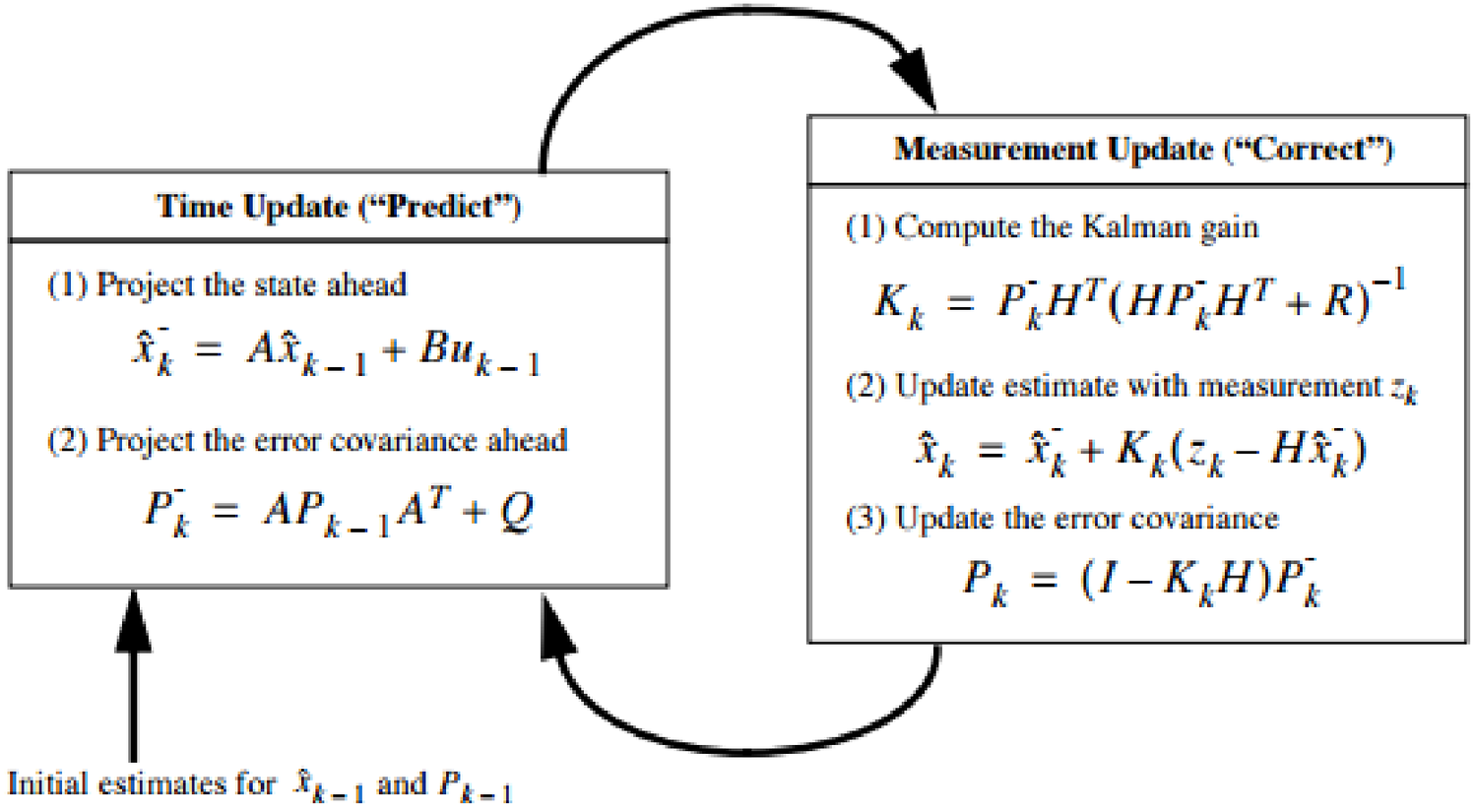
Examples
By Kalman Filter

1 KF & EKF

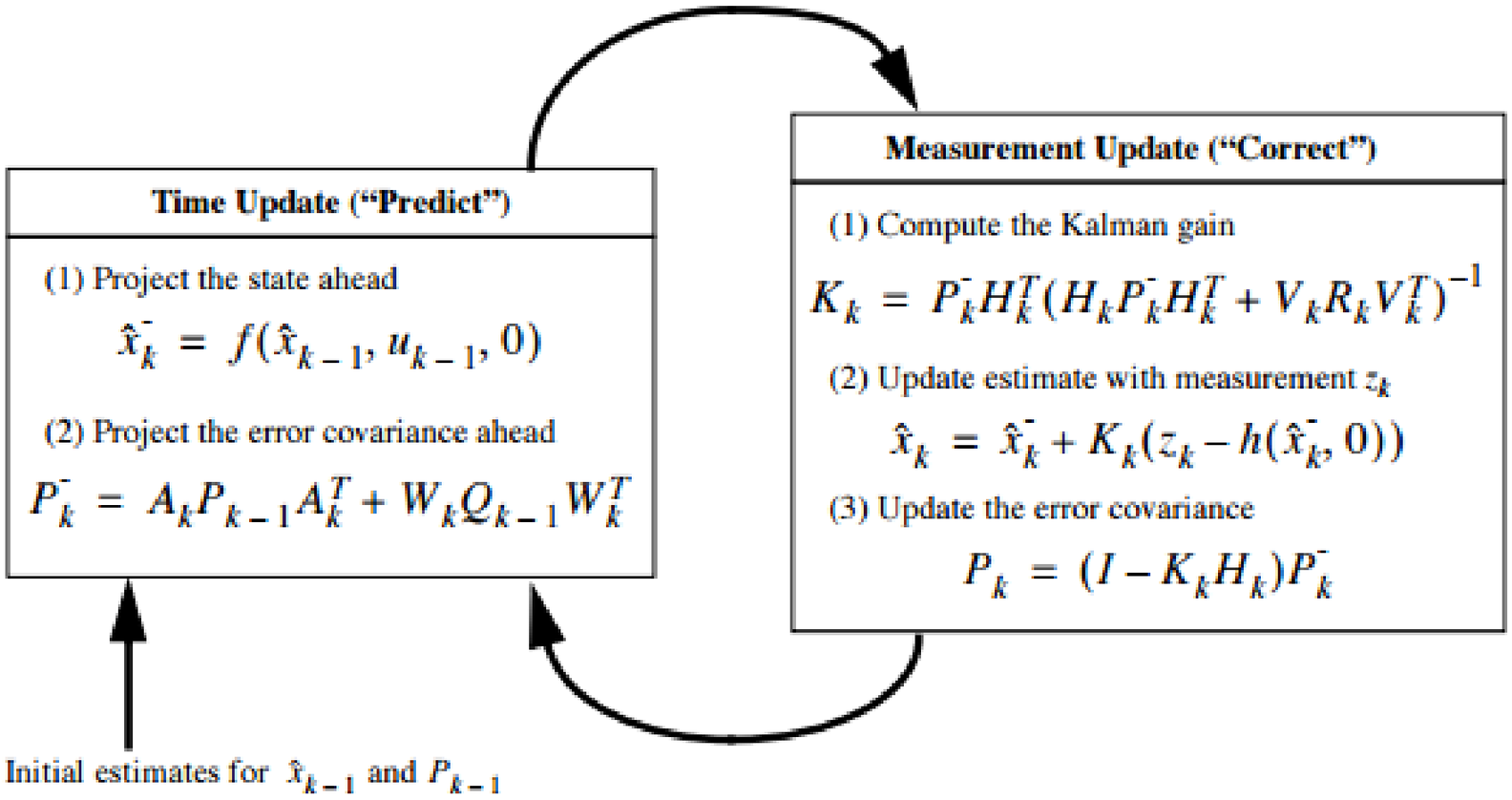
2 GPS + IMU + Motion tracker

6 DVL + IMU + Camera + Depth sensor

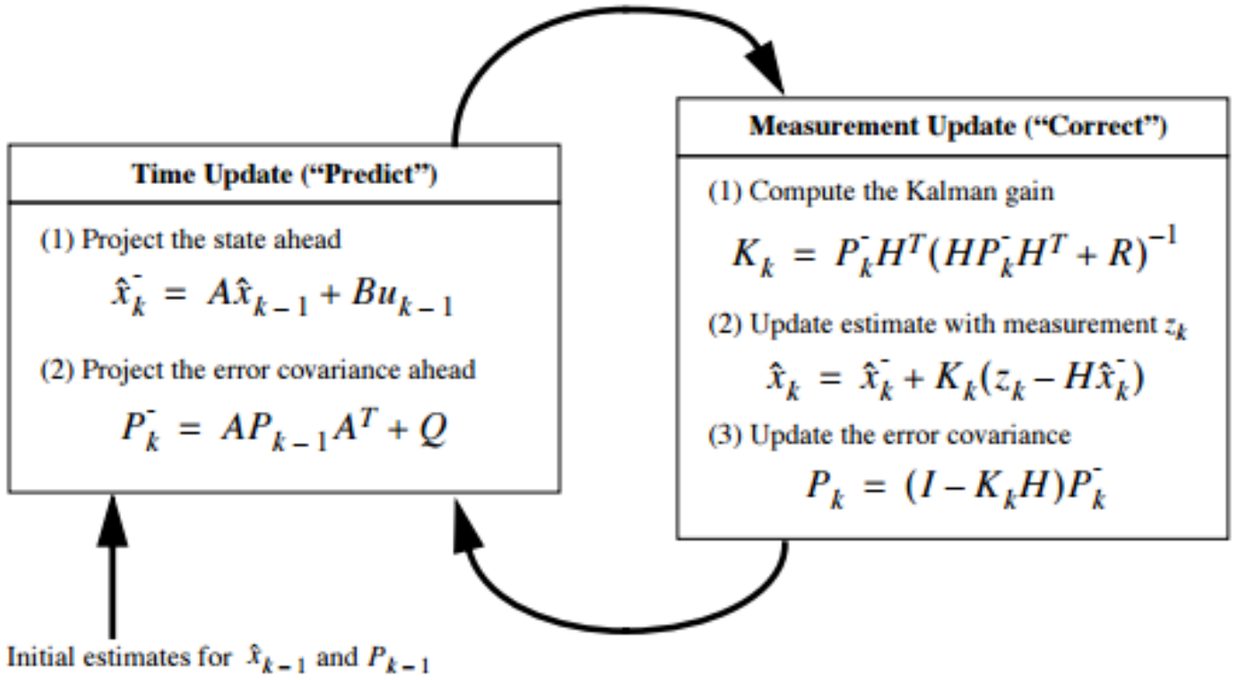
