The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Autonomous Navigation of Mobile Robot based on DGPS/INS Sensor Fusion by EKF in Semi-outdoor Structured Environment

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Abstract—Although GPS/DGPS become the dominant localization solution in the outdoor environment, it needs assistant sensors or algorithms for the covering the area not to get the position information from GPS. Especially, in the robot navigation, the sensor fusion algorithm is needed. In addition, it is hard to get the position information at the area surrounded the high buildings such as the downtown because GPS signals is so feeble. Therefore, this paper illustrates an efficient method for the outdoor localization incorporating DGPS, Encoder, and IMU sensor based on EKF. To show the localization performances of the proposed fusion algorithm, we have implemented the proposed algorithm and applied the advertising robot platform which is operating well during 80 days in the real semi-outdoor structured environment. The proposed sensor fusion algorithm and the experimental results showed the feasibility of our novel sensor fusion algorithm.

I. Introduction

The most well-known location sensing technology using wireless communications may be GPS (Global Positioning System for short); The advantages of GPS are high accuracy, worldwide availability, and the other absolute performance [1]. For the mobile robot application, GPS can solve the kidnapped problem, for instance when the robot has sudden catastrophic failure, the position recovery would be possible. As an additional benefit, the typical GPS installation is very simple. Thanks to the upper distinguished abilities, GPS has especially become a dominant localization solution in the outdoor mobile robot and widely applied in the various research fields like the unmanned air vehicle, the car navigation, and the various military armaments. Although it has many advantages, GPS signals are always not available because the feeble signals of GPS can be disturbed by high buildings, roadside trees in downtown or among others.

The other robot localization research is to use the relative sensors (or it can be described such as dead reckoning sensors-DR) contrary to the GPS which provide the position information by means of an absolute measurement [2]. The relative sensors, e.g., robot odometer and inertial measurement unit (IMU), provide the location and pose information relative to the initial state. In contrast, the absolute sensors like GPS can provide the absolute position in certain coordinate systems. Both the absolute sensors and the relative sensors, have different advantages and disadvantages as stated above, so from that reasons, many researchers have been developed a lot of fusion algorithms. For the sensor fusion, classical approaches to the state estimate problem for a nonlinear stochastic system include the extended Kalman filter (EKF) and the Gaussian sum filter (GSF) [3]. Recently, particle filter techniques have been proposed with promising results [4][5]. The Kalman filter has been widely applied to process GPS data enhanced with dead reckoning in an integrated mode, to provide continuous positioning in built-up areas.

In this paper, we proposed the sensor fusion algorithm to combine the position information from GPS and IMU based on the extended Kalman filter. The proposed fusion algorithm is implemented and applied the advertising robot platform which is operating well during 80 days in the real semi-outdoor structured environment.

This paper is organized as follows. In section II, we will briefly introduce the semi-outdoor structured environments in where the robot is operating and moving. In section III, we propose the novel sensor fusion algorithm of EKF adapted the conditions of DGPS and describe how to navigate the robot based on the proposed algorithm. In section IV, it will be shown for the experimental systems included the robot platform and the results to verify the performances of the proposed algorithm. Finally, in section V, we summarize the contributions and limitations of our proposed algorithm and suggest future works.

This paper is submitted on February 10, 2010. This work was supported partly by the R&D program of the Korea Ministry of Knowledge and Economy (MKE). [2008-S-031-01, Hybrid u-Robot Service System Technology Development for Ubiquitous City]

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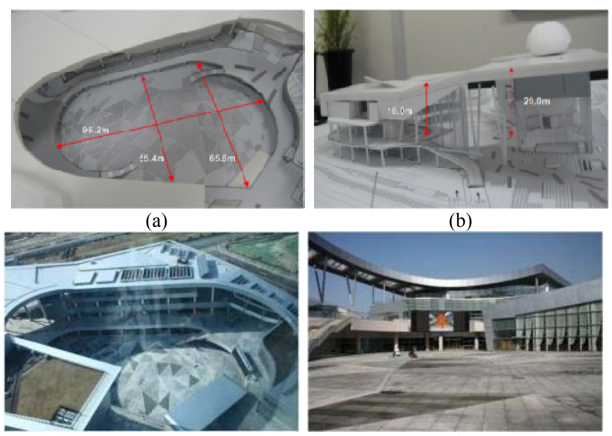
II. Outdoor Environment

A. Semi-Outdoor Structured Environments

The ‘Global Fair & Festival 2009’, which shows the advanced future technology and city, was held 80 days from Aug. 7 to Oct. 25, 2009 at Incheon in Korea. Tomorrow-city (T-city for short) is one of the places to be held the Festival. Fig.1 shows the real environment; in T-city where the outdoor robots installed our proposed algorithm have a role to advertise or announce the information of T-city.

