다중센서 융합 항법

2017. 10. 1

한국항공대 항공전자정보공학부

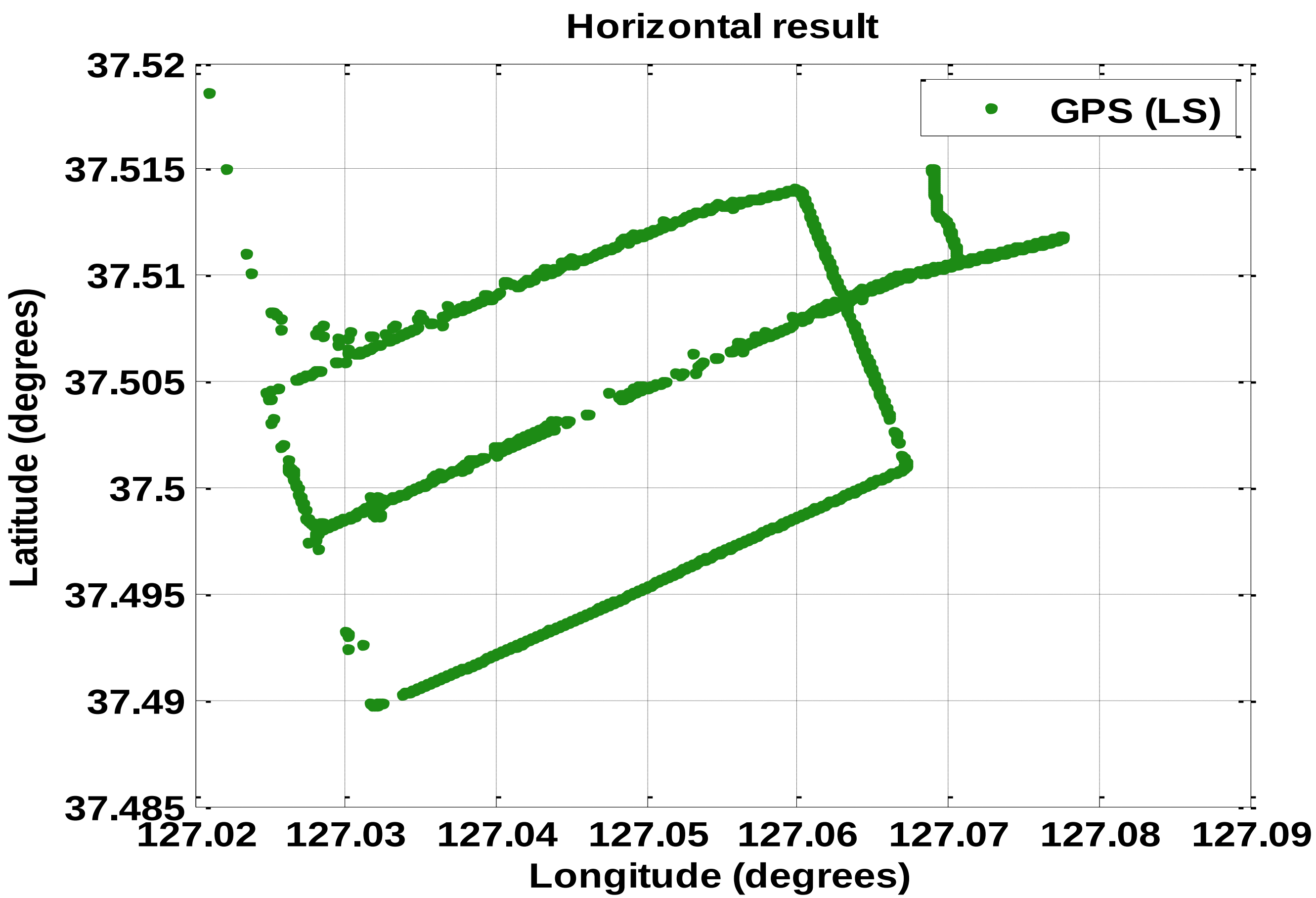
이형근

발표순서

- 센서별 특성
- 칼만필터
- 정보 융합
- 고장 검출
- 연합형 칼만필터
- 시각동기 및 Lever Arm 보상
- 다중센서 통합 구조
- 다중센서 비교 실험

Motivation

- 도심 환경에서 GPS 기반 측위 결과



센서별 특성

관성센서

- 다른 센서에 비하여 출력 빈도가 높으므로 (10 Hz ~ 200 Hz) 항체의 궤적을 상세하게 표현할 수 있음
- 항체 외부로 부터의 신호/도움을 요구하지 않으며 고장에 강건한 특성을 지님
- 재밍/간섭 등의 외란에 영향을 받지 않음
- 가속도계와 자이로의 출력을 적분하는 원리에 기반하므로 오차가 누적 증가하는 단점을 지님
- 다중센서 융합 항법에 있어서 중심 센서로 활용됨

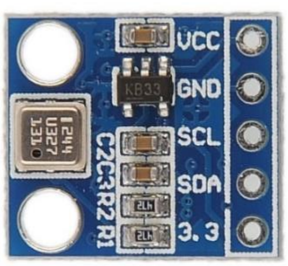
위성항법 수신기

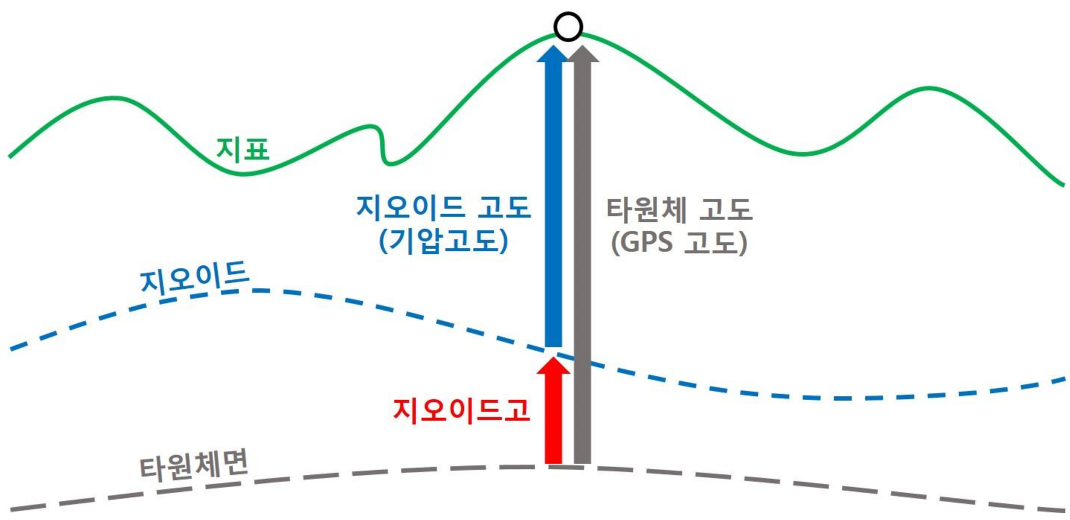
- 높은 정확도의 좌표값과 시간을 전 지구영역에서 측정할 수 있음
- 전파를 활용함으로 인하여 환경적/고의적인 외란에 취약함
  - ❖ 다중경로 오차, 비시선각 오차
  - ❖ 재밍, 간섭

- 정확도가 균등하지 않고 가시위성의 숫자와 기하학적인 배치에 의하여 영향을 받음
- 도심 지역에서 가시위성의 부족으로 인하여 위치해를 제공하지 못할 수도 있음
- 최근에 운용되기 시작한 다중위성군을 활용할 경우에는 도심 지역에서의 가용성을 크게 증가시킬 수 있음

기압 고도계

- 고도에 크게 영향을 받는 기압의 특성을 활용한 센서
- 수십 cm 정확도로 고도 정보를 제공할 수 있음
- 적절히 교정할 경우에는 절대 고도 정보의 제공이 가능함





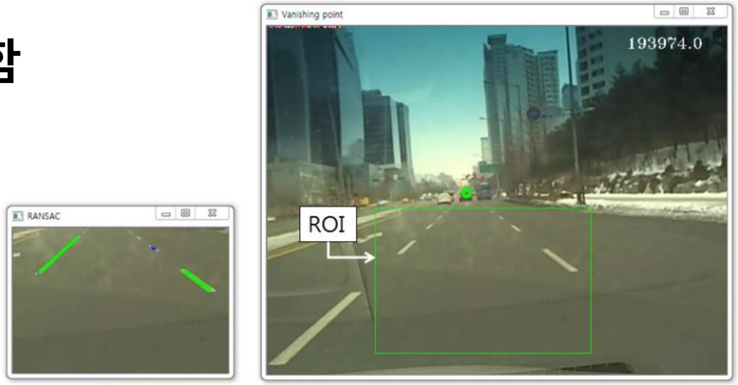
OBD-II

- 대다수의 차량에서 활용 가능함
  - ❖ On-Board Diagnostics 표준
  - ❖ 차량의 고장 및 상태 진단에 활용됨
- 인터페이스가 편리함
  - ❖ Vehicle : OBD-II
  - ❖ Interface Board : USB / Bluetooth
- 차량의 전진방향 속력을 제공할 수 있음
  - ❖ PID 0D (hex)

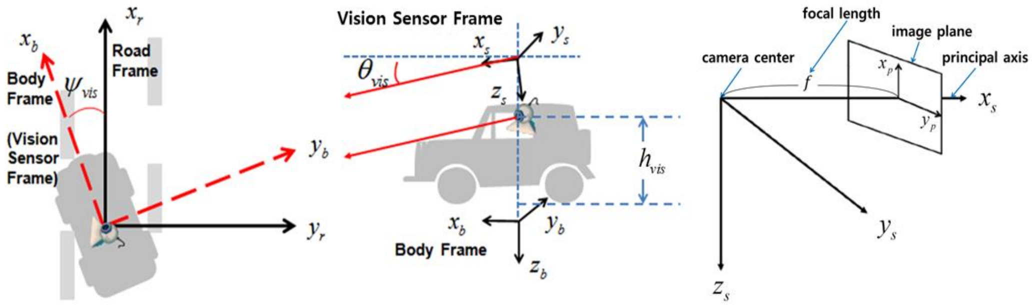
PID(hex)	Data bytes returned	Description	Min value	Max value	Units
0D	1	Vehicle speed	0	255	km/h

영상센서

- 다른 센서들에 비하여 정보량이 많음
- 상대 위치와 자세의 계산이 용이함
- 절대 위치와 자세는 별도의 기준이 필요함
- 일기 및 시계 상황과 조명 환경에 민감함



(a) (b)



(a) (b) (c)

칼만필터

Gaussian 확률 변수

Let's denote $X=\{x_i\}_{i=1,2,3,...}$ $Y=\{y_i\}_{i=1,2,3,...}$ as sequences of random variables with white Gaussian noise. Then

* Expectation (mean): $$m_X := E[X] = \frac{1}{N}\sum_{i=1}^{N} x_i$$

* Variance: $$r_X := E[(X-m_X)(X-m_X)] = \frac{1}{N}\sum_{i=1}^{N}(x_i - m_X)^2$$

* Standard deviation (one-sigma): $$\sigma_X := \sqrt{r_X}$$

* Covariance: $$r_{XY} := E[(X-m_X)(Y-m_Y)] = \frac{1}{N}\sum_{i=1}^{N}(x_i-m_X)(y_i-m_Y)$$

영평균 Gaussian 확률변수의 조합

Given

$$Z = X + Y$$

where

$$X \sim N(0, r_X), \quad Y \sim N(0, r_Y)$$

$$r_{XY} = 0.$$

Then

$$Z \sim N(0, r_X + r_Y)$$

영평균 Gaussian 스칼라 변수의 벡터로의 누적

Given

$$V := \begin{bmatrix} X \\ Y \\ Z \end{bmatrix},\ X \sim (0, r_X),\ Y \sim (0, r_Y),\ Z \sim (0, r_Z)$$

Then

$$V \sim \left(O_{3\times 1}, \begin{bmatrix} r_X & r_{XY} & r_{XZ} \\ r_{YX} & r_Y & r_{YZ} \\ r_{ZX} & r_{ZY} & r_Z \end{bmatrix} \right)$$

동역학 모델

* state: minimum information to describe a system at a specific time instant

$$X_k, \quad X_{k+1}, \quad X_{k+2}, \quad \cdots$$

* dynamics model: a model that relates two states at different time instants

$$X_{k+1} = F_k X_k + w_k$$

* dynamics model can be constructed by

  – given conditions: fixed position or trajectory

  – experiences: a heavy vehicle endures small acceleration changes

  – high speed sensors: odometr, gyro, accelerometer, compass

* a dynamics model acts as an equivalent measurement
  for incremental states

Gauss Markov 프로세스

* A sequence of random vectors $\{X_k\}_{k=0,1,2,\cdots}$ driven by

a **dynamics model** $X_{k+1} = F_k X_k + w_k$

with a **Gaussian initial value** $X_0 \sim (0, P_0)$,

and a **white Gaussian noise sequence** $w_k \sim (0, q)$

is a **Gauss Markov process.**

* **In this case, each** X_k **satisfies the following properties.**

$$X_k \sim (O, P_k),\ P_{k+1} = F_k P_k F_k^T + q\ ,\ E[X_{k+1} X_k^T] = F_k P_k$$

측정치 모델

* A stochastic measurement model is usually given as follows,

$$Y = H X + V$$

where

Y : vector that consists of measured values

H : observation matrix (mapping between the measured values and the state of interest)

X : state vector (contains position, velocity, clock bias, Markov states describing sensor errors)

V : measurement noise (usually white Gaussian)

선형 최소 오차 추정기 (Linear Minimum Error Estimator)

<Problem> Find an estimator $\widehat{X}$ that minimizes the following cost function J

$$J = \frac{1}{2}(Y - H\widehat{X})^T \Omega (Y - H\widehat{X}) \qquad (1)$$

given the vector measurement equation

$$Y = HX + V \qquad (2)$$

where

$\Omega = \Omega^T$: symmetric positive definite square matrix

$$\det(H^T \Omega H) \neq 0 \qquad (3)$$

<Solution>

Optimal solution $\hat{X}$ that minimizes J should satisfy the following condition.

$$\left.\frac{\partial J}{\partial X}\right|_{X=\widehat{X}} = H^T \Omega (Y - H\widehat{X}) = O \qquad (4)$$

$$H^T \Omega Y = H^T \Omega H \widehat{X} \qquad (5)$$

From (3), we know that the matrix $H^T \Omega H$ is invertible, i.e., $(H^T \Omega H)^{-1}$ exists. Thus, by multiplying $(H^T \Omega H)^{-1}$ to (5) from the left, it can be obtained that

$$\widehat{X} = (H^T \Omega H)^{-1} H^T \Omega \; Y \qquad (6)$$

Note 1) The matrix $H^+ \underline{\underline{\Delta}} \; (H^T \Omega H)^{-1} H^T \Omega$ is usually called as the weighted pseudo inverse of H.

Note 2) As the weighting matrix Ω, the inverse matrix R^{-1} of the measurement error covariance matrix $R \; \underline{\underline{\Delta}} \; E\left[VV^T\right]$ is frequently utilized.

