Available online at www.sciencedirect.com
ScienceDirect
Engineering Applications of Artificial Intelligence 20 (2007) 49–61
Engineering Applications of ARTIFICIAL INTELLIGENCE
www.elsevier.com/locate/engappai

Optimizing neuro-fuzzy modules for data fusion of vehicular navigation systems using temporal cross-validation

Aboelmagd Noureldin[a,*], Ahmed El-Shafie[a], Mahmoud Reda Taha[b]

[a]*Department of Electrical and Computer Engineering, Royal Military College of Canada, P.O. Box 17000 STN Forces Kingston, Ont., Canada K7K7B4*
[b]*Department of Civil Engineering, University of New Mexico, Albuquerque, NM 87131-0001, USA*

Received 10 May 2005; received in revised form 14 November 2005; accepted 1 March 2006
Available online 22 May 2006

Abstract

The last two decades have shown an increasing trend in the use of positioning and navigation technologies in land vehicles. Most of the present navigation systems incorporate global positioning system (GPS) and inertial navigation system (INS), which are integrated using Kalman filtering (KF) to provide reliable positioning information. Due to several inadequacies related to KF-based INS/GPS integration, artificial intelligence (AI) methods have been recently suggested to replace KF. Various neural network and neuro-fuzzy methods for INS/GPS integration were introduced. However, these methods provided relatively poor positioning accuracy during long GPS outages. Moreover, the internal system parameters had to be tuned over time of the navigation mission to reach the desired positioning accuracy. In order to overcome these limitations, this study optimizes the AI-based INS/GPS integration schemes utilizing adaptive neuro-fuzzy inference system (ANFIS) by implementing, a temporal window-based cross-validation approach during the update procedure. The ANFIS-based system considers a non-overlap moving window instead of the commonly used sliding window approach. The proposed system is tested using differential GPS and navigational grade INS field test data obtained from a land vehicle experiment. The results showed that the proposed system is a reliable modeless system and platform independent module that requires no priori knowledge of the navigation equipment utilized. In addition, significant accuracy improvement was achieved during long GPS outages.

Keywords: Neuro-fuzzy modeling; Sensor integration; Navigation systems

1. Introduction

The last two decades have shown an increasing trend in the use of positioning and navigation technologies in land vehicle applications including automated car navigation, emergency assistance, fleet management and automotive assistance. The convergence of location, information management and communication technologies have created a rapidly emerging market that is presently pushing hard for the development of reliable in-vehicle navigation and guidance systems (Lobo et al., 1995; El-Sheimy and Selwarz, 1994). Most of the current vehicular navigation systems rely on global positioning system (GPS) that is capable of providing accurate position and velocity information, especially when operating in differential mode (usually called DGPS). To be able to provide such accurate measurements, GPS needs at least four satellites with good geometry. In addition, there must be direct line of sight between the GPS antenna and those satellites. Unfortunately this is not the case at all the time since a GPS signal may be lost when driving around obstacles (downtown area, high passes or tunnels on highways, tree lined streets, etc.), or with poor weather conditions (Farrel, 1998). The satellite signal blockage results in deterioration of the overall position accuracy. Therefore, GPS is usually incorporated with inertial navigation system (INS), which is a self-contained system that incorporates three orthogonal accelerometers and three orthogonal gyroscopes, which measure three linear accelerations and three angular rates respectively. Those sensors, when mounted on the moving platform, point to three mutually orthogonal directions called the body frame (b-frame), which is defined along the

*Corresponding author. Tel.: +1613 541 6000x6366;
fax: +1613 544 8107
E-mail address: noureldin-a@rmc.ca (A. Noureldin).