As can be seen from Fig.1 (a) and (b), the sunken square reached 95 meters long and 60 meters wide. The height of the roofs is from 16 meters to 20 meters. This environment is different to the other general outdoor area. Therefore it is so hard to get the high-quality position information from GPS/DGPS in the T-city because there are surrounded by the high roofs formed the dome. So, we developed a sensor fusion module employing GPS, IMU, laser range finder, and odometry even to be used highly GPS-denying environment such as an outdoor plaza located in the middle of the T-city.



(a) (b) (c) (d)

Fig. 1. (a) (b): Mock-up of the Tomorrow-city, (c)(d): Landscapes of the sunken plaza of T-city.

III. Proposed Sensor Fusion Algorithm

A. Robot Kinematic Model

The kinematic of our platform robot follows the differential type. From the robot controller API, one can be known the pose of the robot at any particular instance based on the encoder calculation so called odometry. During period from time *t-1* to *t,* as shown Fig. 2, the odometry information is considered as the control actions. The control actions consist of two motions that are rotating ($\Delta\theta$) and translating (D). Since the odometry is provided as the pose information, Robot pose at any instance which is given from odometry is shown in Fig. 2. Subscript indicates the time and superscript is abbreviation for odometry.

$$x_t^o = [x_t \quad y_t \quad \theta_t]^T \tag{1}$$

To calculate the control action at time t, (2)~(3) are used.

$$D_t = \sqrt{(x_t^o - x_{t-1}^o)^2 + (y_t^o - y_{t-1}^o)^2} \tag{2}$$

$$\Delta\theta_t = \theta_t - \theta_{t-1} \tag{3}$$

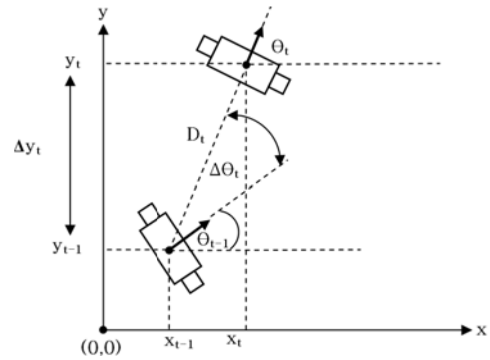


Fig. 2. Kinematics of the advertising robot. Robot is moving from pose at *t-1* to pose *t*.

B. Proposed Fusion Algorithm based on extended Kalman filter (EKF)

Two steps are the core of EKF which are prediction and update step. In prediction step, robot predicts its position one step advance by utilizing the information about control actions which are being taken. EKF formulates the predicted pose under the influence of noise which might exist in control actions information. The noise is assumed to be Gaussian noise with zero mean and its covariance matrix Q.

B.1. Prediction Step

The prediction model is given in (4).

$$\hat{x}_t = g(x_{t-1}, u_t) + w_t; \quad w_t \sim N(0, \mathrm{Q}) \tag{4}$$

Where the function $\mathrm{g}(\mathrm{x}_{t-1}, \mathrm{u}_t)$ is defined in (5) and the control action is wrapped in *u* matrix as (6).

$$g(x_{t-1}, u_t) = \begin{bmatrix} x_{t-1} + D_t \cdot cos(\theta_{t-1} + \Delta\theta_t) \\ y_{t-1} + D_t \cdot sin(\theta_{t-1} + \Delta\theta_t) \\ \theta_{t-1} + \Delta\theta_t \end{bmatrix} \tag{5}$$

$$u_t = \begin{bmatrix} D_t \\ \Delta\theta_t \end{bmatrix} \tag{6}$$

Due to noise existence during the prediction step, one cannot guarantee that the predicted pose is accurate. Up to this point, what the robot believes is the predicted pose with some degree of uncertainty. The degree of uncertainty appears in term of prediction covariance matrix ($\hat{\Sigma}$) as formulated in (7).

