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Improving low cost sensor based vehicle positioning with Machine Learning

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A B S T R A C T

Current fleet management solutions rely on real time vehicle information to efficiently resolve transportation problems. In this study, a novel robust approach based on combining the Extended Kalman Filter (EKF) with Machine Learning techniques, Neural Networks or Support Vector Machines, is introduced to improve the accuracy of vehicle position estimation and circumvent the EKF limitations. The proposed solution guarantees also a low cost by using the Global Positioning System enhanced with Dead Reckoning integrated sensors. To verify our approach, extensive simulation tests are conducted on field data sets and very promising progress is obtained in the estimated vehicle position.

1. Introduction

Context. The main concern of a smart city is to improve the quality of life despite the challenging problems emerged by the rapid urban growth. It relies on the use of information and communication technologies in various functional domains to ensure an intelligent urban development and a sustainable socio-economic growth (Neirotti, Marco, Cagliano, Mangano, & Scorrano, 2014). Smart cities integrate, among other solutions, intelligent transportation systems (ITS) that offer a safe transport environment with regard to cost reduction and efficiency enhancement. One way to meet these expectations is the deployment of fleet management systems as they ensure a real time tracking and an online control monitoring for a fleet of vehicles (Gowda & Gopalakrishna, 2015). This has a positive impact on optimizing vehicle routing and reducing fuel consumption but requires having clear visibility on each vehicle location under real time and low cost constraints.

Most navigation systems rely on the Global Positioning System (GPS) since it determines the location, altitude and velocity based on satellite signals received. However, the GPS performance is limited by different factors such as the effect of atmospheric disturbances and multipath phenomenon, where one or more signals arrive at the GPS antenna by indirect paths (Bilich & Larson, 2007), that can happen within urban environment or beneath dense foliage. With the use of Differential GPS (DGPS), it is possible to remove some GPS errors through corrections that a reference GPS receiver at a known location provides. Another option is to combine GPS and Inertial Navigation Systems (INS) for measuring the position without interruption. The INS are self-contained systems that regroup a set of sensors: three or more accelerometers and gyroscopes and a navigation computer used to calculate the position, velocity and attitude.

To fuse data coming from multiple sensors, a Kalman Filter (KF) is typically applied. The filter is a recursive algorithm that optimally estimates an unknown state of a linear dynamic system starting from uncertain and noisy observations (Gao & Harris, 2002). For non-linear systems, the Extended KF (EKF) is adopted through a linearization procedure using Taylor series expansion.

Problem. The impact of multipath errors on positioning estimates remains even when using differential *high cost* corrections. Additionally, the INS impose restrictions on the environments where they are implemented because of their computational *complexity*. The KF performance depends on the accuracy of the stochastic modeling of sensors. It also requires a priori knowledge of system noises and measurement errors. Relatively, the KF estimated position quickly *diverges* when GPS outage happens.

Contribution. This paper explores the application of a novel low cost robust approach combining EKF and Machine Learning (ML) techniques notably the Neural Networks (NN) or Support Vector Machines (SVM) for an optimal real time car positioning in a smart city. For this, the GPS aided Dead Reckoning (DR) sensors (i.e., an odometer to provide the distance traveled by the vehicle and a gyrometer to measure the angular velocity) is used. It is a simple and easy to deploy mechanism. During

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List of acronyms

BPLA	Backpropagation Learning Algorithm
DGPS	Differential GPS
DR	Dead Reckoning
EKF	Extended KF
GA	Genetic Algorithm
GPS	Global Positioning System
IMU	Inertial Measurement Unit
INS	Inertial Navigation Systems
ITS	Intelligent transportation systems
KF	Kalman Filter
LS-SVM	Least squares SVM
MAE	Mean absolute error
MEMS	Micro-Electro-Mechanical Systems
MFNN	Multilayer feed-forward NN
ML	Machine Learning
MSE	Mean squared error
NN	Neural Networks
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
RMSE	Root mean square error
SRM	Structural Risk Minimization
SVM	Support Vector Machines
UKF	Unscented KF
ε-SVR	ε-Support Vector Regression

GPS signal presence, the EKF computes the vehicle position and the ML module is trained in the meantime with various optimization techniques (i.e., Backpropagation Learning Algorithm (BPLA), grid search, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)) to model the position errors. When GPS outage occurs, the ML module limits the EKF drawbacks by compensating the additional position errors.

