2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

Vehicle Localization in Outdoor Woodland Environments with sensor fault detection

Yoichi Morales, Eijiro Takeuchi and Takashi Tsubouchi

Abstract— **This paper describes a 2D localization method for a differential drive mobile vehicle on real forested paths. The mobile vehicle is equipped with two rotary encoders, Crossbow's NAV420CA Inertial Measurement Unit (IMU) and a NAVCOM SF-2050M GPS receiver (used in StarFire-DGPS dual mode). Loosely-coupled multisensor fusion and sensor fault detection issues are discussed as well. An extended Kalman Filter (EKF) is used for sensor fusion estimation where a GPS noise pre-filter is used to avoid introducing biased GPS data (affected by multi-path). Normalized Innovation Squared (NIS) tests are performed when a GPS measurement is incorporated to reject GPS data outliers and keep the consistency of the filter. Finally, experimental results show the performance of the localization system compared to a previously measured ground truth.**

I. Introduction

A. Research Motivation

Our research motivation is the automation of construction vehicles in woodland mountain environments. The final goal is the achievement of autonomous navigation in such environments where a reliable and robust localization system is crucial. This research objective is the development of a robust, reliable, sensor fault-proof localization system.

Vehicle localization in outdoor woodland environments is a challenging field that is still unexplored and open for research. In such outdoor environments, common odometry fails because of non-flat irregular surfaces, dead reckoning using inertial units is subject to integration errors and GPS which is one of the most used solutions in outdoor is not completely reliable when there are tall obstacles such as trees that can block the signal coming from satellites.

In this paper authors report the particular problems of vehicle localization on forested paths; furthermore, the multisensor localization framework with sensor outlier rejection is also presented.

B. Related Works

Many works in multisensor fusion and fault tolerant localization methods have been proposed in previous works.

P. Sundvall in [1], proposed a method for detecting slip in real time applying the mahalanobis distance using as threshold chi square criteria in a denominated CUSUM test. N. Schmitz et al. in [2] developed a 3D localization system fusing odometry with DGPS, IMU, magnetic field sensor and vision offering 2m precision. J. Huang et al. in [3] proposed a positioning system using a noise preprocessor for DGPS data to reduce non-Gaussian noises from GPS observations obtaining accuracy in the range of 30-50cm. S. Scheding et al. in [4] proposed a metric for determining the detectability of faults using frequency domain techniques in Kalman filter based systems mentioning the importance of sensor redundancy. E. M. Nebot et al. in [5] and [6] treats the issues of sensor faults, decentralized architectures and asynchronous sensor fusion where there are individual loops incorporating information to a master filter. K. Ohno et al. in [7] achieved autonomous navigation in walkways between buildings fusing odometry with DGPS data, rejecting GPS outliers thresholding mahalanobis distance. P. Lamon et al in [8] developed a multisensor system for navigating and mapping in large scale environments. Thrun et al. in [9] describes the multisensor system used for winning DARPA's Grand Challenge 2005 where vehicle autonomous navigation of 142 miles in desert environments was achieved.

The core of this work is the implementation of a multi-sensor localization approach using an EKF on real outdoor paths with tree foliage and to report experimental results.

C. Forested Paths

In this work, a forested path is a paved or graveled path where a common wheeled vehicle can traverse. The path sometimes is surrounded by many variations of trees around it. The surface is sometimes covered with fallen leaves, branches, acorns and small stones that cause wheel slip (non-systematic errors). The length and type of trees and tree percentage around the path vary from each environment. The lowest tree percentage around the path the highest percentage where GPS can be used for vehicle localization. These kind of environments do not present favorable conditions for vehicle localization. For this research, University of Tsukuba's campus woodlands were used as experimental environments.

In this section introduction was provided, in section II sensor fault detection is briefly discussed, sections III and IV present system hardware and software, section V explains the localization approach, section VI presents experimental procedure and conclusions are presented on section VII.

