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# GPS/IMU data fusion using multisensor Kalman filtering: introduction of contextual aspects

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**Abstract**

The aim of this article is to develop a GPS/IMU multisensor fusion algorithm, taking context into consideration. Contextual variables are introduced to define fuzzy validity domains of each sensor. The algorithm increases the reliability of the position information. A simulation of this algorithm is then made by fusing GPS and IMU data coming from real tests on a land vehicle. Bad data delivered by GPS sensor are detected and rejected using contextual information thus increasing reliability. Moreover, because of a lack of credibility of GPS signal in some cases and because of the drift of the INS, GPS/INS association is not satisfactory at the moment. In order to avoid this problem, the authors propose to feed the fusion process based on a multisensor Kalman filter directly with the acceleration provided by the IMU. Moreover, the filter developed here gives the possibility to easily add other sensors in order to achieve performances required.


*Keywords:* Global positioning system; Inertial measurement unit; Kalman filter; Data fusion; Multisensor system

## 1. Introduction

Autonomous land vehicles (ALV) have different potential applications (goods transport, autonomous taxi, automatic highways,...) and are the subject of intensive researches through the world. ALV need continuous and precise positioning information. Integrity of the positioning system is one of the key factors of such systems.

Two types of sensors are able to give position of a mobile vehicle: absolute sensors (GPS, radar) which take their information in the environment outside the mobile and get the position in an absolute reference frame, and dead-reckoning sensors, which take their information on the mobile itself. In this last case, the position is derived from the last point and the positioning error is therefore drifting with time.

At the present time, the global positioning system (GPS), which is an absolute sensor, is the basic component of a land positioning system. In differential mode, it can reach centimeter precision [11]. However, the lack of credibility of GPS in some cases, due to multipath or mask effects, often leads to mix it with other sensors, such as dead-reckoning ones. These sensors, as for instance inertial sensors (gyroscopes and accelerometers), have the advantage of giving continuous positioning information, independent of the external environment. A package of inertial sensors may be classified into two groups [1]: inertial measurement unit (IMU) which delivers raw data from gyroscopes and accelerometers, corrected from scale factors and biases, and inertial

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navigation system (INS), which is an IMU however the output is sent to navigation algorithms to provide position, velocity and attitude of the vehicle.

Many research works have been led on the GPS/INS data fusion, especially using a Kalman filter [1,3,5]. Structures of GPS/INS fusion have been investigated in [1]. However, experimental results show [2,4,14] that, in case of extended loss or degradation of the GPS signal (more than 30 s), positioning errors quickly drift with time. So GPS/INS association is not a satisfactory association and the solution could be to add other absolute or dead-reckoning sensors, in order to have precise positioning information in any environment.

Fault detection of the GPS signal has also been investigated in [2,3,6]. Sukkarieh [2] introduced a threshold derived from a statistical reasoning to determine whether the GPS data is valid, McNeil [6] proposed weightings on GPS and INS measurements according to fuzzy rules and Stephen [3] introduced a condition on the GDOP (geometric dilution of precision, delivered by the GPS sensor) value.

In this paper is developed a multisensor Kalman filter (KF), which is suitable to integrate a high number of sensors, without rebuilding the whole structure of the filter. By introducing contextual information in the KF, validity domains of each sensor are defined in order to reject bad data when detected, thus increasing the reliability of the data fusion. Reliability is defined here as the robustness to system failures. Integrity of a navigation system is the ability to provide reliable navigation information while also monitoring the health of navigation data and either correct or reject bad data [1].

Basics of multisensor Kalman filtering are exposed in Section 2. Section 3 introduces contextual information as a way to define validity domains of the sensors and so to increase reliability. A basic development of the multisensor KF using contextual information is made in Section 4 with two sensors, a GPS and an IMU. Simulation of the algorithm presented in Section 4 is made in Section 5 with data coming from real experiments. Results are compared in terms of accuracy with a structure based on [1] and specifically developed for the fusion of GPS and INS. First results about the integrity of the filter in case of degradation of the GPS signal are also given.

## 2. Multisensor Kalman filtering

Consider a discrete-time linear stationary signal model (1) [8–10]:

$$x(k+1) = Fx(k) + w(k) \tag{1}$$

where $x(k) \in \mathbb{R}^n$ is the state vector, $w(k) \in \mathbb{R}^n$ is a sequence of zero mean white gaussian noise of assumed known covariance matrix $Q(k) = E[w(k)w(k)^{\mathrm{T}}]$. $F \in \mathbb{R}^{n\times n}$ is the known state transition matrix. In the simplest case, measurements are expressed as a linear relation with respect to the state space variables and are corrupted by noise. The following relation (2) describes the measurements for a set of $N$ sensors:

$$z_i(k) = H_i\, x(k) + b_i(k), \quad i = 1, \ldots, N \tag{2}$$

with $z_i(k) \in \mathbb{R}^l$ the measurement vector of the sensor $i$, $b_i(k) \in \mathbb{R}^l$ the white gaussian observation noise for the sensor $i$ with zero mean and with assumed known covariance matrix $R_i(k) = E[b_i(k)b_i(k)^{\mathrm{T}}]$, $H_i \in \mathbb{R}^{l\times n}$ is the measurement matrix associated to the sensor $i$ and $N$ is the number of sensors. Given the model described by Eqs. (1) and (2), the multisensor KF can be computed as an estimation stage and a prediction stage [12,13,15].

- The estimation stage

$$\hat{x}(k \mid k) = \hat{x}(k \mid k-1) + \sum_{i=1}^{N} K_i(k)[z_i(k) - H_i\, \hat{x}(k \mid k-1)] \tag{3}$$

with

$$K_i(k) = P(k \mid k)H_i^{\mathrm{T}} R_i^{-1}(k) \tag{4}$$

the Kalman gain for the data fusion associated to the sensor $i$, the quantity $z_i(k) - H_i\, \hat{x}(k \mid k-1) = v_i(k)$ is called the innovation associated to the observation from the sensor $i$. The uncertainty on the estimate is given by the matrix

$$P^{-1}(k \mid k) = P^{-1}(k \mid k-1) + \sum_{i=1}^{N} H_i^{\mathrm{T}} R_i^{-1}(k) H_i \tag{5}$$

Proofs of these equations from the derivation of the multisensor information filter are given in Appendix A.

- The prediction stage
  The prediction stage is defined by Eqs. (6) and (7)

$$\hat{x}(k+1 \mid k) = F\hat{x}(k \mid k) \tag{6}$$

$$P(k+1 \mid k) = FP(k \mid k)F^{\mathrm{T}} + Q(k) \tag{7}$$

## 3. Contextual information

Nimier [7] developed a theoretic framework on multisensor data fusion taking context into consideration. He proposed a method to combine symbolic and numerical information, in order to have a supervised fusion process. The supervision is realized by a level of treatment which analyses the context using contextual variables, so that the estimation process is adapted to this context. The result is to favor measurements provided by the sensors well-adapted to the context and to minimize the importance of those that are not well-adapted. GPS sen-