State estimation and control of a mobile robot using Kalman filter and particle filter

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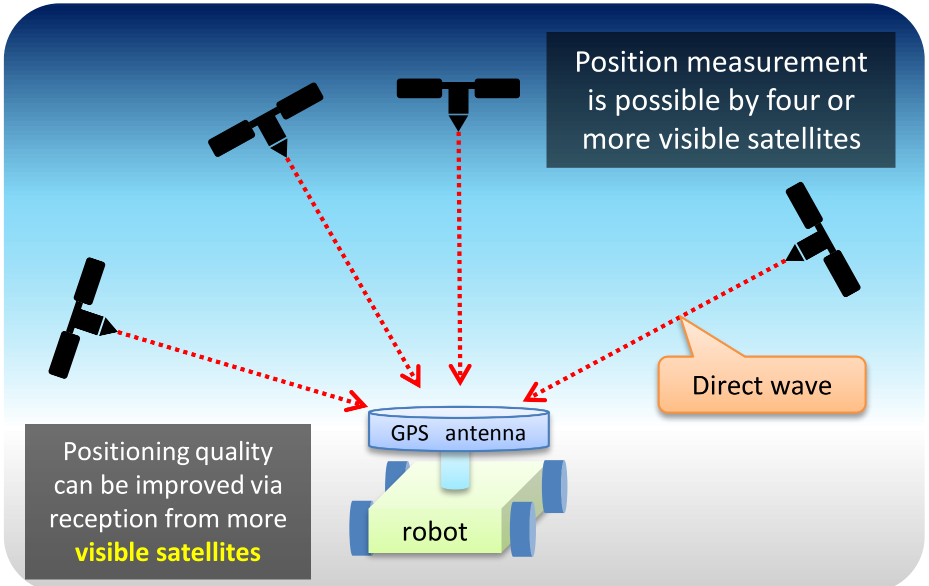
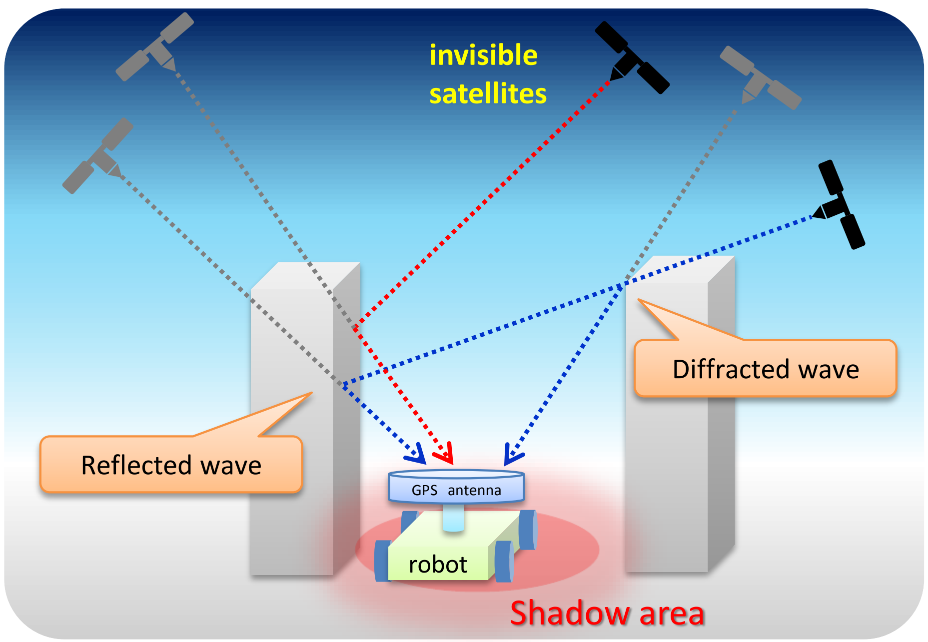
1. Introduction





GPS（Global Positioning System）

Visible and invisible satellite

- ☐ Signal reception directory or not.

Reflected wave and diffracted wave

- ☐ Around high-rise buildings.
- ☐ Around trees.

Shadow area

A required number of visible satellites is not available.

General methods in shadow areas

- ☐ Use of GPS signal ceases
- ☐ Using dead reckoning.

we propose a method for improving a mobile robot's state estimation accuracy

using the statistical character of the reflected and diffracted waves.

2. Proposed hypothesis

hypothesis: GPS signal that contains reflected and diffracted waves = True position information + noise that follows a time-varying Gaussian distribution