II. Sensor Fault Detection

A. Redundancy

It is crucial to construct a system capable of detecting and handling a fault in a localization system. In order to be

This work has been supported by the Japan Society of Promotion of Science (JSPS) Grant-in-Aid for Scientific Research (Scientific Research (B)) under contact number 18360116

Y. Morales, E. Takeuchi and T. Tsubouchi are with Graduate School of Systems and Information Engineering University of Tsukuba, Tsukuba, 305-8573, Japan (yoichi,etake,tsubo)@roboken.esys.tsukuba.ac.jp

able to detect and find faults in a multisensor system, sensor redundancy is necessary. A system with sensor redundancy is a system in which a variable can be measured by two or more sensors with different characteristics. As there is nothing such as a "perfect sensor" multiple sensors with different properties that fail in different ways measuring the same variable are complementary used.

B. Sensor Selection

Three sensors with different characteristics were used for vehicle localization: wheel encoders for vehicle linear velocity, an IMU for angular velocity and GPS for position. Wheel encoders and IMU offer high rate information which are integrated in time to offer vehicle localization which suffers from unbounded errors as traveled distance increases. A low response sensor such as GPS which does not suffer from integration errors is used as external sensor for position correction.

C. Consistency

As defined by Y. Bar-Shalom et al. in [11], in a state estimation filter such as in the Kalman filter framework, a filter is considered consistent if its estimation errors are commensurate with the filter-calculated covariance. This is, if the estimated state with its covariance is within the real ground truth. Kalman Filters rely strongly on the model of the system and observation. If the models are not adequate, the filter will have incorrect innovations and estimations so it will not be consistent. On the other hand, if models are correct but sensor observation data or sensor noise covariance are incorrectly introduced, the filter estimation will not be consistent. Normalized Innovation Squared "NIS" test (section V) for consistency check is used for GPS data outlier rejection to keep filter's consistency.

III. System Hardware

A. Mobile Robot Platform

For this research we use a Yamabico Platform medium sized robot. This robot is a differential drive vehicle with front wheel traction. Its dimensions are 50cm x 50 x 170cm (LxWxH).This robot has two Sanyo Denki 60 Watt DC Motors with rotary encoders attached for odometry computation. The robot is equipped with Crossbow's NAV420CA IMU and NAVCOM SF-2050M GPS receiver (Fig. 1.). The user notebook is a Panasonic Toughbook CF-30 with a 1.66Gz Intel core duo processor, the OS used is Ubuntu Linux, kernel 2.6.20-16.

B. Crossbow's NAV420CA Inertial Measurement Unit (IMU)

NAV420CA IMU is a measurement system composed of three accelerometers, three gyros, four temperature sensors, a three axis fluxgate magnetometer board and a GPS receiver (not used in this work), It operates in a temperature range of -40 to +71 ^{o}C, it detects angular velocities within 200^{o}/sec and accelerations of within 4Gs. Authors have performed several tests in outdoor environments and determined to use and integrate temperature corrected angular velocity information for vehicle orientation.

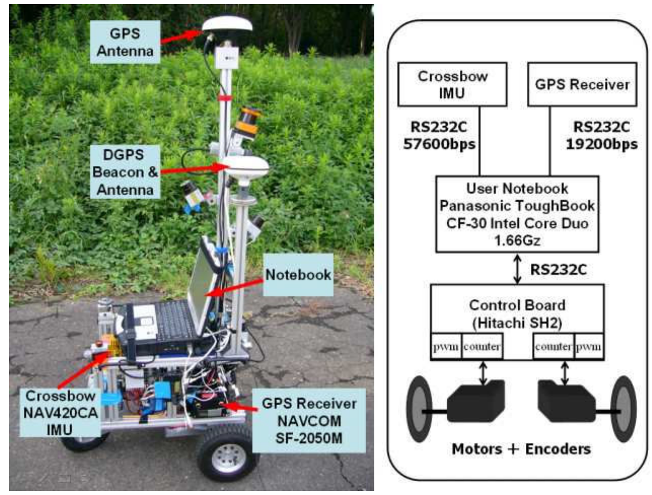

Fig. 1. Yamabico Platform Mobile Robot with GPS Receiver and Antenna

C. NavCom SF-2050M

SF-2050M GPS receiver has 26 tracking channels (12 L1/L2 full wavelength carrier phase tracking GPS + 2 dedicated SBAS), C/A P1 and P2 code tracking. It has a tri-band antenna which can receive GPS and StarFire signals [12][13][14]. It has an accuracy using real-time StarFire system of within 10cm in horizontal position and within 15cm (rms) in vertical position. Antenna Type: Triband Dipole.

