Dynamic Error Sources and Real-Time Compensation Methods in Multi-Sensor Fusion Systems for Autonomous Vehicles

Houji He

{244927555@qq.com}

School of Precision Instrument and Opto-electronics Engineering, Tianjin University, Tianjin, 300072, China

Abstract. This paper analyzes the sources of dynamic errors and the coupling propagation mechanism from the perspectives of sensor systems and the environment, thus clarifying their important impacts on the fusion performance. It further clearly reviews two main methodological approaches, namely the explicit modeling based on physical principles and the implicit modeling driven by data, and also constructs a real-time compensation technology framework from perception-front-end preprocessing to the collaborative optimization of the fusion process. This paper also carries out a comparative evaluation of the performance trade-offs among different methods. Dynamic errors have multiple sources, time-varying characteristics and nonlinearity, which then requires balancing and selecting compensation strategies by weighing model interpretability, computational efficiency and robustness in specific scenarios. Physical models have clear theoretical frameworks, while data-driven approaches show considerable potential in capturing complex error patterns.

Keywords: Multi-sensor fusion system; dynamic errors; real-time compensation; error modeling

1 Introduction

With the rapid development of artificial intelligence and sensing technologies, autonomous driving has gradually become a key point of concern within the evolution of the transportation system. Compared with human driving, self-driving cars have extremely strict requirements for the precision, reliability and robustness of their perception systems, which are meant to replace human senses and ensure safe and autonomous operation in various complex environments. In order to calibrate this perception system, each sensor in the fusion setup has to undergo a precise static calibration before leaving the factory or being installed in the vehicle. However, in the operating conditions of the real world, there are various constantly changing factors that always exist, which cause obvious deviations in sensor measurements, and this is called dynamic error. These errors that seriously damage the accuracy and reliability of the sensor fusion system's output are directly threatening driving safety. The traditional static calibration and compensation

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methods are not enough to deal with such constantly changing error characteristics. Therefore, in the autonomous driving field, the realization of real-time compensation is very important, which means estimating the error parameters online when the system is in operation and then immediately correcting the original data or the intermediate fusion results.

Existing research on multi-sensor fusion systems has developed from static calibration to dynamic error handling with examples like time synchronization and delay compensation, online space-time calibration, independent modeling of multi-sensor units and so on [1]. In order to deal with the error factors in the actual system, the main approaches include online joint estimation using versions of the Kalman filter or optimizing with sliding windows as well as making use of deep learning models to directly learn the implicit mappings of dynamic errors from the original sensor data. However, these methods are rather piecemeal and have not come up with a universal reliable and verifiable solution up to now.

This research is to systematically review, summarize and compare the key technologies within this field. First of all it will analyze the sources and characteristics of dynamic errors, then classify and review the modeling and real-time compensation methods of dynamic errors also carry out a comprehensive evaluation, and finally give a summary.

2 Analysis of dynamic error sources and their impact

2.1 Analysis of dynamic error sources

The autonomous driving vehicle needs to rely on the multi-sensor fusion system to realize the precise and reliable perception of the surrounding environment. In the actual operation, the measurement of sensors will be subject to deviations brought about by various constantly changing factors, which is named dynamic error. If these problems are not resolved, these errors will propagate and amplify during the fusion process, severely impairing the safety and reliability of the system. The dynamic error arises from the complex interactions among the sensor itself, the carrying platform, and the external environment.

The dynamic errors at the sensing device level mainly result from the alterations in the physical properties or the states of the parts inside the sensing device. Temperature drift is a crucial factor. For example, key parameters like the bias and scale factor of electronic components in sensors such as Light Detection and Ranging (LiDAR) lasers, as well as gyroscopes and accelerometers in Inertial Measurement Units (IMU), will drift with the change of ambient temperature, and then directly affect the accuracy of measurement. In the IMU, even a very small deviation, after the second integration, will result in a position error increasing in a quadratic way with respect to time. Another source is mechanical vibration. The minute displacements of the precise internal components in the sensor are caused by the operation of the vehicle engine and driving on uneven roads, which then interferes with the measurement. Additionally, after prolonged use, the performance of core components like the light-emitting and light-sensing elements in the sensor gradually deteriorates, and the acceleration and rate random walks, often called aging, lead to changes in the output signal strength and signal-to-noise ratio [2].

