



Development of an Algorithm for Real Time Vehicle Positioning on Failure of GPS

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ABSTRACT: Positioning is an important area where the researches are going on. This work is related to the area of an automotive transportation system. The real time vehicle positioning is an important area for intelligent transportation system (ITS) applications. Normally low cost GPS receivers do not guarantee accurate continuous data to the positioning system. This is because of the temporary loss of satellite connection and signal error. So in this work to avoid these problems an algorithm would be developed. The algorithm is based on Extended Kalman Filter (EKF) that integrates low-cost GPS data and in-vehicle sensors data to adapt the vehicle model in various driving conditions and to avoid the error due to GPS problem. The proposed system composed of two types of vehicle model set, a kinematic vehicle model and a dynamic vehicle model. These two models are developed using Extended Kalman Filter (EKF) and based on the driving condition a suitable model will be selected.

KEYWORDS: Extended Kalman Filter, In-vehicle Sensors, Vehicle Positioning and Vehicle Model Set.

I.INTRODUCTION

Today the importance of real time vehicle positioning is more than that in the earlier time. Intelligent transportation system (ITS) is one of the important areas where real time vehicle positioning is used. Normally, the satellite-based global position system (GPS) is widely used for positioning the vehicle. But these GPS receivers cannot give accurate information about the positioning of the vehicle due to the temporary or occasional loss of satellite connection and signal errors. To overcome these problems the positioning system should be aided by additional sensors such as inertial navigation system (INS), digital road map, camera, radar or laser sensor, vehicle motion sensors, etc [1]. The previous works will motivate to develop an algorithm for real time vehicle positioning on failure of GPS, which should overcome the entire problem affected in the previous works and that algorithm should give reliable, accurate and continuous data. In the proposed system, the data from in-vehicle sensors such as wheel speed sensors, a yaw rate sensor and a steering angle sensor with GPS data are fused by the help of Extended Kalman filter (EKF). To fuse these data, the algorithm needs good filters. For that numerous Bayesian filters based sensor fusion approaches have been proposed [13]. The extended Kalman filter (EKF) is the most widely used filter for information fusion algorithms because nonlinear localization problems can easily be solved which provides efficient and reliable performance for practical applications.

In this work, an algorithm would be developed, which combines the data from in-vehicle sensors such as wheel speed sensors, yaw rate sensor and steering angle sensor with GPS data. So this algorithm gives a more accurate, continuous and reliable outcome to positioning the vehicle. In this work EKF is used for the fusion of in-vehicle sensor data with GPS data. Another important thing is the analysis of different driving conditions of the vehicle. Depending on the driving conditions, the data from in-vehicle sensors will change and the occurrence of error will be more. So the algorithm should have suitable vehicle model set for different driving conditions. In this work, two-vehicle models would be developed, kinematic and dynamic vehicle model. The kinematic model is suitable for low speed and low slip driving condition such as those in an intersection or parking lot. Dynamic model is suitable under high speed and large slip driving conditions such as those in highway driving. These two models are developed using EKF. Kinematic model is based on the assumption of small wheel slip condition, but in dynamic model tire slip and lateral force are considered. The selection of these models during real time is a challenging process. This approach describes that the system selects one of the models from a finite number of different model based on the speed range of the vehicle.

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II. LITERATURE SURVEY

Many algorithms evolved in the past few decades to achieve real time vehicle positioning. Fusion of GPS data with vehicle sensors data is the common solution to improve the vehicle positioning. In previous works, additional sensors such as an inertial navigation system (INS), vehicle motion sensors, radar or laser sensor, etc. were used along with GPS receiver. The fusion of GPS data with INS is normally done in previous algorithms, where the problem is the installation of an INS requires extra cost and effort; also accurate INS systems are too expensive for automotive application. To tackle the problem associated with GPS, several approaches have been proposed. Combined use of GPS and an inertial measurement unit (IMU) unit is one solution [1], [2], [3]. The main problem in this algorithm is the errors caused by bias in the sensor readings and inaccurate readings which will cause error in the local navigation frame. Another solution is combined use of GPS and MEMS (Micro Electro Mechanical System) inertial sensor [4], [5]. The basic advantages of this method are precise and much faster reaction but the performance of the system would be affected by external factors. Use of Differential GPS is another solution [6]. It will avoid the errors occur due to the synchronization problem. But it does not guarantee correct data at every time. Kalman filter based integration of DGPS and vehicle sensors is another algorithm developed in this area, but this algorithm works only in a linear system, not in a nonlinear system [7], [8], [9]. And another one valid algorithm is the fusion of GPS data with vehicle motion sensor data using particle [10]. This algorithm gives more accurate and correct data to the positioning system, but one problem in this method requires excessive computational power. The other suitable work in this area is the fusion of GPS with INS using interacting multiple model filter algorithms [11], [12]. The only problem is that, INS system is too expensive.