Contents. The rest of this paper is organized into several sections. Section 2 presents an outline of some relevant works on this topic; Section 3 covers the essential background on EKF and ML techniques; Section 4 describes our suggested approach and Section 5 details the simulation results.

2. Related works

Several works (Lucet et al., 2009; Shen, Georgy, Korenberg, & Noureldin, 2011) suggest that vehicle positioning can be achieved by combining GPS and DR system due to their complementarity. The DR system relies on odometer and gyrometer readings to estimate the position given known initial values. Although its full availability and ability to operate independently of any signal outage, the DR precision is limited in a long term because of time growing errors such as bias drift and scale factor change. Consequently, the integrated GPS/DR system helps to mitigate the DR errors when GPS is available and to overcome the positioning discontinuity induced by GPS signal outages. Furthermore, such system costs much lower than other solutions as presented in Table 1.

Godha and Cannon (2005) suggest using the KF to integrate data coming from the system DGPS/INS based on Micro-Electro-Mechanical Systems (MEMS) for the estimation of sensor errors. The MEMS technology is characterized mainly by its affordable cost and small size but suffers from a rapid growth of errors in the position estimation when operating for a long time in stand-alone mode (Park & Gao, 2008). In their work, St-Pierre and Gingras (2004) use a GPS receiver coupled to IMU/odometer/inclinometer sensors for position estimation of land vehicle navigation applications. In this sense, they compare the performance of Unscented KF (UKF) to that of EKF. Experiments show the inability of UKF to provide better results during GPS signal outages in addition to its high computational time.

As an alternative to KF, Chiang et al. (2003) propose the use of multilayer feed-forward NN (MFNN) with BPLA for DGPS/INS data fusion. The principle of NN is processing information in parallel so as to map inputs to desired outputs by learning from given samples. NN are commonly trained using BPLA but there are other techniques namely GA and PSO (Malleswaran, Vaidehib, & Sivasankari, 2014). However, the solution DGPS/INS is very expensive as depicted in Table 1. Also the ML models require that observations should be sufficient enough to enhance the precision of estimated position.

Nevertheless, it can be inadequate to substitute the EKF with NN for all case studies: Belhajem, Ben Maissa, and Tamtaoui (2016) introduce a hybrid approach combining EKF and NN based on a low cost GPS/DR system, the goal is to deal with the precision degradation during the EKF prediction phase. Two MFNN are trained to learn the north and east position errors for given inputs that include time elapsed since last GPS measurement, velocity and heading angle. They can then compensate the EKF drifts when no GPS signal is available. In the same perspective, Xu, Li, Rizos, and Xu (2010) describe the GPS/INS integration module relying on least squares SVM (LS-SVM) and KF hybrid method to correct the INS errors when losing the GPS signal. They obtained better results than INS-only solution during GPS signal outages. SVM are supervised learning algorithms whose objective is to build a model well suited for unseen samples, the common way to select optimally the SVM parameters is the grid search but it is possible to use GA (Tan, Wang, Jin, & Meng, 2015) or PSO (Lin, Ying, Chen, & Lee, 2008).

3. Background

In this section, an overview of the EKF, NN and SVM is presented. Also, a background of evolutionary algorithms notably the GA and PSO is covered.

Table 1
Approximate cost of positioning solutions.

Study	Proposed solution	Experimental setup	Approximate cost
Our approach	GPS/DR system	• GPS Trimble AG132 antenna • Built-in anti-lock braking system • Grove Gyro	<200 $
Bonnabel, Deschaud, and Salaün (2011)	GPS/Inertial Measurement Unit (IMU) coupled to two wheel speed sensors	• GPS Trimble AG132 antenna • Crossbow VG600 IMU • Two speedometers	>11,100 $
Chiang, Noureldin, and El-Sheimy (2003)	DGPS/INS	• NovAtel BDS GPS/IMU (the IMU is a Honeywell HG1700)	>34,000 $
Bhatt, Aggarwal, Devabhaktuni, and Bhattacharya (2012)	GPS/INS	• NovAtel OEM GPS • Crossbow IMU 300CC-100	>10,500 $