

Localization using fuzzy and Kalman filtering data fusion

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ABSTRACT

In this paper a new localisation algorithm for the navigation of a mobile robot in outdoor environments is presented. The algorithm combines together a classical Kalman filter with a set of Fuzzy rules to fuse the information coming from different sensors. Some preliminary experimental results confirm the validity of the proposed approach.

1 INTRODUCTION

The design of a suitable localisation strategy is one of the main target in the development of a mobile robot navigation system. The actual trend to pursue this goal, is to use sensors of different type and to properly fuse together the relative data according to their reliability. For this reason Kalman filtering techniques represents a powerful tool [1],[2],[3].

In this work a new localisation algorithm is described. In this procedure the data provided by the different sensors are fused together by means of an extended Kalman filter combined with a set of a Fuzzy rules.

In the second part of the work a non autonomous four wheels platform, shown in Fig.1, was realised, to test the capabilities of different localisation algorithms. An highly accurate DGPS system was adopted to implement the measures of the absolute position, two encoders mounted in the rear wheels to measure the relative position, an electronic compass to get the absolute orientation and a one axis gyro to measure the angular rotational speed. In order to obtain information about the attitude of the robot, a two channel inclinometer has been integrated in the system.

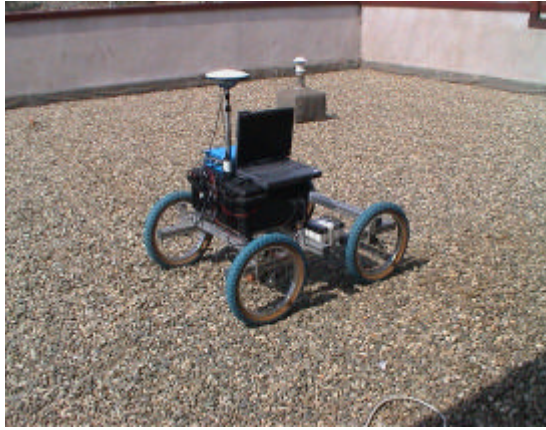


Figure 1. The Realized platform

2. SENSORS FOR LOCALISATION

The following sensors have been selected for the localisation system:

2.1 DGPS

An highly accurate DGPS system was selected (ASHTEC ZXTREME). This instrument in some situation can determine the position of the mobile receiver with a standard deviation lower than one centimeter. However in some situations the measurement error of the DGPS could increase to unsuitable values. This situation could occur when obstacles are present and a multipath effect appears, or when the visibility of some satellites is obstructed, or when the signal coming from the differential correction is lost. In all these situation the precision in the measurement of the location decreases from sub centimetre range to several meters. In any case the DGPS can estimate the standard deviation of its measurement.

2.2 Compass

A magnetic compass is the most classical absolute orientation sensor. However the precision that can be obtained is usually low ($> 0.1^\circ$) and it can be strongly affected by external disturbances.

When an extra magnetic fields (i.e. motors, electrical equipment, magnetic rocks) are present, the precision of the compass can be very bad. Moreover no estimation of the precision in the measurements is given by the sensor.

2.3 Odometry

The odometry is a classical way to compute the relative position of a mobile robot with respect to an initial location. However the precision of odometry decreases in time and big errors are present during vehicle rotations.

In particular if a skid-steering system is adopted the odometry is totally unreliable to compute the orientation of the vehicle. However, since usually very precise encoders are adopted, the odometry allows to obtain measurements with an high resolution and a low sampling time.

2.4 Gyro

The gyroscope is an angular speed sensor that can be adopted to compute the relative orientation of the vehicle [7]. However when this measurement is integrated drift and bias permit to get a good reliability only for short periods.

3 THE EXPERIMENTAL MEASUREMENT SYSTEM

In Fig. 2 a block diagram of the measurement system is shown.