직접 추정 (Direct Estimation)

* Given

$$Y = H X + V, \quad V \sim (O, R), \quad \det(H^T H) \neq 0,$$

apply weighted pseudo inverse $H^+ := (H^T R^{-1} H)^{-1} H^T R^{-1}$ to obtain

– state estimate: $\hat{X} = H^+ Y = X + \hat{V}$

– estimation error: $\hat{V} = H^+ V \sim \left(O, (H^T R^{-1} H)^{-1}\right)$

– residual: $Z = Y - H\hat{X} = [I - HH^+]V$

$$Z \sim (O, \Sigma)$$
$$\Sigma = [I - HH^+]R[I - HH^+]^T$$

간접 추정 (Indirect Estimation)에 의한 측정 갱신

* Consider

$$Y = H\,X + V,\quad V \sim (O, R),\quad \det(H^T H) \neq 0, \tag{1}$$

with intial guess $\bar{X} \sim (X, M)$ (*a priori* state estimate) such that

$$\bar{X} = X - \delta\bar{X},\ \delta\bar{X} \sim (O, M)\ \text{(can be considered as anther measurement)} \tag{2}$$

* Solution by augmented equivalent measurement vector:

The given problem is equivalent to the following vector equation.

$$\tilde{Y} = \begin{bmatrix} \bar{X} \\ Y \end{bmatrix} = \tilde{H}X + \tilde{V},\ \tilde{H} = \begin{bmatrix} I \\ H \end{bmatrix},\ \tilde{V} = \begin{bmatrix} -\delta\bar{X} \\ V \end{bmatrix} \sim \left(O, \tilde{R}\right),\ \tilde{R} = \begin{bmatrix} M & O \\ O & R \end{bmatrix} \tag{3}$$

* The solution of the equivalent problem is computed as follows.

$$\widehat{X} = (\tilde{H}^T \tilde{R}^{-1} \tilde{H})^{-1} \tilde{H}^T \tilde{R}^{-1} \tilde{Y} = \bar{X} + KZ \tag{4}$$

$$K = PH^T R^{-1} = MH^T (HMH^T + R)^{-1},\quad Z = Y - H\bar{X}$$

$$\delta\widehat{X} = (I - KH)\delta\bar{X} + K\,V,\qquad \delta\widehat{X} \sim (O, P) \tag{5}$$

$$P = (\tilde{H}^T \tilde{R}^{-1} \tilde{H})^{-1} = (M^{-1} + H^T R^{-1} H)^{-1} \tag{6}$$

시간 전달

* Consider the discrete random vector satisfying the following dynamics

$$X_{k+1} = F_k X_k + G_k W_k, \qquad W_k \sim (O, Q) \tag{1}$$

* The *a priori* estimate $\bar{X}_{k+1}$ the $(k+1)$–th time step can be obtained as follows.

$$\bar{X}_{k+1} = F_k \hat{X}_k \tag{2}$$

* By differencing (1) and (2), we obtain

$$\delta \bar{X}_{k+1} = F_k \, \delta \hat{X}_k + G_k W_k \tag{3}$$

* Since the *a posteriori* estimation error $\delta \hat{X}_k$ and the white Gaussian process noise W_k

are independent to each other, we obtain

$$E\left[\left(\delta \bar{X}_{k+1}\right)\left(\delta \bar{X}_{k+1}\right)^T\right] = F_k \, E\left[\left(\delta \hat{X}_k\right)\left(\delta \hat{X}_k\right)^T\right] F_k^T + G_k E\left[W_k W_k^T\right] G_k^T \tag{4}$$

or

$$M_{k+1} = F_k P_k F_k^T + G_k Q_k G_k^T \ \text{: time-propagation of error covariance} \tag{5}$$

정보 융합

정보 융합의 대상

- Instantaneous Sensor Output (Measurement):

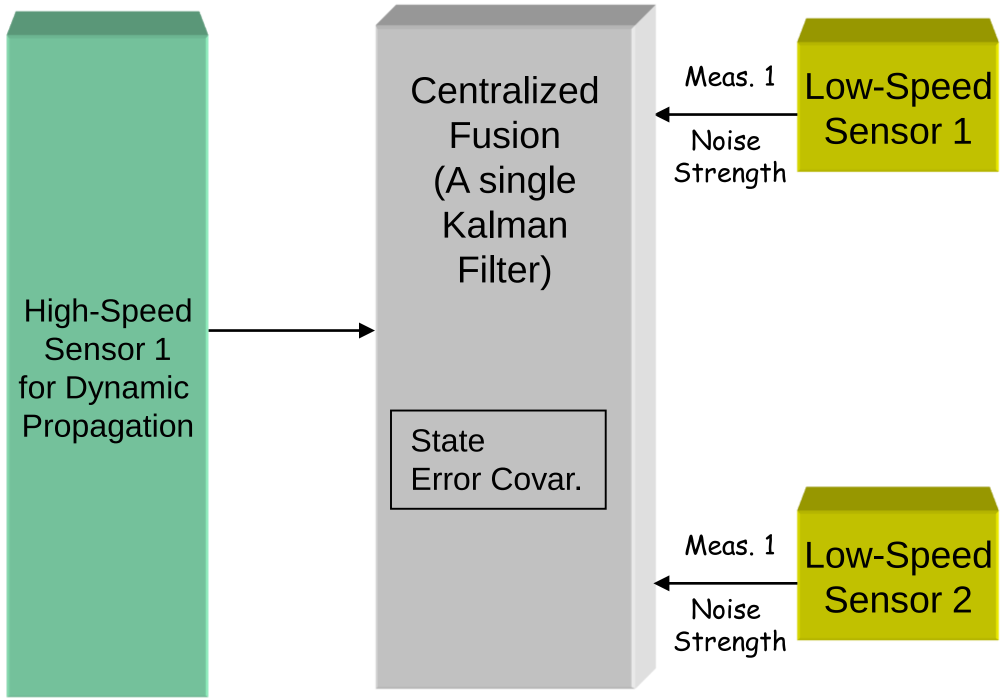
  instantaneous information on system states

- Filter:

  accumulated information on system states

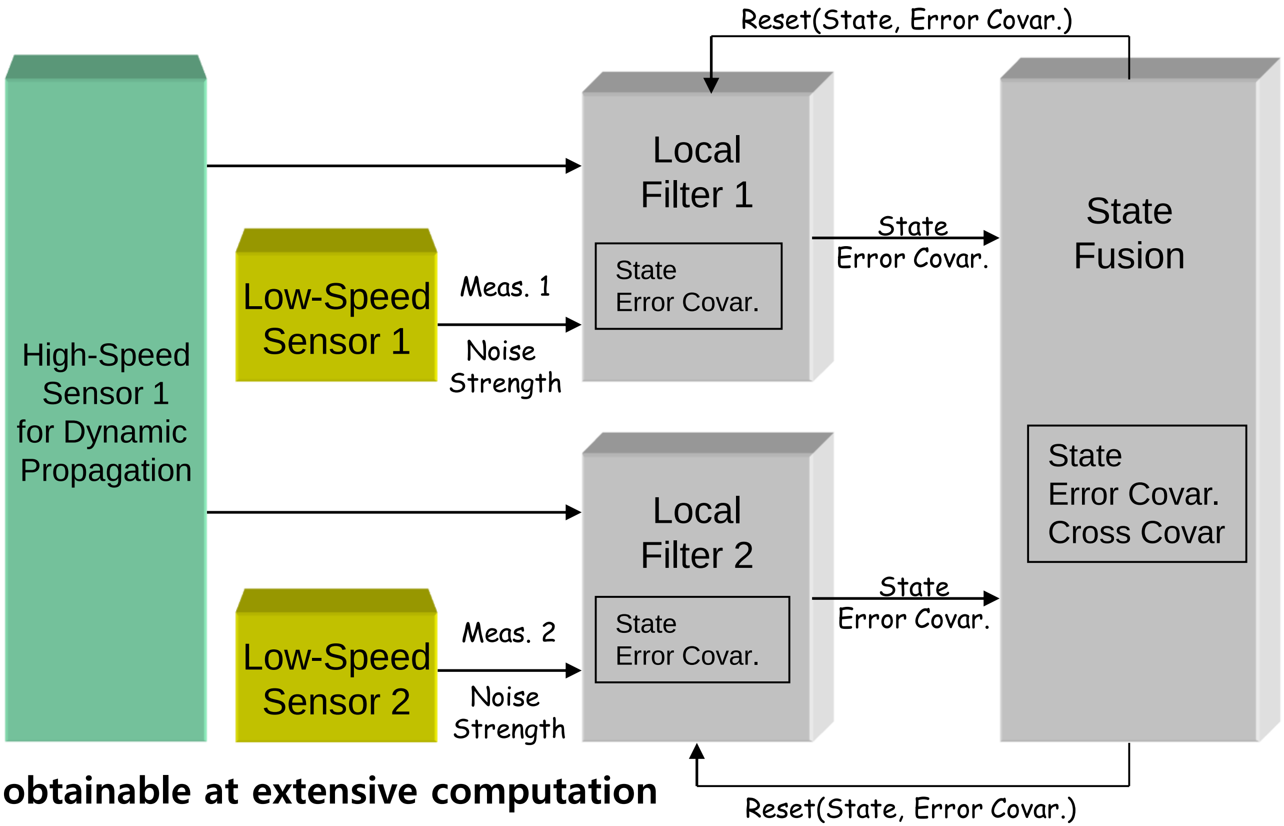
> "Compared to a measurement, a filter combines multiple measurements at different times based on system model and statistical characteristics."

중앙집중형 융합 (Centralized Fusion)



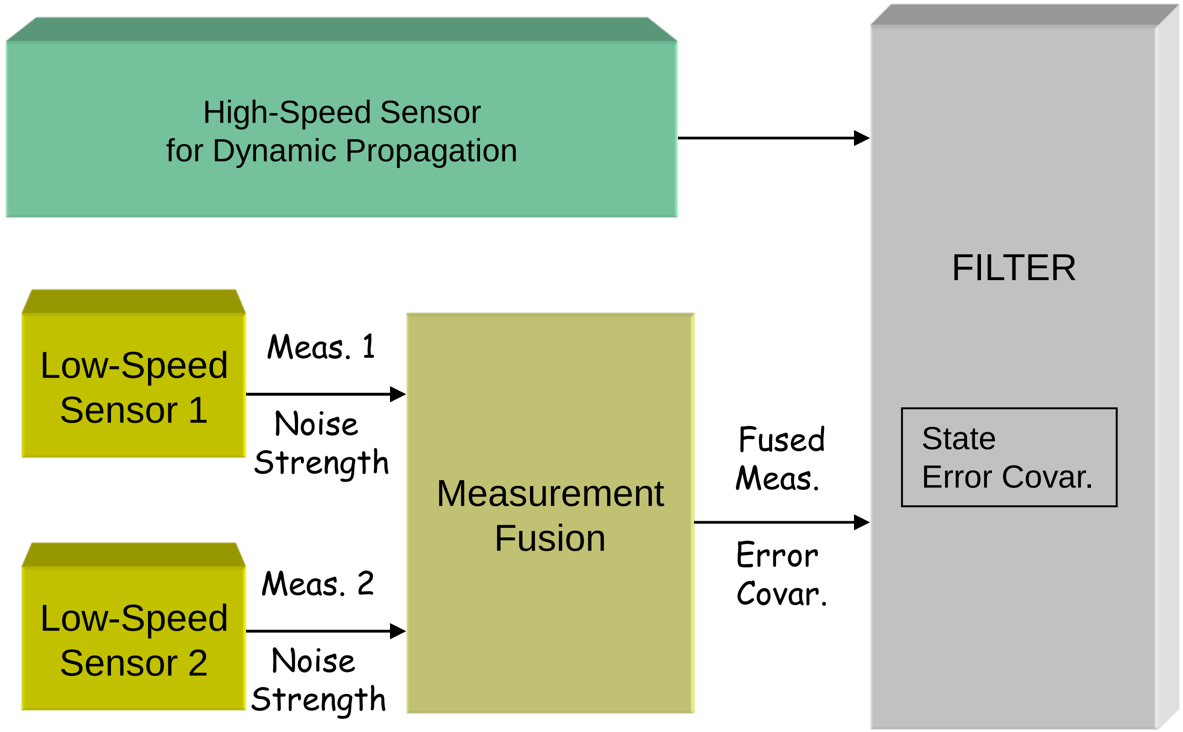
- **Optimality: always guaranteed**
- **Advantage: optimality**
- **Disadvantage:**
  - ❖ **Large computational burden is concentrated on the single filter**
  - ❖ **The single filter can be easily contaminated by a measurement fault`**

상태 융합 (State Fusion)



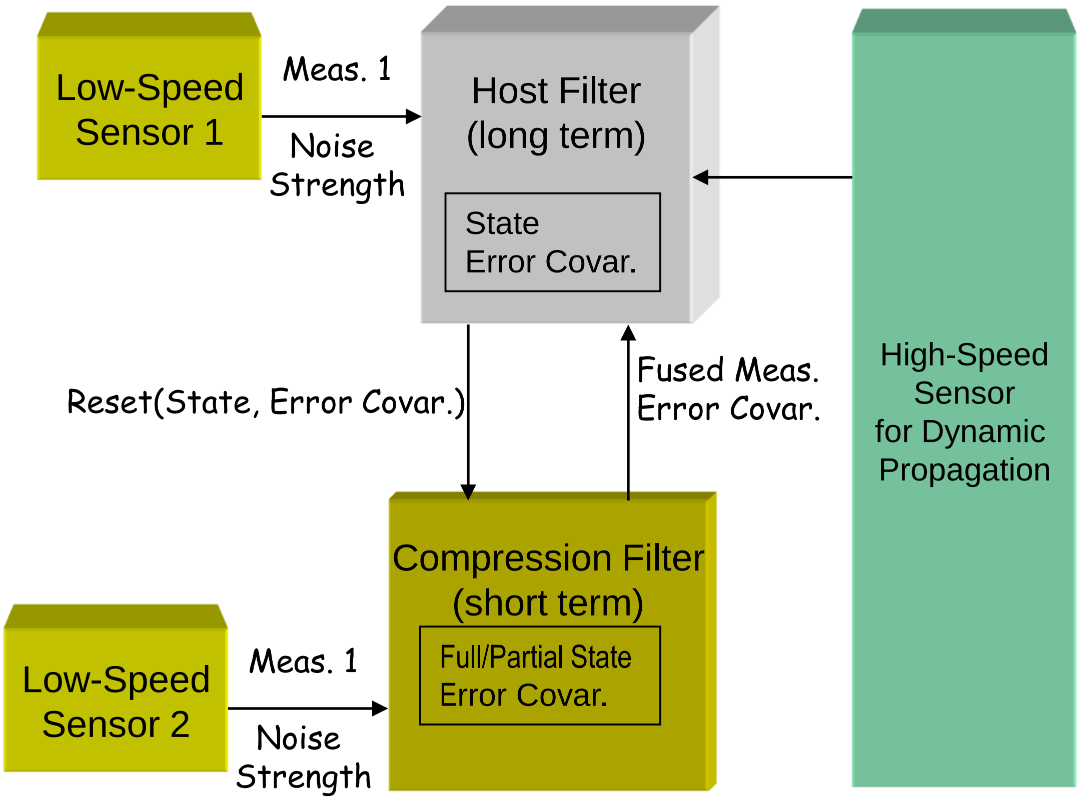
- **Optimality: obtainable at extensive computation**
- **Advantage: structural robustness to faults**
- **Disadvantage:**
  - ❖ **Total computational and communicational burden (even to generate sub-optimal estimate) is largest among the existing fusion methodology**

측정치 융합 (Measurement Fusion)



- **Optimality: easy to obtain**
- **Advantage:**
  - **Computational burden of the single filter is alleviated.**
  - **A hard fault in measurements can be detected and isolated.**
- **Disadvantage: Applicable only to synchronous measurements. Prone to soft faults.**

시전달 측정치 융합 (Time-Propa. Meas. Fusion)



고장 검출

검출 문제의 정의

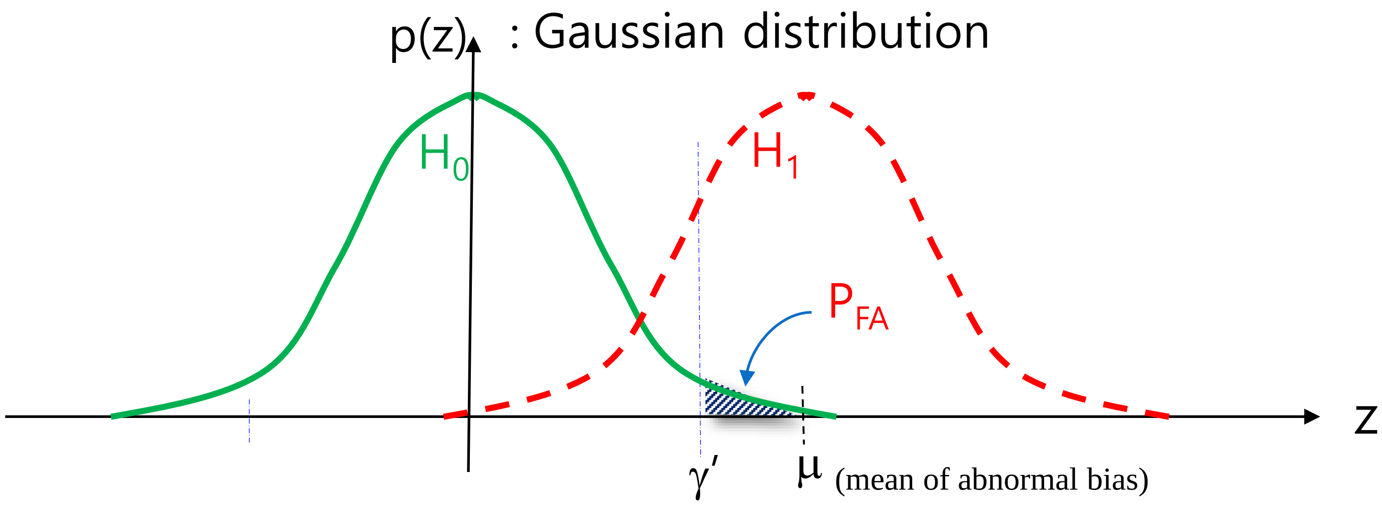
- Assume that there are two hypotheses H_0 and H_1. Affected by either H_0 and H_1, a measurement z is available.

