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State Estimation of Autonomous Ground Vehicle using Kalman Filter

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Abstract: An autonomous ground vehicle has various devices from where it collects data and performs an action. State estimation with noise present in it is one of the key requirements for many real-time problems and engineering. State estimation is an essential requirement for many real-life systems from local to multi-resource information integration. The Kalman filter and its variability have been used successfully in solving state equity problems. The Kalman filter can be used to predict the next set of actions our car will take based on the information received. In this paper we have implemented kalman filter for state estimation and results are obtained.
Keywords: kalman filter, state estimation, velocity control, autonomous vehicles

I. INTRODUCTION

An autonomous ground vehicle is a portable robot that combines multiple sensor navigation with positioning, intelligent decision making and control technology. The aim of the study was to identify autonomous driving in a car instead of human drivers and to improve vehicle safety and transport efficiency. The main purpose of self-driving cars is to transport people from one place to another without the help of a driver.

The self-driving system should control many parameters, including speed, acceleration, orientation, and maneuvering, so that the car can be driven without human help. All of these control parameters are controlled by a decision-making module, which handles all visual data from the vehicle and sensors. The visual module determines the relationship between the ego car and the surrounding environment.

Vehicle stability control is mainly based on various parameters (e.g. lateral acceleration, yaw rate) of movement to determine the appropriate control strategy and achieve the safety of vehicles moving in effective control. Often, the condition of a car can be measured by the variety of sensors in the car.

Restricted by the current level of technology, some important variables require the use of more expensive measuring devices (such as speed, yaw scale), or were unable to take precise measurements (such as slip angle), parameter estimation is the best solution to meet the requirements of a robust vehicle control system.

State estimation having noise in the system is one of the key requirements for many real-time and engineering problems. Accuracy is the primary constraint in applications such as target tracking, automotive land vehicle and flight control systems, non-linear process control and optimization, real time surveillance and life safety applications.

The classical Kalman filtering technique (KF) which is a state estimation technique which can solve this problem and is widely used in many fields. The main objective of KF is tracking the dynamic states in presence of incomplete and noisy measurements. The KF dynamics results from cycles of filtering and prediction.

The Gaussian probability density functions framework is used to derive and interpreters the cycle dynamics. On the other hand, mostly the problems in real are non-linear in nature, and the kalman filter performance degrades when there is a violation of assumptions of the system Gaussian distribution and system linearity

To improve performance and overcome KF limitations compared to system incomprehensibility, the Extension Kalman Filter (EKF) was introduced. EKF manages system irregularities by converting non linear system to linear by inserting limitations of the first Taylor series around the current error and covariance error.It uses the output of the component to represent the rate of change of non-linear functions, which aims to maintain Gaussian sound. If the state is a vector, then the partial derivative parameters can be grouped into new matrix, called the Jacobian matrix.

1) *Prediction:* In this step the Kalman filter predicts new values from initial values and predicts the uncertainty / error / variation of our prediction according to the various processes present in the system. Our model will assume that the AGV will move at a constant speed due to zero acceleration but will actually have a dynamic speed i.e. the speed will change from time to time. This change in speed of this car is uncertain / error / variance and we bring it into our system by processing noise.

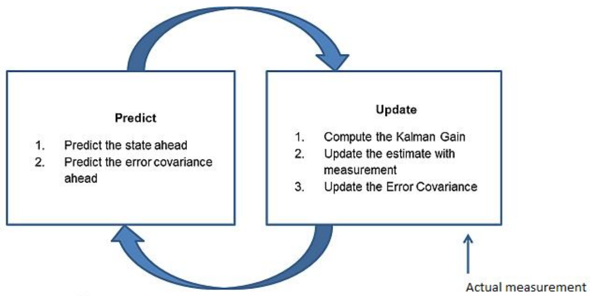

Fig 1: Kalman filter process cycle

2) *Update:* In this step we take the actual estimated value from the system devices. In the event that there is an independent vehicle these devices can be radar or Lidar .Then we calculate the difference between the predicted value and the estimated value and determine which value will keep it i.e. the predicted value or estimated value by calculating Kalman Gain. Based on the decision made for the benefit of kalman we count the new value and uncertainty / error / new variance. This output in the review step is then reverted to the prediction step and the process continues until the difference between the predicted value and the estimated value tends to convert to zero.

