Accurate GNSS Positioning in Urban Canyons with Extended Kalman Filter

髙山, 洋史

(Degree)
博士（工学）
(Date of Degree)
2023-03-25
(Date of Publication)
2025-03-25
(Resource Type)
doctoral thesis
(Report Number)
甲第8654号
(URL)
https://hdl.handle.net/20.500.14094/0100482402

（別紙様式 3）

論文内容の要旨

氏　　名　　　　　　髙山 洋史

専　　攻　　　　　　情報科学専攻

論文題目（外国語の場合は，その和訳を併記すること。）

Accurate GNSS Positioning in Urban Canyons with Extended Kalman Filter

拡張カルマンフィルタによる都市部での GNSS 高精度測位

指導教員　　　　　　浦久保 孝光

Inaccuracy in urban canyons has been a persistent and lingering problem for the Global Navigation Satellite System (GNSS). This thesis reports the results of a study on performance improvement of the extended Kalman filter (EKF) to obtain more accurate positions in urban canyons.

GNSS is a system that provides positioning on a global basis. GNSS receivers on the ground measure distance to satellites based on the time of flight of satellite signals. And then they determine their positions based on trilateration. GNSS positioning accuracy depends on signals' propagation delay due to, e.g., the troposphere and ionosphere. GNSS can achieve accuracy within ten meters with no objects in the lines of sight of satellites. The areas with no objects in the lines of sight of satellites are referred to as open sky areas.

One last great unsolved GNSS problem is inaccuracy in urban canyons. Positioning with GNSS in urban canyons suffers from significant position errors due to Non-Line-Of-Sight (NLOS) reception. NLOS reception occurs where the direct signal is blocked, and the signal is received only via reflection or diffraction. Measurement errors due to NLOS reception are characterized by their sign and size. Since signals via reflection or diffraction arrive later than (blocked) signals via direct paths, measurement errors due to NLOS reception are always positive. Furthermore, their errors depend on their path delays and are potentially unbounded. They can be over a hundred meters and outliers that can degrade position accuracy significantly.

Because of the low computational cost, almost all GNSS receivers employ the extended Kalman filter to determine their positions. The EKF performance is highly dependent on the accuracy of measurement and the setting of parameters in the EKF. Inaccurate and biased measurements due to NLOS reception can reduce the estimation accuracy of the EKF. This research aims to achieve a few meters of accuracy in urban canyons by removing outliers and choosing parameters in the EKF according to remained measurements. The enhanced EKF performance will benefit our society.

This research solves the problem of inaccuracy in urban canyons in two stages. The first stage is to develop a method to reject outliers due to NLOS reception from the computation of the EKF. This stage begins with introducing the model that represents the surrounding environments, e.g., buildings, of a GNSS receiver to compute path delays geometrically due to reflection or diffraction. Since measurement errors in NLOS signals depend heavily on path delays due to reflection or diffraction, computed path delays using the geometric model can predict measurement errors. Based on the predicted values, the method can improve position accuracy by detecting and rejecting outliers due to NLOS reception.

However, removing outliers decreases the number of measurements and may cause poor satellite geometry. Poor satellite geometry means a biased distribution of satellites as seen by a GNSS receiver. As positioning accuracy highly depends on satellite geometry, it is necessary to show how poor satellite geometry affects the EKF performance.

Therefore, the second stage begins with numerical examples to point out the problem caused by poor satellite geometry. These examples illustrate that a fictitious noise approach, which can avoid filter divergence by adding fictitious noise to process noise heuristically, results in excessive inflation of the estimation error covariance matrix in the EKF with poor satellite geometry. Further, this stage provides a theoretical analysis of the sensitivity of the estimation error covariance matrix varying on process noise in the EKF. From the examples and the theoretical analysis, a process noise model that chooses fictitious noise based on satellite geometry is proposed in this stage. The proposed process noise model can suppress inflation of the estimation error covariance matrix when satellite geometry is poor. To our best knowledge, the proposed model in the second stage is the first to choose process noise depending on satellite geometry.

The key findings of this research are twofold and come from each of the stages described above. The first is the performance improvement in urban canyons by removing outliers and demonstrated through driving tests in Shinjuku, Tokyo, known for NLOS reception. The second is also performance improvement in urban canyons by avoiding unintentional inflation of the estimation error covariance matrix. It is revealed through theoretical and experimental results. In addition, the process noise model proposed in the second stage can be applied to applications with a generic EKF other than GNSS. Numerical simulations in robot localization show that the proposed model improves localization performance.

Chapter 1 introduces the background and the main issue of this research. The background begins with the current GNSS status from the point of view of accuracy to define the main issue of this research, which is inaccuracy in urban canyons. And then, this chapter refers to some studies related to this research's main issue to show the difference between the studies and this research. The difference would show our contribution that represents an advance in current knowledge in the GNSS field. Further, this chapter summarizes the main results of this thesis through overviews of each chapter. Finally, three background materials and a mathematical introduction to the EKF are given in this chapter that would be needed in later chapters. Three materials are the single point positioning with the EKF, measurement errors in urban canyons, and the role of satellite geometry in positioning.