1) GPS Receiver Configuration: For experiments reported in this paper, GPS receiver had the next settings:

- Used in StarFire-DGPS dual mode (StarFire Differential Service coupled with CSI-Wireless SBA-I beacon for differential correction). In this configuration, solution changes in a seamless way to the most precise available mode (Fig. 2).
- Satellites Required for solution: 4
- Solution Mode: 3D
- Max HDOP[1]: 5
- Logging Rate: 1Hz
- Antenna Height on Mobile Vehicle: 1.70m

IV. Software

For appropriate sensor data fusion, it is necessary to utilize information from each sensor at the proper time of the measurement, i.e., sensor data has to be fused as precisely as possible in the instant the measurement was realized. For this purpose, in this work, "SSM" (Sensor Sharing Manager) software developed in our laboratory was utilized [15]. SSM is a multiprocess software composed of three sections (see Fig. 3.):

1) Sensor driver: Is in charge of connecting to each sensor, receive data and register it in the SSM. There are

[1]DOP Dilution of Precision is a unit less measure of the magnitude of error in GPS position fixes due to the orientation of the GPS satellites with respect to the GPS receiver. DOP is provided by GPS as output in NMEA format. There are different terms to measure different components of the error (GDOP,PDOP, HDOP, VDOP,TDOP)

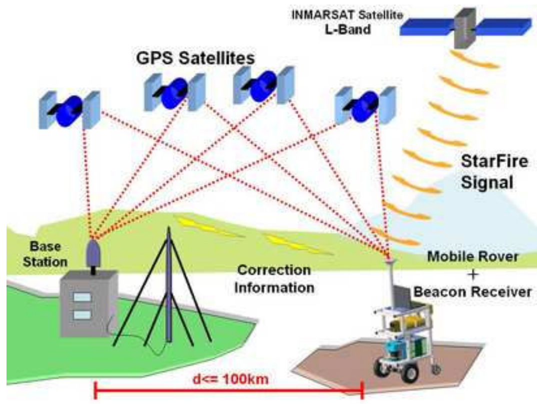

Fig. 2. StarFire-DGPS dual mode

3 sensor drivers running in parallel. One for encoder information running at 20ms (receiving 4 readings each sampling). Second sensor driver is for Crossbow's IMU information running at 10ms. Third sensor driver is for GPS data received each 1 second.

2) SSM (Sensor Sharing Manager): SSM is a shared memory space which receives data from each sensor driver, puts a time stamp to it and keeps a register of the last values in a ring buffer on shared memory. When sensor data is used by a user process, synchronization is performed according to arriving time stamps (also treated in [5][6]).
3) User process: In this case data fusion process which connects to the shared memory block, reads time stamped information of each sensor and fuses each sensor data interpolating them to the closest value in time. Many user processes can be running in parallel accessing sensor information.

SSM software framework is a powerful tool for multisensor data synchronization and fusion because of the capability of increasing the number of sensors simply adding sensor drivers and registering them to the shared memory.

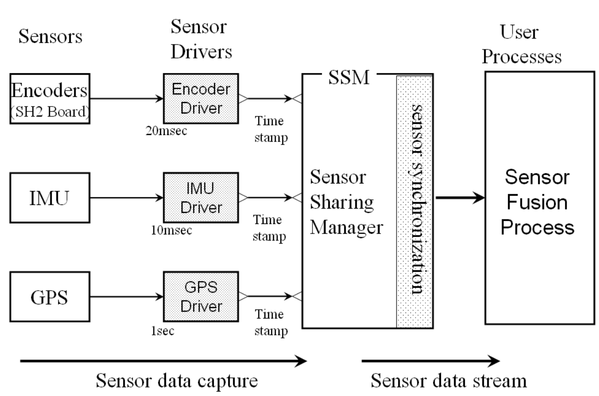

Fig. 3. Sensor Sharing Manager "SSM" illustration

V. Localization Approach

An Extended Kalman Filter (EKF) was used for data fusion where the state vector is given by $x = [x, y, \theta]^T$. First, it is necessary to have a robust dead reckoning method that can keep accurate localization estimation on irregular surfaces when no external sensor observation is available. For air-pressure tire vehicles, it is difficult to accurately determine the wheelbase causing errors in angular velocity calculation. Furthermore, having an erroneous orientation angle produces unbounded positioning error as vehicle travels. In this research, a method similar to "gyrodometry" proposed by J.Borenstein is used for determining vehicle's dead reckoning with the difference that angular velocity was calculated using only the IMU's gyro. The measurement model is given by expression (1):

