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NAME: Mr. Sorasak Khoomboon

THIS THESIS HAS BEEN ACCEPTED BY

________________________________ **THESIS ADVISOR**

(Assistant Professor Teerasit Kasetkasem, Ph.D.)

________________________________ **THESIS CO-ADVISOR**

(Mr. Rachaporn Keinprasit, Ph.D.)

________________________________ **THESIS CO-ADVISOR**

(Associate Professor Nobuhiko Sugino, Ph.D.)

________________________________ **DEPARTMENT HEAD**

(Assistant Professor Srijidtra Charoenlarpnopparut, Ph.D.)

APPROVED BY THE GRADUATE SCHOOL ON ________________________________

________________________________ **DEAN**

(Associate Professor Gunjana Theeragool, D.Agr.)

THESIS

FUSION OF GPS AND PROXIMITY DATA FOR VEHICLE TRACKING: APPLICATIONS FOR FARMING APPLICATORS

SORASAK KHOOMBOON

A Thesis Submitted in Partial Fulfillment of
the Requirements for the Degree of
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The purpose of this research is to improve the positioning accuracy of a stand along global positioning system (GPS) receiver through two techniques, namely, pos error prediction approaches, and time-domain system to estimate positioning error by integrating the positioning data from the GPS data and prior information. The prior information is the position of several control points in the field which may be obtained from proximity sensors. Proximity sensors may be a RF device that periodically broadcasts its location through the cheap short-range RF system, or the landmark in the field to let an operator of a vehicle enter the location information into the system. When a vehicle travels near a proximity sensor, its position will be calibration from the broadcasted information.

In the error prediction approaches, we propose four methods, the last error value, average error value, last error value with memory parameter, and average error value with memory parameter. From our experiment, the last error value yields the maximum improvement whereas the last error value with memory performs poorest. However, the last error value with memory can improve the accuracy when the majority of error is caused by the positioning noise. The time-domain system to estimate positioning error yield slightly lower positioning error reduction when comparing with the last error value. However, it yields the minimum standard deviation which implies the robustness of the time-domain tracking.

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Student's signature   Thesis Advisor's signature

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Sorasak Khoomboon
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TABLE OF CONTENTS

LIST OF TABLES

LIST OF TABLES (Continued)

Table **Page**

LIST OF FIGURES

LIST OF FIGURES (Continued)

Figure **Page**

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

Figure **Page**

LIST OF ABBREVIATIONS

GIS	=	geographically information systems
GISTDA	=	Geo-Informatic and Space Technology Development Agency
GPS	=	Global position system
INS	=	Inertial navigation systems
MSE	=	Minimum mean square error
NTC	=	National Telecommunications Commission
RTK-GPS	=	Real Time Kinematic Global position system
UTM	=	Universal Transverse Mercator
VRF	=	Variable rate fertilization

FUSION OF GPS AND PROXIMITY DATA FOR VEHICLE TRACKING: APPLICATIONS FOR FARMING APPLICATORS

INTRODUCTION

Agriculture Fertilizers are very important to the plant development. There are three fundamental elements; nitrogen, phosphorus and potassium. Each plant in a field needs different combination of these fertilizers depending upon their stage of growth, the composition of soil and the other environmental factors. The plant experts can take these factors into consideration and come up with the optimum combination. The result is a fertilizer map from which the quantities of each nutrient are given for specific location in the farm. Hence, there is a need for some technology that can apply the specified amount of fertilizers at each plant location. This technology is named as the variable rate fertilization (VRF) which is one of the most important technologies for the future precision agriculture. The VRF has the benefit of increasing fertilizer utilization ratio and yield, reducing pollution caused by unnecessary fertilization, and improving agriculture product quality. The applicator makes the use of spatial information technologies, such as global positioning systems (GPSs), geographically information systems (GISs) and remote sensing (RS) to pinpoint the location of the applicator and determine proper amount of the fertilizer to be applied.

A guidance system is very important to the VRF technique because each plant for each position in a fertilizer map need difference amount of fertilizer due to the high variability of the soil composition on the ground (Zhang , 2002). If we has a low precision guidance system then the VRF cannot apply the appropriate amount of fertilizers to the plants, the result is the low grow rate of plant and the increase in the pollution. As result, a guidance system can position a moving vehicle within 30 cm or less using a high precision RTK-GPS. The RTK-GPS is a very suitable sensor to achieve automated guidance with such high precision, i.e., several control laws have been designed for vehicles equipped. However the cost of a RTK-GPS higher than regular GPS and the transmitting frequency range of RTK-GPSs is not in public frequencies. As a result, the specific permission from the national telecommunications commission (NTC) in Thailand must be granted before employing the equipment. For this reason, the use of a standalone GPS receiver is more appropriate for the precision farming in Thailand. Even though a standalone GPS receiver has a lower cost, it has a very limited accuracy ranging from 3 to 100 meters. As a result, we introduce the use of proximity sensors placed on known positions as the auxiliary information to increase the accuracy of the positioning system. Proximity sensors can be a RF device that periodically broadcasts its location through the cheap short-range RF system, or the landmark in the field to let an operator of a vehicle enter the location information into the system. When a vehicle travels near a proximity sensor, its position will be calibration from the broadcasted information. Furthermore, the measurement errors from the GPS are also computed. These measurement errors are used to adjust the GPS data when the vehicle moves away from the proximity sensors.

OBJECTIVES

1. To investigate the utilization of simple positioning error prediction methods for improving the positioning accuracy.

2. To investigate the utilization of a tracking models for both the movement of a GPS receiver and the positioning error for the improving the positioning accuracy.

LITERATURE REVIEW

Nowadays, the variable rate fertilization (VRF) is one of the most important technologies for the future of precision agriculture, but the VRF requires the high precision positioning devices such as the real time kinematic (RTK) together with the geographical information system (GIS) of the soil maps in the field of interest All these devices and systems are needed for a site specific management of nutrient and other production inputs. A high accuracy device such as the RTK-GPS (Zhang, 2002) can position a moving vehicle within 30 cm or less using. The RTK-GPS is a very suitable device sensor for the automated high accuracy guidance system, i.e., several control laws have been designed for vehicles equipped (Eaton *et al.*, 2008). However the cost of a RTK-GPS higher than regular GPS and transmit frequency range of RTK-GPS is not in public frequency. As a result, the national telecommunications commission (NTC) of Thailand must issue a specific permission for the implementation of a RTK-GPS. The use of a standalone GPS receiver is more appropriate for the precision farming in Thailand. Nevertheless, a standalone GPS receiver has a very limited accuracy ranging from 3 to 100 meters (Kong, 2007).

Many researchers have attempted to improve accuracy of a standalone GPS through a sophisticated digital signal processing algorithms. Leandro (Leandro *et al.*, 2005) uses an empirical stochastic approach to create covariance matrices for the GPS data that can improve the quality control of estimated coordinates of the GPS measurements. Kong (Kong, 2007) examines the frequency domain modeling approach for GPS error, and further use of the GPS de-correlation filters to reduce the positioning accuracy. The errors of GPS positioning system are measured by the employment of the inertial navigation systems (INS) which adds extra cost into the system. These techniques require tremendous computational processor, is hard to implement, use high performance processor, and may be too costly to be practically deployed in low cost system such as the marketable precision farming systems in develop country such as in Thailand.

As a result, we have investigated two possible solutions for improve accuracy of a standalone GPS by employing simple error prediction approaches, and the time-domain system for estimate positioning errors, and tracking the location of a standalone GPS receiver. For the positioning prediction model, we assume that if the positioning errors can be correctly determined, the real position of a GPS receiver can be obtained by subtracting the GPS values with the predicted errors. The positioning error can be predicted if the values of previous errors are known. In this research, the position errors at some location can be determined by the use of proximity sensor. When a vehicle travels near proximity the true position is known. Hence, the positioning errors can be obtained. In the first method, we examine three approaches, namely last error value, average error value and last error value with memory parameter.

In the second solution, the time-domain model for the movement of a GPS receiver and positioning errors are employed. To make the algorithm implementable in the real situation, we need the tracking algorithm to be simple. As a result, the particle filter is employed here due to its simplicity. The particle filter is based on the Bayesian filter theory. The main objective of the particle filter is to approximate the *posteriori* probability of the system state given the observed data. In general, the particle filters are implemented in tracking problems (Gustafsson *et al.*, 2002) where it uses process model to predict the prior distribution, and then updates that distribution by incorporating new observations to get posterior distribution. At the end, the list of the *posteriori* distributions of the system states is obtained over time. Let $P(X_0) = P(X_0|Y_0)$ be an initial prior probability of system states where Y_0 the initial observation is. Furthermore, since the system is dynamic, the system states are changed according to some transition probability, $P(X_k|X_{k-1})$, i.e., hence, the system states are modeled as the Markov chain. Here, the notation *k* denotes the time that the system being observed. The *posteriori* probability of a system state at time *k* given all the previous observation can be written as

$$P(X_k|Y_{1:k-1}) = \int P(X_k|X_{k-1})P(X_{k-1}|Y_{1:k-1})dX_{k-1}\,. \tag{1}$$

The subscript $1:k-1$ implies that the set of data from the time 1 to *k*-1. Next, the k-th observation can incorporated into the *posteriori* probability by using the Bayes' rule as

$$P(X_k|Y_{1:k}) = \frac{P(Y_k|X_k)P(X_k|Y_{1:k-1})}{P(Y_k|Y_{1:k-1})} \tag{2}$$

Since the conditional probability $P(Y_k|Y_{1:k-1})$ is independent of a choice of X_k, it can be viewed as a normalizing constant. Hence, the equation (2) can be rewritten as

$$P(X_k|Y_{1:k}) = aP(Y_k|X_k)P(X_k|Y_{1:k-1}) \tag{3}$$

Where *a* is the normalizing constant that makes the sum of probability equal to one. Furthermore, the conditional probability $P(Y_k|X_k)$ is obtained from the observation model of the problem of interest.

The particle filter tries to approximate the *posteriori* probability given in (3) by representing *N* possible system states by a position of *N* particles. In our problem, the position of a particle can be considered as one image transformation. Here, each particle is assigned a weight function according to its *posteriori* probability. Let w_k^i denote a weight function of the *i*-th particle at a time *k*. The integral in (1) can be approximated as

$$P(X_k^i|Y_{1:k-1}) \approx \sum_{i=1}^{N} P(X_k^i|X_{k-1}^i)w_{k-1}^i \tag{4}$$

Where X_k^i denote the position (system state) of the *i*-th particle. Next, the weight at the next time can be obtained from (3). The particle filter recursively solve equation (3) and (4). The approximation can be accurate if a large number of particles are deployed. The obvious drawback of this approach is the computation burden of the algorithm. To reduce the computational complexity, the particle filter introduces resampling technique to re-locate some of the particles in the area of higher weight. Here, a new set of *N* particles is selected from the set of current particle with replacement. The probability that a particle is chosen is proportion to its weight. Next, a new set of particle are move according to the given system model.

To increase the accuracy of the GPS movement tracking model, we need to accurate model of the positioning errors of a standalone GPS. Kong (Kong, 2000) derives the GPS correlated error in the pseudo range is modeled using power spectral density (PSD). It was shown that all the satellites have the same correlated noise statistics. The power spectral density $\psi_i(s)$ of the correlated noise of each satellite has the form of a fourth order system

$$\psi_i(s) = \left[\frac{r(s+\beta)}{s^2 + 2\alpha ks + \alpha^2} \right]^2 \tag{5}$$

The transfer function (5) can be converted to state space form so that the correlated noise can be estimated along with the original filter states. For a single satellite, the correlated noise in the pseudo range at time t is estimated as

$$\begin{bmatrix} \dot{e}(t) \\ \dot{e}_s(t) \end{bmatrix} = \begin{bmatrix} -2\alpha k & 1 \\ -\alpha^2 & 0 \end{bmatrix} \begin{bmatrix} e(t) \\ e_s(t) \end{bmatrix} + \begin{bmatrix} r \\ r\beta \end{bmatrix} \omega_r(t) \tag{6}$$

where $e(t)$ is the state of interest, $e_s(t)$ is the augmented state, $\omega_r(t)$ is a white noise series, α, k, r and β are the model parameters in (5).

Let us note here again that for both techniques to work, the real position of a standalone GPS receiver must be partially known to perform some parameter estimation. The true positions may be obtained cheaply by incorporating the proximity sensors placed on known positions as the auxiliary information to increase the accuracy of the positioning system. Proximity sensors can be a RF device that periodically broadcasts its location through the cheap short-range RF system, or the landmark in the field to let an operator of a vehicle enter the location information into the system. When a vehicle travels near a proximity sensor, its position will be calibration from the broadcasted information. Furthermore, the measurement errors from the GPS are also computed. These measurement errors are used to adjust the GPS data when the vehicle moves away from the proximity sensors. In this research, we use last error value what can best estimate error position for improve accuracy of a standalone GPS are by employing simple linear estimators of positioning errors. we employ the particle filter to track both GPS location and the positioning accuracy in both X and Y direction for improve accuracy of a standalone GPS are by the use of a time-domain system to estimate positioning errors.