II. VEHICLE STATE ESTMATION

The frequency of an autonomous ground vehicle's movement can be measured by the variety of sensors present in the vehicle. Due to the current level of technology restrictions, some important variables require the use of more expensive measuring and sensing devices (such as speed, yaw measure), or some devices are not able to take direct input (such as side angle slip), the parameter estimation problem must be solved by designing the vehicle stability control system. Extended Kalman filter (EKF) is used to measure vehicle condition. We are here considering the longitudinal speed control of the autonomous ground vehicle.

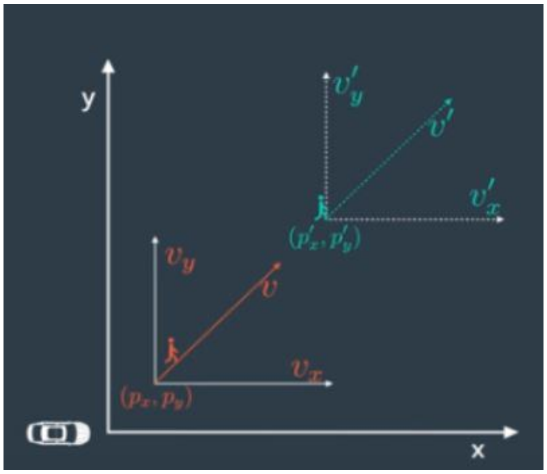

Fig 2: Autonomous car position in xy axis

From the above figure, we can define some variables like px and py determines the 2D position, vx and vy determines the 2D velocity of AGV.

This can be represented as

x = (px, py, vx, vy)

We must predict the position of the vehicle (px ′, py ’) and the 2D velocity (vx ′, vy ′) of autonomous car i.e. x ′

Since the state vector modifies only the position and speed we need to have the uncertainty to model the acceleration, which is done through P, known as process covariance matrix.

A. Prediction step

The prediction step determines the estimated value x ′ and the predicted error P ′ and identifies it as the Process Covariance Matrix using the following formula:

$$x' = F.x + B.\mu + v$$
$$P' = FPF^T + Q$$

The P matrix we have chosen is,

$$P = \begin{bmatrix} 1000 & 0 \\ 0 & 1000 \end{bmatrix}$$

1) *State Transition Matrix(F):* It is used to convert the vector matrix of a state from one form to another i.e. suppose the position of the vehicle is given by position p and velocity v and is not accelerated by time t.

x = [p, v]

After a while it says t + 1, state vector x' will be

$$p' = p + v * \Delta t$$
$$v' = v$$

In the matrix this can be displayed as below:

$$x' = F * x$$

Then the F matrix we have chosen is given by:

$$F = \begin{matrix} 1 & 1 \\ 0 & 1 \end{matrix}$$

2) *Control Matrix input(B):* It determines the change in the input control vector μ due to external forces (longitudinal or latitudinal forces) and internal forces (gravitational force, collisions etc.) In the case of autonomous vehicles we cannot mimic external forces as they vary from region to region and internal power as they vary from one type of vehicle to another. Mostly,
$$B\,\mu = 0$$
3) *Noise / Uncertainty Process(v):* It determines the random sound/noise that can be present in the system. This is added to make predictions more accurate.
4) *Process Noise / Motion Noise(Q):* Provides uncertainty in the location of the object when predicting location. The model assumes that the speed is always intermediate, but we actually know that the speed of the object can change due to acceleration. The model incorporates this uncertainty about process noise.

B. Update step

Step 1: Find the difference between the estimated value and the predicted value

$$y = z - H.x'$$

z: Real measurement data

1) *State Transition Matrix(H)*: It is the same as F using H to convert state vector. But here we are using it to discard information from a state vector that we do not need. On average with the radar taken we only need to focus on the location of the vehicle and we don't have to worry about velocity because radar is only good at determining the position of the velocity. So in this case of our province containing the speed limit of the car the H matrix will be:
$$H = [1\ 0]$$

