Efficient Use of Digital Road Map in Various Positioning for ITS

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Abstract: Recently, there are many R&D improvements on positioning systems for ITS(Intelligent Transportation Systems) adopting GPS, cellular phones or other communication systems. But, a position from any signal is always corrupted to a few meters through several hundreds of meters because of multipath, atmospheric delay, NLOS(none line-of-sight), low DOP and so on. When the positioning systems are employed for ITS, a digital road-map can be used together to display their navigation solutions in most ITS applications.

Due to the fact that land-vehicles almost always run on roads, most of CNS(car navigation systems) translate the measured position onto a road. This methodology called map-matching, if it depends on a contaminated position by a white noise and biased error, has not only low accuracy but also the road ambiguity problems in some crossroads. Therefore, this paper presents an efficient use of an advanced map-matching in order to get a more improved accuracy, which estimates a large bias being main source of errors and corrects a vehicle's position. It is composed of a modeling of biased error and filtering by a Kalman filter. We have applied the proposed map-matching to not only GPS navigation but also CDMA location. The proposed approach represents that in addition to its original visual display, an accurate digital road-map can improve the positioning accuracy effectively by correcting the vehicle's position.

I. Introduction

This paper describes how to use effectively the digital road map to improve the positioning accuracy of the radio-location systems for ITS. The positioning technology, which has been used for the navigation in the sea and the air, is being applied to the ITS(Intelligent Transportation System) area over the whole world.

Several branches of ITS demand very high accuracy of 5~10m because of driver's safety[4]. Those are the route guidance and automated highway system and so on. Currently, there isn't a perfect positioning device gives this accuracy over wide coverage. On the other hand, some digital road map, although they can not measure the vehicle's position, have the accuracy of 3~10m according to the scale. This means that we can get the accuracy of position to the extent of the map. This technique that integrates existing positioning systems with a digital road map is called the map-matching[9].

The position from various sensors is corrupted to a few meters through several hundreds of meters because of multipath, atmospheric delay, NLOS(none line-of-sight), low DOP(dilution of precision) and etc. Under the assumption that land-vehicles almost always run on roads, most of CNS translate a measured position onto a road. Such map-matching, if it depends on a corrupted position by a white noise and biased error, has not only low accuracy but also road ambiguity problems in some crossroads. Therefore, this paper presents new map-matching in order to get the more improved accuracy, which estimates a large bias being main source of errors and corrects a vehicle's position. It is composed of a modeling of biased error and filtering by Kalman filter. We have applied the proposed map-matching to not only GPS navigation but also CDMA location.

This paper is as followings. Chapter 2 shows the basics of the map-matching. It also includes the characteristics of the error in radio-location based positioning. Chapter 3 shows how to estimate such biased error from the measurables and check the observability of it. Such biased error is a major impairment in various positioning systems. On this foundation, chapter 4 shows some results in the real GPS experiments and CDMA location. Finally, chapter 5 leads to conclusions and summaries the future study.

II. Basics of map-matching and error's property

The objective of a CNS is to give various information required for a drive. Among other things, determining the accurate position of a vehicle is very essential. A CNS equipped with GPS, DR(odometer, gyroscopes, accelerators), and the others can inform a driver of the position, velocity and heading of the vehicle continuously. These pieces of information can be combined with the location of surrounding environment. In addition, the fact that "A vehicle moves always on a road network", makes us utilize the map information more effectively. By doing so, we can get more accurate and reasonable position of the vehicle.

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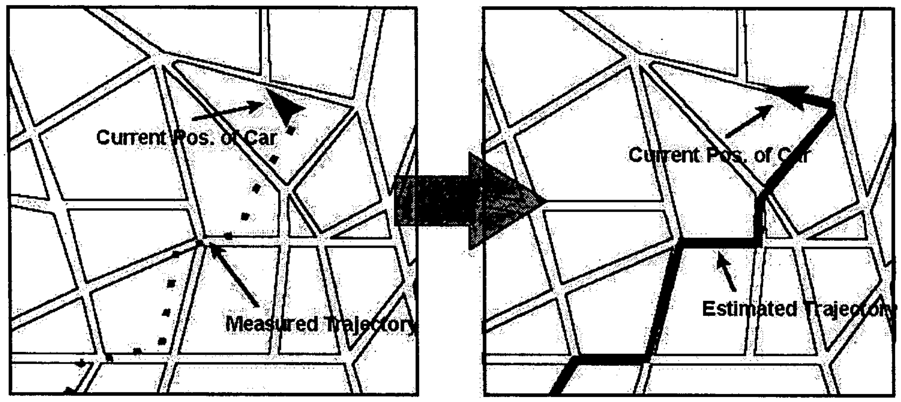

