

Comparison of Data Fusion Techniques for Robot Navigation

Nikolaos Kyriakoulis¹, Antonios Gasteratos¹, and Angelos Amanatiadis²

¹ Department of Production and Management Engineering

² Department of Electrical and Computer Engineering,
School of Engineering, Democritus University of Thrace,
GR-671 00 Xanthi, Greece
agaster@pme.duth.gr

Abstract. This paper proposes and compares several data fusion techniques for robot navigation. The fusion techniques investigated here are several topologies of the Kalman filter. The problem that had been simulated is the navigation of a robot carrying two sensors, one Global Positioning System (GPS) and one Inertial Navigation System (INS). For each of the above topologies, the statistic error and its, mean value, variance and standard deviation were examined.

1 Introduction

Robot navigation is the process that a robot tries to follow a predetermined path, or an obstacle free path. In robotics we are able to use a wide range of different sensors to navigate. The most likely way to provide robustness and flexibility in robot navigation is to mount on the robot more than two sensors that they are integrated correctly and with a proper data fusion technique. However, any measurement is corrupted by noise and device inaccuracies and, thus, isolating this noise is straightforward [1]. Hence, there is a need of a filter in order to obtain measurements that are immune to noise and such one is the Kalman filter [3, 4]. In this paper three topologies were examined, involving the measurements of two sensors, a GPS and an INS. The three proposed topologies include a Kalman filter utilized along with one set of “if...then” rules or with the least mean square method. The data fusion occurs in these set of rules or in the least mean square system. The methods were examined comparatively in both quantitative and qualitative manner.

2 Sensors Selection

The scope of our navigation application is that the robot should be able to determine its real position fast and accurately, i.e. the estimated coordinates to be as close to the real ones as possible. Taking into account the above assumption the outputs of the sensors were obtained in absolute coordinates. The GPS selection was based on its technical characteristics, so that it also produces absolute coordinates, time etc. Besides using the time and the coordinates the robot velocity is obtained. The INS selection was based on its capability to produce output of the same format as the one of the

GPS. The GPS and INS are complimentary sensors and the disadvantages of each other are ideally cancelled. In case of an absence of the GPS signal (due to satellite signal loss), the INS is activated to navigate until the GPS signal is recovered [2].

3 Sensors Fusion for Robot Navigation

To establish accuracy, availability and robustness, the measurements from GPS and INS should be fused. The selection of Kalman filter was based on the nature of the problem itself, i.e. the requirement to compute the actual coordinates. This is to say that the navigation was not about path finding or object evasion. On the other hand, the Kalman filter is capable to manage the coordinates in such a way, that the noise is isolated and the final output is coordinates with lower noise corruption.

3.1 Topologies

Three different topologies were composed and studied. The different topologies involve, apart the Kalman filter, a least mean square function and an expert system, in different arrangements. They all were assessed towards our aim, i.e. the accurate estimation of the coordinates of the robotic platform. These three topologies are described below as thoroughly as possible.

3.1.1 If Then Rules Along with the Kalman Filter

This topology is depicted in Fig. 1. The Kalman filter function is cascaded to a simple “if...then” rules expert system. The system obtains the measurements from the sensors, which subsequently are fed into the “if...then” rules expert system, where the data fusion occurs. Only one measurement will be the input to the Kalman filter.

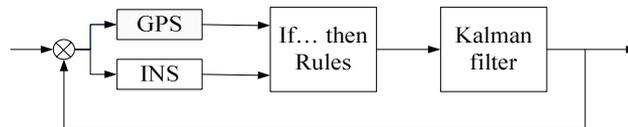


Fig. 1. A Kalman Filter utilized along with an “If...Then” rules expert system

The selection is based on a comparison of the distances between measurements and real coordinates which takes place. The shorter distance is preferred to the longer as it is corrupted lesser by noise. So the input to the filter exhibit as little noise as possible. In the case of both sensors sharing the same noise then the more reliable (comparing to) measurement is selected.

3.1.2 Least Mean Square with the Kalman Filter

The second of the proposed topologies utilizes a “least mean square method” followed by the Kalman filter, as illustrated in Fig. 2. The sensor data fusion occurs in the system that implements a least mean square method. The topology is competed with a cascaded Kalman filter, were the output of the least mean square method is fed, in order to produce the final output.

