Performance evaluation of GNSS/INS integration

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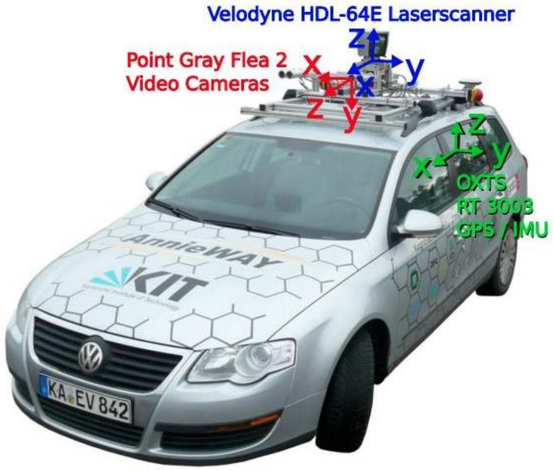
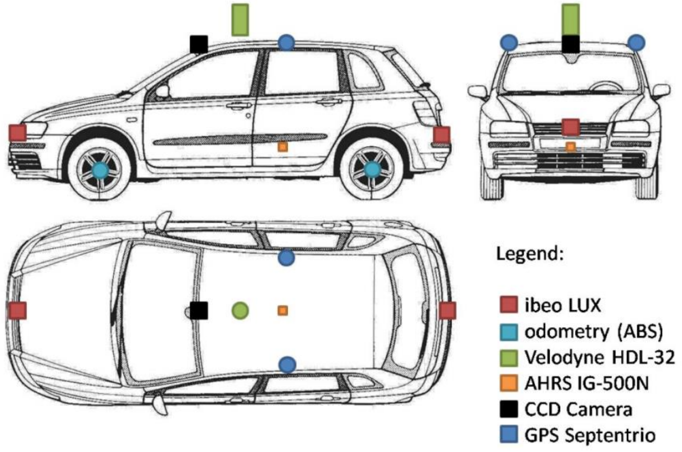
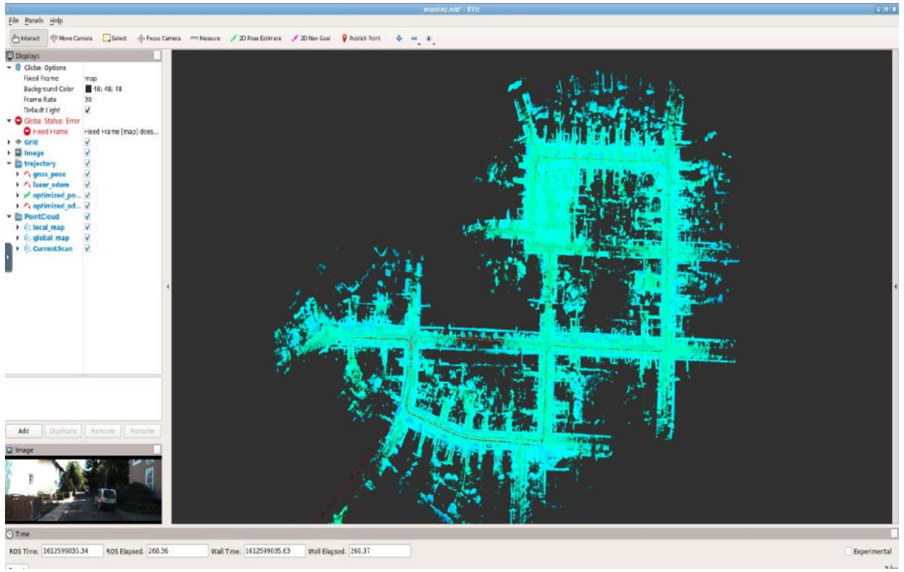
1. Objectives

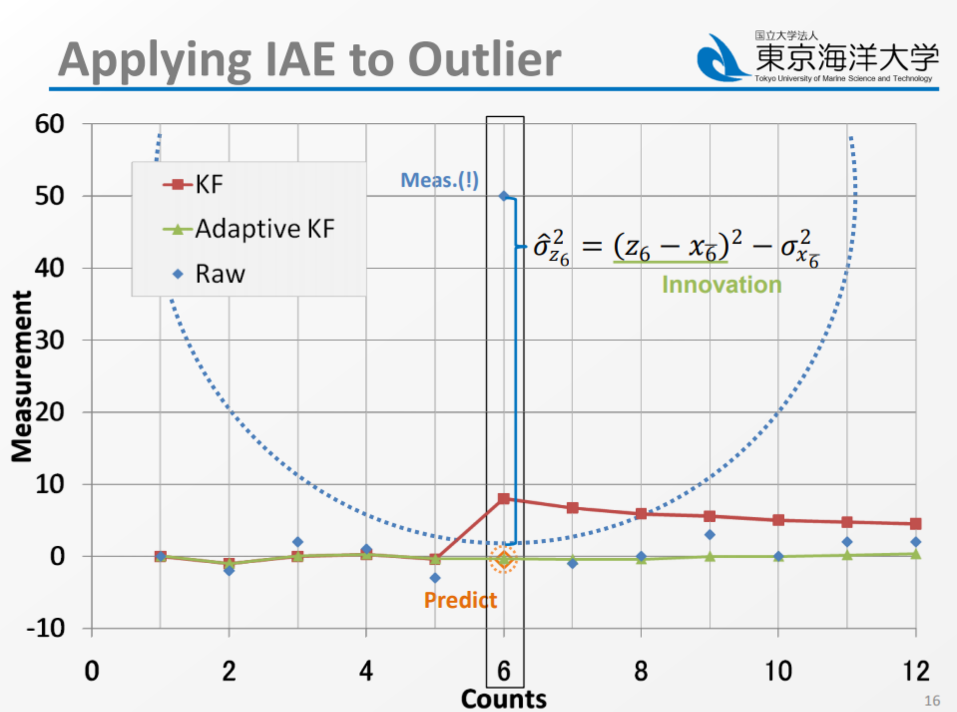






With the rise of automatic driving, the research of vehicle integrated navigation and positioning becomes very important. In the face of market-oriented demand, what kind of technical solutions to achieve **low-cost, high reliability and accurate positioning** have become an important research topic.

1. Objectives

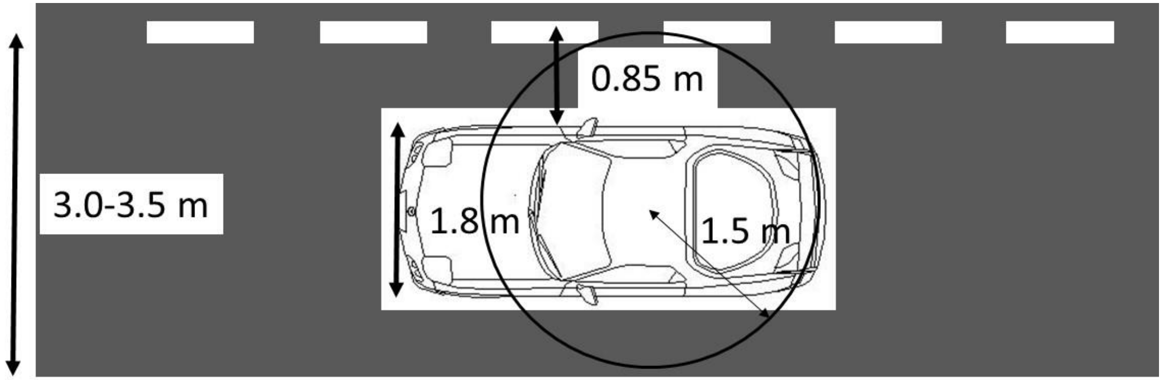


- Our laboratory has study in GNSS and INS for many years.
- Dr. Tominaga showed the IAE (innovation-based adaptive estimation) Kalman filter, and compare the estimation result with classical Kalman filter, we continue his study, and use this method in the tightly coupled.

- **Reference: Takaki Tominaga, A study on improvement of GNSS positioning system in urban area**

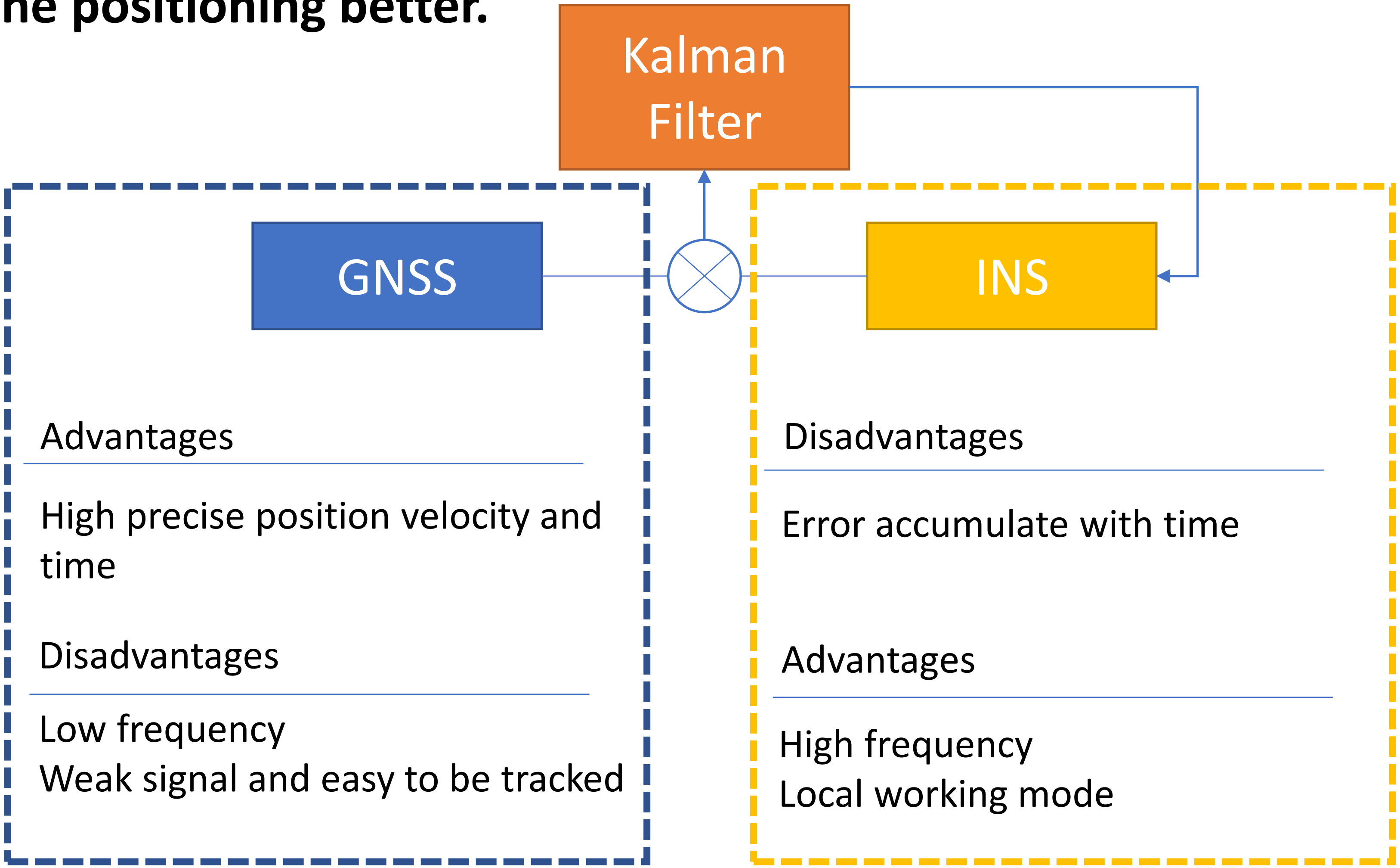
1. Objectives

- Our laboratory has achieved accuracy within 1 m (95%) even in dense urban area (Marunouchi) using low-cost GNSS/IMU + speed sensor.
- However, we have not investigated the difference of performance between loosely coupled (LC) and tightly coupled (TC) thoroughly. In this paper, the TC program was built and mainly focused on the difference between LC and TC.
- The accuracy leaves in the TODO list and set as the future study.