$$\hat{\Sigma}_t = \nabla g(x_{t-1}, u_t) \cdot \Sigma_t \cdot \nabla g(x_{t-1}, u_t)^T + Q \tag{7}$$

Where $\nabla g(x_{t-1}, u_t)$ is a gradient matrix of $g(x_{t-1}, u_t)$ evaluated at x_{t-1} and shown in (8).

$$\nabla g(x_{t-1}, u_t) = \begin{bmatrix} 1 & 0 & -D_t \cdot sin(\theta_{t-1} + \Delta\theta_t) \\ 0 & 1 & D_t \cdot cos(\theta_{t-1} + \Delta\theta_t) \\ 0 & 0 & 1 \end{bmatrix} \quad (8)$$

As the distance increases, the level of uncertainty increases as well. The process results the accumulated error. The update step is needed to bring back robot predicted pose closer to its real position. The update step is performed immediately after the measurement from the DGPS receiver and gyroscope come. To do this step, the Kalman gain and residual between measurement likelihood and real measurement need to be calculated in advance. The measurement likelihood is equal as the process of predicting a measurement based on current predicted pose. On the other hand, Kalman gain gives amplification to the residual so that it can correct the predicted pose closer to robot's real position. The measurement model shown in (9) takes into account the noise which might exist during measurement process. The measurement noise is assumed to follow Gaussian distribution with zero mean and has its covariance matrix R.

$$\hat{z}_t = h(\hat{x}_t) + v_t; \quad v_t \sim N(0, \mathrm{R}) \quad (9)$$

$$\mathrm{R} = \begin{bmatrix} \Sigma_{gps} & 0 \\ 0 & \Sigma_{gyro} \end{bmatrix} = \begin{bmatrix} \sigma^2_{x\,gps} & 0 & 0 \\ 0 & \sigma^2_{y\,gps} & 0 \\ 0 & 0 & \sigma^2_{gyro} \end{bmatrix}$$

Where $\mathrm{R} \in \Re^{3x3}, \Sigma_{gps} \in \Re^{2x2}, \Sigma_{gyro} \in \Re^1$

Since the robot receives the measurement already as (x_{gps}, y_{gps}) from the DGPS and (θ_{gyro}) from the gyroscope, the likelihood of measurement $h(\hat{x}_t)$ is the predicted pose itself. The measurement likelihood and its gradient evaluated at $\hat{x}_t$ are shown in (10) and (11) respectively.

$$h(\hat{x}_t) = \begin{bmatrix} \hat{x}_t \\ \hat{y}_t \\ \hat{\theta}_t \end{bmatrix} \quad (10)$$

$$\nabla h(\hat{x}_t) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (11)$$

B.2. Evaluation on Measurement

One key of the successful application of EKF is about the level of conformity between the real world and what we have modeled. It is related to the noise parameters both in prediction and update step as well. As long the noise we receive during robot operation conform to a priori noises parameter setting, the EKF will perform well. However, it is difficult to tackle all condition which might occur in the real world. Mainly, in the measurement part, the DGPS may suffer from drift and outlier at some place and at any particular period of time. In this case, the standard EKF will tend to perform bad or even fail. This happens since the EKF believes that the current measurement is correct and will be used in normal way. Thus, it will result very wrong estimation since the Kalman gain will amplify this current measurement normally, as if it is a correct data. The inconvenient fact is that robot cannot distinguish whether the current measurement is correct or not without any additional means. One of the simplest solutions is using threshold distance by comparing current predicted pose and current measurement. If the distance exceeds the threshold distance, robot will not use the current measurement data. However, we experienced that this method could not perform well. This is due to the reason that predicted pose has accumulated error and also we cannot guarantee that the threshold always valid in any condition because modeling DGPS error is a difficult task especially in T-city where the multipath phenomenon exists extremely. By simply comparing predicted pose and current measurement makes sense if one can make sure that the threshold will be valid in any circumstance and the odometry has small accumulated error when the comparison is performed.