Chapter 2 is devoted to developing a method to detect and reject outliers due to NLOS reception. This chapter begins with a review of the adaptive extended Kalman filter proposed in previous studies to deal with measurement outliers in urban canyons. The adaptive EKF can determine the appropriate noise input level in real time with innovations or residuals of measurements. Although the adaptive EKF reduces the impacts of NLOS reception on estimates, measurement errors due to NLOS reception may make biased position errors because they are always positive. Thus, the adaptive EKF should not use measurements due to NLOS reception, even with the adjustment of noise input level.

This chapter proposes a method to reject outliers from the adaptive EKF to reduce biased position errors, introducing a model that represents the surrounding environments in urban canyons to predict path delays of signals due to NLOS reception. Since measurement errors due to NLOS reception depend on path delays of reflected or diffracted signals to direct signals, measurement errors can be predicted geometrically using the model. The proposed method has a threshold to detect signals whose path delay is nearly equal to or longer than the predicted values of path delays. The threshold is chosen as a smaller predicted value so that it can detect NLOS signals as much as possible. Removing measurements whose path delays are too long can reduce biased position errors. Note that the prediction of path delays with the geometric model is sometimes inaccurate. And some NLOS signals might be accepted and used in the computation of the EKF. Since the adaptive EKF can determine the appropriate noise input level for accepted NLOS signals, it can reduce the impacts of the accepted NLOS signals on state estimates. The results of experiments in urban canyons show the performance improvement of the adaptive EKF with the proposed method.

Chapter 3 begins with numerical examples to highlight the problem caused by fictitious noise for avoiding filter divergence. The problem is that estimation errors by adding fictitious noise to process noise can be distributed more widely in a particular direction determined by satellite geometry. Since the estimation error covariance matrix in the EKF varies depending on fictitious noise, the sensitivity analysis of the matrix due to fictitious noise can explain the cause of the problem. From the sensitivity analysis, the variation of the estimation error covariance matrix depends on measurement matrices, that is, satellite geometry. This analysis and numerical examples indicate that fictitious noise may result in excessive inflation in a particular direction of the estimation error covariance matrix and eventually degrade filter performance.

Based on the results of numerical examples and the sensitivity analysis, this chapter presents a process noise model that varies depending on satellite geometry. The process noise model can suppress the inflation of the estimation error covariance matrix due to poor satellite geometry by choosing a small or zero fictitious noise in a particular direction. The improvement of position accuracy due to the proposed model is demonstrated through experiments of stationary GNSS positioning with poor satellite geometry.

Chapter 4 presents a process noise model extended from the proposed model in Chapter 3. As stated earlier, the proposed model in Chapter 3 is derived based on the sensitivity analysis of the estimation error covariance matrix under some assumptions. Although one of the assumptions is that the state transition matrix is an identity matrix, the assumption does not often hold in the EKF for GNSS positioning. This explains that the proposed model in Chapter 3 should be extended.

This chapter begins with a sensitivity analysis of the estimation error covariance matrix without the assumptions introduced in Chapter 3. From this analysis, fictitious noise varies the estimation error covariance matrix. Keeping this in mind, let fictitious noise be chosen so that the variation of the estimation error covariance matrix will be a given value. For this purpose, the value is designed in two ways later described.

Since the size of the estimation error covariance matrix is usually large, it is difficult to determine appropriate values for all elements. Therefore, the value should be constrained in some way to be able to determine. Recall that unintentional inflation of the estimation error covariance matrix may degrade filter performance, as Chapter 3 pointed out. This indicates that the directions exist such that inflation in the estimation error covariance matrix is unnecessary. Based on the consideration, the constraint by measurement matrices can be effective in forming the value.

In the first design, the value is chosen through a trial-and-error process. In the second design, the value is chosen to minimize the sum of the square of measurement residuals. In the sense of minimization, the value is referred to as a decision variable. Position accuracy improvement is demonstrated through stationary GNSS positioning for the first choice and in GNSS/INS positioning for the second choice.

Moreover, the extended process noise model can be applied to applications other than GNSS and GNSS/INS. For example, robot localization is one important system to determine the robot's position with range and vision sensors, such as LiDAR devices and cameras. It tends to suffer from unexpected dynamics errors in the prediction of robot motion. Furthermore, the information from these sensors often degenerates, for example, when the robot moves along the wall. This indicates that using the extended process noise model may improve the EKF performance by varying fictitious noise based on measurement matrices. Numerical simulations in robot localization show the improved performance of the EKF for the localization system.

Chapter 5 concludes this thesis. This chapter begins with a brief revisit of the contents of each chapter and the key findings of this thesis. And then, it states the importance and significance of those findings compared with previous studies. Further, this chapter refers to possible applications to other areas with the proposed process noise model and the possibility of expanding the proposed process noise model to other nonlinear filters. Finally, future work on obtaining more accurate positions in urban canyons is presented.