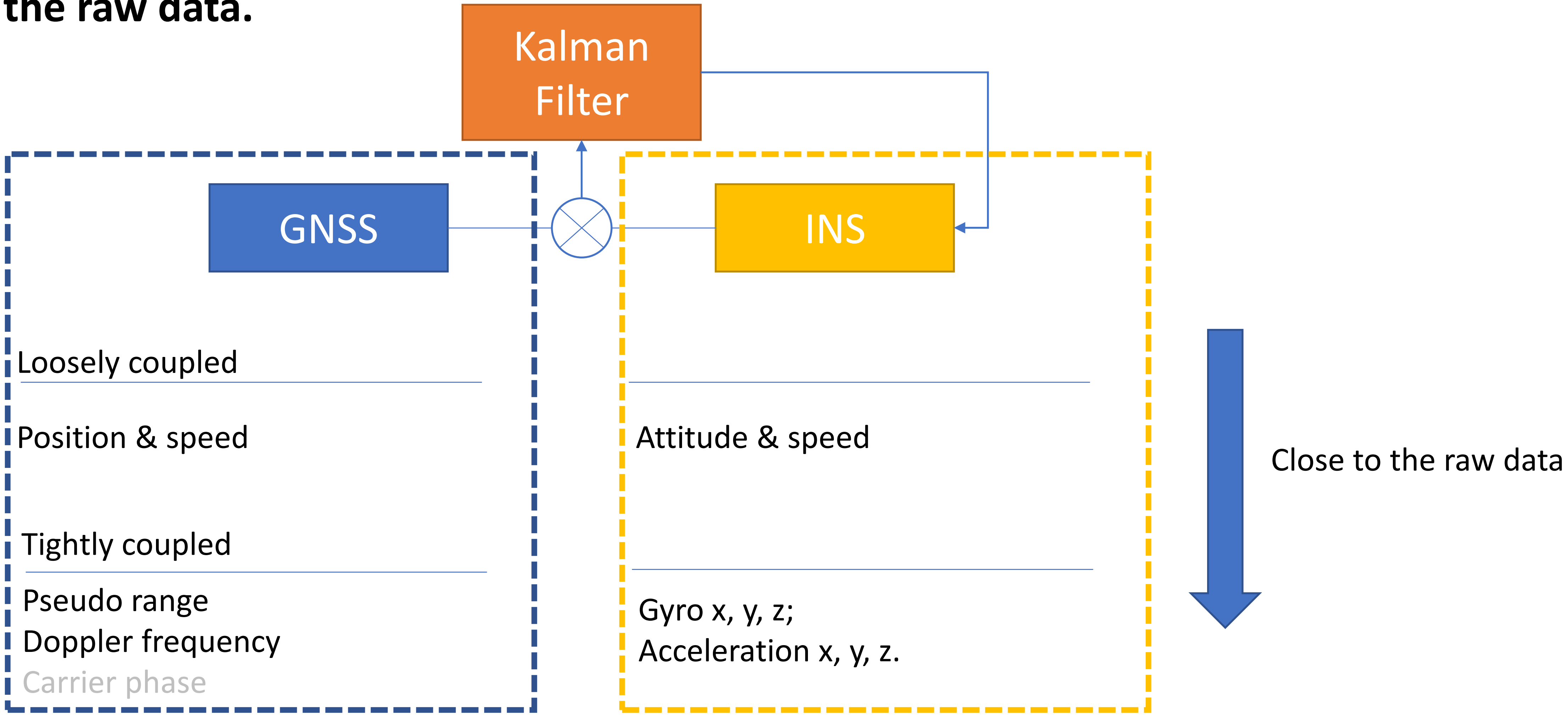
2. GNSS/INS coupled

Each sensor has its advantages and disadvantages, GNSS/INS coupled can improve the positioning better.



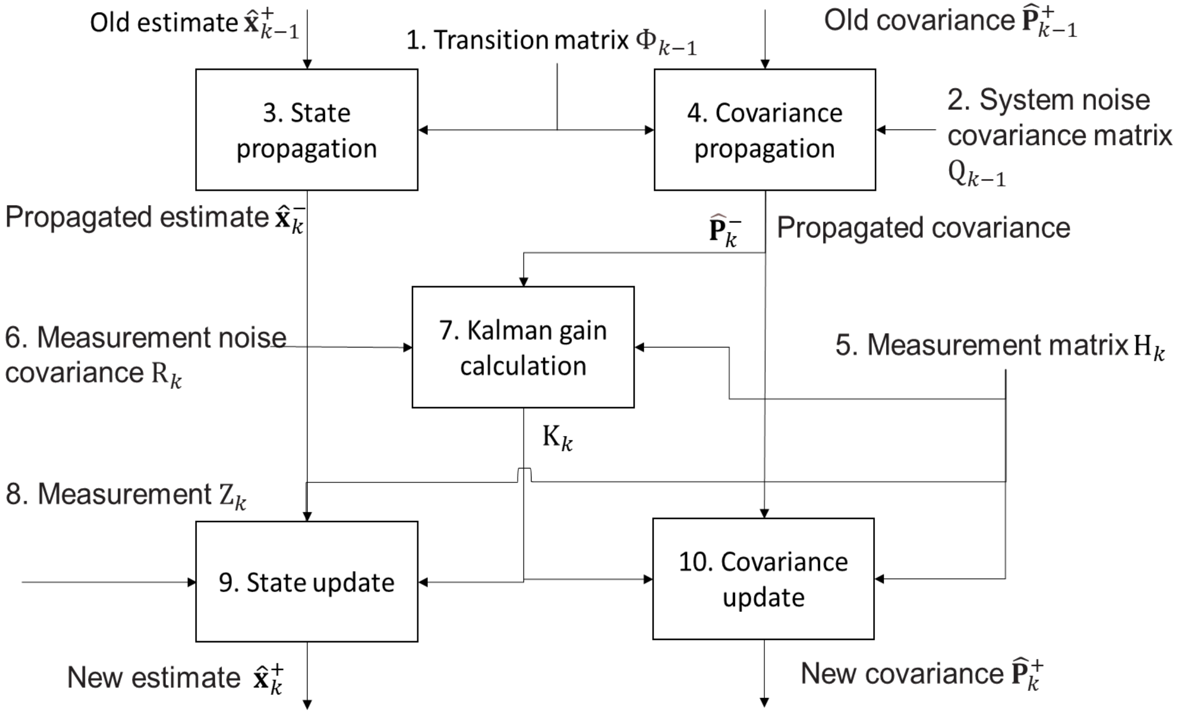
2. GNSS/INS coupled

The difference between two methods is the measurements, tightly coupled is closer to the raw data.



2. GNSS/INS coupled

Basic Kalman filter in GNSS/INS integration.



In Kalman filter, the state vector estimation is:

$$\hat{\boldsymbol{x}}_k^- = \boldsymbol{\Phi}_{k-1}\hat{\boldsymbol{x}}_{k-1}^+$$

Error covariance matrix is:

$$\boldsymbol{P}_k^- = \boldsymbol{\Phi}_{k-1}\boldsymbol{P}_{k-1}^+\boldsymbol{\Phi}_{k-1}^{\mathrm{T}} + \boldsymbol{Q}_{k-1}$$

Observation matrix is:

$$\boldsymbol{h}(\boldsymbol{x}_k, t_k) = \boldsymbol{H}_k\boldsymbol{x}_k$$

Kalman gain is:

$$\boldsymbol{K}_k = \boldsymbol{P}_k^-\boldsymbol{H}_k^{\mathrm{T}}\left(\boldsymbol{H}_k\boldsymbol{P}_k^-\boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k\right)^{-1}$$

Update state vector:

$$\begin{aligned}\hat{\boldsymbol{x}}_k^+ &= \hat{\boldsymbol{x}}_k^- + \boldsymbol{K}_k(\boldsymbol{z}_k - \boldsymbol{H}_k\hat{\boldsymbol{x}}_k^-)\\ &= \hat{\boldsymbol{x}}_k^- + \boldsymbol{K}_k\delta z_k^-\end{aligned}$$

Update of error covariance matrix:

$$\boldsymbol{P}_k^+ = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_k^-$$

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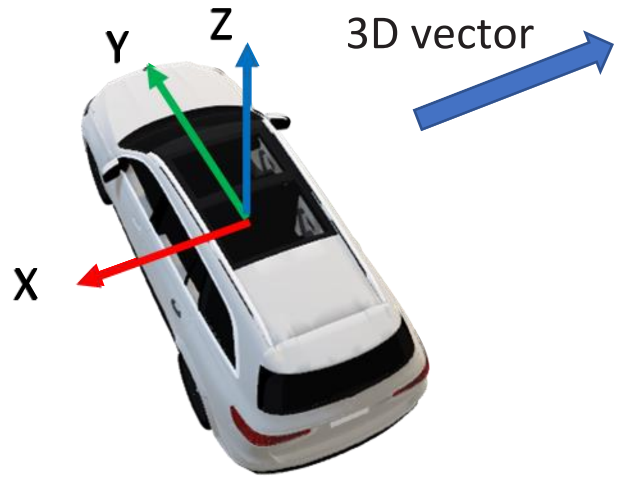
Mechanization equation in ECEF

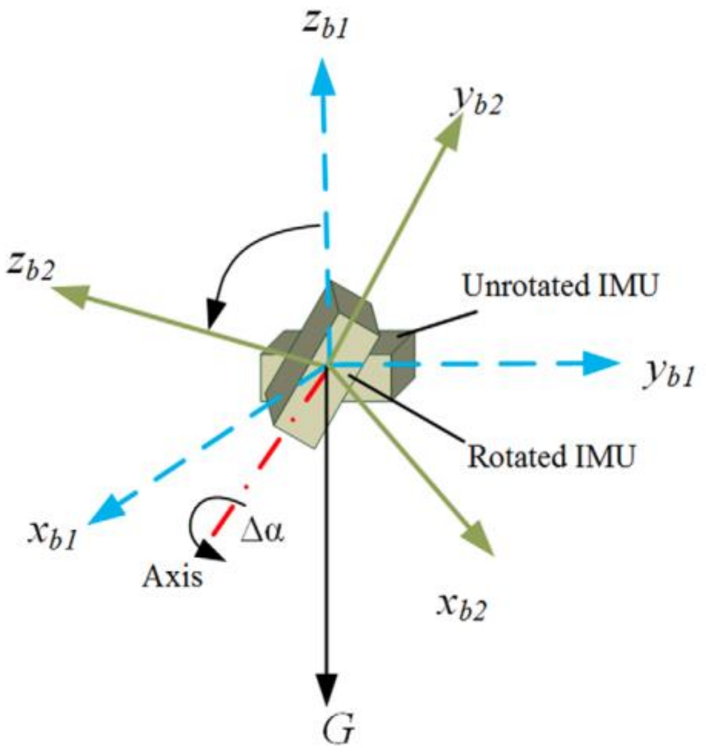


INS position methods called mechanization equation. For mechanization equation, there are four steps:

1. Using gyro increments to update the attitude;
2. Convert the acceleration specific force from body frame to navigation frame (ECEF or ENU);
3. Using old velocity, the acceleration and the time interval, the new speed can be calculated;
4. The new position can be calculated from the old position, new speed and time interval.

2. GNSS/INS coupled

Design Kalman filter for GNSS/INS integration

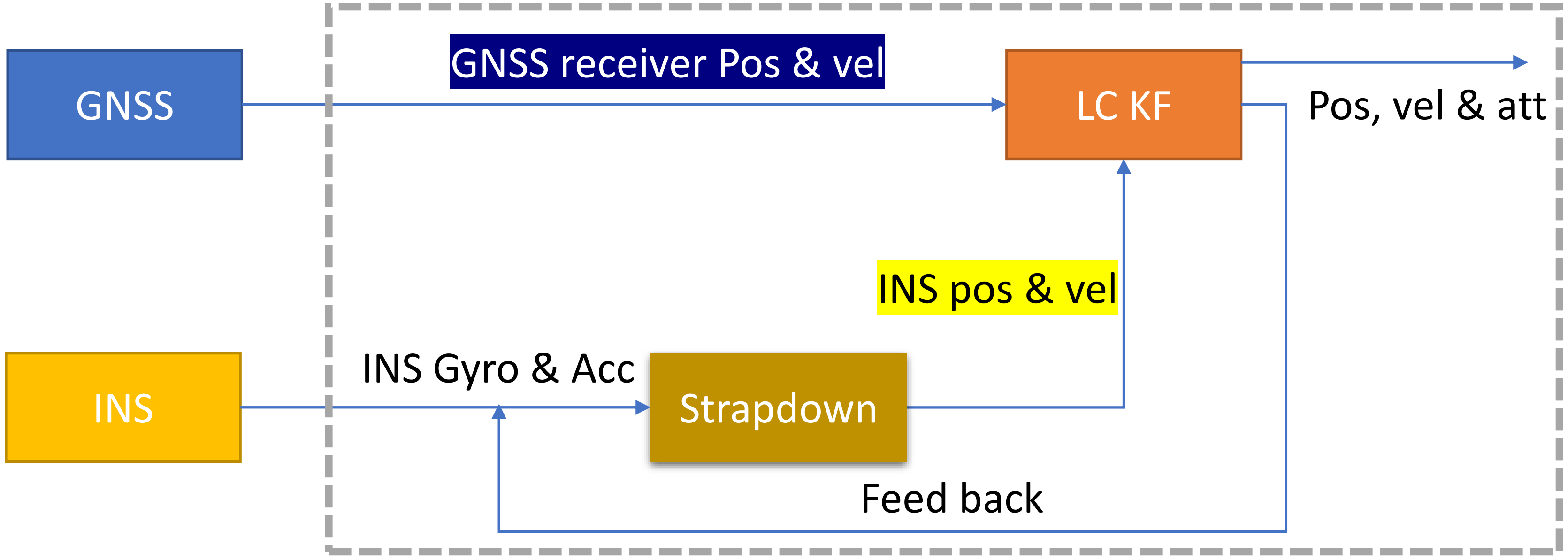


The GNSS/INS integration using INS as the main sensor. The INS attitude integral is obtained by gyro, and velocity integral is obtained by acceleration.

INS, as a dead-reckoning method, needs accurate attitude $\boldsymbol{\psi}_{eb}^{e}$, velocity $\boldsymbol{v}_{eb}^{e}$, position $\boldsymbol{r}_{eb}^{e}$, acceleration bias $\boldsymbol{b}_a$ and gyro bias $\boldsymbol{b}_g$ to do positioning. So, in the Kalman filter, these five values are settled as the state vector estimation.

$$\delta x = \begin{pmatrix} \delta\boldsymbol{\psi}_{eb}^{e} \\ \delta\boldsymbol{v}_{eb}^{e} \\ \delta\boldsymbol{r}_{eb}^{e} \\ \delta\boldsymbol{b}_a \\ \delta\boldsymbol{b}_g \end{pmatrix}$$

2.1 GNSS/INS loosely coupled



GNSS/INS loosely coupled means using GNSS position and velocity as Kalman filter measurements, which use it to estimate the INS. The Kalman filter will feed back the INS bias and output the position, velocity and attitude.