1 KF & EKF



Linear system

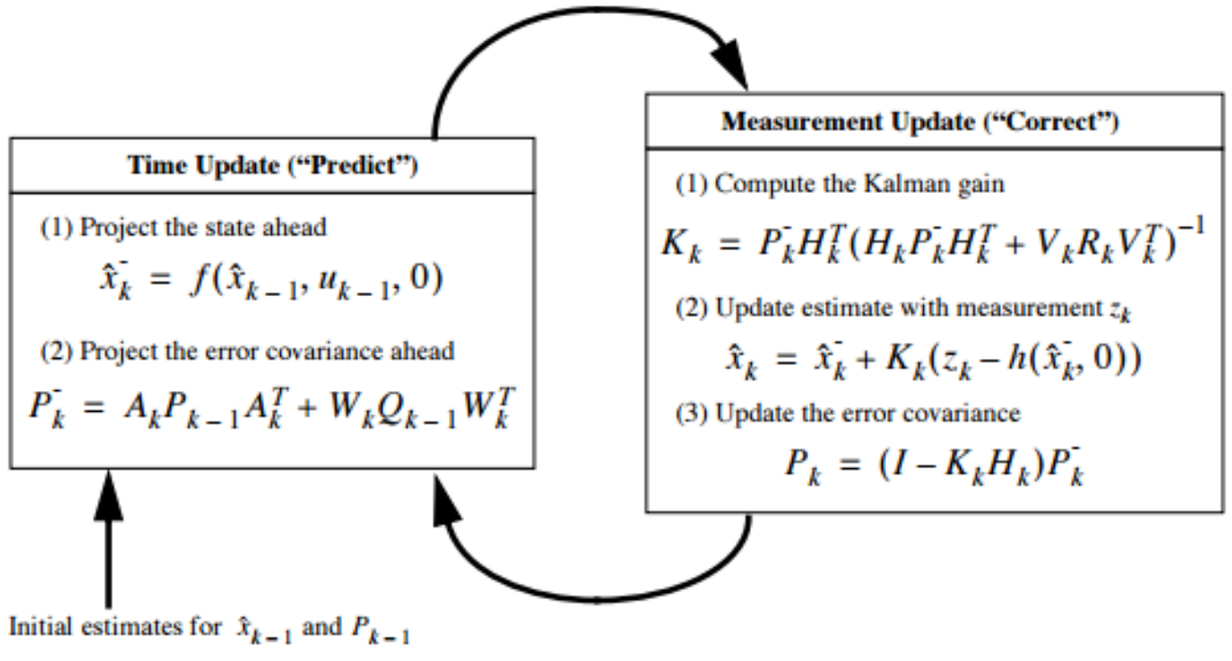


Nonlinear system



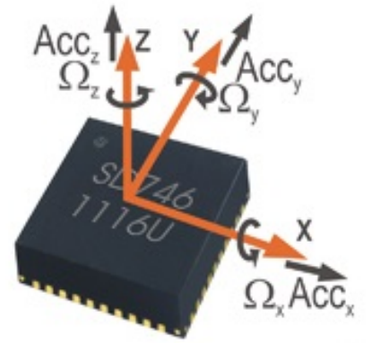
Nonlinear system

Linear system

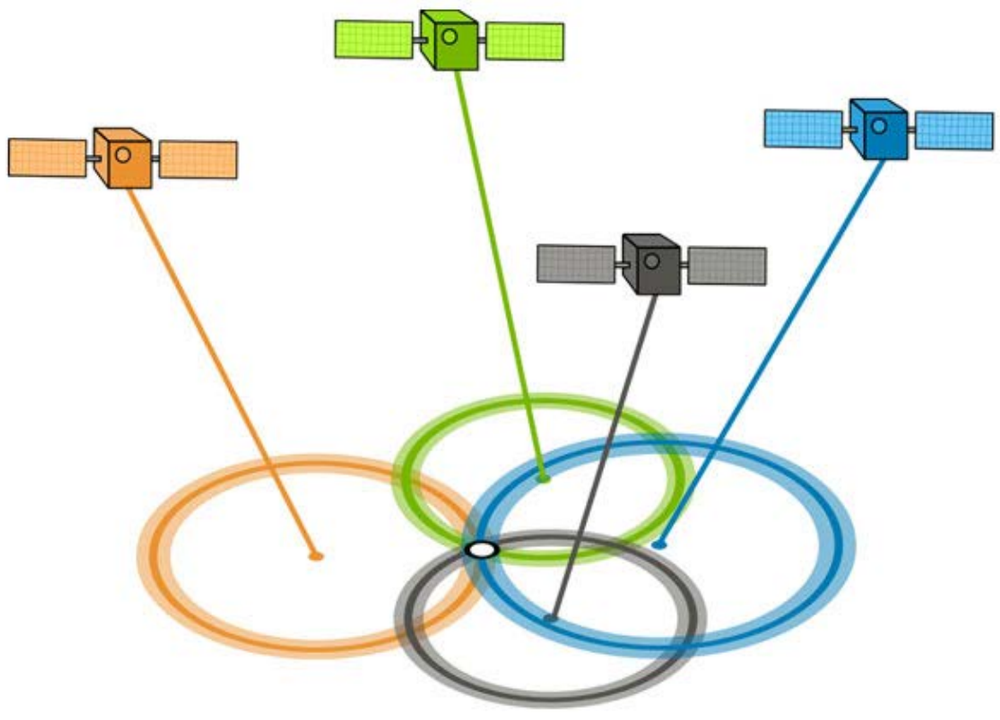


