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# An GPS/DR Navigation System Using Neural Network for Mobile Robot

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*Dead reckoning (DR) is frequently used for mobile robot navigation as it can provide precise short term navigation information but the errors of a DR system can accumulate over time. A global positioning system (GPS) can be used for outside navigation and localization but the error of a single GPS receiver is still big even though an error intentionally introduced into the system called the selective availability policy (SA) was already removed. Standard differential GPS (DGPS) can provide an accuracy of less than one meter but it is too expensive for the mass market aside from the need of having a base station to provide differential data. This paper proposes a new GPS/DR fusion method based on the data characteristics of a cheap single GPS receiver and use neural network to estimate the output of the GPS receiver to provide precise navigation information to the mobile robot. Simulation results validated the performance of the proposed method and showed its potential use in outdoor mobile robot navigation.*

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## 1. Introduction

Autonomous mobile robot technology is continuously getting popular with extensive application prospect in industry, agriculture, medical and social services thus receiving much attention from academic and industrial researchers. Navigation is an important element of autonomous mobile robot technology that utilizes sensors to identify its status and its surrounding environment to move from one point to another without running into any of the obstacles. Precise and reliable navigation system is necessary for the mobile robot in order to successfully finish its mission.

Dead reckoning (DR) is the most basic approach to the localization and navigation problem of a mobile robot[1] wherein the mobile robot position is derived by calculating the distance travelled. The vehicle speed, usually given by wheel sensors such as an encoder, is multiplied by the time it took to travel to calculate the travelled distance.[2] This type of navigation system can provide short term precise navigation information but it cannot be used to navigate the mobile robot alone without any validation since the errors of the wheel/ motor and heading sensors accumulate over time without limit. It needs an external aid that will provide compensation information to improve its long term navigation precision.

GPS is a widely used global positioning system with many applications such as position and location determination, navigation, survey and time determination. Most land vehicles today are equipped with GPS to provide accurate position and velocity information.[3] A GPS receiver relies on signals that include system time and ephemeris information received from several non-geostationary satellites. The antenna position and the GPS system time can be calculated if four or more pseudoranges are available knowing the absolute satellite positions from the received messages. A lot of work has been done so far on using GPS to navigate mobile robots and autonomous vehicles.[4-6] Hanzel et al. dealt with the problem of the robot localization in an outdoor environment by using GPS.[7] They experimentally evaluated a set of low-cost GPS receivers applicable as position sensors for small outdoor mobile robots. Aghili and Salerno focused on the integration of inertial measurement unit with two real-time kinematic GPS units in an adaptive Kalman filter for drift less estimation of a vehicle's attitude and position.[8] Atia et al. proposed a mixture particle filter integrated navigation system for land vehicles based on GPS and Reduced Inertial Sensors System.[9] The GPS receivers used in most of the above mentioned studies were DGPS. The absolute error of a civilian use GPS receiver is still big even though the SA policy has been removed. A single GPS receiver may have an error of more than 20 meters based on previous experiments[10] while reflected signals and relatively poor geometries further degrade its accuracy.[11] The GPS cannot be used for mobile robot navigation when the receiver loses the signals from the satellites and our experiments also showed that the accuracy is affected when there is a change in the satellites detected.

All of these factors show that a single GPS receiver cannot be used to navigate a mobile robot effectively without any other auxiliary sensors. DGPS can provide navigation information with an error of less than one meter but it is very expensive aside from the need of a base station to provide differential data. Furthermore, DGPS will degrade to normal GPS operation when the receiver loses the differential signal from the base station. It is with these reasons that there is a necessity to fuse the GPS with other navigation sensors.

GPS has complementary characteristics with the DR system[12] and it is a good idea to combine them to provide a more robust and accurate navigation information. Kalman filter is frequently used to fuse multi-sensors data[4,13,14] but it does possess several inadequacies related to sensor error model and immunity to noise. Kalman filter needs the noise to be a white Gaussian noise but the GPS has complicated noise which cannot be white noise. This decreases the precision of Kalman filter based approaches and also sometimes makes the system unstable, so it is better to design a data fusion algorithm based on the characteristics of GPS data.