2.1 GNSS/INS loosely coupled

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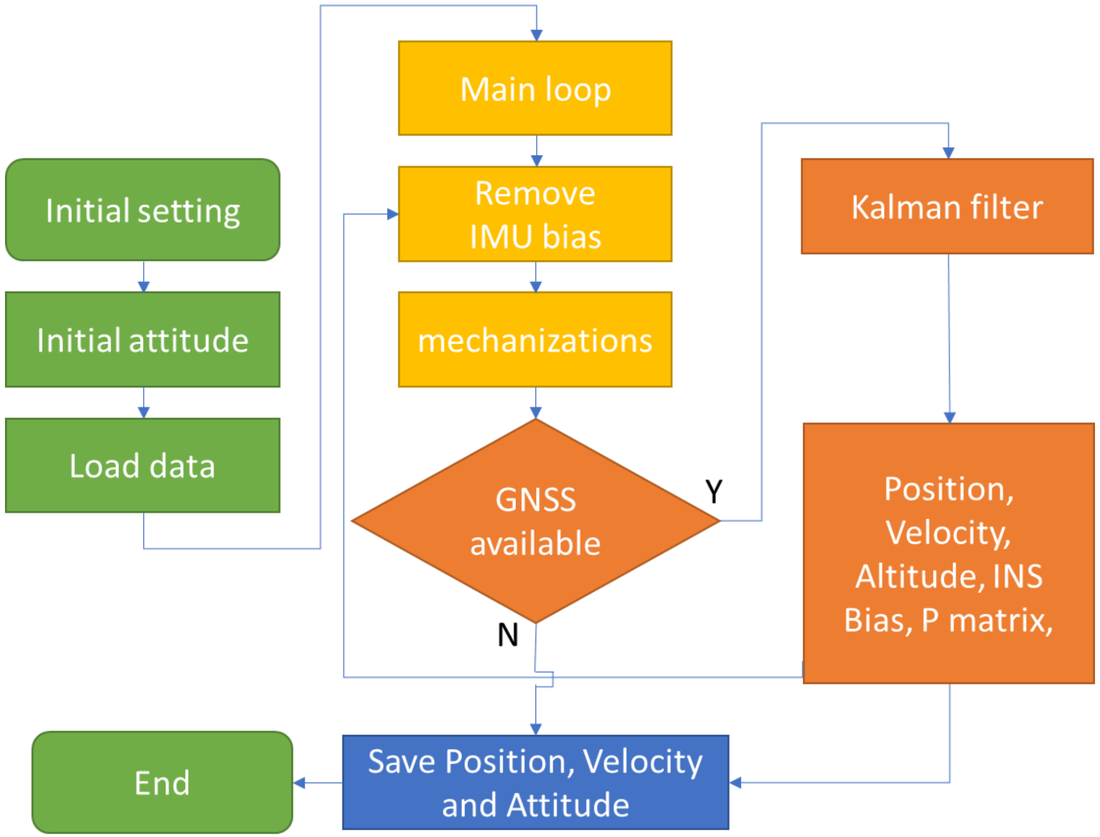

The GNSS/INS loosely coupled flow chart was showed in the left;

The initial attitude of INS is the Euler angle from body frame the navigation frame (ECEF);

If GNSS available, do Kalman filter. If not, output the INS result;

This program has close-loop correction, so after the Kalman filter, the estimate bias will feed back to the INS.

2.2 GNSS/INS tightly coupled

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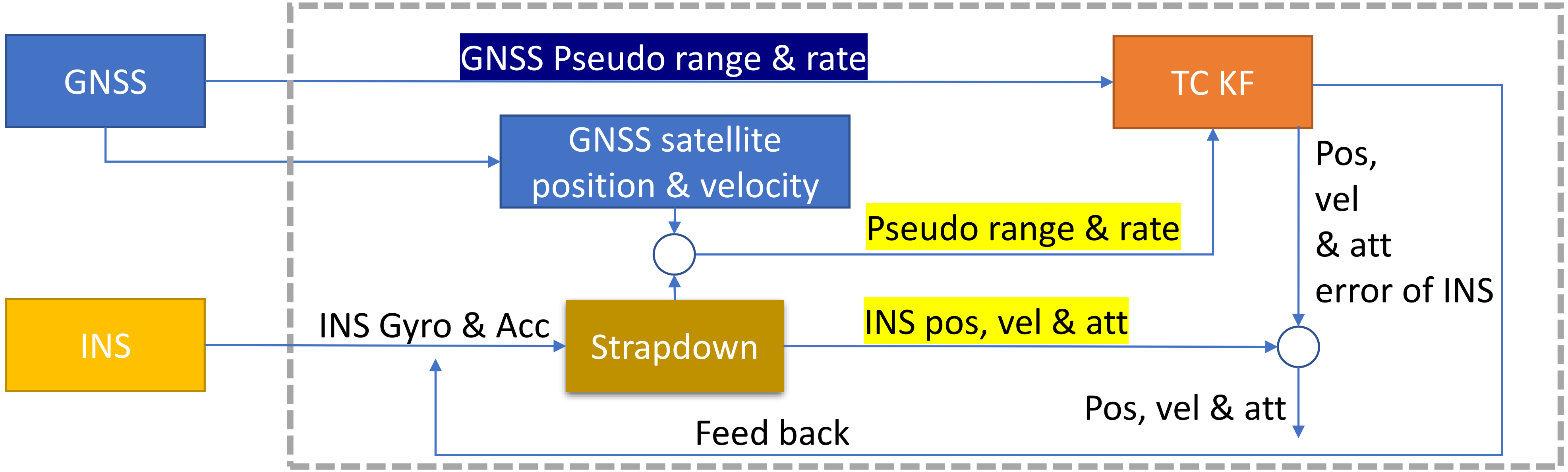
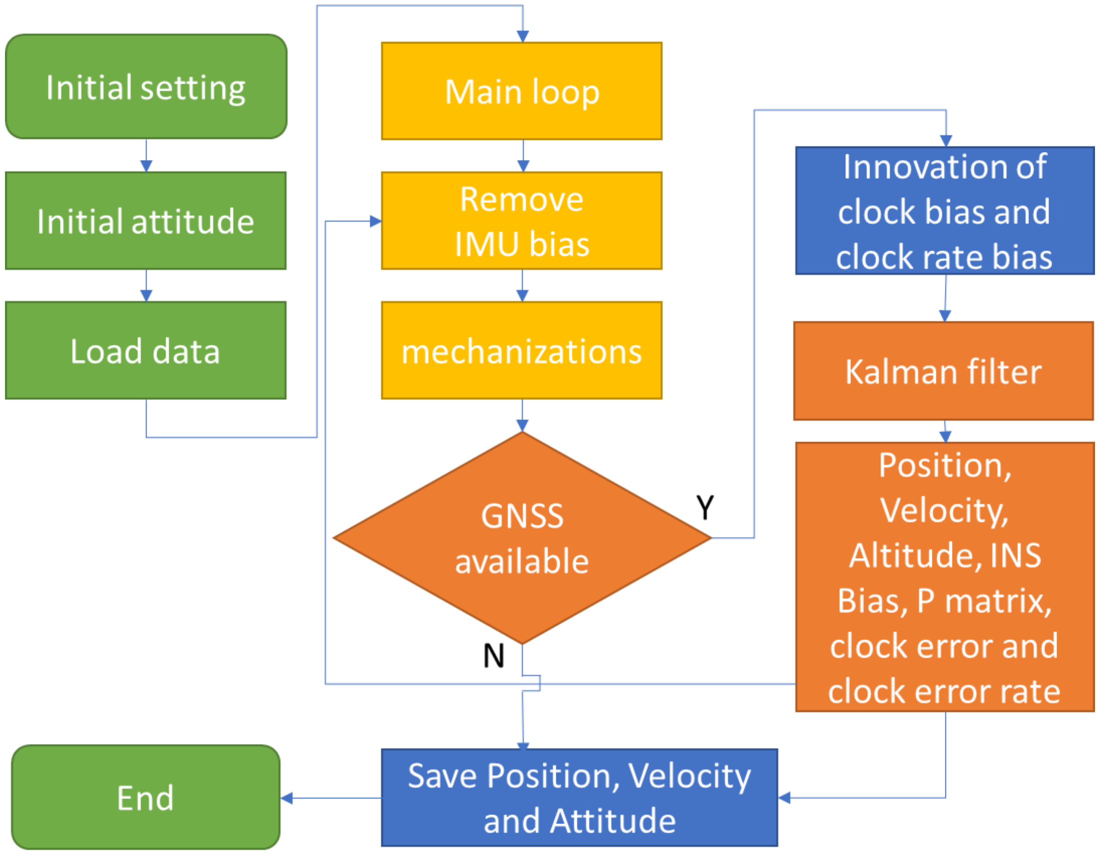


GNSS/INS tightly coupled means using GNSS pseudo range and pseudo range rate (Doppler frequency) as Kalman filter measurements, using INS position and velocity to calculate the estimate pseudo range and pseudo range rate, Kalman filter will estimate the INS errors, and eliminate the error of INS.

2.2 GNSS/INS tightly coupled



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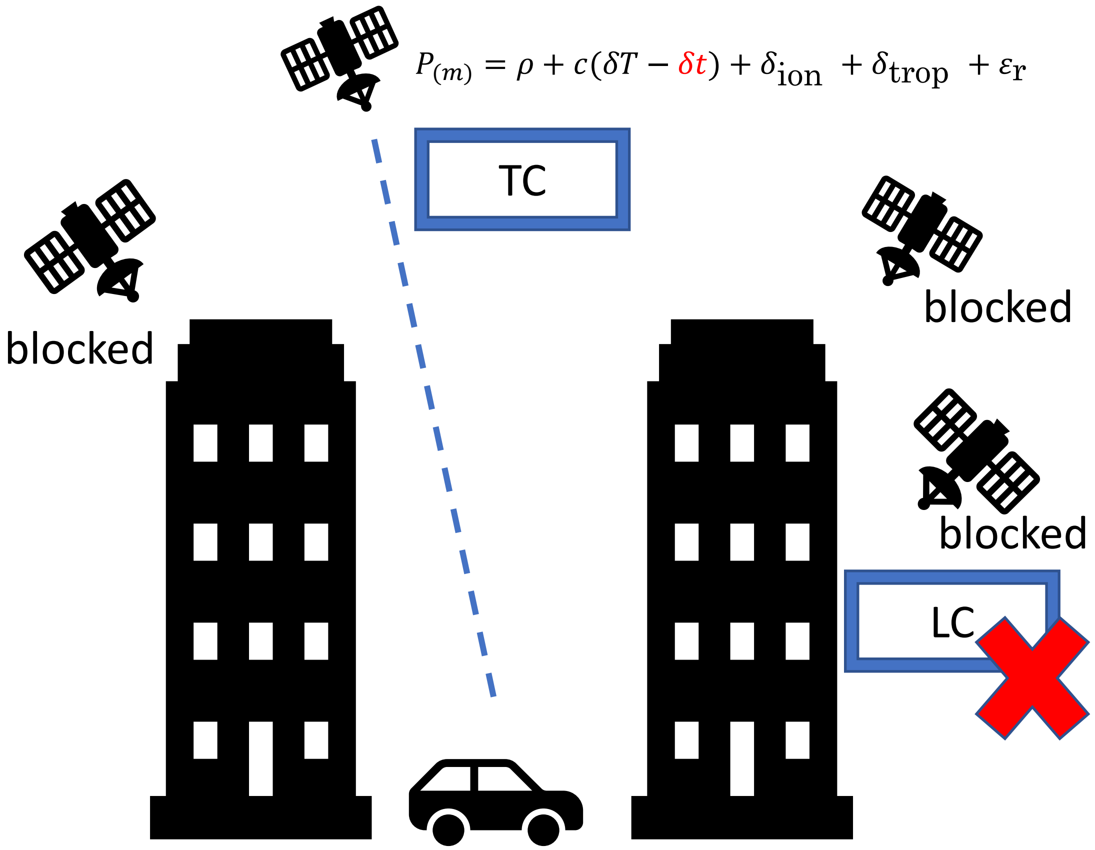
2.3 Difference with LC & TC



The difference between loosely coupled and tightly coupled is:

When the number of the satellites is less than 4, loosely coupled can't provide the measurements, but the tightly coupled can continuously provide the measurements when the satellites is one or more.

The satellite position, Ionospheric delay tropospheric delay are as the known quantity, we just need to estimate the receiver clock error and clock error rate.

It means that the tightly coupled can provide more continue measurement than loosely coupled. When the GNSS receiver in the urban environment, tightly coupled result should be more stable than loosely coupled.

Even in this case (only 1 sat.), TC can compare the measurement pseudo-range with predicted pseudo-range through INS.