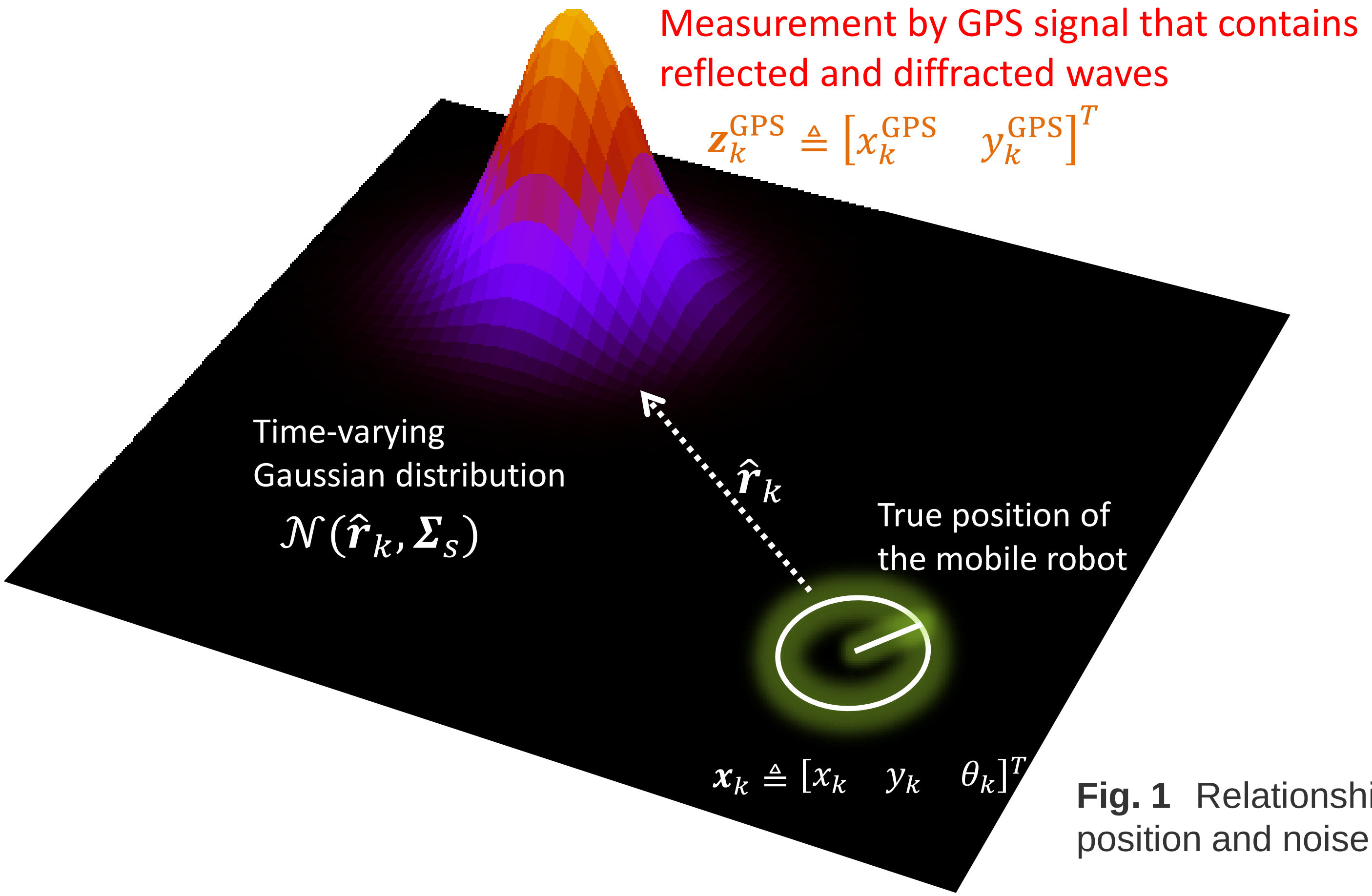


Fig. 1 Relationship of the robot position and noise distribution.