2 IMU + GPS + Motion tracker

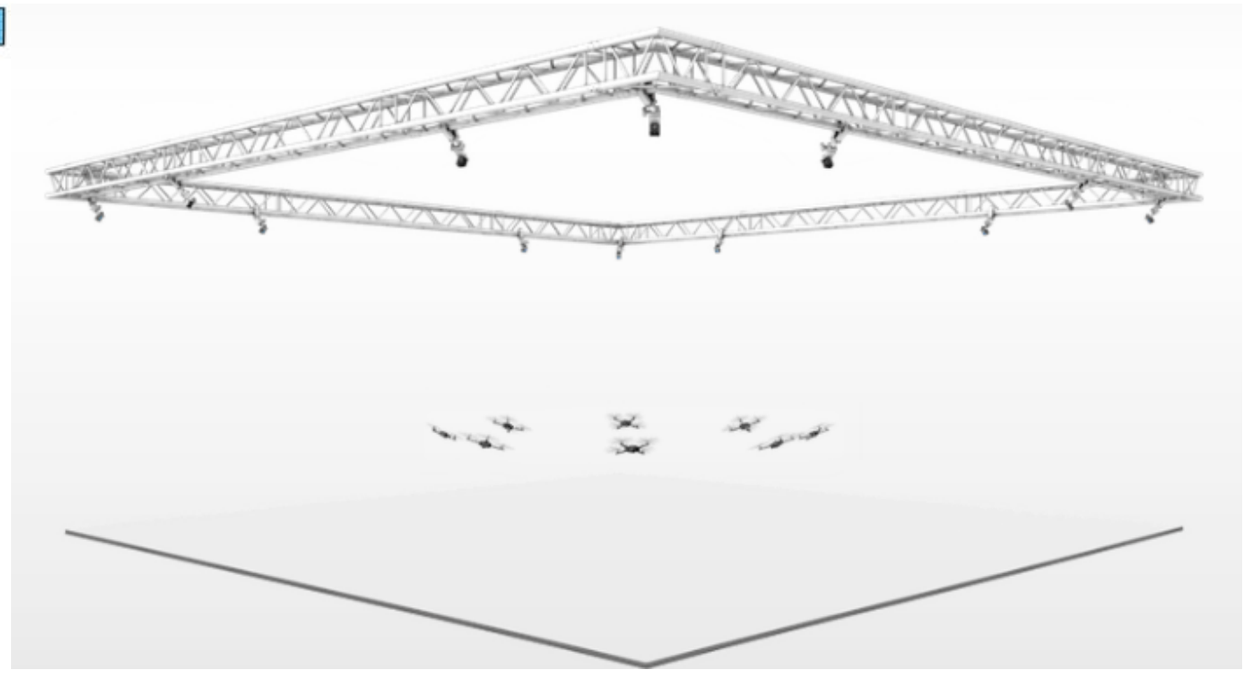
IMU

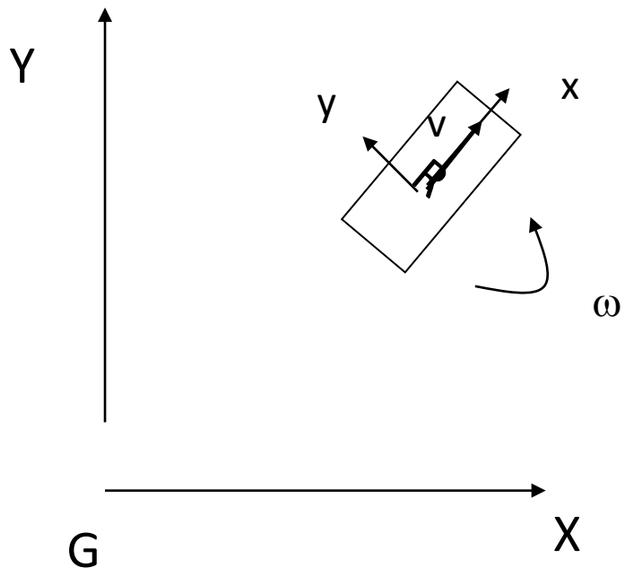


GPS



Motion tracker





From a robot-centric perspective, the velocities look like this:

$$\dot{x}_t = V_t$$
$$\dot{y}_t = 0$$
$$\dot{\phi}_t = \omega_t$$

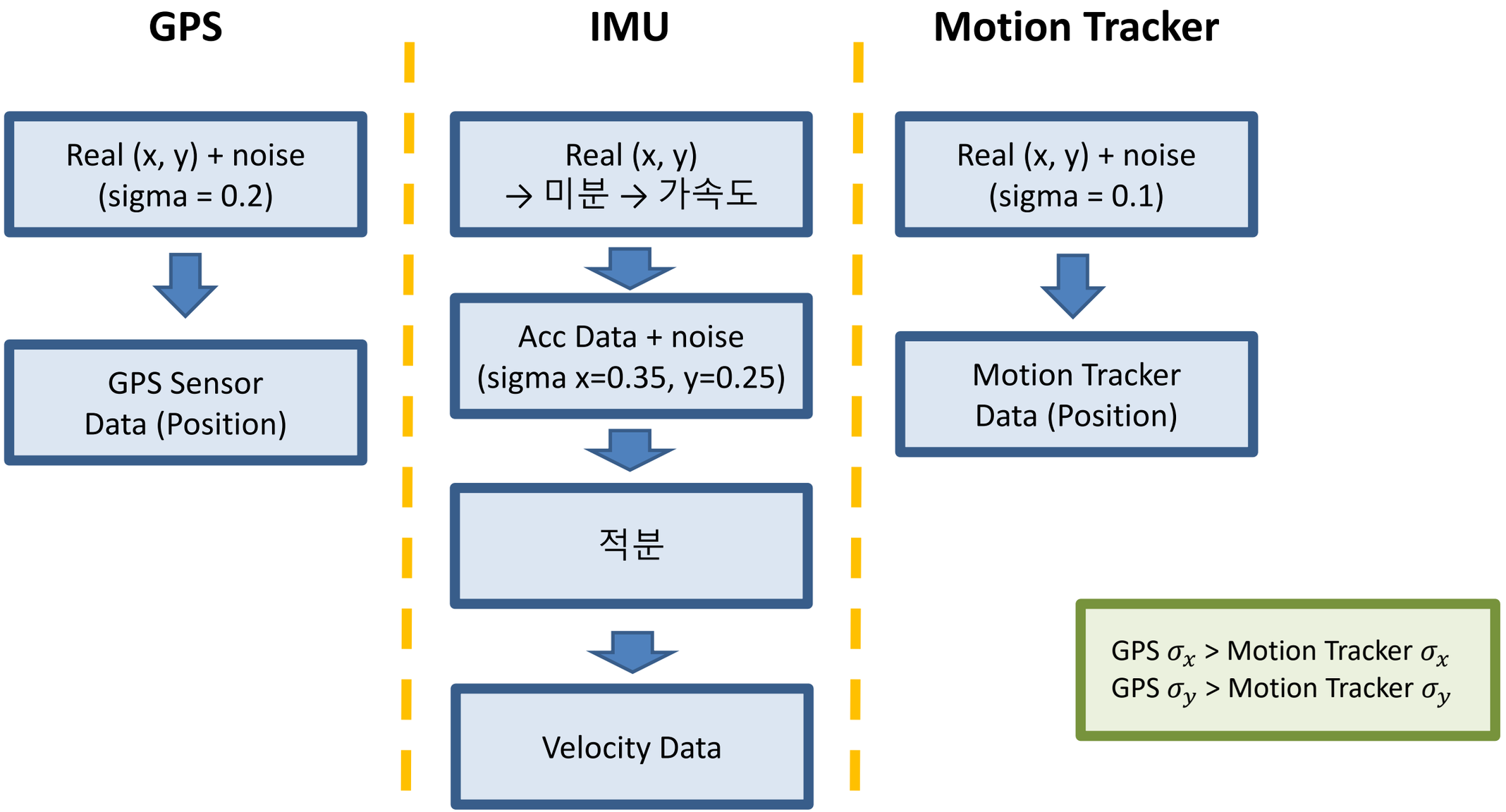
From the global perspective, the velocities look like this:

$$\dot{x}_t = V_t \cos\phi_t$$
$$\dot{y}_t = V_t \sin\phi_t$$
$$\dot{\phi}_t = \omega_t$$

The discrete time state estimate (including noise) looks like this:

$$\hat{x}_{t+1} = \hat{x}_t + (V_t + w_{V_t})\delta t \cos\hat{\phi}_t$$
$$\hat{y}_{t+1} = \hat{y}_t + (V_t + w_{V_t})\delta t \sin\hat{\phi}_t$$
$$\hat{\phi}_{t+1} = \hat{\phi}_t + (\omega_t + w_{\omega_t})\delta t$$