- The detection problem is to design a test statistic (decision function) T and its threshold λ to discriminate the two hypotheses to maximize P_D subject to $P_{FA} < \alpha$

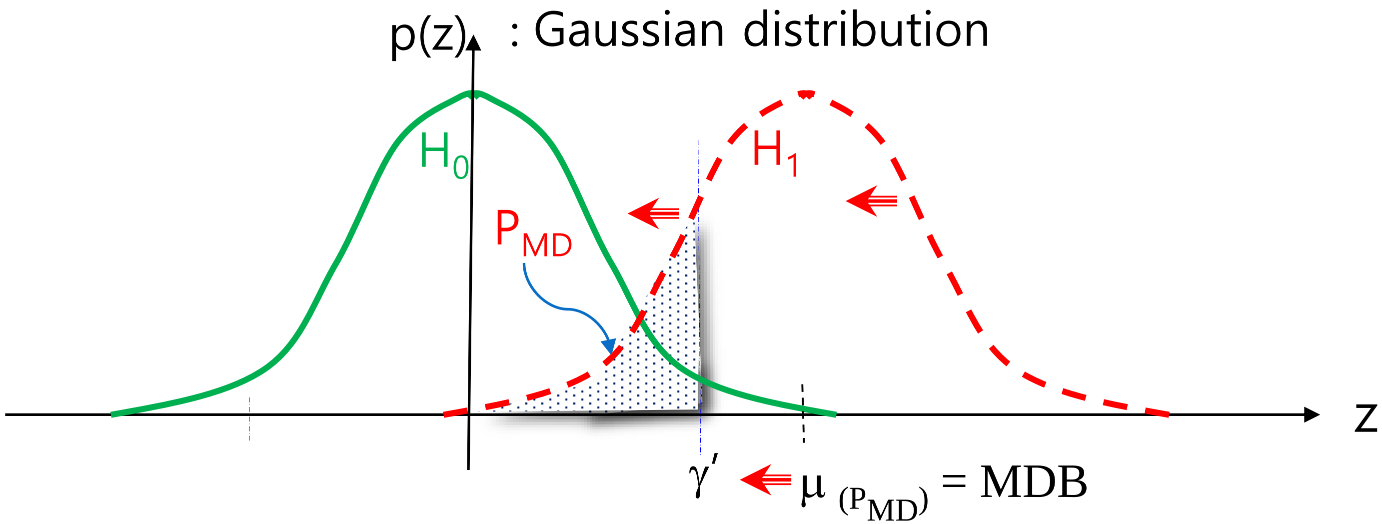
$$H_0: \quad T(z) < \lambda$$

$$H_1: \quad T(z) \geq \lambda$$

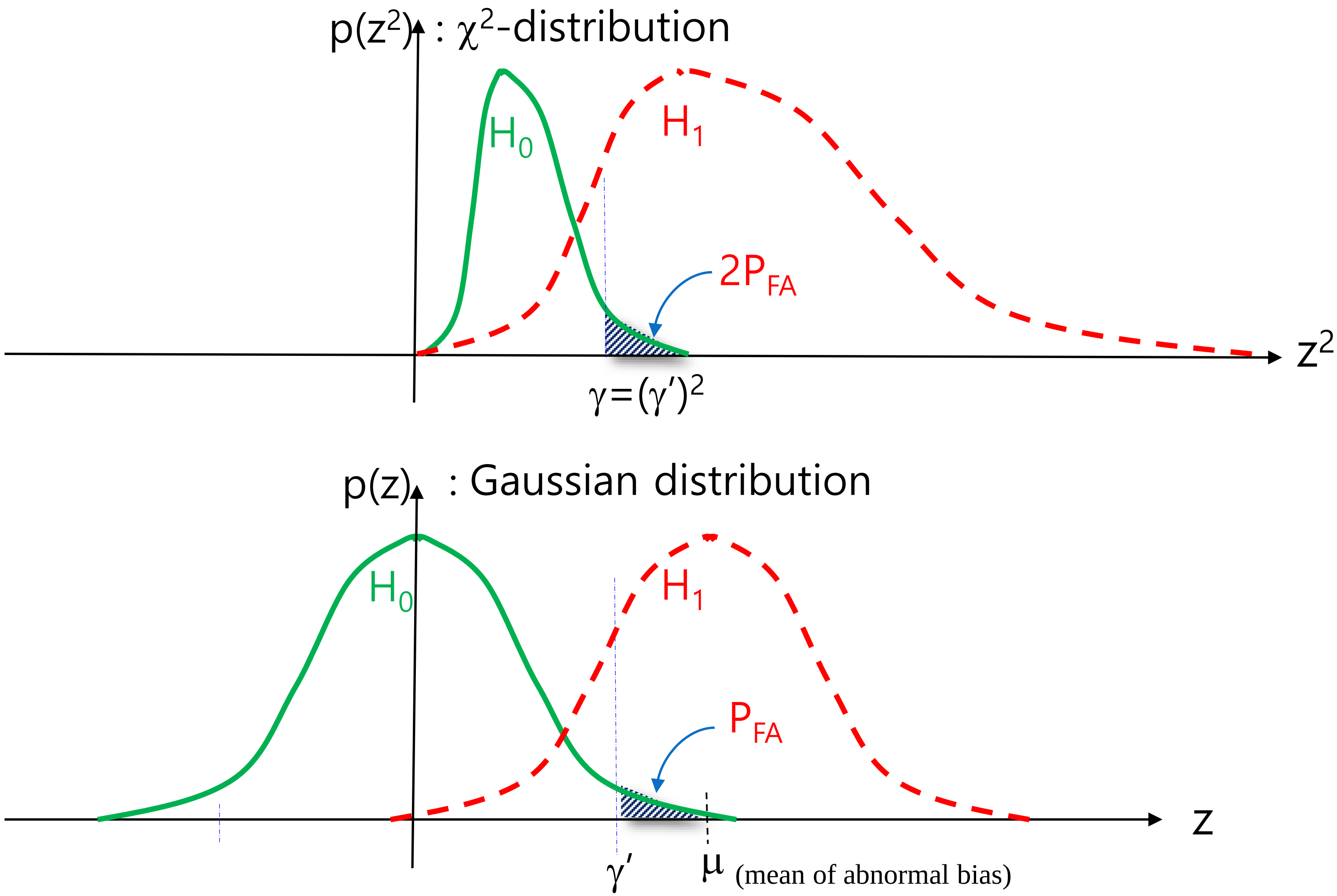
오경고 확률 P_{FA}와 임계치의 관계



미검출 확률 P_{MD}와 최소검출가능 바이어스의 관계



가우시안 분포와 χ^2 분포의 연계성



잉여값을 활용한 시험값

- **Consider Gaussian random variable z satisfying**

$$H_0: \quad z \sim N(O, C_z)$$

$$H_1: \quad z \sim N(\mu, C_z)$$

- **In the case when there is no fault, the weighted square sum of residuals is χ^2-distributed**

$$T = z^T C_z^{-1} z = (z')^T (z') \sim \chi^2(0, N)$$

$$z' = \sqrt{C_z^{-1}}\, z \sim N(O, I_{N \times N})$$

$$C_z^{-1} = \sqrt{C_z^{-1}}\sqrt{C_z^{-1}}$$

- **Thus, it can be used as a test statistic for fault detection**

시험값 형성 방법

- **시험값 유형 1 : 측정치 사이의 비교 (no prior information)**

$$z = PR_{meas} - PR_{comp} = -H\delta X + V = \left[I - H(H^T R^{-1} H) H^T R^{-1} \right] V$$

$$z \sim (O, C_Z)$$

$$C_Z = \left[I - H(H^T R^{-1} H)^{-1} H^T R^{-1} \right] R \left[I - H(H^T R^{-1} H)^{-1} H^T R^{-1} \right]^T = R - H(H^T R^{-1} H)^{-1} H^T$$: positive semidefinite (rank deficient)

- **시험값 유형 2 : 필터와 측정치 사이의 비교**

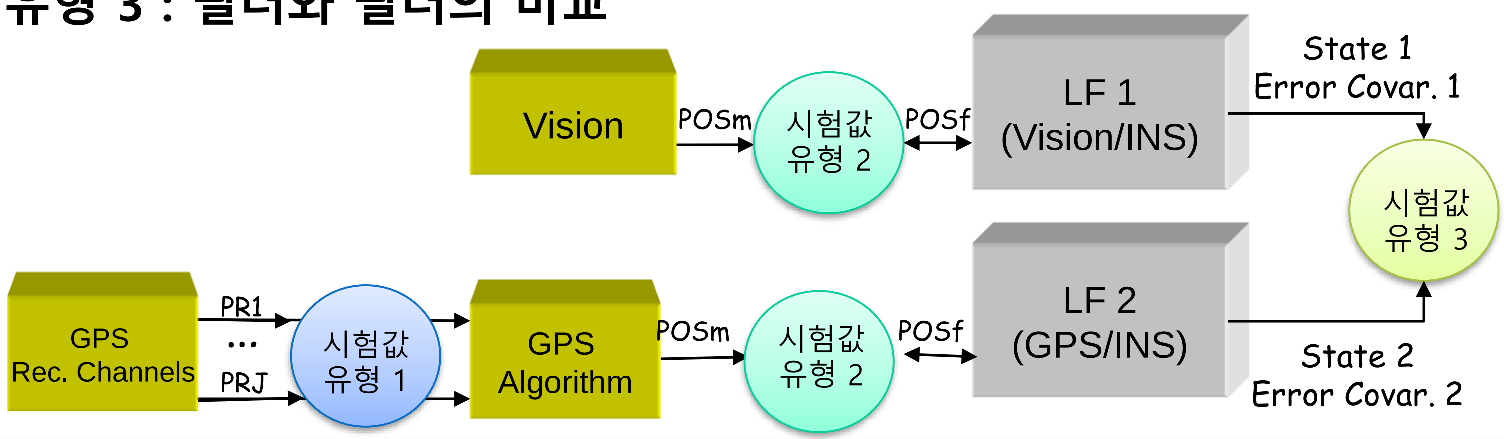
$$z = POS_{GPS} - POS_{filter} = -H\delta X_{filter} + V$$

where δX_{filter} and V are indepent to each other

$$z \sim (O, C_Z)$$

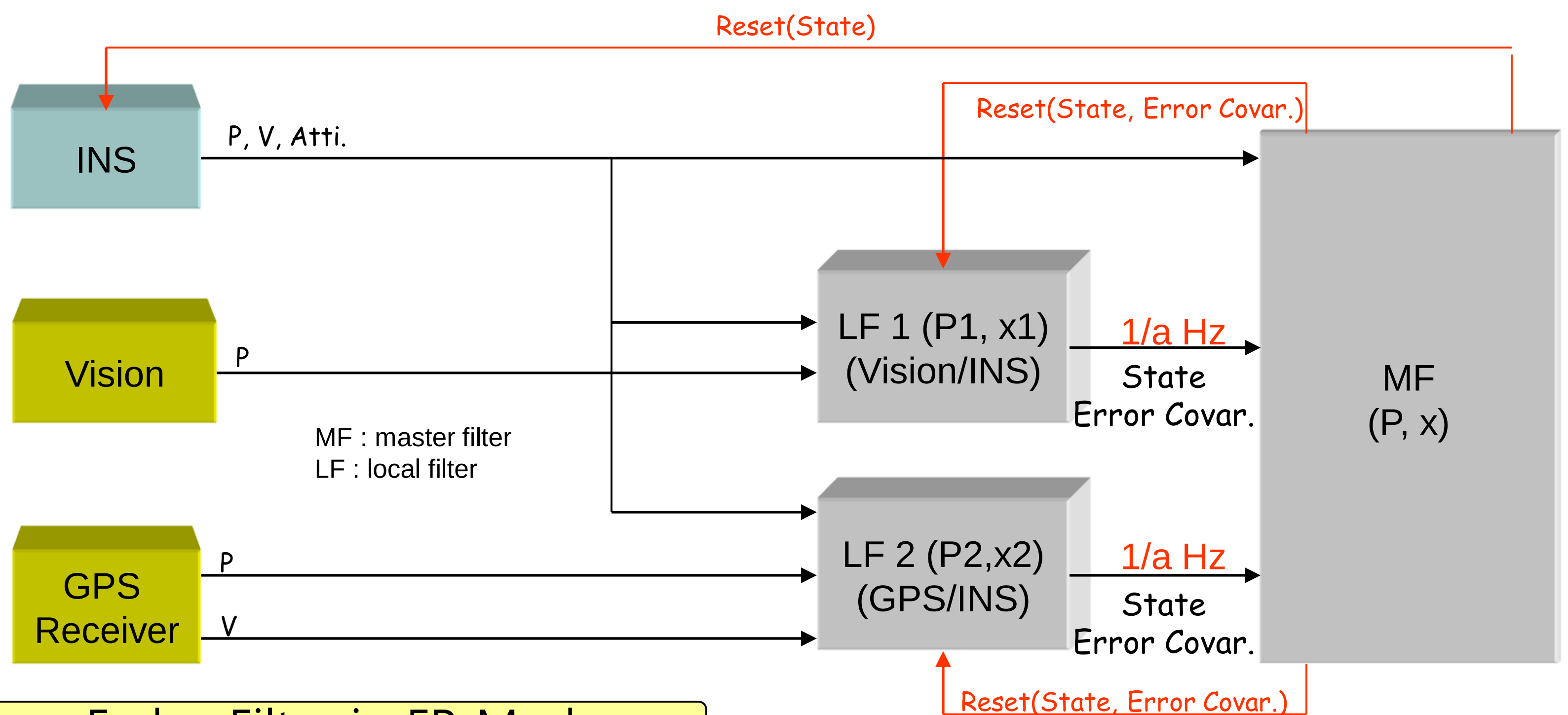
$C_Z = HPH^T + R$: strictly positive definite

- **시험값 유형 3 : 필터와 필터의 비교**



연합형 칼만필터 (상태 융합)

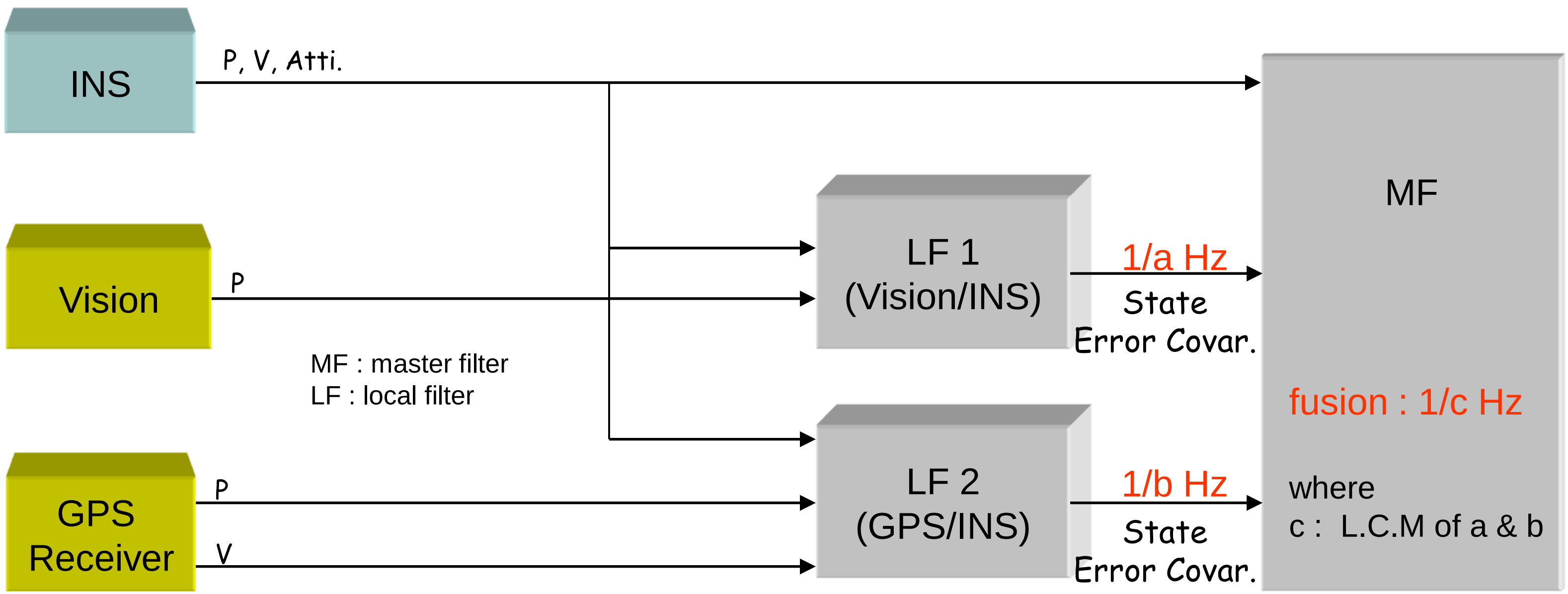
Fusion Reset 모드 연합형 칼만필터



Feder. Filter in FR Mode

장점 : 최적해
단점 : 많은 계산과 통신 필요
GPS와 Vision 센서의 동일 출력주기 가정
오염된 측정치를 검증 못할 경우 모든 필터가 연쇄적으로 고장

