Simulation of Mobile Robot Navigation with Sensor Fusion on an Uneven Path

D.M.G.A.I.N. Sumanarathna
isurasumanarathna@gmail.com

I.A.S.R. Senevirathna
srs.ruwantha@gmail.com

K.L.U. Sirisena
fwmlaksith@yahoo.com

H.G.N. Sandamali
hgnsandamali@gmail.com

M. Branesh Pillai
pillaibranesh@elect.mrt.ac.lk

A.M. Harsha S. Abeykoon
harsha@elect.mrt.ac.lk

Department of Electrical Engineering, University of Moratuwa, Katubedda, Moratuwa, Sri Lanka.

***Abstract*- This paper describes the navigation of a two-wheel drive mobile robot along a predefined path under uneven road conditions where it cannot solely rely on encoders, GPS or an accelerometer individually. There are conditions when low friction or slippery ground surfaces such as sandy paths and pits cause one or both encoders to halt or rotate less as the robot moving forward. Areas covered with clouds, trees or structures can block GPS signals. Sudden pickups and halts give false information from accelerometers. Therefore Kalman filter based sensor fusion algorithm is implemented in order to get the best position estimation for the mobile robot using above sensor outputs. The Special feature of this algorithm is that it includes a simple method to overcome the effects of encoder errors due to the slipping of wheels of the mobile robot, which does not require complex computations to additional measurement units to directly measure the slipping of the wheels of the robot. Finally the validity of the proposed algorithm is demonstrated via simulation.**

Keywords: robot navigation; sensor fusion; encoder slipping; relative localization information; absolute localization information; uneven path

I. Introduction

The task of the mobile robot is to move from a given point to a destination along a given course. The localization and positioning in a reference frame is necessary to navigate the mobile robot in the given environment. Three sensors, Encoder, GPS and Accelerometer are used to localize and decide the next move to reach the waypoints.

But each sensor mentioned above has unique weaknesses of its own. They may be inherent errors of the sensors or errors caused by external factors.

Encoders are the most accurate sensor used in the research. Using Encoder outputs, kinematics model and dead reckoning current position and attitude angle of the mobile robot can be estimated. (For dead reckoning, successive velocity, angular displacement feedback and the previously calculated position and attitude angle are also needed).This method is popular because of its simplicity. But problems arise when the encoder outputs are erroneous due to some environmental factors such as slippery ground surfaces and uneven road conditions. When the robot is moving long distances errors are also accumulated and creates a considerable error. These reasons make encoder outputs faulty. So to get precise estimation errors of the encoders should be re-corrected.

GPS and accelerometer also have higher errors. Due to cloudy skies, large trees and structures GPS signal can be blocked and geometry of satellites also causes its error vary over time. But it is useful in navigating the robot for long distances. Accelerometer measures the acceleration of the robot and by double integration position of the robot can be estimated. But then error is also integrated twice.

Due to this reasons each sensor cannot be used individually. Therefore the sensory information are fused using a Kalman filter based sensor fusion algorithm to locate the mobile robot.

Slipping of the wheels of the mobile robot and uneven road conditions has great impact to the precision of position estimation. Therefore Many Research have been done on mobile robot navigation with slip estimation, mobile robot navigation using sensor fusion and even on mobile robot navigation and slip estimation using sensor fusion [1]. This involves complicated calculations related to slip rates. Wheel soil interaction models and Terramechanics models are more relevant in rover navigation under special soil conditions such as extra-planetary explorations. But For small scale mobile robot navigation purposes (like this study), those calculations and soil condition investigations may not be useful. Another research proposes estimating the wheel slip to provide the accurate information to the controller [3]. Here, wheel slip and tire radius errors are lumped together as an effective radius and estimated. However due to the radius estimation changes with the speed; it causes some degradation of the solution especially when the speed is low as in our case. There are different methods proposed to estimate the slip for controlling its effect on navigation of the mobile robot [2], which does involve different models, tests and bothersome calculations [4] which is not beneficial for systems like ours.

In this paper, it is not the objective to calculate the slip or controlling the slip. Instead multiple Kalman filter [7] algorithm is used such that weight on Encoder measurements is switched from higher to lower level automatically when slipping is detected. This method avoids unnecessary calculations and models while providing a precise positioning of the mobile robot.