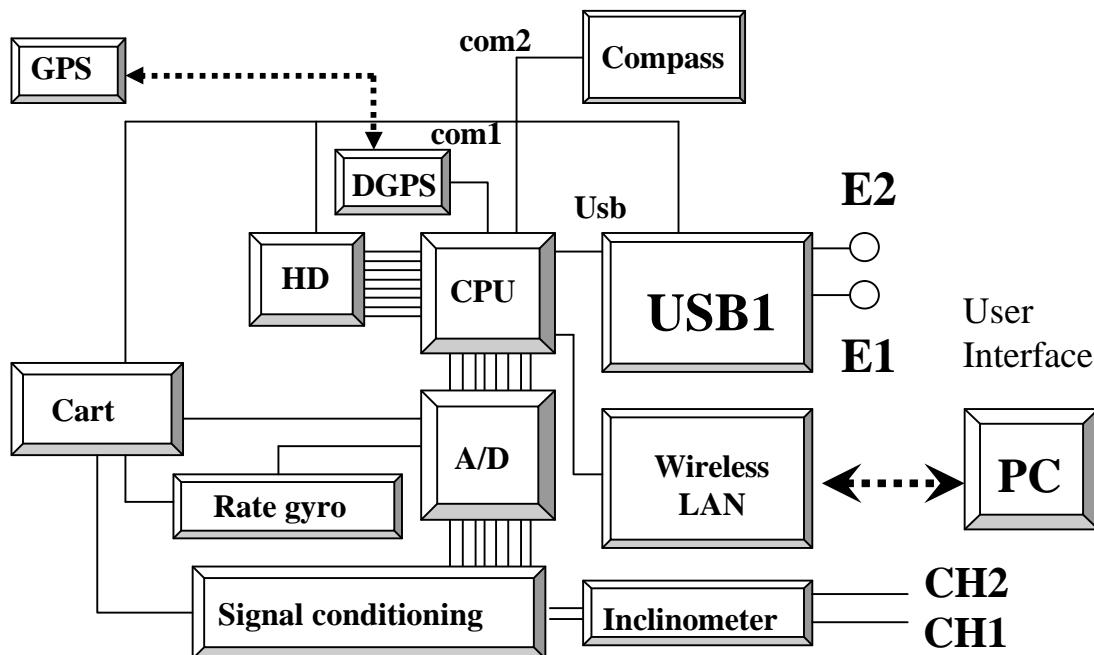


Figure 2. Block diagram of the measurement system

The GPS receiver used in our test is an ASHTECH Z-XTREME DGPS a greatly accurate instrument that in some situation can determine the position of the receiver with a standard deviation below one centimetre. An ADXL210 biaxial accelerometer chip is used as an inclinometer by adding a supplementary circuitry.

The BEI Gyrochip Horizon gyro is a compact, high reliability, solid-state angular rotation sensor. It features a monolithic quartz sensing element, internal power regulation, and a simple interface. An HMR3300 Honeywell was adopted as compass. The odometry sensors installed in the system are two quadrature encoder that gives 2000 pulse per revolution.

The main component of the acquisition system is the smart CPU MSMP5SEV (produced by Digital Logic) that integrates all the standard functions of a personal computer in a PC104 board (99mm x 90 mm). The CPU core is an INTEL Pentium 166 MHz 64 Mb RAM with one USB port two RS232 COM an E-IDE hard disk interface in which an HD of 20 GB with a Windows98 OS was installed. It is possible to expand this board with other boards of the same format. The acquisition of the analog signal of the inclinometer is implemented with the

expansion module AXIOM 10411 of the same PC/104 standard that can be easily installed on the CPU board.

The AX10411 board is a low cost solution for data acquisition applications such as temperature, humidity, pressure and level; this board implements a 16 channels 12-bit A/D converter. It is possible to change the gain of the input amplifier in order to get the best resolution.

The acquisition of the digital signal of the encoders was implemented by using USB1 interface of US Digital Corporation. This instrument tracks up to four encoders with dedicated hardware counters that are individually programmable with respect to count mode, maximum count, quadrature filtering, and index of reset. The counters are 24 bit wide, and may be programmed to accept quadrature signals in excess of 1 MHz. The measurements of the encoders are get simultaneously so as to provide positions without time skew, and the data is sent via USB port every milliseconds.

The last expansion module is the MSMJ104/D that allows to install in the system PCMCIA hardware. In our case we use a wireless radio LAN PCMCIA in order to telecontrol the program running in the CPU using a remote P.C. The program used to connect the two PCs is Microsoft Net meeting that allows to have in the remote PC the desktop of the remote measurement system PC .