No Reset 모드 연합형 칼만필터

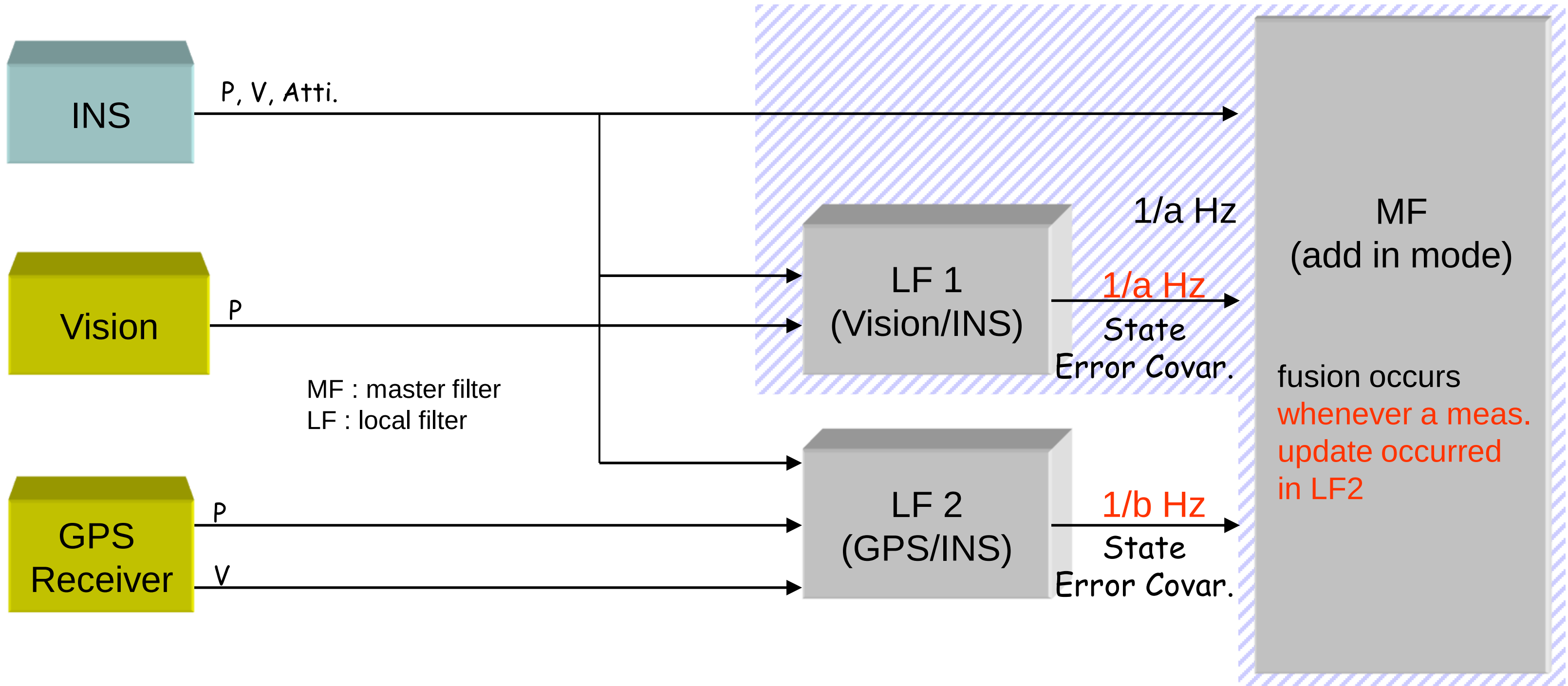


Fed. Filter in NR Mode

장점 : 오염된 측정치에 의한 각 필터의 오염현상 회피 가능
한 개의 부필터가 고장진단 되었을 경우 신속한 복구 가능

단점 : 부필터 및 주필터 동작의 흐름제어 복잡
최적해 제공하지 못함

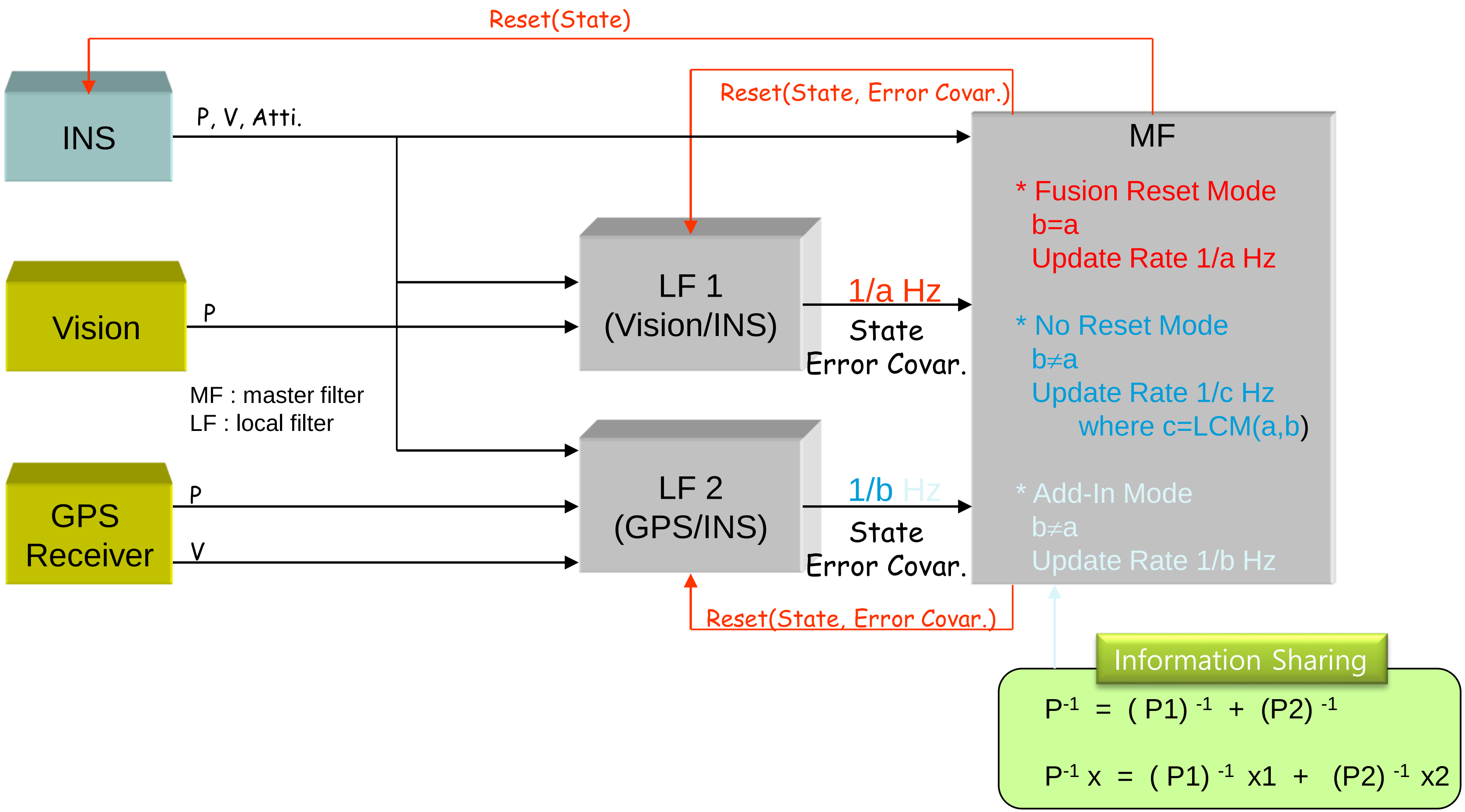
Add-In 모드 연합형 칼만필터



Fed. Filter in Add-In Mode

장점 : 오염된 측정치에 의한 각 필터의 오염현상 회피 가능
한 개의 부필터가 고장진단 되었을 경우 신속한 복구 가능
부필터 및 주필터 동작의 흐름제어 비교적 간단
단점 : 최적해 제공하지 못함

정리



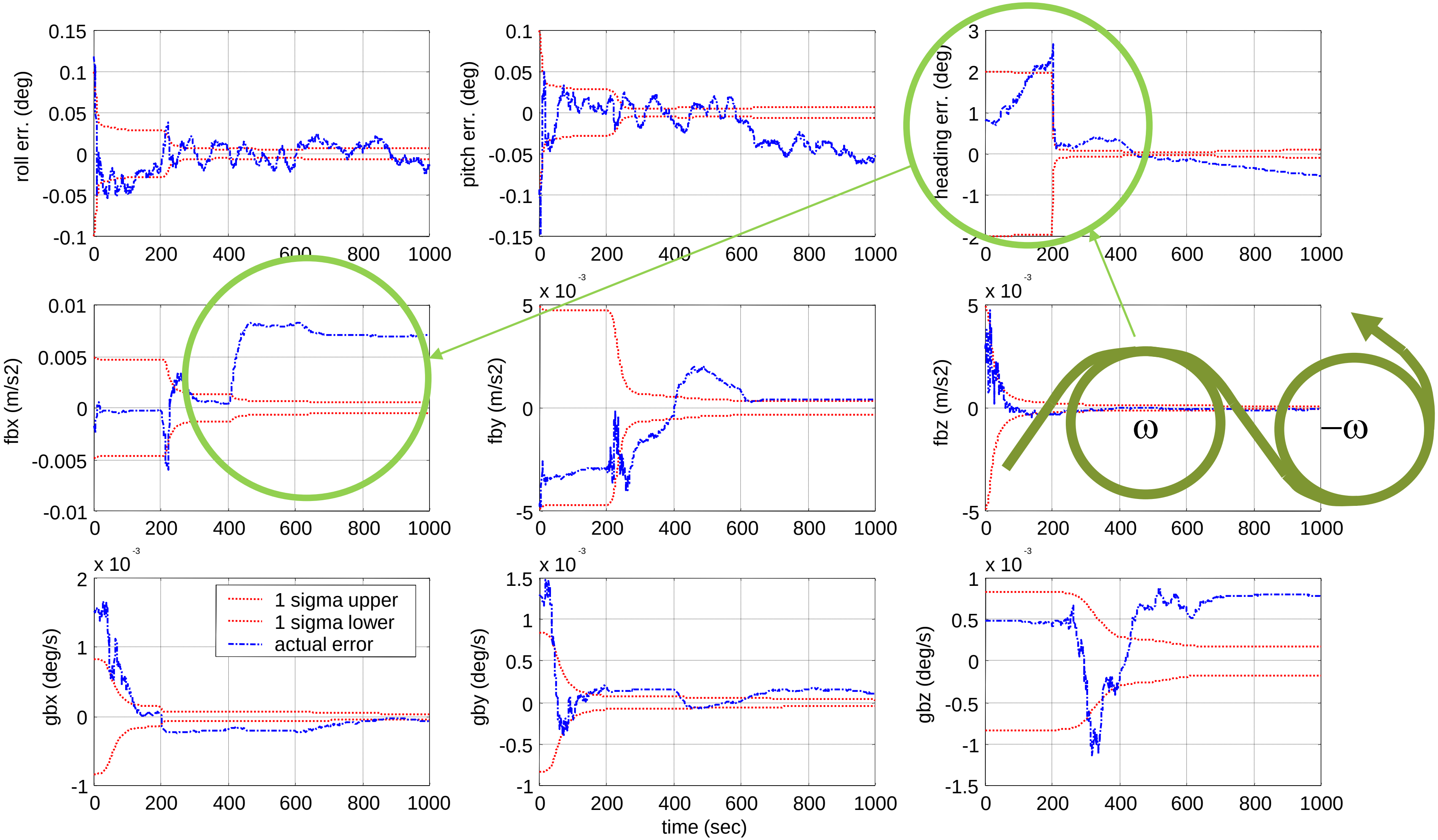
Reset(State)
INS
P, V, Atti.
Reset(State, Error Covar.)
MF
* Fusion Reset Mode
b=a
Update Rate 1/a Hz
Vision
P
LF 1
(Vision/INS)
1/a Hz
State
Error Covar.
* No Reset Mode
b≠a
Update Rate 1/c Hz
where c=LCM(a,b)
MF : master filter
LF : local filter
GPS
Receiver
P
V
LF 2
(GPS/INS)
1/b Hz
State
Error Covar.
* Add-In Mode
b≠a
Update Rate 1/b Hz
Reset(State, Error Covar.)
Information Sharing
P-1 = (P1) -1 + (P2) -1
P-1 x = (P1) -1 x1 + (P2) -1 x2

시각동기 및 Lever Arm 보상

시각동기의 필요성

- 시각동기오차가 존재하면 가속도계 바이어스 추정에 비정상적으로 큰 오차를 발생시킴
  - I. Y. Bar-Itzhack, Y. Vitek(1985), "The enigma of false bias detection in a strapdown system during transfer alignment", *Journal of Guidance and Control*, 8, 2, 175-180
- 시각동기오차에 의하여 먼저 자세오차가 편향되며, 편향된 자세오차는 가속도계 바이어스 추정 오차를 급격하게 증가시킴
  - H. K. Lee, J. G. Lee, and G. I. Jee(2002), "Calibration of measurement delay in GPS/SDINS hybrid navigation", *Journal of Guidance, Control, and Dynamics, 25, 2, 240*-247
- GPS 측정치가 간헐적으로 가용하지 않을 경우, 잘못 추정된 가속도계 바이어스와 자세오차는 GPS/INS의 오차를 매우 빠르게 증가시킴

시각동기오차의 영향

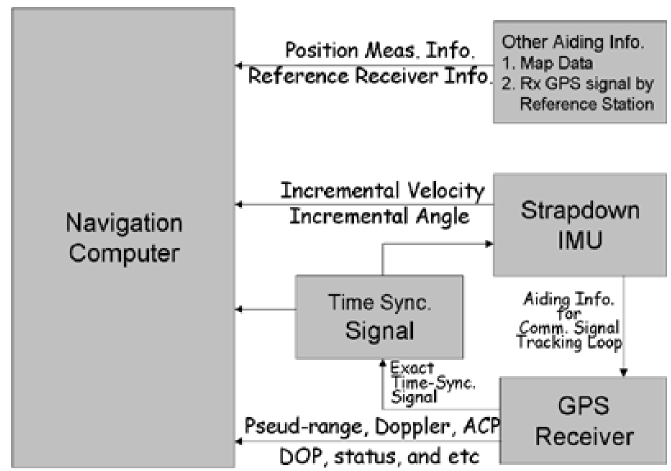


roll err. (deg)
pitch err. (deg)
heading err. (deg)
fbx (m/s2)
fby (m/s2)
fbz (m/s2)
gbx (deg/s)
gby (deg/s)
gbz (deg/s)
time (sec)
1 sigma upper
1 sigma lower
actual error
ω
−ω

GPS/INS 시각동기 구현 방법

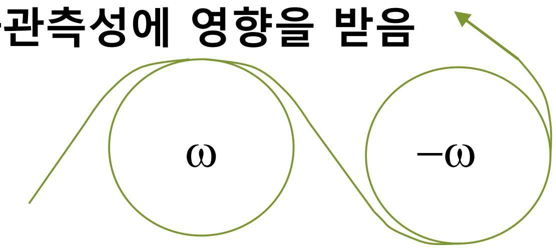
- 하드웨어에 의한 시각동기
  - ❖ IMU와 GPS 수신기 설계레벨에서 고려, 고비용

- 하드웨어/소프트웨어에 의한 시각동기
  - ❖ GPS에서 제공하는 정확한 시각정보 PPS(Pulse Per Second)를 이용
  - ❖ 시간 표식(time-tag)을 위한 별도의 하드웨어 제작 필요



- 소프트웨어에 의한 시각동기
  - ❖ 시각동기오차를 GPS/INS 통합 칼만필터의 상태변수로 고려함
  - ❖ 제어 기동 (controlled maneuver)이 요구됨
  - ❖ 궤적에 의한 가관측성에 영향을 받음

$$T = \frac{-\Delta\Psi}{2\omega}$$



Lever Arm 오차

❖ **Lever Arm 오차란?**

- 센서의 설치 위치가 일치하지 않아

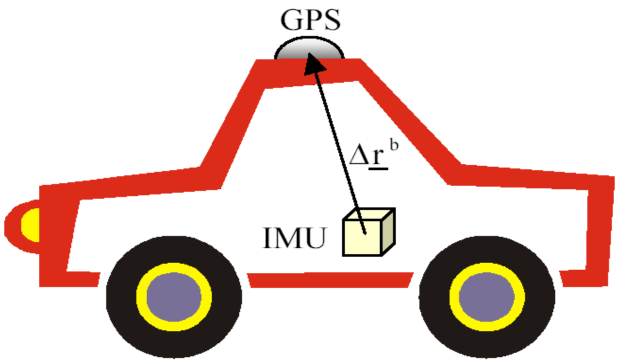
  측정 기준점의 차이로 발생하는 오차를 말함.

