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An Enhanced Path Planning of Fast Mobile Robot based on Data Fusion of Image Sensor and GPS

Jin-Hwan Joo[1], Dae-Han Hong[2], Yoon-Gu Kim[3], Ho-Geun Lee[4], Ki-Dong Lee[2], Suk-Gyu Lee[1]

[1] Department of Electronic Engineering, Yeungnam University, Gyeongsan, Korea
(Tel : +82-53-810-3923; E-mail:hwany2145@nate.com, sglee@ynu.ac.kr)
[2] Department of Computer Engineering, Yeungnam University, Gyeongsan, Korea
(Tel : +82-53-810-3910; E-mail:akorea82@ynu.ac.kr, kdrhee@yu.ac.kr)
[3] Daegu Gyeongbuk Institute of Science & Technology, Daegu, Korea
(Tel : +82-53-430-8423; E-mail:ryankim9@dgist.ac.kr)
[4] Electronics and Telecommunication Research Institute, Daegu, Korea
(Tel : +82-53-810-3923; E-mail:leehg@etri.re.kr)

Abstract: This paper presents a path planning algorithm for a fast mobile robot based on Extended Kalman Filter (EKF) by fusing the satellite navigation and the vision system in the outdoor environment. The suggested approach offers several improvements that result in smoother trajectories and greater reliability. The noisy location information of a robot is enhanced by using the vision system which contains abundant information with high accuracy but is subject to noise. This research consists of a motion segmentation stage which gets motion information of moving objects form motion model, and a motion estimation stage which estimates the position and the motion of moving object using EKF. EKF based approach is served as the de-facto approach to SLAM with shortcomings of quadratic complexity and sensitivity to failures in data association. The simulation results show a greater reliability for fast mobile robot navigation under outdoor environment.

Keywords: Extended Kalman Filter, GPS, Sensor fusion, Navigation, Vision.

1. INTRODUCTION

Despite a lot of researches and developments of mobile exploration robots in an unknown environment, a reasonable or perfect solution for performing Simultaneous Localization and Mapping (SLAM) has still not been found and proposed in recent decades.

It is difficult for a mobile robot to estimate its exact location even given a map of a specific environment. In addition, the exploration of the unknown environment of the robot's location is more difficult [1-3]. These difficulties are mainly caused by the accumulative error of the measured sensor, dynamics, and organic problems. As a solution to minimize the error due to the problems, multiple high-accuracy devices such as Differential Global Positioning System (DGPS) and laser scanners have been developed. However, those devices are not appropriate in the respect of the environmental and low-power issue of mobile robot industry to optimize energy consumption [4]. The intelligent systems for the unmanned autonomous navigation have been developed so that there have been introduced the qualified path planning robust to the surrounding environment changes as well as the driving systems of much more enhanced reliability.

There are 3 types of reasons that decrease the accuracy of Global Positioning System (GPS) position information. First, there are such structural factors as time and position error of a satellite, signal refraction by the water vapor in the troposphere and the charged particles of the ionosphere, and various noises. And secondly, the geometric schematism between a GPS receiver and satellites is also an important factor. When a GPS receiver is located at a specific point, the ideal geometric schematism is that four satellites are located with the GPS receiver as the center constructing a regular tetrahedron. Thirdly, Selective Availability (SA) is an intentional degradation of accuracy intended to prevent the enemy from making tactical use of the full accuracy of GPS. SA means the orbit data of navigation messages and the frequency of satellite clock are manipulated intentionally according to the military policy of the Department of Defense (DoD) [5]. Military receivers can use the encrypted P code to get 20 meter accuracy, or better, regardless of the state of SA. Among the reasons of error, the third one, SA, has been off at these times for civilian emergency use, but there is apparently no official confirmation. And the second one is out of range that we deal with because that is a problem of the control segment. So the error compensation mentioned here is mainly related to the first reason.