2. Proposed 1st idea −construction of a state feedback control system−

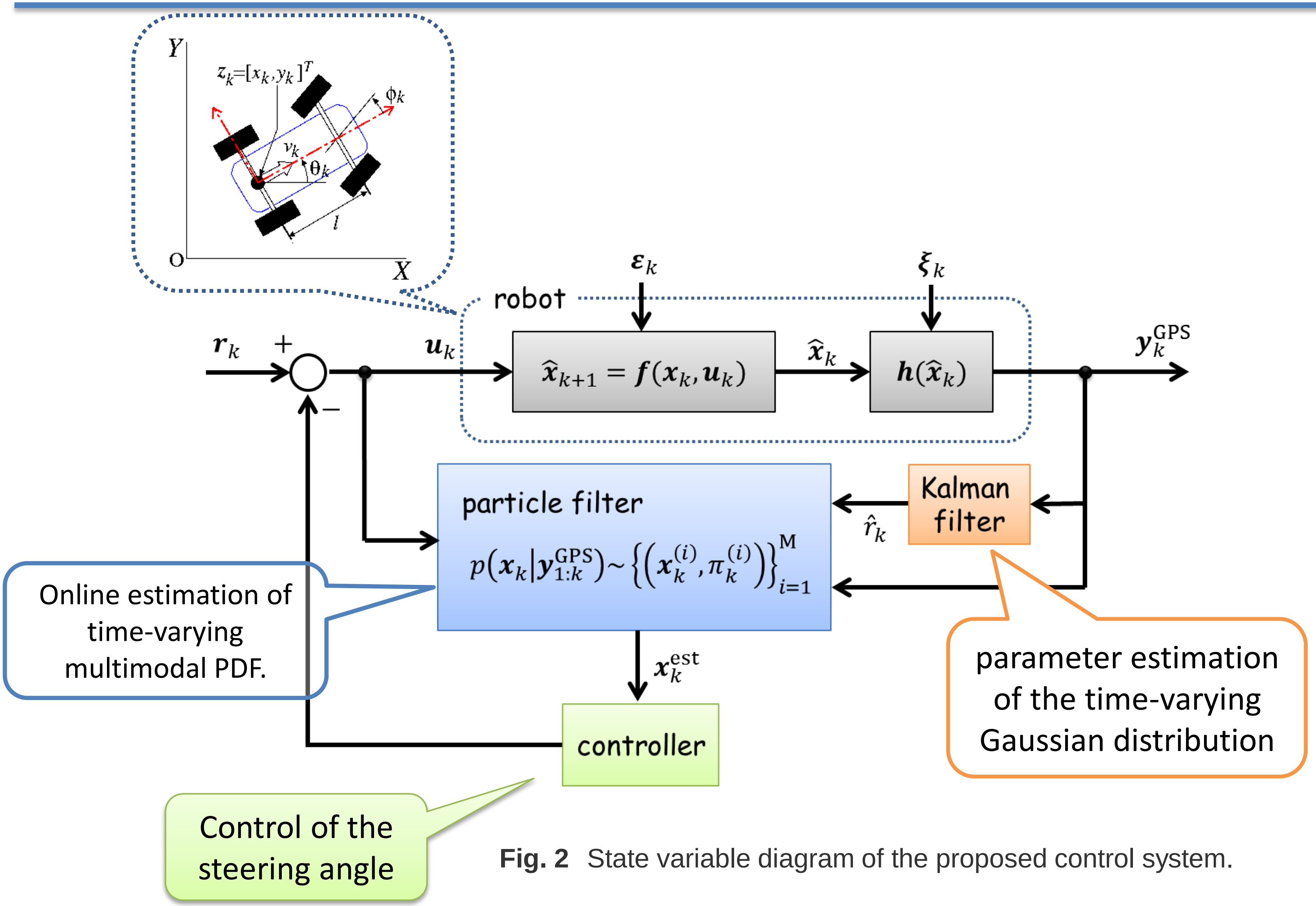


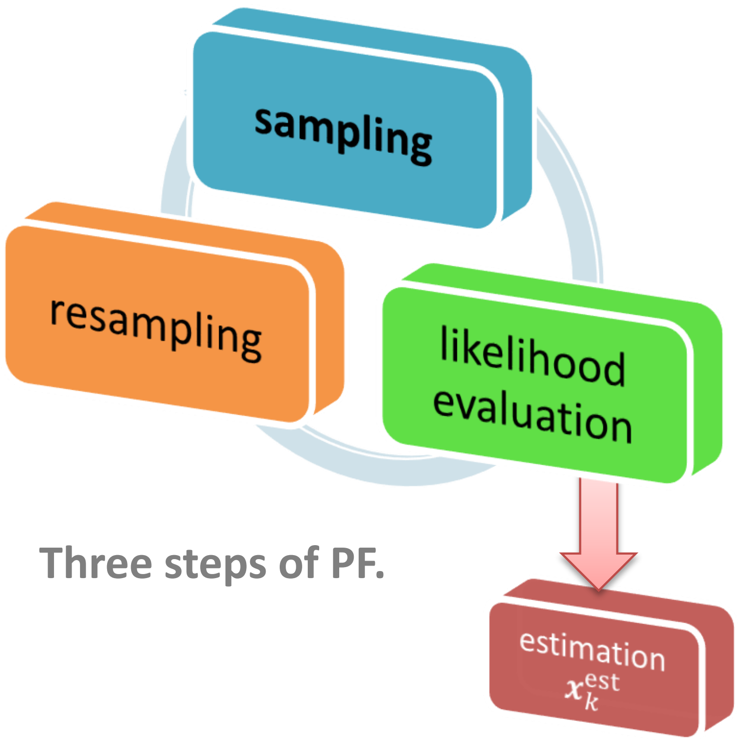
Fig. 2 State variable diagram of the proposed control system.

2. Proposed 1st idea −construction of a state feedback control system−

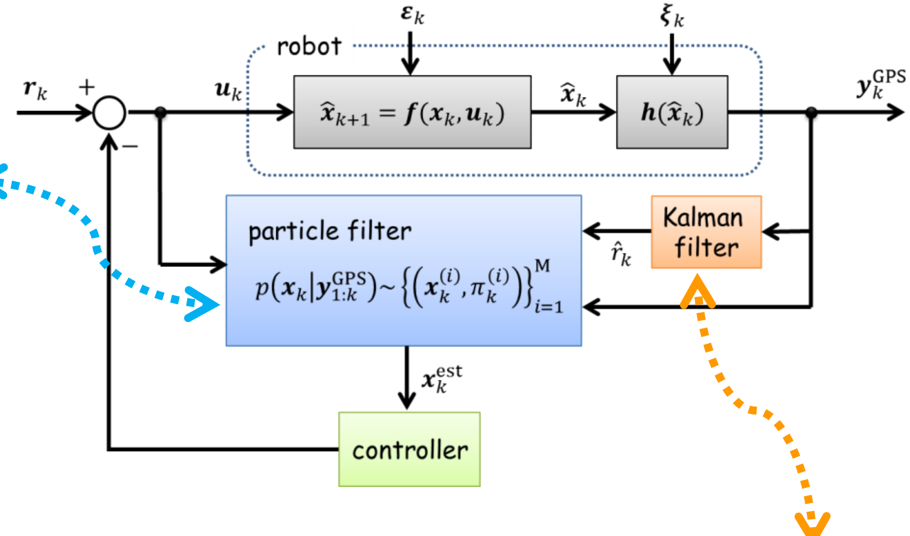
State estimation using a Kalman filter and a particle filter

Tracking and estimation of the time-varying multimodal PDF. by a PF

PF is suitable for an estimation of the multimodal PDF.



Three steps of PF.



The bias of noise estimated by a KF

- The variance Σ_s of GPS measurement including reflected and diffracted waves tends to become large.
- The value of the bias $\hat{r}_k$ changes with time.

Adaptive estimation of the Gaussian noise.