We used in this paper a single cheap GPS receiver with absolute error of approximately 10-20 meters to provide navigation information to the outdoor mobile robot. A new GPS/ DR data fusion method whose design is based on the characteristics of the GPS output and the back propagation (BP) neural network is proposed to fuse the data of GPS and DR system. The proposed data fusion method can provide an accurate and robust navigation result by modifying the reliability of the GPS. It can adaptively switch to DR-only navigation when the GPS receiver loses the GPS satellites signal and recover to GPS/ DR when the GPS provides good navigation information again. Simulations using real GPS data were conducted to validate the proposed data fusion method and results showed good potential for mobile robot navigation.

This paper is split into several sections to explain the results of the study. The second section gives information about the GPS navigation system and the characteristics of the cheap single GPS receiver while the third section presents the BP neural network used to estimate the GPS output. The fourth section describes the proposed data fusion method which is then demonstrated via simulation in section five. The concluding remarks are then given afterwards.

## 2. Characteristics of the Single GPS Receiver

The GPS was initially developed for military use but is now freely available for civilian purposes such as navigation. There are at least twenty-four operational GPS satellites with each satellite continuously transmitting data that indicates its location and the current time. The GPS satellites synchronize their transmissions so that their signals are sent at the same time. When a GPS device receives the transmission from two or more satellites, the arrival time differences inform the device as to its relative distance to each satellite. A GPS receiver uses the pseudoranges obtained from the signals to calculate the positioning information.[15] The GPS receiver can even calculate the GPS receiver's antenna position when four or more satellites can be detected.

The accuracy of GPS relies in the precise knowledge of the satellite orbits and the time. The main goal of a GPS application is to derive the position of a receiver as accurately as possible based on its distance to the GPS satellites. Many sources of disturbances can affect the precision of GPS since GPS works in an outside environment. These disturbance sources include clock offset, atmospheric and ionospheric effect, multipath effect and receiver noise. The geometry of the receiver with respect to the satellites can also influence the accuracy of the GPS. The horizontal dilution of precision (HDOP) is used in a two-dimensional positioning case to indicate the effect of the geometry of the satellites on the precision of the GPS. The estimate of the position is more accurate when the satellites recognized by the GPS receiver are geometrically well distributed, as indicated by a small HDOP factor. Moreover, the number and the position of the available satellites changing over time influence the system precision accuracy. It is very difficult to obtain the GPS error model because of so many disturbance sources.

Standard DGPS can be used to get an accuracy of less than one meter and there are several ways to operate in differential mode based on the information sent from the DGPS base station. The straightforward methods rely on having a base station receiver and a mobile receiver, and then analyzing the differences between the signals received in real time at each receiver. DGPS can provide very precise positioning service but the cost of DGPS is very high and it needs a base station to provide the differential data. We used a cheap single GPS receiver with absolute error of approximately 10-20 meters to provide the navigation information for the mobile robot.

Experiments were done to collect data from a single GPS receiver in order to analyze the data characteristics. Several locations were chosen such as open fields, bushy areas and near high trees and buildings. GPS data gathering was done at various times including morning, noon, afternoon, and night. We found out that the number of satellites detected by GPS receivers varies and the atmospheric/ ionospheric effect are also different at different times hence the precision of the GPS also changes.

Data taken near the high trees and buildings were worse than that in open fields due to the multipath effect with no satellite signal sometimes received. In this case, the GPS cannot provide good positioning information since its error is very big. We were still able to obtain some useful information which can be used to identify the characteristics of the GPS data in spite of the given drawbacks.

All of the data collected from different locations and varying time showed one similar feature and in order to explain this feature, we choose a set of typical GPS output data. Fig. 1 shows the single GPS data collected in a fixed point. This data is subtracted by its mean value for better analysis and description. The GPS data shown in Fig. 1 oscillates a lot which means that the errors of this GPS receiver are very big and changes frequently. It is difficult to get some meaningful information from the data shown in Fig. 1 only, so we subtracted the current data from its last sampling time data. Fig. 2 gives the difference between the consecutive sampling time GPS data and it shows something interesting. It can be seen in Fig. 2 that the error range of the

