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Optimal multisensor integrated navigation through information space approach

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ABSTRACT

Although the centralized Kalman filtering (CKF) solution is widely accepted as providing the globally optimal parameter estimation for multisensor navigation systems, it has inherent defects such as heavy communication and computational load and poor fault tolerance. To address these problems decentralized Kalman filtering (DKF) methods have been proposed. The DKF is configured as a bank of filters instead of the central filter, and aims to achieve the same level of accuracy as the CKF. This CKF-based approach however is found to be too rigorous to limit the further development of DKF algorithms. This paper proposes an alternative framework for resolving the optimal state estimation problem of multisensor integration. The data fusion algorithm is implemented through a series of transformations of vectors from one space into another. In this way, the vectors in the source information spaces are transformed into the estimate information space, where the globally optimal solution is obtained simply by a sum of these transformed vectors. The paper demonstrates how easy it is to derive the conventional DKF algorithms, such as the federated Kalman filter that has been widely applied in the multisensor navigation community. A new global optimal fusion algorithm is derived from the proposed approach. Simulation results demonstrate that the algorithm has higher accuracy than the CKF.

1. Introduction

Although Global Navigation Satellite System (GNSS) technology is now widely used in more and more applications, the major disadvantage of GNSS will still remain even when the Russian GLONASS system, the European Galileo system, or the Chinese Compass system are fully operational, that is, signal blockage due to obstructions in urban canyons and extreme power attenuation of the signals in indoor environments. The combination of GNSS with other sensors, such as a self-contained inertial navigation system (INS), provides an ideal solution which can not only address the weakness of GNSS, but also bound the INS error that otherwise would grow with time when the INS operates alone. The current progress in the development of microelectromechanical sensors (MEMS) offers an attractive option for an integrated system of small size, low power-consumption, and low cost [1,2]. However the accuracy of MEMS-based inertial solutions degrades rapidly during a GNSS outage. Therefore it is necessary to integrate the GPS/INS system with additional sensors such as Locata [3], magnetometers, CCD cameras, ultrasonic sensors, and RFID for land applications, laser scanners, barometers, or SAR radar for aviation applications, or earth/sun/star sensors for space applications. The integrated system can also be aided with additional information sources such as maps, constraints from the knowledge of the vehicle's dynamics, and so on [2].

To achieve the optimal solution, the Kalman filter (KF) is usually used as the estimator that fuses the data from the different sensors. The conventional approach is the so-called centralized Kalman filtering (CKF) method which, as the name implies, processes all sensor measurements at a central processor. CKF has some inherent defects such as heavy computational load and poor fault tolerance.

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To deal with the above problems, decentralized Kalman filtering (DKF) methods have been developed in fields such as distributed control systems and integrated navigation [5–12]. A typical DKF configuration is a spider-web style sensor network, in which a processor at the centre of the network is used to manage all nodes. Each node consists of the sensor and its accompanying local processor. The local estimates are sent to the centre, where they are fused to obtain the globally optimal estimate.

According to the widely used global optimality criterion, a DKF solution is globally optimal if it has the same level of accuracy as the CKF solution. The DKF algorithms presently used are based on this global optimality criterion and include the federated Kalman filtering (FKF) algorithm, and the parallel Kalman filtering (PKF) algorithm [9,10]. Although PKF utilizes the local predictions in the local Kalman filters, the local predictions are removed from the global estimate in the global filter, in order to ensure PKF at the same level of accuracy as CKF. FPK employs the so-called 'information-sharing' principle in order to ensure FKF at the same level of accuracy as CKF. The FKF-based multisensor navigation system has received considerable attention in the last decade [10,12].

Data fusion methods for sensor networks are being developed in parallel in the fields of multi-target and multi-tracker systems [13–17]. The algorithms can be applied to the multisensor navigation system. Two methods have been proposed, the measurement fusion (MF) approach and the state vector fusion (SVF) approach. The MF approach fuses the local measurements from different sensors to produce a global measurement, which is then sent to the central processor to generate the global estimate. However, in the SVF, the local processors produce independently the local estimates, which are subsequently fused at the central processor to obtain the global estimate. For the situation of multiple sensors tracking the same target, the local predictions are correlated. This correlation problem limits the current MF and SVF algorithms to a two-sensor system because of the difficulty of de-correlating the local predictions.

To implement a practical multisensor navigation system, the challenges include, but are not limited to, the time-synchronization of sensor outputs, communications in the sensor network, and computational load allocation for local/central processors. Nevertheless, this paper addresses the questions concerning the optimal state estimation in multisensor systems, and in particular

- What information (e.g. the data from the sensors and information from a priori knowledge) can be used in the estimation?
- How do we compare the accuracies of different algorithms? Is it sufficient to consider the CKF-based optimal criterion or the two-level optimal criterion?
- Is it necessary to develop a unified theoretical framework to deal with the multisensor data fusion problem? How?
- Does the framework provide a means for understanding multisensor data fusion as well as the conventional optimal estimations?

To address the questions above, a framework based on the random vector space (RVS) is introduced first [18]. In that framework, the sources of information have been identified and used as the bases of the space. A local filter is associated with a so-called 'sub-space'. These sub-spaces are used to construct a global space, which is associated with the global filter. The estimation is mathematically described as the procedure for finding the projection of the state vector on the bases of the space. The fusion algorithm therefore describes how the global state estimate is combined by the projections and associated bases.

This paper further develops the framework. From the point of view of the information space, optimal fusion is implemented by a series of transformations between the information spaces. The transformations map the source information vectors from the measurement information spaces to the estimate information space to produce the fused information vector. The information space approach provides a means by which the accuracies of different algorithms can be compared on a theoretical basis. Consider the fact that there are multiple sources of information available for estimation in a multisensor system. An algorithm can use either some or all of the information to derive the solution, and therefore algorithms using different source information will have different estimation accuracies although they all can be considered optimal on basis of the source information that was utilized. CKF is just one of the optimal fusion algorithms. In addition, it is not necessary to use the CKF as the global optimality criterion for multisensor data fusion in the information space frame.

2. Statement of the problem

In a multisensor navigation system, the GPS/INS subsystem can be considered the fundamental system because both GPS and INS have the capability of providing full-dimension navigation parameters including position, velocity and attitude. The other sub-systems such as Locata can provide supplementary outputs to enable the integrated system to operate effectively in any environment or scenario [3]. Most state-of-the-art GPS/INS systems are designed to estimate the INS solution errors using the GPS measurement data through either loose or tight integration, or even deep integration to aid the GPS receiver's signal acquisition and tracking. Recent progress in nonlinear filtering methods such as the sigma-point Kalman filter (SPKF) provides a potential integration scheme, which uses the INS mechanical equation directly, in place of the error propagation equation for the system dynamic model [4].

There are applications in which the movement of the platform can be accurately described by the dynamic equation such as the case of in-orbital spacecraft, their movements are governed by Newton's second law and the gravitational and non-gravitational forces. In such applications accurate dynamics can contribute to the estimation process, and thus such information should be taken into account in the data fusion in some way.

Overall, in addition to the multiple information sources from the sensors themselves, there are also multiple information sources from knowledge about the movement—such as the INS error propagation, physical laws,