Real Time Speed Analysis of moving Vehicle using Kalman Filter: Literature Review Paper

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***Abstract*—GPS or Global Positioning System is basically a ratio navigation system that provides location and information using the ratio waves sent between satellites and receivers. Using this one will be able to receive data from four or more of the 28 satellites in orbit that are dedicated for geolocation use. GPS receivers are now an integral part of smartphones. However, phone-based GPS measurements display much less accuracy as compared to professional grade receivers.**

The aim of our project is to predict vehicle speed using mobile phone GPS, and alert users at various speed levels set by them. The alert of the speed limit will be given using a dynamic voice message at a regular interval of time till the user reduces/decreases the speed.

For this to be successful we are required to estimate the true speed of the vehicle. In this paper, we have described the methods which can be implemented to achieve the estimated speed of a moving vehicle.

Key Words: GPS, Satellites, Geolocation.

I. Introduction

In recent times, driving has become an important part of our lives. Driving is the controlled operation and movement of a vehicle, including cars, motorcycles, trucks, buses, and bicycles. Permission to drive on public highways is granted based on a set of conditions being met and drivers are required to follow the established traffic laws in the location. The Driving type is classified into two types: aggressive and non-aggressive driving. Aggressive driving refers to dangerous driving that disregards safety and courtesy. Recently it is a great subject for study and research as it is directly correlated to accidents. It includes excessive speeding, sudden lane changes, and hard breaks.

Speed thrills but kills. If we speed, we will be liable to a hefty amount of Rs.4000 depending on the type of vehicle we are driving. The high-speed limits are often the cause of accidents leading to serious injuries and death. The speed limit should be in control so that we can avoid accidents caused by high-speed driving, pollution, and the high cost of operation and insurance (speed ticket). Hence, it's not surprising to see the authorities' imposing penalties on traffic rule violators, with the severity of the punishment varying as per the nature of the offense. Many drivers exceed the posted speed limits. Sometimes this may be intentional, sometimes it is unintentional. So, to avoid speed tickets and accidents, we are proposing a system that predicts the vehicle speed using mobile GPS and alerts the user at various speed levels set by them.

Theoretically GPS based measurement is not dependent on the phone's orientation and this can be used to measure the driving behavior. However, GPS satellites broadcast their signals in space with a certain accuracy but the accuracy of GPS receivers depend on a number of additional factors like satellite geometry, signal blockage influenced by buildings or trees, atmospheric conditions and receiver design features/quality. Mobile GPS comes handy when we need to detect a one-time position, but its accuracy is not sufficient enough when we need a sequence of measurements for predicting distance or velocity values due to the error accumulation. So, in this research paper to reduce the error to some extent we are implementing a Kalman filter. The Kalman Filter is an effective recursive filter that estimates the state vector of a dynamic system using a series of incomplete and noisy measurements.

II. Literature Survey

This chapter deals with the survey of various papers that have contributed to the estimation of the speed of vehicles.

Aziz, T., Faisal, T. M., Ryu , H. G., & Hossain, M. N. proposed Vehicle Speed Control and Security System [1]. It introduces a multi-layer security system which includes a theft alerting feature, owner speed-limiting system, and emergency monitoring vehicle feature.

It introduces limiting the speed of the vehicle if it is robbed and geolocation tracking using GPS and GSM module. By GPS module we get the longitude and latitude and using that we get our location on the map and by GSM module we get the text message where the location is mentioned. And also monitoring the vehicle through a webcam.

Lattanzi , E., & Freschi , V. proposed Machine learning techniques to identify unsafe behavior by means of in-vehicle sensor data [2]. It introduces unsafe driving behaviors of a driver by taking advantage of sensors already present in modern vehicles using machine learning techniques (SVM, Artificial Neural Network). Here relationship between acceleration and speed which when plotted, splits out in two areas representing safe and unsafe driving domains.train the two classifiers: Support Vector Machines(SVM), Artificial Neural Networks. A binary- class SVM was used to find a hyperplane that best divides the dataset into the desired classes. A simple feedforward network was used with a single hidden layer composed of 50 neurons. The network was trained by means of a backpropagation Levenberg . Lastly, graphs were plotted for a dataset showing safe(blue circle) and unsafe(red triangle) against different features.