II. KINEMATICS OF WHEELED MOBILE ROBOT (WMR)

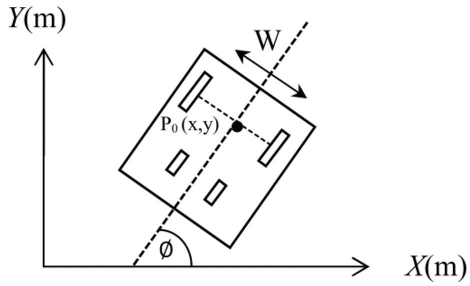

Figure 1. The kinematics model in world coordinate system

The velocity and displacement instructions are given to the WMR with respect to a world coordinate system. But the angular velocities and displacements of the driven wheels of the WMR, measured by the encoders are in joint co-ordinate system. Therefore encoder outputs are converted to the world coordinate system data using the following kinematic model.

As shown in Figure 1 the position of the robot (P_0) which is the middle point of the line connecting the axis of two wheels is defined using the world coordinate system. It consists of, *X* coordinate (x) which is the distance the robot platform has travelled in *X* direction, the *Y* coordinate (y) which is the distance the robot platform has travelled in *Y* direction and the attitude angle (φ) which is the angle formed between the perpendicular to the mobile robot's axis and the x axis. Therefore, if the angle of rotation of left and right wheels (θ_l, θ_r respectively) and the pose vector of robot platform in the surface is described in equations (1) and (2).

$$\theta = [\theta_l , \theta r]^T \tag{1}$$

$$X = [x, y, \emptyset]^T \tag{2}$$

Then the direct kinematic equation can be represented in equation (3),

$$\dot{X} = Jaco.\dot{\theta} \tag{3}$$

Where J_{aco} represent the Jacobean matrix calculated as in equation (4),

$$Jaco = \begin{bmatrix} \frac{R.Cos\emptyset}{2} & \frac{R.Cos\emptyset}{2} \\ \frac{R.Sin\emptyset}{2} & \frac{R.Sin\emptyset}{2} \\ \frac{R}{W} & \frac{-R}{W} \end{bmatrix} \tag{4}$$

However, the inverse kinematic equation is also required to convert the world co-ordinate system data to joint co-ordinate data in order to plan the robot motion and the robot control. Since Jacobean matrix is not a quadratic matrix, the pseudo inverse matrix $Jaco^+$ is used. The kinematic equation has to be differentiated to calculate the inverse kinematic equations.

$$\dot{\theta} = Jaco^+ (\emptyset).\dot{X} \tag{5}$$

$$\ddot{\theta} = Jaco^+ (\emptyset).\ddot{X} + \dot{Jaco}^+(\emptyset).\dot{X} \tag{6}$$

Where $Jaco^+$ represents the inverse Jacobean matrix,

$$Jaco^+ = \frac{1}{R}\begin{bmatrix} Cos\emptyset & Sin\emptyset & \frac{W}{2} \\ Cos\emptyset & Sin\emptyset & \frac{-W}{2} \end{bmatrix} \tag{7}$$

By neglecting the inverse Jacobean derivative,

$$\ddot{\theta} = Jaco^+ (\emptyset).\ddot{X} \tag{8}$$

A. Dead Reckoning

The current position and attitude angle of the WMR can be estimated using dead reckoning. For calculation It requires the velocity, angular displacement feedbacks and the previously calculated position and attitude angle data.

The x and y positions are estimated as follows [5].

$$x_k = x_{k-1} + V_{p,k}.cos\left(\frac{\emptyset_k + \emptyset_{k-1}}{2}\right)\Delta t \tag{9}$$

$$y_k = y_{k-1} + V_{p,k}.sin\left(\frac{\emptyset_k + \emptyset_{k-1}}{2}\right)\Delta t \tag{10}$$

Where, Vp is the velocity of the WMR in world coordinate system and Δt is the sampling time. The subscript k indicates the respective values at k^{th} sampling moment and the subscript k-1 denotes the values at the pervious occasion of k^{th} sampling moment.
The attitude angle is calculated using the encoder outputs from the equation (11),

$$\emptyset = \frac{R}{W}(\theta_r - \theta_l) \tag{11}$$

B. GPS Data Conversion

While encoders and the three axis accelerometer provide the relative localization information, GPS module provides absolute localization information. To convert GPS latitude and longitude data to useful world coordinate system, following equations are used in the research.

$$y = R.(b2 - b1).\frac{\Pi}{180} \tag{12}$$

$$x = R.(a2 - a1).\frac{\Pi}{180}.cos\,(b1) \tag{13}$$

Here, *(b2-b1)*, *(a2-a1)*, *R* and *b1* represent latitude difference between two positions, longitude difference between the same two points, earth radius and latitude of initial position respectively.