In order to compensate for the demerits of GPS based localization and path planning, this paper proposes an enhanced path planning for the autonomous navigation system which uses a low-cost GPS receiver and an image sensor in the fast mobile robot. The proposed approach is implemented by designing a path planning estimator based on the EKF. The data fusion of multiple local sensors and a vision system is applied to an effective navigation system in this paper. This paper is organized as follows: Section 2 shows the system configuration of fast mobile robot. The proposed data fusion algorithm for the effective path planning is

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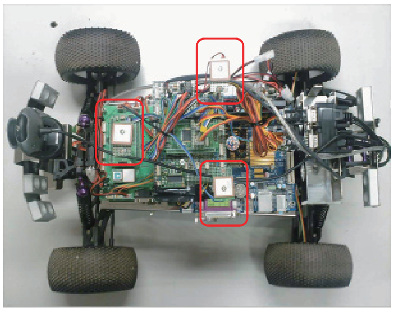
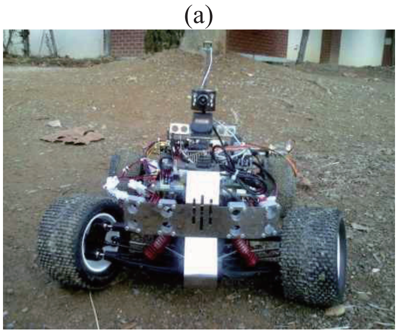
introduced in section 3. In Section 4, the simulation and experiment results are explained to evaluate the performance of the proposed approach in comparison with the conventional approach. Finally, this paper is concluded with summaries and future extensions of this work in Section 5.

2. SYSTEM ARCHITECTURE

To prove the effectiveness of the proposed algorithm, we built a four-wheel-drive robot which is composed of 5 parts: fast-mobile robot frame, main controller, driving sub-controller, local sensors, and driving part as shown in Fig. 1. It is designed for driving both on-road and off-road navigation. The robot frame has the symmetric characteristics to sustain all the parts mounted on the frame. The main controller collects and analyzes all data acquired from local sensors such as Universal Serial Bus (USB) camera for image data, GPS for global positioning information, ultrasonic sensors for obstacle detection and avoidance, and encoders of both wheels for driving information. The driving part is composed of MUCH-MORE 50 Turn DC-motor and transmission for the propulsion of robot.



(a)



(b)

Fig. 1 Mobile robot structure for off-road driving.

In this paper, the fast mobile robot used a low-cost GPS receiver providing the satellite navigation for localization. When using just one single GPS receiver, the reception impediment and noise resulted in the serious difficulty and inaccuracy of positioning [6]. Therefore, three low-cost GPS receivers were used and devised as a triangle-structured GPS module to make the positioning of GPS more accurate and reliable.

The system architecture for the unmanned autonomous driving system is illustrated in Fig. 2. The main operations are the image processing, GPS receiving, EKF algorithm, and communication with a micro-controller. The micro-controller operates several motors: steering motor, driving motor, brake motor, and camera positioning motor, and acquires and sends the ambient context information to a main controller based on PC.

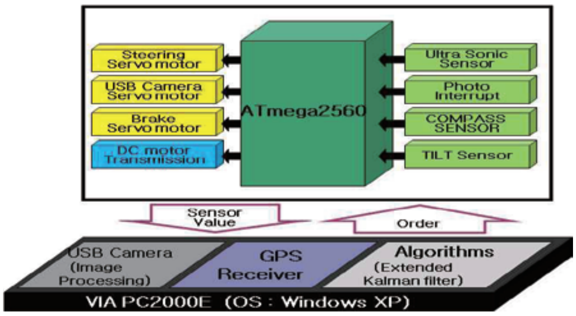
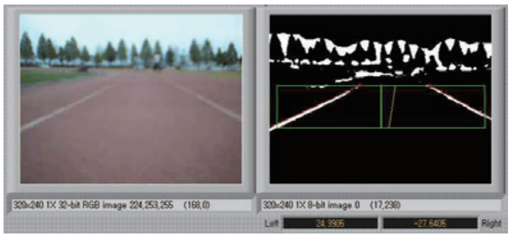
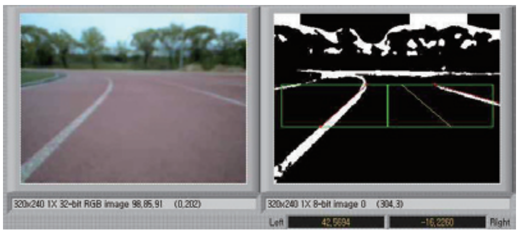


Fig. 2 System Architecture.

