Quantitative Analysis of Sensor Errors and Disturbance Compensation Strategies for Combined Navigation Systems in Dynamic Scenarios

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Abstract. In vehicle-carried dynamic situations, because of Global Navigation Satellite System (GNSS) signal disappearance and temperature shift errors inside the Micro-Inertial Measurement Unit (MIMU), the positioning precision of combined navigation systems often experiences big reduction, which becomes one of the core difficulties to realize high-reliability intelligent driving. To deal with this problem, this research mainly uses a loose coupling structure that integrates GNSS, Strapdown Inertial Navigation Systems (SINS) and Odometry (OD), and applies adaptive algorithms like Interactive Multi-Model (IMM) to carry out multi-source information fusion. Multi-sensor fusion and intelligent error compensation technologies are two vital methods for integrated navigation systems. This review shows that their combined application can strongly improve the accuracy and robustness of these systems, especially in dynamic environments. Hence, this provides an important technical direction for the engineering realization of this technology.

Keywords: Integrated navigation; Odometer; MEMS inertial measurement unit; Interactive multi-model; Neural network

1 Introduction

With the progress of intelligent driving and Internet of Vehicles technology, realization of high-precision, high-reliability integrated vehicle navigation has become basic element for guaranteeing vehicle environmental perception and decision control capabilities. Among these technologies, integrated navigation solutions combine absolute positioning superiority of Global Navigation Satellite Systems (GNSS) with autonomous high-dynamic features of Strapdown Inertial Navigation Systems (SINS), hence it has become mainstream technical method in automotive domain because of their complementary performance. However, in real dynamic application scenarios, this system confronts two big challenges: first, in complex environments like tunnels and urban canyons, GNSS signals easy suffer blockage and multipath interference, which leads to system failure or sharp accuracy decrease; second, micro-inertial measurement unit (MIMU) shows obvious time-varying drift in key parameters under wide temperature changes, causing quick accumulation of SINS errors. Therefore, effective

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suppression of navigation error divergence during GNSS signal failures, and compensation of MIMU's time-varying drift in dynamic temperature fields, these two problems have become core research topics for improving environmental adaptability and reliability of integrated navigation systems [1].

In reply to the difficulty of GNSS signal breakdown, academic circles have brought forward multiple auxiliary sensing methods. Visual navigation technology calculates position and direction by catching environmental texture messages via cameras, and LiDAR gets high-accuracy three-dimensional point clouds by sending out laser beams. However, visual programs have instability problems, with feature tracking easy to fail in situations with texture loss, sudden lighting changes, or high-speed movement. The expense of high-precision LiDAR systems limits their wide use in automobile applications [2]. On the contrary, the vehicle's own odometer (OD) acts as a low-cost, high-data-speed relative motion sensor, offering a dependable auxiliary information resource for dead reckoning in GNSS-unavailable environments. By combining the velocity limitations provided by the OD with the SINS, the accumulation and spread of inertial navigation errors during GNSS failure time can be effectively controlled [3]. Additionally, in environments with big temperature changes, MEMS Inertial Measurement Units (MIMUs) may gather large amounts of errors, thus reducing the accuracy of in-vehicle navigation systems. Therefore, research on temperature compensation has become important, including methods like building non-linear temperature drift models through data collection during cyclic temperature changes. However, traditional error models calibrated for narrow temperature ranges have difficulty adapting to dynamic temperature variations, leading to limited compensation effects. Hence, developing high-precision temperature error modeling and real-time compensation methods has become very necessary for improving the performance of in-vehicle MIMUs. This is a key focus of current research on intelligent compensation algorithms [4].

This paper sets as its target to offer a systematic checking-over of error suppression and compensation tactics for vehicle-based combined navigation systems in dynamic scene situations. First of all, the basic principles and framework of GNSS/SINS/OD loose coupling navigation will be outlined. Secondly, during situations of GNSS failure, this review puts its focus on technical means that use odometry help and adaptive filtering like interactive multi-model algorithms to keep navigation accuracy at a certain level. Hence, a deep-going analysis is carried out on the mechanism bases of MIMU temperature errors, and research advancement is also reviewed in intelligent temperature compensation methods which rely on data-driven ways such as neural networks. Finally, current challenges are discussed, and future development directions including multi-source deep fusion and online learning compensation are pointed out. Through reviewing the existing technical framework, insights are provided for enhancing the robustness and accuracy of integrated navigation systems.