센서 데이터 생성 방법 조건



Geometric Sensor Fusion

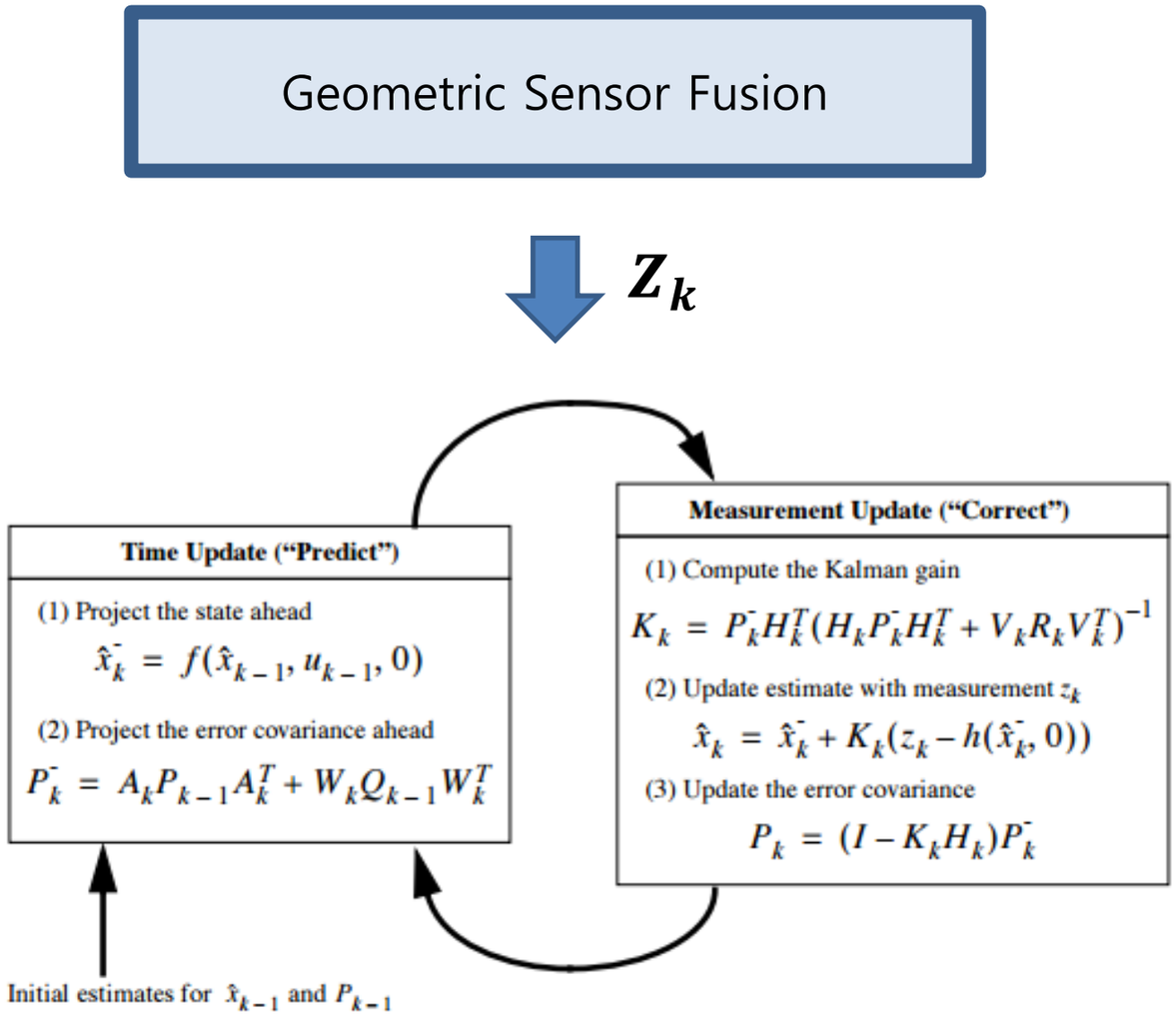
$$\hat{X}_k = w_{A,k} * Z_{A,k} + w_{B,k} * Z_{B,k}$$

$$\hat{X}_k = \left(\frac{\sigma_{B,k}^2}{\sigma_{A,k}^2 + \sigma_{B,k}^2} \right) * Z_{A,k} + \left(\frac{\sigma_{A,k}^2}{\sigma_{A,k}^2 + \sigma_{B,k}^2} \right) * Z_{B,k}$$