MATERIALS AND METHODS

Materials

1. Computer
2. MATLAB Simulation software
3. Microsoft Excel software
4. Microsoft Visual C++ 2008 Express Edition software
5. NCS-NAVI Bluetooth GPS receiver
6. QuickBird image stored in the GeoTiFF Format

Methods

1. Studied area and experimental setup

The NCS-NAVI Bluetooth GPS receiver is employed to collect data for this experiment. Here, we have 20 reference positions which are chosen from a part of QuickBird image of Kasetsart University, (shown in Figure 1.) The location of each pixel to the real world position is embedded in the GeoTiFF Format. The image is provided by the Geo-Informatic and Space Technology Development Agency (GISTDA), and was acquired on September 04, 2006. Since the coordinates of each pixel are embedded into the GeoTiFF file, we can use this information as the ground truth for our experiment and we can assume 20 reference positions as proximity sensors.

Figure 1 QUICKBIRD image.

Data are collected through the serial port communication of notebook. Figure 2 displays the moving path and the reference location of this experiment. The red dots are the known position whereas the green and blue dots the start and end locations, respectively. For each reference location, we wait for five second to collect GPS data then move to the next reference location. After the data collection, we transform the latitude and longitude coordinate is into universal transverse mercator (UTM) coordinate (John, 1987).

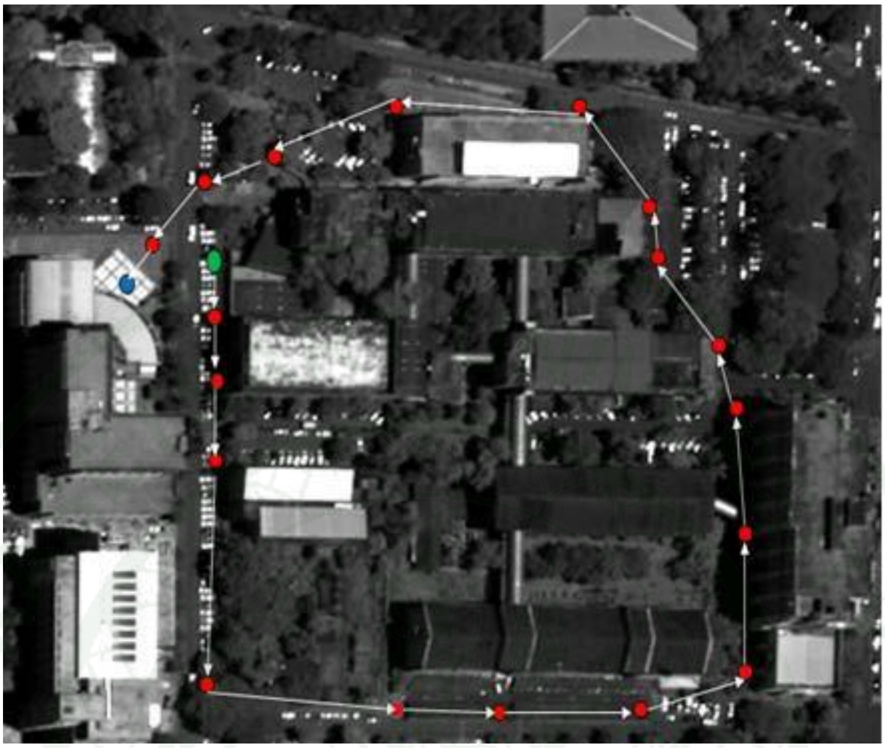

Figure 2 The moving path and the reference location.

2. Error prediction approaches

In this sub-section, we examine three different approaches to estimate the positioning error of the GPS receivers. All approaches are performs on the same dataset. Let $X_{GPS}(n)$ denote the vectors of position information in 2-dimensional space produced by the GPS receiver mentioned in Section's Studied area and experimental setup where n = $1,2,\ldots,M$ is the acquisition number. Furthermore, let Y_i denote the vector of the true world coordinate acquired from of the known location in Figure 2. We note, here, again that there are a total of 20 points. Let $n_1^i, n_2^i, \ldots, n_{M_i}^i$ be indices of the GPS data when the GPS receiver stays at the *i*-th location. As a result, for the known location, the position error is given by

$$e\left(n_j^i\right) = X_{GPS}\left(n_j^i\right) - Y_i \tag{7}$$

Where *j* is between 1 to M_i.

2.1 *Last error value*

The simple last error value of the last known location is used to estimate the positioning error in the next position. Here, we assume that the positioning error is a martingale process; i.e., the mean of positioning error is the positioning error of the last known location. The estimate of the current error is given by

$$\hat{e}(n_j^i) = e(n_{M_{i-1}}^{i-1}) \tag{8}$$

is estimated GPS receiver positioning error vector at all the received data at the *i* location. Furthermore, the corrected position of the GPS receiver is given by

$$\hat{Y}(n_j^i) = X_{GPS}(n_j^i) - e(n_{M_{i-1}}^{i-1}) \tag{9}$$

2.2 *Average error values*

Since the GPS data are collected for 5 seconds on each reference locations, the average locating error should be a better estimate the last known value. As a result, the second approach employed the average positioning error of the last reference location as the estimate of positioning error for the next location. Again, the odd location number is used as the estimate of the even location. Hence, the estimated position error can be written as

$$\hat{e}(n_j^i) = \frac{1}{M_{i-1}} \sum_{k=1}^{M_{i-1}} e(n_k^{i-1}) \tag{10}$$

and the corrected position is given by

$$\hat{Y}(n_j^i) = X_{GPS}(n_j^i) - \frac{1}{M_{i-1}} \sum_{k=1}^{M_{i-1}} e(n_k^{i-1}) \tag{11}$$

2.3 *Last error value with memory parameters*

Similar to last error value, the third approach uses the last error vector to estimate the error in the next location. However, the estimate of position error is set to be a scaled version of the last error vector, i.e. the estimate error for this approach can be written as

$$\hat{\mathbf{e}}(n_j^i) = \lambda \mathbf{e}(n_{M_{i-1}}^{i-1}) \tag{12}$$

λ is the scale factor ranging from 0 to 1. Approach 1 is the special case of this approach when λ = 1. In this approach, the scale factor is fixed for all points. The corrected position is given by

$$\hat{Y}(n_j^i) = X_{GPS}(n_j^i) - \lambda e(n_{M_{i-1}}^{i-1}) \qquad (13)$$

2.4 *Average error value with memory parameters*

Similar to average error value, the third approach uses the average error vector to estimate the error in the next location. However, the estimate of position error is set to be a scaled version of the average error vector, i.e. the estimate error for this approach can be written as (12) λ is the scale factor ranging from 0 to 1. Approach 2 is the special case of this approach when λ = 1. In this approach, the scale factor is fixed for all points. The corrected position is given by

$$\hat{Y}(n_j^i) = X_{GPS}(n_j^i) - \frac{\lambda}{M_{i-1}} \sum_{k=1}^{M_{i-1}} e(n_k^{i-1}) \qquad (14)$$

3. Proposed Technique of the use of a time-domain system to estimate positioning errors technique.

From the work by Kong (Kong, 2000), the GPS correlated positioning error is modeled as a color noise whose he power spectral density $\psi_i(s)$ is given by (5). This implies that the positioning error of each satellite has the form of the second order system. The transfer function (5) can be converted to state space form so that the correlated noise can be estimated along with the original filter sates. The state space of the positioning error at the time *t* can be written as (6).

The above differential equation can be approximated by the different equation as

$$e(n) = \gamma e(n-1) + e_s(n) + r\omega \qquad (15)$$

$$e_s(n) = e_s(n-1) - \zeta e(n-1) + \beta r\omega \qquad (16)$$

Where $\gamma = 1 - 2\alpha k$ and $\zeta = -\alpha^2$

Next, a GPS receiver is assumed to move by the unknown and changing force. Hence, the state system of a GPS receiver can be written as

$$x(n) = x(n) + v(n-1) + \frac{1}{2}a\Delta t^2 \tag{17}$$

$$v(n) = v(n-1) + a\Delta t \tag{18}$$

Where $x(n)$ and $v(n)$ are the true location and velocity vector of the GPS receive at the *n* data point. In this work, we use the particle filter to estimate both positioning error and the location of the GPS receiver. Hence, in the next section, we provide some detail of it.

In this subsection, the tracking algorithm is divided into two stages: 1) error estimation and 2) tracking. In the error estimation stage the true location of the GPS receiver is assumed to known, and therefore, the actual value of the positioning error can be determined by subtracting the GPS location with the actual value. To estimate error, we need to determine the values ofγ, ζ, r, and β. Here, we initially generate *N* particle where each particle represent different values of the model parameters given above. Here, all particles are assigned to random values of the parameter between the maximum and the minimum value. As long as, the GPS receiver stays in the known location, the particle filter tries track the position error by adjusting these model parameters. Here, for each movement of a particle, the parameter is adjusted by the random amount, i.e.,

$$\gamma(n) = \gamma(n-1) + \gamma_s u_1 \tag{19}$$

$$\varsigma(n) = \varsigma(n-1) + \varsigma_s u_2 \tag{20}$$

$$r(n) = r(n-1) + r_s u_3 \tag{21}$$

And

$$\beta(n) = \beta(n-1) + \beta_s u_4 \tag{22}$$

Where γ_s, ς_s, r_s, and β_s are the maximum allowable movement of the parameter. Here, u_i is the independent uniform random number between -1 and 1.

After leaving the proximity sensor, the GPS receiver no longer knows the true position and, hence, the positioning error is unknown and enters the tracking stage.

The goal in this stage is to track the location of a GPS receiver and the position error at the same time. Here, the estimations of all model parameters are hauled. To gain highest accuracy, the minimum mean square error (MSE) estimates of these model parameters are employed and they are given by

$$\gamma_{mse} = \sum_{m=1}^{N} \gamma_m (M_i) w_m \tag{23}$$

$$\varsigma_{mse} = \sum_{m=1}^{N} \varsigma_m (M_i) w_m \tag{24}$$

$$r_{mse} = \sum_{m=1}^{N} r_m (M_i) w_m \tag{25}$$

And

$$\beta_{mse} = \sum_{m=1}^{N} \beta_m (M_i) w_m \tag{26}$$

We denote, here, again that M_i is the maximum index of the GPS data coming from the *i*-th proximity sensor. The particle in this stage uses the movement model in (17) and (18) and error model in (15) and (16) to estimate both position since the summation of the estimated location and the error should be closed to the estimated location obtained from the GPS receiver.

RESULTS AND DISCUSSION

Results

1. Results from the error prediction approach

Tables 1 and 2 display the averages of the positioning error reduction for *x* and *y* direction, which is the transformation of the latitude and longitude coordinate is into universal transverse mercator (UTM) coordinate (John, 1987), for each error prediction approaches in percentage and meter, respectively. We observe that the averaged error value yields the maximum error reduction in *x* direction error which is about 39.13% or 4.44 meters, but the error in the *y* direction increase by 13.71% or 0.66 meters from original error (error from GPS) of 4.81 meters. With last error value, we can reduce the error in the x direction nearly average error value but, the error y direction is less more than average error approach.