2 Fundamentals and error analysis of integrated navigation

At present, GNSS systems are the navigation systems which are most widely applied and technically most mature, yet they have easy susceptibility to interferences brought by complex environmental elements. The core superior points of SINS are its autonomous working ability and strong anti-interference performance. Therefore, during long-time running processes, measurement errors will accumulate step by step, thus making SINS not fit for long-duration utilization. Moreover, the integrated navigation system that is built through combining GNSS and SINS can guarantee navigation precision under majority of operation conditions [5].

2.1 GNSS error sources and signal failure challenges

GNSS carries out position determination via receiving signals transmitted from a plurality of satellites. Taking GPS as an illustrative instance, its system is composed of the space satellite constellation, ground control segment, and user segment. Therefore, it is necessary to obtain observations from no less than four satellites so as to get a complete positioning solution.

The basic positioning rule of GNSS (such as GPS) is pseudorange measurement. By measuring signal spread time, the user receiver computes the pseudorange to satellite, and the observation equation is shown in (1). Geometric distance, receiver clock offset, atmospheric delay, and ephemeris error are multiple errors contained in this pseudorange. Therefore, when visible satellites number at least four, the receiver's position and clock offset can be calculated [6]. However, in scenes like urban canyons and tunnels, satellite signals are easy to be blocked or produce multipath reflections, leading to insufficient usable satellites or lowered observation quality. Hence, this becomes one of the main error sources for GNSS in vehicle-carried dynamic environments.

$$D_j = \sqrt{\left(X - X_j\right)^2 + \left(Y - Y_j\right)^2 + \left(Z - Z_j\right)^2} + c\Delta t \tag{1}$$

2.2 SINS/MIMU error sources and the challenge of temperature-induced accumulation

SINS carries out real-time continuous calculation of a vehicle's attitude, velocity, and position by integrating the force and angular increment data that are measured by the Micro-Inertial Measurement Unit (MIMU) inside the navigation coordinate system. Its core sensing device, the MIMU, is usually made up of a three-axis accelerometer and a three-axis gyroscope. Therefore, the calculation accuracy of SINS fundamentally relies on the measurement precision of the MIMU. MEMS inertial sensors have notable errors that will accumulate with time during the solving process; hence, this causes divergence in navigation results [7-9].

3 Adaptive odometer-aided fusion during GNSS failure

3.1 Odometer-assisted constraint model

In dynamic situations like tunnels and urban canyons which GNSS signals are blocked or strongly weakened, the quantity of visible satellites is frequently lower than four, thus causing GNSS positioning solutions to fail or accuracy to drop sharply [10]. At this time, extra sensors have to be added so that navigation system reliability can be maintained. The odometer (OD), being a sensor based on vehicle kinematics that has high data update speed and low expense, offers unbroken longitudinal vehicle velocity information. Therefore, it is a usual selection to help the SINS carry out dead reckoning (DR) when GNSS is not working.

3.2 SINS/OD loosening combination method

The core principle of odometer-assisted navigation is to make utilization of the vehicle's longitudinal velocity constraint that is provided by the odometer. In vehicle kinematics, people generally make the assumption that vehicles move on flat surfaces without skidding or bouncing, which means their lateral and vertical velocities are zero. Therefore, based on this non-complete constraint, the output speed of the OD under the vehicle system can be built into a model as shown in (2):

$$v_D^m = [0 \quad v_D \quad 0]^T \tag{2}$$

Where v_D represents the vehicle's forward moving speed. By means of the attitude matrix obtained through SINS processing, this velocity constraint can be transformed into the navigation frame; therefore, it provides velocity observation updates to the SINS. Thus, error divergence inside pure inertial navigation systems during GNSS failure periods is effectively suppressed. Its basic principle is to compute the vehicle's relative position changes by carrying out integration on the heading and velocity information that is provided by the odometry system [11].

The module-type configuration keeps relatively independent state between each subsystems, making engineering execution more easy to carry out, meanwhile thus ensuring system operation can still go on even when single sensors have failure problems. SINS is employed as the core part of the system, therefore it uses GNSS position observation results and OD velocity restriction conditions to do continuous correction work on inertial navigation errors.

In general, application of OD information into the integrated navigation system usually makes use of an error-state-based indirect Kalman filter framework. This framework takes the SINS output as a reference standard and carries out estimation of its error state. Based on the error dynamics of inertial navigation, the state equation is built up; its error state vector is usually made up of position, velocity, and attitude errors, as well as bias errors of inertial sensors gyroscopes and accelerometers. Therefore, during the observation update stage, two kinds of observation models are established consequently.