Rather than using simple threshold, we take into account the uncertainty level which is shown by the covariance matrix. By using the Mahalanobis distance [2], robot decides whether current measurement is feasible to be used or not. The location (*x, y*) and heading (θ) information from measurement are assumed to be uncorrelated. Therefore, robot calculates two mahanolobis distance: location (d_{loc}) and heading (d_θ) distance. Intuitively, the covariance used in mahalobis distance calculation is a combination of current predicted pose covariance and the measurement covariance. The mahalanobis covariance is defined in (12) and (13).

$$\Sigma_{Loc} = \hat{\Sigma}_{Loc} + \Sigma_{gps}, \quad \Sigma_{Loc}, \hat{\Sigma}_{Loc}, \Sigma_{gps} \in \Re^{2x2} \quad (12)$$

$$\Sigma_\theta = \hat{\Sigma}_\theta + \Sigma_{gyro} \quad , \Sigma_\theta, \hat{\Sigma}_\theta \in \Re^1 \quad (13)$$

$\hat{\Sigma}_{Loc}$ and $\hat{\Sigma}_\theta$ are taken from the predicted pose covariance $\hat{\Sigma}_t$ for the corresponding random variables.

$$\hat{\Sigma}_t = \begin{bmatrix} \hat{\Sigma}_{Loc} & & e_{x\theta} \\ & & e_{y\theta} \\ e_{\theta x} & e_{\theta y} & \hat{\Sigma}_\theta \end{bmatrix} \quad , \hat{\Sigma}_t \in \Re^{3x3} \quad (14)$$

The mahalanobis distances are calculated in (15) and (16).

$$d_{Loc} = ([x_{gps} \quad y_{gps}] - [\hat{x}_t \quad \hat{y}_t])^T \, [\Sigma_{Loc}]^{-1} \left(\begin{bmatrix} x_{gps} \\ y_{gps} \end{bmatrix} - \begin{bmatrix} \hat{x}_t \\ \hat{y}_t \end{bmatrix} \right) \quad (15)$$

$$d_\theta = \left(\theta_{gyro} - \hat{\theta}_t\right)^T [\Sigma_\theta]^{-1} \left(\theta_{gyro} - \hat{\theta}_t\right) \tag{16}$$

If the $d_{Loc} > d_{Loc\_Threshold}$, the DGPS measurement will not be used for the update. Same policy is also applied if the $d_\theta > d_{\theta\_Threshold}$.

B.3. Update Step

A set of policy is needed to exclude covariance of wrong measurement from being counted. The set of policy follows.

(a) if $d_{Loc} < d_{Loc\_Threshold}$ and $d_\theta < d_{\theta\_Threshold}$.

$$W = \begin{bmatrix} \left(\sigma_{x\,gps}^2\right)^{-1} & 0 & 0 \\ 0 & \left(\sigma_{y\,gps}^2\right)^{-1} & 0 \\ 0 & 0 & \left(\sigma_{gyro}^2\right)^{-1} \end{bmatrix} \tag{17}$$

(b) if $d_{Loc} < d_{Loc\_Threshold}$ and $d_\theta > d_{\theta\_Threshold}$.

$$W = \begin{bmatrix} \left(\sigma_{x\,gps}^2\right)^{-1} & 0 & 0 \\ 0 & \left(\sigma_{y\,gps}^2\right)^{-1} & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{18}$$

(c) if $d_{Loc} > d_{Loc\_Threshold}$ and $d_\theta < d_{\theta\_Threshold}$.

$$W = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \left(\sigma_{gyro}^2\right)^{-1} \end{bmatrix} \tag{19}$$

(d) if $d_{Loc} > d_{Loc\_Threshold}$ and $d_\theta > d_{\theta\_Threshold}$, update step is skipped.

After that, the Kalman gain is calculated based on following formulation (20).

$$K = \left(\hat{\Sigma}_t^{-1} + W\right)^{-1} W \tag{20}$$

Therefore, the update state will be amplified by Kalman gain as in (21) and its covariance in (22).

$$x_t = \hat{x}_t + K(z_t - \hat{z}_t) \tag{21}$$

$$\Sigma_t = \left(I - K_t \cdot \nabla h(\hat{x}_t)\right)\hat{\Sigma}_t \tag{22}$$

Where the z_t is taken from the measurement device at time *t*.

$$z_t = \begin{bmatrix} x_{gps} \\ y_{gps} \\ \theta_{gyro} \end{bmatrix} \tag{23}$$

C. Navigation

Navigation is performed with incorporating with location estimate, which is described in Section III.B. We apply our robot navigation library, uRON (Fig. 3). It has a set of small task such as path planning, path following, and obstacle avoidance.