$$\hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} + \begin{pmatrix} v_k \cos(\theta_k) \\ v_k \sin(\theta_k) \\ \omega_k \end{pmatrix} t \qquad (1)$$

where "v_k" is the velocity calculated by left and right motor encoders $v_k = \frac{v_r + v_l}{2}$ and "ω_k" is the vehicle's yaw angular velocity determined by IMU. "t" is the sampling time.

With this method, yaw angle is not affected by wheel slip. However, slip still produces error in the calculation of v_k. The predicted covariance $P_{k|k-1}$is a 3x3 matrix given by expression:

$$P_{k|k-1} = G_k P_{k-1|k-1} G_k^T + Q_k \qquad (2)$$

where G_k is the Jacobian of the model and Q_k is the process noise.

GPS on forested paths

GPS receiver outputs on-line text sentences in NMEA 0183 format. NMEA sentence GGA was used for position information $z_k = [x_{GPS}, y_{GPS}]^T$and quality indicator (coordinate conversion was done according to Japanese Geographical Survey Institute [17]). GSA sentence is used for Dilution of Precision (DOP) parameters. GST sentence (Pseudorange noise statistics) for measurement standard deviation information. Standard deviation information is used to calculate covariance matrix of GPS observation $R_k = \begin{pmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 \end{pmatrix}$ Under tree shading, biased GPS position data with small covariance can be rejected thresholding measurements with small HDOP values and large number of satellites used for solution (Y. Morales et al. in [18]). A value under 4 for HDOP and a number of 5 or more satellites were used as thresholds for GPS data pre-selector. GPS data that does not satisfy this condition is discarded under the assumption that for filter consistency and position accuracy, it is better to have reliable data even if availability percentage in GPS measurements is decreased. Fig. 4. shows the general scheme for GPS data fusing. Before filtering, GPS data is pre-selected for reducing non-Gaussian non white noise observations.

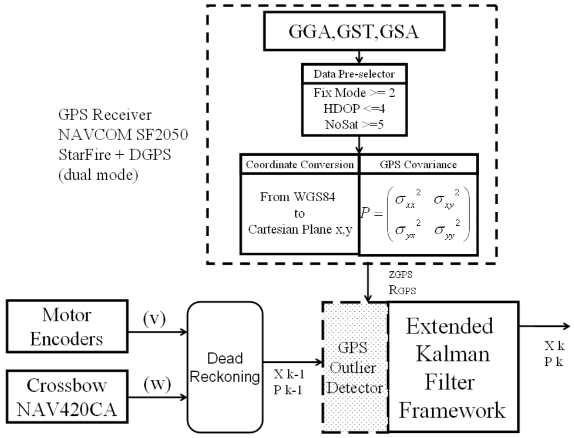

Fig. 4. Scheme for GPS data fusing

NIS test for Consistency Checking

Despite that GPS measurements passed the previously explained pre-filtering test, there is the case that data affected by multipath is considered as reliable (erroneous position data with small covariance). For GPS outlier detection and rejection, a NIS test is performed before incorporating GPS measurement for state estimation. Under the consideration that the model of the system and the filter is consistent, the normalized innovation squared (NIS) test (which can also be seen as the mahalanobis distance using the innovation matrix as normalizer) has a chi-square distribution. This test is sensitive to variance changes as well as changes in the mean.

$$NIS = \chi^2 = (z_k - \hat{x}_{k|k-1})^T S^{-1} (z_k - \hat{x}_{k|k-1}) \quad (3)$$

where "$S = \bigtriangledown H_k P_{k|k-1} \bigtriangledown H_k^T + R_k$" is the innovation matrix in the Kalman filter correction step, "$z_k = [x,y]^T$" is the GPS observation and $\hat{x}_{k-1} = [x,y]^T$ is the state vector before update. χ^2 can be shown to be the sum of the squares of n independent zero mean univariate Gaussian random variables [16]. The fitting error χ^2 ("goodness of fit") has to be below a threshold in order to be acceptable. In this work, according to the degrees of freedom of the system, the 95% confidence level was used as threshold.