Figure 1. Concept of the map-matching(right)

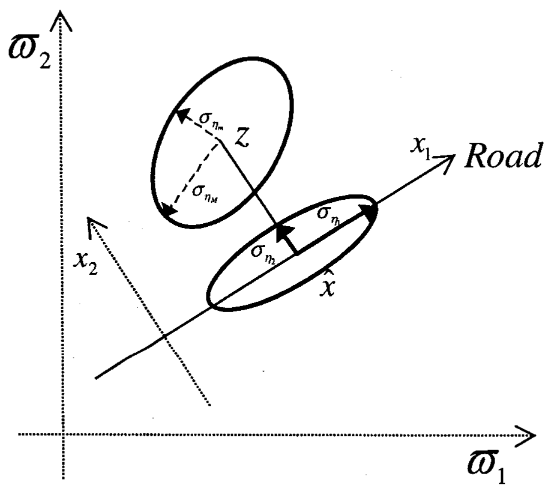

Figure 2. Transformed error ellipse of the map-matched position($\hat{x}$)

2.1 Basics of the map-matching

Since navigation systems using GPS and the other radio-waves serve for the multi-users of airs, ships, autos, low-orbiter and the others, they does not consider the constraint that land vehicles run on roads. And therefore, they may give the positions that land-vehicle cannot be located, e.g, on a building, on river and etc. Therefore, most CNSs employ the map-matching like Fig. 1. R. L. French defines it as a following sentence[9]. "As a driver compares the signposts and the road-shape on his paper map with neighboring signposts and the real road-shape, so a map-matching is the process that correlates continuously the mathematical shape of vehicle's path to the shape of a corresponding digital road DB".

Fundamentally, all the map-matching translates the measurement sequences from GPS, and the other sensors onto the nearest road using a digital road DB. This process can be expressed as Eq.(1).

$$\hat{x} = f(Z^k; G(X, A)) \tag{1}$$

where, $Z^k = \{z_1, z_2, \cdots, z_k\}$: measurement sequence

$G(X, A)$: a road network of node X, link A

But, GPS has the mean error of 100m (2DRMS) due to various causes. Moreover, its error becomes not a white Gaussian but biased on account of atmospheric delay, SA(selective availability), multipath and etc. The performance improvement of a map-matching using these biased measurements is difficult to anticipate. Consequently, as you can see in Fig.2, the cross-track error is well-mitigated but, the along-track error is not all decreased[5][6]. Therefore, the along-track error is larger than the error in the direction of short-axis of one sample measurement error covariance.

$$\sigma_{\eta_m} \le \sigma_{\eta_t} \le \sigma_{\eta_M} \qquad (2)$$

where, σ_{η_t} : along-track error

$\sigma_{\eta_m}, \sigma_{\eta_M}$: error in the direction of short (long)-axis of measurement covariance

Because of this reason, the positioning in the densely built-up areas does not determine the correct road and is out of the required accuracy.

Thus, we have to decrease the biased error which is not averaged out in short times. And so, we should find the way how to decrease a vehicle's along-track error.

2.2 Characteristic of GPS error

The accuracy of a map-matching depends on that of positioning sensor. Thus, in the case that GPS is available, the inherent errors of GPS determine the performance of overall system. Ephemeris error, SA, atmospheric delay, receiver noise, multipath, DOP and the others affect GPS. Eq.(3) shows the pseudorange between a satellite and a GPS receiver.

$$\begin{aligned}\rho_u^j &= D_u^j + c\cdot(b_u - B^j) + c\cdot(T_u^j + I_u^j + v_u) \\ &= \bar{1}_u^j \cdot [\bar{r}^j - \bar{r}_u] + c\cdot(b_u - B^j) + c\cdot(T_u^j + I_u^j + v_u)\end{aligned} \qquad (3)$$

where, ρ_u^j : pseudorange between satellite and user

D_u^j : distance between satellite and user

$\bar{r}^j = \hat{\bar{r}}^j - \Delta\bar{r}^j$: position vector of j-th satellite