When GNSS signal can be obtained, the value of subtracting SINS-calculated position from GNSS-measured position shall be served as the observation. Therefore, thus, this is the content of GNSS position observations.

When GNSS does not work normally, the velocity constraints of the vehicle system provided by the OD will be made use of. Through carrying out attitude matrix transformation towards the navigation system, this velocity will be compared with the velocity calculated by the SINS. Therefore, the difference generated from this comparison will form the observation measurement.

Through recursion of Kalman filter, the error state of the SINS is estimated and corrected in real time; therefore, high navigation accuracy can be maintained even in dynamic scenarios where GNSS availability is intermittent. Due to its character of modularity and ease of implementation, the loose coupling architecture is widely adopted by relevant personnel.

3.3 Adaptive filtering algorithms for dynamic scenes

The working effect of standard Kalman filter (KF) depends on a precise system model and known noise statistical data, which are hard to be ensured in actual application situations that include dynamic vehicle movement and changing sensor properties. Therefore, hence, in order to raise the robustness and adaptability of combined navigation systems inside dynamic scenarios, relevant researchers have developed multiple kinds of adaptive or robust tracking filter algorithms.

For instance, the Sage-Husa adaptive filter can carry out online estimation and adjustment for the statistical characteristics of system noise and measurement noise; strong tracking filters introduce a decay factor, hence enhancing the filter's capability to trace sudden changes of system state or model mismatches. Especially for multi-modal dynamic situations which involve intermittent GNSS availability and intermittent activation of odometry constraints, the Interactive Multi-Model (IMM) algorithm provides an effective settlement. Concurrently executing multiple filter models customized for different scenarios, the IMM algorithm conducts real-time weighted fusion of outputs according to each model's alignment degree with current actual measurements, therefore enabling the system to realize seamless transition among different navigation modes, and thus remarkably improving overall estimation accuracy and robustness in complex dynamic environments [3].

4 MIMU error modeling and compensation in varying temperatures

4.1 MIMU temperature error

MIMU errors can be generally divided into three main kinds: deterministic errors, random errors, and temperature-relevant errors. Deterministic errors mainly include zero bias, proportional error, and installation error; mathematical models of these errors can be acquired by use of linear or weak non-linear calibration methods [7]. Random errors mainly show as angular random walks and zero-bias instability; therefore, Allan variance or ARMA models are usually adopted by scholars [4].

Temperature error is the most prominent and difficult-to-restrain error type under temperature-changing circumstances. Therefore, it frequently acts as the main factor that reduces system accuracy in complex application environments such as vehicle-mounted scenarios [11].

From the angle of error generation mechanisms, temperature changes bring about alterations to materials' elastic modulus, circuit parameters, and structural stress conditions inside MEMS devices. Therefore, this leads to drift of gyroscopes' and accelerometers' zero bias and proportional factor. In wide temperature range situations, the zero bias of MIMU shows a very obvious non-linear connection with temperature change, and there exists a certain degree of thermal hysteresis among different temperature curves. Hence, this makes traditional error models calibrated under standard temperatures not fit for usage. Thus, under temperature-changing conditions, temperature error is the core problem in MIMU error modeling and compensation research. Only through deep analysis on temperature error's mechanisms and mathematical features can reliable support be provided for later non-linear modeling of temperature drift and design of compensation algorithms [4, 9].

4.2 Error optimization in vehicle-mounted scenarios

Traditional temperature error compensation: methods and limitations. Early temperature compensation mainly depended on laboratory calibration work. Through carrying out temperature circulation tests inside an oven, sensor outputs at different temperature points were recorded for building a mapping model between temperature and error parameters. Polynomial fitting is one of the most widely applied models, its form being as shown in (3). Therefore, this method has straight-forward principles, yet its modeling ability has limits. Hence, it cannot fully capture higher-order nonlinearity and thermal hysteresis phenomena, and its performance is very much dependent on the completeness of calibration data and matching degree.

$$b(T) = a_0 + a_1 T + a_2 T^2 + \cdots + a_n T^n \tag{3}$$

Neural Network-Based Intelligent Temperature Compensation Method. To get over the restrictions of traditional models under complicated dynamic temperature changes, researchers have shifted to data-based methods. Hence, these approaches make use of large amounts of experimental or real-world vehicle data to study the complicated mapping connection between temperature and sensor errors, therefore.