2.3 Difference with LC & TC

The difference of transformation matrix is as follows:

$$\boldsymbol{\Phi}_{\mathrm{LC}}^{e} \approx \begin{bmatrix} \boldsymbol{I}_3 - \boldsymbol{\Omega}_{ie}^{e}\tau_s & 0_3 & 0_3 & 0_3 & \widehat{\boldsymbol{C}}_b^e\tau_s \\ \boldsymbol{F}_{21}^{e}\tau_s & I_3 - 2\boldsymbol{\Omega}_{ie}^{e}\tau_s & \boldsymbol{F}_{23}^{e}\tau_s & \boldsymbol{C}_b^e\tau_s & 0_3 \\ 0_3 & I_3\tau_s & I_3 & 0_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & I_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & 0_3 & I_3 \end{bmatrix}$$

$$\boldsymbol{\Phi}_{\mathrm{TC}}^{e} \approx \begin{bmatrix} I_3 - \Omega_{ie}^{e}\tau_s & 0_3 & 0_3 & 0_3 & \hat{C}_b^e\tau_s & 0_3 & 0_3 \\ F_{21}^{e}\tau_s & I_3 - 2\Omega_{ie}^{e}\tau_s & F_{23}^{e}\tau_s & C_b^e\tau_s & 0_3 & 0_3 & 0_3 \\ 0_3 & I_3\tau_s & I_3 & 0_3 & 0_3 & 0_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & I_3 & 0_3 & 0_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & 0_3 & I_3 & 0_3 & 0_3 \\ 0 & 0 & 0 & 0 & 0 & 1 & \tau_s \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Where:

$$F_{21}^{e} = \left[-\left(\widehat{\boldsymbol{C}}_b^e \hat{f}_{ib}^{b}\right)\wedge\right]$$

$$F_{23}^{e} = -\frac{2\hat{\gamma}_{ib}^{e}}{r_{eS}^{e}(\hat{L}_b)} \frac{\hat{r}_{eb}^{e\,\mathrm{T}}}{|\hat{r}_{eb}^{e}|}$$

- **Reference: Paul D Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems**

2.3 Difference with LC & TC

The difference in observation matrix is as follows:

$$\boldsymbol{H}_{LC} = \begin{pmatrix} 0_3 & 0_3 & -\boldsymbol{I}_3 & 0_3 & 0_3 \\ 0_3 & -\boldsymbol{I}_3 & 0_3 & 0_3 & 0_3 \end{pmatrix}$$

$$\boldsymbol{H}_{TC} \approx \begin{pmatrix} 0_{1,3} & 0_{1,3} & u_1^{\gamma T} & 0_{1,3} & 0_{1,3} & 1 & 0 \\ 0_{1,3} & 0_{1,3} & u_2^{\gamma T} & 0_{1,3} & 0_{1,3} & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0_{1,3} & 0_{1,3} & u_m^{\gamma T} & 0_{1,3} & 0_{1,3} & 1 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0_{1,3} & u_1^{\gamma T} & 0_{1,3} & 0_{1,3} & 0_{1,3} & 0 & 1 \\ 0_{1,3} & u_2^{\gamma T} & 0_{1,3} & 0_{1,3} & 0_{1,3} & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0_{1,3} & u_m^{\gamma T} & 0_{1,3} & 0_{1,3} & 0_{1,3} & 0 & 1 \end{pmatrix}_{x=\hat{x}_k} , \gamma \in i, e$$

The difference in innovation matrix is as follows:

$$\delta z_{LC} = \begin{pmatrix} \hat{\boldsymbol{r}}_{eaG}^{e} - \hat{\boldsymbol{r}}_{eb}^{e} - \hat{C}_b^e \boldsymbol{L}_{ba}^b \\ \hat{\boldsymbol{v}}_{eaG}^{e} - \hat{\boldsymbol{v}}_{eb}^{e} - \hat{\boldsymbol{C}}_b^e \left(\hat{\boldsymbol{\omega}}_{ib}^b \wedge \boldsymbol{L}_{ba}^b\right) + \boldsymbol{\Omega}_{ie}^e \hat{\boldsymbol{C}}_b^e \boldsymbol{L}_{ba}^b \end{pmatrix}_k$$

$$\delta z_{TC} = \begin{pmatrix} \left(\tilde{\rho}_{a,C}^1 - \hat{\rho}_{a,c}^{1-}, \tilde{\rho}_{a,C}^2 - \hat{\rho}_{a,C}^{2-}, \cdots \tilde{\rho}_{a,C}^m - \hat{\rho}_{a,C}^{m-}\right)_k \\ \left(\tilde{\dot{\rho}}_{a,C}^1 - \hat{\dot{\rho}}_{a,C}^{1-}, \tilde{\dot{\rho}}_{a,C}^2 - \hat{\dot{\rho}}_{a,C}^{2-}, \cdots \tilde{\dot{\rho}}_{a,C}^m - \hat{\dot{\rho}}_{a,C}^{m-}\right)_k \end{pmatrix}$$

Where:

$u_m^{\gamma T}$ is the satellite m predict line of sight

- **Reference: Paul D Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems**

3. Multi-sensor fusion method

Besides using GNSS position and velocity, there are several choices for Kalman filter measurements, for the attitude $\boldsymbol{\psi}_{eb}^{e}$, velocity $\boldsymbol{v}_{eb}^{e}$, position $\boldsymbol{r}_{eb}^{e}$, acceleration bias $\boldsymbol{b}_a$ and gyro bias $\boldsymbol{b}_g$, the measurements are as follows:

$$\delta x = \begin{pmatrix} \delta\boldsymbol{\psi}_{eb}^{e} \\ \delta\boldsymbol{v}_{eb}^{e} \\ \delta\boldsymbol{r}_{eb}^{e} \\ \delta\boldsymbol{b}_a \\ \delta\boldsymbol{b}_g \end{pmatrix}$$

$\delta\boldsymbol{v}_{eb}^{e}$

Vehicle motion model , Wheel speed sensor

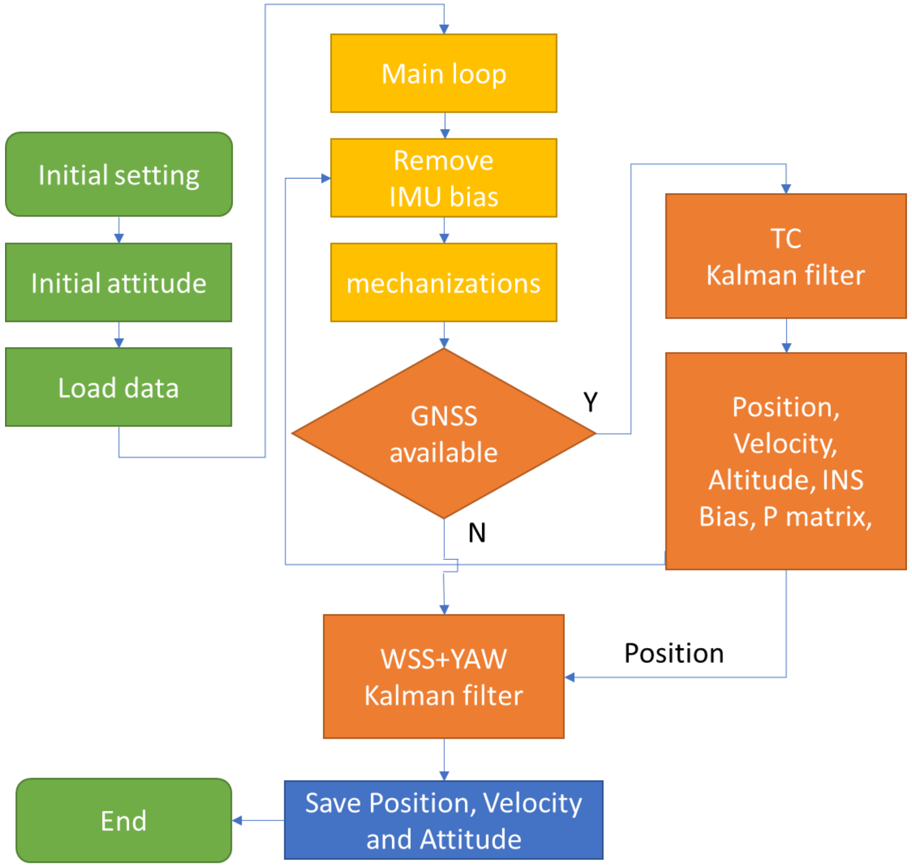
$\delta\boldsymbol{r}_{eb}^{e}$

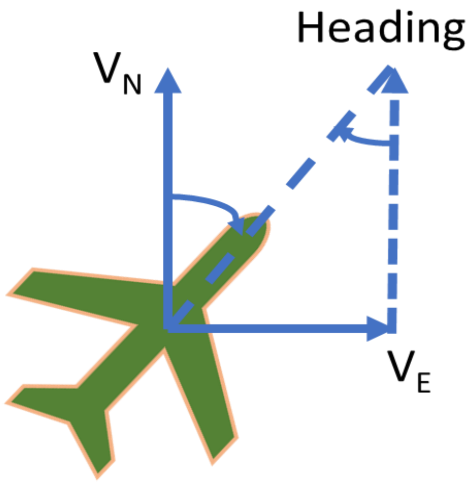
Barometer

$\delta\boldsymbol{b}_g$

Zero angular rate update

3.1 Wheel speed sensor



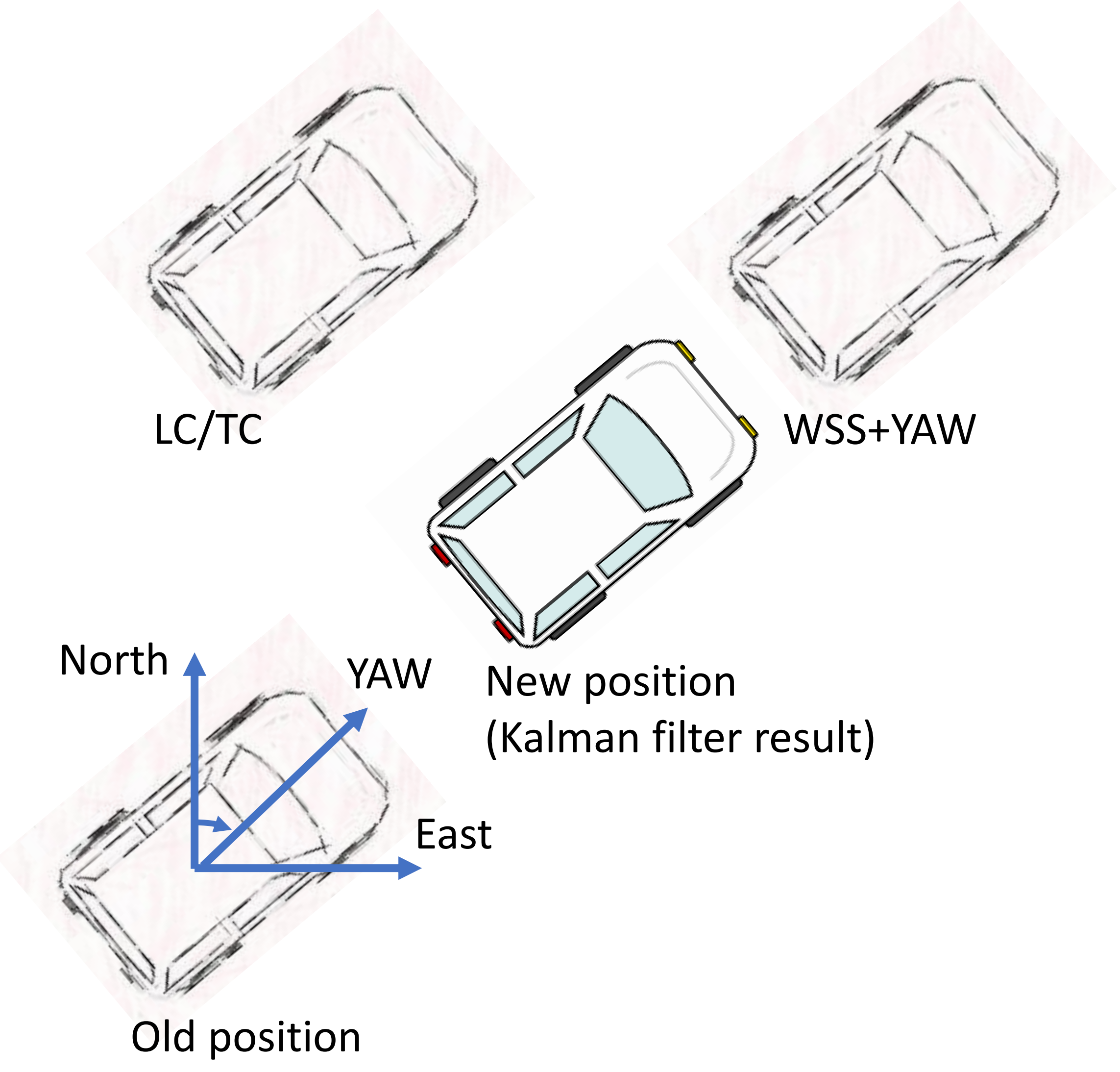


$$
\begin{cases}
v_E^n = \sin(heading)\boldsymbol{v}_{WSS}^{b} \\
v_N^n = \cos(\text{heading})\boldsymbol{v}_{WSS}^{b} \\
v_U^n \approx 0
\end{cases}
$$

For the vehicle motion model, in the ENU coordination, the vertical velocity is zero. The horizontal velocity is the component of the forward velocity of the body coordinate in the East and north directions.

Where:
WSS is wheel speed sensor, car speed in the front direction.