$\bar{r}_u = \hat{\bar{r}}_u - \Delta\bar{r}_u$: position of user

$\bar{1}_u^j = \hat{\bar{1}}_u^j - \Delta\bar{1}_u^j$: line of sight

$b_u = \hat{b}_u - \Delta b_u$: receiver clock error

$B^j = \hat{B}^j - \Delta B^j - SA^j$: satellite clock error including SA

$T_u^j = \hat{T}_u^j - \Delta T_u^j$: trospheric delay

$I_u^j = \hat{I}_u^j - \Delta I_u^j$: ionospheric delay

c : light vacuum speed(m/s)

v_u : receiver measurement noise

Especially, SA is a intentional and influential error that the total error of GPS reaches 100m 2drms. Generally, the only way to determine the model of SA is through actual data collection. It can be one among 2nd-order Markov model, autoregressive model, or lattice filter. Fig. 3 shows the error distribution when a test vehicle drives for 30 minutes.

Because the differential of a planar error of GPS is almost a normal distribution, the position error about one axis becomes the below 2nd order Markov model.

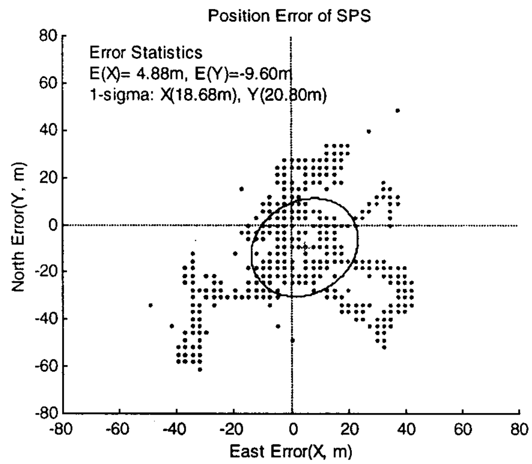

Figure 3. An example of error distribution and error ellipse: GPS measures the position of a moving vehicle

$$\ddot{x}_p + 2\beta\omega_0\dot{x}_p + \omega_0^{\,2}x_p = c \times w \qquad (4)$$

where, ω_0 : natural frequency,

β : damping factor(<1),

c : constant,

w : white gaussian noise

In above equation, each parameter's value is determined to satisfy 600 seconds' period and 20~30 meter's 1-sigma standard deviation of positioning error. In the following chapter, we are to estimate the biased error of GPS.

III. Estimation of GPS inherent bias using a digital road map

We have looked the error characteristic of GPS. The distorted position by GPS is hardly recovered without DGPS and WAAS(Wide Area Augmentation System)[3]. Recently, the prevalence of N-GIS and ITS causes many digital road maps with high accuracy to be produced. These maps has mostly the accuracy of less than 10m, further we can find some maps of the accuracy less than 3m.

Therefore, if a map-matching integrating with these maps could make an estimation of GPS bias, its positioning accuracy would be improved. Fig.4 represents the measured position of a vehicle by GPS and the translated position by such map-matching. The variables in this chapter are like below.

$\vec{X}_T$: real position of a vehicle

$\vec{X}_{GPS}$: measured position by GPS

$\vec{X}_{MM}$: map-matched position

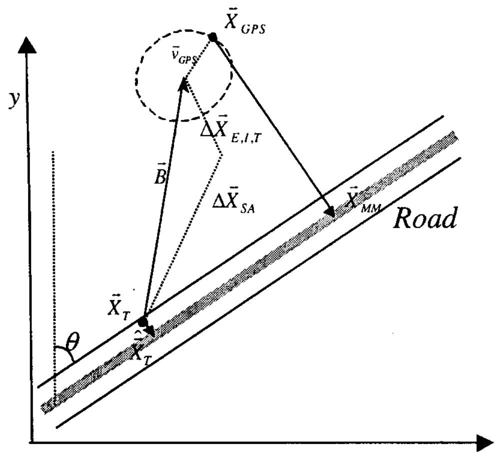

Figure 4. Geometry of Two positions : Positions by GPS and map-matching

- $\hat{\hat{X}}_T$: error-free estimated position on the road
- $\vec{B}$: biased error in GPS
- $\vec{b}_N$: cross-track error
- $\vec{b}_D$: along-track error
- $\vec{b}_x$: x-axis bias in a map coordinate system
- $\vec{b}_y$: y-axis bias in a map coordinate system
- $\vec{b}_{lane}$: lane error
- $\vec{v}_{GPS}$: white noise of GPS
- θ : road angle to north