GPS σ_x > Motion Tracker σ_x
GPS σ_y > Motion Tracker σ_y

GPS와 Motion Tracker를 Geometry Sensor Fusion

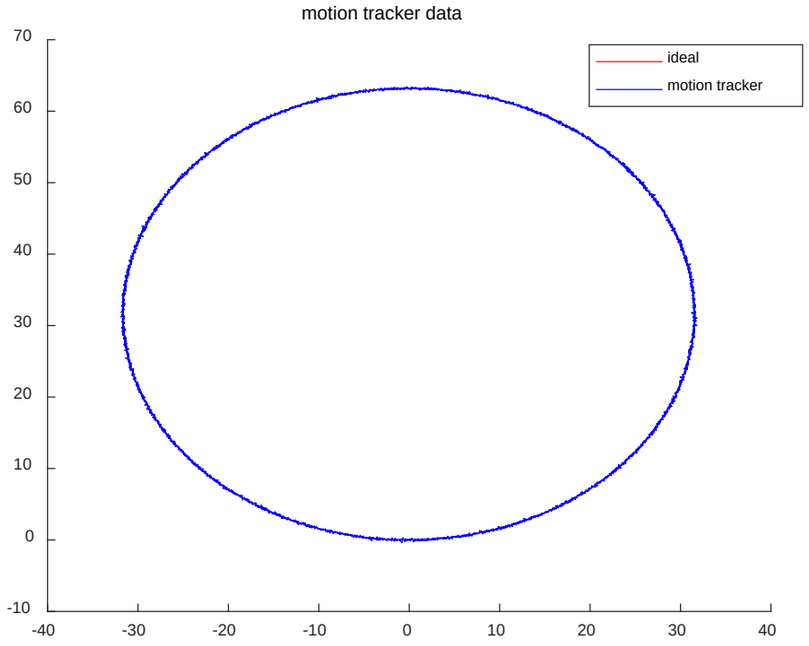
EKF

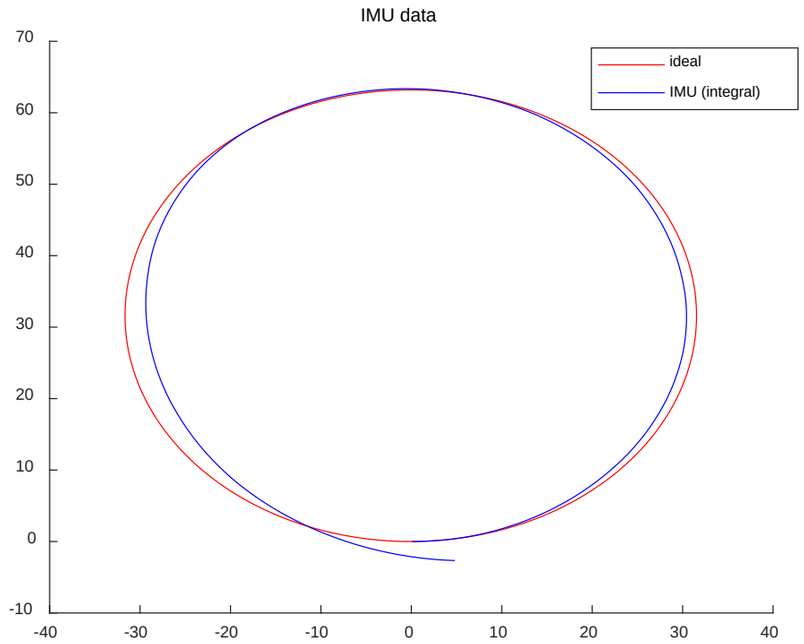


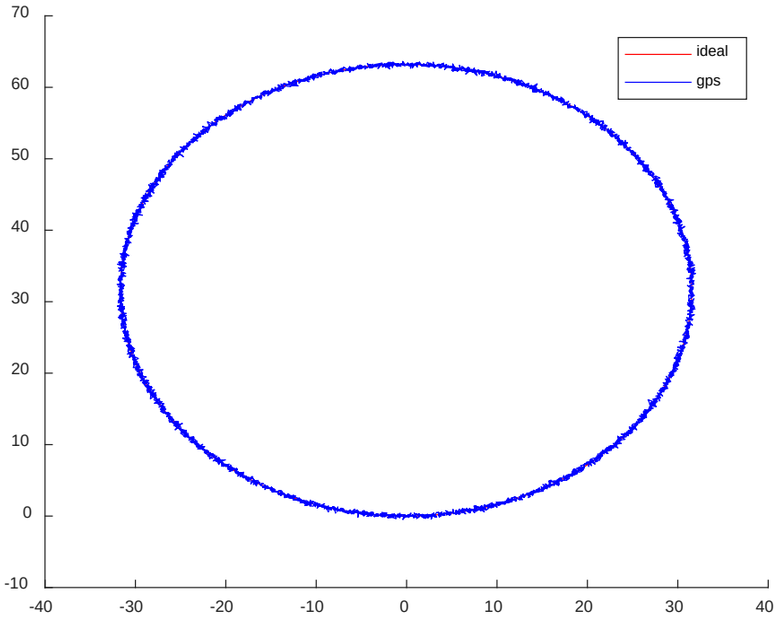
$Q = diag(0.1, 0.1, 0.1, 0.1)$

$P = I$

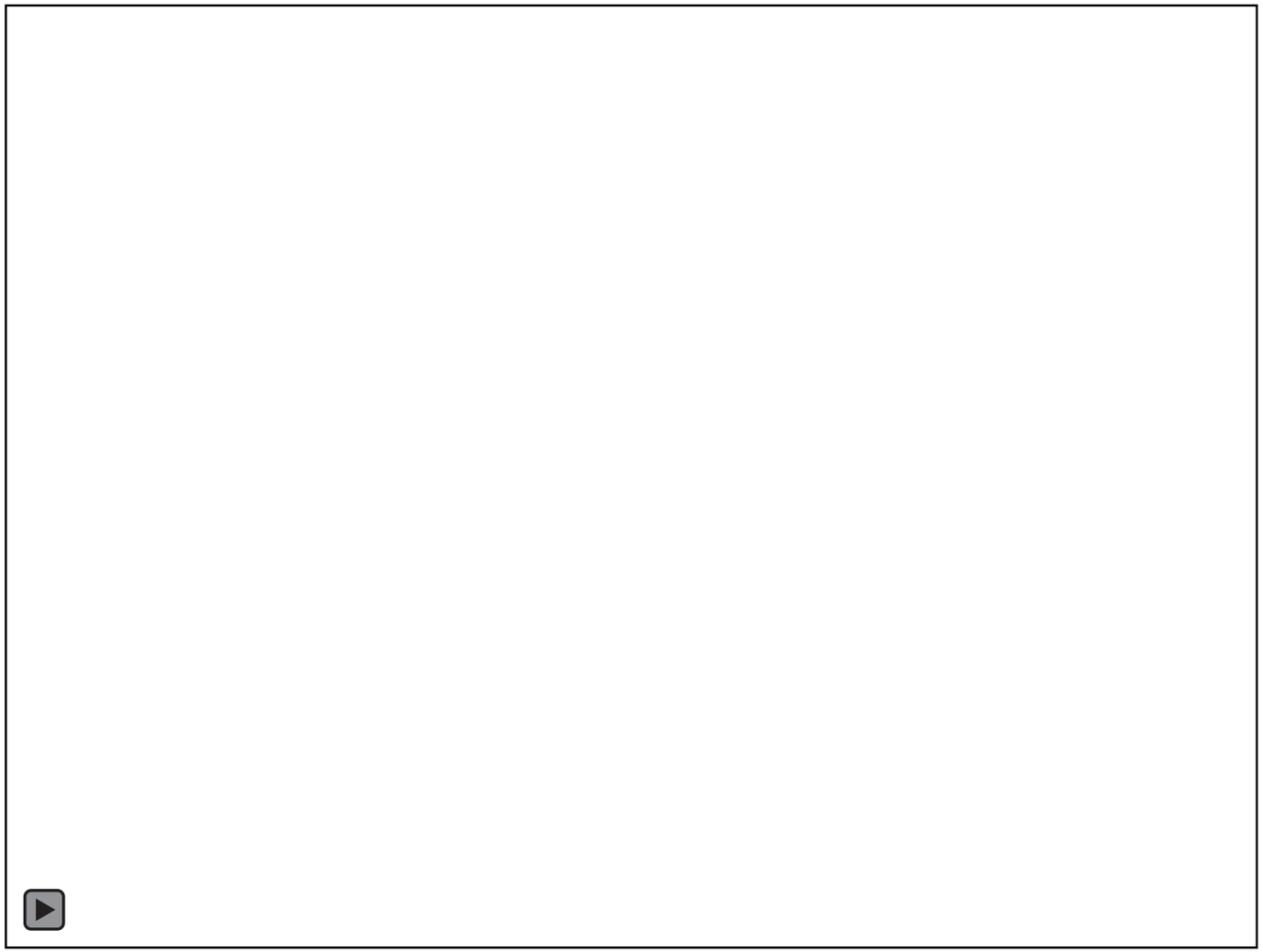
$R = diag(100,100,100,100)$


motion tracker data
ideal
motion tracker
70
60
50
40
30
20
10
0
-10
-40
-30
-20
-10
0
10
20
30
40


IMU data
ideal
IMU (integral)
70
60
50
40
30
20
10
0
-10
-40
-30
-20
-10
0
10
20
30
40


GPS data
ideal
gps
70
60
50
40
30
20
10
0
-10
-40
-30
-20
-10
0
10
20
30
40

EKF

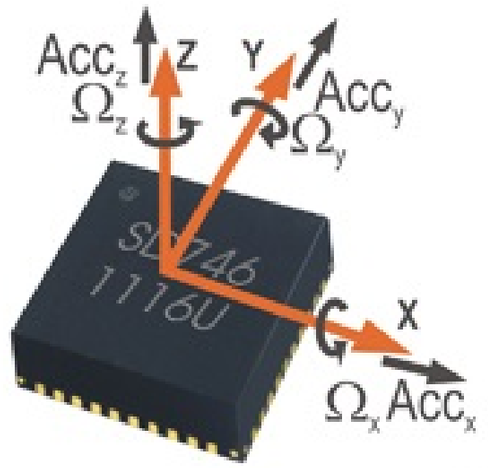


Ideal position

EKF position

2 DVL + IMU + Depth sensor

IMU



DVL

Depth sensor

○ 센서 데이터 생성 방법 조건

DVL

Real ($\dot{x}$, $\dot{y}$, $\dot{z}$) + noise
(bias=0.01,sigma = 0.05)