If the observation pass the NIS check test, then Kalman gain is calculated and state vector and covariance matrix are updated. The update step of the Extended Kalman Filter is standard and equations are omitted on this paper. Finally, if check test is not passed then GPS observation is discarded and no update is performed.

On outdoor forested environments, there are three different types of configurations for vehicle localization estimation:

1) Dead reckoning position corrected by GPS on open sky (normally, reliable GPS data is available).
2) Dead reckoning position occasionally corrected when reliable GPS information is available (partial open sky) and NIS test for consistency is passed.
3) Dead reckoning without correction when there is not reliable or no GPS data at all because of tree foliage around the path (barely or no open sky).

VI. Experimental Setup & Results

A. Experiment Location

Experiments were done on a forested path at the Campus of the University of Tsukuba (depicted on Fig. 5). A total of fourteen points connected by straight lines were measured and used as ground truth. Ground truth points were measured in stand still mode (with a GPS tripod) using Trimble's 5700 RTK-GPS in fixed solution (precision within 2 cm) taking 10 minutes for each point. The total length of the path is of 303.3 meters. The testing path is classified as follows:

1) Both sides of the path covered by trees (barely or none open sky available). Segments D-E, and E-F, covering 32.062% of the total path.
2) One side of the path covered by trees (half open sky). Segments F-G, G-H, H-I, M-N, covering 24.346% of the path.
3) Open sky available. Segments A-B, B-C, C-D, I-J, J-K, K-L, L-M: 43.574%

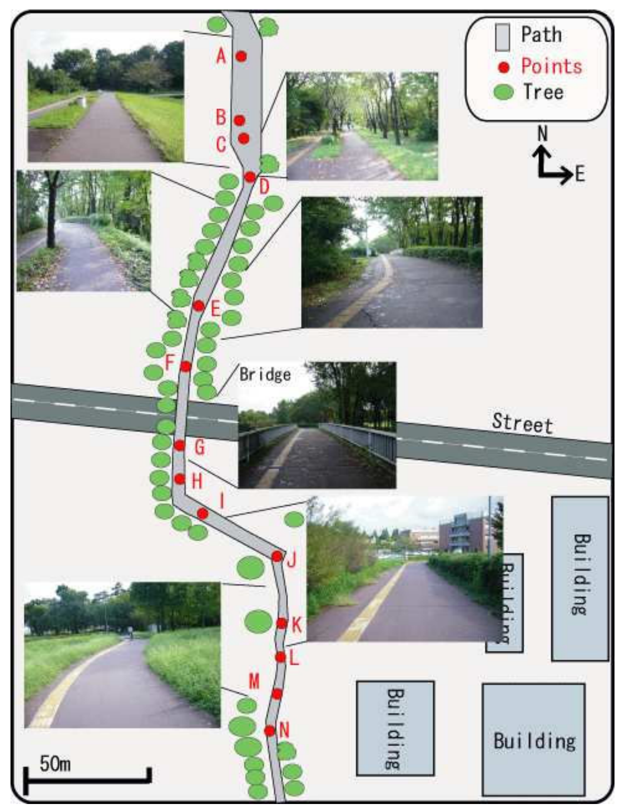

Fig. 5. Map of RTK-GPS measured points on the Forested path

B. Running Experiments

Start position was selected to be a tree free environment (point "A"), where GPS could be initialized. After initialization, mobile platform was moved by remote control at a maximum speed of 1m/sec traveling in straight line passing through all the points marked in the map (Fig. 5.) until finishing on point "N", while sensing and fusing data.

C. Experimental Results

First, DGPS-StarFire measurements information is shown on Fig. 6. Preselected data considered as reliable is shown on red and discarded DGPS data is shown on blue.