Above variables satisfies the following equation.

$$\vec{X}_{GPS} = \vec{X}_T + \vec{B} + \vec{v}_{GPS} = \hat{\hat{X}}_T + \vec{b}_D + (\vec{b}_N - \vec{b}_{lane}) + \vec{v}_{GPS} \qquad (5)$$

where, $\vec{B} = \vec{b}_N + \vec{b}_D = \vec{b}_x + \vec{b}_y$,

$\vec{b}_N = \vec{X}_{GPS} - \vec{X}_{MM} + \vec{b}_{lane} - \vec{v}_N$,

$\vec{b}_D = \vec{X}_{MM} - \hat{\hat{X}}_T - \vec{v}_D$, $\vec{b}_{lane} = \hat{\hat{X}}_T - \vec{X}_T$

We decomposed the GPS bias into a cross-track error and an along-track error. Of two components, the measurable by a map-matching is only the cross-track error. And we are to estimate the biases in two directions and compensate for GPS measurement by getting continuosly the cross-track error. This process is shown in the Fig. 5. The positioning accuracy is defined as RMS error like Eq.(6). That is, since the cross-track error is to be removed by the projection onto the road, only the along-track error remains.

Hence, the minimization of above positioning accuracy J_D is the objective for an estimation of the

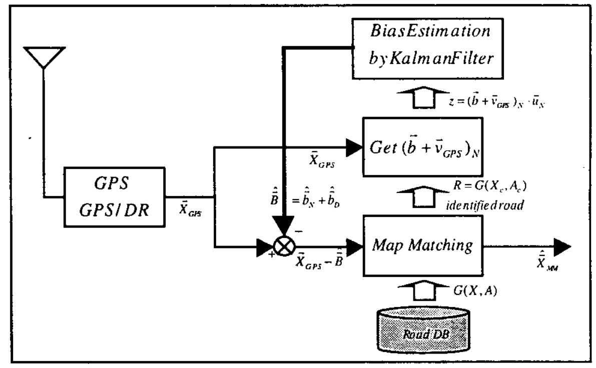

Figure 5. Alogorithm of estimating GPS Biased error

GPS's biased error using the map-matching.

$$\begin{aligned} J_D &\cong \sqrt{E\{(\hat{\hat{X}}_{MM} - \hat{\hat{X}}_T)^T \cdot (\hat{\hat{X}}_{MM} - \hat{\hat{X}}_T)\}} \\ &= \sqrt{E\{\left\|\hat{\hat{b}}_D - \vec{b}_D\right\|^2\}} \qquad (6) \\ &= \sqrt{E\{\tilde{\tilde{b}}_D{}^2\}} \end{aligned}$$

In the chapter 2, the planar error of GPS is modeled into a second-order Markov model. This chapter presents an algorithm that estimates the biased error using the error model and continuous measurables from the map-matching. Eq.(4) is changed to the discrete-time model as Eq.(7) about x, y-axis.

$$\begin{bmatrix} b_i \\ \dot{b}_i \end{bmatrix}_{k+1} = \Psi \cdot \begin{bmatrix} b_i \\ \dot{b}_i \end{bmatrix}_k + U \cdot \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \quad i = x, y \qquad (7)$$

where, $b_i = \vec{b}_i \cdot \vec{u}_i$, $i = x, y$

Ψ, U : appropriate constant matrix[1],

$w_i \sim N(0, 1^2)$: white noise

By comparing with the current road determined by the map-matching, some measurable information from the GPS data is the cross-track error perpendicular to the road. Applying the state model of Eq.(7), a system model and a measurement equation of Eqs.(8~9) are built up.