Sampling of particles

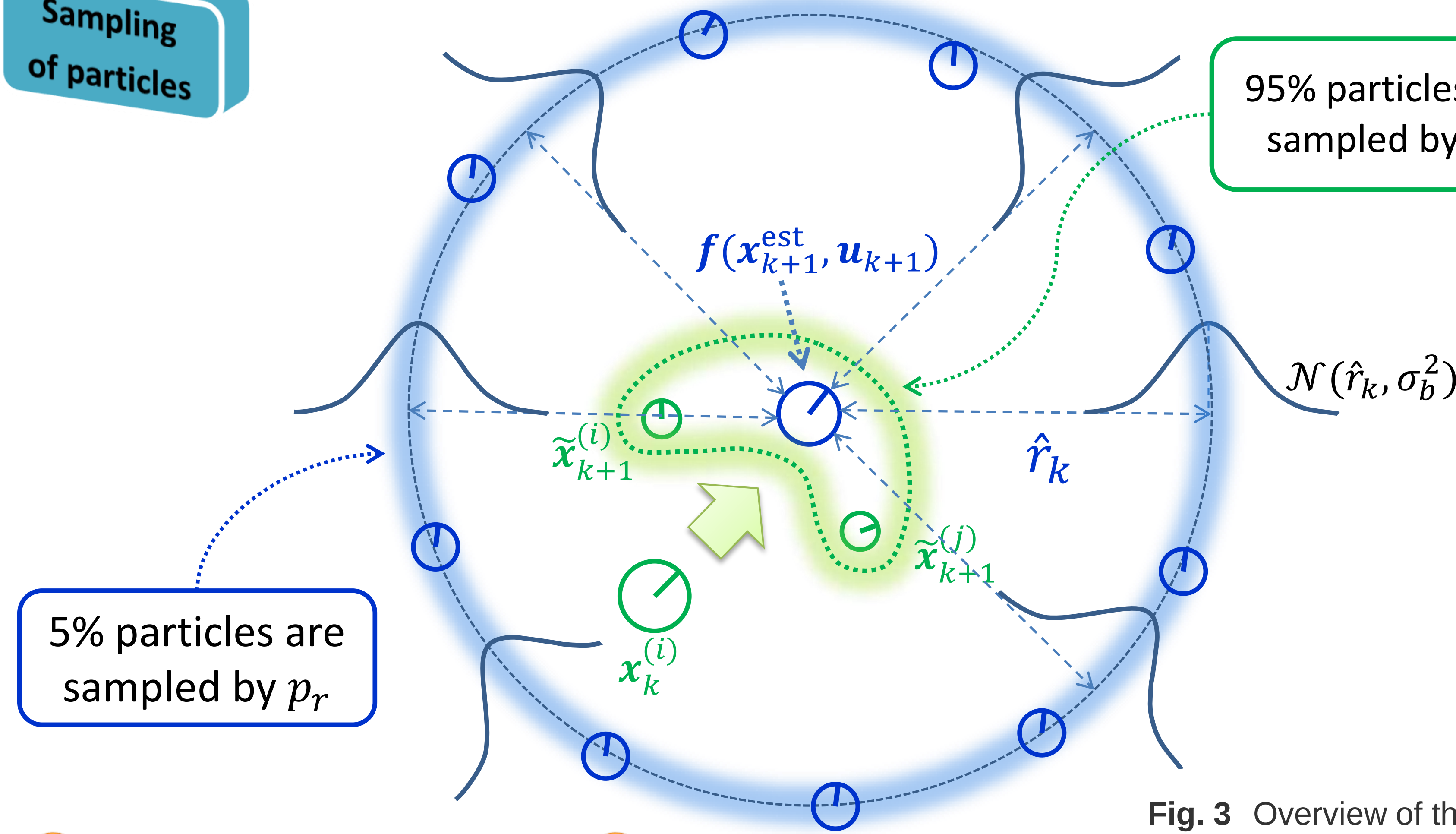


Fig. 3 Overview of the sampling procedure.

1. For reflected and diffracted waves, some particles are arranged concentrically.
2. The concentric radius (bias of the noise $\hat{r}_k$) is estimated by KF.
3. The estimated bias $\hat{r}_k$ is used in the likelihood evaluation of PF.

likelihood evaluation

$$P_h\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) = \frac{1}{2} P_{\mathrm{direct}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) + \frac{1}{2} P_{\mathrm{shadow}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right)$$

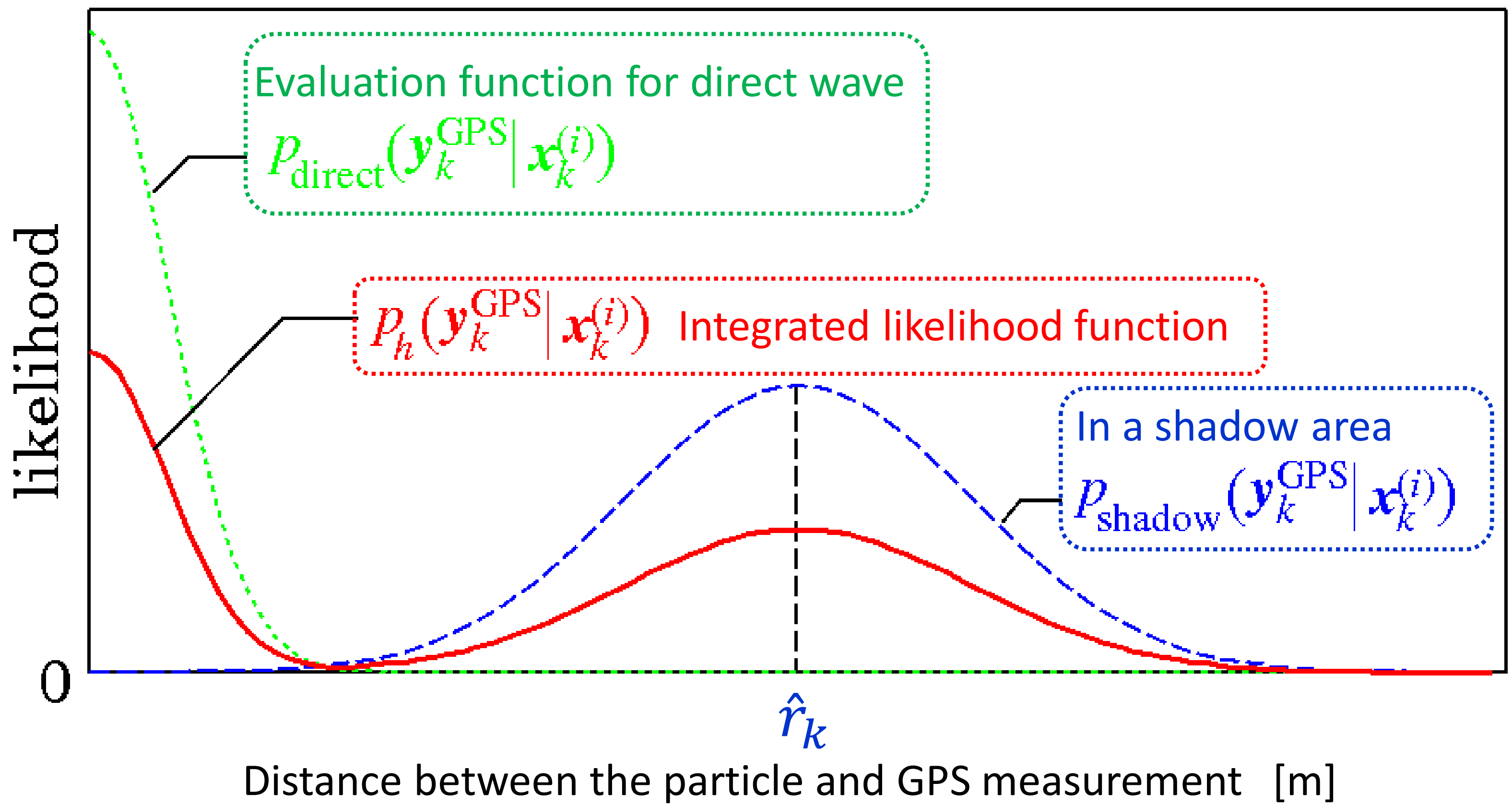


Fig. 4 Likelihood function of a measurement model

control

The estimate $\boldsymbol{x}_k^{\mathrm{est}}$ is calculated after the resampling procedure.