Fig. 3 illustrates the angle detection and calculation of a tangent path and a curve path, respectively. The lane detection and steering angle calculation have implemented by developing a LabVIEW based user application.



(a)



(b)

Fig. 3 (a) the angle detection of tangent path and (b) the angle detection of curve path.

The image sensor, the CCD color camera with the resolution of 320 x 240 pixels, captures the real-time images from the image processing part. The captured color images are converted to black and white images, and then mapped to binary images by a specific intensity threshold that is determined by the histogram analysis. For reducing the computational throughput, the specific region of interest (ROI) set in an image frame. Furthermore, we split the ROI into the left and right region, and performed the lane detection process starting from the leftmost or rightmost direction. First, the vertical or horizontal edge finding computes the absolute value of the vertical or horizontal derivative of the image using a Canny-Deriche filter [7, 10-11].

The angle of lane relative to the heading of robot is calculated by using the obtained two edge information in the ROI [12]. The difference between the angle of lane and heading angle of robot is applied to the steering control.

3. PROPOSED ALGORITHM

This paper proposes an effective path planning for the fast-mobile robot by fusing vision information of the image sensor and global positioning information of GPS. The current location of mobile robot is estimated by using the positioning data received from the GPS. However, the various error factors such as the basic precision error, the slow data update, the propagation obstacle, and the number of visible satellites make it difficult for the mobile robot to perform the autonomous navigation using only GPS. Therefore, the proposed path planning is conducted as follows: mutually compensate each other different error feature between the vision and the GPS, apply EKF for the error decrease as shown in Fig. 4.

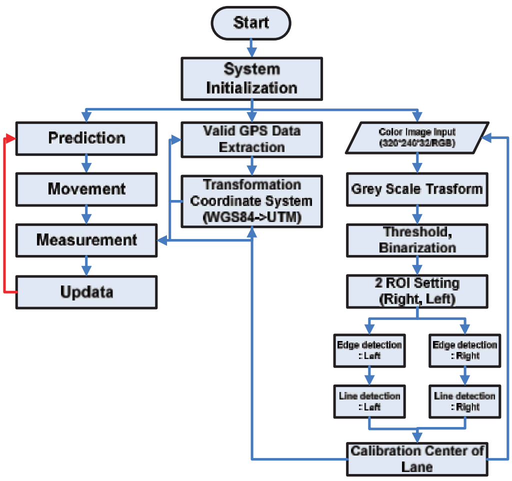


Fig. 4 Flowchart of data fusion for path planning.

The Robot's location estimation is based on the data from encoder, GPS receiver and vision system. The assumptions that observations are linear functions of the state and that the next state is a linear function of the previous state are crucial for the correctness of the Kalman filter. The observation that any linear transformation of a Gaussian random variable results in another Gaussian random variable played an important role in the derivation of the Kalman filter algorithm. The efficiency of the Kalman filer is then due to the fact that the parameters of the resulting Gaussian can be computed in closed form [8]. Unfortunately, state transitions and measurements are rarely linear in practice. For example, a robot that moves with constant translational and rotational velocity typically moves on a circular trajectory, which cannot be described by linear state transitions. This observation, along with the assumption of uni-modal beliefs, renders plain Kalman filters, as it has been discussed. Even though this observation is inapplicable to all, the most trivial robotics has problems.