✓ **일반적으로 GPS 안테나는 차량 외부에 설치하고 IMU는 차량 내부에 설치하므로 Lever Arm 오차가 발생함**

✓ **정확한 항법 해를 얻기 위해선 Lever arm 보상이 필요.**

Lever Arm 오차에 대한 대처 방안

- **IMU와 GPS 안테나 장착 위치의 차이를 고려한 측정 모델 설계**

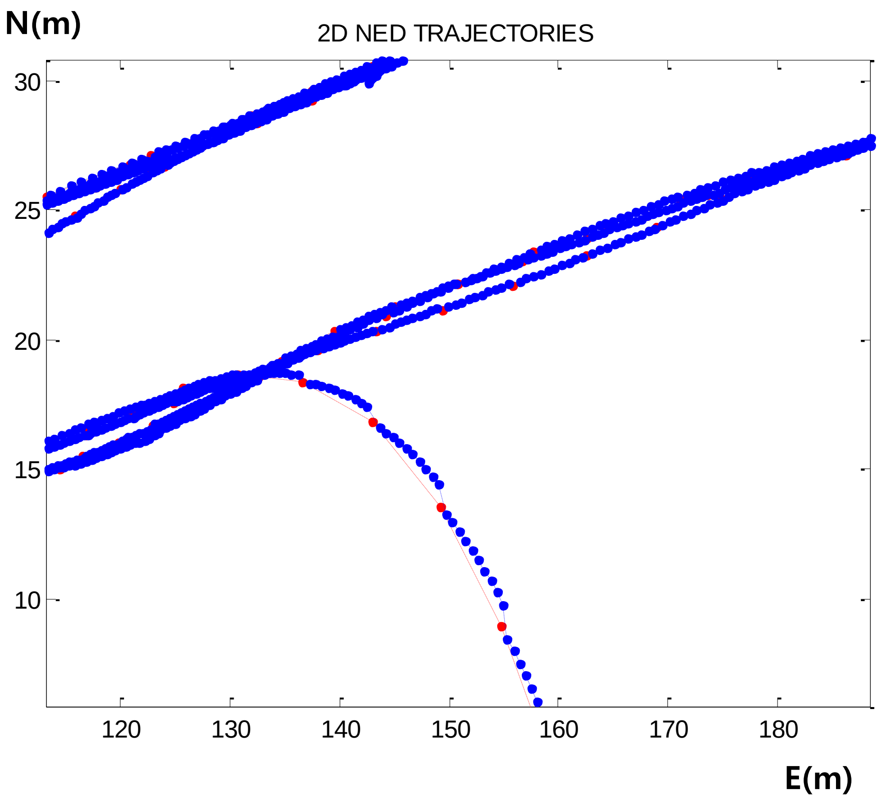


- GPS로부터 얻은 IMU의 위치 측정 모델

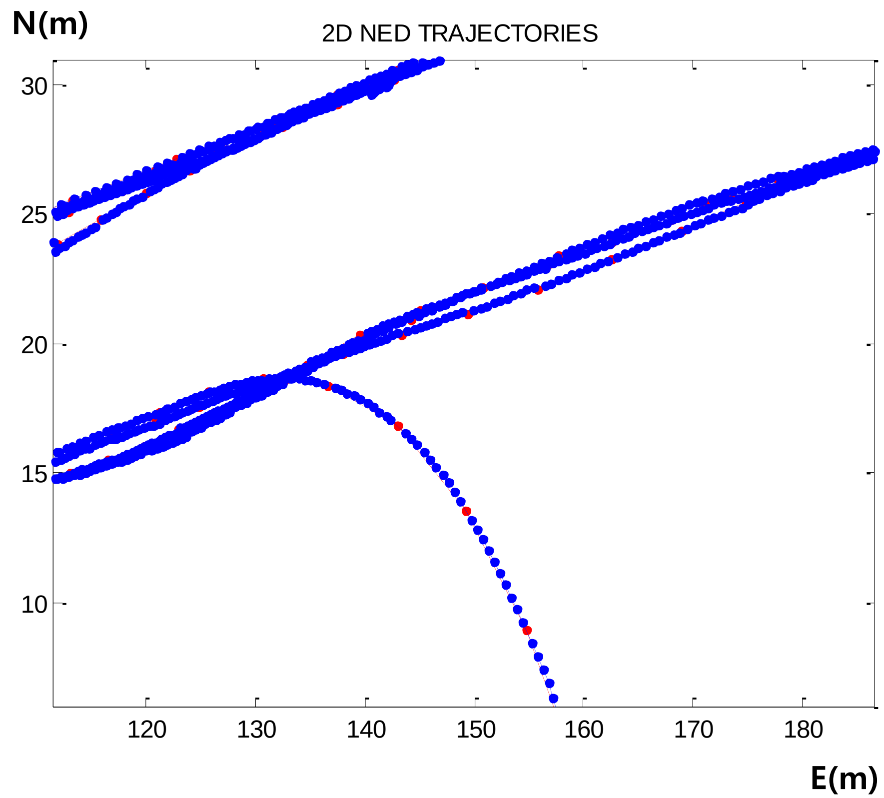
$$r_{IMU}^{n} = r_{GPS}^{n} - \begin{bmatrix} \frac{1}{M+h} & 0 & 0 \\ 0 & \frac{1}{(N+h)\cos L} & 0 \\ 0 & 0 & -1 \end{bmatrix} C_b^n \Delta r^b$$

Lever Arm 보상 전후 비교(1/3)

✓ Lever Arm 보상전

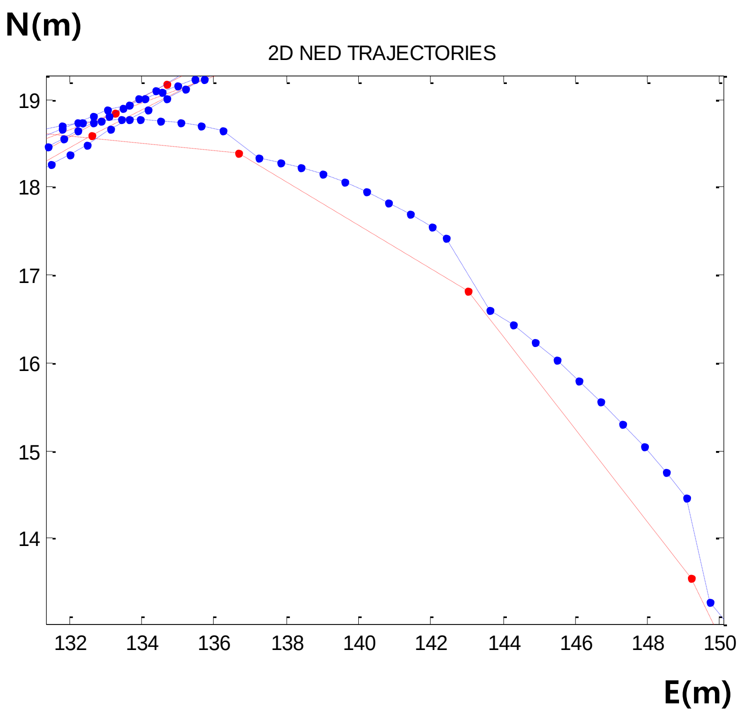


✓ Lever Arm 보상후

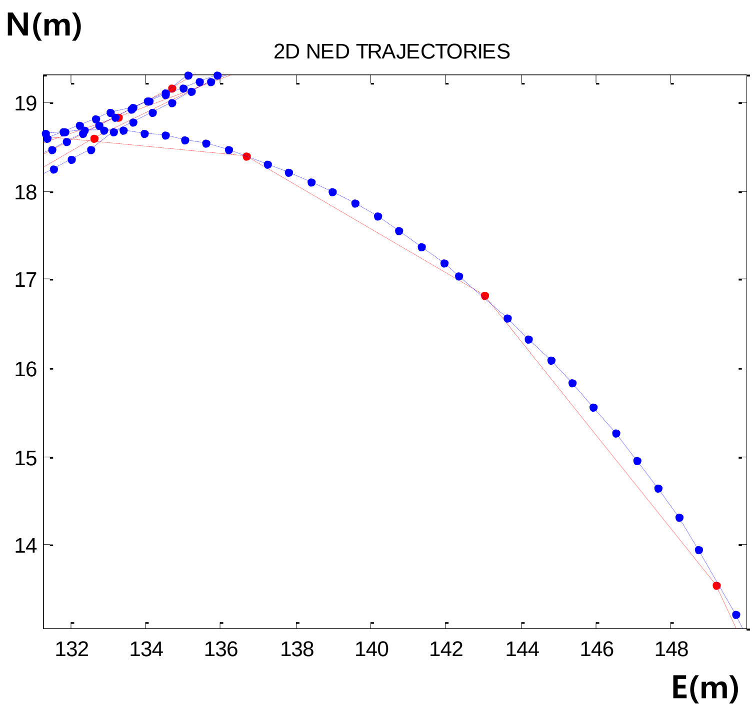


Lever Arm 보상 전후 비교(2/3)

✓ Lever Arm 보상전



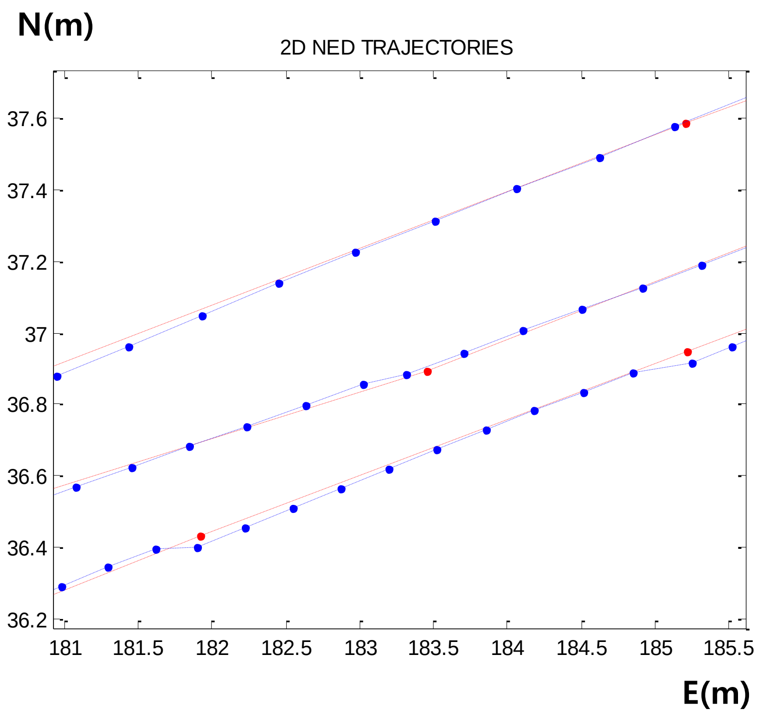
✓ Lever Arm 보상후



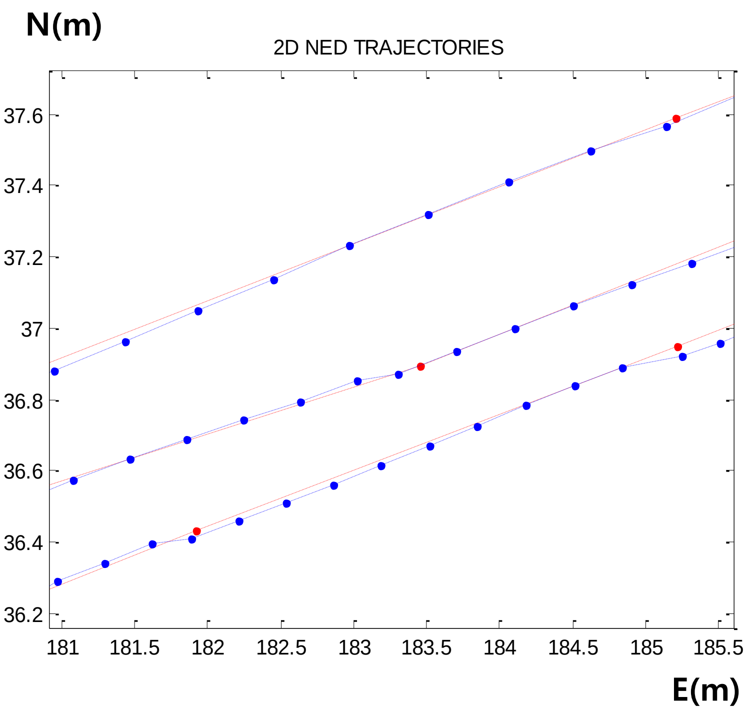
✓ Lever Arm 보상 후 곡선 주행에서 약 30cm~50cm 정도 오차 감소

Lever Arm 보상 전후 비교(3/3)

✓ Lever Arm 보상전



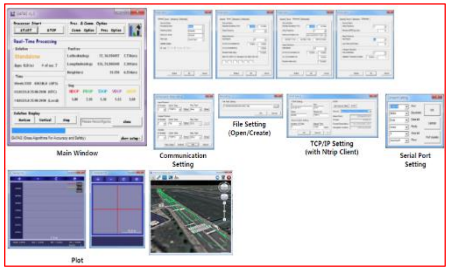
✓ Lever Arm 보상후



✓ 직선 주행에서는 Lever Arm 보상 전, 후의 차이가 거의 없음.

