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A novel hybrid approach based-SRG model for vehicle position prediction in multi-GPS outage conditions

Vincent Havyarimana[a], Damien Hanyurwimfura[b], Philibert Nsengiyumva[b], Zhu Xiao[c,*]

[a] Department of Applied Sciences, Ecole Normale Supérieure, 6983, Bujumbura, Burundi
[b] College of Science and Technology, University of Rwanda, Kigali, 3900, Rwanda
[c] College of Computer Science and Electronic Engineering, Hunan University, 410082, Changsha, China

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ABSTRACT

Trajectory prediction in autonomous driving system is an important aspect for preventing for instance the multi-vehicle collision. However, predicting accurately the future location of a vehicle is still a delicate task especially in intelligent transport systems. This paper proposes a hybrid approach of solving the position prediction problem of vehicle in multi-GPS outage conditions such as free and partial as well as short and long complete GPS outages. The proposed approach aggregates the advantages of both fuzzy inference system (FIS) and sparse random Gaussian (SRG) models, consequently named FIS-SRG, leading to a significant decrease in position prediction error of vehicle. The aforementioned outages are defined by adjusting the GPS propagation weight monitored by the Gaussian model and updated by fuzzy logic system. Experimental results based on data from GPS and INS and the comparison study with the existing prediction methods illustrate the good performance of the proposed approach, in all considered GPS outage conditions.

1. Introduction

Since 1940s, predicting vehicle information is an increasing requirement for the development of advanced driver assistance and collision avoidance systems in intelligent transportation system (ITS). In practice, the problem of vehicle localization becomes even more complex especially in challenging environments where GPS signals are weak (i.e., partial GPS outage [1,2]) or absent (i.e., complete GPS outage [2,3]) due to high buildings, multipath reflections, tunnels, etc. Partial GPS outage conditions occur when the number of GPS satellites in-view is less than four [4] or when four satellites in view present a higher geometric dilution of precision (GDOP) [5]. In order to continuously provide vehicle information even during these challenging environments, different data fusion techniques based on global positioning system (GPS) and inertial navigation system (INS) hybridation have been proposed in the literature [6–9]. For example Toledo-Moreo et al. [6] developed an approach (IMM-EKF) based on the interacting multiple models (IMM) and EKF for tracking highly targets whose state and/or measurement models changes during motion transition. Despite the advantages of IMM for solving problems of objects tracking with strong nonlinear dynamics, EKF makes the overall method divergent since the latter is sensitive to the linearization errors which lead to worse estimation accuracies especially during the GPS outage periods [10]. On the other hand, for the successful prediction operation based on GPS/INS integration, the intelligent adaptive neuro-fuzzy inference system (ANFIS) predictor has been also widely used in the literature. The better performance of ANFIS in terms of prediction accuracy, with regard to the other intelligent methods is essentially due to the combination of neural network (NN) and fuzzy logic (FL) system [11]. However, the main drawbacks are related to the training and updating of ANFIS parameters and the poor dynamic adaptation as well as the large calculation amount. Consequently, different methods such as particle swarm optimization (PSO) [12] and genetic algorithm (GA) [9] have been presented to handle the parameter optimization problems. For instance, Hasan et al. [12] proposed ANFIS based on PSO to integrate GPS and INS systems with the intention of providing a robust navigation solution during different GPS outage periods. Although the proposed method presents good performance during short and long GPS outages, the method was not tested under other GPS signal conditions, for example during partial GPS outages. Recently, a probabilistic approach named Bayesian-sparse random Gaussian prediction (B-SRGP) [2] has been proposed to deal with vehicle prediction during free, partial and complete GPS outages. Even

* Corresponding author.
E-mail addresses: havincent12@gmail.com (V. Havyarimana), hadamfr@gmail.com (D. Hanyurwimfura), nsenga_philibert@yahoo.com (P. Nsengiyumva), zhxiao@hnu.edu.cn (Z. Xiao).

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though the proposed prediction method presents better performance, when compared with some existing prediction methods, it also presents some weaknesses related to especially the high computational cost due to the bad managing of the measurement matrix parameters, mainly when the number of sample increases.

Given the above observations, this paper proposes a novel hybrid prediction approach based on low-cost GPS/INS model that provides a better vehicle positioning accuracy even during complete and partial GPS outages. The proposed approach aggregates the advantages of both fuzzy inference system (FIS) and sparse random Gaussian (SRG) models, consequently named FIS-SRG, leading to a substantial decrease in position prediction error of vehicle. The aforementioned outages are defined by adjusting the GPS propagation weight monitored by the Gaussian model and updated by the fuzzy logic system. The strengths of FIS rely on the fact that they are able to not only handle linguistic concepts but also perform non-linear mappings between inputs and outputs. The success of this approach also derives from the fact that it was able to handle the measurement model based on the GPS/INS integration model using sparse random Gaussian (SRG) technique. In order to cope with the optimization problem related to the matrix sparsification, the least absolute shrinkage and selection operator (LASSO) technique is used. Selection (LASSO) technique is one of the suitable estimators widely used to handle the variable selection problem. On the other hand, with the intention of controlling the data flow generated by both INS and GPS and then getting acceptable prediction accuracy during the partial GPS outage periods, the size of sliding window is used as suggested in [13].

