GNSS Localization Techniques and Improvement Methods

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1. Review of Localization GNSS Techniques

a) Differential GPS (DGPS) -

- Differential GPS (DGPS) is a technique that enhances the accuracy of standard GPS by using fixed ground-based reference stations.
- Standard GPS (Global Positioning System) provides accuracy within 5-10 meters for normal use, which may not be sufficient for certain applications that require higher precision.
- Since the exact location of each reference station is known, any discrepancy between the GPS-derived location and the actual known position can be attributed to errors in the GPS signal.
- The reference stations calculate the error and generate a correction signal. This correction represents the difference between the observed position (from GPS) and the true position.

Advantages and Applications

- DGPS can improve the accuracy of GPS positioning from around 10 meters to less than a meter. DGPS is also cost effective compared to Real-Time Kinematic (RTK). It can also cover large areas with a network of ground-based reference stations.
- Applications include Automated machines like drones or ground robots, to ensure precise navigation and positioning
- Marine navigation, surveying and Mapping are also some applications.

b) Real-Time Kinematic (RTK) -

- Real Time Kinematic positioning is highly accurate satellite navigation technique that enhances the precision of position data derived from GNSS(Global Navigation Satellite system).

- RTK achieves centimeter level accuracy by using the phase of carrier wave of the satellite signals, rather than information content itself.
- Compared to DGPS, RTK generally provides superior accuracy, typically reaching precisions of 2-5 cm horizontally and 3-8 cm vertically. However, RTK systems also require more complex hardware and software, and the range between the reference station and rover is limited, typically to within 10-20 km.
- RTK is commonly used in applications that demand the highest possible positioning accuracy, such as construction, mining, and precision agriculture.

c) Assisted GPS (A-GPS)

- Assisted GPS (A-GPS) is a technique that improves the initial positioning time and sensitivity of standard GPS receivers by using network assistance.
- A-GPS receivers obtain aiding data, such as satellite ephemeris and clock information, from cellular or Wi-Fi networks, which reduces the time required for the receiver to acquire and track the GPS signals.
- The main benefit of A-GPS is its ability to provide faster time-to-first-fix (TTFF) and better positioning performance in challenging environments, such as urban canyons or indoors, where the GPS signals may be weak or obstructed.
- However, A-GPS does not improve the long-term positioning accuracy compared to standard GPS.

d) Precise Point Positioning (PPP)

- Precise Point Positioning (PPP) is a GNSS positioning technique that allows for precise positioning with a single GNSS receiver, without the need for a local reference station.
- PPP achieves this by using precise satellite orbit and clock information, as well as other correction data, which are typically provided by a service or network.
- Compared to RTK, PPP can provide similar or even higher positioning accuracy, with precisions often reaching the centimeter level.
- However, PPP requires more complex algorithms and access to specialized correction data, which can make it more expensive and have a higher convergence time than RTK.

2. Methods to Improve GNSS Localization

a) Kalman Filter and EKFs

- The Kalman Filter is an algorithm used to smooth and predict position data in GNSS localization. It works by using a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of the unknown variables that tend to be more accurate than those based on a single measurement alone.
- In the context of GNSS, the Kalman Filter can be used to reduce noise and compensate for errors in the positioning data. By modelling the dynamics of the receiver's motion and the GNSS measurement process, the Kalman Filter can effectively remove high-frequency noise and provide a more accurate and stable position estimate. This is particularly useful in scenarios where the GNSS signals are prone to multipath effects, signal blockage, or other sources of error.
- The Kalman Filter functions through two primary steps: prediction and update. During the prediction step, the filter uses a mathematical model to predict the next state based on the current state and the known control inputs. The update step then corrects this prediction using the actual measurement data, weighted by their estimated uncertainty. This process allows the Kalman Filter to mitigate errors from various sources, such as atmospheric disturbances or multipath effects, thereby enhancing the accuracy of GNSS positioning.
- The EKF follows the same general process as the Kalman Filter, with the additional step of linearizing the nonlinear functions at each iteration. This allows the EKF to provide more accurate and stable estimates in scenarios where the standard Kalman Filter would struggle, particularly in the presence of significant non-linearities.