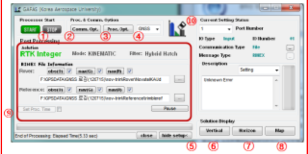
다중센서 통합 구조

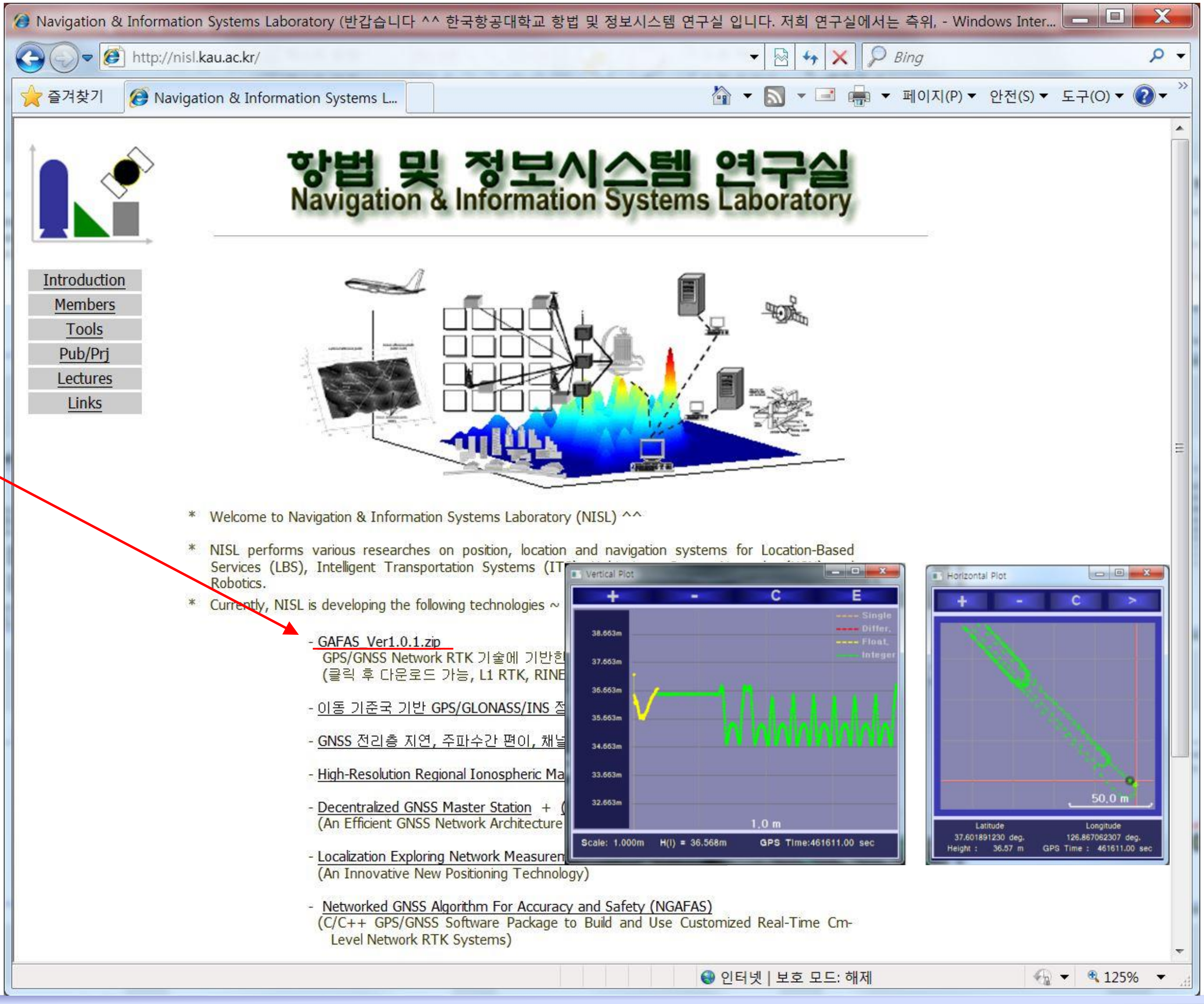
다중 GNSS（*GAFAS* 활용）



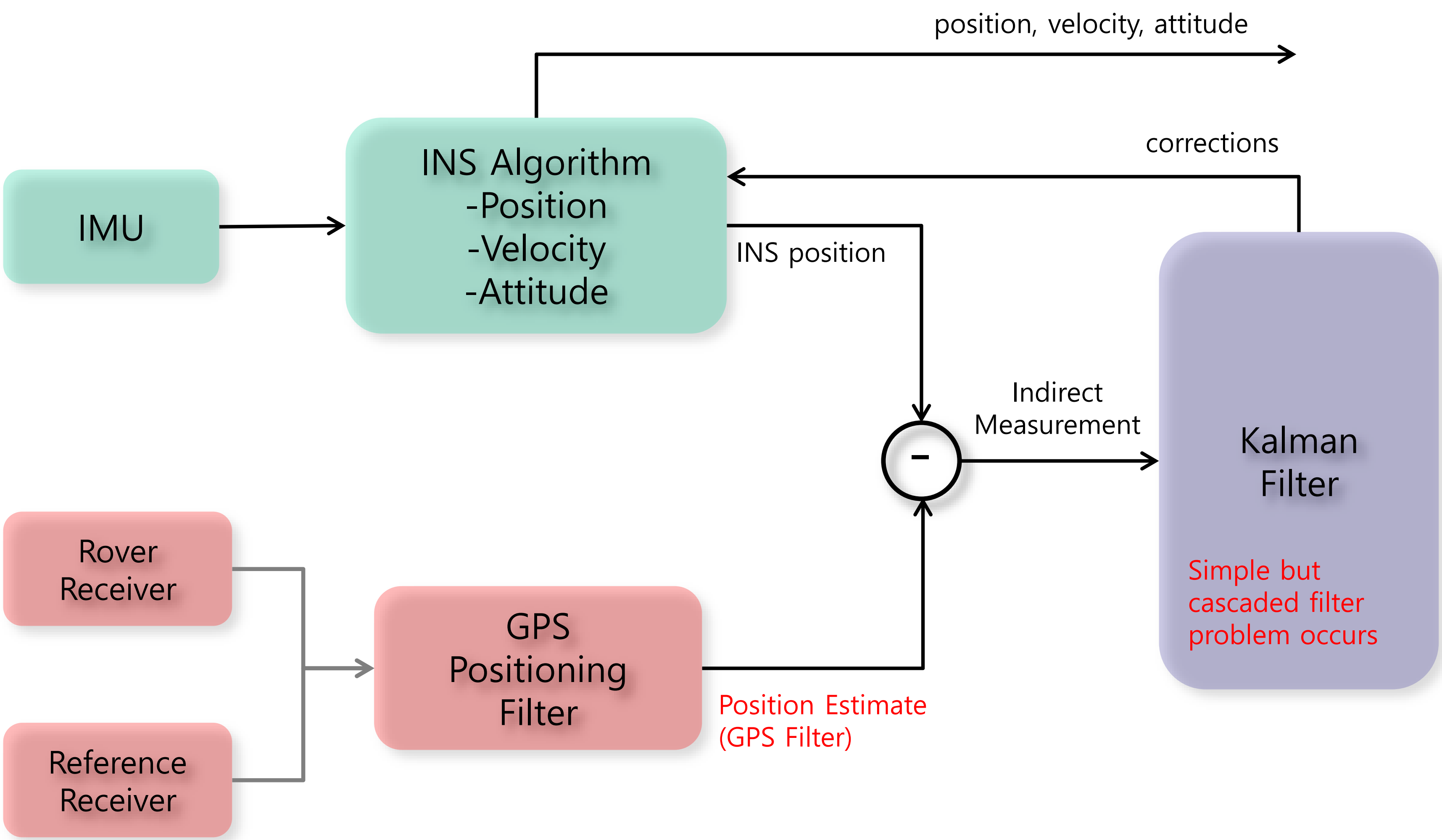
(http://nisl.kau.ac.kr)에서 GAFAS 링크를 클릭하면 실행파일과 매뉴얼을 다운로드 가능함

① Start: 데이터 처리 시작
② Stop: 데이터 처리 중단
③ Comm. Option: GNSS 데이터 입/출력 설정
④ Proc. Option: GNSS 데이터 처리관련 변수 설정
⑤ Show Setup: 확장 화면 표시/사라짐
⑥ Vertical: 고도축 측위 결과 도시
⑦ Horizon: 수평 측위 결과 도시
⑧ Map: 지도 상에 측위 결과 도시 (TBC)
⑨ GAFAS 후처리 Main Window: RINEX 사용자/기준국 파일 경로 및 존재 여부 도시
⑩ GAFAS 개발 및 연구실 정보



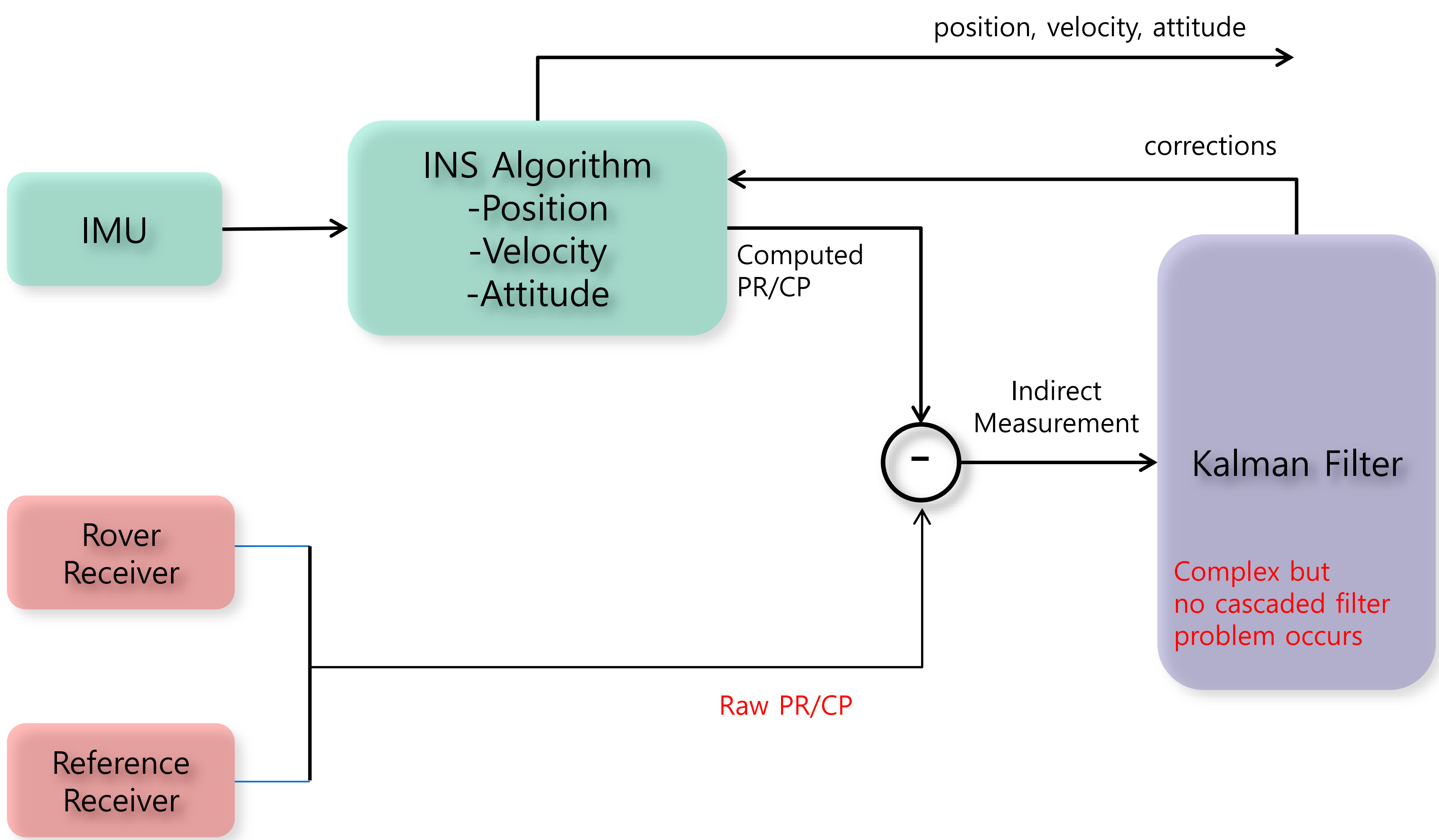


약결합 GPS/INS

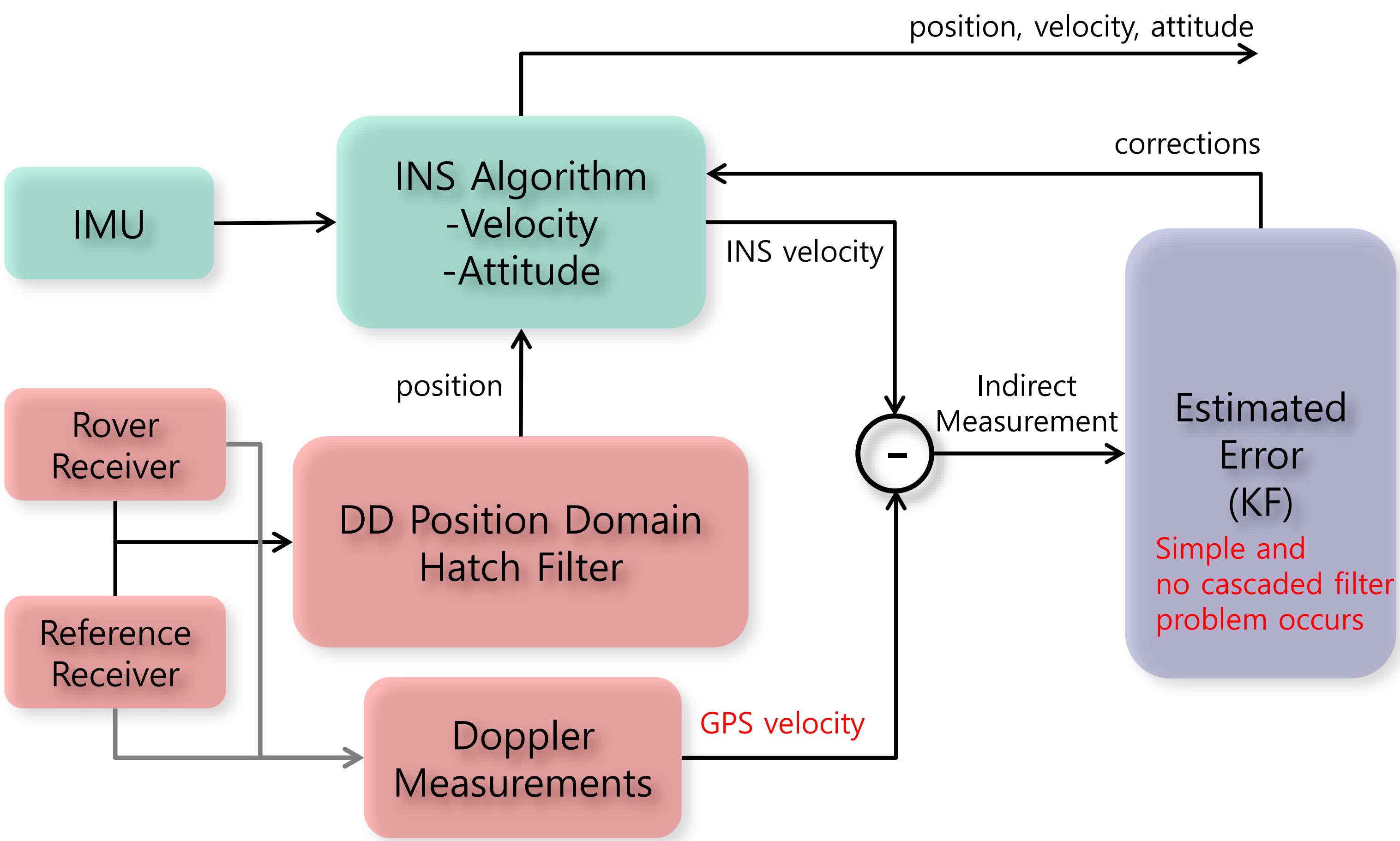


position, velocity, attitude
corrections
IMU
INS Algorithm
-Position
-Velocity
-Attitude
INS position
Indirect
Measurement
-
Kalman
Filter
Simple but
cascaded filter
problem occurs
Rover
Receiver
Reference
Receiver
GPS
Positioning
Filter
Position Estimate
(GPS Filter)

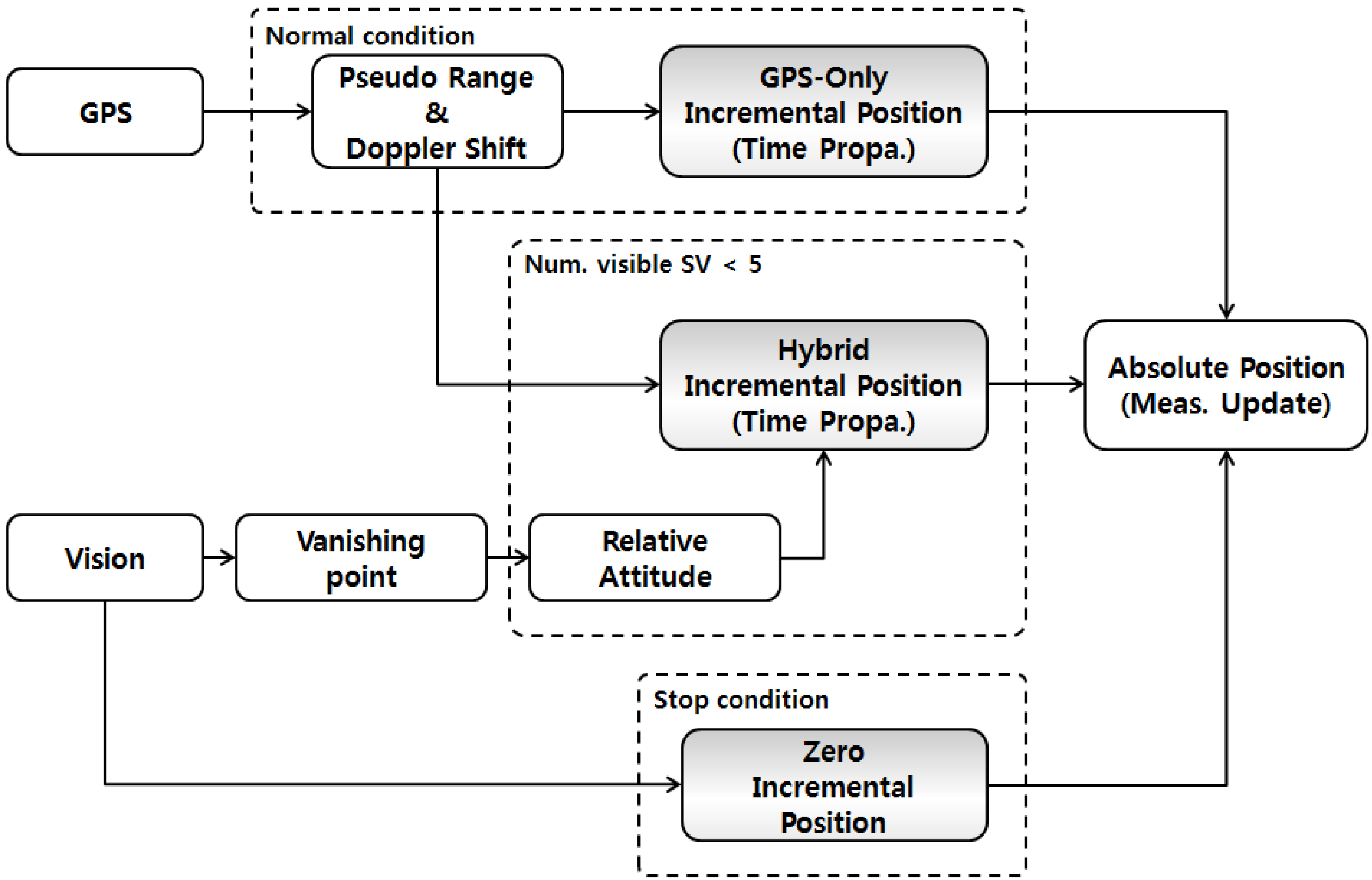
강결합 GPS/INS


position, velocity, attitude
corrections
IMU
INS Algorithm
-Position
-Velocity
-Attitude
Computed
PR/CP
Indirect
Measurement
-
Kalman Filter
Complex but
no cascaded filter
problem occurs
Rover
Receiver
Reference
Receiver
Raw PR/CP

