Addressing Urban GNSS Signal Degradation with Extended Kalman Filtering

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확장 칼만 필터를 활용한 도시 환경에서의 GNSS 신호 열화 대응

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Abstract

GNSS positioning in urban canyons is often unreliable due to signal blockage, multipath effects, and limited satellite visibility. This paper presents an extended Kalman filter (EKF)-based GNSS-only method to improve accuracy and continuity in such environments. By combining a constant-velocity motion model with recursive prediction and measurement updates, the EKF maintains position estimates even during temporary satellite outages. Simulations for a vehicle moving at 60 km/h show that the proposed method reduces the mean positioning error by 28%, eliminates invalid fixes, and stabilizes error fluctuations. The results demonstrate that EKF-based GNSS positioning offers a robust and practical solution for urban mobility and autonomous driving applications.

Ⅰ. Introduction

Accurate and reliable positioning is a fundamental requirement for a wide range of applications, including autonomous driving, logistics, and urban mobility services [1]. Global navigation satellite systems (GNSS) have been widely adopted due to their global coverage and relatively low infrastructure cost. However, in dense urban environments, often referred to as urban canyons, GNSS performance degrades significantly due to signal blockage, multipath effects, and non-line-of-sight (NLOS) receptions caused by skyscrapers and narrow streets [2].

One of the most critical limitations in such environments is the insufficient number of visible satellites. When fewer than four satellites are available, GNSS receivers cannot compute a position fix, making GNSS-only localisation either impossible or highly unstable. Even when four or more satellites are available, poor satellite geometry often leads to large positioning errors.

To address these challenges, estimation techniques, such as the extended Kalman filter (EKF), have been adopted to improve the robustness of GNSS-only positioning. by leveraging the temporal correlation of consecutive GNSS measurements, the EKF can propagate the user's position using a motion model and filter out spurious updates caused by noisy or degraded measurements. In this paper, we propose and evaluate an EKF-based GNSS-only positioning method tailored for urban canyon environments.

Ⅱ. Methodology

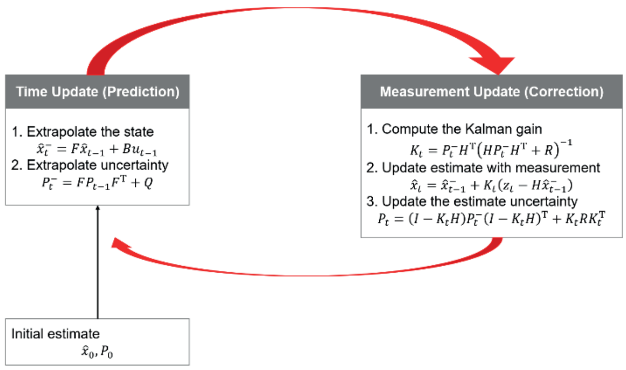

Fig.1 Operation of EKF.

This study applies the EKF to enhance GNSS-only positioning in urban canyon environments, where signal blockage and limited satellite visibility can degrade accuracy. The EKF estimates the user's state recursively through two steps: time update (prediction) and measurement update (correction), as illustrated in Fig. 1 [3].

The system state vector at time step k is defined as:

$$x_k = [x_{UE,k} \quad y_{UE,k} \quad h_{UE,k} \quad v_x \quad v_y \quad v_h]^T \tag{1}$$

where $[x_{UE} \quad y_{UE} \quad h_{UE}]^T$ represent the user's 3D position, and $[v_x \quad v_y \quad v_h]^T$ denote the corresponding velocity components. The EKF begins with an initial state estimate x_0 and covariance matrix P_0, which represent the system's priori belief.

The time update (prediction) step uses a constant velocity motion model to extrapolate the state forward in time:

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1|k-1} \tag{2}$$

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q \tag{3}$$

where F is the 6-by-6 state transition matrix, and Q is the process noise covariance matrix.

If GNSS pseudo-range measurements from four or more satellites are available, the measurement update (correction) step is performed. Each measurement z_k^i from satellite i is modelled as:

$$z_k^i = \sqrt{\left(x_{UE,k} - x^i\right)^2 + \left(y_{UE,k} - y^i\right)^2 + \left(h_{UE,k} - h^i\right)^2} + cb_k + n_k^i \quad (4)$$

where $\left(x^i, y^i, h^i\right)$ is the known satellite position, c is the speed of light, b_k is the receiver clock bias, and n_k^i is the pseudo-range noise.