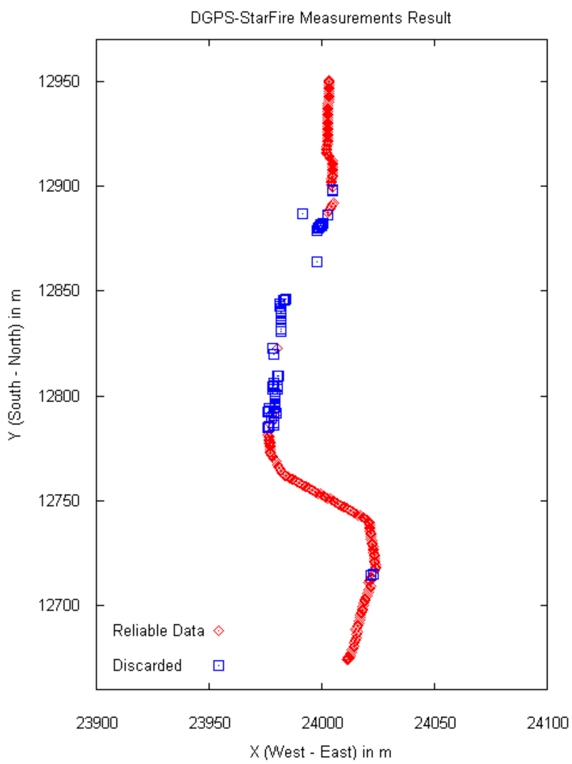

Fig. 6. DGPS-StarFire Dual Mode Result of one running experiment

Estimated final results are shown on figure Fig. 7 which shows estimated vehicle position in dark blue, estimated covariance ellipses in light blue and previously measured ground truth in red. When there is reliable GPS data available, dead reckoning prediction is corrected with such data canceling accumulated error. Experimental results also show that after the longest period when GPS data is not available (Segment D-H), the maximum error of position estimation is within 3m. It has to be noticed that even is position estimation has error, the ground truth is within the estimated covariance ellipses.

Several running tests were performed on the same environment at different times obtaining similar results. If the EKF is not initialized with reliable GPS observations and there is an immediate GPS outage, all GPS data could be rejected by NIS test. To avoid this, several minutes were taken for GPS receiver initialization before going into the tree foliage.

VII. CONCLUSIONS AND FUTURE WORKS

In this paper a localization strategy for a differential drive wheeled vehicle in forested paths was proposed. The hardware and software framework were also described. Moreover, loosely coupled sensor fusion approach with GPS data pre-selector and GPS outlier rejection were presented and discussed. Experimental results on real outdoor woodland paths show the performance of our approach, where in the path sections where GPS was not available, dead reckoning precision was within 3 meters. When available, GPS could correct accumulated error. This method works with periodically GPS observations, in the case of large periods without GPS, the method can fail if dead reckoning error is too big so that correct GPS data is rejected by NIS test. If there is the certainty that a GPS observation is correct, this problem could be solved reseting the EKF, setting new mean and covariance. As future work in a map based localization framework (using a previously measured map as presented in this paper), authors plan to incorporate a laser range scanner for road detection and vehicle's position and orientation correction towards the map.

VIII. ACKNOWLEDGMENTS

The authors acknowledge the contribution of A. Carballo and W. Tokunaga, members of the Intelligent Robot Laboratory for their support in outdoor experimental procedures.