$$\begin{aligned} x_{k+1} &= A \cdot x_k + B \cdot w_k \\ &= \begin{bmatrix} \Psi & 0_{2\times2} \\ 0_{2\times2} & \Psi \end{bmatrix} \cdot x_k + \begin{bmatrix} U & 0_{2\times2} \\ 0_{2\times2} & U \end{bmatrix} \cdot w_k \qquad (8) \end{aligned}$$

$$z_k = \vec{b}_N \cdot \vec{u}_N + \vec{v}_{GPS} \cdot \vec{u}_N = H_k \cdot x_k + v_k \qquad (9)$$

where, $x_k = [b_x\ \dot{b}_x\ b_y\ \dot{b}_y]_k^T$, $w_k \sim N(0, I_{4\times4})$, $v_k \sim N(0, r_k^2)$
$H_k = [\cos\theta_k\ \ 0\ -\sin\theta_k\ \ 0]$

The biased component $\vec{B}$ of GPS satisfies Eq.(10) about the difference angle θ to the north. Hence, using a transformation matrix T_k, the error model of the cross-track and the along-track can be formed like Eqs.(10~11).

$$y_{k+1} = F_k \cdot y_k + G_k \cdot w_k = T_{k+1} A T_k^{-1} \cdot y_k + T_{k+1} B \cdot w_k \quad (10)$$

$$z_k = C_k \cdot y_k + v_k = H_k T_k^{-1} \cdot y_k + v_k \quad (11)$$

where, $y_k = [b_N\ \dot{b}_N\ b_D\ \dot{b}_D]_k^T$, $w_k \sim N(0, I_{4\times4})$, $v_k \sim N(0, r_k^2)$

$$y_k = T_k x_k = \begin{bmatrix} \cos\theta_k & 0 & -\sin\theta_k & 0 \\ -\sin\theta_k & \cos\theta_k & -\cos\theta_k & -\sin\theta_k \\ \sin\theta_k & 0 & \cos\theta_k & 0 \\ \cos\theta_k & \sin\theta_k & -\sin\theta_k & \cos\theta_k \end{bmatrix} x_k$$

In Eq.(11), the measurement matrix becomes Eq.(12). It means that the biased error in the normal direction to the road is measurable.

$$C_k = H_k T_k^{-1} = [1\ 0\ 0\ 0] \quad (12)$$

The observability of GPS bias is explained below, when the cross-track error can be measured by a map-matching.

Here, the interesting state is $x = y_k = [b_N, \dot{b}_N, b_D, \dot{b}_D]_k^T$.

$$A^m = \begin{bmatrix} \Psi^m & 0_{2\times2} \\ 0_{2\times2} & \Psi^m \end{bmatrix}, \quad \Psi^m = \begin{bmatrix} a_m & b_m \\ c_m & d_m \end{bmatrix}$$

1) $\theta_m = \theta_1$, and one sample measurement in a straight road(M=1)

$$\Im_O(1) = Cx = x_1$$

The null space of $\Im_O(1)$ is $Null(\Im_O(1)) = \{x \mid x_1 = 0,\ x \in R^4\}$. And so, the state is not observable. Consequently, one sample measurement cannot estimate the biased error.

2) $\theta_m = \theta_1$, and M measurements in a straight road ($M \geq 2$)

$$\Im_O(m) = C\Phi(m,1)x = C(T_1 A^m T_1^{-1})x = a_m x_1 + b_m x_2 + b_m x_3,\ m = 1,\cdots,M$$

Because θ_k are the same, $T_m = T_1$. The null space of $\Im_O([1,M])$: $Null(\Im_O([1,M])) = \{x \mid a_m x_1 + b_m x_2 + b_m x_3 = 0,\ x \in R^4, m = 1,2\cdots,M\}$.

And also, the states are not observable. When $M \geq 2$, we can only x_1, the cross-track error.

3) $\theta_m \neq \theta_1 (N < m \leq M, N \geq 2, M \geq N+2)$ and M measurements in a crossroads or a curved road

$$\Im_O(m) = C\Phi(m,1)x = C(T_m A^m T_1^{-1})x$$
$$= \begin{cases} a_m x_1 + b_m x_2 + b_m x_3, & m = 1,\cdots,N \\ (a_m \cos\delta\theta_m + b_m \sin\delta\theta_m)x_1 + b_m \cos\delta\theta_m x_2 \\ \quad + (-a_m \sin\delta\theta_m + b_m \cos\delta\theta_m)x_3 - b_m \sin\delta\theta_m x_4, \\ & m = N+1,\cdots,M \end{cases}$$

Since $\theta_m = \theta_1 + \delta\theta_m$, $T_m \neq T_1$ $(N < m \leq M)$. The null space of $\Im_O([1,M])$ is $Null(\Im_O([1,M])) = 0$. And therefore, the states are observable from [8]. So, we can estimate the GPS biased error under this condition $\theta_m \neq \theta_1 (N < m \leq M, N \geq 2, M \geq N+2)$.