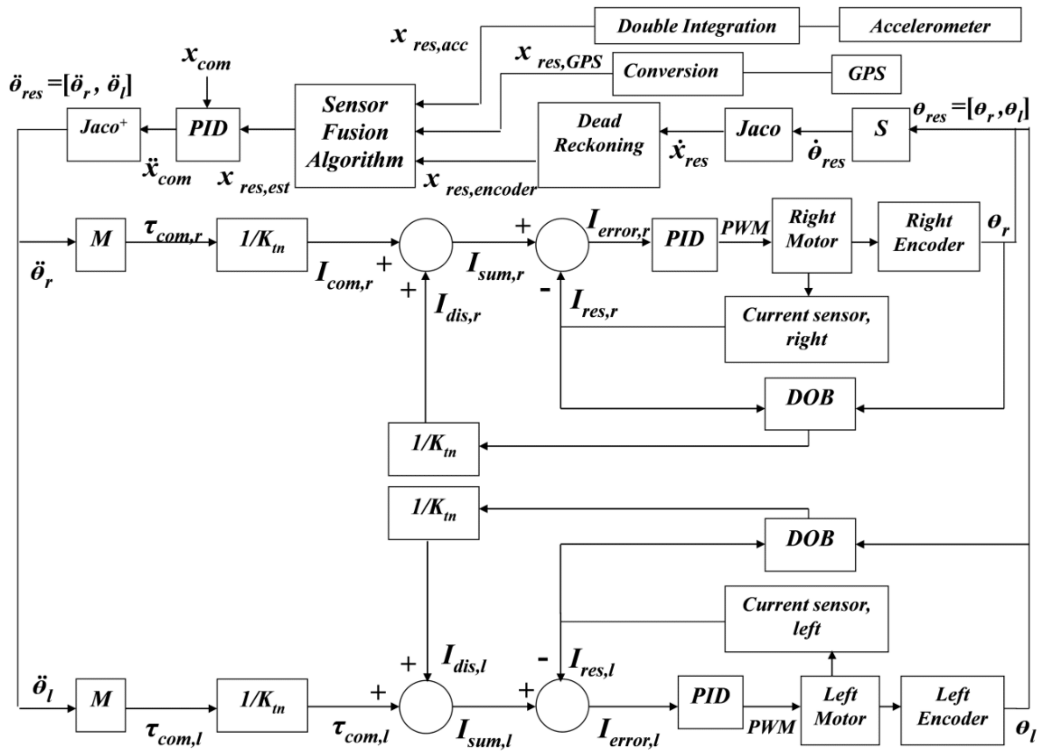

Figure 2. Control block diagram of the mobile robot

C. Accelerometer Data Conversion

The raw output of the accelerometer is the acceleration in X, Y and Z directions. But in this case only the acceleration in X and Y directions are required ($\ddot{x}$, $\ddot{y}$). These values are subject to noise and therefore an 'Exponential Moving Average Low Pass Filter' is included for noise reduction. (As in equation (14) and (15) a smoothing factor α is introduced where 0<α<1). $\ddot{x}_{raw}$, $\ddot{y}_{raw}$ are the raw readings of the accelerometer and $\ddot{x}_{filtered\_old}$ and $\ddot{y}_{filtered\_old}$ are the previously filtered values of $\ddot{x}$, $\ddot{y}$.

$$\ddot{x}_{filtered\_new} = (1-\alpha)^* \ddot{x}_{filtered\_old} + \alpha^* \ddot{x}_{raw} \quad (14)$$

$$\ddot{y}_{filtered\_new} = (1-\alpha)^* \ddot{y}_{filtered\_old} + \alpha^* \ddot{y}_{raw} \quad (15)$$

The filtered values are then processed using quaternion theorem and still they are a combination of both static and dynamic acceleration [6]. Dynamic components are calculated from respective quaternion components and integrated twice to get position estimation. ∅ is the 'Yaw' of Euler angles.

III. SENSOR FUSION ALGORITHM

The sensor fusion algorithm used in the research is derived from the Kalman filter. Mobile robot is a dynamic system hence it can be represented in a state-space model. The kalman filter addresses the problem of estimating the state of a discrete time controlled process that is governed by the models below.

$$X_k = AX_{k-1} + BU_k + w_{k-1} \quad (16)$$

$$Z_k = HX_k + V_k \quad (17)$$

Equation (16) is the process model and equation (17) is the measurement model.