$$\pi_k^{(i)} \propto \pi_{k-1}^{(i)} P_h\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right)$$

$$\sum_{i=1}^{M} \pi_k^{(i)} = 1$$

$$\boldsymbol{x}_k^{\mathrm{est}} = [x_k^{\mathrm{est}} \quad y_k^{\mathrm{est}} \quad \theta_k^{\mathrm{est}}]^T = \sum_{i=1}^{M} \pi_k^{(i)} \delta\left(\boldsymbol{x}_k^{(i)}\right)$$

The control input is derived by $\boldsymbol{x}_k^{\mathrm{est}}$

$$\phi_{k+1} = k_\phi(\phi_k^* \ominus \phi_k)$$

$$v_{k+1} = \mathrm{const.}$$

$$\phi_k^* = \tan^{-1} \frac{y_j^{\mathrm{target}} - y_k^{\mathrm{est}}}{x_j^{\mathrm{target}} - x_k^{\mathrm{est}}}$$

$$\phi_k^*, \phi_k \in [0, 2\pi)$$

k_ϕ Feedback gain

4. Conditions of a simulation

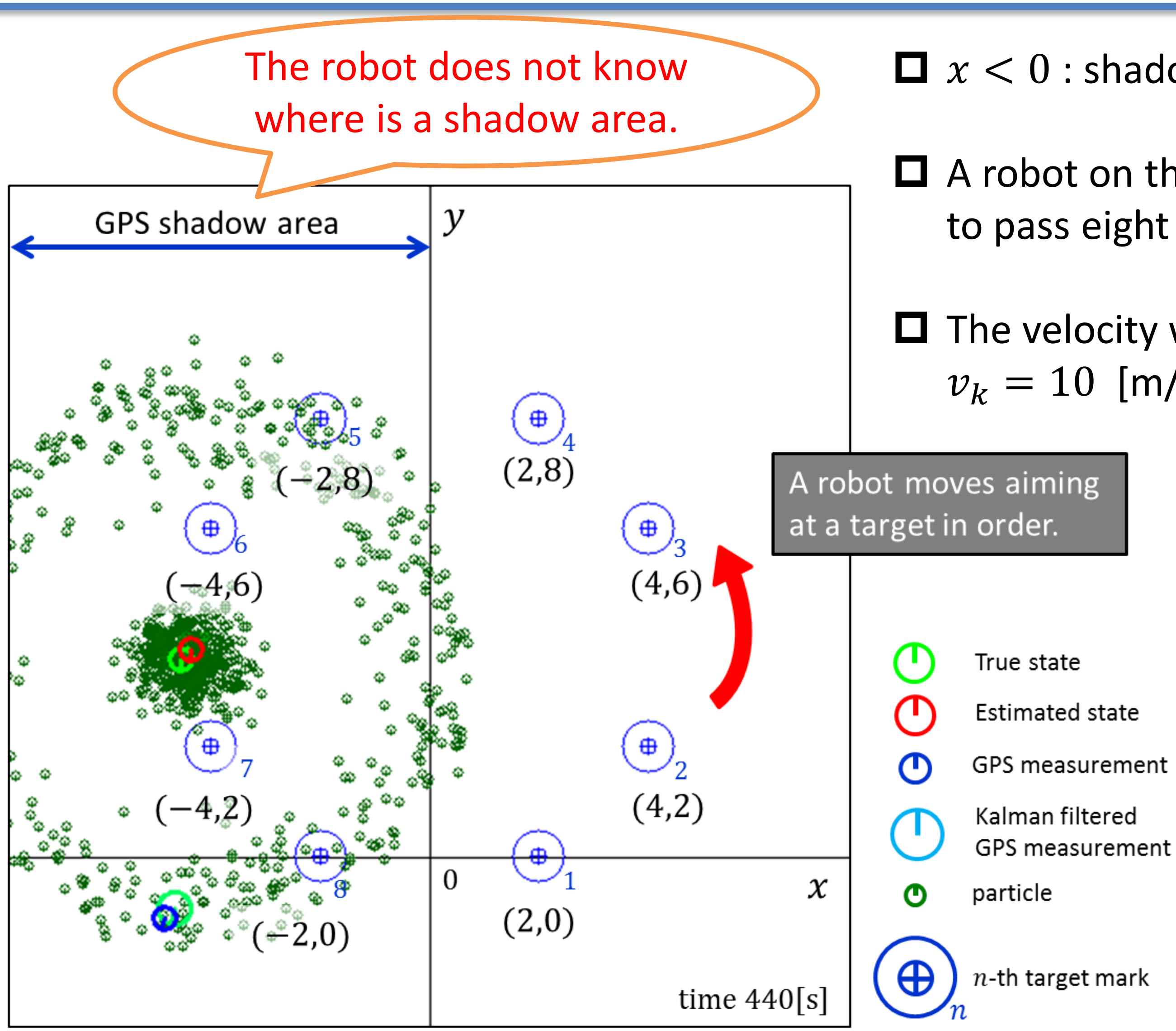
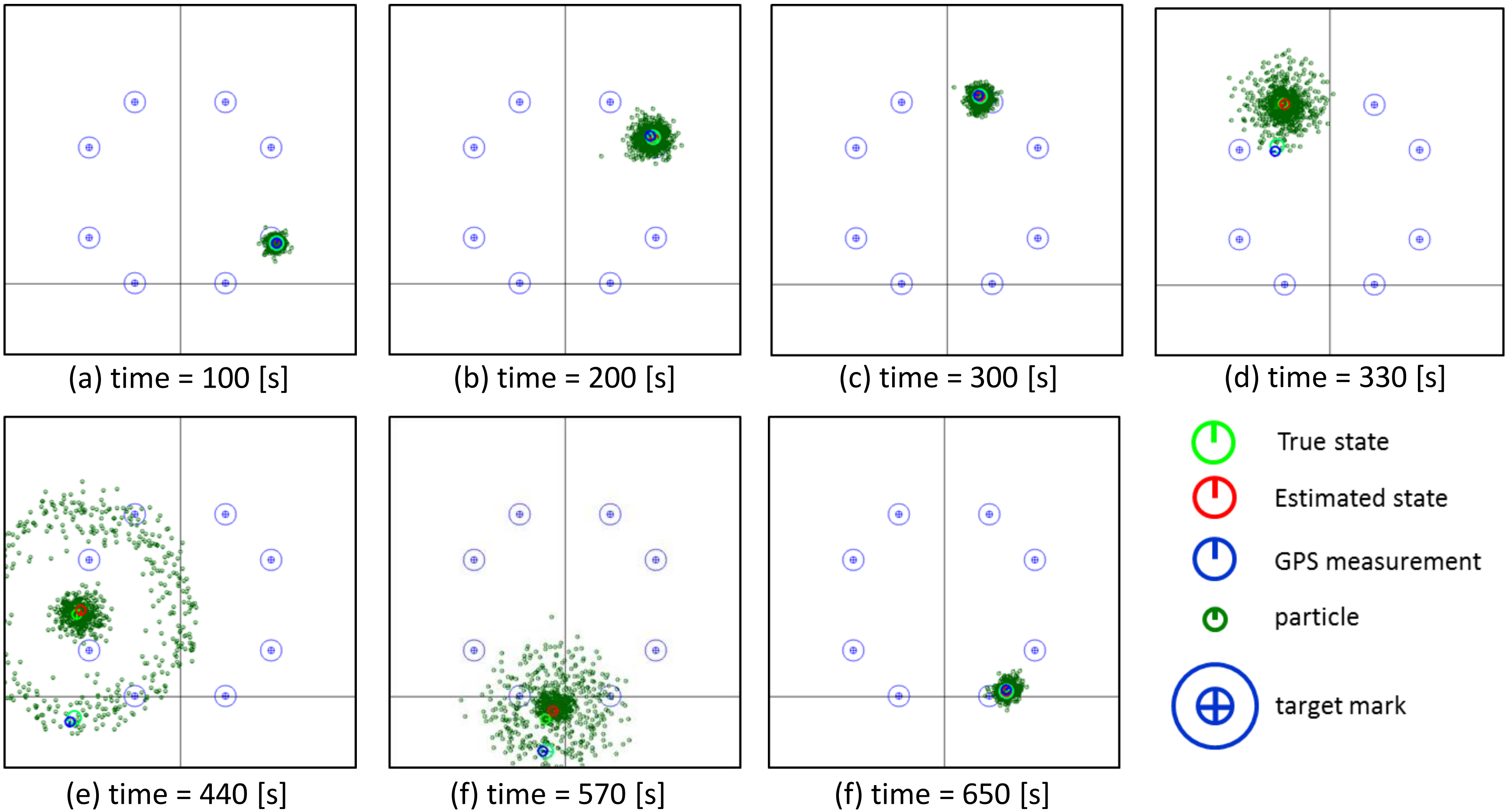