4 THE EXTENDED KALMAN FILTER ALGORITHM AND THE SET OF FUZZY RULES

In order to try to get the best from all the previously described sensors, a multisensor fusion algorithm has been designed.

The algorithm adopted to estimate the position and the orientation of the vehicle is an adaptive extended Kalman filter [3] in which the orientation of the rover is computed by using a fuzzy rules based algorithm.

The complementary characteristic of the sensors used, suggests some empirical rules that can be used to select in some situations one sensor instead of another.

We considered the angular speed measured by using the gyro and the odometry.

The gyro measurements present a limited range out of which the accuracy decrease; an angular velocity too high or too low can let to wrong measures.

In this cases the odometry or a linear combination of the odometry and the gyro measurement can improve the final accuracy.

So the idea is that of translating this kind of rules in a set of fuzzy rules by defining its membership functions.

Let us consider the kinematic model of a dual drive system, we can indicate with $[x(k) \ y(k) \ \mathbf{q}(k)]^T$ the estimate of the state of the vehicle and with $P(k)$ the estimate of the state covariance matrix at time k (2),(3).

When the DGPS measurements are not available, we compute the estimate of the state and the covariance matrix at time $k+1$ just with the predict phase of the EKF algorithm:

$$\begin{pmatrix} x(k+1|k) \\ y(k+1|k) \\ \mathbf{q}(k+1|k) \end{pmatrix} = \begin{pmatrix} x(k) + T\mathbf{n}(k)\cos(\mathbf{q}(k)) \\ y(k) + T\mathbf{n}(k)\sin(\mathbf{q}(k)) \\ \mathbf{q}(k) + T\mathbf{w}(k) \end{pmatrix} \quad (1)$$

where T is the sampling time and $v(k)$ is computed from the encoder measurements. The predicted state covariance matrix is computed by using equation (3)

$$P(k+1|k) = J_x(k)P(k)J_x^T(k) + C_v(k) \quad (3)$$

where $C_v(k)$ is a constant covariance matrix of the noise of model computed from resolution of the encoder and the accuracy of the gyro, $J_x(k)$ and $J_u(k)$ are the jacobian of the system and measurement model

$$J_x(k) = \begin{pmatrix} 1 & 0 & -T\mathbf{n}(k)\text{sen}(\mathbf{q}(k)) \\ 0 & 1 & T\mathbf{n}(k)\cos(\mathbf{q}(k)) \\ 0 & 0 & 1 \end{pmatrix} \quad J_u(k) = \begin{pmatrix} T\cos(\mathbf{q}(k)) & 0 \\ T\text{sen}(\mathbf{q}(k)) & 0 \\ 0 & T \end{pmatrix} \quad (4)$$

and $\hat{z}(k)$ is the result of the fuzzy rules based algorithm described in the following. The predicted measurements vector is:

$$\hat{z}(k+1|k) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x(k+1|k) \\ y(k+1|k) \\ \mathbf{q}(k+1|k) \end{pmatrix} = H \begin{pmatrix} x(k+1|k) \\ y(k+1|k) \\ \mathbf{q}(k+1|k) \end{pmatrix} \quad (2)$$

where z_1 and z_2 comes from the DGPS, while \hat{z} comes from the compass.

If we indicate with $\hat{z}_o(k)$ $\hat{z}_g(k)$ the angular speeds measured respectively with the encoders and the gyro and define the fuzzy set with the membership functions F_o and F_g reported in figure 4 we can obtain the rules that produce $\hat{z}(k)$.

