>119.183</td>
<td>99</td>
<td>2.586×10⁵</td>
<td>7.480×10⁴</td>
</tr>
<tr>
<td>altitude</td>
<td>-7.079</td>
<td>86.714</td>
<td>115.538</td>
<td>-33</td>
<td>427.985</td>
<td>328.102</td>
</tr>
</tbody>
</table>

Figure 7 shows that in the case of a GPS signal lost, conventional Kalman filter will choke: up to 126km error in latitude! While with the proposed adaptive solution, the error is only 47 meters. As to the error variances, the value of the gain is almost close to 100%.

CONCLUSION

A standard Kalman filter is usually being used for data fusion so as to provide better position estimates while using several poor sensors. The occurrences of sensor faults, which tend to degrade or paralyze the navigation solution, are simply not acceptable. In order to minimize the unexpected impact, many fruitful research efforts in the field of FDI have been made. Actually, by computing the differences between the estimates and the measurements, a residual can be generated and the sensor fault can be detected by a decision making process based on the residual statistical properties. In this paper, fault detection and data fusion are combined
into a single Kalman architecture to construct a fault tolerance, robust and adaptable vehicle positioning system. Tests results show that the proposed Kalman filter based state estimation scheme ensures that the position estimate is always optimal and brings significant benefit to the data fusion system comparing with the conventional fusion architecture, as illustrated in particular for the frequent GPS signal lost case.

ACKNOWLEDGMENTS

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