Step 2: Count Kalman Gain

$$S = HP'H^T + R$$
$$K = P'H^TS^{-1}$$

2) *Measurement noise(R):* Noise measurement refers to the uncertainty of sensor measurements, It means that the devices themselves are noisy and inaccurate and therefore these noise measurement values are provided by the device manufacturer itself and do not need to be modified.
$$R = [0.01]$$

3) *Total error(S):* Total error is sum of prediction error and estimation error. We need to have total error so as to formulate the S matrix and kalman gain.
4) *Kalman Gain(K):* Kalman Gain: Kalman gain determines whether our estimated or actual value is closer to real value. Its value ranges from 0 to 1. If its value is closer to 0 it means that the predicted value is closer to real value or if the value is closer to 1 it means that the estimated value is closer to real value. Its value ranges from 0 to 1 because it uses uncertainty / errors than the predicted value and estimated value.

Step 3: Based on the Kalman Gain result find the new x and P.

$$x = x' + K.y$$
$$P = (I-KH)\,P'$$

Finally we update the state vector and covariance matrix and will move on to the next step of predicting to get more values.

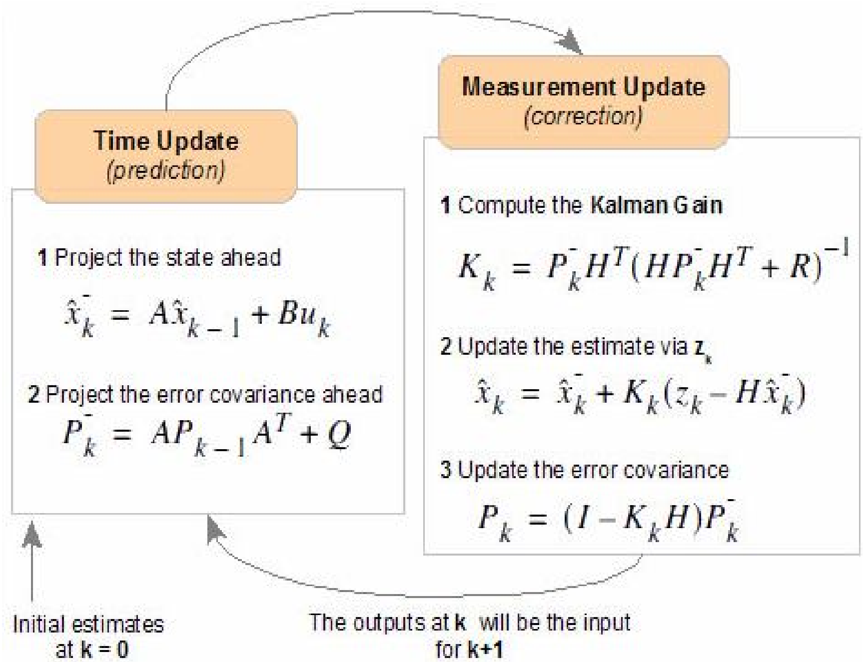

Fig 3: Prediction and update cycle of kalman filter

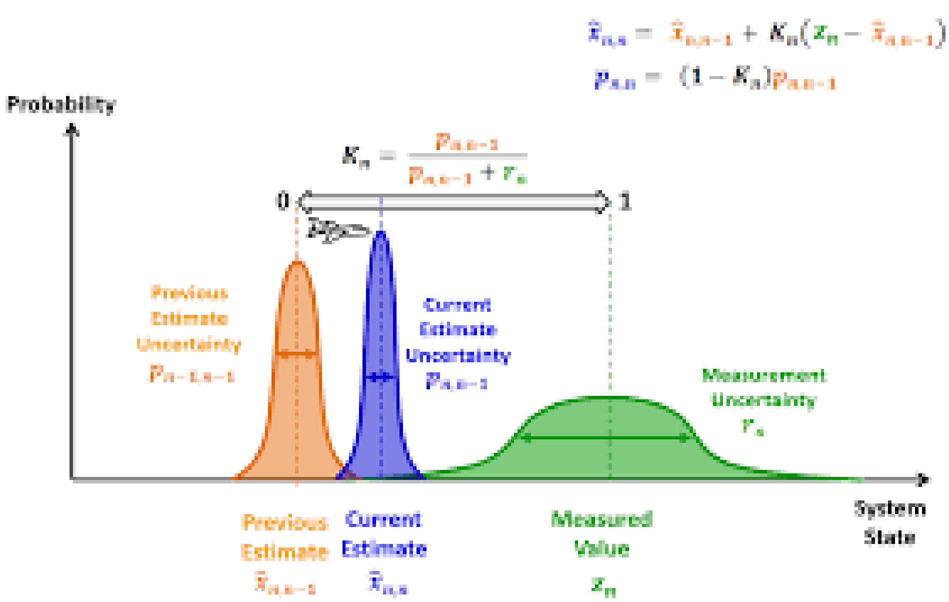

Fig 4: Working of Kalman filter

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III. SIMULATION

The block shown is the autonomous vehicle, which is moving in a straight road. The two graphs are of velocity graph and error graph. In the first case speed is increasing and we can infer from the graph that it takes time to reach its reference speed. From the error graph we can see that error is also present.

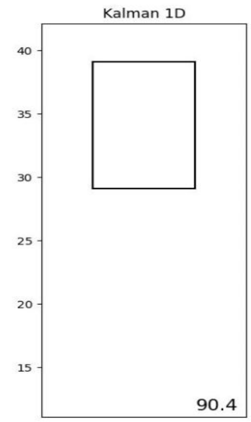