Table 1 Reduction of x direction and y direction estimation error for all approaches in percentage compared to the value of GPS

Solutions	Error reduction in x direction in (%)	Error reduction in y direction in (%)
Last error value.	37.82	-1.87
Average error value.	39.13	-13.71
Last error value, λ=0.9	35.89	-0.23
Last error value, λ =0.8	33.27	1.00
Last error value, λ =0.7	30.14	1.94
Last error value, λ =0.6	26.50	2.62
Last error value, λ =0.5	22.47	3.04
Last error value, λ =0.4	18.31	3.23
Last error value, λ =0.3	13.99	3.12
Last error value, λ =0.2	9.47	2.49
Last error value, λ =0.1	4.79	1.49
Average error value, λ=0.9	39.90	-10.33

Table 1 Reduction of x direction and y direction estimation error for all approaches in percentage compared to the value of GPS (Continued)

Solutions	Error reduction in x direction in (%)	Error reduction in y direction in (%)
Average error value, λ=0.8	39.28	-7.52
Average error value, λ=0.7	37.21	-5.00
Average error value, λ=0.6	33.83	-2.91
Average error value, λ=0.5	29.37	-1.17
Average error value, λ=0.4	24.19	0.22
Average error value, λ=0.3	18.50	1.21
Average error value, λ=0.2	12.57	1.53
Average error value, λ=0.1	6.38	1.12

Table 2 Reduction of x direction and y direction estimation error for approaches in meter compared to the value of GPS

Solutions	Error reduction in x direction in meter	Error reduction in y direction in meter
Last error value.	4.30	-0.09
Average error value.	4.44	-0.66
Last error value, λ =0.9	4.08	-0.01
Last error value, λ =0.8	3.78	0.05
Last error value, λ =0.7	3.42	0.09
Last error value, λ =0.6	3.01	0.13
Last error value, λ =0.5	2.55	0.15
Last error value, λ =0.4	2.08	0.16
Last error value, λ =0.3	1.59	0.15
Last error value, λ =0.2	1.08	0.12
Last error value, λ =0.1	0.54	0.07
Average error value, λ=0.9	4.53	-0.50
Average error value, λ=0.8	4.46	-0.36
Average error value, λ=0.7	4.23	-0.24

Table 2 Reduction of x direction and y direction estimation error for approaches in meter compared to the value of GPS (Continued)

Solutions	Error reduction in x direction in meter	Error reduction in y direction in meter
Average error value, λ=0.6	3.84	-0.14
Average error value, λ=0.5	3.34	-0.06
Average error value, λ=0.4	2.75	0.01
Average error value, λ=0.3	2.10	0.06
Average error value, λ=0.2	1.43	0.07
Average error value, λ=0.1	0.73	0.05

Tables 3 display the overall reduction of the positioning errors in percentage and meters, respectively. Here, the last error value method yields the maximum reduction of 28.32 % or 3.72 meters from original error 13.15 meters.

Table 3 The improvement in term of the displacement errors from all approaches in percentage and unit meter compared to the value of GPS

Solutions	Displacement (%)	Displacement (meter)
Last error value.	28.32	3.72
Average error value.	26.64	3.50
Last error value, λ =0.9	27.17	3.57
Last error value, λ =0.8	25.53	3.36
Last error value, λ =0.7	23.50	3.09
Last error value, λ =0.6	21.12	2.78
Last error value, λ =0.5	18.37	2.42
Last error value, λ =0.4	15.28	2.01
Last error value, λ =0.3	11.88	1.56
Last error value, λ =0.2	8.20	1.08
Last error value, λ =0.1	4.25	0.56
Average error value, λ=0.9	27.67	3.64
Average error value, λ=0.8	27.64	3.63

Table 3 The improvement in term of the displacement errors from all approaches in percentage and unit meter compared to the value of GPS (Continued)

solutions	Displacement (%)	Displacement (meter)
Average error value, λ=0.7	26.57	3.49
Average error value, λ=0.6	24.62	3.24
Average error value, λ=0.5	21.94	2.89
Average error value, λ=0.4	18.62	2.45
Average error value, λ=0.3	14.71	1.94
Average error value, λ=0.2	10.26	1.35
Average error value, λ=0.1	5.35	0.70

Table 4 display standard deviation of x direction and y direction of GPS alone and error prediction method, respectively. With the error prediction method, we have standard deviation of x and y direction error better than GPS.

Table 4 Standard deviation of error of x direction and y direction

Standard deviation	Error reduction in x direction in meter	Error reduction in y direction in meter
GPS alone	7.32	4.33
Last error value.	6.66	3.58
Average error value.	6.95	4.17
Last error value, λ =0.9	6.50	3.58
Last error value, λ =0.8	6.37	3.59
Last error value, λ =0.7	6.29	3.62
Last error value, λ =0.6	6.25	3.68
Last error value, λ =0.5	6.26	3.75
Last error value, λ =0.4	6.35	3.85
Last error value, λ =0.3	6.51	3.96
Last error value, λ =0.2	6.73	4.08

Table 4 Standard deviation of error of x direction and y direction (Continued)

Standard deviation	Error reduction in x direction in meter	Error reduction in y direction in meter
Last error value, λ =0.1	7.00	4.20
Average error value, λ=0.9	6.80	4.10
Average error value, λ=0.8	6.69	4.03
Average error value, λ=0.7	6.60	3.99
Average error value, λ=0.6	6.53	3.97
Average error value, λ=0.5	6.49	3.98
Average error value, λ=0.4	6.50	4.01
Average error value, λ=0.3	6.58	4.08
Average error value, λ=0.2	6.75	4.15
Average error value, λ=0.1	7.00	4.24

Figure 3 and 4 show estimated position by the use of average error value. Here, the green line show the estimated GPS position, blue line is reference position and red line is position from GPS receiver. Here, we fill in the position of the GPS receiver between two known locations with a straight line which implies that we assume that the GPS receiver is moved with a constant speed between any adjacent know locations. This assumption may not be valid, but the illustrations in Figures 3 and 4 can provide some idea about the positioning accuracy at the unknown location.

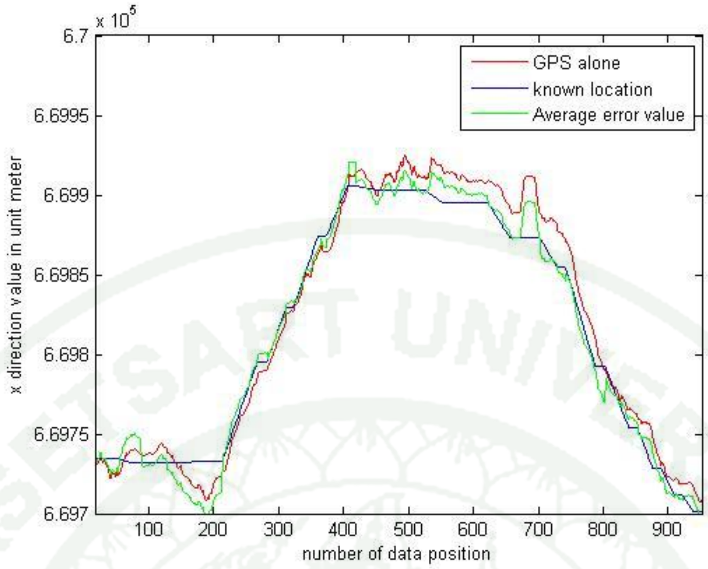

Figure 3 Comparison of positioning data in x direction from GPS, our average error value, and the ground truth.

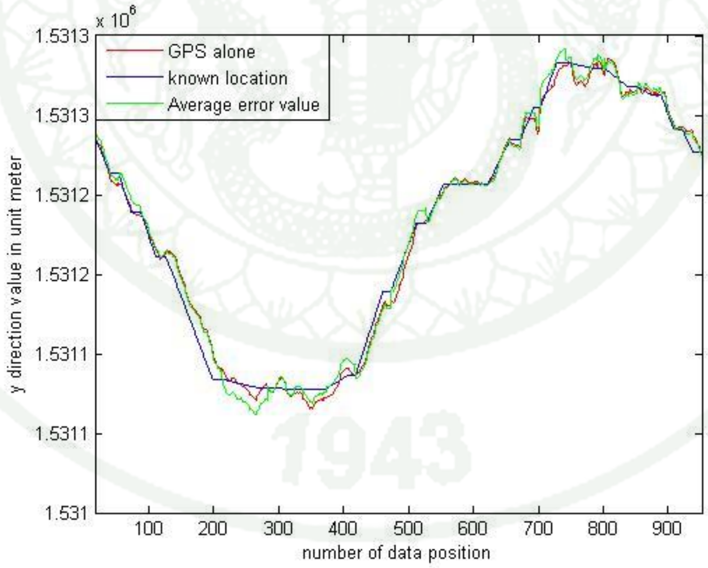

Figure 4 Comparison of positioning data in y direction from GPS, our average error value, and the ground truth.

Figure 5 and 6 show estimated position x direction and y direction by last error value. Figures 7, 9, 11, 13, 15, 17, 19, 21, and 23 show estimated position x direction by last error value with memory parameter λ = 0.9, 0.8, …, 0.1 and figure 8, 10, 12, 14, 16, 18, 20, 22, and 24 show estimated position y direction by last error value with memory parameter λ = 0.9, 0.8, …, 0.1. Figures 25,27,29,31,33,35,37,39, and 41 show estimated position x direction by average error value with memory parameter λ = 0.9, 0.8, …, 0.1 and figure 26, 28, 30, 32, 34, 36, 38, 40, and 42 show estimated position y direction by average error value with memory parameter λ = 0.9, 0.8, …, 0.1.

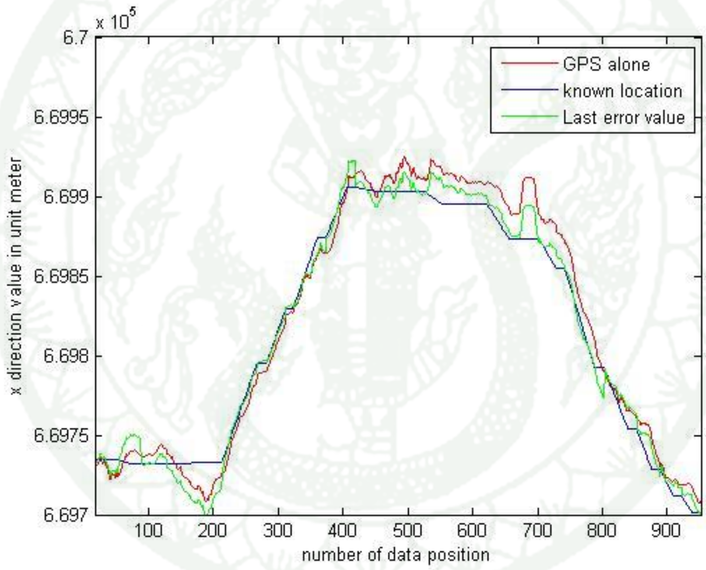

Figure 5 Comparison of positioning data in x direction from GPS, our last error value, and the ground truth.

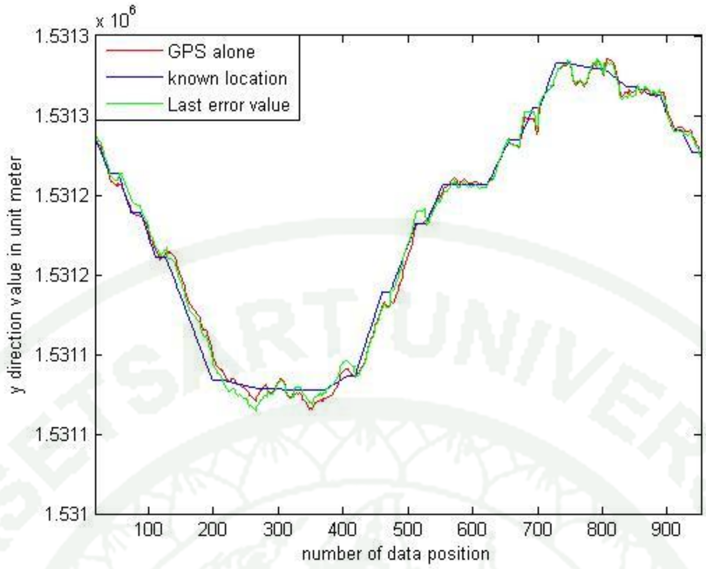

Figure 6 Comparison of positioning data in y direction from GPS, our last error value, and the ground truth.

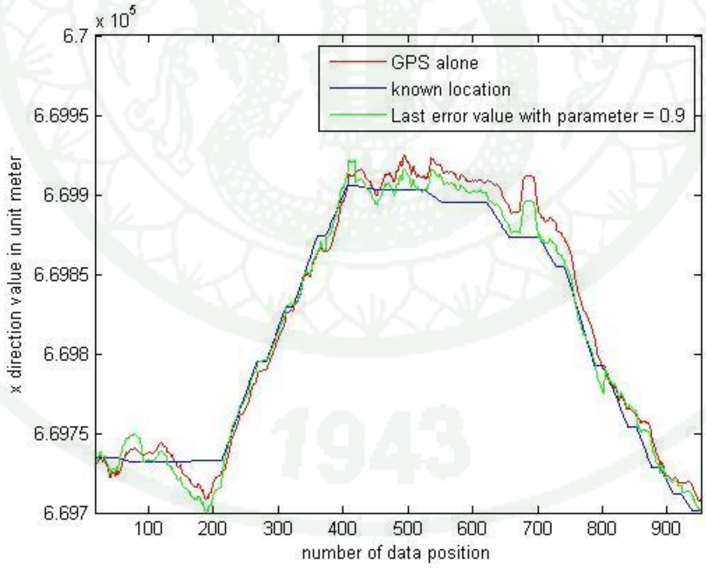

Figure 7 Comparison of positioning data in x direction from GPS, our last error value with $\lambda = 0.9$, and the ground truth.