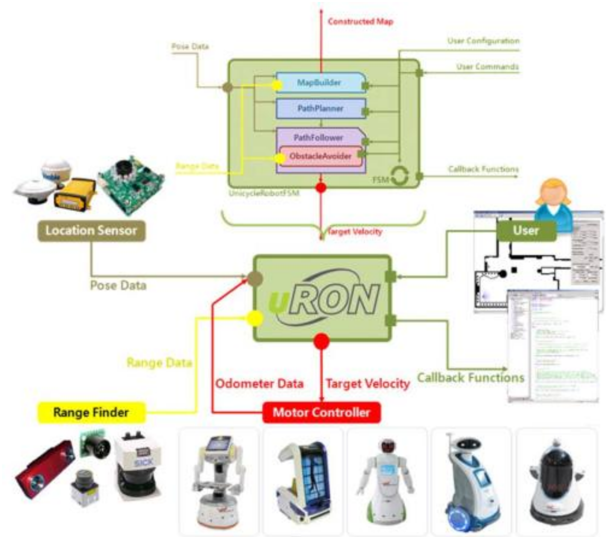


Fig. 3. System architecture of uRON

Coarse-to-Fine A* (CFA*) [6] is equipped for fast path planning on outdoor environments. CFA* automatically generates a coarse map from the given fine map using scaling. It performs path planning twice on the coarse map and fine map. At first, A* is performed on the coarse map, and marks its path on the fine map. Again, A* finds path on the fine map, but only inside of marked region. Such hierarchical search accelerates A* more than 20 ~ 40 times faster than the original A*.Pure pursuit [7] is utilized for following the resultant path. It selects a pivot point on the path (Fig. 4.), which is ahead from the current location. Error is represented by linear and angular components as follows:

$$D = \sqrt{(x_t - x_r)^2 + (y_t - y_r)^2} \tag{24}$$

$$\delta\theta = atan2(y_t - y_r,\, x_t - x_r) \tag{25}$$

Where $(x_t - y_t)$ is the pivot point and $(x_r - y_r)$ is location of robot. The target velocity can be derived to approach the pivot point as follows:

$$v_c = v_{max} \tag{26}$$

$$w_c = \frac{2v_c \sin(\delta\theta)}{D} \tag{27}$$

Where v_{max} is the given linear velocity to follow the path. The robot platform will control its linear and angular velocity toward the target velocity, v_c and w_c. Pure pursuit is simple, but effective on significant error in location estimate [8].

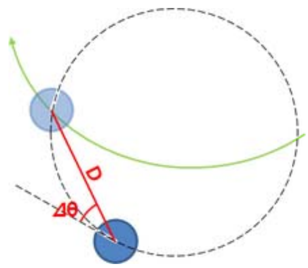


Fig. 4. Pure Pursuit (Green: Path, Red: Error)

IV. EXPERIMENTAL SYSTEM AND RESULT

A. Experimental Systems

For the evaluation of localization performance of the proposed EKF algorithm, we have developed the robot platform named the Piero which is originally for the advertisement of events or ceremonies at the outdoor sunken square in the T-city. Fig. 5 shows the base station of Differential GPS installed on the top of the T-city building and Piero robot equipped all sorts of devices included GPS receiver, gyro, laser range finder, bumper sensor and so on.

For the experiment, we have used commercial sensors like Novatel FlexPak-V1 GPS mounted on the robot and CruizCore R1001H gyro installed in the Piero robot.

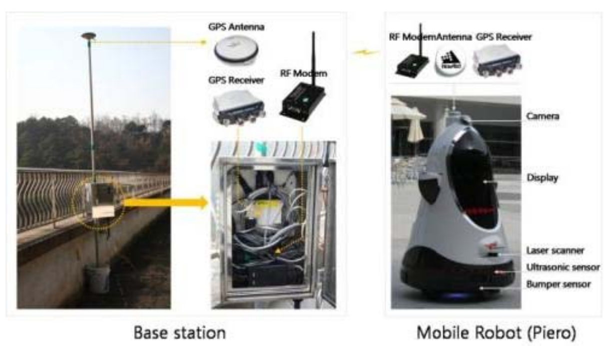
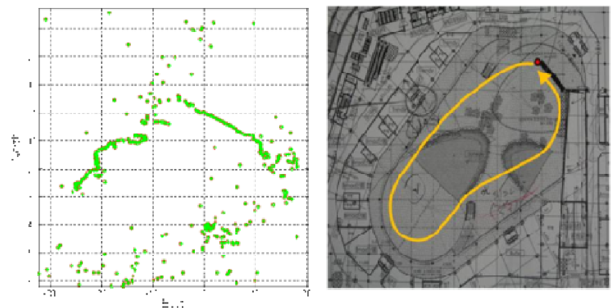