Kang JM, Kim HS, Park JB, Choi YH proposed An Enhanced Map-Matching Algorithm for Real-Time Position Accuracy Improvement with a Low-Cost GPS Receiver [3].It introduces accuracy of a low-cost GPS receiver based on map data without using any additional sensors. It loaded the digital databases and constructed RPS the Iterative Closest Point(ICP) algorithm and the translation vector from which minimized horizontal position error is concluded. However, this transformation does not sufficiently reflect the change value between the trajectory and the GPS information, which were newly obtained, hence least squares method was used to calibrate the rotational error. The state estimation which implies the correct position of the vehicle is linked to RPS to eliminate the residual disparity using vector projection theorem, which is from the current state estimation and the two points near the estimation point. The lateral error is reduced, and the vehicle position is located on the road of the digital map.

Merry, K., & Bettinger, P.proposed Smartphone GPS accuracy study in urban environment[4].This paper aims to understand relative position accuracy in an urban environment by an iPhone 6 using Avenza software for capturing horizontal position. locations were captured during two seasons of the year(leaf-on and leaf-off), two times of day(AM and PM) and two perceived WiFi usage periods(High and Low, when human activity was high and low respectively) and also -GPS-only and WiFi enabled. It was concluded that overall average horizontal position error of the iPhone 6 is in the 7–13 m range, depending on conditions(the time of year and weather conditions did not influence the average horizontal position error), which is consistent with the general accuracy levels observed of recreation-grade GPS receivers in potential high multipath environments. Horizontal position error seemed to improve in general during perceived high WiFi usage periods (when more people were present) within each season and during each time of day most prominently in the afternoon. In general, directional error was consistent at each data collection point during both GPS-only and WiFi collection.

Feng, K., Li, J., Zhang, X., Zhang,X., Shen, C., Cao, H., ... & Liu, J. proposed An improved strong tracking cubature kalman filter for GPS/INS integrated navigation systems[5]. An improved strong tracking cubature Kalman filter is proposed to suppress the process uncertainty induced by the severe maneuvering for the low-cost GPS/INS integrated navigation systems. Based on the improved strong tracking technique, the process uncertainty can be detected and suppressed by modifying the prior state estimate covariance online according to the change in vehicle dynamics. The car-mounted experiments are utilized to demonstrate that the proposed IST-7thSSRCKF can achieve high estimation accuracy and has better robustness for the suppression of process uncertainties.

Lohrer, J., & Lienkamp, M. proposed An approach for predicting vehicle velocity in combination with driver turns [6]. The model revolves around the two main stages, The first stage is the prediction of upcoming turns and trip segments based on the historical features and the currently driven road segments. The second stage uses this information to predict the vehicle’s speed. The model is completely based on the prediction, it analyzes the data obtained from Field operational testing in order to detect the future turns, trip and vehicles velocity. The main setback for the model is, if the destination is unknown, the preview is limited to the end of the road section, which limits the user to a particular region.

Reddy, N. R., & Subhani, S. proposed Monitoring Vehicle Speed using GPS and Categorizing Driver [7]. The proposed work is an endeavor to control speed of the vehicle structured with Pc programming to empower the outsider or proprietor to get the area, speed and action of the driver. GSM/GPRS are utilized to track the objects and provide the up-to-date data. This data is stored in the server and sent to the users.

Hua, S., Kapoor, M., & Anastasiu, D. C. proposed Vehicle tracking and speed estimation from traffic videos [8]. The model was basically designed to aid the traffic department in empowering the traffic rules, to prevent vehicles from rash driving and over speeding. the basic approach of the model to track the vehicles using vehicle detection algorithms and then detecting the speed of vehicles using optical flow and speed estimation algorithms. In order to predict the speed of a moving vehicle and track the vehicle the camera recording traffic should be static, which also adds ups as a downfall of the proposed model.

Shukla, D., & Patel, E. proposed Speed determination of moving vehicles using Lucas Kanade Algorithm [9]. The model takes simple video file as input and calculates speed of vehicle using Lucas- kanade algorithm, which makes use of Optical flow of the input video to derive the necessary equations which are then replaced by the values as per rate of change of pixels will give the velocity of the moving vehicle.

Yu, J., Zhu, H., Han, H., Chen, Y. J., Yang, J., Zhu, Y., ... & Li, M. proposed Sen speed: Sensing driving conditions to estimate vehicle speed in urban environments [14]. Estimating the speed using GPS reading often suffers from low accuracy, low update frequency. To overcome this new approach of estimating the speed using accelerometer (embedded in phone) reading comes into play. But it is observed that directly integrating the speed provides a large deviation ang is linearly dependent on time. This is because the accumulative error causes large deviations. Therefore, to overcome this the accumulative error needs to be eliminated, hence the model proposes the use of unique reference points (making turns, stopping (at traffic light, due to traffic or at stop sign), even road surfaces). Then the model measures the error in the readings between two adjacent reference points and eliminates such error to obtain high accuracy.