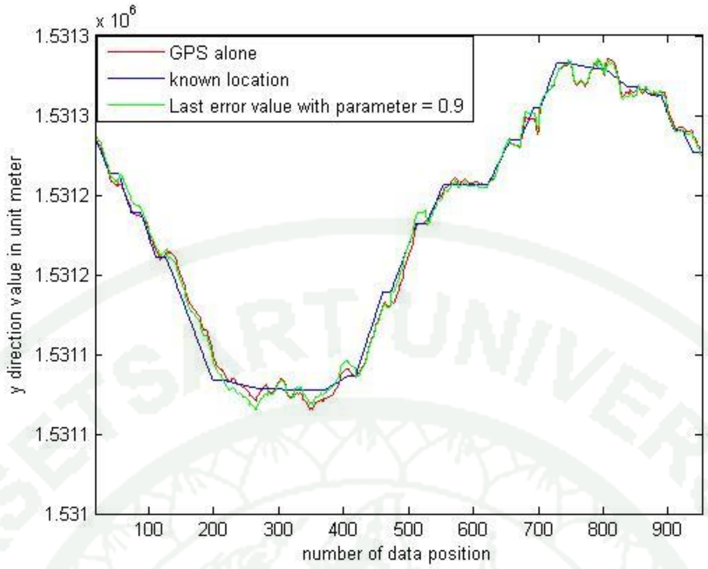

Figure 8 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.9, and the ground truth.

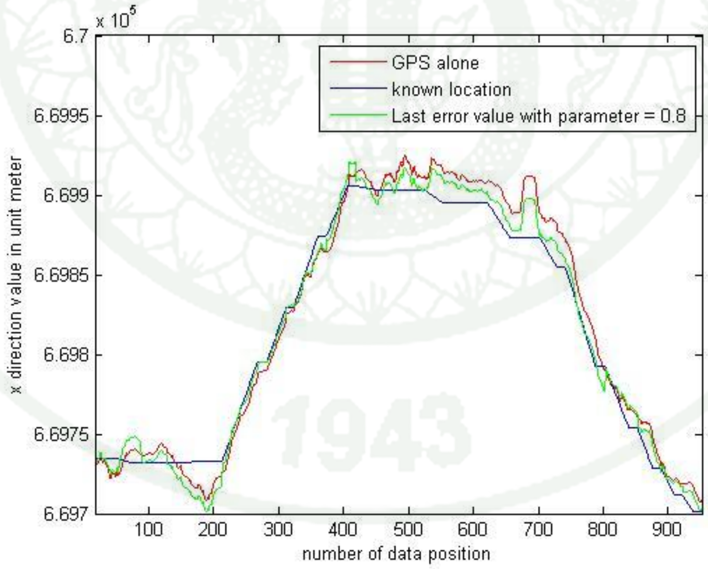

Figure 9 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.8, and the ground truth.

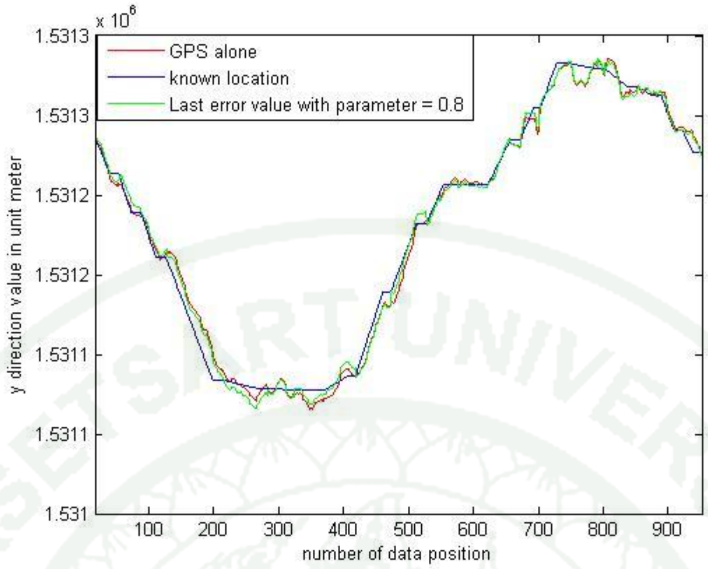

Figure 10 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.8, and the ground truth.

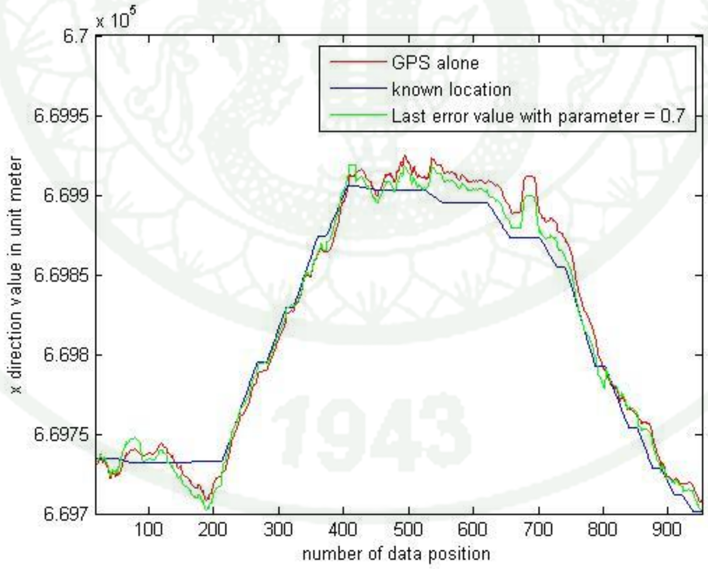

Figure 11 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.7, and the ground truth.

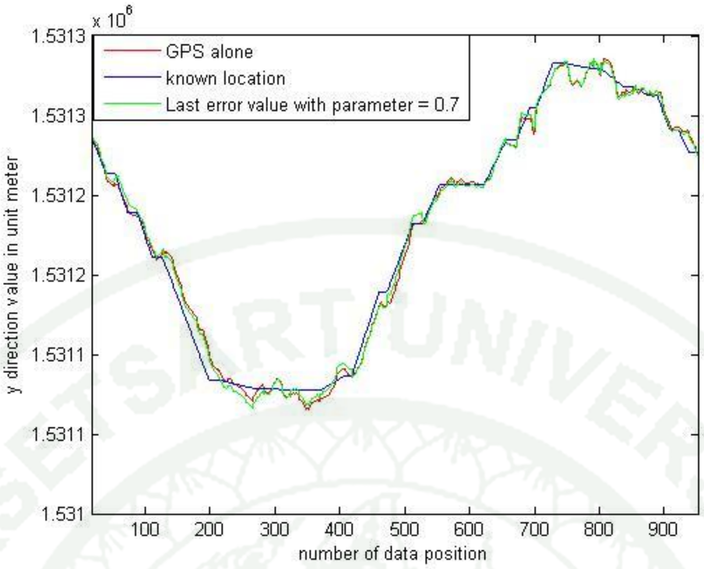

Figure 12 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.7, and the ground truth.

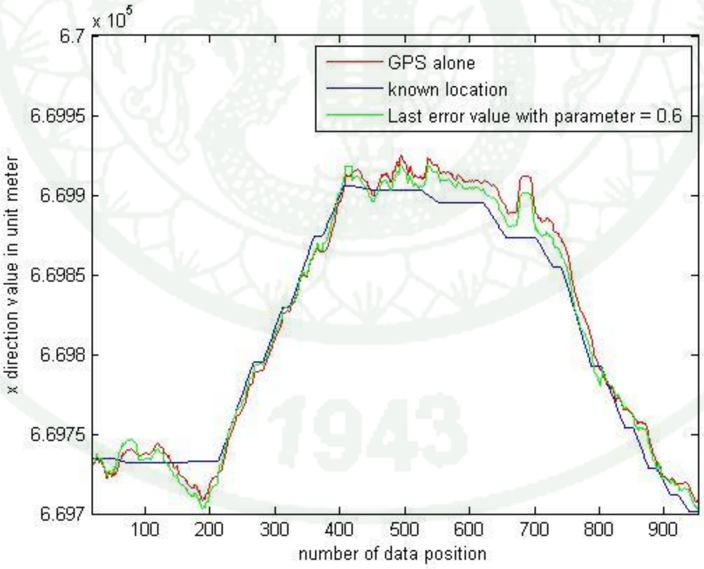

Figure 13 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.6, and the ground truth.

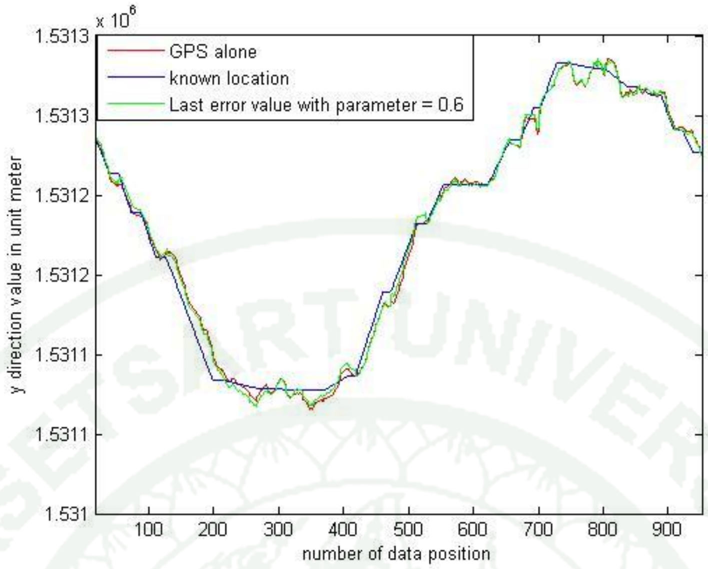

Figure 14 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.6, and the ground truth.

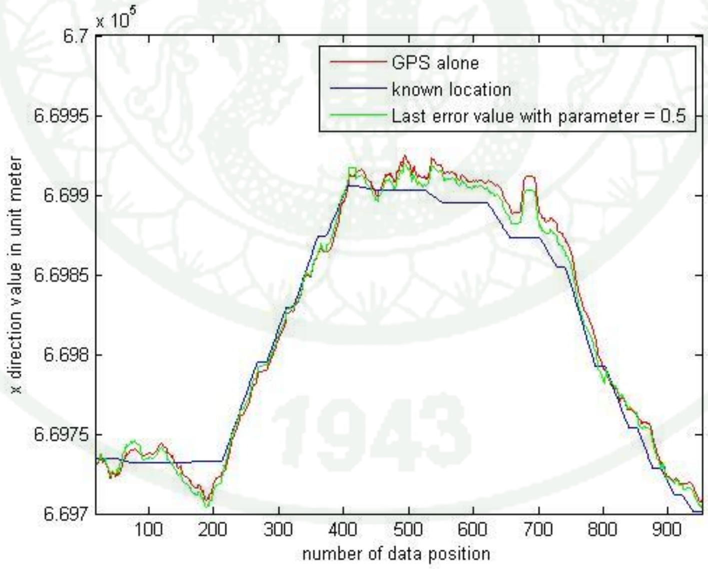

Figure 15 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.5, and the ground truth.

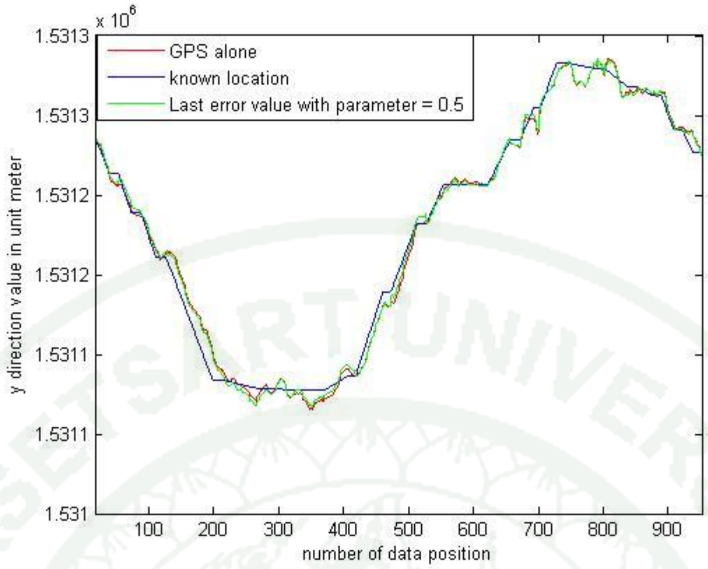

Figure 16 Comparison of positioning data in y direction from GPS, our last error value with $\lambda = 0.5$, and the ground truth.