Fig. 5. Experimental systems (Differential GPS and Piero robot platform)

B. Initial Localization Result

First of all, we needed the initial test results of DGPS to estimate whether DGPS will be operating well in the sunken plaza of T-city shown in Fig.1 or not. For the initial tests, we controlled the robot to be followed the designed path shown in Fig. 6 (b). As can be seen from Fig.6 (a), the DGPS data is not always available over the whole T-city Square. The maximum error of the initial test is rarely about 25~30 meter under the influence of the multi-pass of GPS. Worst of all, it is impossible to get position information from DGPS in the several areas.

But our main goal is to create a localization sensor and to develop an autonomous navigation. Although DGPS can't provide continuously the position information to the robot, we came to the conclusion that it is possible to realize the navigation using DGPS if our proposed EKF algorithm is adopted [9][10].



(a) (b)

Fig. 6. Initial localization test results of DGPS: (a) Experimental result, (b) Designed path for the initial test.

C. Navigation Result

This section shows the experiments of the proposed algorithm at T-City sunken area. The main goal of the experiment is to know the performance of algorithm under condition (i) GPS is not always available (it might occur for long period), (ii) GPS position information suffers multipath phenomenon which causes drift and error position.

The robot was controlled to follow the designed path as the ground truth. While the robot was running, all the necessary data was saved. The EKF was performed as the tracking mode.

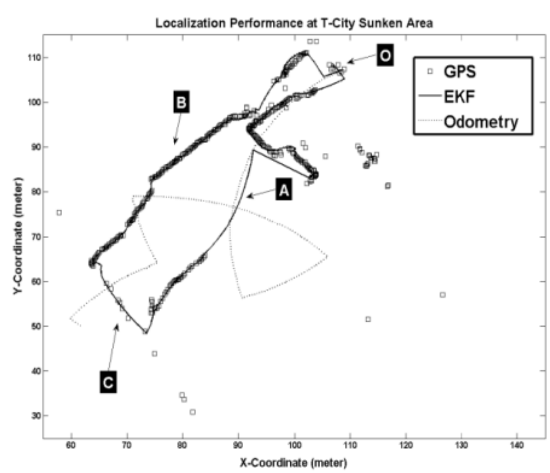


Fig. 7. Experimental result

The robot initial position was located at O (Fig. 7). The robot started to move counterclockwise to create close loop. Even though the robot was at initial position, the GPS measurement was already showing large position error. If we were using just a simple EKF, the tracking process could already fail immediately. Here is the benefit of calculating the mahanolobis distance. It can filter out the wrong measurement by taking into account the level of uncertainty. Indeed, the robot is more certain about its position at initial. As the time goes by, if the uncertainty level is increasing, the robot is forced to accept the measurement as update since there is no choice on how to update the position.

The blue line shows the odometry reading. It has accumulated error as the time is increasing. At the B area, the robot could receive GPS measurement continuously. Though, the received GPS position has error, that information was used in update step of EKF to refine the predicted position. At the C area, the robot received many erroneous GPS position for some period. It could be sourced from an abrupt changes of satellite set used for fixing GPS position. However, the EKF performed well under such kind of situation. At the A area, the robot could not receive enough GPS satellites signal for a long time. Thus, robot was greatly depending only on the predicted position with its accumulated error. During this period, the uncertainty increased as the distance increased. When the robot acquired the GPS position again, robot suddenly used that GPS position to recover the current position. For the overall result, the robot could be tracked until the last position even though it experienced long period worse condition (at area A).

V. Conclusion

We proposed the localization and navigation algorithm based on EKF in the semi-outdoor structured environment (the sunken plaza in T-city) and we have developed the robot platform named 'Piero' and DGPS for the evaluation of localization/navigation performance of the proposed algorithm in term of operating the robot during 80 days in the real field. Our future work will be focused on that if GPS signals are blocked continuously, the covariance in EKF is increasing and then it can't guarantee the fine localization information. We will adopt the other absolute sensor such as the ultra wideband in place of GPS. In addition, we will apply the novel sensor fusion algorithm with the way of adding the map matching algorithm in the present proposed fusion algorithm.

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