Chowdhury, A., Chakravarty, T., & Balamuralidhar, P. proposed Estimating true speed of moving vehicle using smartphone-based GPS measurement [11]. This paper proposed a speed calculation approach using the GPS measurement in smartphones. The readings may suffer due the urban canyon effects, also the accurate speed turn measurements are required to be captured. Since the GPS measurements are not dependent on phone orientation, it is better to use. GPS data provides the values timestamp, horizontal accuracy, latitude, longitude. The GPS measurement takes some time to deflect the sudden change in speed. To overcome this the model proposes the use of two moving average filters with normalized weight coefficients.

Laghari, S. M. N. U. Z., & Farrukh, M. A. M proposed GPS Estimation using Kalman Filter [12]. GPS receiver links with four satellites provide four values (longitude, latitude, elevation). The accuracy of GPS values relies on the respective devices. To avoid this Kalman filter is brought in use which takes noisy data as input and provides less noisy data.

Ustun, I., & Cetin, M. proposed Speed estimation using smartphone accelerometer data [13]. The integration of the acceleration values theoretically provides the value of speed. Using this basic approach, the idea of the paper was to estimate the speed using the accelerometer (embedded inside the smartphone) readings. However, this may accumulate other factors also like gravity component, sensor bias, noise effect, vibrations etc. The accelerometer provides three readings (along x, y, z axis). For the purpose of calculation readings along y axis are only taken into consideration.

Yu, J., Zhu, H., Han, H., Chen, Y. J., Yang, J., Zhu, Y., ... & Li, M. proposed Sen speed: Sensing driving conditions to estimate vehicle speed in urban environments [14]. Estimating the speed using GPS reading often suffer from low accuracy, low update frequency. To overcome this new approach of estimating the speed using accelerometer (embedded in phone) reading comes into play. But it is observed that directly integrating the speed provides a large deviation ang is linearly dependent on time. This is because the accumulative error causes large deviations. Therefore, to overcome this the accumulative error needs to be eliminated hence the model proposes the use of unique reference points (making turns, stopping (at traffic light, due to traffic or at stop sign), even road surfaces). Then the model measures the error in the readings between two adjacent reference points and eliminates such error to obtain high accuracy.

Tamilselvan, K., Murugesan, G., & Suthagar, S. Android Based Vehicle Speed Control System In Critical Zones Using GPS Technology [15]. This paper proposed a technique to develop an android application with GPS technology in order to identify the critical location and control the speed of the vehicle automatically in two wheelers. The speed measurement and control are accomplished via microcontroller with signal being received wirelessly from GPS. In this system when the vehicle reached the critical zone, the GPS device transmitted the message to the hardware(receiver) to reduce the speed through Bluetooth and the mechanism automatically reduced the speed.

ÖZDEMİR, Z., & TUĞRUL, B. proposed Geofencing on the Real-Time GPS Tracking System and Improving GPS Accuracy with Moving Average, Kalman Filter and Logistic Regression Analysis[16]. In his paper real-time tracking and geofence were performed. Here we distance between the coordinates. Smooth circle-shaped geofence area is useless. This problem was solved by defining geofence in the form of polygonThe geofence area is customized in two ways: static and dynamic. Static predefined polygon. The fact that the polygon drawn in real-time in a newly traveled area can be used as a geofence without saving is defined as dynamic geofence and has provided a very flexible use to the study.GPS data has errors for various reasons. It is aimed to reduce the error rate in the data in order to make the system run faster and to be stable.The comparative results given. Moving average, logistic regression and Kalman filter were applied for error reduction.

Li, Z., Wang, R., Gao, J., & Wang, J. proposed An Approach proposed to Improve the Positioning Performance of GPS/INS/UWB Integrated System with Two-Step Filter[17]. AN enhanced GPS/INS/UWB integrated schema with position error correction is proposed to improve the position accuracy, which is based on predicting the position difference between GPS/INS and GPS/INS/UWN. Based on analytical and experimental results, the GPS/INS/UWB integrated navigation with error correction outperforms the GPS/INS integrated navigation by 48% and 23% in the north and east directions, respectively, when the UWB signal is unavailable. The integrated positioning method based on a multi-sensor is able to realize the integration of advantages from different sensors. The ability of UWB was tapped further in the proposed method, but the cooperative level of different sensors was also not high, such as the modification of system error from the UWB observation and robustness of the original observation.