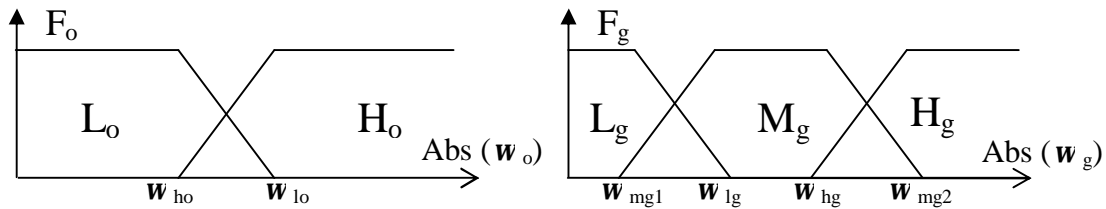


Figure 3. The membership functions

- If (\hat{z}_o is L_o and \hat{z}_g is L_g) then $\hat{z}(k) = \hat{z}_o(k)$
- If (\hat{z}_o is L_o and \hat{z}_g is M_g) then $\hat{z}(k) = (\hat{z}_o(k) + \hat{z}_g(k)) * 0.5$
- If (\hat{z}_o is L_o and \hat{z}_g is H_g) then $\hat{z}(k) = \hat{z}_o(k)$
- If (\hat{z}_o is H_o and \hat{z}_g is L_g) then $\hat{z}(k) = \hat{z}_o(k)$
- If (\hat{z}_o is H_o and \hat{z}_g is M_g) then $\hat{z}(k) = \hat{z}_g(k)$
- If (\hat{z}_o is H_o and \hat{z}_g is H_g) then $\hat{z}(k) = (\hat{z}_o(k) + \hat{z}_g(k)) * 0.5$

When the DGPS and compass measurements are available we can update the state of the vehicle and the covariance matrix

$$K(k+1) = P(k+1|k)H^T[HP(k+1|k)H^T + C_w(k+1)]^{-1} \quad (5)$$

$$\begin{pmatrix} x(k+1) \\ y(k+1) \\ \mathbf{q}(k+1) \end{pmatrix} = \begin{pmatrix} x(k+1|k) \\ y(k+1|k) \\ \mathbf{q}(k+1|k) \end{pmatrix} + K(k+1)[Z(k+1|k) - Z(k+1)] \quad (6)$$

$$P(k+1) = [I - K(k+1)H]P(k+1/k) \quad (7)$$

where $Z(k+1)$ is the measurement vector obtained from DGPS and compass and $C_w(k)$ is obtained directly from DGPS measurements quality.

The block diagram of figure 5 describe how the algorithm works.

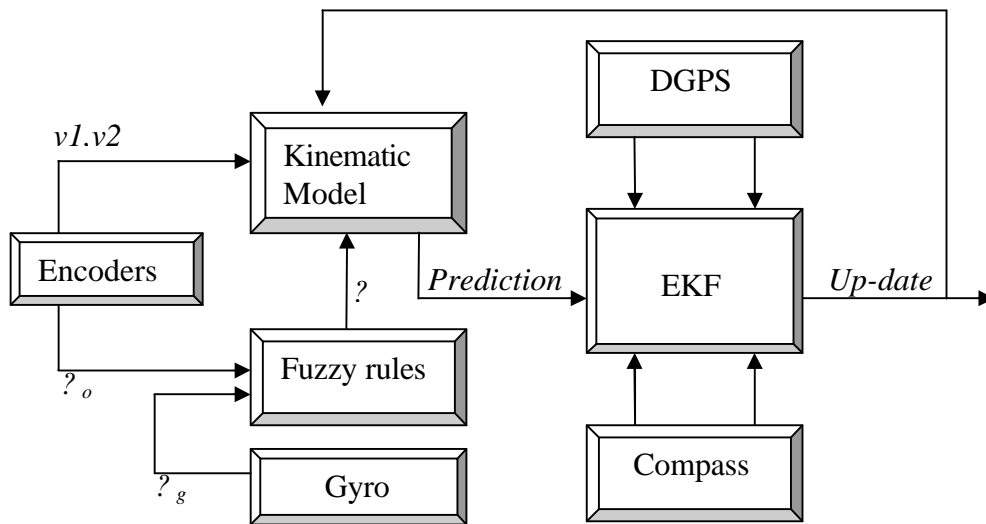


Figure 4. Block diagram of the algorithm

5 THE RESULTS

Preliminary results concerns the fusion of the DGPS with odometry. The results show that the algorithm is able to change its behaviour according to the reliability of the measures.