III. SYSTEM OVERVIEW

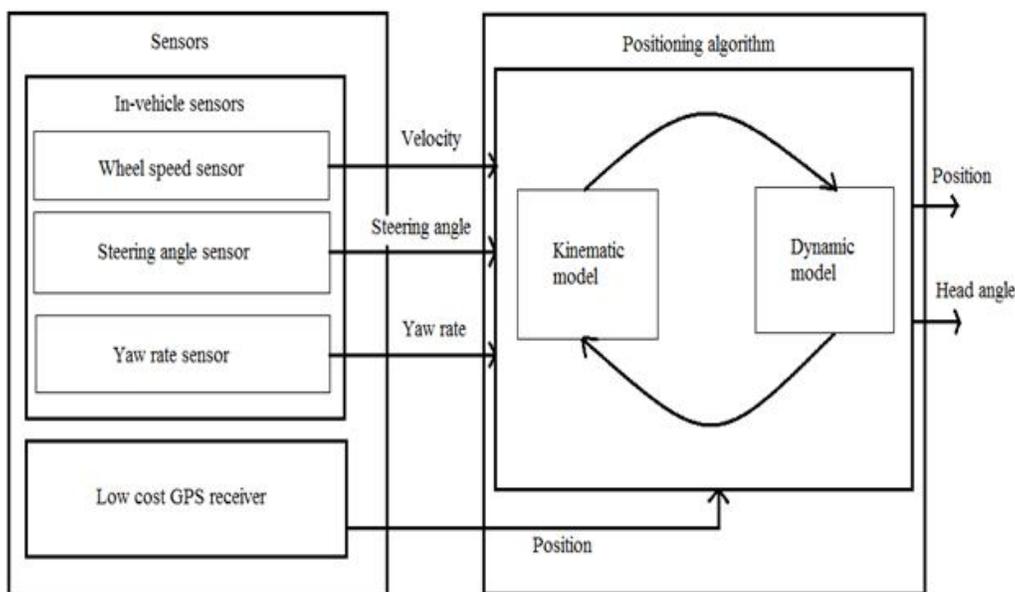


Fig.1: System overview of proposed system.

The above fig.1 describes the overall system overview the proposed work. The proposed algorithms combine the data from in-vehicle sensors with GPS receiver and provide reliable and continuous position information. Proposed system is classified into two parts, a sensor part and a position algorithm part. The sensor part is composed of a group of in-vehicle sensors and a low-cost GPS receiver. The positioning algorithm part composed of two different model, kinematic model and dynamic model. These two models indicate the vehicle in different driving condition. In the proposed system, the positioning algorithm that estimates the vehicle position by combining data from in-vehicle

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sensors with GPS receiver data. This algorithm is the combination of Extended Kalman Filters. EKF is used as information fusion algorithm and predicts the next state with respect to the current state. The basic advantage of EKF is that it will avoid the nonlinear localization problem. Then based on the vehicle speed any one of the vehicle models will be selected. Normally, kinematic vehicle model is suitable in low speed and small tire slip condition, and dynamic model is suitable for high speed and large tire slip condition. So at high speed dynamic model should be selected and similarly at low speed kinematic model is selected.

IV.VEHICLE MODEL SET

Vehicle movement should be dynamic in nature depending upon the road condition, traffic, environment, etc. This dynamic change of vehicle movement also changes the motion parameter related to the vehicle such as velocity, heading angle, lateral force acting on the tires, vehicle slip, etc. [16]. So to develop a suitable algorithm to overcome these errors, we should be design and select a suitable vehicle model. In this work, the kinematic and dynamic models are used to represent a possible type of vehicle motion. Basic parameter considered in these vehicle models are tire slip and lateral force.