The EKF updates the state and uncertainty as follows:

$$K_k = P_{k|k-1} H_k^{\mathrm{T}} \left(H_k P_{k|k-1} H_k^{\mathrm{T}} + R\right)^{-1} \quad (5)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left[z_k - h\left(\hat{x}_{k|k-1}\right)\right] \quad (6)$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (7)$$

where H_k is the Jacobian matrix of the measurement function $h(\cdot)$, which linearises the mapping from state to pseudo-range space, and R is the measurement noise covariance matrix.

In the urban canyon environments, satellite visibility is often intermittent. If fewer than four satellites are visible, the correction step is skipped, and only the prediction step is performed. This allows the EKF to maintain approximate positioning even during temporary GNSS outages, improving continuity and robustness.

Ⅲ. Results

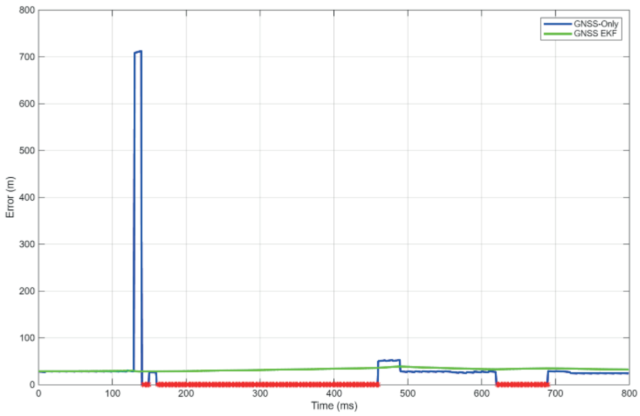

Fig.2 Positioning performance.

Table I. Positioning Performance Analysis.

Method	Mean Error (m)	Max Error (m)	Min Error (m)	NaN (%)
GNSS-Only	45.37	711.92	24.14	47.5
GNSS-EKF	32.54	38.98	28.10	0

To evaluate the effectiveness of the proposed EKF-based GNSS-only positioning approach, a vehicle scenario is simulated. The user equipment (UE) is assumed to move at a constant speed of 60 km/h with a height of 3 m. In the baseline scenario without filtering, the UE position is directly computed using standard GNSS pseudo-range measurements. Due to limited satellite visibility and poor geometry, the system frequently failed to obtain a valid position fix. As depicted in Fig. 2, among the valid epochs, the mean, maximum, and minimum positioning errors are 45.17 m, 711.92 m, and 24.14 m, respectively. The NaN rate reaches 47.5%. By applying the proposed EKF-based positioning algorithm, significant improvements are observed. The NaN rate is reduced to 0%, as the EKF is able to continue predicting the UE's location during satellite outages. The mean positioning error decreases to 32.54 m, while the maximum and minimum errors are 38.98 m and 28.10 m, respectively. The positioning performance between these two methods are summarised in Table I.

Compared to the unfiltered GNSS-only approach, the EKF method not only reduced the average positioning error by approximately 28%, but also provided a much more stable and bounded error profile, with no extreme outliers or sudden spikes. The absence of NaNs further highlights the EKF's robustness in maintaining continuous positioning, even in highly degraded GNSS environments.

IV. Conclusions

In this paper, we propose an EKF-based GNSS-only positioning method tailored for urban canyon environments, where signal blockage, multipath effects, and limited satellite visibility significantly degrade GNSS performance. By leveraging a constant-velocity motion model and recursively combining prediction and measurement updates, the EKF is able to maintain continuous position estimates even when fewer than four satellites are visible. Simulation results in a vehicle scenario demonstrate that the proposed method substantially improves positioning reliability and accuracy compared to unfiltered GNSS-only measurements. Specifically, the EKF reduces the mean positioning error by approximately 28% and eliminates NaN occurrences caused by temporary satellite outages. These results highlight the potential of EKF-based approaches to enhance GNSS-only positioning robustness in challenging urban environments, providing a practical solution for applications such as autonomous driving and urban mobility services.

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