The performance of the new prediction method is evaluated with respect to real-world data collected using Smartphone-based vehicular sensing model. FIS-SRG is also compared with the existing prediction methods such as IMM-EKF, ANFIS and B-SRGP during the free, partial, and complete GPS outage periods. The effectiveness of the proposed method was also assessed taking into account not only different dynamics for both short and long complete GPS outages but also different sizes of sliding window for partial GPS outage. According to the experimental results analysis, the proposed FIS-SRG shows great superiority to the aforementioned adopted methods in terms of both prediction accuracy of the vehicle position and mean absolute percentage error (MAPE).

This paper is organized into the following sections: Section 2 describes the system model and problem formulation where a hybrid technique for modeling the free, partial and complete GPS outages is presented. In Section 3, the proposed FIS-SRG algorithm for vehicle position prediction is highlighted whereas the potential of our approach is assessed in Section 4, by presenting the experimental setup and tests as well as the analysis of the results. Conclusions are finally given in Section 5.

2. System model and problem formulation

2.1. Design of the prediction model

Inspired from [2], the values of a continuous dependent variable X from a set of independent variables Z can be predicted using the following nonlinear model:

$$Z_i = f(X_i) + \alpha_i\,, \quad i = 1, \dots, n \tag{1}$$

where Z_i represents the $n \times 1$ response or measurement vector. The variable $X_i \in IR^p$ indicates the $p \times 1$ input to be predicted. The variable α_i stands for the $n \times 1$ error vector and is supposed to be non-Gaussian distributed whereas $f(\cdot)$: $IR^p \to IR^n$ is an unknown prediction function and can be transformed as:

$$Z_i = FX_i + \alpha_i, \; i = 1, \dots, n \tag{2}$$

Here, F indicates the $n \times p$ measurement matrix or predictor matrix, with $n < p$ and is assumed to be a sparsified random Gaussian matrix whose entries F_{ij} are given by:

$$F_{ij} = \begin{cases} N\left(0, \frac{1}{\delta}\right) & w.p.\ \delta \\ 0 & w.p.\ 1-\delta \end{cases} \tag{3}$$

where $\delta \in [0, 1]$ is the measurement sparsification parameter. Random matrix has been used as measurement matrix in many situations to model systems from the physical world independent [14]. Moreover, mathematical theory of random matrices can help to solve statistical problems where a large number of variants are involved. The choice of this sparsified matrix is motivated by the fact that the sparse property not only enhances the speed of measurement model but also increases the memory space to store the sample data and therefore provokes a significant impact on measurement accuracy. However, due to its rectangular dimensions, F should satisfy the restricted isometry property (RIP) [15] and for better prediction, the sparsified random Gaussian matrix F requires the RIP with high probability [2].

Based on (2), the measurements of GPS and INS are given by $Z_{GPS,\,t}$ and $Z_{INS,\,t}$ where $Z_{GPS,\,t} = F_{s,t}X_{GPS,\,t} + \alpha_{GPS,\,t}$ and $Z_{INS,\,t} = F_{s,t}X_{INS,\,t} + \alpha_{INS,\,t}$ respectively; where $F_{s,\,t}$ is the s-sparse predictor matrix constructed based on (3). The variable $X_{GPS,\,t}$ indicates the position in terms of latitude and longitude provided by GPS and $X_{INS,\,t}$ represents data provided by INS over the sample time t. Moreover, variables $\alpha_{GPS,\,t}$ and $\alpha_{INS,\,t}$ are the GPS and INS measurement noises and are assumed to follow the multivariate t-distribution [16,17]. The main reasons of modeling measurement noise as non-Gaussian instead of Gaussian distributed for state estimation can be found in [2, 17–19]. On the other hand, the GPS weight denoted as λ_{GPS} is assumed to be Gaussian distributed and is determined based on the Gaussian PDF as follows [2]:

$$\lambda = \left[(2\pi)^{1/2}|R|_{GPS}\right]^{-1} \exp\left[-\frac{1}{2}(GPS - \mu_{GPS})^T {R_{GPS}}^{-1}(GPS - \mu_{GPS})\right] \tag{4}$$

where R_{GPS} and $|R|_{GPS}$ indicate the covariance matrix of GPS and its determinant respectively whereas μ_{GPS} represents the mean value of GPS measurement. Moreover in Eq. (4), "GPS" indicates that measured information is coming from the GPS unit.

Since the GPS weight is defined using Gaussian PDF, its values vary from 0 to 1 [20] (i.e.$\lambda_{GPS} \in [0, 1]$). In fact, the GPS weight λ_{GPS} is calculated by integrating the PDF λ.

The aim of λ_{GPS} is to determine free, partial and full GPS outages based on its different values. These values especially depend on the number of GPS satellites in view as explained in the following Section.

2.2. A hybrid technique for modeling the free, partial and complete GPS outages

Instead of trying to adjust parameters related to both the GPS weight and measurement sparsification, we used respectively fuzzy inference system (FIS) and the suitable optimizer technique to define a set of these parameters. That leads to good performance and convergence of the proposed method. In this procedure, the initial state variable estimates are obtained by means of sparsified random Gaussian (SRG) model and then, all current states are updated using fuzzy inference system (FIS) to obtain optimal predicted states. Indeed, during the free GPS outage where the number of available satellites is at least four [4], all available GPS measurements are trained according to Eq. (5). In this case λ_{GPS} is supposed to be equal to 1 and the inputs coming from INS are ignored. Moreover, when GPS signals are absent (no GPS satellites available to the receiver), that is, during the complete GPS outage, the GPS weight is assumed to be small or negligible (in our case, that is $\lambda_{GPS} = 0$) and the FIS trained measurements was provided only by