Kinematic Vehicle Model

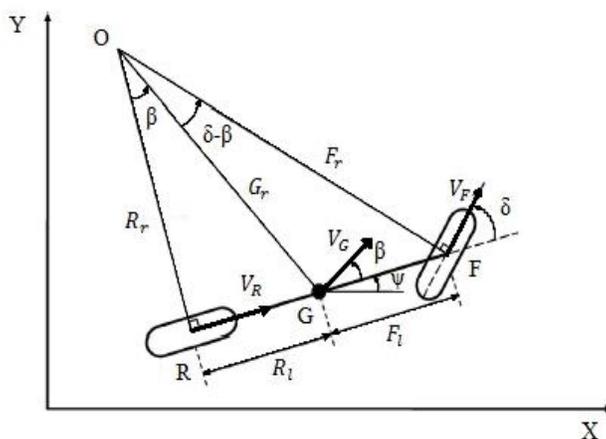


Fig.2: Kinematic Vehicle Model.

The kinematic vehicle model represents the vehicle motion parameter when the vehicle moves in slow speed. That is, the tire slip does not exist between the road and tires. Example if the vehicle is in traffic situation or in a parking lot. The fig.2 represents the kinematic model developed by using the fundamental bicycle model [13]. In this model, the pair of front and rear wheels of the vehicle should be considered as a single wheel. G is the centre of gravity of the vehicle. The distance from G to front and rear wheel are represented as F_l and R_l . The point O is the instantaneous rotation centre. The co-ordinate X and Y represents the location of G in the global frame. The angle δ , ψ and β represent the front steering angle, heading angle and vehicle slip angle respectively. The velocity at point F, G and R are V_F , V_G and V_R respectively.

Kinematic model does not consider tire slip between wheels and the ground for vehicular positioning. By using the above kinematics model, the parameter required for the calculation of vehicular position can be derived. The derivation should be explained below,

Consider triangle OFG and ORG, by applying the sine rule to both following equations can be obtained:

$$\frac{\sin(\delta - \beta)}{F_l} = \frac{\sin(\frac{\pi}{2} - \delta)}{G_r} \quad (1)$$

$$\frac{\sin(\beta)}{R_l} = \frac{\sin(\frac{\pi}{2})}{G_r} \quad (2)$$

By rearranging (1) and (2)

$$\text{Form (1)} \quad \tan \delta \cos \beta - \sin \beta = \frac{F_l}{G_r} \quad (3)$$



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$$\text{Form (2)} \quad \sin \beta = \frac{R_l}{G_r} \quad (4)$$

Add (3) and (4)

$$\tan \delta \cos \beta = \frac{F_l + R_l}{G_r} \quad (5)$$

If the radius of the vehicle path G_r slowly changes due to low vehicle speed than the rate of change of orientation of the vehicle should be equal to the angular velocity of the vehicle γ as follows:

$$\gamma = \dot{\psi} = \frac{v_G}{G_r} \quad (6)$$

Substitute (5) in (6)

$$\dot{\psi} = \frac{v_G}{F_l + R_l} \tan \delta \cos \beta \quad (7)$$

The vehicle slip angle β can be calculated by dividing (3) by (4) as

$$\beta = \tan^{-1} \left(\frac{R_l \tan \delta}{F_l + R_l} \right) \quad (8)$$

The global motion of the vehicle can be represented in terms of vehicle velocity V_G and course angle $\psi + \beta$,

$$\dot{X} = v_G \cos(\psi + \beta) \quad (9)$$

$$\dot{Y} = v_G \sin(\psi + \beta) \quad (10)$$

Dynamic vehicle model

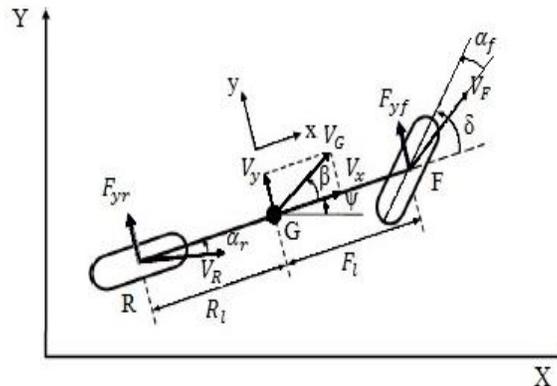


Fig.3: Dynamic vehicle model.