3.1 Wheel speed sensor

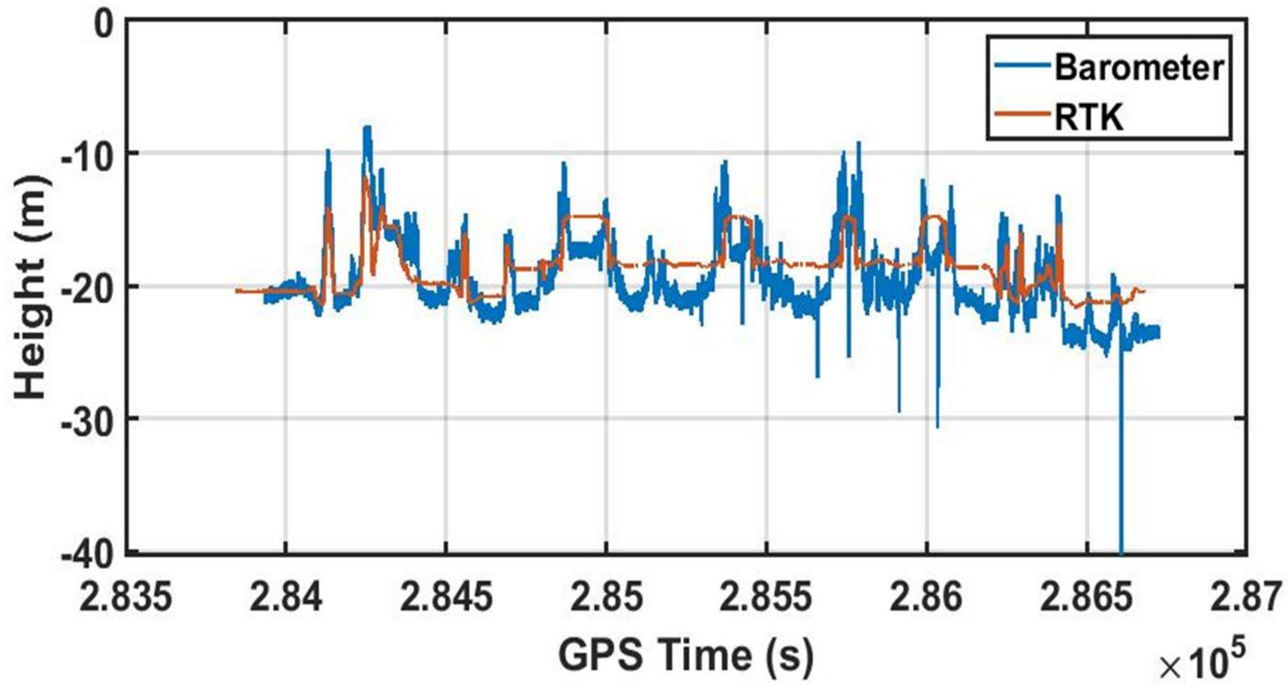


The WSS+YAW can provide the velocity in ENU. Using old position and velocity, we can get the WSS+YAW dead-reckoning position, do Kalman filter with the LC/TC position, can remove some error from the GNSS.

The Kalman filter is a very simple filter, the WSS+YAW error covariance is set as 0.1 m, the LC/TC position error covariance is set as 1 m.

The WSS+YAW dead-reckoning position has accumulate error because of the speed and the YAW angle. So the position accuracy can't hold in a long time.

3.2 Barometer

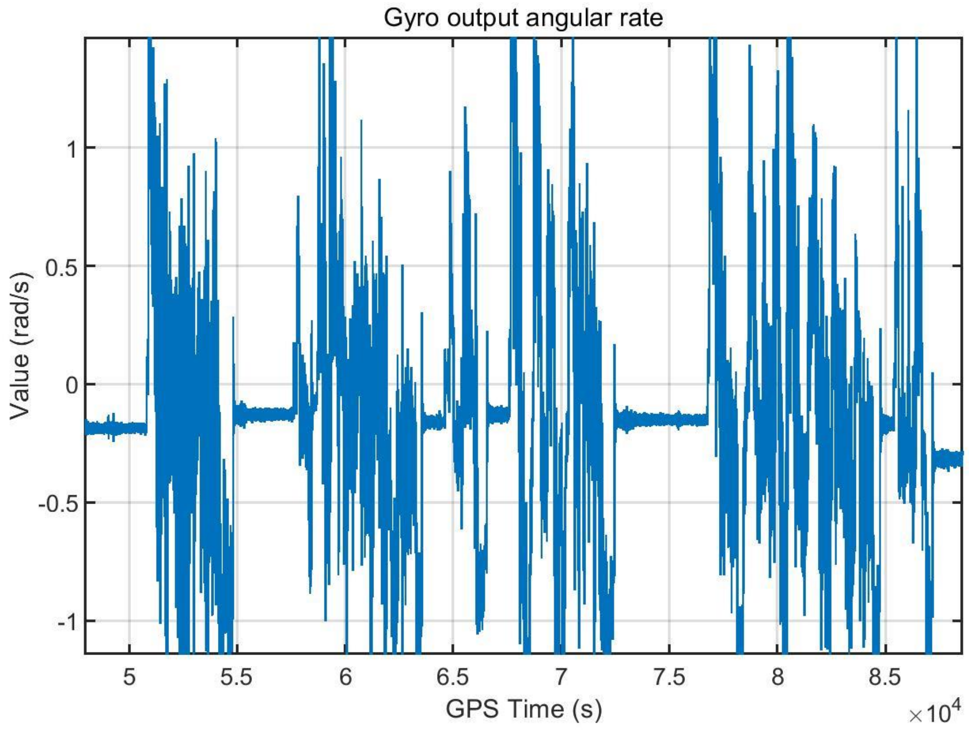


$$h = 153.8 * (t_0 + 273.2) * \left(1 - \left(\frac{p}{p_0}\right)^{0.1902}\right)$$

Where:
P_0 is the Sea level standard atmospheric pressure, about 1013.25 hPa

The barometer can be used to calculate the stable height, and the GNSS error can be obtained by comparing with the height of GNSS in the local horizontal coordinate system. If the difference between GNSS height and barometer height is greater than **6m**, we will discard this GNSS information.
However, the temperature is from the inside sensor, and the air pressure is easily affected by the weather, the height has noise and bias.

3.3 Zero angular rate update



The measurement matrix is:

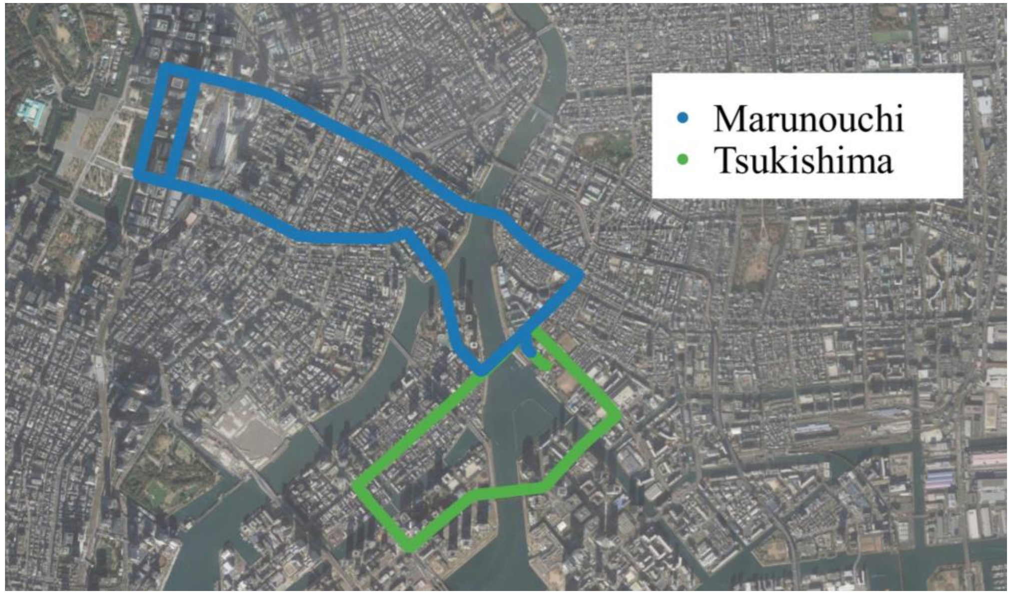
$$\boldsymbol{H}_{ZA,k} = \begin{pmatrix} 0_3 & 0_3 & 0_3 & 0_3 & -I_3 & 0 \end{pmatrix}$$

The measurement innovations of gyro is:

$$\delta z_{\boldsymbol{b}_g,k}^{-} = \mathbf{0} - \boldsymbol{b}_g$$

Bias always exists in the INS, when the car is static, the gyro values should be zeros. In this time, the gyro measurements are available, and the Kalman filter can predict bias completely as above.

4. Experiment and result



Two portions were selected, as considered more relevant for the objective of the tests, for each dataset tested twice:

1. In Tsukishima, some places the GNSS signal is poor, but the environment isn't always challengeable;

2. In Marunouchi, there are many tall buildings and it is hard to receive continuous GNSS signals. Also, it has one of the largest railway station, there are many overhead bridge, limiting the number of the satellites in view. It is a typical urban canyon environment.

4. Experiment and result

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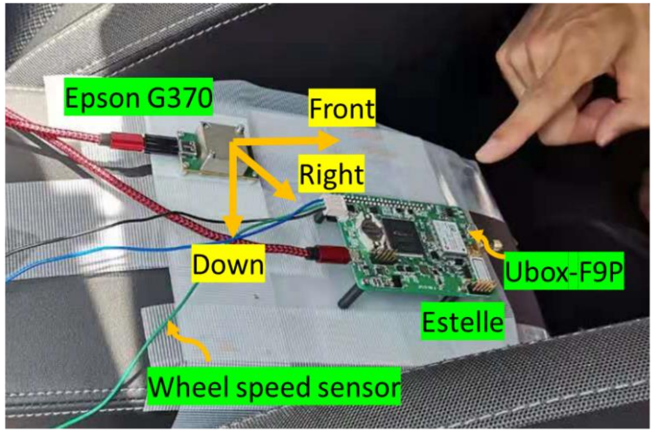
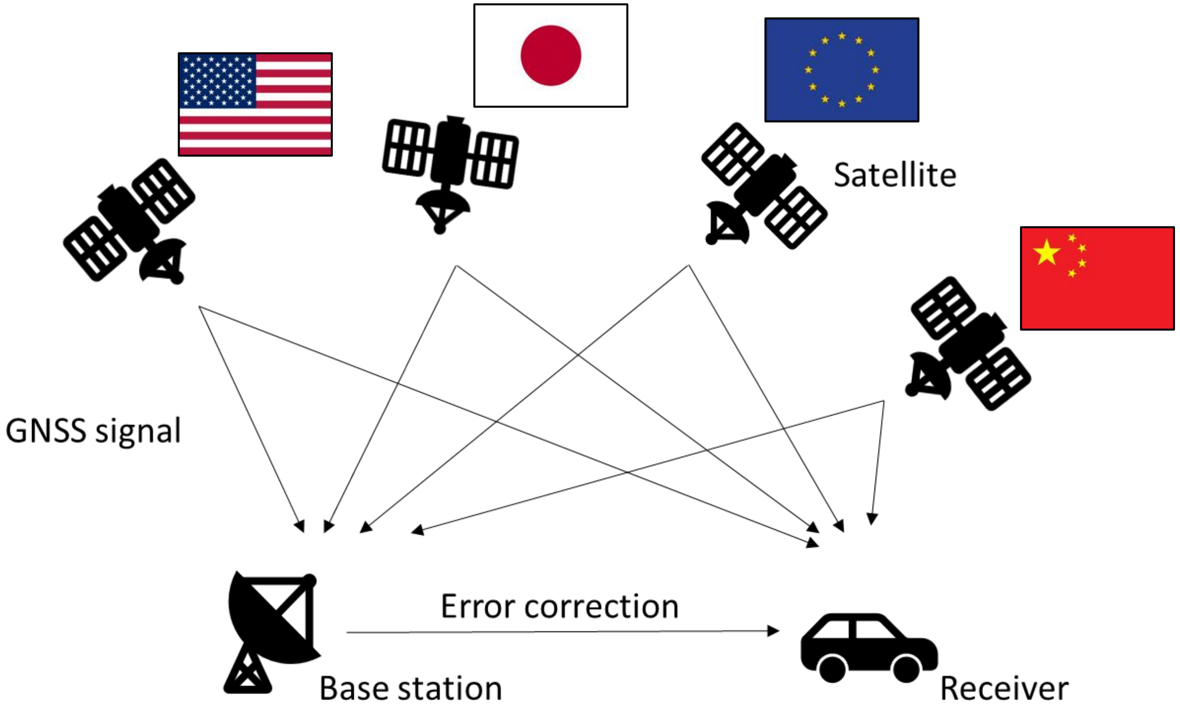
Hardware list and setting:

Equipment	Output	Frequency	Note
Ublox-F9P	GNSS measurements	5 Hz	Integrated with Estelle, synchronize the clock of sensors
Epson G370	Gyro and acceleration	50 Hz	Be used in Tsukishima 1st test and Marunouchi 2nd test
Estelle	Wheel speed sensor, temperature, air pressure	50 Hz	Be used in Tsukishima 2nd test and Marunouchi 1st test
poslv	Position	200 Hz	



4. Experiment and result

The GNSS setting is as follows:



GNSS parameters setting	
Satellites	GPS, QZSS, GALILEO and BDS
Elevation mask (degree)	15
SNR mask (dBHz)	35
GNSS measurements	
Loosely coupled	RTK and DGNSS
Tightly coupled	DGNSS