0952-1976/$ - see front matter
doi:10.1016/j.engappai.2006.03.002

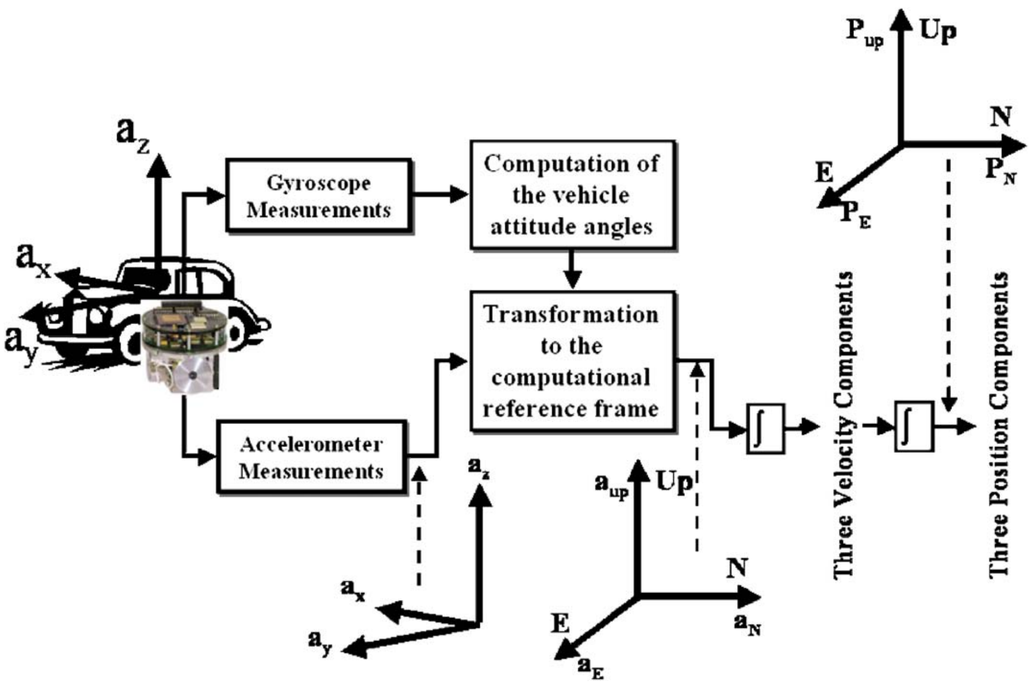

Fig. 1. Schematic diagram showing INS mechanization process.

forward, transverse and vertical directions of the vehicle (See Fig. 1). The position of the vehicle (determined by GPS or INS) is provided at the local level frame (*l*-frame). As shown in Fig. 1, the *l*-frame axes are defined along the East (E), the North (N) and the vertical (Up) directions. Transformation between both frames is possible through a 3×3 transformation matrix (Titterton and Weston, 1997).

As shown in Fig. 1, a set of mathematical transformations and integrations with respect to time are applied to the raw measurements from the INS sensors that monitor the vehicle acceleration and angular velocities along three mutually orthogonal directions. The angular velocity measurements of the three-axes gyroscopes are employed to determine the vehicle attitude angles that are utilized to obtain the transformation matrix (Titterton and Weston, 1997). This matrix is mathematically used to transform the vehicle accelerations (a_x, a_y and a_z) from the body frame to the *l*-frame. The transformed accelerations (a_E, a_N and a_{up}) are then integrated to determine the vehicle velocities and position components along the East, North and vertical directions.

During the mechanization process, the accuracy of INS position components deteriorate with time due to the inherit sensor errors that exhibit considerable long-term growth (Mynbaev, 1994; Noureldin et al., 2002). Those errors include white noise, correlated random noise, bias instability, and angle random walk (IEEE Std. #647, 1995). In fact, these errors can cause a significant degradation in the INS performance in the long-term. To overcome the shortcomings of stand alone GPS or INS, both systems are integrated into a single navigation system. Data fusion of the integrated system has been carried out for many years using Kalman filtering (KF) (Hostetler and Andreas, 1983; Hargrave, 1989), which utilizes a dynamic model of INS position, velocity and attitude errors as well as stochastic model of sensor errors. In fact, several shortcomings related to KF-based INS/GPS have been reported in the literature (Hargrave, 1989; Scherzinger and Reid, 1994; Algrain and Ehlers, 1995; Nassar et al., 2004; Brown and Hwang, 1992). The major inadequacy related to the utilization of KF for INS/GPS integration is the necessity to have a predefined accurate stochastic model for each of the sensor errors (Scherzinger and Reid, 1994; Algrain and Ehlers, 1995). Furthermore, prior information about the covariance values of both INS and GPS data as well as the statistical properties (i.e. the variance and the correlation time) of each sensor system has to be known accurately (Nassar et al., 2004; Brown and Hwang, 1992).

1.1. AI-based data fusion techniques

Limitations of KF-based INS/GPS motivated researchers to investigate alternative methods, predominantly based on artificial intelligence (AI) (Vanicek and Omerbasic, 1999; El-Sheimy et al., 2004). Recently, INS/GPS integration algorithms based on multi-layer perceptron (MLP) neural networks have been suggested and applied to different types and grades of INS (Vanicek and Omerbasic, 1999). It has been shown that a position and velocity update architecture (PVUA) utilizing two MLP networks can process the INS azimuth and velocity and provide the position components along both the East and North directions (El-Sheimy et al., 2004). The parameters of the MLP networks are adapted using GPS position and velocity updates. However, the PVUA system did not provide an update scheme for the vertical position