Fig 5(a):The autonmous car with increasing velocity

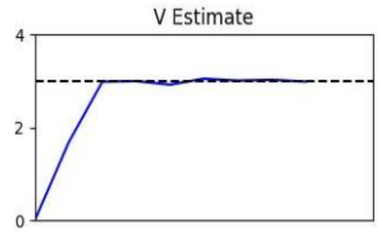

Fig 5(b): Velcoity time graph

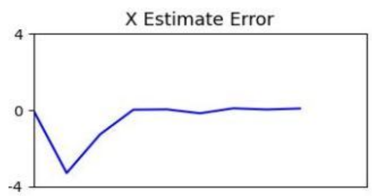

Fig 5(c): Error time graph

From case 2, the block is decreasing its speed.
Hence the vecolity time graph and error time graph results are not very smooth and upto the mark.

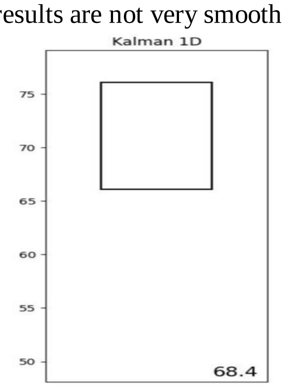

Fig 6(a):The autonmous car with decrasing velocity

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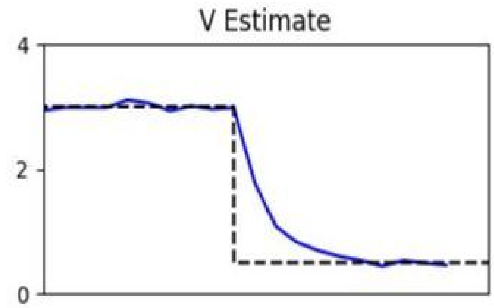

Fig 6(b):Velocity time graph

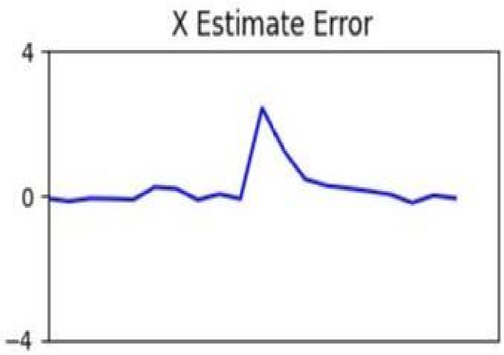

Fig 6(c):Error time graph

IV. CONCLUSION

In this paper, a 2D model of the Kalman filter on autonomous ground vehicle has been done. The state estimation in presence of noise effects the stability off the system. The values obtained from state estimation is used for advanced level feedback control that helps to make intelligent driving decisions. The Kalman filter estimates the current state variables, which have some uncertainties. As soon as the results of the next states (really damaged by a certain error rate, including noise) are observed, the estimated values are revised, by giving more weight to estimate having higher accuracy. It is used only for the linear system which is a major drawback of the kalman filter. In fact, the speed of a car has a profound effect on traffic signals, often requiring non-linear models to accurately describe traffic. To solve this problem, Extended Kalman filter (EKF) is used. The result shown in this paper is not very smooth and can be improved. We can observe that it takes a lot of time to reach the reference velocity and the error produced is also large. The results can be improved with an extended kalman filter