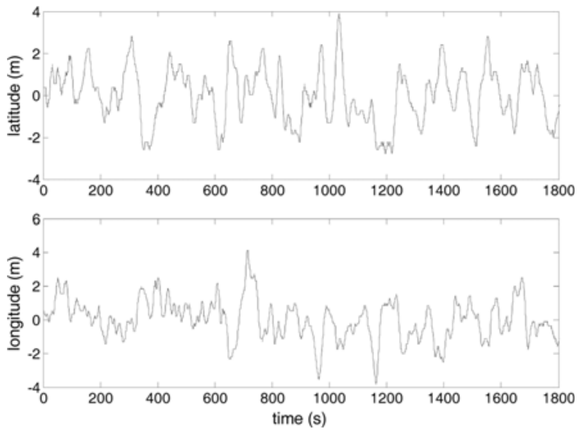


Fig. 1 Data of single GPS receiver after subtracting the mean value

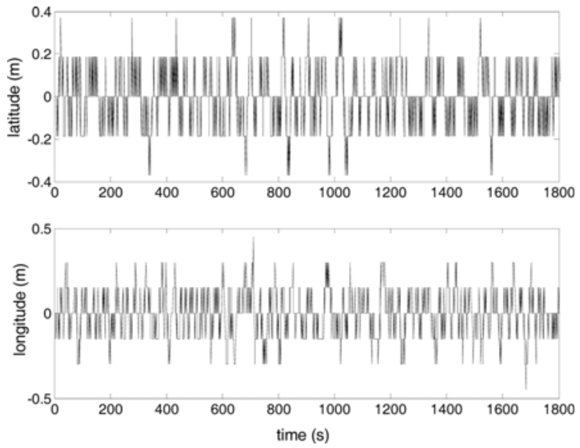


Fig. 2 Difference between consecutive sampling time GPS data

Table 1 HDOP values of the two acquisitions

| First acquisition | | Second acquisition | |
|---|---|---|---|
| Value of HDOP | Samples | Value of HDOP | Samples |
| 0-0.9 | 289 | 1.5 | 275 |
| 0.9-1.0 | 444 | 1.6 | 1210 |
| 1.0-1.1 | 667 | 1.7 | 215 |
| >1.1 | 426 | >1.7 | 89 |

Table 2 Standard deviation (*m*) of the two acquisitions

| First acquisition | | | Second acquisition | | |
|---|---|---|---|---|---|
| HDOP | S-N | E-W | HDOP | S-N | E-W |
| 0-0.9 | 0.9281 | 0.8858 | 1.5 | 1.1692 | 1.0181 |
| 0.9-1.0 | 1.3653 | 1.2006 | 1.6 | 2.1090 | 1.7128 |
| 1.0-1.1 | 1.3968 | 1.1744 | 1.7 | 1.8410 | 1.2318 |
| >1.1 | 1.1644 | 1.0228 | >1.7 | 2.0375 | 1.7307 |
| Total | 1.2895 | 1.1925 | Total | 1.9828 | 1.6251 |

single GPS receiver is big but the data drift between consecutive sampling times is small, no more than three times of the GPS resolution, 0.1854 m for latitude and 0.1503 m for longitude. That means the successive errors are tightly related and therefore the error is strongly colored. In other words, the current sampling time output of the chosen single GPS receiver has something to do with the previous one or several sampling times output.

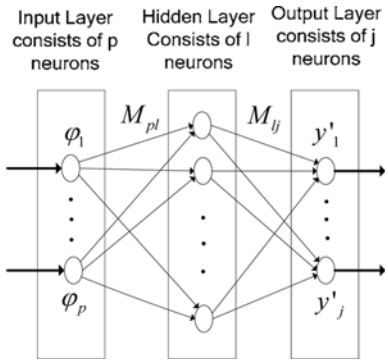


Fig. 3 Configuration of the BP neural network

The parameter HDOP is an important indicator for the operational status of the GPS. The HDOP values are error multipliers that indicate how the accuracy of the position estimate changes with the number and the geometry of the available satellites. We collected the single GPS receiver data twice in a fixed point which lasted about 30 minutes each with a sampling period of one second, resulting to about 1800 measures per acquisition. Table 1 refers to the HDOP values in the two acquisitions while Table 2 is the standard deviation of the measures for each acquisition computed according to the value of HDOP for all the measures. It can be seen by observing these two tables that the value of HDOP can provide a rough indication of the accuracy of the measures.

