GNSS and environment map integration for autonomous navigation aid

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1. Introduction

Autonomous vehicle systems prone to become a reality nowadays, with systems making use of several sensors. Satellite positioning systems provide accurate positioning for several applications, but still not a reality for autonomous navigation due to low availability in complex environment due to signal outages, multipath and high convergence times. However, the integration of GNSS with other sensors can improve and allow continuous positioning.

This work proposes an integration of GNSS solution (PPK) with a mapped environment to use as aid to the filter. The main idea of the work is to use a street centerline as support to a positioning filter. This integration has the aim of helping an autonomous vehicle system.

2. Approach

Positions (E, N) of this car are (observed) obtained in a post-processing kinematic filter (PPK), at every second. This dynamic situation can be written as the following equations:

$$E_K = E_{K-1} + ve_{k-1}.dt.\cos(Az)$$
$$N_k = N_{k-1} + vn_{k-1}.dt.\sin(Az)$$
$$ve_k = ve_{k-1}$$
$$vn_k = vn_{k-1}$$

Prediction step: the state and error covariance are estimated from previous timestep $(k-1)$ to the current timestep k.

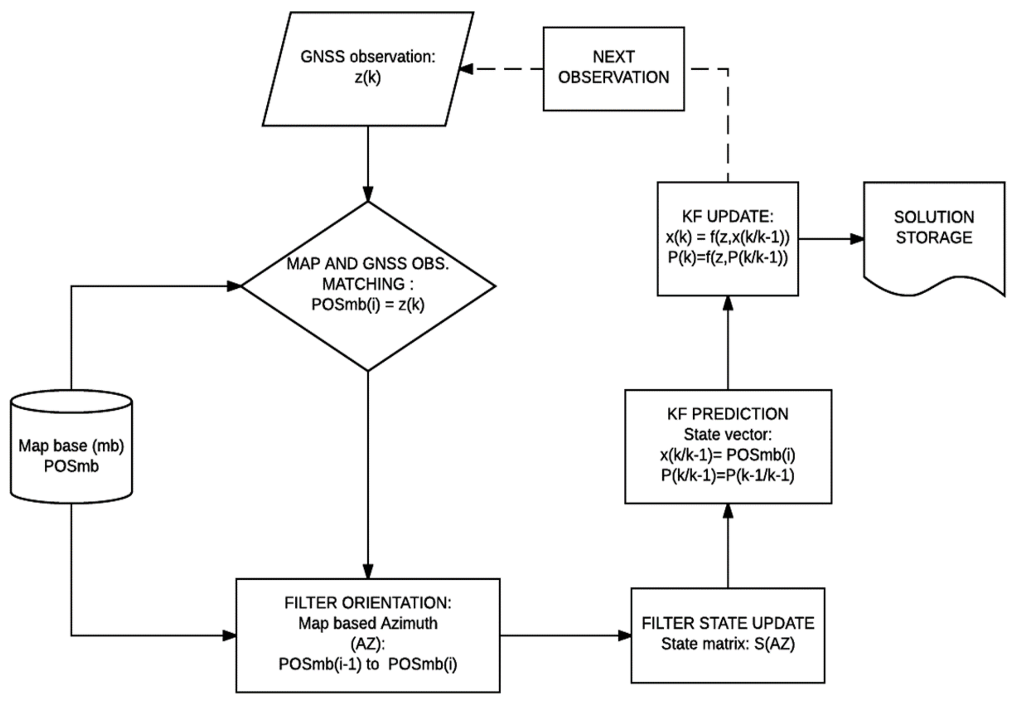
$$\hat{x}_{k|k-1} = F_{k-1}.\hat{x}_{k-1|k-1}$$
$$P_{k|k-1} = Q_{k-1} + F_{k-1}.P_{k-1|k-1}.F_{k-1}^T$$

Update step: the measurement updating equations correct the state and covariance estimates with measurements z_k.

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + k_k.(z_k - H_k.\hat{x}_{k|k-1})$$
$$P_{k|k} = P_{k|k-1} - k_k S_k K_k^T$$

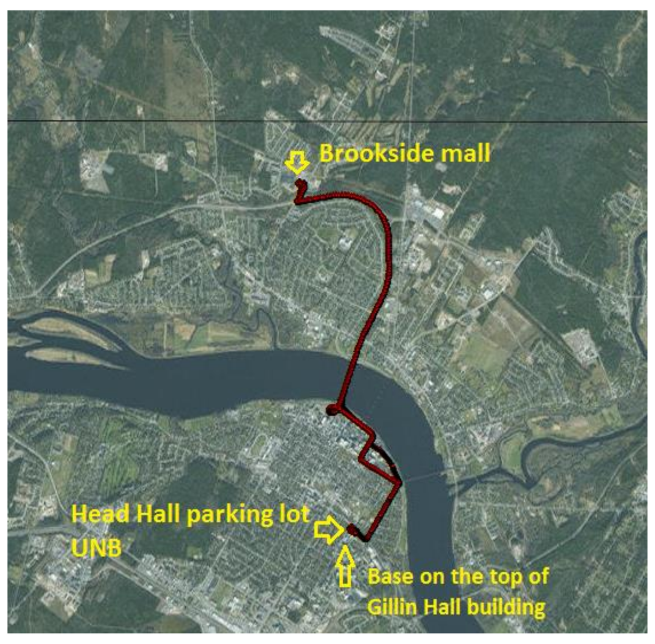
where $S_k = H_k P_{k|k-1} H_k^T + R_k$ is the covariance of the updated term; and $k_k = P_{k|k-1} H_k^T S_k^{-1}$ is the Kalman gain.