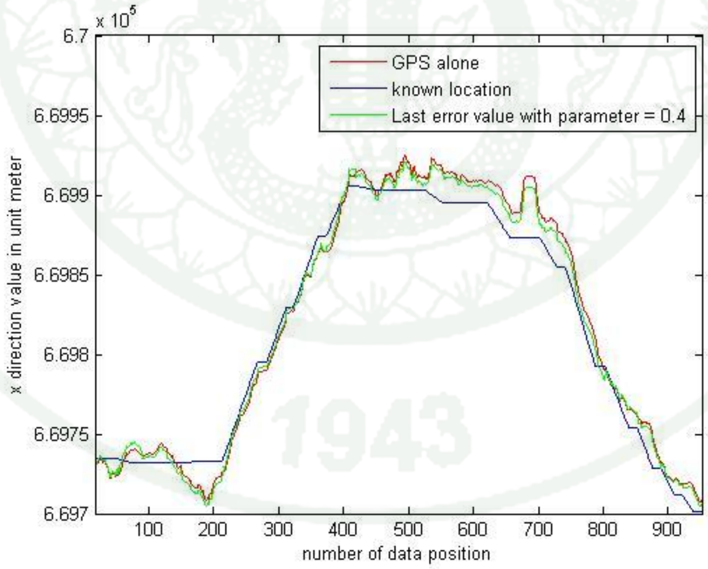

Figure 17 Comparison of positioning data in x direction from GPS, our last error value with $\lambda = 0.4$, and the ground truth.

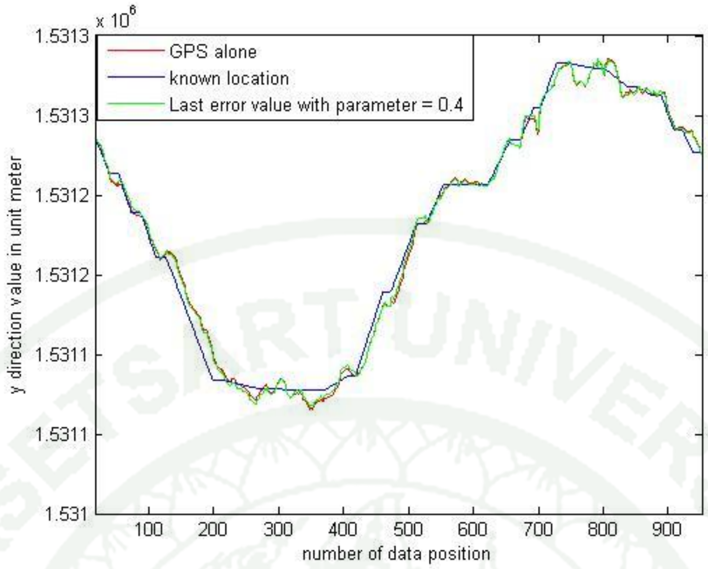

Figure 18 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.4, and the ground truth.

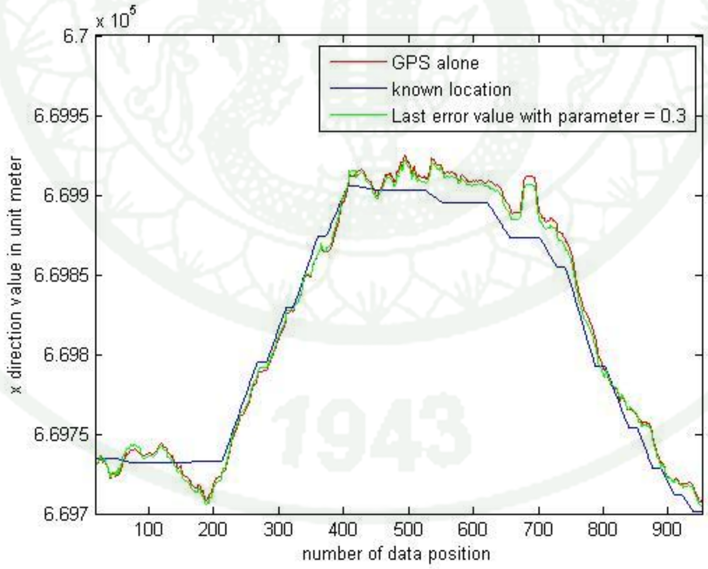

Figure 19 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.3, and the ground truth.

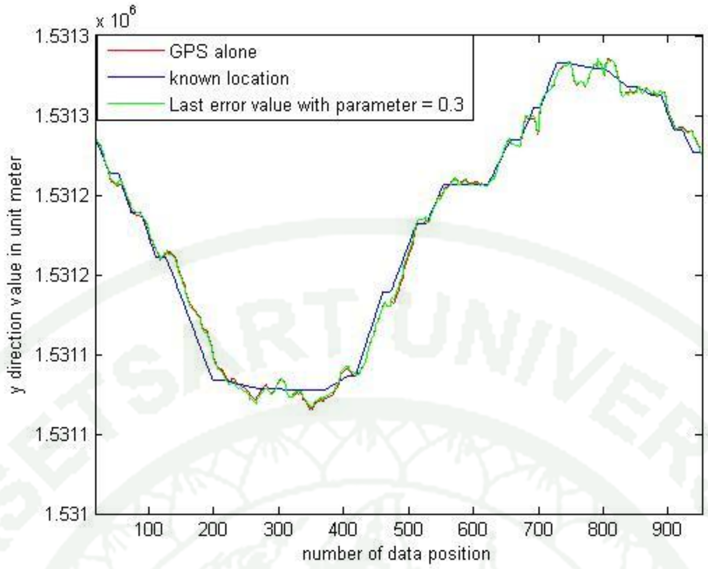

Figure 20 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.3, and the ground truth.

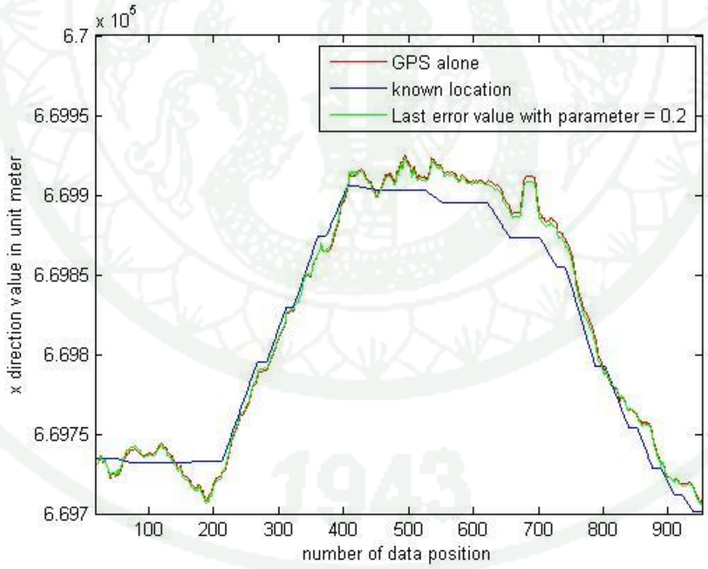

Figure 21 Comparison of positioning data in x direction from GPS, our last error value with λ = 0.2, and the ground truth.

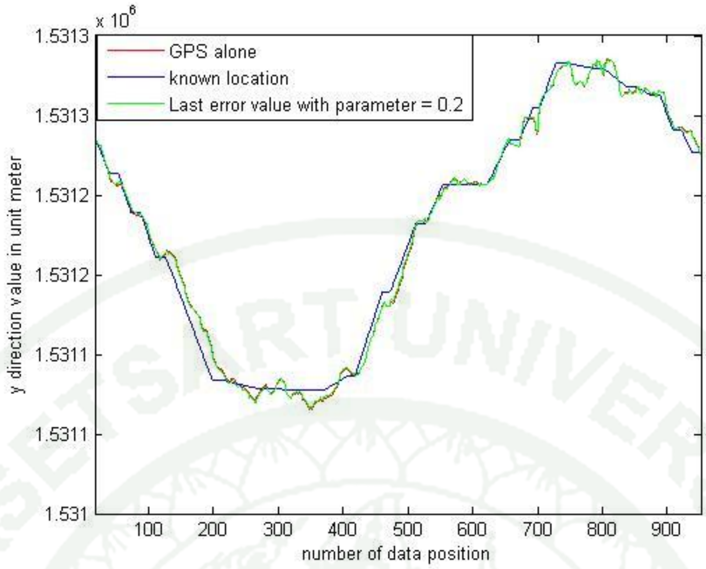

Figure 22 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.2, and the ground truth.

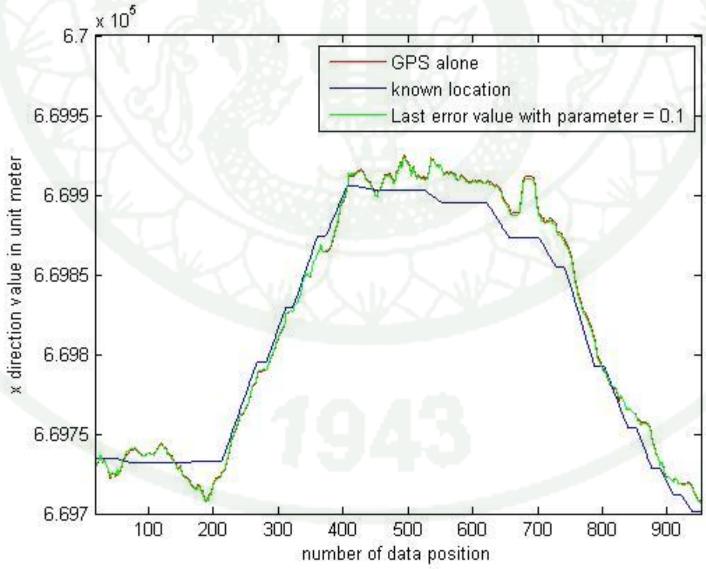

Figure 23 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.1, and the ground truth.

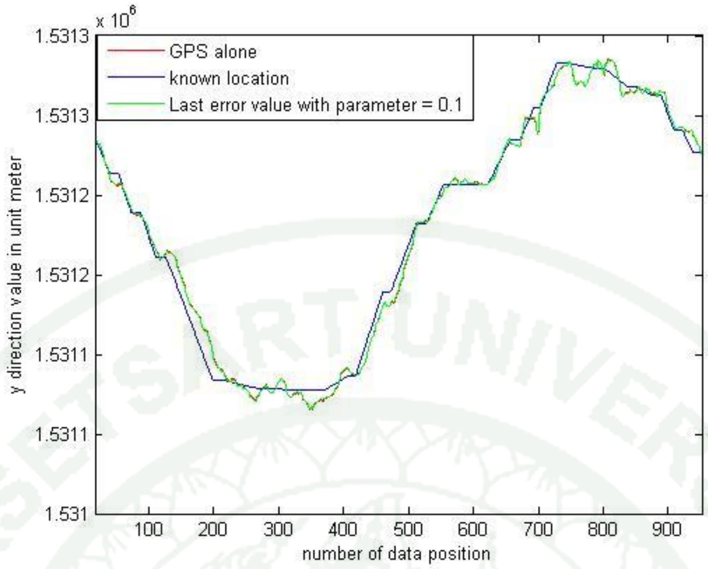

Figure 24 Comparison of positioning data in y direction from GPS, our last error value with λ = 0.1, and the ground truth.