To summarize, we can observe and correct the biased error in GPS according to the following steps.

1. to model the biased error of GPS into fourth order Markov model
2. to measure the cross-track error using a map-matching
3. to estimate the biased errors in two directions when a vehicle runs at a crossroads or a curved road.

IV. Experimental Result

In the prior chapters, we looked into the observability of GPS-inherent bias by the map-matching. This chapter compares some results of the map-matching in several field tests with DGPS.

25 minutes' drives in a squared district are executed several times. To estimate the biased error of GPS, the algorithm of Fig. 5 is implemented. By using the bias model of each (x,y) axes, first we measure the cross-track error, the second estimate the bias using Kalman filter, and the third, we estimate together the along-track error and cross-track error of a vehicle's GPS position from coordinates transformation. Below steps (1)~(3) show the estimation algorithm of bias.

(1) x, y-axis bias-error model and measurement equation of Eqs.(8~9)

$$x_{k+1} = A \cdot x_k + B \cdot w_k$$

$$z_k = H_k \cdot x_k + v_k$$

(2) Estimation of bias using Kalman filter
Time Update :

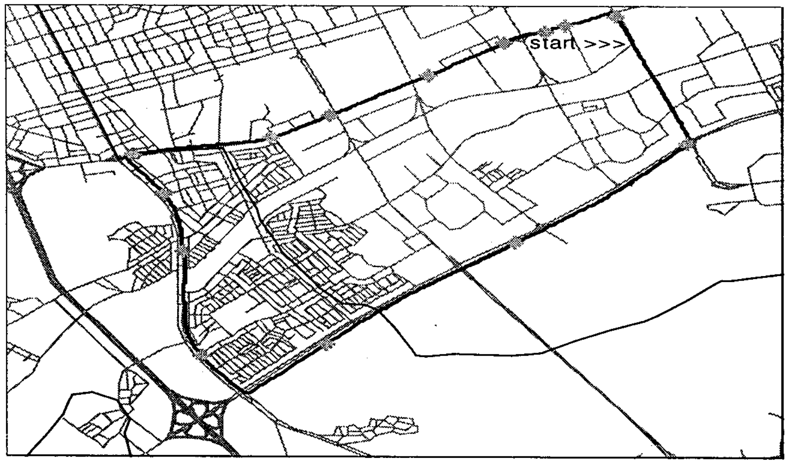

Figure 6. GPS Position of experiment trajectory

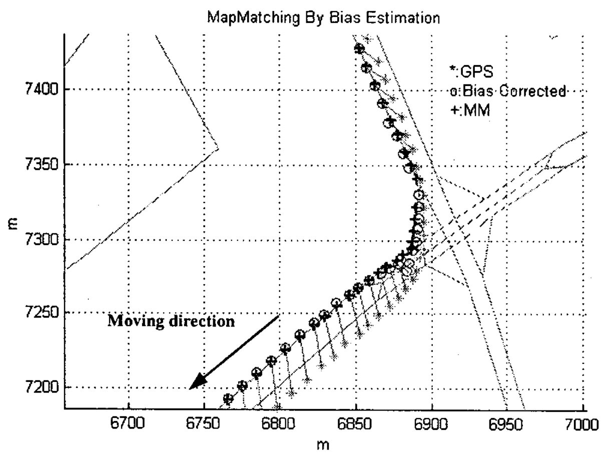

Figure 7. GPS(star), bias-compensated position(circle) and map-matched position(cross)