The process noise sequence tries to account for any or unforeseen disturbances in the motion. Tests led us to adopt the value of 0.2 m/s² as a reasonable process noise for this type of model.



3. Data sets

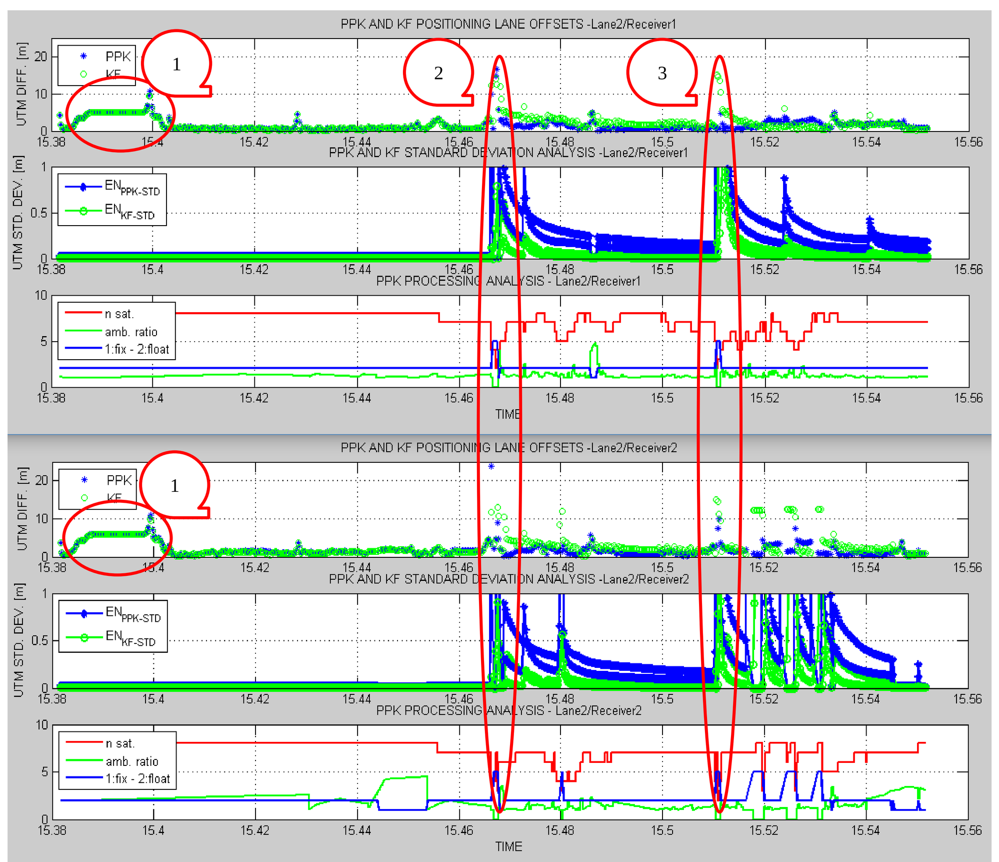
GPS data collected by two JAVAD Triumph LS receivers placed on the roof of a vehicle. Kinematic data collected in Fredericton (figure). GPS data processed in Post-Processing Kinematic (PPK) mode with RTKLIB. Lanes Information extracted from the orthophotos of 15 cm resolution from the public GIS data of NB. Reference points generated at every 2 m from the streets centerlines using ArcGis



4. Test Results

General behaviour on straight street segments:

Receivers 1 and 2



1: Change of lane

2: Receiver 1 outage

4. Discussion

- Kalman Filter with Lane information brought improvements in some points:
  - When observations were stable and continuous
  - On rapid observation outages, Lane information helped the KF to keep the solution in the lane.
- Receiver 2 was more difficult to work due to several outages.
- Precision was not achieved at the PPK level.
- Continuous observation is essential for this approach
- PPK level accuracy was achieved under certain circumstances; but not precision
- Future challenges:
  - Filter re-initialization
  - Poor satellite visibility
  - Integration of more sensors

5. Acknowledgements

Research partly funded by program Science without Borders, Brazil.

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IAG Commission 4 Symposium 2016
Wrocław, Poland, September 4-7