## 3. Neural Network

We consider using neural network to estimate the current GPS data based on several previous sampling of GPS and HDOP data due to the characteristics of the GPS output and the importance of the HDOP values. Neural networks have the ability to "learn" the system characteristics through nonlinear mapping and provide a strong degree of robustness because of their ability to exhibit fault tolerance. It can also improve adaptability by means of both off-line and on-line weight adaptation. A BP neural network is adopted to perform the estimation job whose configuration with respect to the input-output relationship is shown in Fig. 3 while its model structure is given in Fig. 4. It consists of three layers: an input layer, a hidden layer and an output layer. $x(k-1)$, $x(k-2)$, and $x(k-3)$ are the three previous sampling times GPS data (latitude or longitude); HDOP($k$-1), HDOP($k$-2), and HDOP($k$-3) are the three previous sampling times GPS HDOP values, and $x(k)$ is the estimation of the current sampling time GPS output (latitude or longitude).

The neural network has six neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer. The transfer function of the hidden layer is $f_h(x) = tanh(x)$ while the transfer function of the output layer is $f_o(x) = x$. The inputs of the neural network are the three previous sampling times GPS data (latitude or longitude) and the HDOP values, while the output of the neural network is the estimation of the current sampling time GPS output (latitude or longitude). The error signal used to adjust the weights of the neural network is the

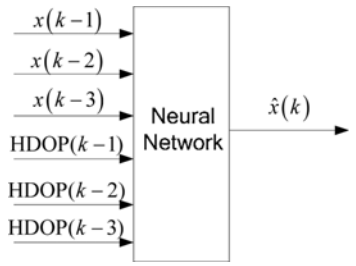


Fig. 4 The neural network model structure

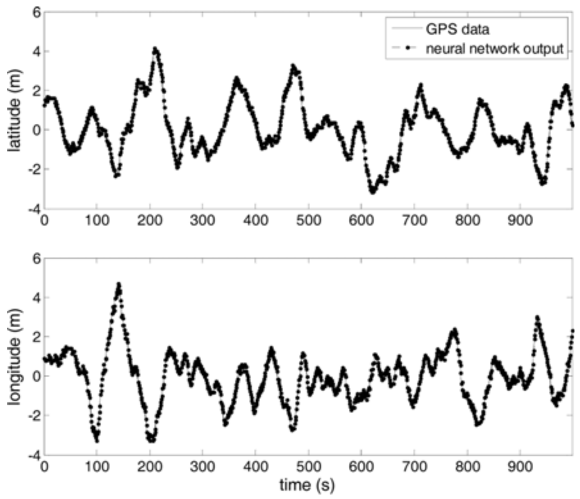


Fig. 5 estimation results of the training data

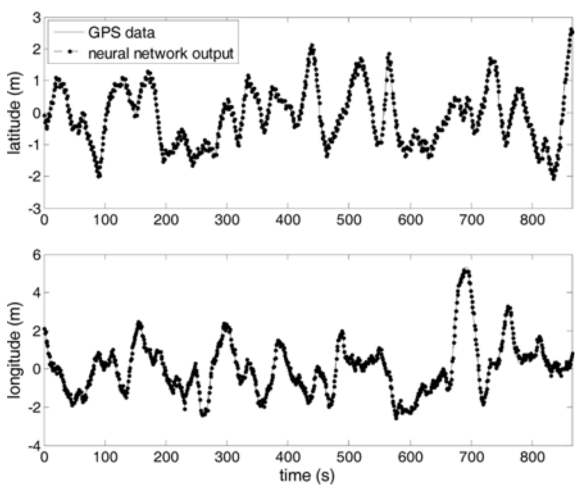


Fig. 6 estimation results of the test data

difference between the real GPS output and the neural network output.

GPS data were collected from various places (open fields, bushy areas, near high trees and buildings) and at different times (morning, noon, afternoon, night) to train and test the neural network. The training and test results are good for all of the GPS data collected from these various places and different times. Here one of the typical training and test results is given to present the estimation performance of the neural network. A total of 1860 sampling time measurements were used to

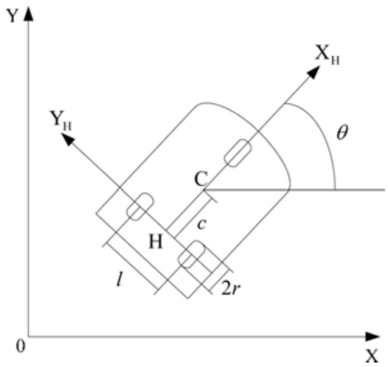


Fig. 7 Sketch of a three wheeled mobile robot

train and test the neural network for the simulation presented in this paper. The first 998 measurements were used as the training data for the neural network and the remaining 862 measurements were used as the test data. The training and test results in Fig. 5 and Fig. 6 respectively, show that the neural network can estimate the single GPS receiver output effectively.