4. Experiment and result

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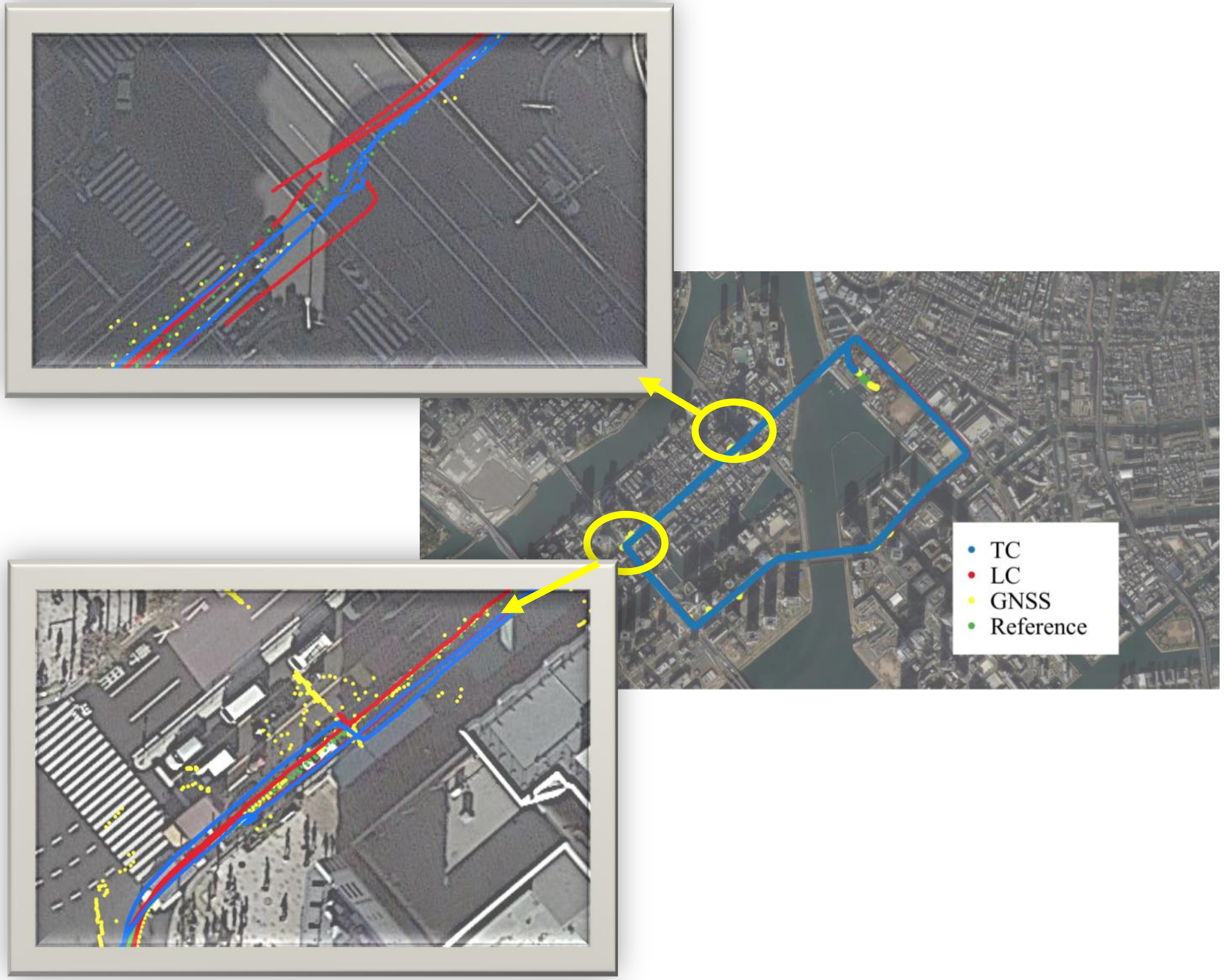
The Kalman filter parameters are as follows:

Kalman filter initial setting	
Initial attitude uncertainty (deg)	20
Initial velocity uncertainty (m/s)	0.1
Initial position uncertainty (m)	10
Initial acceleration bias uncertainty (uG)	1e-4
Initial gyro bias uncertainty (deg/hour)	10
Initial clock offset uncertainty (m)	10
Initial clock drift uncertainty (m/s)	0.1

Measurement noise		
LC	GNSS positioning noise (m)	3e-2
	GNSS velocity noise (m/s)	1e-3
TC	GNSS pseudo range noise (m)	1
	GNSS pseudo range rate noise (m/s)	6e-3
Multi-sensor	WSS+YAW (m)	0.1
	Zero angular rate (rad/s)	5e-4

System noise	
Gyro bias Instability (deg/hour)	0.8
Acceleration bias Instability (uG)	12
Acceleration velocity random walk (m/sec/hour^0.5)	0.025
Gyro angular random walk (deg/hour^0.5)	0.06
Receiver clock frequency-drift PSD (m^2/s^3)	1
Receiver clock phase-drift PSD (m^2/s)	1

4.1 Tsukishima result



In Tsukishima result:

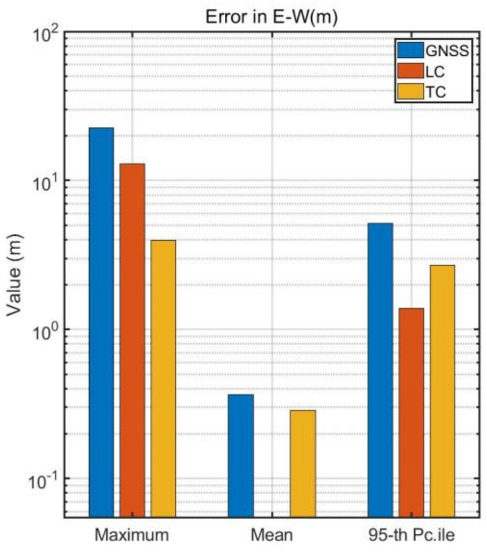
When the car under the viaduct, no GNSS signal, the TC error is smaller than the LC error, the TC attitude estimation is better than LC;

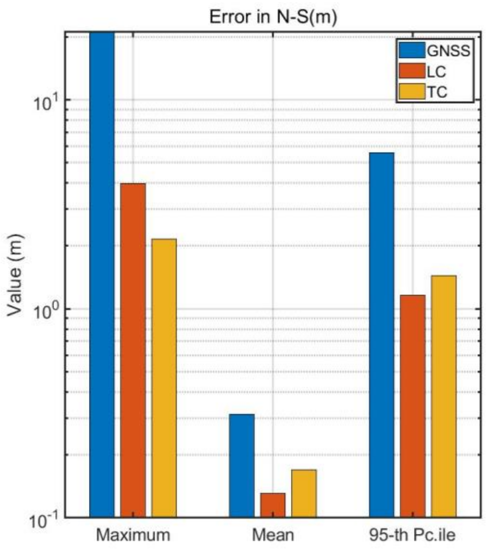
In multi-path effect, due to the GNSS velocity and pseudorange rate measurements, both LC and TC have stable positioning result;

LC position measurement using RTK fix and float solutions, so the TC mean error is lager than LC.

Note: GNSS means RTK fix solution and float solution

4.1 Tsukishima result 1st





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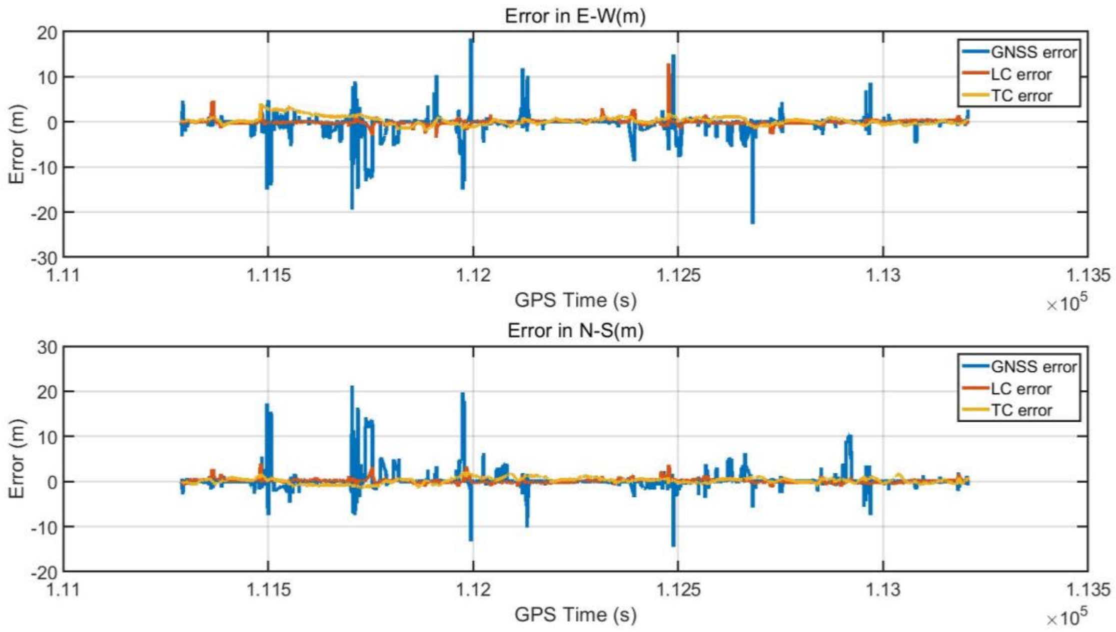
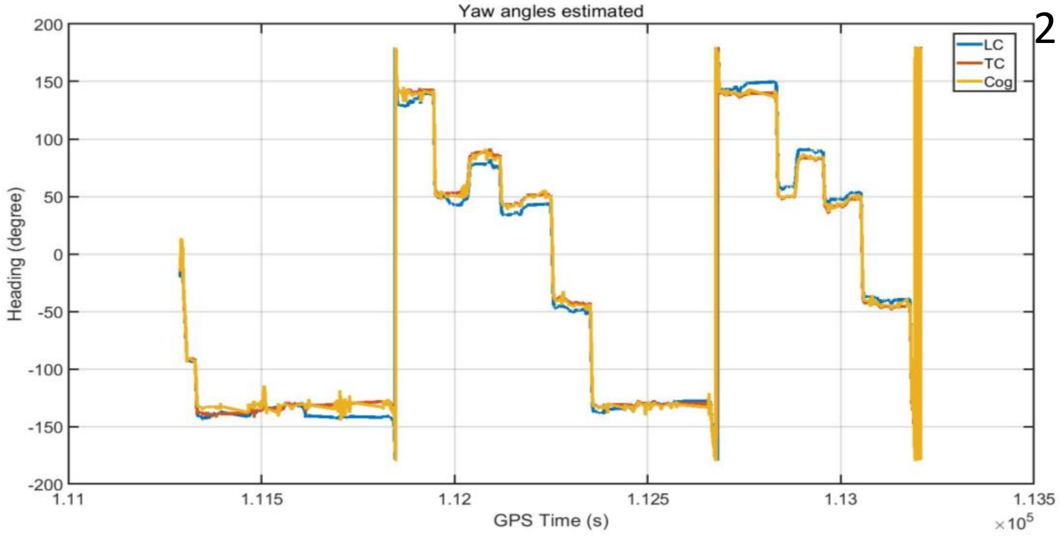
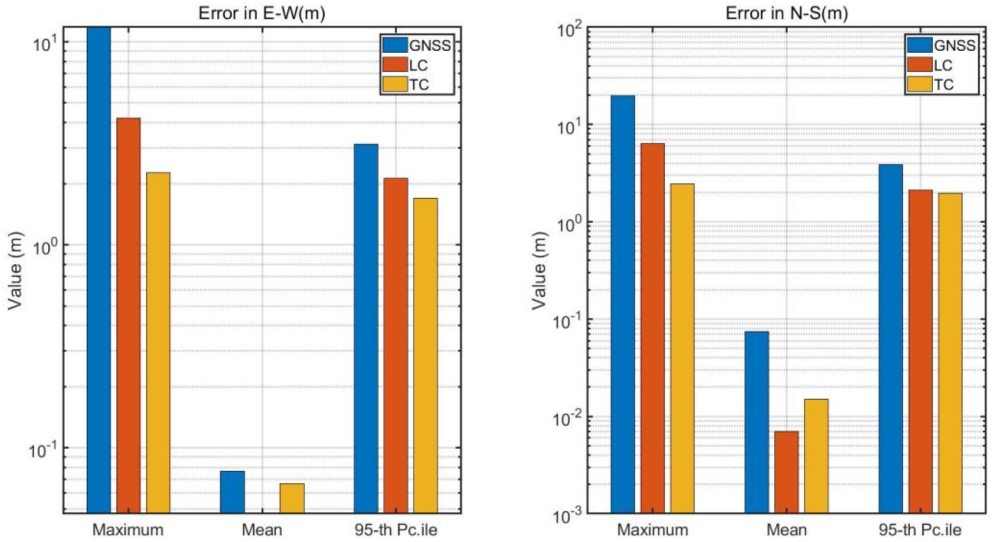