b) Particle Filter

- The Particle Filter is another powerful estimation method, particularly suited for non-linear and non-Gaussian systems, which are common in GNSS applications. Unlike the Kalman Filter, which relies on Gaussian assumptions and linear models, the Particle Filter uses a set of particles to represent the probability distribution of the state. These particles are propagated according to the system dynamics and reweighted based on the likelihood of the observed measurements.

- This makes the Particle Filter particularly useful in challenging GNSS environments, such as urban areas or indoors, where the measurement noise and system dynamics are highly non-linear.
- The need to maintain and update many particles which makes the Particle Filter more resource-intensive than the Kalman Filter, which can be a limiting factor in real-time applications. However, the Particle Filter's robustness to model inaccuracies and its ability to capture multi-modal distributions can lead to significantly improved localization accuracy in challenging environments.

c) Sensor Fusion

- Sensor fusion is the process of integrating data from multiple sensors to enhance the accuracy and robustness of GNSS localization. In GNSS applications, sensor fusion typically involves combining GNSS measurements with data from other sensors, such as inertial measurement units (IMUs), light detection and ranging (LiDAR) systems, or cameras.
- By fusing GNSS data with information from complementary sensors, the overall localization performance can be significantly improved, especially in environments where GNSS signals are degraded or unavailable. For example, integrating GNSS with an IMU can provide continuous position, velocity, and orientation estimates, even during GNSS outages, while combining GNSS with LiDAR can enhance positioning accuracy in urban canyons or indoor settings.
- **Improvement in GNSS Performance**
  Sensor fusion can significantly enhance GNSS performance, especially in environments where GNSS signals are weak or unavailable. In urban canyons, where buildings obstruct the direct line of sight to satellites, sensor fusion can help maintain accurate positioning by relying more heavily on IMU data and correcting for the GNSS signal's degradation. Similarly, indoors, where GNSS signals are often completely unavailable, sensor fusion with LiDAR or camera-based systems can provide reliable localization by mapping the environment and tracking movement relative to known features.