Fig. 5 Conditions of the simulation.

- $x < 0$: shadow area.
- A robot on the field is controlled to pass eight targets in order.
- The velocity was set constant as $v_k = 10$ [m/s].

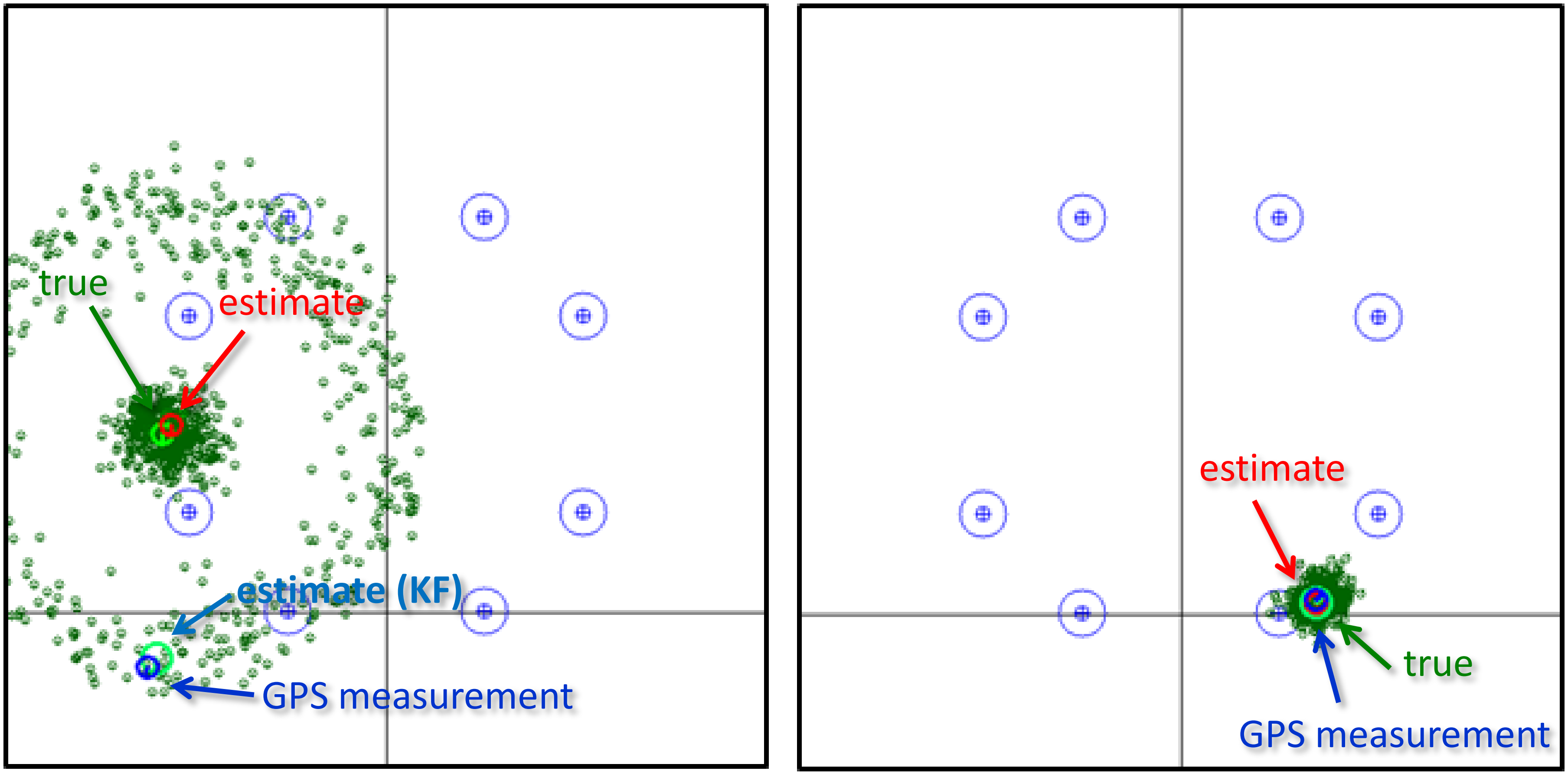
4. Simulation



Sampling $\tilde{\boldsymbol{x}}_{k+1}^{(i)} \sim p_q\left(\tilde{\boldsymbol{x}}_{k+1}^{(i)} \middle| \boldsymbol{x}_k^{(i)} \boldsymbol{u}_k\right)$

Likelihood $P_h\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) = \frac{1}{2} P_{\mathrm{direct}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) + \frac{1}{2} P_{\mathrm{shadow}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right)$

Fig. 6 A part of the result of the state estimation using the proposed method.



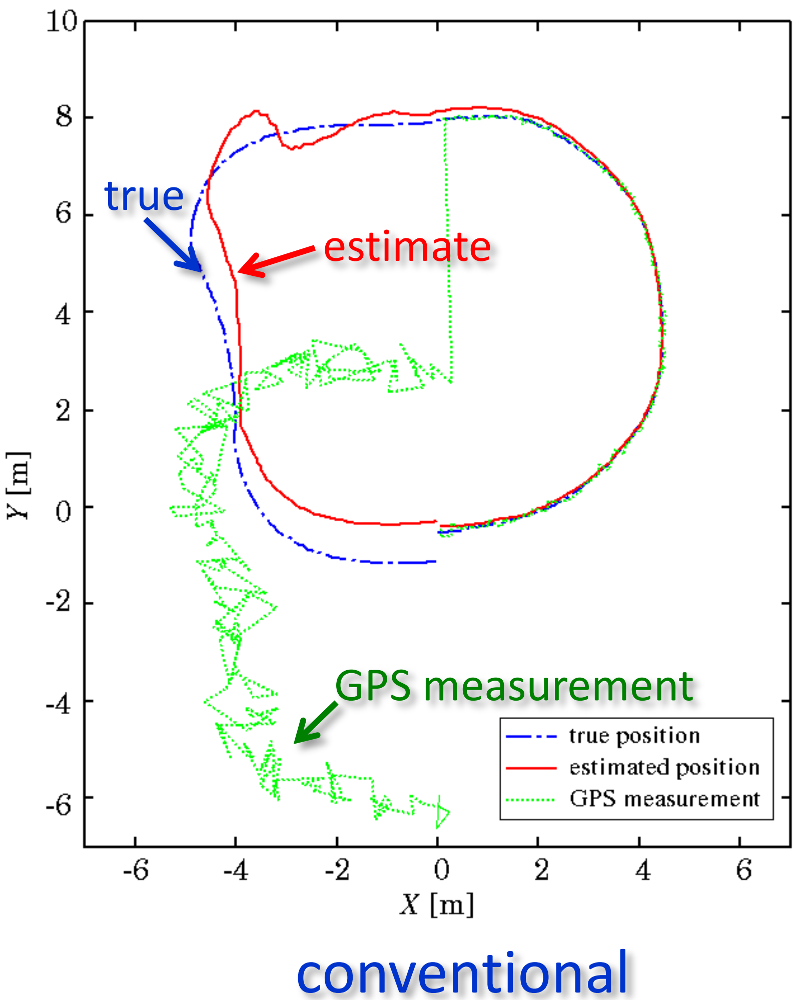
(e) time = 440 [s]

(f) time = 650 [s]

Fig. 6 A part of the result of the state estimation using the proposed method.

Sampling $\tilde{\boldsymbol{x}}_{k+1}^{(i)} \sim p_q\left(\tilde{\boldsymbol{x}}_{k+1}^{(i)} \middle| \boldsymbol{x}_k^{(i)} \boldsymbol{u}_k\right)$

Likelihood $P_h\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) = \frac{1}{2} P_{\mathrm{direct}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right) + \frac{1}{2} P_{\mathrm{shadow}}\left(y_k^{\mathrm{GPS}} \middle| \boldsymbol{x}_k^{(i)}\right)$