## 4. Data Fusion Method

The well trained BP neural network can be used to design the proposed data fusion algorithm for GPS/ DR. Assume that one electronic compass and two encoders are located in the two driving wheels of the mobile robot to indicate the direction and velocity of the mobile robot whose geometrical model is shown in Fig. 7. This wheeled mobile robot has two driving wheels (radius $r$) and one caster. Point $H(x_H, y_H)$ defines the intersection of the axis of symmetry with the driving wheel axis, and is assumed to be the origin of the coordinate frame $\{X_H, Y_H\}$. Point $C(x_c, y_c)$ is the center of mass of the mobile robot. Length $c$ is the distance between point $H$ and point $C$, and $l$ is the length of the rear wheel axis. By knowing the direction $\theta$ and the velocity $v$, we can use Eq. (1) to calculate the position of the mobile robot.

$$\begin{cases} \dot{x}_H = v(t)\cos(\theta) \\ \dot{y}_H = v(t)\sin(\theta) \end{cases} \tag{1}$$

A DR system can provide precise short-term navigation information but its error can accumulate without limit; on the other hand the error of the single GPS receiver is big but with limit. The GPS/DR system can be used to navigate the mobile robot since GPS has the synergistic characteristics with the DR system. The proposed method will use the DR system to provide accurate short-term navigation information and the single GPS to modify the long term navigation information. The error of a single GPS receiver changes frequently but the error between consecutive sampling times is closely related and the difference between two neighboring data is no more than three times the GPS resolution, about $0.1854m$ and $0.1503m$ for latitude and longitude respectively. A BP neural network is trained to estimate the current sampling time GPS output based on the three previous sampling times GPS data and HDOP values. Fig. 8 shows the sketch of the GPS/DR data fusion algorithm.

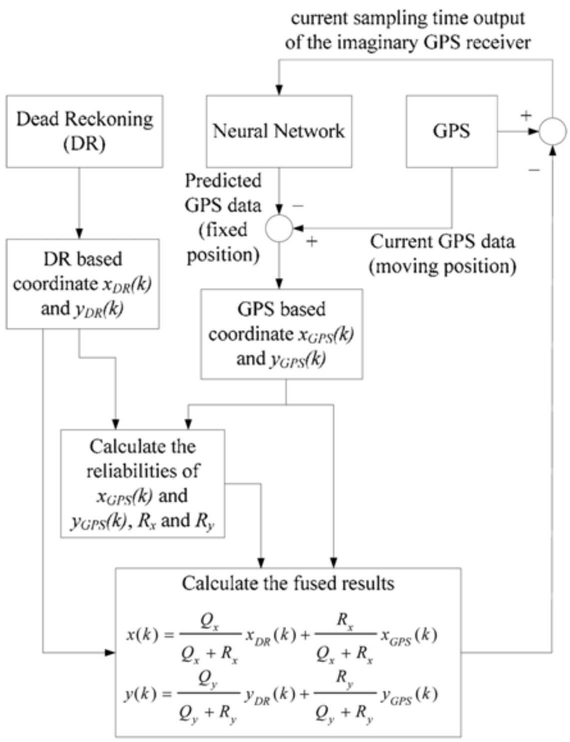


Fig. 8 the sketch of the GPS/DR data fusion algorithm

The details of the proposed GPS/DR data fusion algorithm is as follows: We used (*x, y*) to indicate the coordinate of the mobile robot in (*latitude, longitude*) format. For the proposed GPS/DR data fusion algorithm the velocity of the mobile robot can be usually set as 0.5 m/s to 1.5 m/s. Assume that the reliabilities of the DR in $x$ and $y$ are $Q_x$ and $Q_y$, respectively; and the reliabilities of the chosen GPS receiver in $x$ and $y$ are $R_x$ and $R_y$, respectively. Obviously, $Q_x$ and $Q_y$ are much bigger than $R_x$ and $R_y$.

Assume that an imaginary single GPS receiver which has the same characteristics with the chosen GPS receiver is fixed at the starting point and the real single GPS receiver moves with the mobile robot. A BP neural network is trained and used to estimate the current time output of the imaginary GPS receiver fixed in the starting point. The output of the neural network is the estimation of the imaginary GPS receiver's output.

1) First collect the chosen GPS data and train the neural network to estimate the current sampling time output of the GPS.