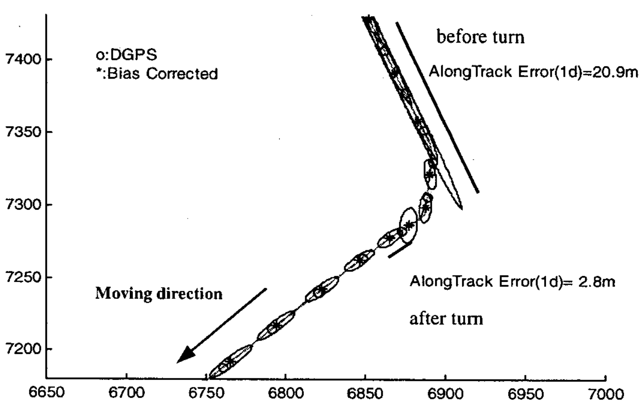

Figure 8. Propagation of error ellipse in estimated position(after turn, it shrinks)

$$\hat{x}_{k+1/k} = A\hat{x}_{k/k}$$
$$P_{k+1/k} = AP_{k/k}A^T + BQB^T$$

Measurement Update :

$$\hat{x}_{k+1/k+1} = \hat{x}_{k+1/k} + P_{k+1/k+1}H_{k+1}^T R_{k+1}^{-1}(z_{k+1} - H_{k+1}\hat{x}_{k+1/k})$$
$$P_{k+1/k+1} = [(P_{k+1/k})^{-1} + H_{k+1}^T R_{k+1}^{-1} H_{k+1}]^{-1}$$

where, P, Q, R : Covariance of $\hat{x}$, w, and v

(3) Coordinates transformation

$$y_k = T_k x_k = \begin{bmatrix} \cos\theta_k & 0 & -\sin\theta_k & 0 \\ -\sin\theta_k & \cos\theta_k & -\cos\theta_k & -\sin\theta_k \\ \sin\theta_k & 0 & \cos\theta_k & 0 \\ \cos\theta_k & \sin\theta_k & -\sin\theta_k & \cos\theta_k \end{bmatrix} x_k$$

where, $x_k = [b_x\, \dot{b}_x\, b_y\, \dot{b}_y]_k^T$, $y_k = [b_N\, \dot{b}_N\, b_D\, \dot{b}_D]_k^T$

Above steps lead to Fig. 7 : a result of the bias corrected map-matching. When the vehicle turns round at a crossroads, its along-track error can be measured. And though the error's magnitude(rms) is as large as 20.9m before a turn, it is reduced to 2.8m after the turn by the estimation and correction of its biased error.

Since DGPS gives the positioning accuracy less than 5m, we employ DGPS as a reference to check the performance of the proposed bias estimation. Table 1 shows the comparison of results. The measured position by GPS has the same 1 DRMS error 40.19m as informed[1]. In the case of a conventional map-matching, the remained along-track error has an important meaning. When such along-track error is estimated and compensated the proposed method, the result shows 53 % improvement of the positioning accuracy in the direction of along-track.

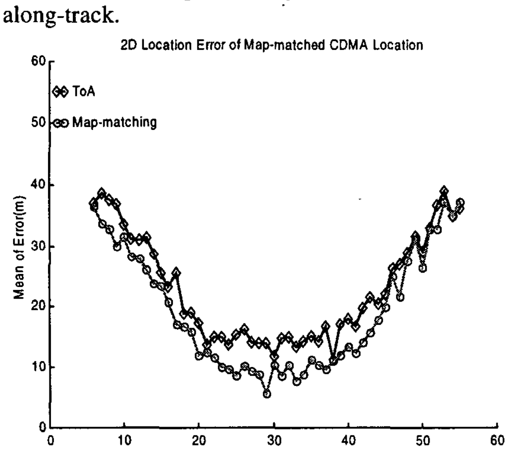

Figure 11. Map-matching applied to CDMA location(with NLOS)

Table 1. Comparison of the positioning error

	along track error(J_D)	cross track error	
GPS	22.77m	33.12m	J=40.2m
map-matching	22.77m	1.0m	bias included
bias compensation map-matching	10.64m	1.0m	

The proposed map-matching is also applied to CDMA location. Like GPS, CDMA location has more severe biased error due to mutipath, NLoS and etc. A result viewed in Fig. 11 has 21% improvement by the bias compensation under NLoS error occurrences.

V. Conclusions

This paper considers the improvement of positioning accuracy through integrating radio-location systems with a digital-road map. Generally, the biased error from SA, atmospheric delay, and multipath is hardly reduced by the integration with DR or INS(Inertial Navigation System).

A Comparison between a sequence of measured positions and a digital road map makes the cross-track error of a vehicle's position to be measured. Using these continuous measurables, this paper presents an algorithm that can estimate the decomposed bias error and can improve its positioning accuracy. Also we analyzes its observability. The proposed map-matching can be applied effectively to various location systems, which is any of GPS based, CDMA location and the others.

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