DVL Data
(Velocity)

Depth Sensor

Real (z) + noise
(bias=0.5, sigma = 0.01)

Depth sensor Data
(earth-fixed frame)

IMU

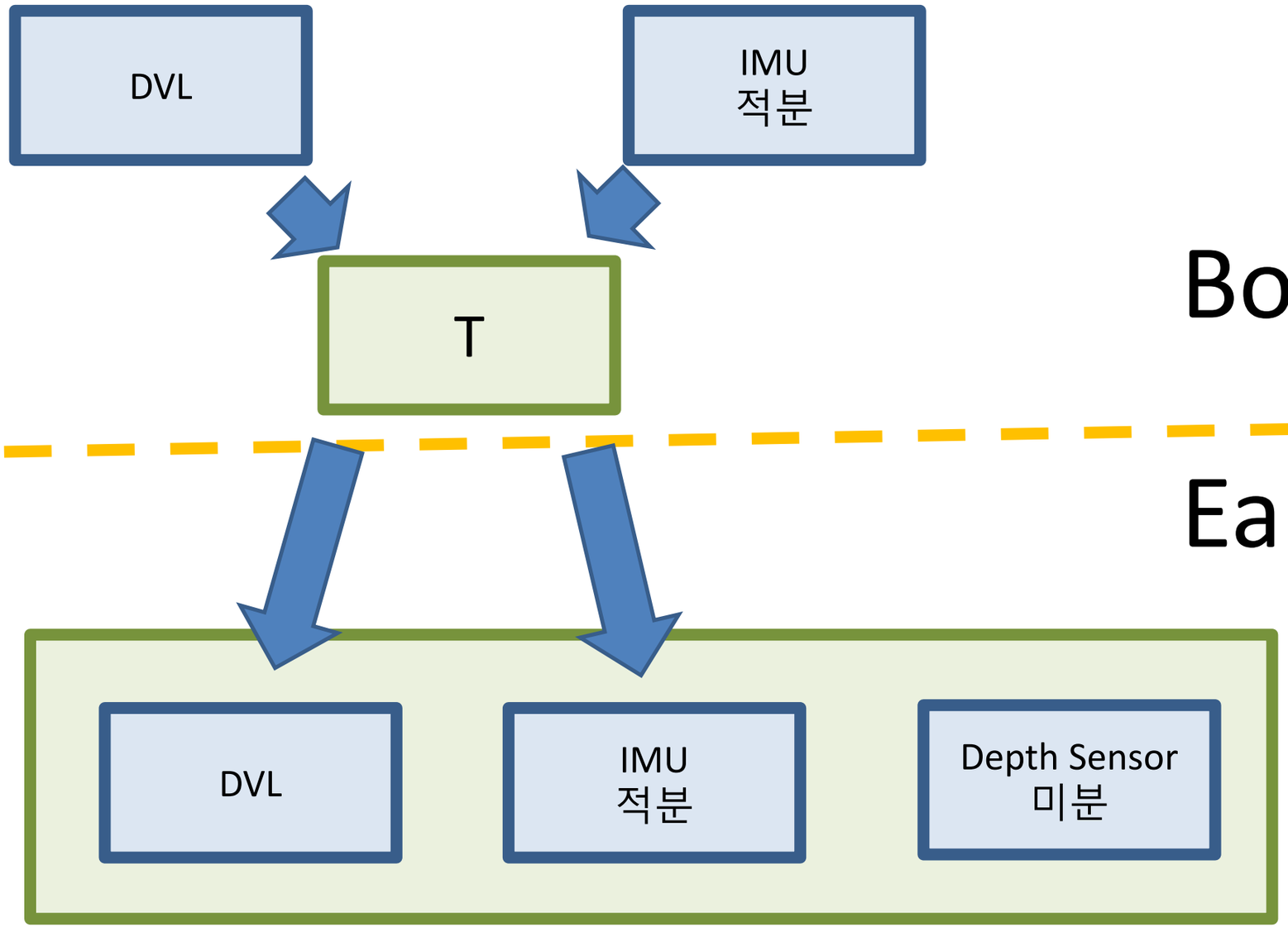
Real ($\ddot{x} + \ddot{y} + \ddot{z}$) + noise
(bias=0.0013,sigma = 0.001)

IMU Data
(acceleration)

Real (ϕ, θ, ψ)
(sigma = 0.001)

Angle Data
(earth-fixed frame)