2) At the starting point when the robot does not run, collect three sampling times GPS data to get $GPS_x(0)$, $GPS_x(1)$, $GPS_x(2)$, $GPS_y(0)$, $GPS_y(1)$, $GPS_y(2)$ and corresponding *HDOP* values. The $GPS_x(0)$, $GPS_x(1)$, $GPS_x(2)$, $GPS_y(0)$, $GPS_y(1)$ and $GPS_y(2)$ are the GPS output in the latitude and longitude direction at time $t = 0$, 1, 2 s in the start point, respectively. The imaginary GPS receiver which is fixed in the starting point has the same output of the chosen GPS receiver, i.e., $GPS_{I\_x}(0) = GPS_x(0)$, $GPS_{I\_x}(1) = GPS_x(1)$, $GPS_{I\_x}(2) = GPS_x(2)$, $GPS_{I\_y}(0) = GPS_y(0)$, $GPS_{I\_y}(1) = GPS_y(1)$, and $GPS_{I\_y}(2) = GPS_y(2)$. Here $GPS_{I\_x}(0)$, $GPS_{I\_x}(1)$, $GPS_{I\_x}(2)$, $GPS_{I\_y}(0)$, $GPS_{I\_y}(1)$, and $GPS_{I\_y}(2)$ are the imaginary GPS receiver's output in the latitude and longitude direction at time $t = 0$, 1, 2 s, respectively. We can also get the *HDOP* values of these three sampling times namely *HDOP*(1), *HDOP*(2) and *HDOP*(3).

3) Run the robot with navigation data fusion timing at 1 *s* since the frequency of the chosen single GPS receiver is 1 *Hz*. We can obtain the actual DR system based coordinate $x_{DR}(3)$ and $y_{DR}(3)$ at time $t = 3$ *s*. The $x_{DR}(3)$ and $y_{DR}(3)$ is the current position of the mobile robot based on DR. Let us assume the reliabilities of $x_{DR}(3)$ and $y_{DR}(3)$ are $Q_x$ and $Q_y$ respectively.

4) Now we use the previous three sampling times output of the imaginary GPS receiver and the corresponding HDOP values to estimate the current sampling time imaginary GPS receiver's output. Using $GPS_{I\_x}(0)$, $GPS_{I\_x}(1)$, $GPS_{I\_x}(2)$, $GPS_{I\_y}(0)$, $GPS_{I\_y}(1)$, $GPS_{I\_y}(2)$, *HDOP*(1), *HDOP*(2) and *HDOP*(3) to pass through the neural network, we can get $GPS_{I\_\hat{x}}(3)$ and $GPS_{I\_\hat{y}}(3)$. The "^" indicates that the output of the imaginary GPS receiver is the estimated data.

5) At time $t = 3$ *s* we get the real GPS output: $GPS_x(3)$ and $GPS_y(3)$.

6) We then estimate the mobile robot's GPS based coordinate at time $t = 3$ *s* using the difference between the real and imaginary GPS receivers' output: $x_{GPS}(3) = GPS_x(3) - GPS_{I\_\hat{x}}(3)$ and $y_{GPS}(3) = GPS_y(3) - GPS_{I\_\hat{y}}(3)$. Here $x_{GPS}(3)$ and $y_{GPS}(3)$ is the current sampling time position of the mobile robot based on GPS.

7) Set the reliabilities of $x_{GPS}(3)$ and $y_{GPS}(3)$, denoted by $R_x$ and $R_y$, respectively. The DR system based coordinate is precise since it can provide precise short term navigation information in a sampling interval of one second. We can use this knowledge to calculate the reliabilities of GPS based coordinate. The differences between the errors of the consecutive samples of the single GPS are no more than three times the GPS resolution. It is with this reason that we can set the reliabilities of GPS based coordinate as follows: For latitude direction, if $|x_{GPS}(3) - x_{DR}(3)| \le 0.1854m$ we set the reliability of $x_{GPS}(3)$ as $R_{x1}$; if $|x_{GPS}(3) - x_{DR}(3)| \le 0.1854 \times 2m$ we set the reliability of $x_{GPS}(3)$ as $R_{x2}$; if $|x_{GPS}(3) - x_{DR}(3)| \le 0.1854 \times 3m$ we set the reliability of $x_{GPS}(3)$ as $R_{x3}$; else, when $|x_{GPS}(3) - x_{DR}(3)| > 0.1854 \times 3m$, the error of GPS jumps a lot that the precision of GPS will degrade and so we set the reliability of $x_{GPS}(3)$ as $R_{x4}$. The same method can be used to set the reliability of the longitude direction GPS based coordinate. Based on the value of $|y_{GPS}(3) - y_{DR}(3)|$ we can set the reliability of $y_{GPS}(3)$ as $R_{y1}$, $R_{y2}$, $R_{y3}$ or $R_{y4}$, respectively. Since DR's short term (1*s*) precision is much better than that of the chosen single GPS receiver, $Q_x$ and $Q_y$ should be much larger than $R_{xi}$ and $R_{yi}$ ($i = 1, 2, 3, 4$), respectively. And the following inequalities exist.