When the measured data are applied to the Extended Kalman Filter [9] that has the two dimensional environment, the robot's state vector $\vec{x}_{(k)} = [x, y, \theta]^T$ has the x position, y position, and θ heading angle. The robot is driven by four wheels, and the state variables are described as the followed equation, through present state and control input.

$$\begin{aligned} \vec{x}_{(k+1)} &= f(\vec{x}_{(k)}, u_{(k)}) + w_{(k)} \\ x_{(k+1)} &= x_{(k)} + \Delta t\, v_{(k)} \cos\theta_{(k)} \\ y_{(k+1)} &= y_{(k)} + \Delta t\, v_{(k)} \sin\theta_{(k)} \\ \theta_{(k+1)} &= \theta_{(k)} + \frac{\Delta t\, v_{(k)} \tan\phi_{(k)}}{L} \end{aligned} \quad (1)$$

To linearize f, a matrix of partial derivatives is computed by the following eq. (2):

$$F_{(k)} = \begin{bmatrix} 1 & 0 & -\Delta t\, v_{(k)} \sin\theta_{(k)} \\ 0 & 1 & \Delta t\, v_{(k)} \cos\theta_{(k)} \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

We can make observation model through the Fig. 5

$$\begin{aligned} \vec{z}_{(k+1)} &= h(\vec{x}_{(k+1)}, m_{(k)}) \\ r &= \sqrt{(x_{GPS} - x_k)^2 + (y_{GPS} - y_k)^2} \\ \phi_{GPS} &= \tan^{-1}\left(\frac{y_{GPS} - y_k}{x_{GPS} - x_k}\right) - \theta \end{aligned} \quad (3)$$

The function f can be used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state. However, f and h cannot be applied to the covariance directly.

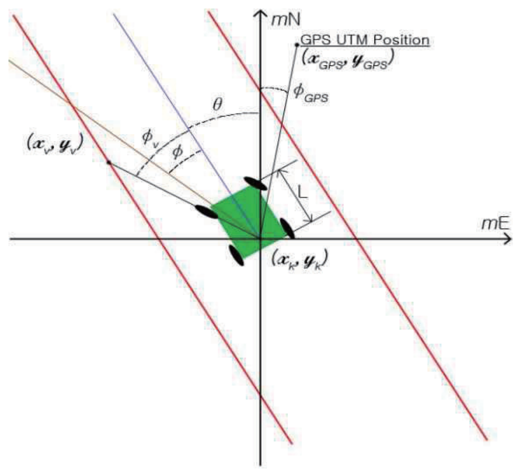


Fig. 5 Configuration of robot localization.

To apply to the EKF using already explained system model, first, the predictions of the state and the covariance are computed by:

$$\begin{aligned} \hat{x}_{(k+1|k)} &= f(\hat{x}_{(k|k)}, u_{(k+1)}, 0) \\ P_{(k+1|k)} &= F_{(k)} P_{(k|k)} F_{(K)}{}^{T} + G_{(k)} Q_{(k)} G_{(k)}{}^{T} \end{aligned} \tag{4}$$

Once we have the measures of the distance to the beacon, the innovation and the covariance of the innovation can be computed by eq. (5) and (6):

$$\widetilde{A}_{(k+1)} = z_{(k+1)} - h(x_{(k+1|k+1)}, 0)\,, \tag{5}$$

$$S_{(k+1)} = H_{(k+1)} P_{(k+1|k)} H_{(k+1)}{}^{T} + R_{(k+1)}\,, \tag{6}$$

where H is the jacobian matrix of observation model. After that, the gain of the filter can be computed by:

$$S_{(k+1)} = H_{(k+1)} P_{(k+1|k)} H_{(k+1)}{}^{T} + R_{(k+1)}\,, \tag{7}$$

$$K_{(k+1)} = P_{(k+1|k)} H_{(k+1)}{}^{T} S_{(k+1)}{}^{-1}\,, \tag{8}$$

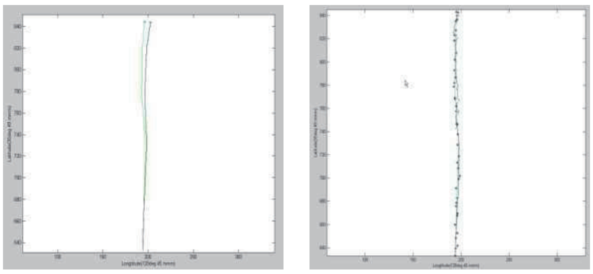
and the estimation of the state and covariance of the system are finally obtained by:

$$\hat{x}_{(k+1|k+1)} = \hat{x}_{(k+1|k)} + K_{(k+1)} \widetilde{A}_{(k+1)}\,, \tag{9}$$

$$P_{(k+1|k+1)} = P_{(k+1|k)} - K_{(k+1)} S_{(k+1)} K_{(k+1)}{}^{T}. \tag{10}$$

4. EXPEIMENTAL RESULTS

The efficiency of driving navigation by the proposed method has been verified using the MATLAB simulation. Fig. 7 shows the comparison between the robot's position estimation using odometer and EKF. Due to the cumulative error of odometer in the case of position estimation by only odometer in Fig. 6(a), the experiments have showed that the actual path of a robot is beyond the goal path. The localization based on EKF showed a more accurate and reliable path planning as shown in Fig. 6(b).



(a) (b)

Fig. 6 comparison of robot's position: (a) estimation by odometer and (b) localization based on EKF.

Fig. 7 shows the conditional arithmetic average of the received three positions at a time have produced more accurate and less biased positioning results. The conditional average means that some of the received values can be excluded considering out of tolerance range, the previous location, and the current velocity and heading.

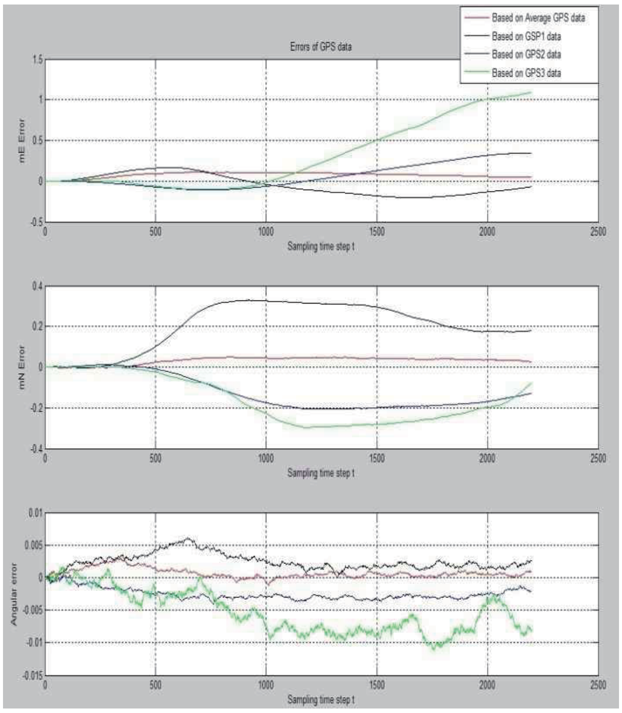


Fig. 7 Mutual error compensation of the received locations using three GPS receivers.

Fig. 8 shows the navigation result based on GPS data that are measured driving a 400-meter running track at Yeungnam University. When the simulation results are described as the follow figure, the green-line is the real 400-meter track, the blue points are the converted UTM coordinates data which are received from GPS receiver. The black-line is the path of the robot and the red points are the UTM coordinates data updated by the proposed algorithm. The tracking experiment by using only GPS data showed that the path of the robot has seriously biased path error in comparison with the real track as shown in Fig. 8. For the error compensation, the difference between the initial GPS data and the real coordinate data at the start point is applied to the currently received path information by coordinate shift as shown in Fig. 9. Fig. 10 shows a specific path tracking based EKF using the compensated GPS position and the heading determined by lane detection. The simulation results showed more enhanced path tracking performance.

This work places an important weight on enhancing the reliability of GPS data and the performance of a specific path navigation using the common and low-cost environmental information acquisition devices, three GPS receivers and one vision sensor.