Dynamic vehicle model represents the vehicle motion parameter when the vehicle moves into high speed. The tire slip and lateral force are two factors that will affect the motion of the vehicle during high speed. So these two parameters are also considered during the development of the dynamic model [17]. The figure.4 represents the dynamic model of the vehicle developed by using the fundamental bicycle model [13]. Similar to kinematic model, all the variables represent the same in addition α represent tire slip angle and F_{yf} and F_{yr} represent lateral force acting on front and rear wheels respectively.

The dynamic vehicle model assumes that the lateral force acting on a tire is proportional to the tire slip angle. The tire slip angle can be defined as the angle of the wheel velocity vector relative to the longitudinal wheel axis,

$$F_{yf} = 2C_f \alpha_f \approx 2C_f \left(\beta + \frac{l_f \dot{\psi}}{v_x} - \delta \right) \quad (11)$$

$$F_{yr} = 2C_r \alpha_r \approx 2C_r \left(\beta - \frac{l_r \dot{\psi}}{v_x} \right) \quad (12)$$

We can calculate the overall vehicle motion of the dynamic vehicle model using the following equation:

$$\dot{\beta} = -\gamma + \frac{2C_f}{mv_x} \left(\delta - \beta - \frac{l_f \gamma}{v_x} \right) + \frac{2C_r}{mv_x} \left(-\beta + \frac{l_r \gamma}{v_x} \right) \quad (13)$$



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$$\dot{\gamma} = \frac{2C_f I_f}{I_z} \left(\delta - \beta - \frac{l_f \gamma}{v_x} \right) - \frac{2C_r I_r}{I_z} \left(-\beta + \frac{l_r \gamma}{v_x} \right) \quad (14)$$

$$\dot{\psi} = \gamma \quad (15)$$

$$\dot{X} = v_G \cos(\psi + \beta) \quad (16)$$

$$\dot{Y} = v_G \sin(\psi + \beta) \quad (17)$$

V. EXTENDED KALMAN FILTER

The proposed positioning algorithm is based on the working of extended Kalman filter. Here two type of vehicle model set are used. These two models are developed by using EKF. Under high speed and high slip driving conditions, the dynamic model based filter is used because it considers lateral force and tire slip. Similarly, under low speed and low slip driving conditions, the kinematic model based filter is used because the slip angle of the tire is very small.

Extended Kalman filter has proven to be a useful method of obtaining good estimates of the system state [15]. It consists of two steps, prediction step and update step. In predict step, the state and covariance matrix of the previous state are predicted. And in the update step, update the predicted state and covariance matrix. The predict and update equations of EKF are give below [14],

Predict equation

Predicted state estimate

$$\hat{x}_{k/k-1}^i = f_i(\hat{x}_{k-1/k-1}^i, u_k) \quad i = 1, 2$$

Predicted covariance estimate

$$\hat{P}_{k/k-1}^i = F_k^i \hat{P}_{k-1/k-1}^i (F_k^i)^T + G_k^i Q_{k-1} (G_k^i)^T \quad i = 1, 2$$

Update equation

Innovation or measurement residual

$$\tilde{y}_k = z_k - h(\hat{x}_{k/k-1}^i)$$

Innovation (or residual) covariance

$$S_k^i = H \hat{P}_{k-1/k-1}^i H^T +$$

Near-optimal Kalman gain

$$K_k^i = \hat{P}_{k/k-1}^i H^T (S_k^i)^{-1}$$

Updated state estimate

$$\hat{x}_{k/k}^i = \hat{x}_{k/k-1}^i + K_k^i (z_k - H \hat{x}_{k/k-1}^i)$$

Updated estimate covariance

$$\hat{P}_{k/k}^i = (I - K_k^i H) \hat{P}_{k-1}^i$$

Where the state transition and observation matrices are defined to be the following Jacobians

$$\frac{\partial f_i}{\partial x} = F_k^i \quad i = 1, 2$$

$$\frac{\partial h_i}{\partial x} = H_k^i \quad i = 1, 2$$

The states of both vehicle models are represented as

$$x_k = [v_k \ \beta_k \ \gamma_k \ \psi_k \ X_k \ Y_k]^T \quad (18)$$

The model input is described as

$$u_k = [v_{whl} \ \delta_{SAS}]^T \quad (19)$$

Measurement input is described as

$$z_k = [V_{GPS} \ \gamma_{yawrate} \ (\beta + \psi)_{GPS} \ X_{GPS} \ Y_{GPS}]^T \quad (20)$$

Using the above equations we can develop kinematic and dynamic vehicle model after that introduce these models in to the proposed algorithm. The algorithm will select one of the models from these models based on the current speed of the vehicle.