Here $X = [x, y, \emptyset]^T$

Where X_k, X_{k-1} are current and previous values of x,y and ∅, U_k is the control input and W_{k-1}, V_k represent the process and measurement noise respectively. Z_k is the actual output by the measurement sensor. A, B and H are transition, control and observation matrices.
In the research therefore encoder is chosen as the process sensor while the GPS and three axis accelerometer are the measurement sensors.

Kalman filter is recursive process of two steps.

Time update (Prediction or priori step)

$$\hat{X}_{k|k-1} = A\hat{X}_{k-1|k-1} + BU_k \quad (18)$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k \quad (19)$$

Measurement update (Correction or posterior step)

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R_k)^{-1} \quad (20)$$

$$\hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k(Z_k - H\hat{X}_{k|k-1}) \quad (21)$$

$$P_{k|k} = (I - K_kH)P_{k|k-1} \quad (22)$$

Here, $\hat{X}_{k|k-1}$is the prior estimate, $P_{k|k-1}$is the prior error covariance, $\hat{X}_{k|k}$, $P_{k|k}$ are posterior state and covariance and K_k is the Kalman gain. Q_k and R_k are the system noise covariance and the measurement noise covariance which were found in empirically.

.

In the research, the authors have used multiple Kalman filtering. There Kalman filter based two algorithms are applied, switching from one algorithm to other occurs according to the behavior of the encoder outputs.

A. *Algorithm I*

When the robot is moving on the predefined path it uses the information derived from the three sensors Encoder, GPS and 3-Axis Accelerometer. Encoder measurements are highly affected by the uneven road conditions and slipping of the WMR. GPS has a higher noise and high probability for being unavailable. (GPS signal lost) 3-Axis accelerometer gives the measurement with the highest noise.

When the WMR is moving on a flat surface, Encoder measurement is very accurate. For such conditions Algorithm 1 can be used to estimate the robot positioning on the path. Here, encoder measurement is fused with GPS measurement using Kalman filter and Kalman output is directed to the switching algorithm. However this method has been used by some other authors also.

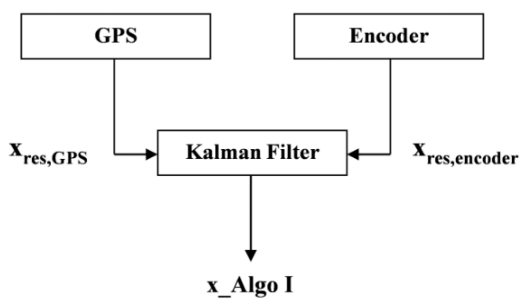

Figure 3. Algorithm I

B. *Algorithm II*

This algorithm is a new concept to find the robot positioning over time along the path when the encoder measurement is not available or reliable. Here, first Encoder and GPS data is fused and that output is fused again with the accelerometer data using Kalman Filter to get a reliable positioning estimation especially in slipping of WMR or uneven road conditions

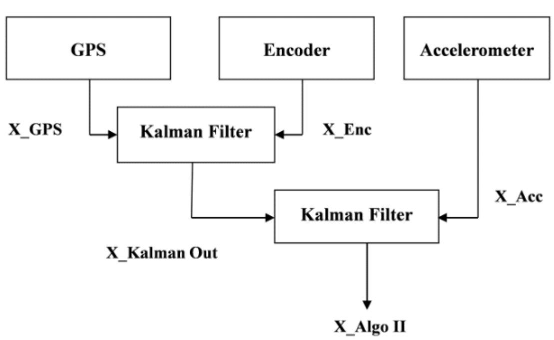

Figure 4. Algorithm II

C. *Switching Algorithm*

Algorithm I and II are the inputs to the switching algorithm. The intention here is to select the best position estimation from either Algorithm I or II which is very close to the actual position.

Generally, for a flat surface where slipping is negligible, the commanded position of the mobile robot and the encoder measurement outputs are approximately the same. A range for difference between commanded position and the encoder output can be defined for such a surface using practical data gained from multiple tests.

As long as the difference between commanded position and the encoder measurement lies in that practically obtained range, it can be assumed that encoder is accurate and Algorithm I can be utilized to get the position data to navigate the robot. When the encoder measurement exceeds the above range, Algorithm II is chosen by the Switching Algorithm.