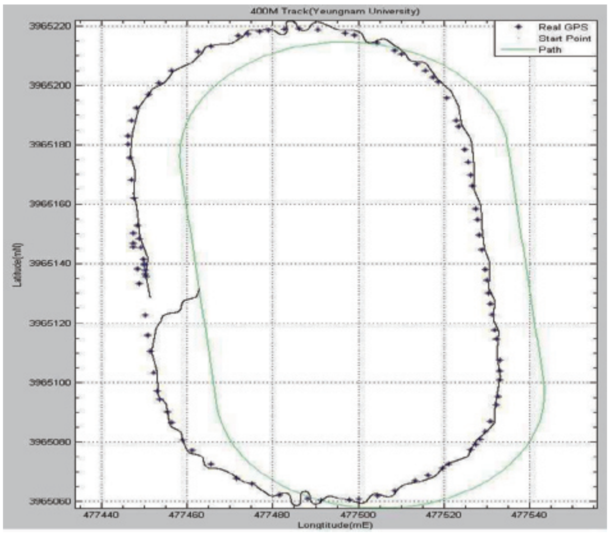


Fig. 8 Navigation used only GPS data.

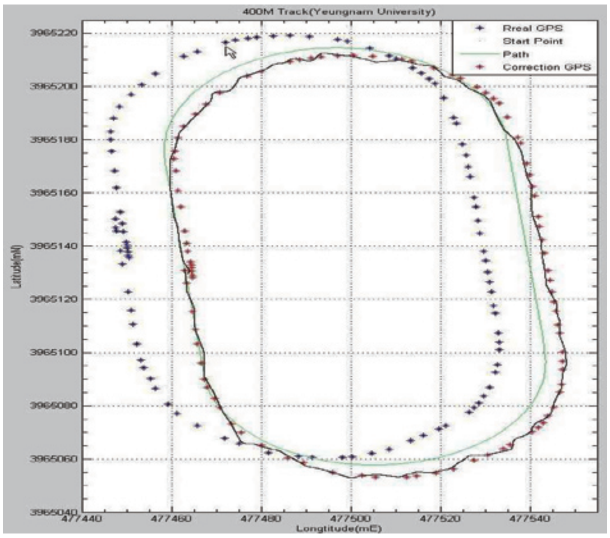


Fig. 9 Error compensation of GPS data by coordinate shift.

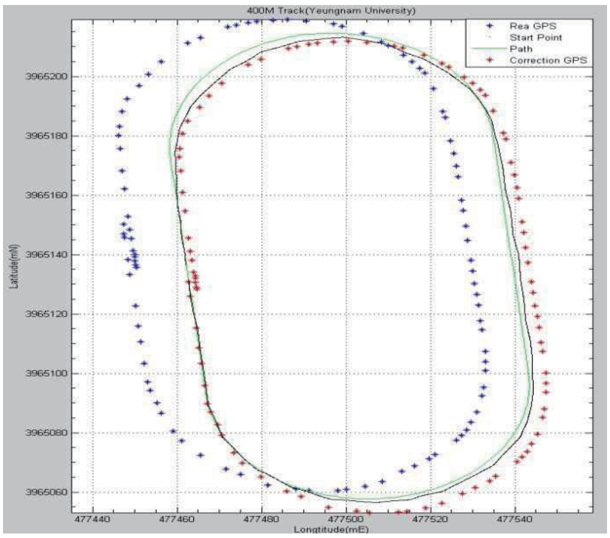


Fig. 10 path tracking based EKF using the compensated GPS position and the heading determined by lane detection.

5. CONCLUSION

For an efficient path planning of the fast mobile robot in the outdoor environment, the data fusion between GPS and vision, which are generally equipped by the mobile robot, has been conducted with the mutual compensation, and then the result has been applied to compensate the tracking error between the real path and the target path through EKF. The simulation results showed the effectiveness with greater reliability for the fast mobile robot navigation under outdoor environment.

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