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VI. SIMULATION AND RESULT

The proposed algorithm was analysed through intensive simulation and results of simulation are plotted as graphs. The simulation was performed using MATLAB software and Simulink package is used to analyse the algorithm. The kinematic and dynamic vehicle models are developed by using user defined blocks in Simulink where the inputs given to the blocks are velocity, steering angle, yaw rate and position. The outputs from the blocks are plotted in XY plot. The results are given below,

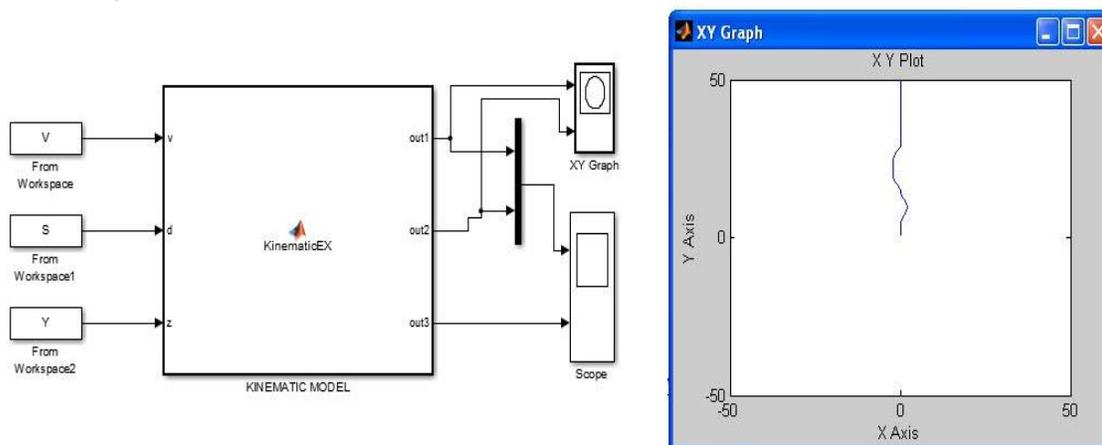


Fig.4: Simulation result of kinematic model in Simulink.

Fig.4 shows the Simulink model of kinematic vehicle model and its output plot based on the inputs. The inputs given to the models are velocity, steering angle, yaw rate and position. The kinematic model is suitable only when the vehicle moving at slow speed. If the vehicle is moving at high speed then the model will not predict accurate position and output contain more error. The inputs to this Simulink model, typically velocity are given as gradually increasing manner. So in high velocity, the graph plotted using the kinematic model is inaccurate that we can see inside Fig.4.

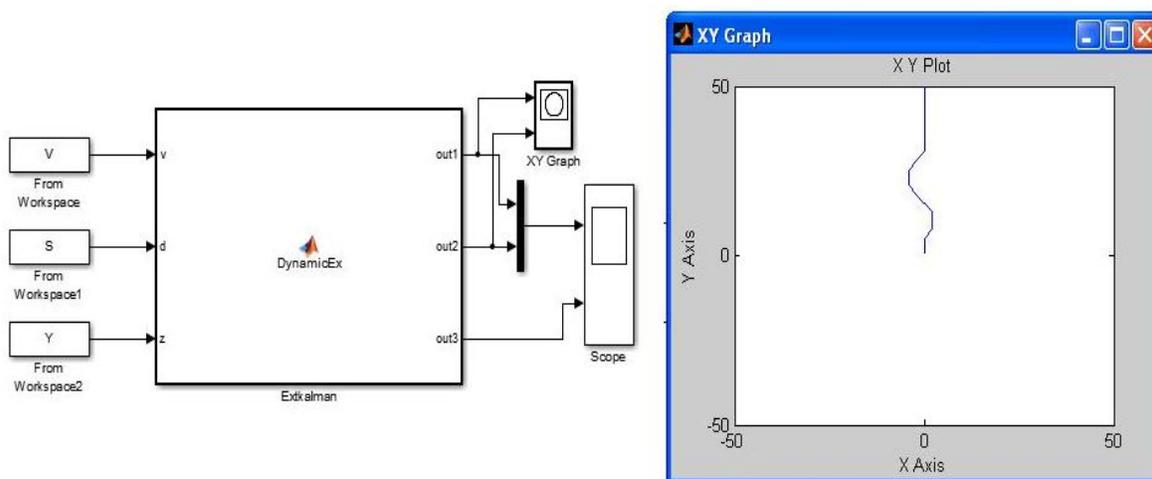


Fig.5: Simulation result of dynamic model in Simulink.