REFERENCES

[1] P. Sundvall and P. Jensfelt. "Fault detection for mobile robots using redundant positioning systems" *Proc. of the IEEE International Conference on Robotics and Automation (ICRA'06)*
[2] N. Schmitz, J. Koch, M. Proetzsch and K. Berns. "Fault-Tolerant 3D Localization for Outdoor Vehicles" *Proc. of the 2006 IEEE/RSJ Int Conf. on Intelligent Robots and Systems, October 2006*
[3] J. Huang and H. S. Tan. "A Low order DGPS-Based Vehicle Positioning System Under Urban Environment" *IEEE/ASME Transactions on Mechatronics, Vol.11. No.5, October 2006*
[4] S. Scheding, E. M. Nebot and M. Durrant-Whyte "The detection of faults in navigation systems: A frequency domain approach." *Int. Proc. of the IEEE International Conference of Robotic and Automation, Belgium, pp. 2117-2222*
[5] E. M. Nebot and H. F. Durrant-Whyte "A high integrity navigation architecture for outdoor autonomous vehicles" *Robotics and Autonomous Systems 26(2-3): 81-97 (1999)*
[6] E. M. Nebot M. Bozorg and H. F. Durrant-Whyte "Decentralized Architecture for Asynchronous Sensors" *Autonomous Robots, Vol. 6 No. 2 (147-164), 1999 Robotics and Autonomous Systems 26(2-3): 81-97 (1999)*
[7] K. Ohno, T. Tsubouchi, B. Shigematsu and S. Yuta. "Proper Use of GPS for Outdoor Navigation by an Autonomous Mobile Robot", *Proc. of Int. Conf. on Intelligent Autonomous Systems (2004)*1070-1079
[8] P. Lamon, C. Stachniss, R. Triebel, P. Pfaff, C. Plagemann, G. Grisetti, S. Kolsky, W. Burgard, and R. Siegwart. "Mapping with an autonomous car." *IEEE/RSJ IROS 2006 Workshop: Safe Navigation in Open and Dynamic Environments, Beijing, China, 2006*
[9] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L.-E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney. "Stanley: The Robot that Won the DARPA Grand Challenge." *Journal of Field Robotics, 2006*
[10] J. Borenstein and L. Feng. "Gyrodometry: A New Method for Combining Data from Gyros and dometry in Mobile Robots". *Proceedings of the 1996 IEEE International Conference on Robotics and Automation, Minneapolis, Apr. 22-28, 1996, pp. 423-428.*
[11] Y Bar-Shalom, X.R. Li and T. Kirubarajan "Estimation with Applications to Tracking and Navigation." *2001 - Wiley-Interscience*
[12] K. Dixon, "StarFire: A Global SBAS for Sub-Decimeter Precise Point Positioning", *Proceedings of ION GNSS 2006*