As an example a test performed in a square path of five meters each side, is shown in fig. 5(a). In the first part of the path the behaviour of the filter is similar to that of the inertial sensors because of the presence of a wall in the nearness that increase the standard deviation of the DGPS measurements. In a second time the behaviour changes and becomes similar to the DGPS measure that is now more reliable ,as reported in fig.5(b).

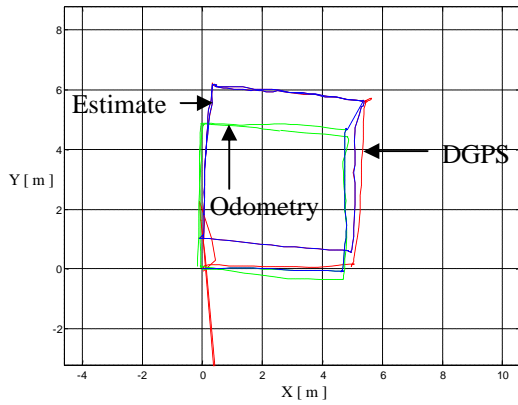


Figure 5(a). Square path of five meter

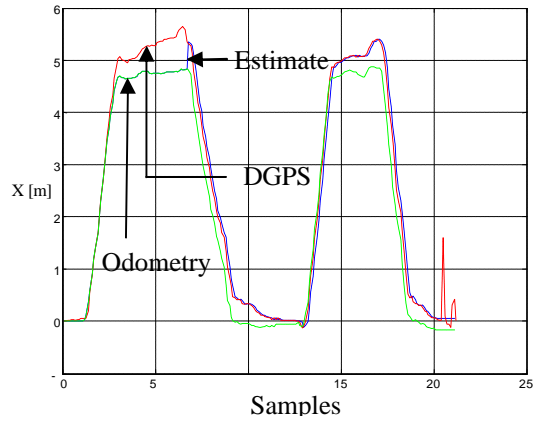


Figure 5(b). Variable X versus Time

The following experimental tests have been performed in a long track in which the accuracy of the DGPS was very high.

Indeed, if we simulate a low DGPS accuracy by artificially increasing its standard deviation, adding noise in the measurements, we can compare the results obtained by the algorithm with the true measurements. The figures 6(a) and 6(b) show the test in which the standard deviation of the DGPS measurements has been artificially increased for 50 seconds.

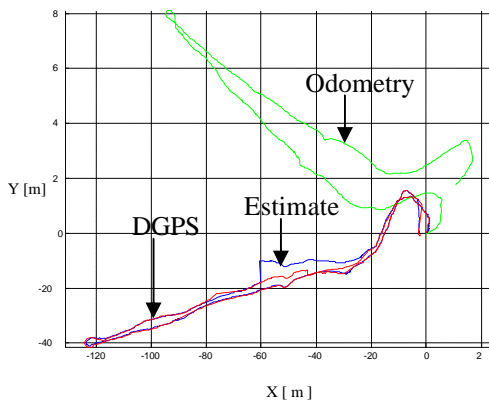


Figure 6(a). Long random track.

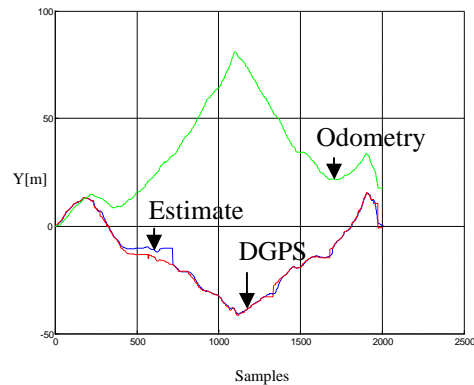


Figure 6(b). Variable Y versus Time

The total amount of the error accumulated by the odometry is very small considering that the track was performed in about four minutes.

6 CONCLUSIONS

In this work a new algorithm that allow to fuse the information coming from several different sensors for localisation is presented. The algorithm mixes the peculiarity of a classical Extended Kalman Filter with a set of fuzzy rules. An experimental platform has been realized to test the localisation algorithms.

Several preliminary results have been shown. Work is in progress to test and to improve the algorithm using all others sensors. The designed system will be implemented as localisation system in the ROBOVOLC project [4, 5, 6].

ACKNOWLEDGEMENTS

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