The dynamic vehicle model is similar expect the inclusion of the parameters, tire slip and lateral force which is depicted in fig.5. The figure shows the Simulink model of dynamic vehicle model and its output plot based on the inputs. The dynamic model is suitable only when the vehicle moving at high speed. If the vehicle is moving at slow

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speed then the model will not predict accurate position and output contain more error. The inputs to this Simulink model, typically velocity are given as gradually increasing manner. So in low velocity, the graph plotted using the dynamic model is inaccurate that we can see inside Fig.5.

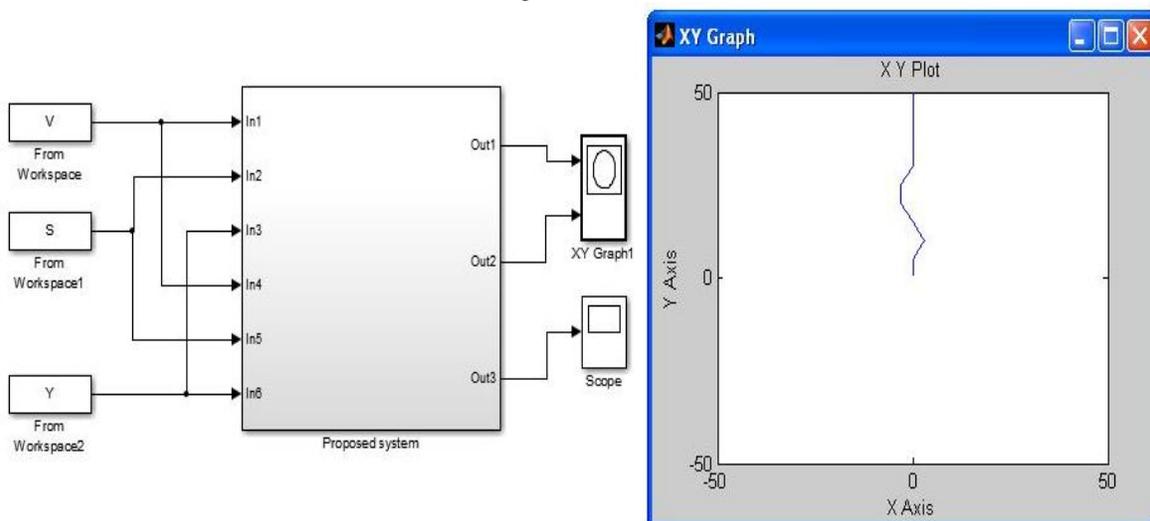


Fig.6: Simulation result of proposed model in Simulink.

Finally, fig.6 shows the proposed model which encapsulated both kinematic and dynamic model where the velocity of the vehicle acts as the condition for selecting the model to be performed. The inputs to this Simulink model, typically velocity are given as gradually increasing manner. So based on the velocity of the vehicle the proposed system will select a suitable model. If the vehicle is moving at slow speed then the proposed system select kinematic model and the vehicle is moving at high speed then the proposed system select dynamic model. The output of the proposed model found to be more precise when compared to the output shown in fig.4 and fig.5.

VII.CONCLUSION

An algorithm for real time vehicle positioning system is successfully simulated which incorporates both kinematic and dynamic vehicle model using EKF. The platform used for simulating the algorithm is Simulink which is an additional package of MATLAB software. The simulation result showed that the estimates of the developed algorithm were accurate and reliable under the various driving conditions. Due to the limitations of the two degree of freedom, the estimation of vehicle position in a very sharp sloped driving environment and large longitudinal tire slip condition was prohibited. As an extension of this work, stochastic algorithms can be integrated, which helps to improve the accuracy in the outcome of the system.

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