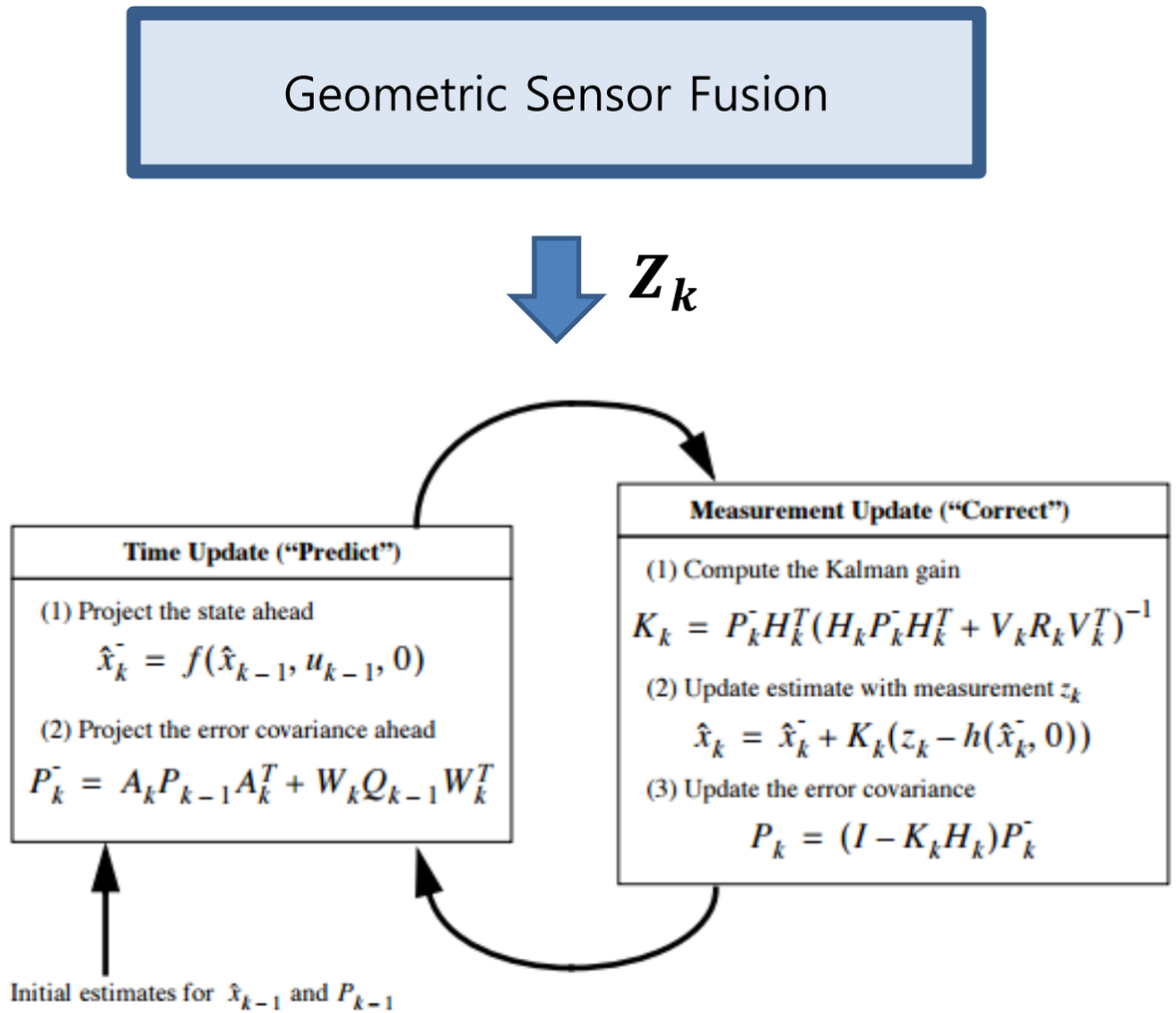
○ **Geometry Sensor Fusion ($\dot{x}, \dot{y}, \dot{z}$**



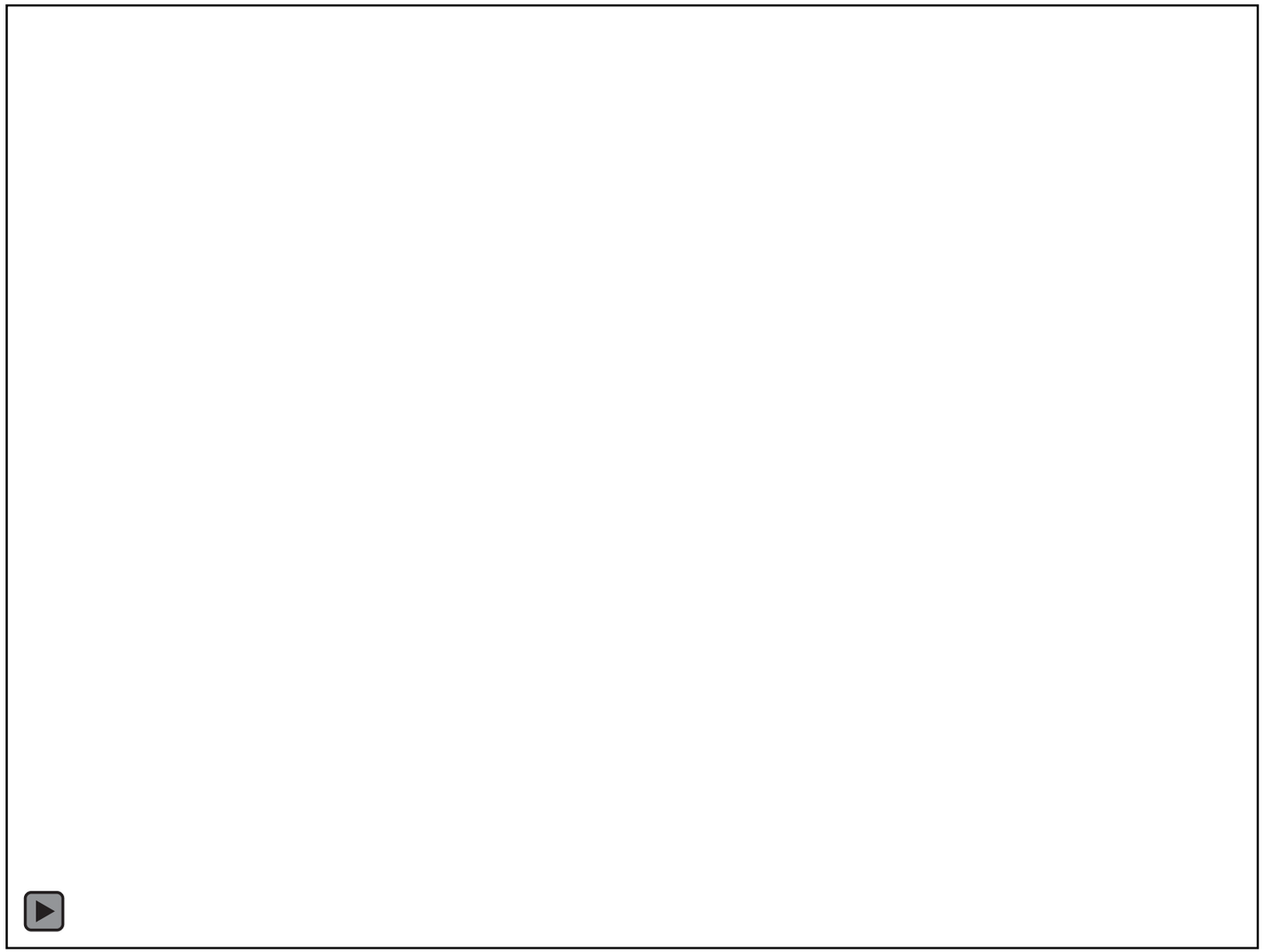
Body-fixed frame

Earth-fixed frame

EKF


Geometric Sensor Fusion
Z_k
Time Update ("Predict")
(1) Project the state ahead
$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0)$
(2) Project the error covariance ahead
$P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T$
Measurement Update ("Correct")
(1) Compute the Kalman gain
$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + V_k R_k V_k^T)^{-1}$
(2) Update estimate with measurement z_k
$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-, 0))$
(3) Update the error covariance
$P_k = (I - K_k H_k) P_k^-$
Initial estimates for $\hat{x}_{k-1}$ and P_{k-1}

EKF



Ideal position

EKF position