$$\begin{gathered} R_{x1} > R_{x2} > R_{x3} \gg R_{x4} \\ R_{y1} > R_{y2} > R_{y3} \gg R_{y4} \end{gathered} \tag{2}$$

8) Next, the fused results of DR and GPS based positioning results at time $t = 3$ *s* are calculated using the following equations.

$$x(3) = \frac{Q_x}{Q_x+R_x}x_{DR}(3) + \frac{R_x}{Q_x+R_x}x_{GPS}(3) \tag{3}$$

$$y(3) = \frac{Q_y}{Q_y+R_y}y_{DR}(3) + \frac{R_y}{Q_y+R_y}y_{GPS}(3) \tag{4}$$

Here, $x(3)$ and $y(3)$ are fused robot's position results. The direction of the robot is measured using the electronic compass.

9) The current sampling time output of the imaginary GPS receiver fixed in the starting point is:

$$\begin{aligned} GPS_{I\_x}(3) &= GPS_x(3) - x(3) \\ GPS_{I\_y}(3) &= GPS_y(3) - y(3) \end{aligned} \tag{5}$$

10) At time $t = ks$ ($k = 4, 5, \ldots$) from the DR system we can get the current time DR system based coordinate $x_{DR}(k)$ and $y_{DR}(k)$. The reliabilities of $x_{DR}(k)$ and $y_{DR}(k)$ are $Q_x$ and $Q_y$, respectively.

11) Use the previous three sampling times output of the imaginary GPS receiver and the corresponding HDOP values of the real GPS receiver to pass through the neural network to estimate the current sampling time imaginary GPS output: $GPS_{I\_\hat{x}}(k)$ and $GPS_{I\_\hat{y}}(k)$.

12) At the same time we get the real GPS output: $GPS_x(k)$ and $GPS_y(k)$.

13) Predict the current sampling time GPS based coordinate: $x_{GPS}(k) = GPS_x(k) - GPS_{I\_\hat{x}}(k)$ and $y_{GPS}(k) = GPS_y(k) - GPS_{I\_\hat{y}}(k)$.

14) Set the reliabilities of $x_{GPS}(k)$ and $y_{GPS}(k)$ using the process given in 7).

15) Calculate the fused results of DR and GPS based positioning results at time $t = ks$ using the following equations.

$$x(k) = \frac{Q_x}{Q_x + R_x} x_{DR}(k) + \frac{R_x}{Q_x + R_x} x_{GPS}(k) \tag{6}$$

$$y(k) = \frac{Q_y}{Q_y + R_y} y_{DR}(k) + \frac{R_y}{Q_y + R_y} y_{GPS}(k) \tag{7}$$

16) The current sampling time output of the imaginary GPS receiver fixed in the starting point is:

$$\begin{aligned} GPS_{I\_x}(k) &= GPS_x(k) - x(k) \\ GPS_{I\_y}(k) &= GPS_y(k) - y(k) \end{aligned} \tag{8}$$

## 5. Simulation

MATLAB is employed to simulate the proposed data fusion method by using real GPS data. The proposed GPS/DR data fusion method is tested by using the real GPS data collected from various places (open fields, bushy areas, near high trees and buildings) and at different times (morning, noon, afternoon, night). All of the simulation results are good and indicate the feasibility of the proposed GPS/DR data fusion method. Here the simulation results using a set of typical GPS data is presented. The BP neural network presented in Section 3 is trained to estimate the current sampling time output of the single GPS receiver. GPS data was initially collected to train and test the neural network using the Matlab Neural Network Toolbox to build and train the neural network, whose results are shown in Figs. 5 and 6. A total of 3600 real GPS data were used to simulate the data fusion whose results were compared with those of a Kalman filter based fusion in Figs. 9 and 10. It can be observed in Fig. 9 that the GPS performance degrades at about t=1800*s* and then recovers gradually at t=2600*s*. Both Kalman filter and the proposed data fusion method degrade but the proposed method has comparatively better result attributed to its flexible weight adjustment ability. This observation is not easily obvious in Fig. 10 but the same trend also exists.