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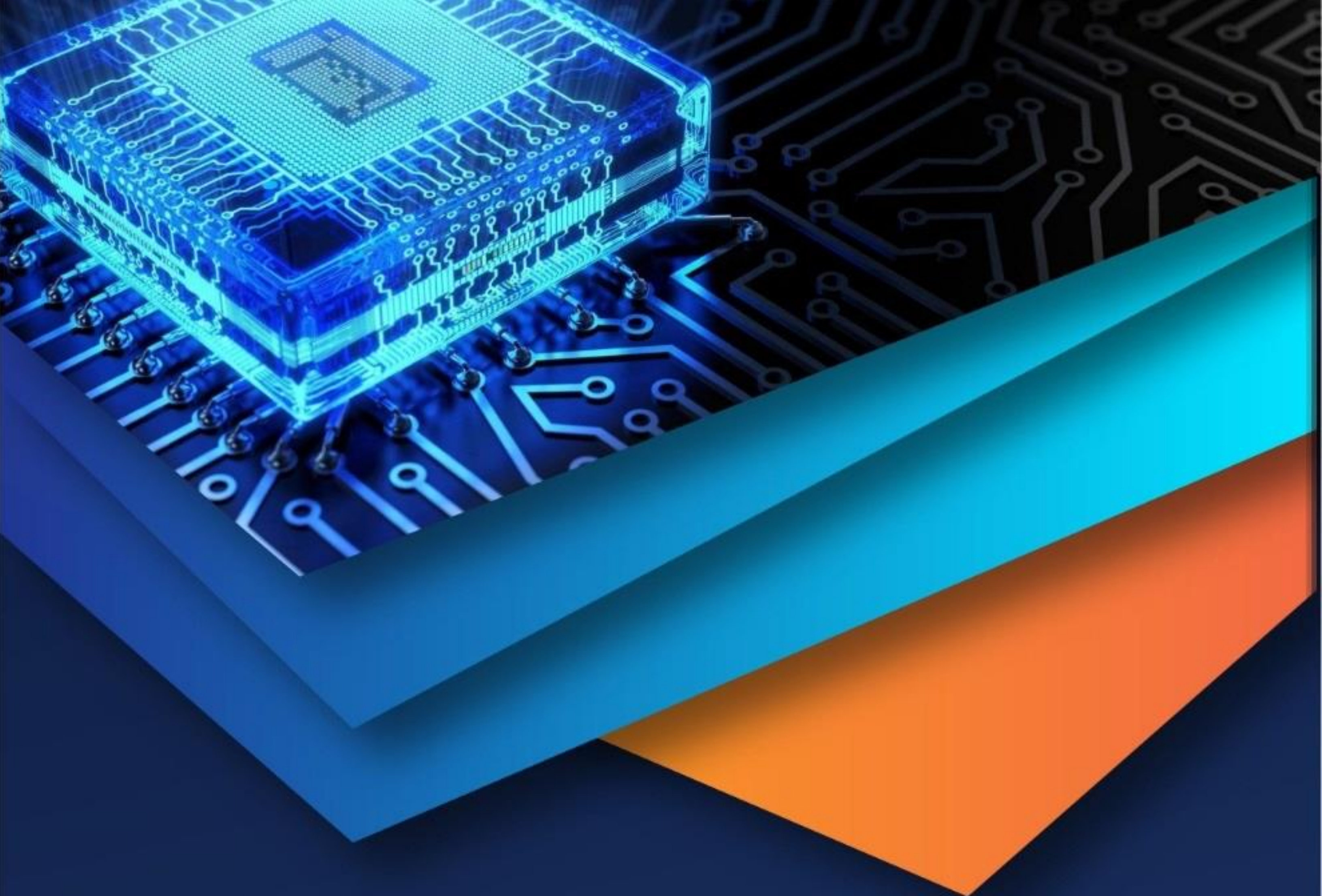

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