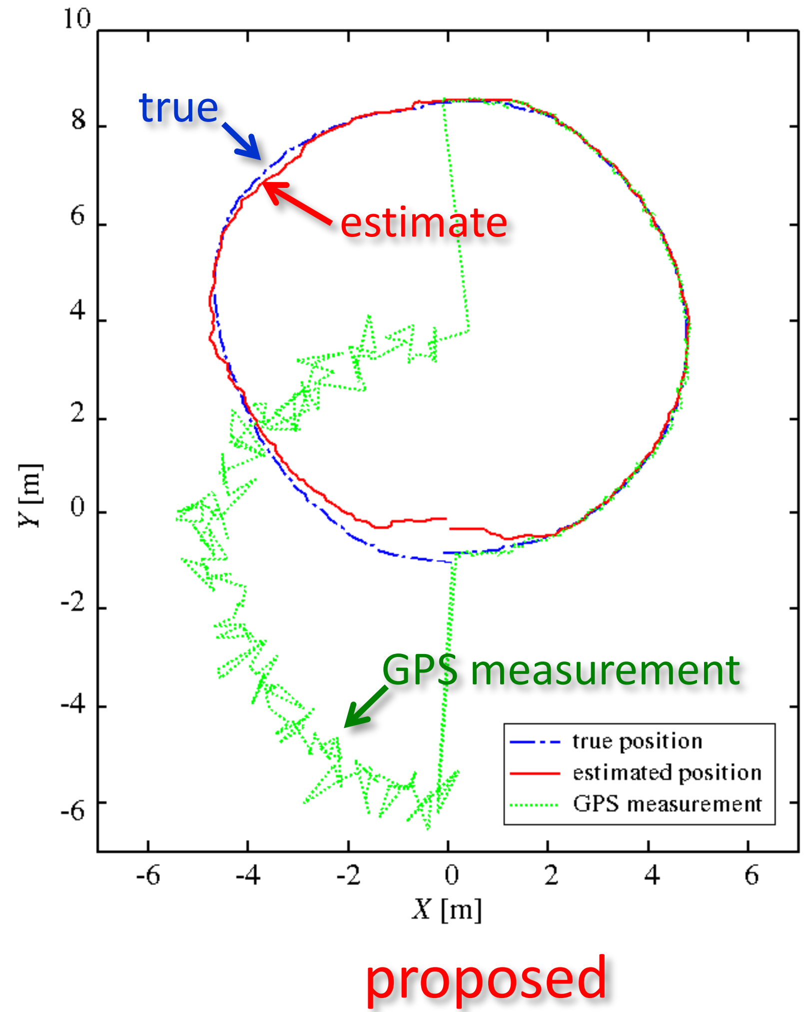


Fig. 7 Trajectories of the estimation, measurement, and true state values on the third track.

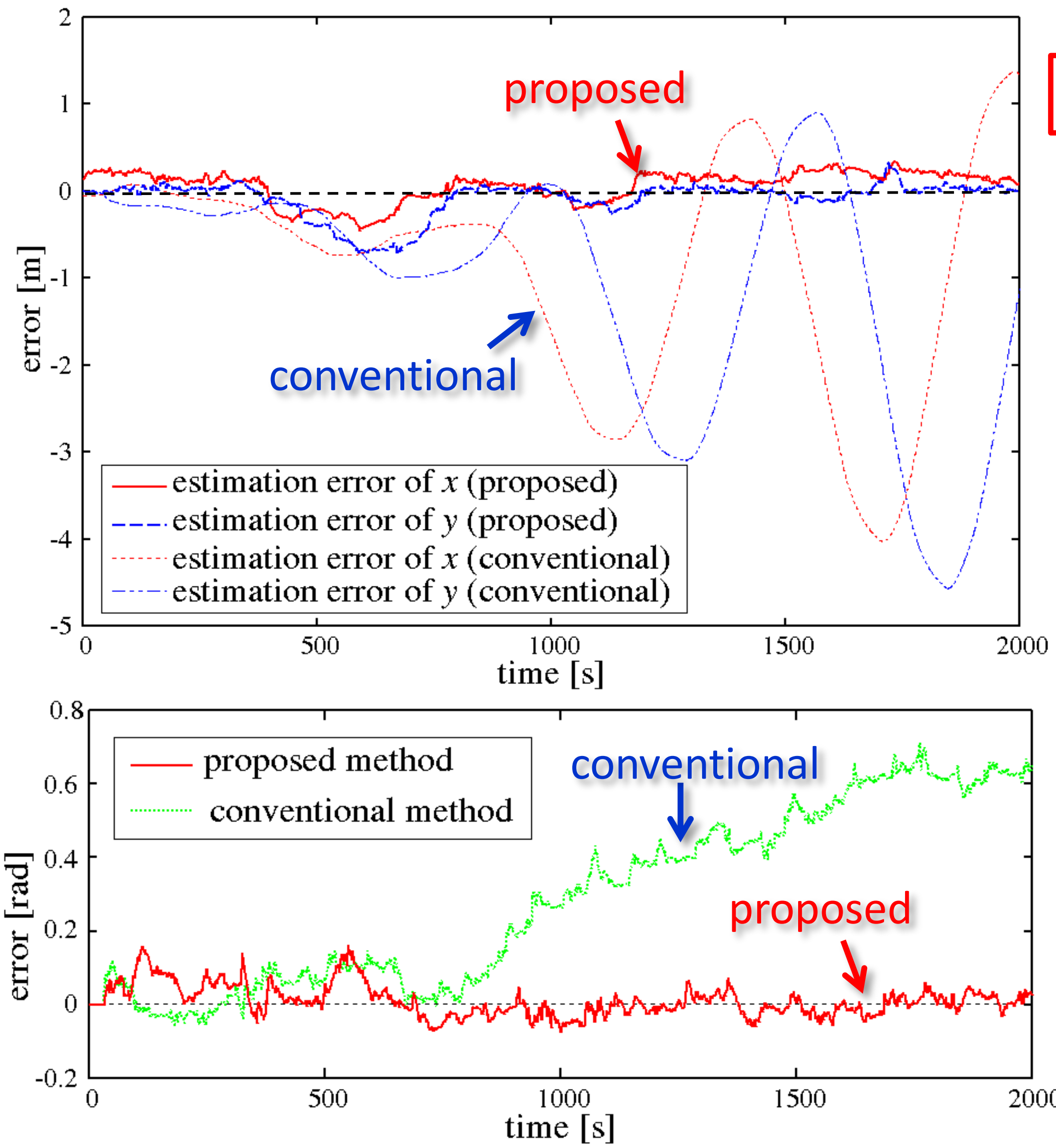


Fig. 8 Time evolution of the estimated error of each state variable.

Proposed method

- The state variables are estimated with sufficient accuracy using the proposed method.

Conventional method

- The state estimation using the conventional method became unstable with time.
- This is attributable to the error of state estimation being amplified by the feedback control system.

1 We proposed a method to improve the state estimation accuracy of mobile robots near high-rise buildings using the statistical property of reflected wave and diffracted wave of a GPS signal.

- New capital investment is not required.
- Shadow areas are reduced.
- Because the number of available satellites is increases, the accuracy of the GPS measurement improves.
- Combined use with dead reckoning is possible.

2 For future work, the validity of the proposed method will be verified by performing experiments in an actual outdoor environment.