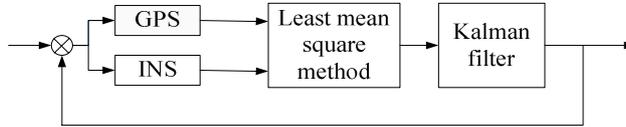


Fig. 2. A Kalman Filter in cascade with a least mean square method

3.1.3 Two Kalman Filters with Least Mean Square

This topology uses similar building blocks as the previous one. Here the sensor data is firstly filtered out by the Kalman filter module, whilst the fusion takes place afterwards. Two parallel Kalman filters are implied, each of which is applied on the sensor data. The outputs from the two filters are fused by the system with the least mean square, where the functions are exactly the same to the previous topology. A block diagram of the process is demonstrated in Fig. 3.

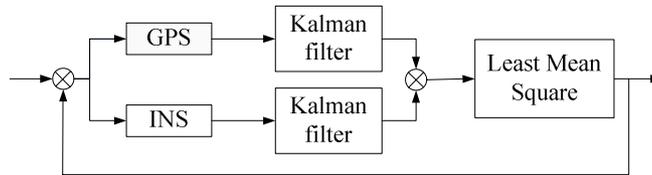


Fig. 3. Two Kalman Filters followed by a least mean square method

4 Comparative Study

All the above proposed topologies were statistically examined. The mean value, the standard deviation and the variance were used as benchmarks. The topology exhibiting the least mean value is the third one (Fig. 4c). The topology with the lowest variance and standard deviation is the second one (Fig.4b). As it is shown to the Fig. 4a, which refers to the first topology, the error’s distribution range is quite long and the density is mostly about 6. In the Fig. 4b and 4c the distribution is bell shaped and the range of the error is from -0.2 to 0.15. Although Fig 4b and 4c are quite similar it is shown that the second one has bigger mean value as the density varies mostly about 5 to 6 above the zero, instead of the third one’s where are distributed around zero.

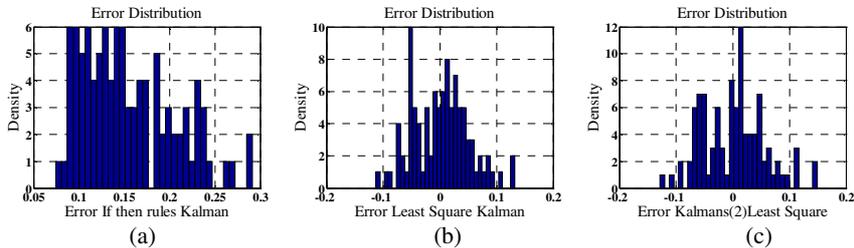


Fig. 4. The error density distribution of the proposed topologies presented in Figs 1, 2 and 3, respectively

Apart from the quantitative comparison, a qualitative one should be approached. Considering the Fig. 5a, 5b and 5c, it could be easily shown that the second topology provide better results. The second topology responses close enough to the ideal landmarks, the bold spots at the referring Figure. The third topology, though it responses closer to the ideal landmarks than the other two, is not as stable as the second one. As it is shown below to the Fig. 5a, 5b and 5c the robot has to follow the bold line which is the ideal one. There are some measurements that take place from the two sensors which are marked with the squares. The final output of the above topologies is the light gray line.

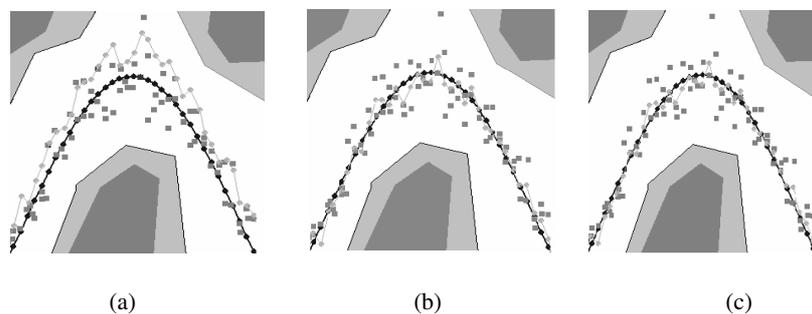


Fig. 5. A mobile robot trajectories corresponding to the topologies presented in Figs 1, 2 and 3, respectively. The rhombuses are the measurements, the bold squares are the real states and the gray cycles are the outputs of the fusion techniques.

5 Conclusion

A comparative study of three different topologies of sensor data fusion was carried out in this paper. The target application is that of determining the exact position of a robot, in order to perform autonomous navigation. The sensors utilized are a GPS and an INS. The choice among the three topologies relies strongly on the nature of the problem that the topology is to be implemented. There are cases in which we want to have a good mean value, but others that we want to have an overall low variance or standard deviation. Furthermore, it is obvious that the implementation of the topology with the If...Then rules requires a high cost, as there are more calculating resources, in contrary to the topology with the least mean square system.

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