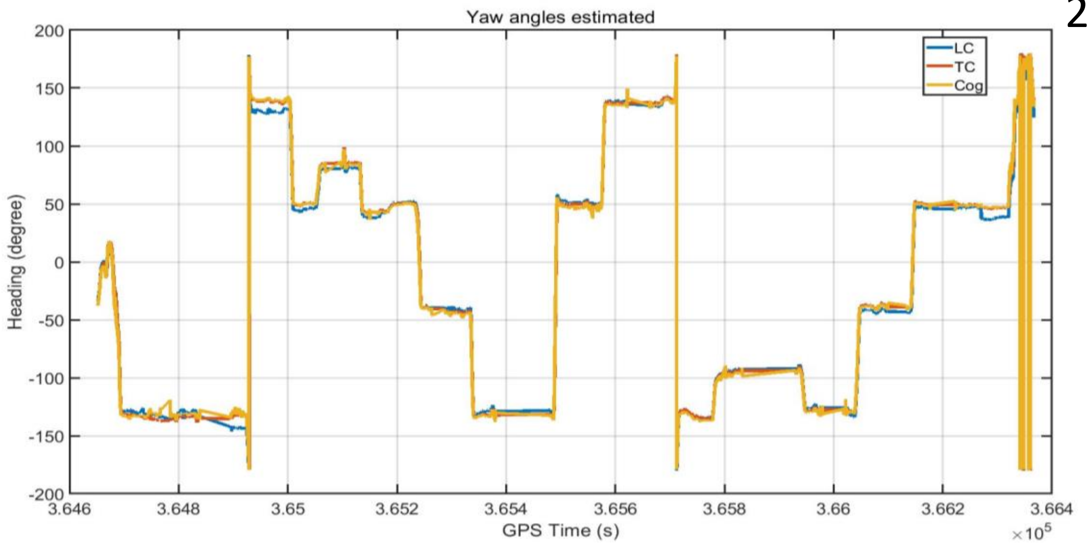


UNIT (M)	MAX-E	MAX-N	MEAN-E	MEAN-N	95%-E	95%-N
GNSS	22.6471	21.2237	0.3653	0.3127	5.1651	5.5614
LC	12.9120	3.9714	0.0544	0.1307	1.3885	1.1613
TC	3.9694	2.1577	0.2866	0.1700	2.6873	1.4457

4.1 Tsukishima result 2nd

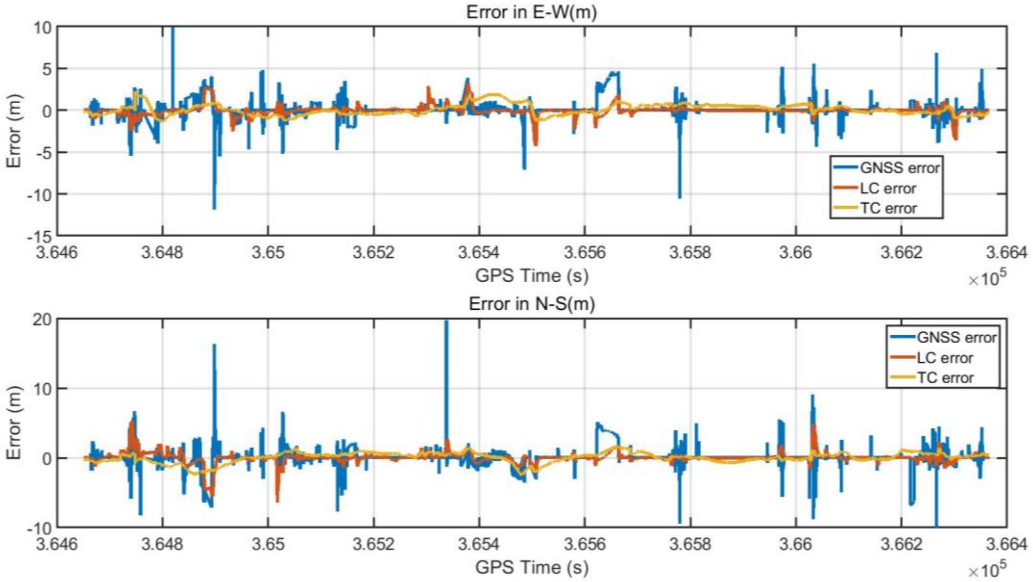


1



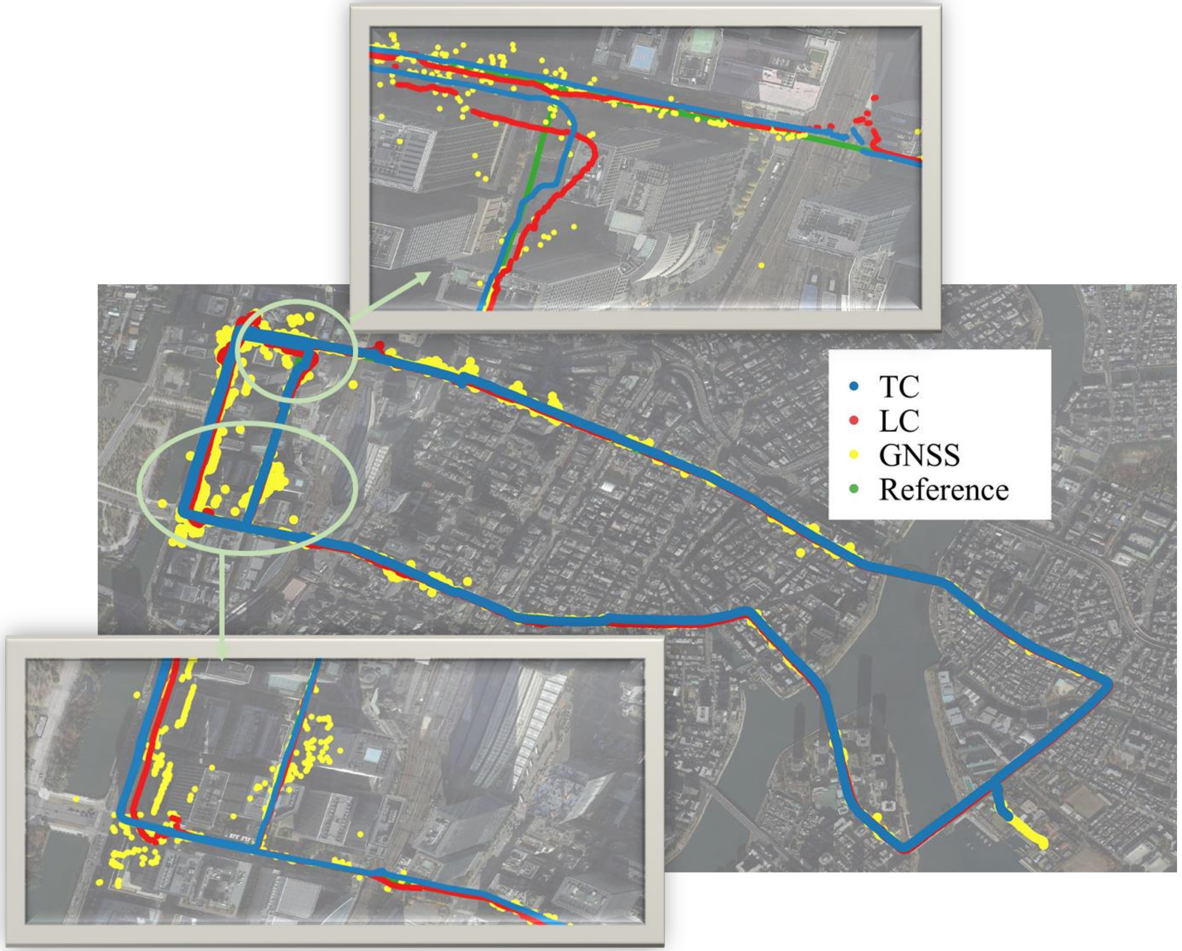
2

3



UNIT (M)	MAX-E	MAX-N	MEAN-E	MEAN-N	95%-E	95%-N
GNSS	11.7968	19.6548	0.0767	0.0739	3.1382	3.8893
LC	4.2219	6.3466	0.0474	0.0070	2.1314	2.1126
TC	2.2633	2.4547	0.0669	0.0151	1.6963	1.9741

4.2 Result of Marunouchi



In Marunouchi 1st result:

In multi-path effect is strong in the left side of the figure, the GNSS signal is not continues and the error is huge.

LC heavily dependents on on the GNSS position and velocity, it is hard for LC to give accurate position here;

For TC, it can provide more measurements than LC in urban canyon environment, so the error is smaller than LC.

4.2 Result of Marunouchi 1st

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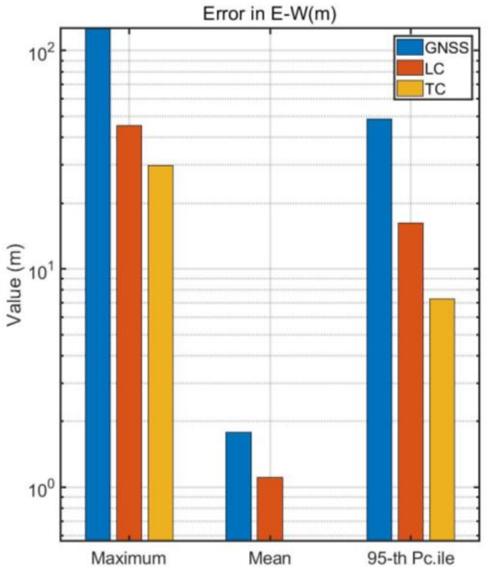
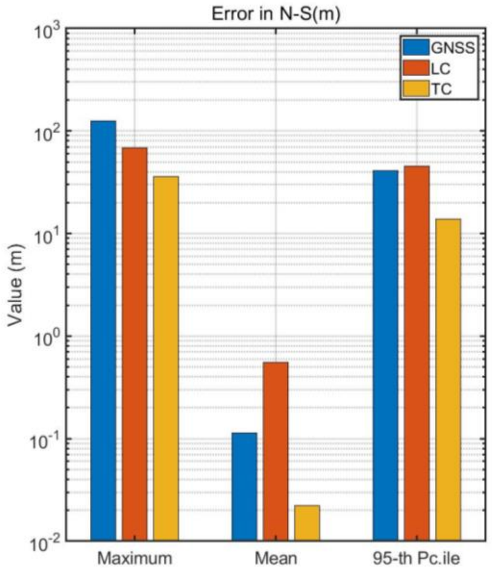
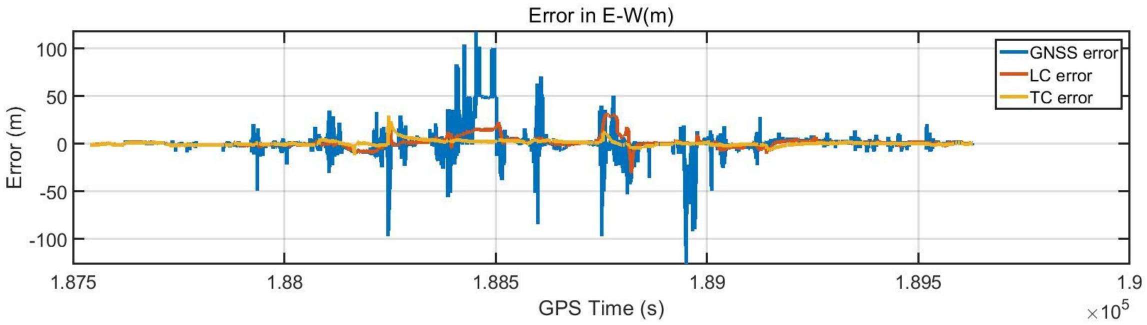
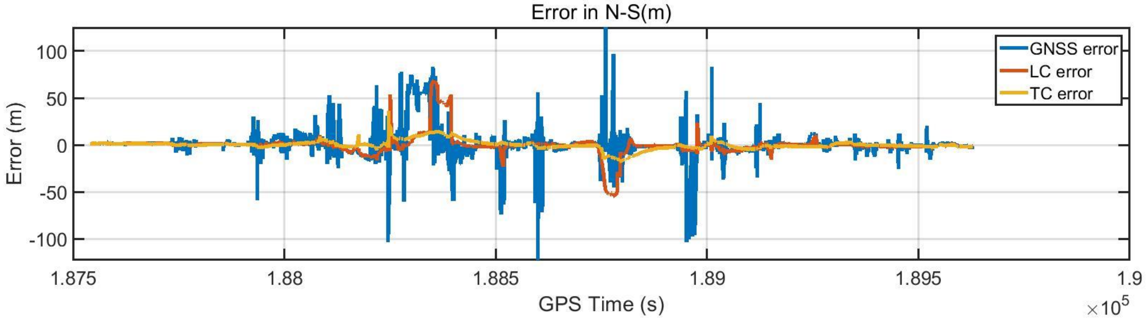