It can be seen that the proposed GPS/DR data fusion method can provide better data fusion performance than Kalman filter. The Kalman filter performance degrades a lot when the GPS fails to provide navigation information due to the loss of GPS satellites' signals. In this case, the proposed data fusion method can adaptively adjust the reliability of GPS to switch to DR navigation and when GPS recovers it can switch back to GPS/DR navigation. This capability improves the performance of the GPS/DR navigation system.

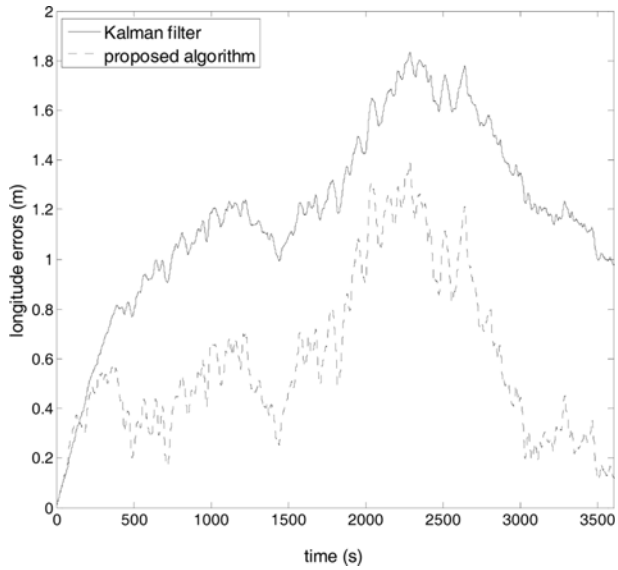


Fig. 9 latitude errors of proposed fusion method & Kalman filter

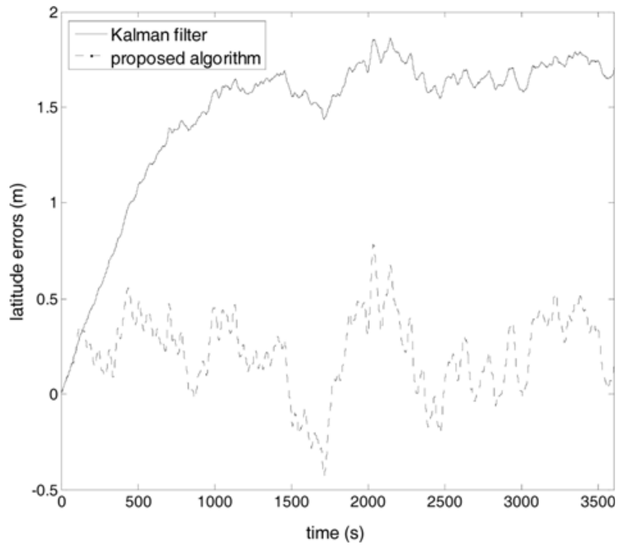


Fig. 10 longitude errors of proposed fusion method & Kalman filter

## 6. Conclusion

A precise and reliable navigation system is very important for the mobile robot to finish its mission. A DR system can provide short term precise navigation information but it can accumulate error over time without limit and so it cannot by itself navigate a mobile robot. GPS has complementary characteristics with the DR system which can provide positioning information with a bounded error. The absolute error of the cheap single GPS receiver used in this study is about 10-20 meters which is so big that it cannot be used to navigate the mobile robot directly. This paper proposes a GPS/ DR data fusion method based on the characteristics of the data of the single GPS receiver using a BP neural network. A BP neural network is first trained to estimate the output of the single GPS receiver then a new GPS/DR date fusion method is designed based on the characteristics of the single GPS output. The proposed method can fuse the navigation information coming from the cheap single GPS receiver and DR system and provide precise and robust navigation information for the mobile robot. The proposed data fusion method can adjust the reliability of the GPS based on its performance. Good simulation results verify the effectiveness of the proposed data fusion method for use of outdoor mobile robots.

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