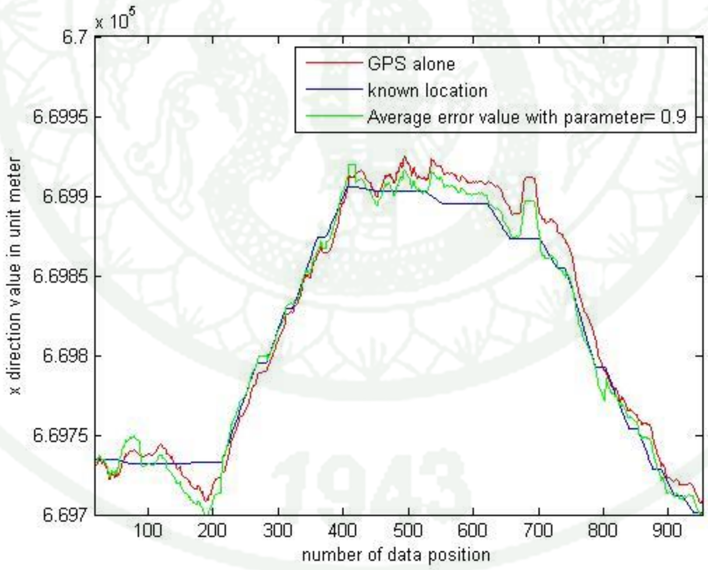

Figure 25 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.9, and ground truth

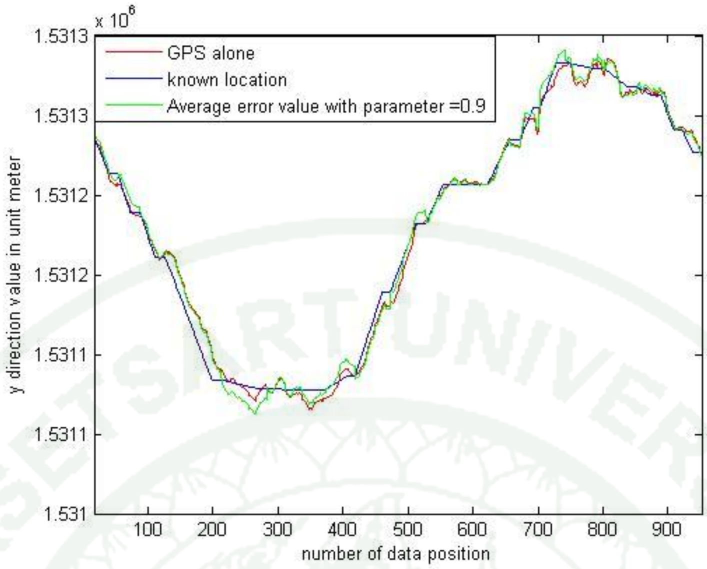

Figure 26 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.9, and ground truth

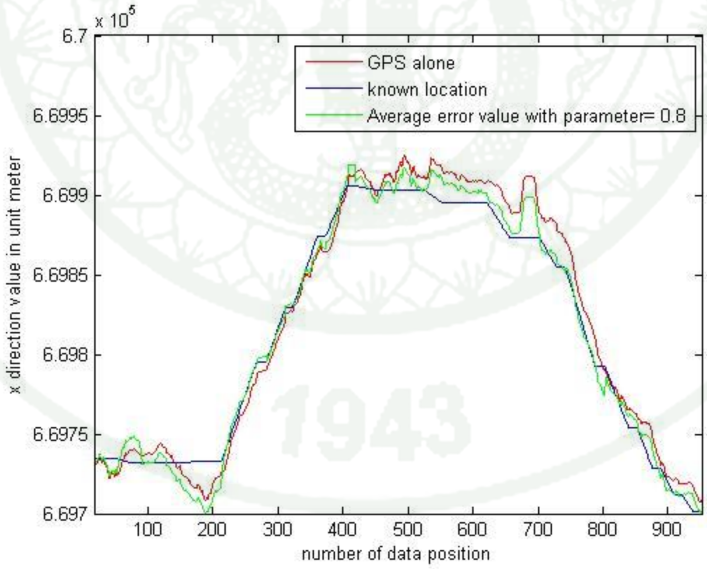

Figure 27 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.8, and ground truth

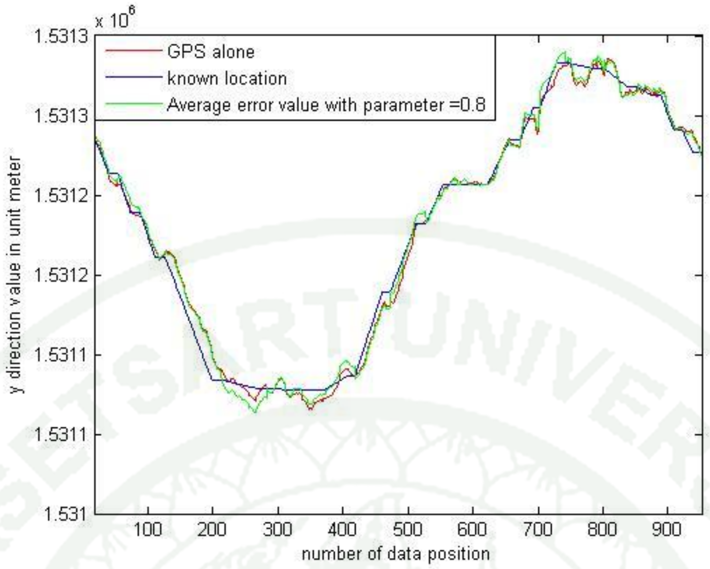

Figure 28 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.8, and ground truth

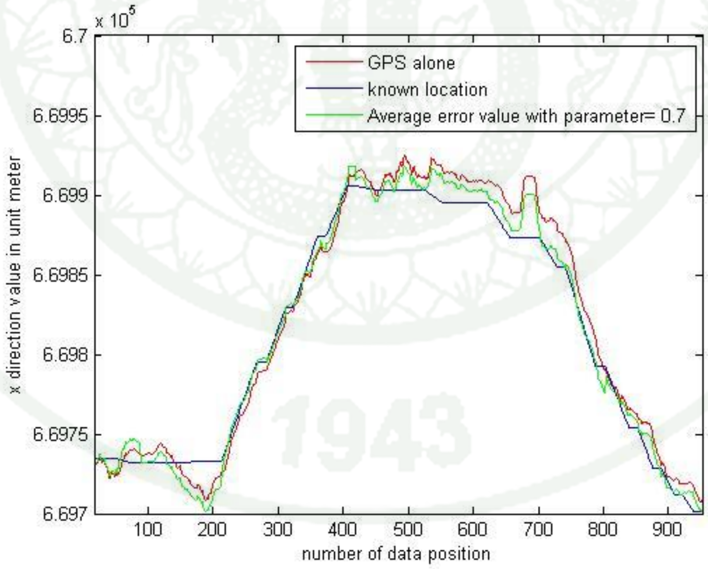

Figure 29 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.7, and ground truth

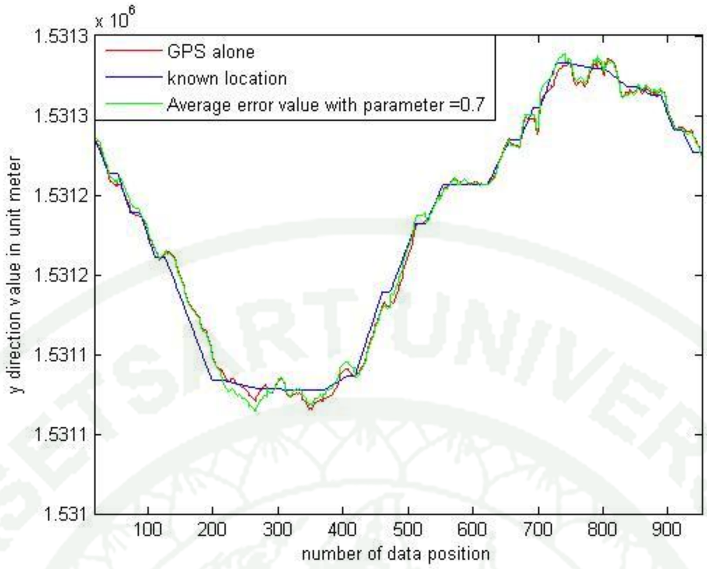

Figure 30 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.7, and ground truth

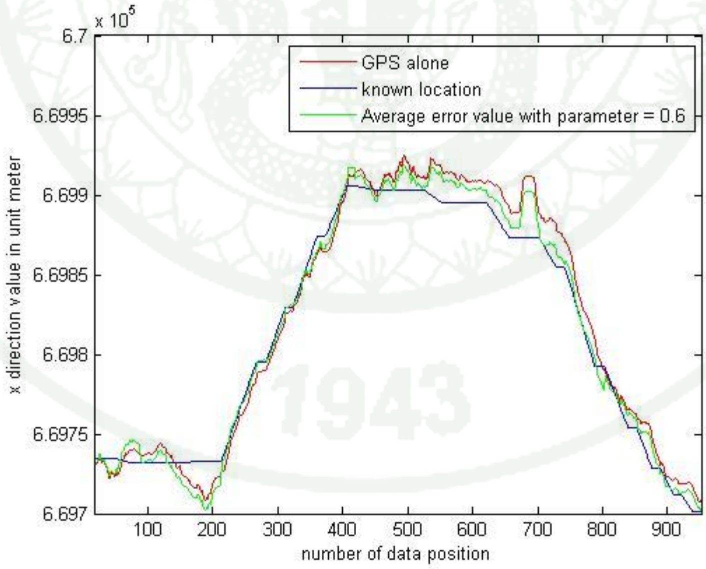

Figure 31 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.6, and ground truth

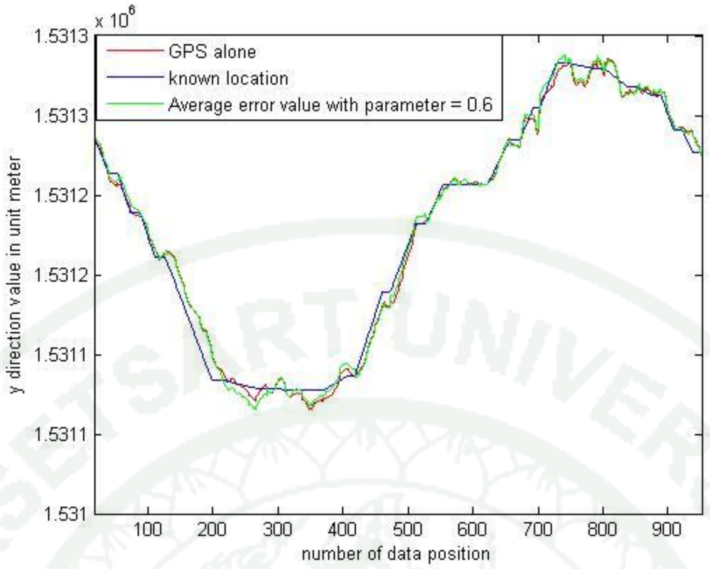

Figure 32 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.6, and ground truth

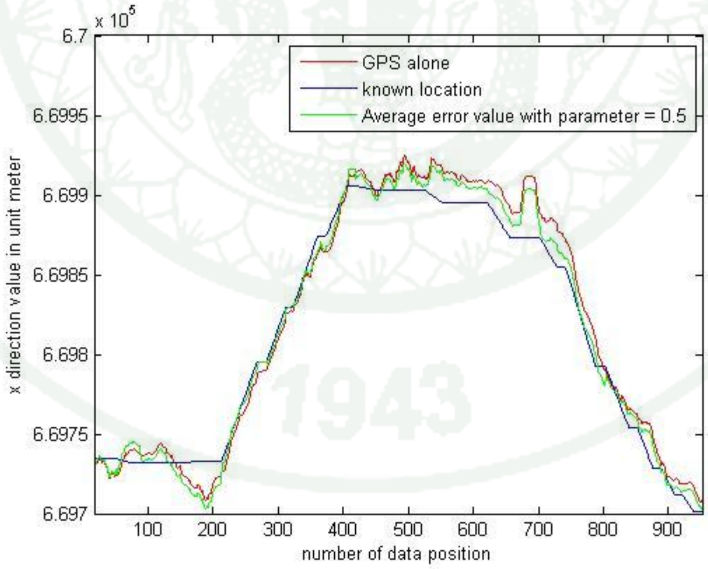

Figure 33 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.5, and ground truth

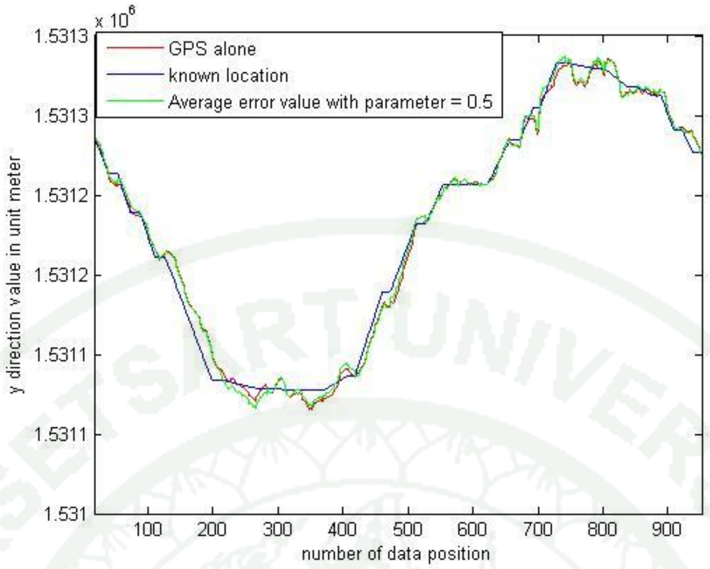

Figure 34 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.5, and ground truth