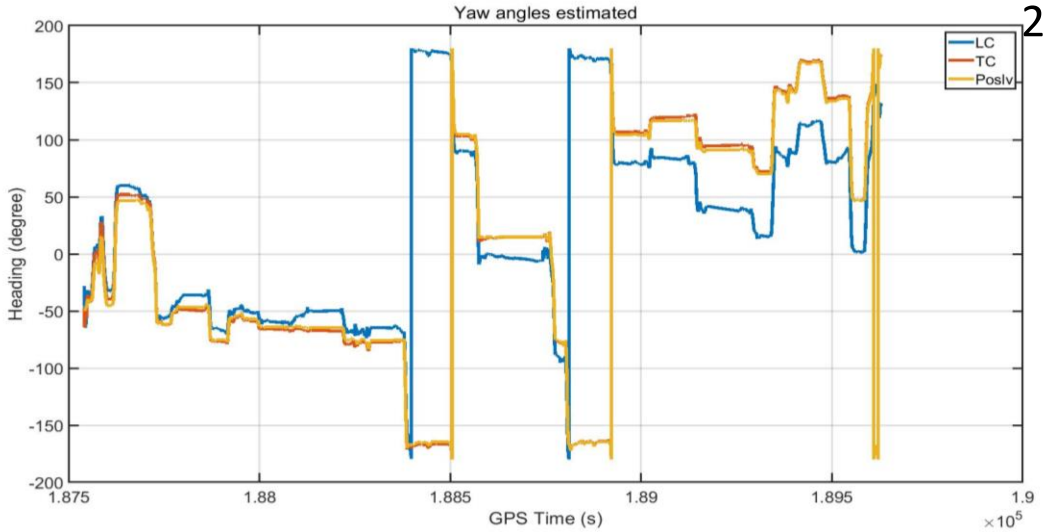




1

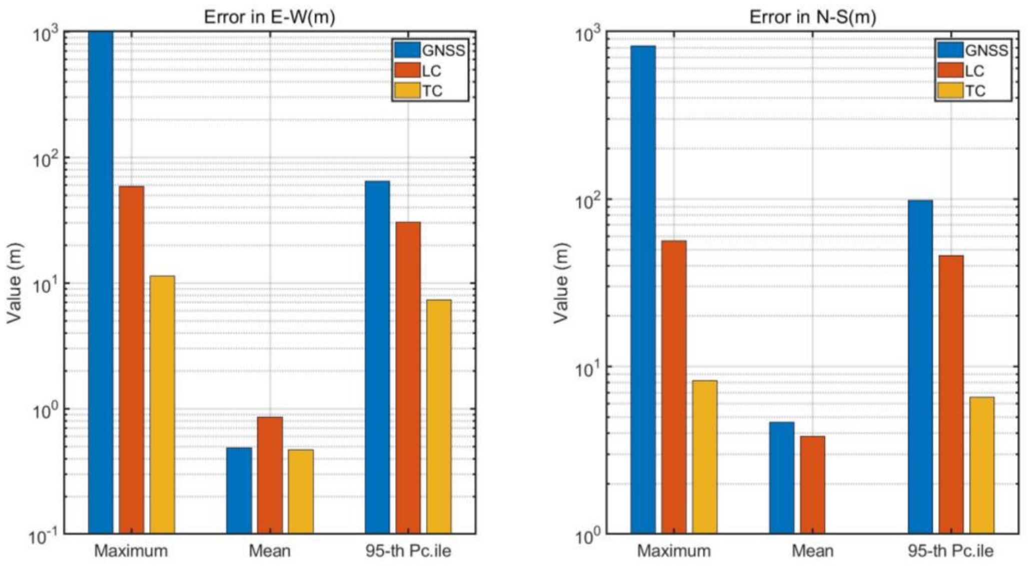
3

2

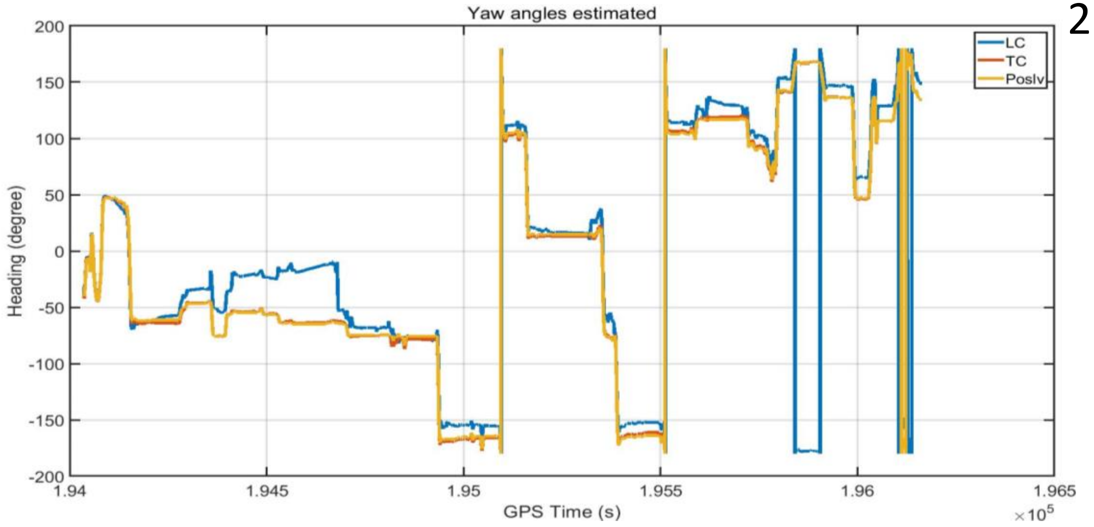


UNIT (M)	MAX-E	MAX-N	MEAN-E	MEAN-N	95%-E	95%-N
GNSS	126.1871	124.9765	1.7869	0.1131	48.5011	40.8056
LC	45.1765	68.9323	1.1100	0.5589	16.2394	45.2281
TC	29.6913	36.1436	0.5658	0.0224	7.2646	13.8202

4.2 Result of Marunouchi 2nd

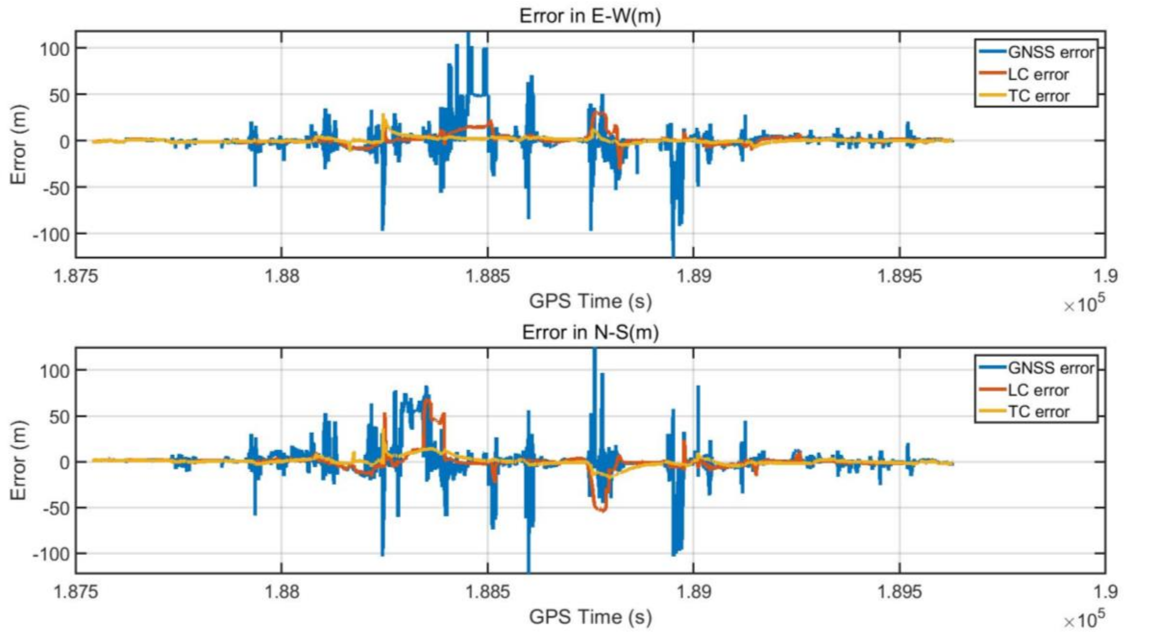


1



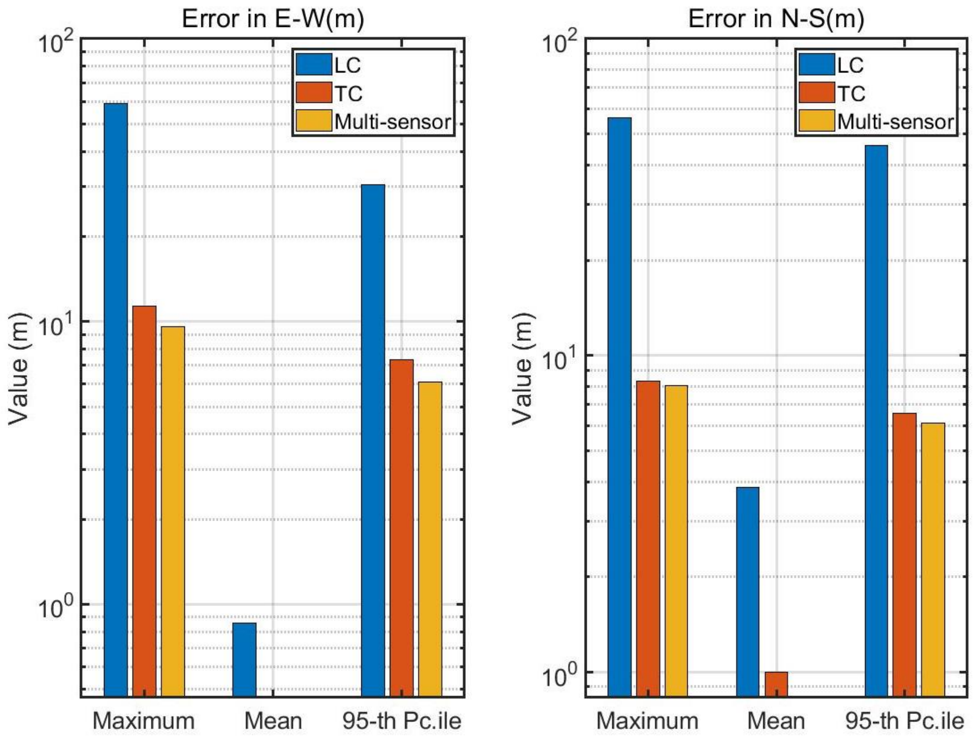
2

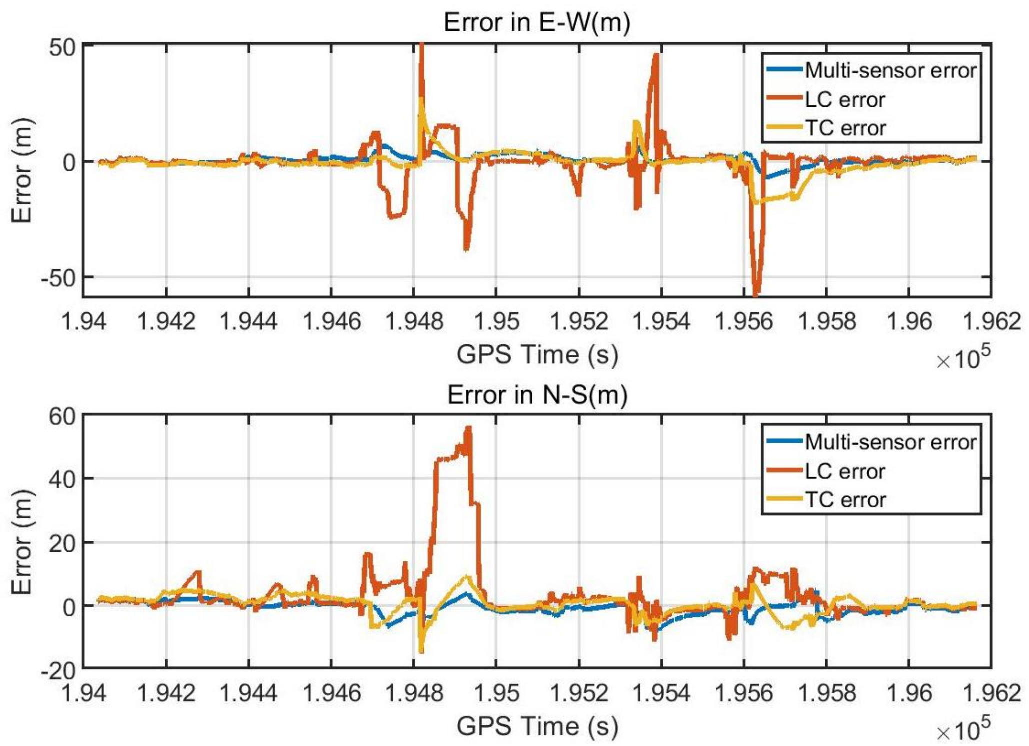
3



UNIT (M)	MAX-E	MAX-N	MEAN-E	MEAN-N	95%-E	95%-N
GNSS	1003.853	820.0854	0.4863	4.6508	64.6970	97.8188
LC	59.0915	56.4772	0.8582	3.8423	30.5077	45.9571
TC	11.3592	8.2782	0.4679	1.0031	7.3340	6.5890

4.4 Multi-sensor fusion result





UNIT (M)	MAX-E	MAX-N	MEAN-E	MEAN-N	95%-E	95%-N
GNSS	1003.853	820.0854	0.4863	4.6508	64.6970	97.8188
LC	59.0915	56.4772	0.8582	3.8423	30.5077	45.9571
TC	11.3592	8.2782	0.4679	1.0031	7.3340	6.5890
MULTI-SENSOR	9.6177	8.0312	0.4673	0.8318	6.1176	6.1178

In the result of Marunouchi, the Multi-sensor fusion result is from the TC position and WSS+YAW. The maximum error is reduced, and positioning accuracy is improved.

5. Summary

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After serious of the vehicle data test and analyzed the results, the conclusions are as follows:

1. In norm urban environment, LC mean error and 95th percentile are smaller than TC, maximum error is larger than TC;
2. In urban canyon conidiation, LC error is morse than TC;
3. LC is easier affected by GNSS error than TC;
4. The estimate yaw angle form LC is worse than TC;
5. Multi-sensor fusion can reduce the maximum error effectively.

- In norm urban environment, TC result is stable than LC;
- In urban canyon environment, TC is better than LC;

5. Summary

For this master thesis there are several shortages:

- The IMU bias affected by the temperature, but here is no temperature compensate;
- The initial attitude ROLL and PITCH are set as zeros, the attitude error is exist;
- The loosely coupled without anti-error Kalman filter, so the error is affected by the GNSS easily;

For the future research:

- The program was written by MATLAB, it is necessary to replace it by C/C++;
- Carrier phase will be included in TC to improve the positioning accuracy;
- Multi-sensor in tightly coupled, which include GNSS compass;

Thank you for your watching!