Dual-Filtering GPS/INS

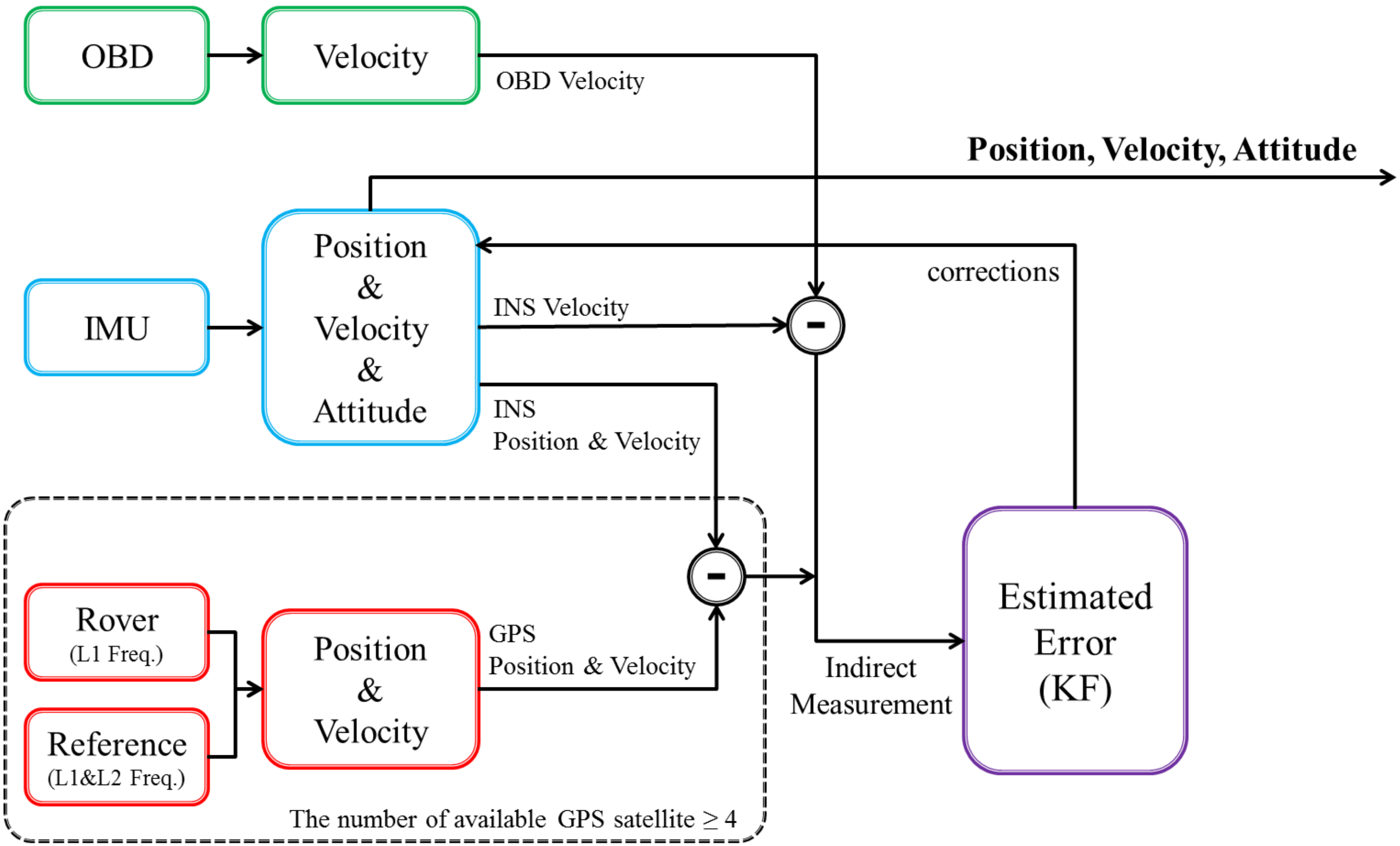


GPS/영상센서



Normal condition
GPS
Pseudo Range & Doppler Shift
GPS-Only Incremental Position (Time Propa.)
Num. visible SV < 5
Hybrid Incremental Position (Time Propa.)
Absolute Position (Meas. Update)
Vision
Vanishing point
Relative Attitude
Stop condition
Zero Incremental Position

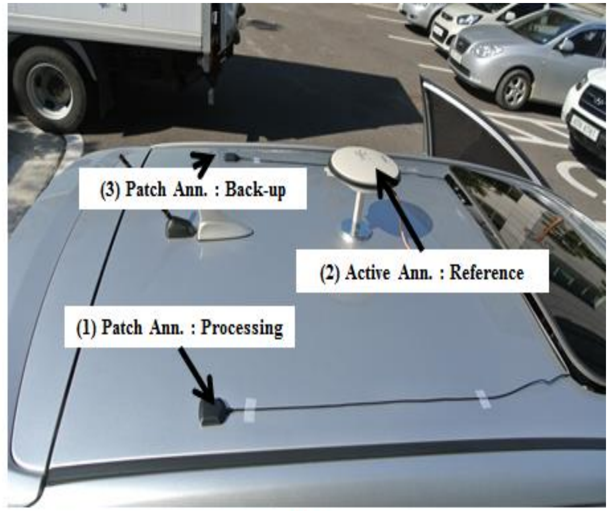
GPS/OBD-II/IMU



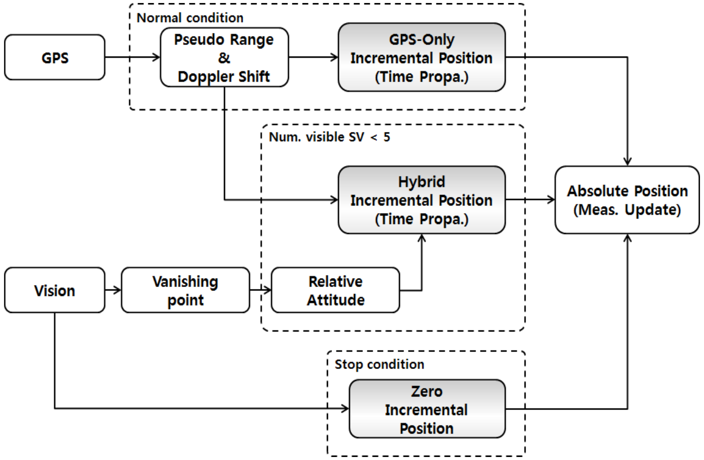
다중센서 비교 실험

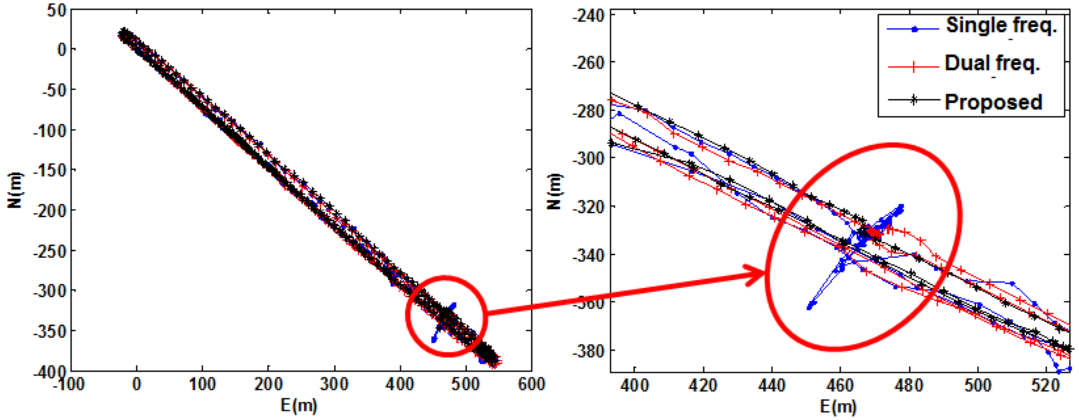
GPS/Vision

(a)



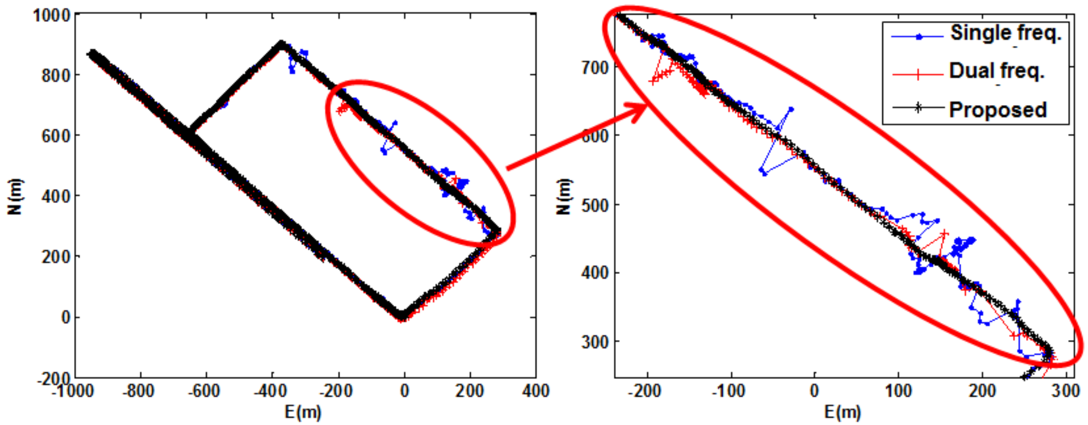
(b)





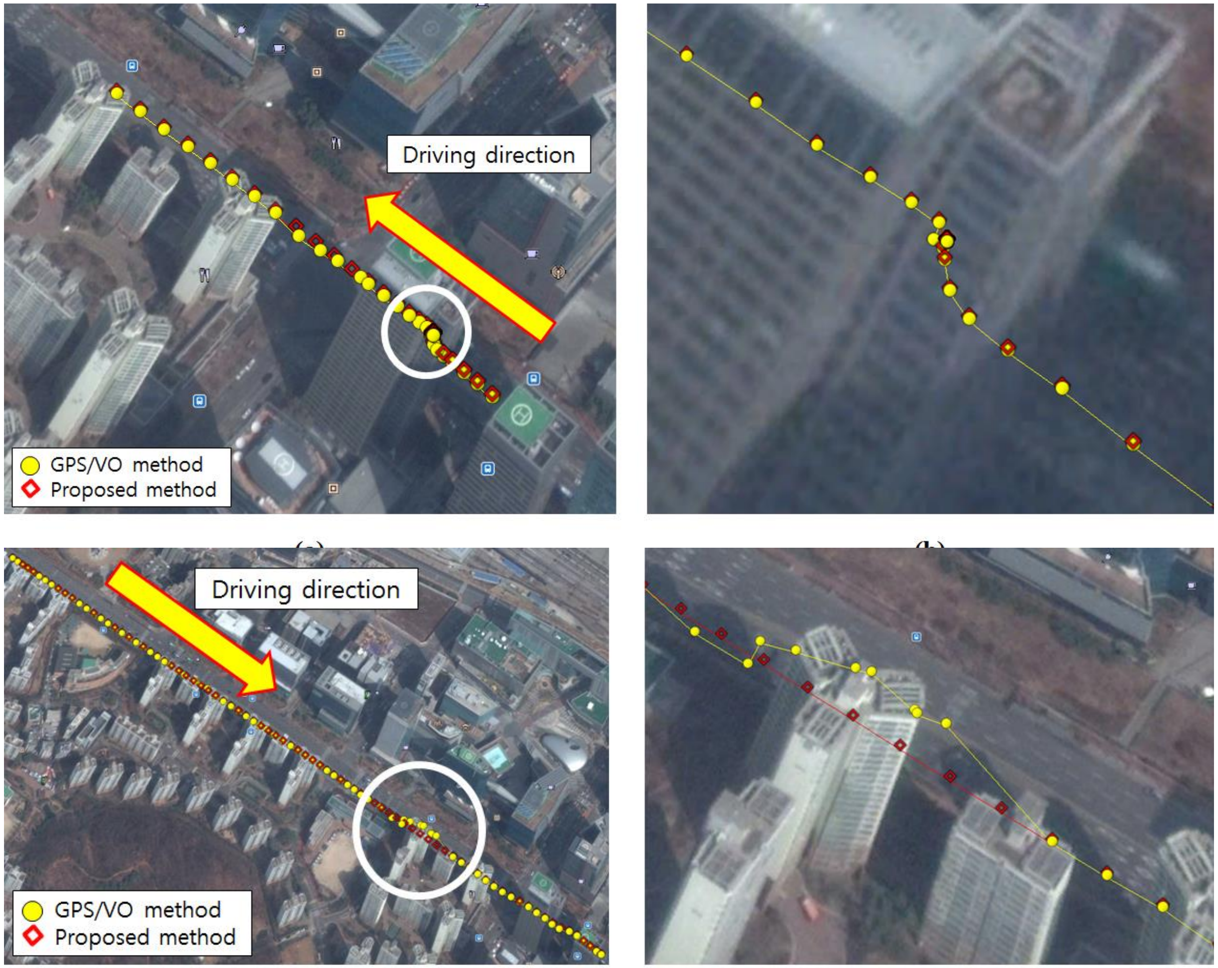
Single freq.
Dual freq.
Proposed
E(m)
N(m)

(a)



Single freq.
Dual freq.
Proposed
E(m)
N(m)

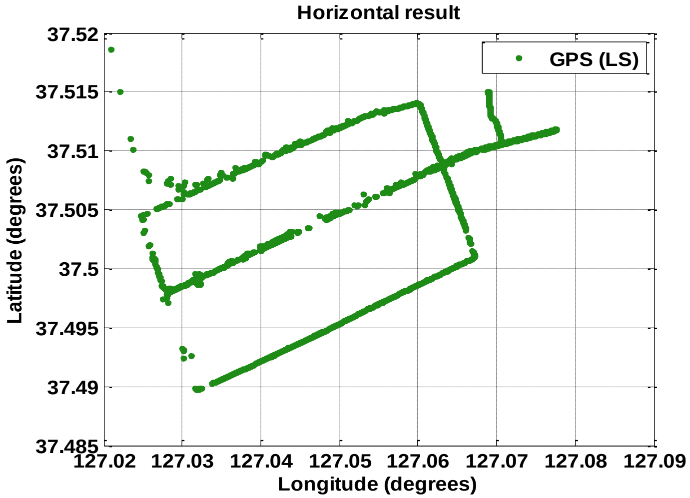
(b)

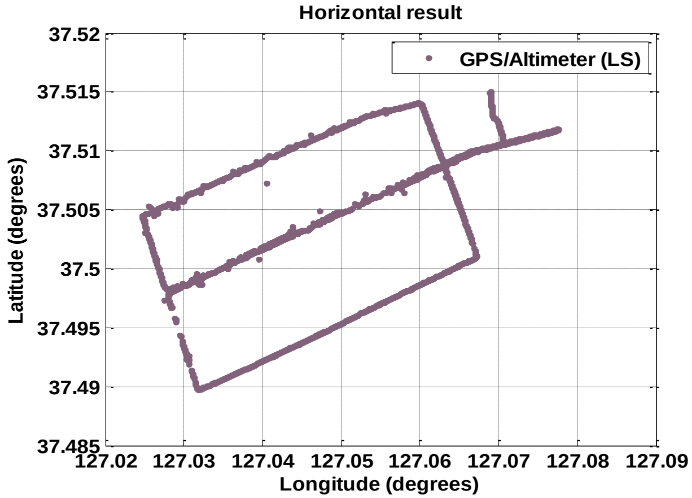

Driving direction
GPS/VO method
Proposed method
Driving direction
GPS/VO method
Proposed method