The dynamic errors at the system level mainly come from the motion of the vehicle itself and the dynamic relationships between the sensors and the vehicle body. A typical manifestation is motion distortion which can occur when the vehicle is continuously moving within a single sensor scan or exposure cycle and this will lead to frame data distortion. Another issue is the drift of external parameter calibration. The installation parameters of the sensor relative to the vehicle coordinate system are not constant. During driving, continuous vibrations, momentary impacts, and minor deformations of the vehicle body or sensor bracket caused by temperature changes and other factors can all change these external parameters [3].

The dynamic errors in the environmental aspect mainly come from the interference of external physical conditions with the sensing capability of the sensors. Harsh weather brings great challenges. Rain, snow, fog and haze which can impede optical sensors like LiDAR and cameras will cause situations of signal scattering or attenuation. Changes in light conditions like intense glare, backlighting, or heavy shadows also directly affect visual and optical sensing, severely reducing the image quality as well[4]. In addition, the disturbances brought about by the moving objects around like vehicles and pedestrians will cause continuous noise to the positioning and environmental interpretation of the sensor system. During the online self-calibration or positioning that is based on dynamic scenarios, this situation is especially likely to result in mismatching errors [5].

2.2 Impact of Dynamic Errors on Fusion System Performance

The impact of dynamic errors on the performance of the fusion system consists in that they can destroy the consistency, the accuracy and the reliability of the output data within the multi-sensor fusion system. These interconnected, spreading and magnifying errors in the fusion framework will eventually lead to performance degradation or system malfunctions.

First of all, the movement of dynamic objects will interfere with the environmental features that are used for online self-calibration. For example, when using static environmental features to estimate the extrinsic parameters between the lidar and the camera, the erroneous features on the moving object may be mistakenly regarded as reliable static features, thus causing deviations in the online estimation of the extrinsic parameters [6]. Second, when the LiDAR point cloud is projected onto the image plane with incorrect extrinsic parameters, the static point cloud that should be aligned with the image edge is no longer aligned, and the point cloud on the dynamic object may happen to form false matches [7].These mismatched situations, if being fed into state estimators such as Kalman filters or factor graph optimizers as erroneous data, will further mess up the state estimation. This makes it difficult to precisely correct the drift in attitude estimation through subsequent observations then [6]. Finally, the flawed localized results will cause the formation of distorted maps, and then a vicious cycle will be established where errors continuously magnify here.

Generally speaking, the dynamic error is not merely an isolated thing that affects the readings of individual sensors only. On the contrary, they will gradually intensify the situation of performance deteriorating by affecting the entire multi-sensor fusion system. Therefore thoroughly understanding this mechanism is extremely crucial for developing reliable dynamic error modeling and real-time compensation methods.

3 Dynamic Error Modeling and Real-Time Compensation Methods

3.1 Physics-Based Explicit Modeling

Based on the physical explicit modeling principle that relies on those physical mechanisms which trigger errors, mathematical models that have clear analytical expressions will be constructed. Such a model which provides direct theoretical basis for real-time compensation is mainly centered on four types of error models, including the time synchronization error model, the spatial (external) calibration drift model, the internal sensor distortion model, and the environment-coupled error model.

A clock error model that includes fixed offsets and linear drifts and is as shown in Figure 1 usually models the synchronization errors over time. Figure 1 demonstrates a simplified clock error system. The control input $u(t_i)$ drives the sensor system forward, while a second sensor provides periodic updates $y(t_k)$. An unknown relative delay τ is introduced between the sensor data streams, which results in the updated measurement $y(t_k) = x(t_k + \tau)$. This delay can cause the update to occur either ahead of or behind the expected timing.

A common way to relieve such errors is to construct the model of the sensor's position and attitude as a function of time. This approach gets rid of the loss of precision linked with discrete interpolation by optimizing time parameters [8,9].

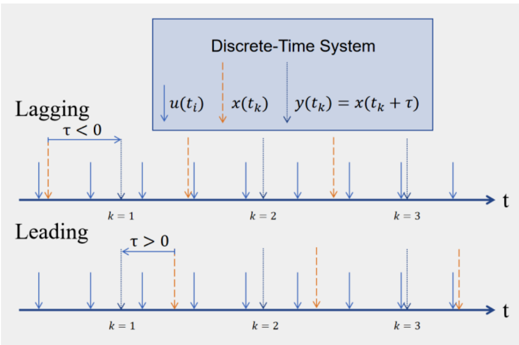

Fig. 1. A simplified clock error system.

Based on the principles of kinematics, mechanics of materials and thermodynamics, the spatial external calibration drift model measures the alterations of external parameters brought about by vibrations, temperature changes and deformations, and does this as a function of the relevant physical variables. By establishing measurement constraints among multiple sensors such as IMU, LiDAR, cameras, and millimeter-wave radars, then high-precision online calibration can be realized [9].