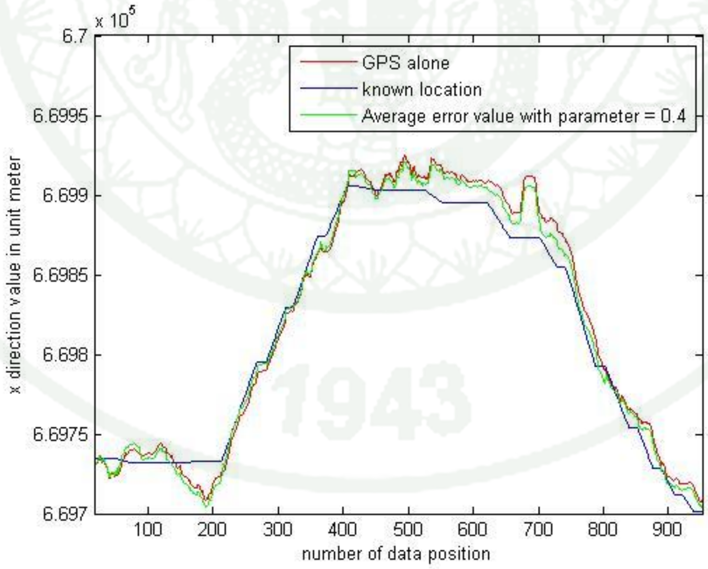

Figure 35 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.4, and ground truth

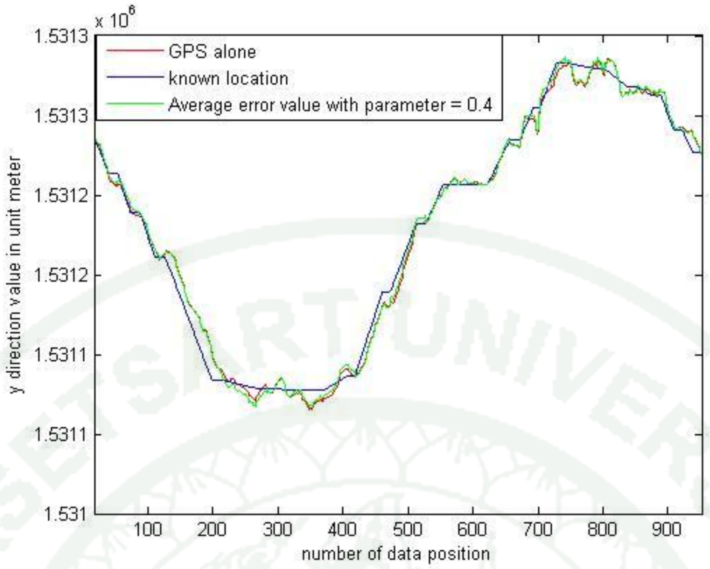

Figure 36 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.4, and ground truth

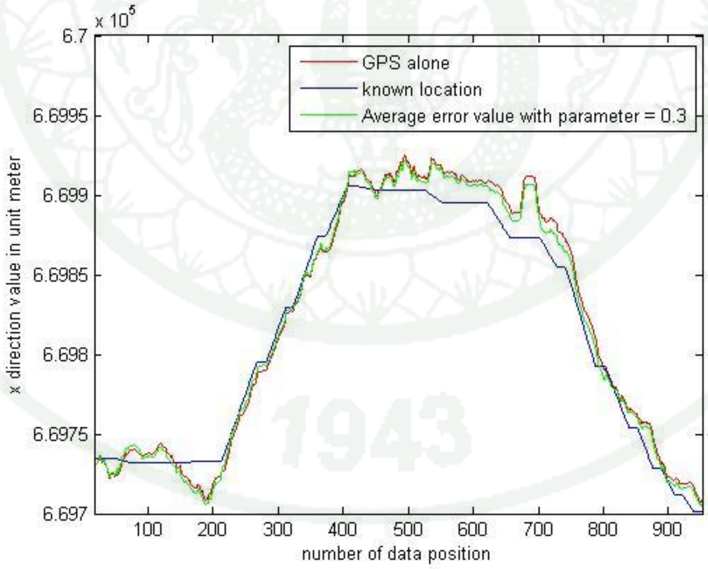

Figure 37 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.3, and ground truth

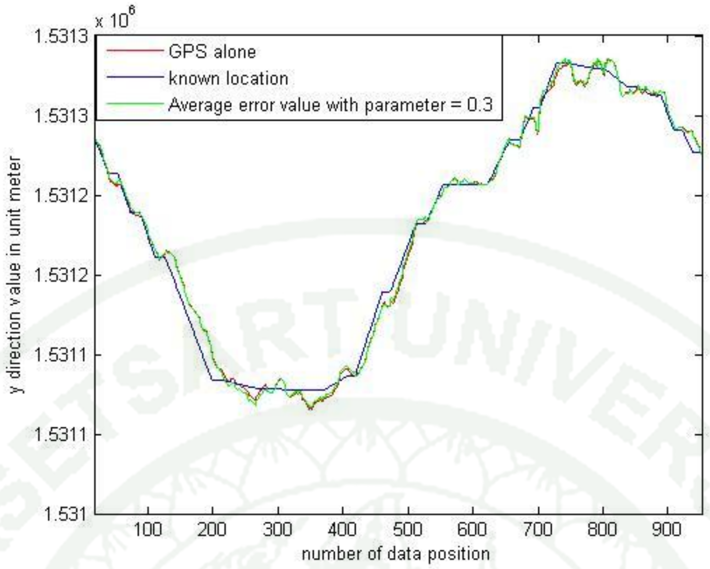

Figure 38 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.3, and ground truth

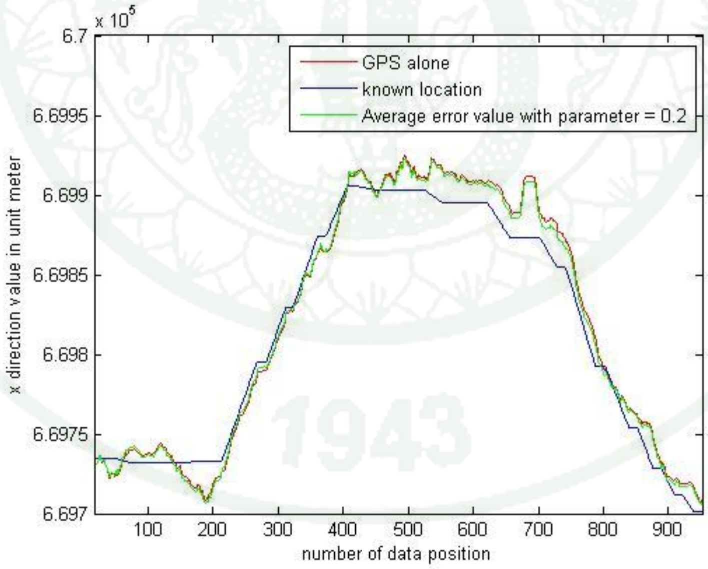

Figure 39 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.2, and ground truth

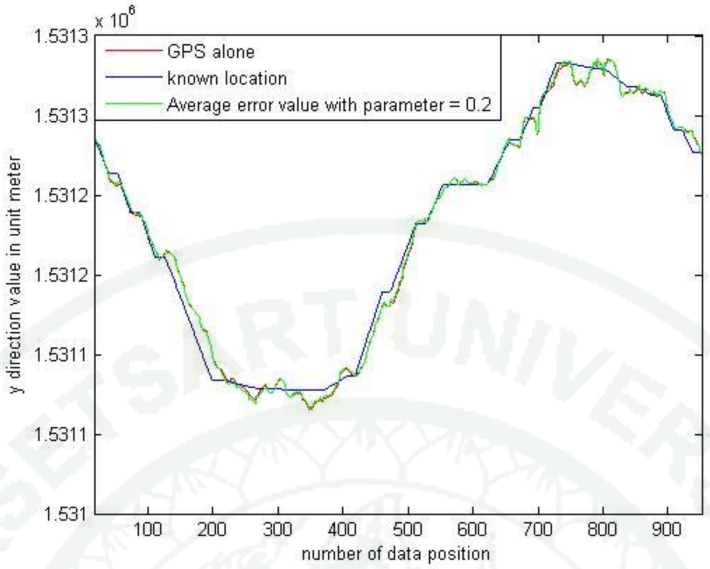

Figure 40 Comparison of positioning data in y direction from GPS, our average error value with λ = 0.2, and ground truth

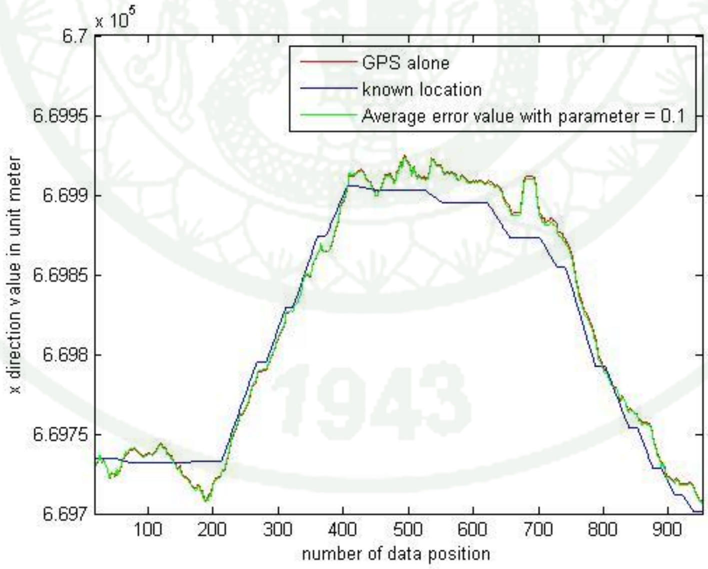

Figure 41 Comparison of positioning data in x direction from GPS, our average error value with λ = 0.1, and ground truth

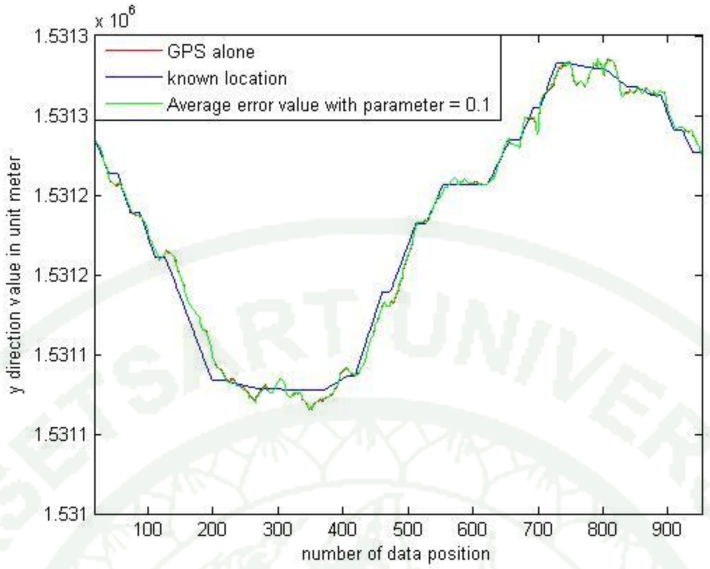

Figure 42 Comparison of positioning data in y direction from GPS, our average error value with $\lambda = 0.1$, and ground truth

2. Improve accuracy by a tracking model.

Table 5 displays the averages error of a standalone GPS and the tracking model in x direction and y direction in unit meter, respectively. With the tracking model, we can reduce x direction error by 3.87 meter or 34.08% and the error in the y direction by 1.4 meter or 29.05%.

Table 5 Average error of x direction and y direction in unit meter

Average error	x direction (meter)	y direction (meter)
GPS alone	11.35	4.82
Tracking model	7.49	3.42

Table 6 displays the overall displacement errors in unit meter error of GPS alone and tracking model. With the tracking model, we can reduce overall displacement error by 3.20 meter or 24.35%.

Table 6 The overall displacement errors in unit meter

Average error	Displacement (meter)
GPS alone	13.15
Tracking model	9.95

. Tables 7 and 8 display the maximum error and minimum error of GPS alone and tracking model as x direction and y direction in unit meter, respectively. With the tracking model, we have x direction error and y direction error less than GPS alone.

Table 7 Maximum error of x direction and y direction in unit meter

Maximum error	x direction (meter)	y direction (meter)
GPS alone	38.88	21.34
Tracking model	35.98	20.31

Table 8 Minimum error of x direction and y direction in unit meter

Minimum error	x direction (meter)	y direction (meter)
GPS alone	0.032	0.025
Tracking model	0.012	0.001

Table 9 displays standard deviation of x direction and y direction error of GPS alone and tracking model, respectively. With the tracking model, we have standard deviation of x and y direction error better than GPS alone. As result, we conclude these tracking model can reduce direction error of GPS alone error.