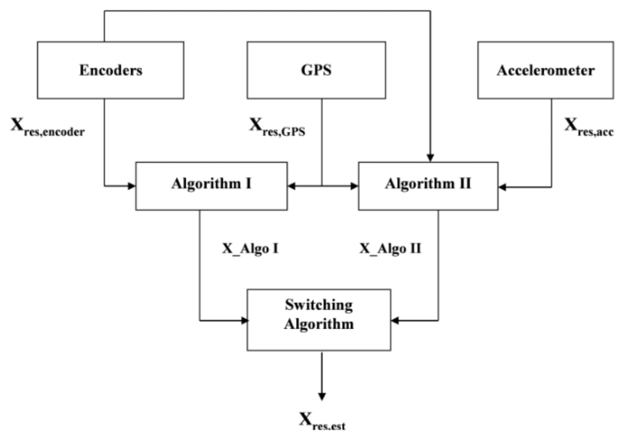

Figure 5. Sensor Fusion Algorithm

IV. SIMULATION AND RESULTS

Matlab is used for the simulation. [9]

As Kalman filter is used for this simulation several assumptions are made. They are; this is a linear system and all the noises (process and measurement noise) are Gaussian.

Encoder is a comparably a very low noise sensor. Its resolution is 1024 PPR. It is used in quadrature multiplication mode such that we get 4096 PPR. But in slipping situations and other uneven road conditions this noise is increased.

The typical error of the GPS is taken as 3 to 4 meters.

GPS has a considerable noise but not as large as the accelerometer.

A. When sensory data is available

1. Raw measurement from GPS and Encoder

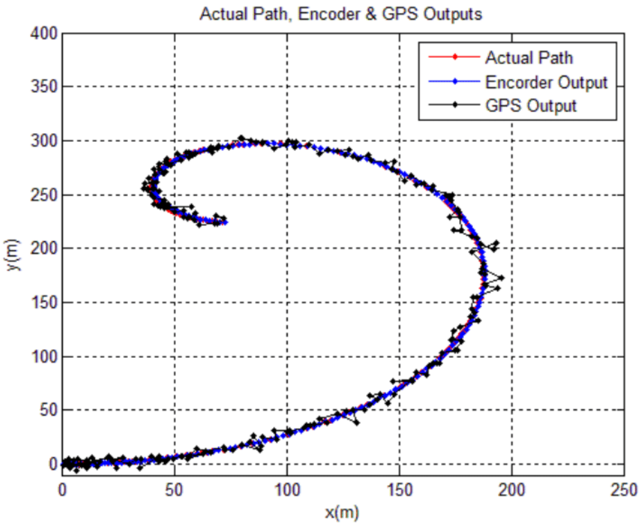

Figure 6. Raw measurements from GPS and Encoder

Figure 6 is plotted using raw GPS and Encoder data. As Encoder's noise is low it is very close to the actual path. GPS output with high noise is randomly deviated from the actual path as shown in the figure.

2. Kalman output of the GPS and Encoder Data

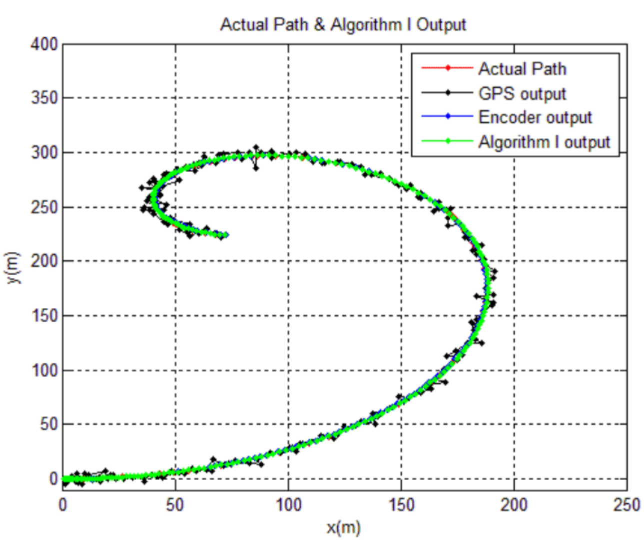

Figure 7. Kalman output of the GPS and Encoder Data

Figure 7 shows the output of the Algorithm I (shown in figure 3). Therefore it can be concluded that Algorithm I output in this case is a sufficiently accurate estimation of the actual path.