Implementation

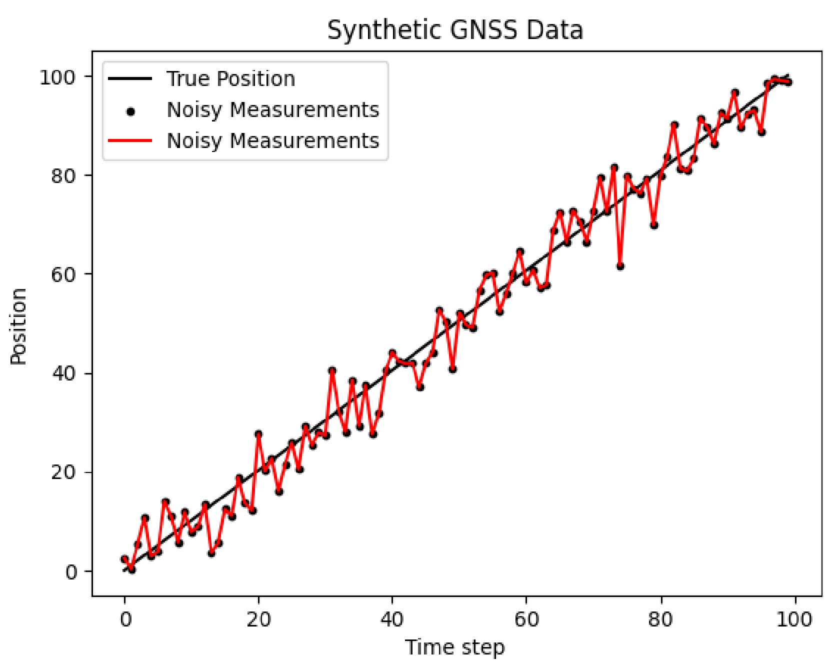
Python Code of the Kalman Filter

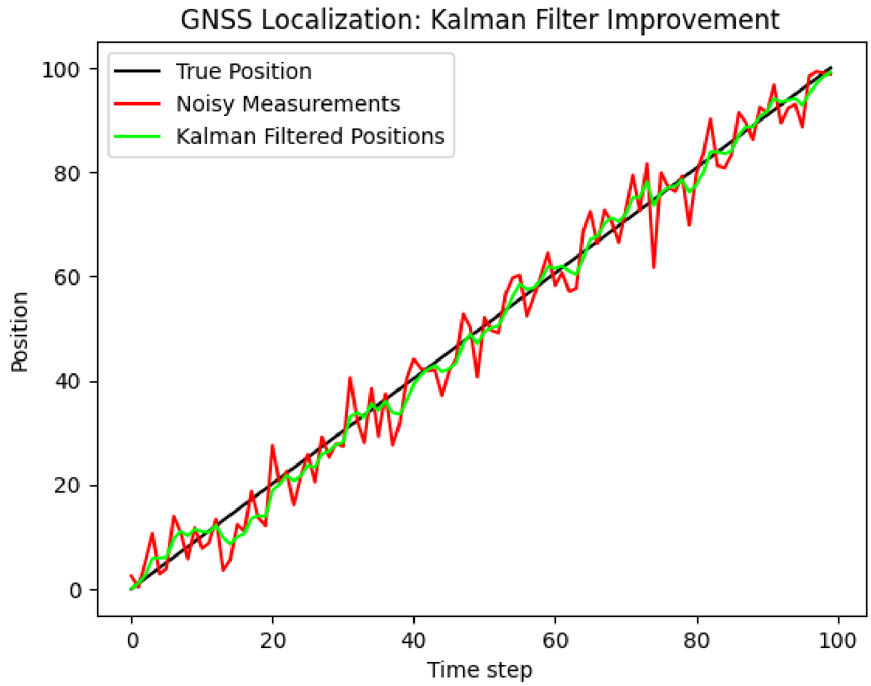
A Kalman Filter is fully specified by its initial conditions **(initial_state_mean and initial_state_covariance**), its transition parameters **(transition_matrices, transition_offsets, transition_covariance)**, and **its observation parameters (observation_matrices, observation_offsets, observation_covariance).** These parameters define a probabilistic model from which the unobserved states and observed measurements are assumed to be sampled from. Sensible default values are given for all unspecified parameters (zeros for all 1-dimensional arrays and identity matrices for all 2-dimensional arrays).

CODE – kalmanfiltercode

In the provided code, the Kalman Filter is applied to a simulated GNSS scenario where the receiver moves in a straight line with constant velocity. Noisy measurements are generated by adding random noise to the true position. The Kalman Filter effectively filters out the noise and provides a more accurate estimate of the receiver's position.

Results and Benefits





The plot titled "GNSS Localization: Kalman Filter Improvement" visually demonstrates the effectiveness of the Kalman Filter. The filtered positions (green line) closely track the true position (black line), while the noisy measurements (red line) exhibit significant fluctuations.

Quantitatively, the RMSE (Root Mean Squared Error) is calculated to assess the accuracy of the estimates. The RMSE of the noisy measurements is significantly higher than the RMSE after Kalman filtering, indicating a substantial improvement in localization accuracy.

Conclusion

The Kalman Filter proves to be a valuable tool for enhancing GNSS localization accuracy by effectively mitigating the impact of noisy measurements. Its ability to fuse noisy data with a dynamic system model enables more precise and reliable position estimation, contributing to improved navigation and positioning applications.

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