Table 9 Standard deviation of error of x direction and y direction

Standard deviation	x direction (meter)	y direction (meter)
GPS alone	7.32	4.33
Tracking model	6.15	4.21

Figure 43 and 44 show estimated position by tracking model . Overall, green line or algorithm tracking model can track nearly with reference line or blue line.

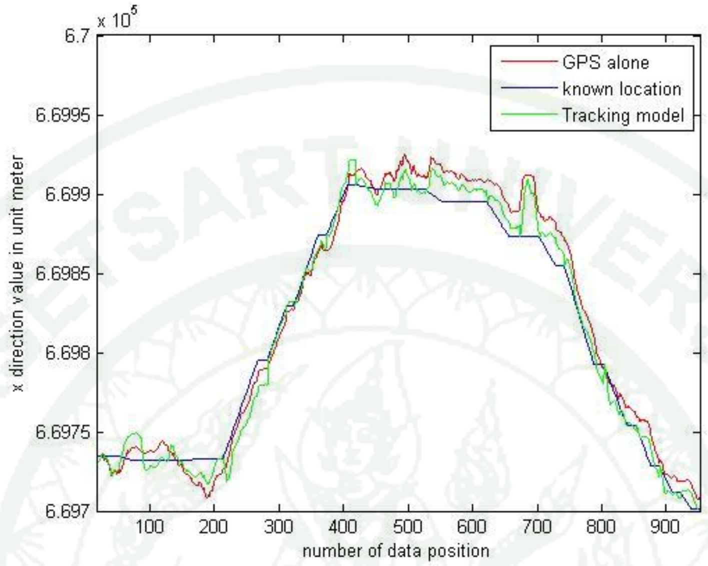

Figure 43 Comparison of positioning data in x direction from GPS, our tracking model, and the ground truth.

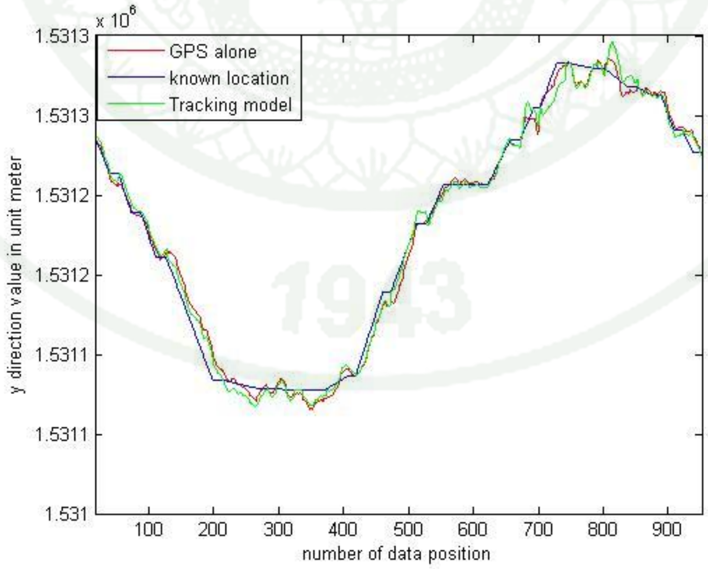

Figure 44 Comparison of positioning data in y direction from GPS, our tracking model, and the ground truth.

Furthermore, we investigate the correlation of the positioning errors and find that the correlations between X and Y of the GPS alone and our method are equal to 0.062 and 0.228.

Table 10 Average error of x and y direction of tracking model for each time by determine parameter in 5 minute

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
5 minute	3.82	1.67	6.91	5.37
10 minute	3.00	1.54	8.29	7.55
15 minute	3.09	5.17	8.74	8.35
20 minute	2.96	6.98	8.33	8.03
25 minute	2.90	7.99	7.56	7.35
30 minute	3.19	9.06	6.36	6.15

Table 11 Overall displacement error in unit meter by determine parameter 5 minute

Average error	GPS alone (meter)	Tracking model (meter)
5 minute	8.90	5.95
10 minute	9.42	7.95
15 minute	9.67	10.62
20 minute	9.14	11.54
25 minute	8.40	11.84
30 minute	7.77	12.26

Table 12 Average error of x and y direction of tracking model for each time by determine parameter in 10 minute

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
5 minute	2.17	1.71	9.68	0.37
10 minute	2.73	2.29	9.65	0.60
15 minute	2.67	2.31	8.80	1.35
20 minute	2.67	2.36	7.72	2.45
25 minute	3.06	2.72	6.25	3.95
30 minute	3.77	3.77	5.77	5.50

Table 13 Overall displacement error in unit meter by determine parameter 10 minute

Average error	GPS alone (meter)	Tracking model (meter)
5 minute	9.93	1.80
10 minute	10.05	2.41
15 minute	9.23	2.85
20 minute	8.28	3.76
25 minute	7.55	5.16
30 minute	7.66	6.81

Table 14 Average error of x and y direction of tracking model for each time by determine parameter in 15 minute

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
5 minute	3.28	2.20	9.62	0.90
10 minute	2.92	2.44	8.37	1.86
15 minute	2.84	2.43	7.07	3.17
20 minute	3.29	2.89	5.40	4.87
25 minute	4.09	3.74	4.98	6.56
30 minute	4.91	4.62	4.82	7.79

Table 15 Overall displacement error in unit meter by determine parameter 15 minute

Average error	GPS alone (meter)	Tracking model (meter)
5 minute	10.16	2.40
10 minute	8.86	3.16
15 minute	7.72	4.26
20 minute	6.95	5.91
25 minute	7.21	7.79
30 minute	7.67	9.28

Table 16 Average error of x and y direction of tracking model for each time by determine parameter in 20 minute

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
5 minute	2.56	1.71	7.12	2.83
10 minute	2.62	2.44	5.79	4.33
15 minute	3.29	3.04	3.99	6.22
20 minute	4.29	5.10	3.82	7.99
25 minute	5.23	7.86	3.86	9.20
30 minute	7.04	10.86	3.92	8.67

Table 17 Overall displacement error in unit meter by determine parameter 20 minute

Average error	GPS alone (meter)	Tracking model (meter)
5 minute	7.57	3.33
10 minute	6.50	5.14
15 minute	5.88	7.05
20 minute	6.47	9.79
25 minute	7.17	12.55
30 minute	8.78	14.92

Table 18 Average error of x and y direction of tracking model for each use of previous position predict next position

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
Position 2	5.61	4.80	3.04	4.05
Position 3	5.79	10.17	1.46	3.71
Position 4	7.67	2.77	2.23	4.23
Position 5	11.65	19.52	13.38	8.88
Position 6	7.29	17.18	2.63	5.75
Position 7	5.59	2.00	3.38	3.65
Position 8	6.75	5.13	6.78	5.63
Position 9	7.97	7.55	3.82	3.97
Position 10	6.21	4.26	7.37	6.69
Position 11	12.39	4.78	6.41	3.77
Position 12	16.87	9.72	1.55	2.2
Position 13	18.16	8.20	2.26	2.33
Position 14	32.02	21.81	5.38	5.51
Position 15	20.79	10.81	4.1	7.31
Position 16	13.33	6.27	5.75	5.84
Position 17	6.27	4.63	4.93	6.75
Position 18	13.72	5.71	1.32	1.37
Position 19	6.19	3.65	3.21	4.25
Position 20	11.18	4.91	6.48	5.04
Mean	11.34	8.10	4.49	4.78

Table 19 Overall displacement error in unit meter for each use of previous position predict next position from 100 results data

Average error	GPS alone (meter)	Tracking model (meter)
Position 2	6.63	7.06
Position 3	6.03	11.22
Position 4	8.13	5.62
Position 5	18.26	21.72
Position 6	7.92	18.3
Position 7	6.78	4.38
Position 8	9.81	7.99
Position 9	9.13	9.18
Position 10	10.26	8.28
Position 11	14.57	7.12
Position 12	16.98	10.11
Position 13	18.35	8.68
Position 14	32.92	22.89
Position 15	21.28	13.7
Position 16	15.23	9.87
Position 17	8.84	8.62
Position 18	13.84	6.3
Position 19	7.5	6.33
Position 20	13.06	7.33
Mean	12.92	10.24

Table 20 Standard deviation error of x and y direction of tracking model for each use of previous position predict next position from 100 results data

Average error	x direction of GPS alone (meter)	x direction of tracking model (meter)	y direction of GPS alone (meter)	y direction of tracking model (meter)
Position 2	3.72	3.51	2.65	2.52
Position 3	2.44	5.66	1.16	2.07
Position 4	2.52	2.59	1.24	1.54
Position 5	6.58	8.55	4.06	4.42
Position 6	2.18	2.61	2.2	3.07
Position 7	1.89	1.8	1.76	1.63
Position 8	3.33	3.32	3.15	3.6
Position 9	3.98	5.96	1.77	2.92
Position 10	3.53	2.99	1.81	1.65
Position 11	4.69	4.08	4.34	2.99
Position 12	3.52	4.5	1.25	1.68
Position 13	2.08	2.17	1.22	1.34
Position 14	8.33	8.6	4.42	3.63
Position 15	3.81	3.9	2.63	5.18
Position 16	5.79	3.12	4.4	4.59
Position 17	3.89	4.13	2.66	5.27
Position 18	5.95	4.47	0.7	1.32
Position 19	2.5	2.35	1.93	2.59
Position 20	3.65	3.96	3.77	3.41
Mean	3.91	4.11	2.48	2.91

Discussion

The average error value performs the best in the *x* direction in term error reduction, but poorly in the *y* direction .On other hand, the last error value can reduce the positioning error in the *x* direction, but less than those of the average error value. However, the error increment in the *y* direction is less than the average error value approach. Since, in this experiment, the movement occurs in *x* directions rather than in *y* direction, the error in the *y*-direction largely depends on the position noise of a GPS receiver whereas the errors in the *x* direction may result from positioning noise and misregistration from the embedded coordinate of the GeoTiff file. Because the misregistration in the remotely sensed image is highly correlated from one pixel to the neighboring pixels, the last and average error value methods can respond to this type of error very well. However, both techniques perform poorly when the major source of error is the positioning noise.

The last error value with memory parameter responds to both type of positioning errors. For example, when the parameter is set at 0.4, the error in y direction is minimized where the error in the *x* direction can still be reduced. This implies that there is the optimum parameter that minimizes the effect of the positioning noise and the misregistration. In practice, it is still a difficult task to find the optimum memory value that yield the minimum error in all cases.

The use of time domain systems to estimate positioning error can also reduce the positioning error but mostly in the *x* direction which implies that this technique responds to the misregistration error rather than the positioning noise. Regarding the optimum distance between proximity sensors, we have found in the last example that the positioning errors are temporally related in about ten minutes. As a result, the distance between adjacent proximity sensors should be reachable within 10 minutes. From the data, it appears that the standard deviation of our technique is more than GPS alone because the number of particles in the particle filters may not be sufficient.

CONCLUSION AND RECOMMENDATION

Conclusion

In this research, we introduce several techniques for improving the positioning accuracy by integrating the positioning data from a standalone GPS receiver with the prior information. This information is carried out in the form of the control points in the study area. In practice, the location of control point may be extracted by the use of a proximity sensor.

We proposed two different approaches for this problem, namely, error prediction approaches and time-domain system to estimate positioning error. In the error prediction approaches, we studied three different methods which are the last error value, average error values and last error value with the memory parameter. From our experiment, the last error value method yields the maximum reduction of the position error whereas the last error value with parameter performs poorest. Furthermore, we also observe that the last error value and the average error value methods respond to the misreistration error rather than the position noise from a GPS receiver. With the memory parameter, the positioning noise error can also be reduced.

In the time-domain system to estimate positioning error, the overall improvement is less than those of the last error value method and the robustness (standard deviation) worst than GPS alone when testing 100 times in same initial range random parameters. However, it can be adjustable to high accuracy parameter in long time. As a result, the time-domain system to estimate positioning error may be more suitable for real applications.

Recommendation

Since this experiment is based on the world coordinate embedded with the Geotiff image, the further study where the true coordinates from the ground survey are used is essential for the testing of our proposed techniques. Furthermore, we also recommend the field test of our approaches to validate the robustness and real-time implementation.

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CIRRICULUM VITAE

NAME : Mr. Sorasak Khoomboon

BIRTH DATE : September 20, 1985

BIRTH PLACE : Bangkok, Thailand

EDUCATION :

YEAR	INSTITUTE	DEGREE/DIPLOMA
2008	Kasetsart Univ.	B.Eng. (Electrical Engineering)
2010	Kasetsart Univ.	M.Eng. (Information and Communication Technology for Embedded Systems)

POSITION/TITLE : -

WORK PLACE : -

SCHOLARSHIP/AWARDS : TAIST ICTES Master Degree Scholarship

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