B. When sensory data is not available

1. When Sensory data is not accurate (i.e. Encoder is slipping and GPS signal is lost)

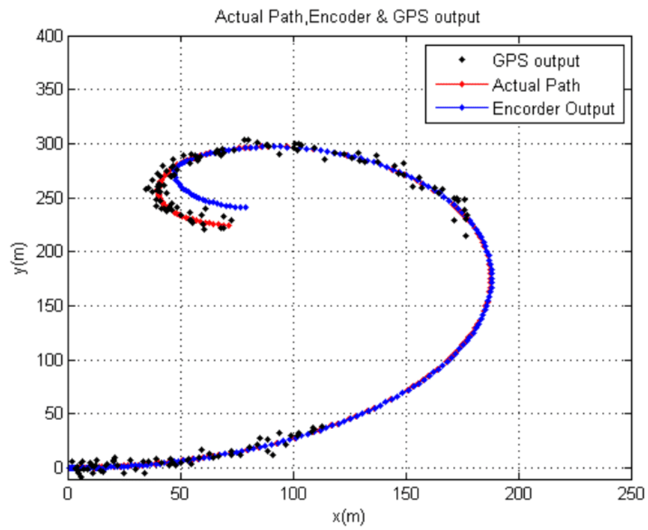

Figure 8. Raw measurements from GPS and Encoder

Figure 8 is plotted considering scenarios like when one of the sensors or both sensors would not be available or reliable. i.e. when the wheels of the mobile robot is slipping (Encoder is no more reliable) and GPS signal is lost.

2. Kalman output when Sensory data is not accurate (i.e. Encoder is slipping and GPS signal is lost)

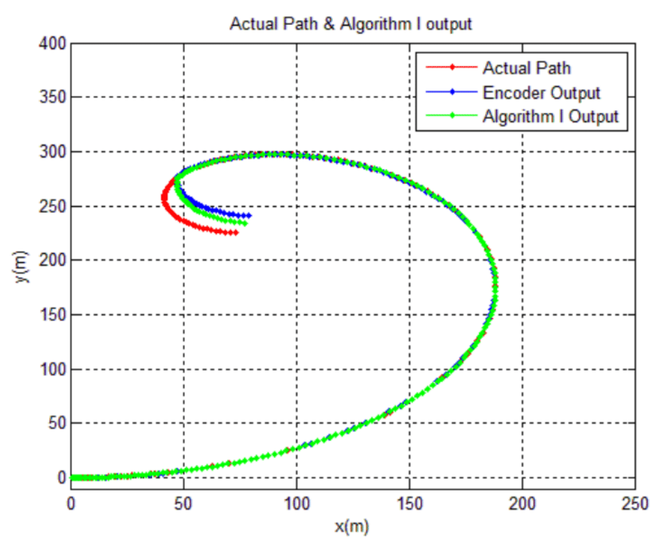

Figure 9. Kalman output of the GPS and Encoder Data

Figure 9 shows that when Encoder is accurate, in that case Encoder and GPS Kalman output is sufficient for the requirement. But when encoder is not precise (i.e.: slipping conditions) that Kalman output is no longer reliable.

Using Algorithm II

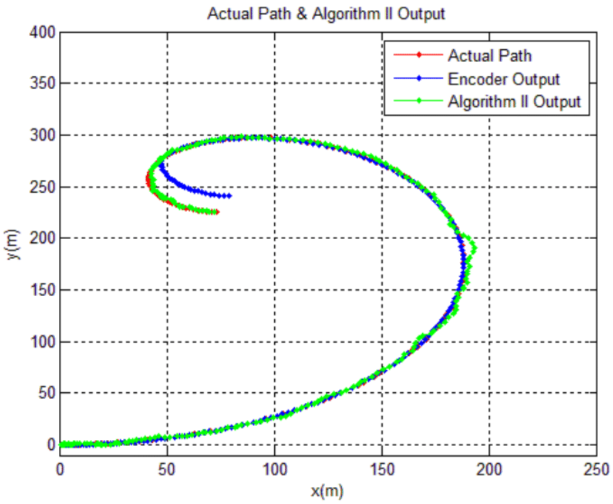

Figure 10. Output of the Algorithm II

Algorithm II shown in the figure 4 has been used to plot figure 10 considering same faulty conditions as in the previous case. This graph shows that the fault due to the slipping of the Encoder is successfully overcome. But most of the time, encoders would be accurate. But at that time accuracy of Algorithm II is less than the Algorithm I. it is a disadvantage of this method.