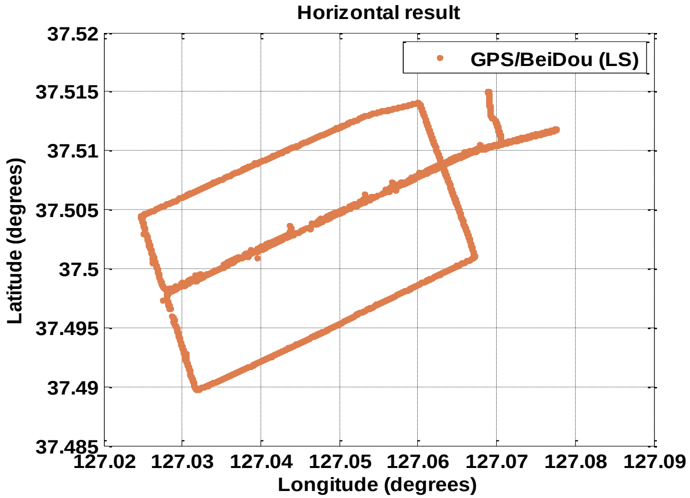
(a) (b)

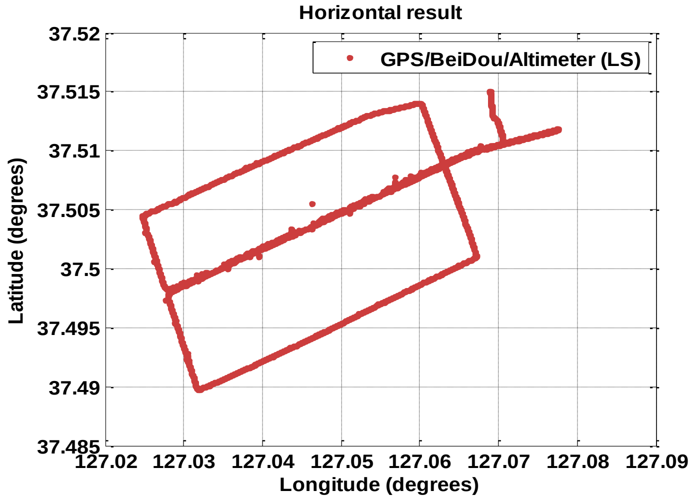
GPS/BeiDou/ALT

- 강남 테헤란로에서 수행됨
- 실험의 참값이 존재하지 않아 측위 결과에 대한 오차 분석은 불가능
- 위치 추정 결과와 위치 정보 가용성을 분석함


Horizontal result
GPS (LS)
Latitude (degrees)
Longitude (degrees)
37.52
37.515
37.51
37.505
37.5
37.495
37.49
37.485
127.02
127.03
127.04
127.05
127.06
127.07
127.08
127.09

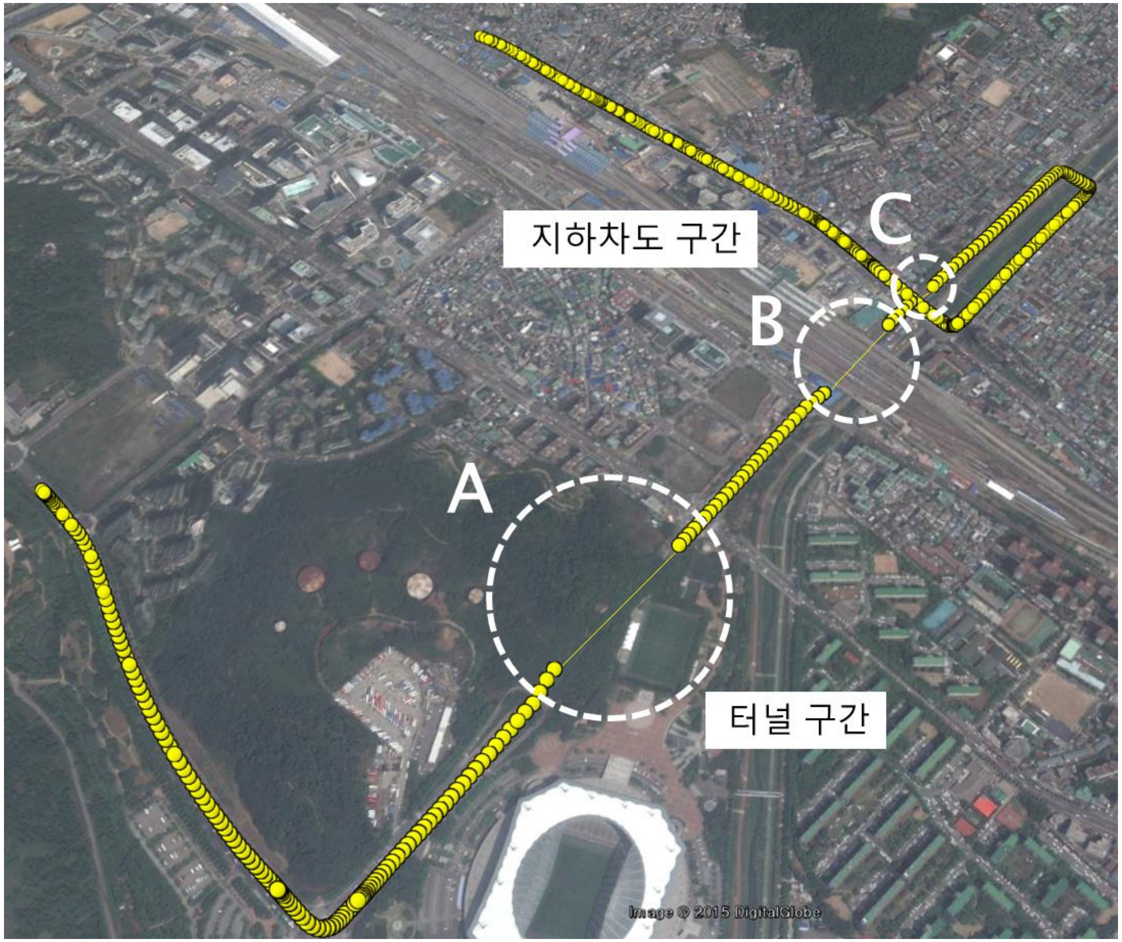

Horizontal result
GPS/Altimeter (LS)
Latitude (degrees)
Longitude (degrees)
37.52
37.515
37.51
37.505
37.5
37.495
37.49
37.485
127.02
127.03
127.04
127.05
127.06
127.07
127.08
127.09


Horizontal result
GPS/BeiDou (LS)
Latitude (degrees)
Longitude (degrees)
37.52
37.515
37.51
37.505
37.5
37.495
37.49
37.485
127.02
127.03
127.04
127.05
127.06
127.07
127.08
127.09

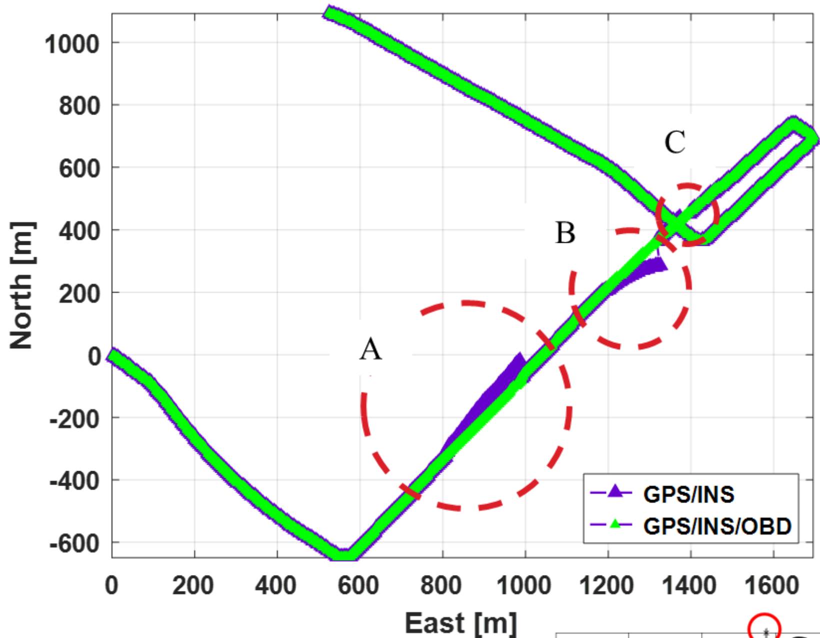

Horizontal result
GPS/BeiDou/Altimeter (LS)
Latitude (degrees)
Longitude (degrees)
37.52
37.515
37.51
37.505
37.5
37.495
37.49
37.485
127.02
127.03
127.04
127.05
127.06
127.07
127.08
127.09

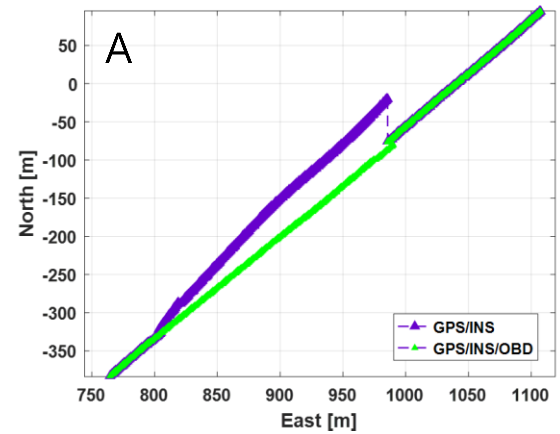

GPS/BDS/Alt Hatch Trajectory
1500
1000
500
0
-500
-1000
-1500
-2000
North (meters)
-3000
-2000
-1000
0
1000
2000
3000
East (meters)

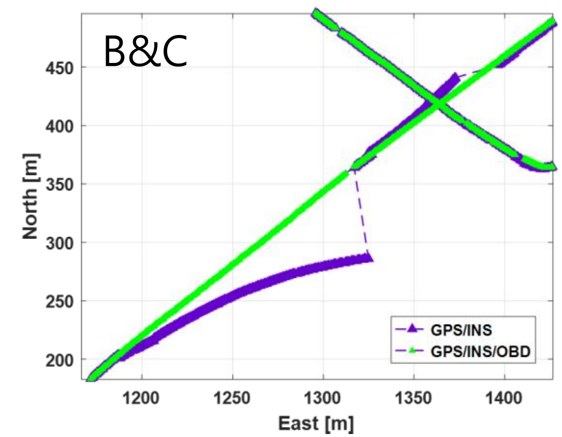
GNSS/IMU/OBD

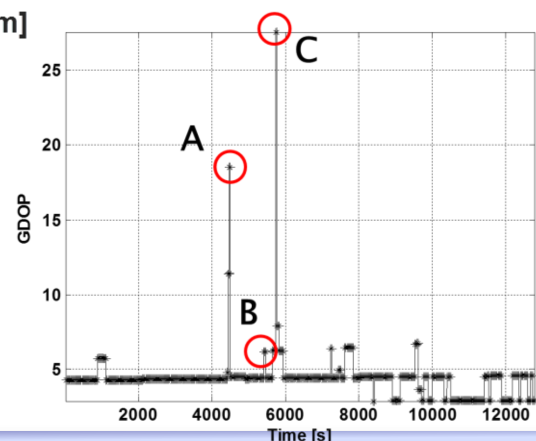


확대 궤적

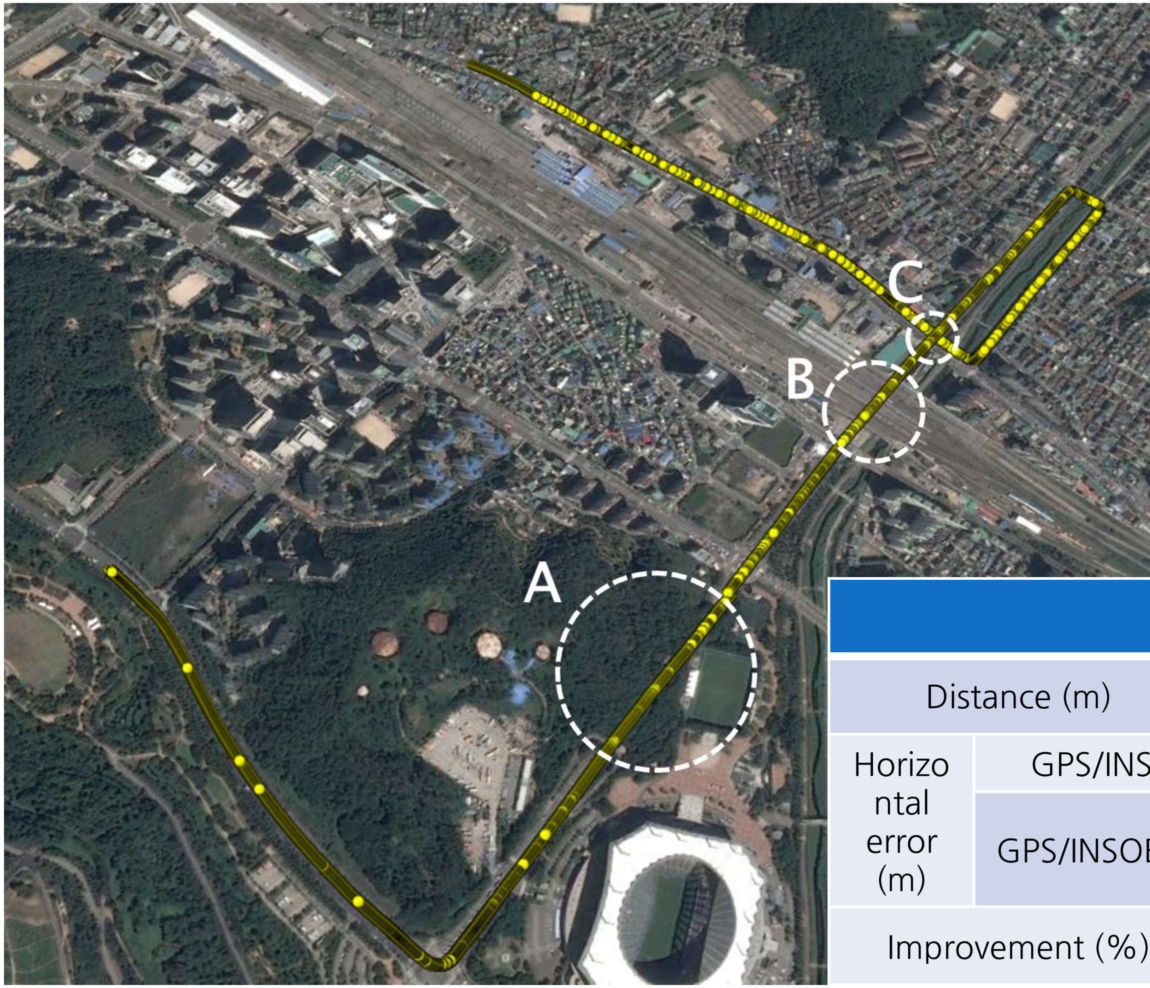

A
B
C
North [m]
East [m]
1000
800
600
400
200
0
-200
-400
-600
0
200
400
600
800
1000
1200
1400
1600
GPS/INS
GPS/INS/OBD


A
North [m]
East [m]
50
0
-50
-100
-150
-200
-250
-300
-350
750
800
850
900
950
1000
1050
1100
GPS/INS
GPS/INS/OBD

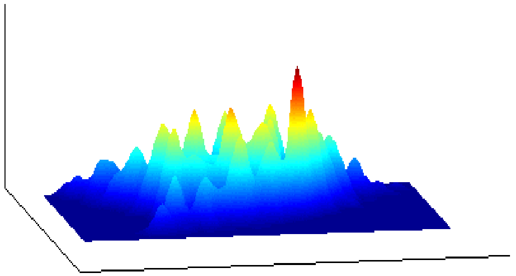

B&C
North [m]
East [m]
450
400
350
300
250
200
1200
1250
1300
1350
1400
GPS/INS
GPS/INS/OBD


A
B
C
GDOP
Time [s]
25
20
15
10
5
2000
4000
6000
8000
10000
12000

오차 비교



		A	B	C
Distance (m)		268.38	183.88	54.23
Horizontal error (m)	GPS/INS	56.8	70.91	26.32
	GPS/INSOBD	5.94	6.56	3.26
Improvement (%)		89.5	90.7	87.6



THANK YOU !