The distortion model of the internal sensor is used to embody the errors that are brought about by the operation mechanism of the sensor itself during dynamic operation. One way is to create high-fidelity physical modeling through ray tracing, and the other is to use deep learning networks to directly make up for the distortion by predicting scene features, thus reducing the dependence on additional sensors then [10].

The environment-coupled error model portrays the distortions which are brought about by the interaction between sensing signals and the environment. To address the physical interference of the environment on signals, the exponential decay model can be used to describe the weakening effect of rain or fog on LiDAR signals. Combined with ray tracing for modeling novel propagation channels, this approach is further supported by systematic experimental validation of the interaction mechanisms between automotive radar and the environment [11].

3.2 Data-Driven Implicit Modeling

When the physical mechanism of dynamic error is too complicated to be clearly described or modeled, a data-driven implicit modeling will present an alternative approach. The core concept of these methods is that based on the real-time and historical data gathered from sensors, machine learning algorithms automatically learn the complex mapping relationships between dynamic errors and factors such as carrier platforms and environments. The main advantage of this kind of method consists in being able to capture the high-order non-linear factors that are extremely hard to model with analytical methods. According to the different technical approaches, this kind of method can actually be roughly divided into two main types.

One method, which is to utilize a framework of a state estimator, can perform estimations within a state-space vector model. Here the complex time-varying characteristics erros are passively tracked by the state estimator. The Kalman filter and its nonlinear variants are typical examples. The advantage of this method lies in its capacity to offer uncertainty measures for state estimation. However, its performance depends to a large extent on the accuracy of the pre-defined state space model, and when coming across unmodeled or strongly nonlinear error sources, it may indeed perform very badly [12].

The second way is to apply deep learning to the implicit modeling of the dynamic errors. This approach, through deep neural networks, automatically learns from a large quantity of multi-modal raw sensor data, seizing the complex patterns of dynamic errors as well as the non-linear mappings and their relations with specific sensor factors and environmental interferences [7]. One implementation method is to construct an end-to-end compensation network, in which specific modules are designed to directly predict incremental sensor rotations and translations so as to correct the original point cloud data [13]. Alternatively, error modeling can be incorporated into the perception task itself. In the bird's-eye view (BEV) 3D detection network, the situation of sensor misalignment is clearly simulated through data augmentation which can be used to jointly estimate the misalignment parameters and the detection results [7]. The remarkable aspect of this method is that it has the ability to grasp the high-dimensional and non-linear error characteristics well.

3.3 Real-Time Compensation Techniques for Dynamic Errors

The real-time compensation of the dynamic errors in the autonomous driving vehicles means the process of deducing those error parameters that change with time and then carrying out reverse correction when the autonomous driving system is in operation. At present the latest progress of relevant technologies exhibits a trend of developing towards more collaboration and integration. This mainly consists of the preprocessing of the perception front end and the collaborative optimization during the fusion process.

In the perceptual front-end preprocessing level, the compensation is directly applied to the original sensor data. This method, by making use of the non-holonomic constraints of the vehicle itself or the motion estimation between consecutive frames, realizes the continuous online optimization of the external parameters. At the same time, for the situation of LiDAR point cloud distortion caused by vehicle movement, the high-frequency IMU data can be used to interpolate and reconstruct the sensor pose at the exact emission time of each laser point, thereby enabling the realization of distortion correction and providing high-quality inputs for the subsequent tracking and detection tasks [14].

In the aspect of collaborative optimization in the fusion process, the error compensation and the state estimation that are fused together. One way is to integrate the adaptive mechanism and data-driven learning into the closely-related filtering system. For instance, in the integrated navigation system composed of the Inertial Navigation System (INS) and the Two-Dimensional Laser Doppler Velocimeter (2D-LDV), the Long-Short Term Memory (LSTM) network can predict the measurement values of the 2D-LDV as well as the lateral velocity of the vehicle. Then an adaptive filter will adjust the covariance of the measurement noise in accordance with the uncertainty of LSTM and even when the sensor has been degrading for a long time, it can still maintain a reliable state. Additionally, there exists a completely data-driven Model-Free Adaptive Control (MFAC) scheme which, through dynamic linearization, generates a time-varying pseudo-gradient model, thereby enabling real-time tracking without prior knowledge of vehicle dynamics as per [15].