Therefore to avoid this drawback, the switching algorithm is used to get the most reliable output from both algorithm outputs.

Final output (after using the switching Algorithm)

Here the weaknesses of both algorithms have been overcome by automatically switching above two algorithm outputs as required using the sensor fusion algorithm shown in figure 5.

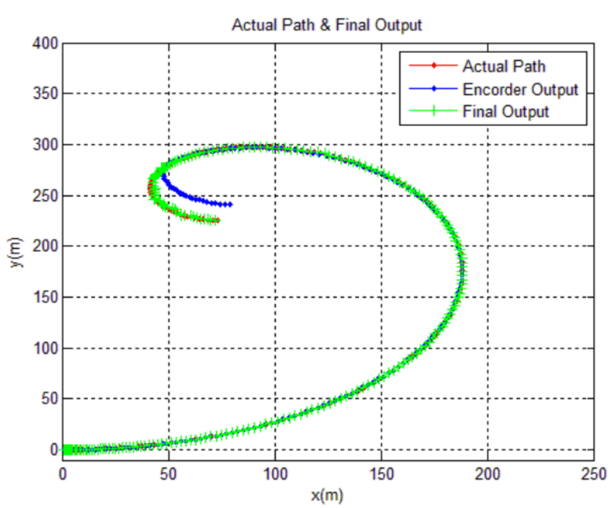

Figure 11. Final output

V. Conclusion

This paper presents a new method to obtain a more precise position estimation to navigate the mobile robot precisely even when slipping conditions or uneven path conditions affect the accuracy of the encoder data where encoder data cannot be directly used. Some parameters of soil and lots of complex calculations are required to correct encoders in slipping to correct encoders in slipping. But this paper suggests a rather simple method to avoid the effect of encoder errors to obtain accurate mobile robot navigation.

For theoretical emphasis a simulation is done using Matlab software and presented here. In future, practical implementation of WMR would prove the accuracy of this sensor fusion algorithm

.

VI. References

[1] Damien Lhomme-Desages, Christophe Grand, Fa¨ız Ben Amar and Jean-Claude Guinot, Member, IEEE, "Doppler-based Ground Speed Sensor Fusion and Slip Control for a Wheeled Rover", *IEEE/ASME Transactions On Mechatronics*, vol. 14, no. 4, August 2009

[2] Puneet Goel, Stergios I. Roumeliotis and Gaurav S. Sukhatme, "Robot Localization Using Relative and Absolute Position Estimates"

[3] Benjamin J. Clark, David M. Bevly, and Shane Farritor, "Analysis of Improvement to Two-Wheel Robot Navigation Using Low-Cost GPS/INS Aids"

[4] Seyr M. and Jakubek S., "Proprioceptive Navigation, Slip Estimation and Slip Control for Autonomous Wheeled Mobile Robots", *Robotics, Automation and Mechatronics, 2006 IEEE Conference* , vol., no., pp.1,6, Dec. 2006

[5] H.A.N.D. Dayarathna, L.L.G. Prabuddha, K.L.D.N.J. Ariyawansha, M.K.C.D. Chinthaka, A.M. Harsha S. Abeykoon and M. Branesh Pillai, "Sensorless Contact Position Estimation of a Mobile Robot in Pushing Motion"

[6] Emily L. C. Shepard1,*, Rory P. Wilson1, Lewis G. Halsey2, Flavio Quintana3, Agustina Gómez Laich3, Adrian C. Gleiss1, Nikolai Liebsch1, Andrew E. Myers4 and Brad Norman5, "Derivation of body motion via appropriate smoothing of acceleration data", vol. 4: 235–241, December 2008

[7] Louis Drolet1,2, François Michaud2 and Jean Côté1, "Adaptable Sensor Fusion Using Multiple Kalman Filters", *In proceeding of: Intelligent Robots and Systems, 2000. (IROS 2000). Proceedings. 2000 IEEE/RSJ International Conference on*, Volume: 2

[8] Greg Welch, Gary Bishop, "An Introduction to the Kalman Filter", University of North Carolina at Chapel Hill Department of Computer Science, 2001

[9] M.S.Grewal, A.P. Andrews, "Kalman Filtering - Theory and Practice Using MATLAB", Wiley, 2001