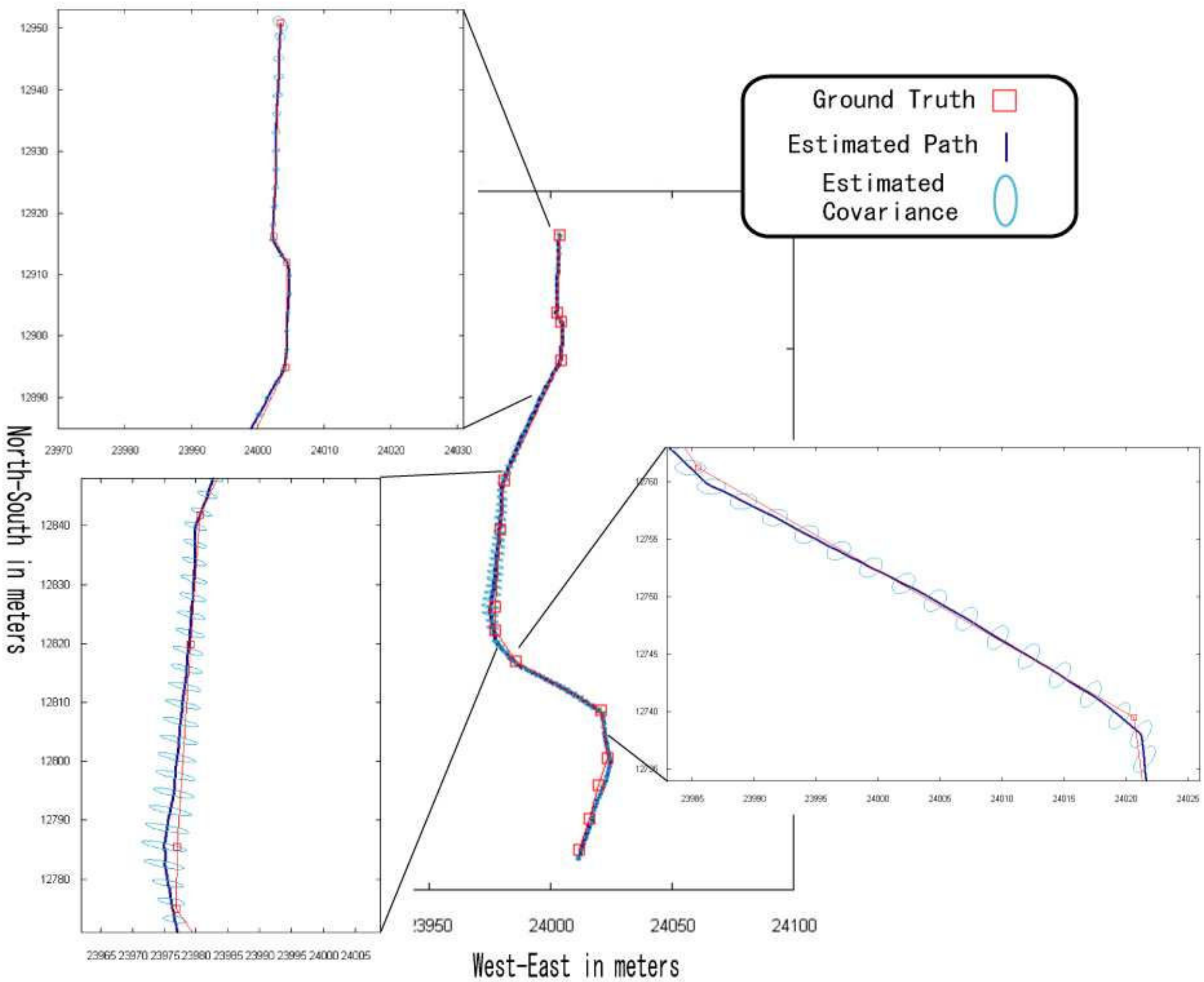

Fig. 7. Localization estimation with its covariance ellipses and ground truth path

[13] R. Hatch, T. Sharpe and P. Galyean, “StarFire: A Global High Accuracy Differential GPS System”, *Technical paper*

[14] R. R. Hatch and R. T. Sharpe, “Recent Improvements to the StarFire Global DGPS Navigation Software” *Journal of Global Positioning Systems (2004) Vol.3, No.1-2:143-153*

[15] E. Takeuchi, T. Tsubouchi and S. Yuta. “Integration and Synchronization of External Sensor Data for a Mobile Robot” (in japanese) *SICE Annual Conference in Fukui, August 4-6 2003, Fukui University, Japan*

[16] H.O. Lancaster. “The Chi-Square Distribution”. *Wiley Publications in Statistics (1969)*

[17] Geographical Survey Institute of the government of Japan. http://vldb.gsi.go.jp/sokuchi/ (In Japanese)

[18] Morales Y. and Tsubouchi T. “GPS Moving Performance on Open Sky and Forested Paths” *2007 IEEE International Conference on Intelligent Robots and Systems (IROS 2007, to be published)*

[19] Y. Lu, E. Collins, and M. Selekwa. “Parity relation based fault detection, isolation and reconfiguration for autonomous ground vehicle localization sensors” *in 24th Army Science Conference, 2004*

[20] S. Roumeliotis, G. Sukhatme, and G. Bekey. “Sensor fault detection and identification in a mobile robot” *International Conference on Intelligent Robots and Systems (IROS), 1998*

[21] Morales Y. and Tsubouchi T. “DGPS, RTK-GPS and StarFire DGPS Performance Under Tree Shading Environments” *2007 IEEE International Conference on Integration Technology*

[22] M. Grewal, L. Weill, and A. Andrews, “Global Positioning Systems, Inertial Navigation and Integration”, Wiley-Interscience, 2001

[23] J. A. Farrell and M. Barth, “The Global Positioning System & Inertial Navigation”, *McGraw-Hill, 1999*

[24] P. E. Greenwood, M.S. Nikulin. “A Guide to Chi-Squared Testing”. *Wiley Series in Probability and Statistics (1996)*

[25] H. Chung, L. Ojeda, and J. Borenstein. “Sensor fusion for Mobile Robot Dead-reckoning With a Precision-calibrated Fiber Optic Gyroscope” *2001 IEEE International Conference on Robotics and Automation, Seoul, Korea, May 21-26, pp. 3588-3593.*