Because of their powerful nonlinear fitting abilities, neural networks are widely used to carry out modeling work for MIMU temperature errors. Different from polynomial models which only use temperature (T) as input, neural network models can take temperature, its change rate (T), and even longer-time temperature sequences as input contents. Therefore, thus, their mapping relation may be written as what is shown in (4):

$$b_T = f_{NN}(T, \dot{T}) \tag{4}$$

This method has more superior performance in capturing the nonlinear and hysteresis characteristics in the course of dynamic temperature change processes [8]. Therefore, the compensation process is that the error estimate predicted by the model is subtracted from the original sensor output, as it is shown in Equation (5).

$$b_{comp} = b_{raw} - \hat{b}_T \tag{5}$$

With the put-into-effect of a temperature compensation strategy in the vehicle-mounted scene, the rising speed of inertial navigation velocity and positional errors has been lowered, thus effectively holding back the error accumulation during long-time operation. In vehicle thermal surroundings, only depending on traditional calibration cannot satisfy accuracy demands; therefore, temperature error modeling and compensation must be a core procedure [4, 8].

5 Challenges and prospects

5.1 Existing challenges

Although existing solutions have achieved big advance in dynamic situations, a number of basic difficulties still wait for solving so that they can satisfy the requirements for all-weather, high-reliability navigation.

A core difficult problem exists in error control during long-time GNSS stop working periods. In such scenes as tunnels or underground car parks, therefore, where the system only depends on SINS and odometer-based dead reckoning to carry out navigation work, positioning errors gradually increase and spread as time goes by. Hence, keeping the error inside acceptable limits under this mode is of crucial importance to guarantee the system's continuous and reliable running operation.

Secondly, the temperature compensation function of MIMU still owns insufficient adaptation ability under extreme operation conditions. Data-driven models, for example neural networks, have performance that relies heavily on training data. When they face extreme temperature points which are not included in training data, the predictive performance of the model will drop by a large margin therefore. Hence, to raise the model's ability of predicting temperature changes is a very important path for improving its generalization capability and robustness.

Discrepancies are present in the time lags of data acquisition, transmission, and processing for parts like GNSS, IMU, and odometers. Therefore, this insufficient consistency directly leads to notable positioning mistakes when the vehicle carries out high-speed movement. Hence, to realize high-precision time synchronization and delay compensation is a necessary procedure for improving multi-source information fusion.

5.2 Future outlook

In order to face against the challenges, integrated navigation technology is held expectation for further advance in the following directions: First, deep heterogeneous architecture fusion. This fusion does not only integrate GNSS, IMU, and odometers, but also takes low-cost LiDAR point cloud matching and visual feature tracking as equal observation sources. Through a tightly coupled optimization framework, these elements are subject to deep fusion for constructing navigation systems that have strengthened environmental understanding and higher redundancy. Second, inside the error compensation model itself, thus it may be necessary to explore models that combine physical principles with data-driven methods, or to develop compensation strategies which have ability of online adaptation and continuous learning. Therefore, this can let the system deal with sensor ageing, individual differences, and unforeseen environmental changes. Hence, such efforts will together push integrated navigation systems to move toward higher intelligence and stronger reliability.

6 Conclusion

In dynamic vehicle application scenarios, the precision of combined navigation is mainly restricted by two key problems: GNSS signal loss and MIMU temperature shift. Therefore, this paper studies above-mentioned problems through reviewing existing technical methods. Thus, in the aspect of signal processing, the use of a GNSS/SINS/OD loose coupling structure, together with adaptive filtering methods such as Interactive Multi-Model (IMM), can make odometer information be used effectively so as to restrain error accumulation during short-term GNSS signal failures.

Furthermore, compared with traditional calibration approaches, the intelligent temperature compensation strategy based on neural network demonstrates enhanced modeling of the nonlinear and dynamic features of MIMU errors. Therefore, thus it can carry out suppression of temperature drift at the algorithm level.

In brief, the utilization of a multi-source fusion method together with compensation technologies to solve signal loss problem and reduce sensor core errors constructs an effective technical route for improving the robustness and accuracy of navigation systems in dynamic situations. Therefore, this overview of related methodological frameworks can provide a reference for the engineering compensation of integrated vehicle navigation systems.

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