3.4 Performance Evaluation and Comparison of Modeling and Compensation Strategies

The evaluation and selection of dynamic error modeling and real-time compensation techniques are highly dependent on specific sensor configurations, operating scenarios and safety level requirements.

The physically-based explicit model has the highest interpretability and theoretical clarity but has limited ability in simulating unknown or overly complex coupling errors. In contrast, data-driven implicit modeling generally has lower interpretability than explicit models and is also theoretically not so clear. Through end-to-end learning, deep learning models can capture those complex and high-dimensional nonlinear patterns and also demonstrate quite considerable potential as well. However, this leads to a result that the traceability in the decision-making process is decreased, thus bringing about difficulties for security certification. The method that is based on the state estimator, which lie between the two aforementioned approaches, can attain a good balance in the circumstance where the dynamic framework is relatively clear yet the parameters change over time. However, their performance is still restricted by the accuracy of the pre-defined state equation indeed [16].

The model that is based on physics along with the front-end preprocessing technology, which shows the highest computing efficiency, usually only needs the resources at the controller level to satisfy the processing requirements. For example, in the positioning based on LiDAR, adjusting the positioning frequency can reduce the amount of calculation by more than 30% and also keep the translation error below 0.05 meters and the rotation error below 0.1 degrees [17].

The state estimator method, when properly optimized, can also operate efficiently on the vehicle-mounted computing unit as well. In contrast the deep learning method faces relatively strict real-time challenges because its complex reasoning process requires the support of high-performance GPUs resulting in significantly increased deployment costs and power consumption. Although the fusion process collaborative optimization technology can achieve system-level compensation and has good performance, it will inevitably introduce higher computational complexity.

There are also physics-based models and state estimators that can provide stable and repeatable high-precision in terms of accuracy and robustness. In a specific research, Fan et al. improved the method of LiDAR-inertial odometry, reducing the average trajectory error from 0.34 meters in the baseline approach to 0.18 meters, and there is a 47.1% increase in precision [18]. But when the system dynamics exceed the boundary of the model, their stability will turn worse. Conversely, when the data of the deep learning model is insufficient, the accuracy rate may drop sharply, but in situations where the training data coverage is very good, they can attain extremely high precision. On the TUM RGB-D dataset, a dynamic SLAM framework that is based on deep learning, specifically used for reducing the interference of dynamic objects, achieves a reduction of the trajectory error on average by 69.16% or even 91.94%, respectively [19]. This kind of nearly an order of magnitude performance leap presents the unique advantages of deep learning in simulating the errors of complex environment interactions.

4 Conclusion

This paper is to systematically explore the dynamic error issues of the multi-sensor fusion system in autonomous driving. It analyzes their sources and influence mechanisms, and also reviews the current mainstream dynamic error modeling and real-time compensation methods, and emphatically highlights the key role of real-time compensation in ensuring the safe and reliable operation of autonomous driving. This paper clarifies the generation mechanisms of various dynamic error sources such as temperature drift, mechanical vibration, external parameter drift and bad weather from the aspects of the sensor itself, the carrier platform and the external environment. It expounds the chain reaction in which these errors are interrelated and spread during the fusion process, and finally results in systematic malfunctions such as positional deviations and map distortions.

Regarding these erroneous dynamic characteristics, this paper reviews two core modeling approaches. The explicit modeling method based on physics offers a distinct theoretical framework for error compensation, whereas the data-driven implicit modeling method demonstrates significant potential in capturing complex nonlinear error patterns. At the level of real-time compensation technology, this paper sorts out multi-level solutions from the preprocessing of perceptual front-end data to the collaborative optimization of the fusion process. Through methods like online calibration, adaptive filtering, and deep learning fusion, the immediate correction of dynamic errors will be achieved. The balancing among the model's accuracy, computational efficiency, system stability and engineering feasibility needs to be carried out for evaluating and selecting these methods.

Dynamic errors are a crucial bottleneck restricting the safety and reliability of autonomous driving because they directly damage the consistency and reliability of the output of the fusion system, thus greatly impeding the safe deployment of autonomous driving vehicles. In the future, research should place emphasis on developing a hybrid modeling framework which integrates physical models and data-driven methods, and also establish an open dynamic error benchmark testing environment, and further combine the prior knowledge in physical models, the probabilistic framework of state estimation, and the representation ability of de ep learning. Moreover, efforts have to be made to explore a light-weight and understandable real-time compensation algorithm that satisfies the requirements of functional safety certification, in order to promote the practical application and deployment of autonomous driving perception systems in extreme and long-tail scenarios.

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