Verma, P., & Bhatia, J. S. proposed Design and Development of GPS-GSM based tracking system with Google Map based monitoring[18]. GPS is one of the technologies that are used in a huge number of applications today. One of the applications is tracking your vehicle and keeping regular monitoring on them. This tracking system can inform you the location and route traveled by vehicle, and that information can be observed from any other remote location. It also includes a web application that provides you the exact location of the target. This system enables us to track targets in any weather conditions. This system uses GPS and GSM technologies.

Singhal, M., & Shukla, A. proposed Implementation of Location based Services in Android using GPS and WebServices[19] . Location based Services offer many advantages to the mobile users to retrieve the information about their current location and process that data to get more useful information near to their location. With the help of A-GPS in phones and through Web Services using GPRS, Location based Services can be implemented on Android based smartphones to provide these value-added services: advising clients of current traffic conditions, providing routing information,helping them find nearby hotels. In this paper, we propose the implementation of Location based services through Google Web Services and Walk Score Transit APIs on Android Phones to give multiple services to the user based on their Location.

Liu, W., Yamazaki, F., & Vu, T. T. proposed Automated Vehicle Extraction and Speed Determination From QuickBird Satellite Images[20]. A new method has been developed to automatically extract moving vehicles and subsequently determine their speeds from a pair of QuickBird (QB) panchromatic (PAN) and multispectral (MS) images. Since the PAN and MS sensors of QB have a slight time lag (approximately 0.2 s), the speed of a moving vehicle can be determined from the difference in the positions of the vehicle observed in the PAN and MS images due to the time lag. An object-based approach can be used to extract a vehicle from the PAN image, which has a resolution of 0.6 m. However, it is difficult to accurately extract the position of a vehicle from an MS image because its resolution is 2.4 m. Thus, an area correlation method is proposed to determine the location of a vehicle from an MS image at a sub-pixel level. The speed of the moving vehicle can then be calculated by using the vehicle extraction results.

III. METHODOLOGY

In Order to Calculate velocity of a moving vehicle using values of Latitude and Longitude given by mobile GPS. We need to convert these values into x and y coordinate systems in order to perform mathematical calculations on values of latitude and longitude in 2-D. We will have to use 2-D kalman filter which will take values of latitude and longitude convert them into x, y coordinate using below given formula:

$$x = r * \cos(lat) * \cos(lon)$$

$$y = r * \cos(lat) * \sin(lon)$$

where, r is the radius of earth i.e. 6.371×10^6m , lat and lon signifies latitude and longitude obtained from GPS.

Kalman filter which is an iterative mathematical process to quickly estimate the true position and velocity of the moving object. In the case of 2D kalman filters we have to input values of position in the form of matrix along with the velocity of the object in the respective direction. The Kalman filter will mainly perform two functions: Filtering and Prediction. In the filtering state (also known as correction state) the kalman filter predicts the value of kalman gain which is basically error in estimation divided by sum of error in estimation and error in the measurement. The next step is updating the state matrix using the values of kalman gain and measurement noises present in values taken from GPS due to interference of other electric and magnetic components of the mobile phone. The final step in the correction state of the kalman filter is updating the error covariance matrix. Process covariance matrix is basically the matrix which contains the values of variance and covariance of x and y. The prediction state predicts the projection of the new state matrix using the values of the previous state matrix and control variable matrix in our case readings from the accelerometer of the mobile phone. The next step involves prediction of process covariance matrix which uses values of previous process covariance matrix and process noise covariance matrix. We can represent the above information in the form of a flow diagram which is given below.

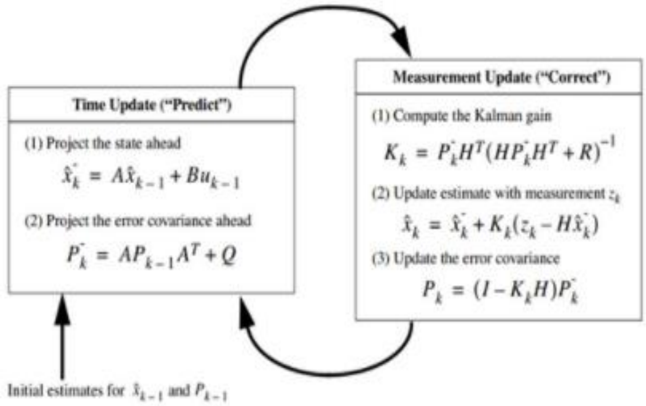

Fig.1 Basic approach of kalman filter

Fig.1 shows how the kalman filter will continuously take input values from mobile GPS and accelerometer in order to process the inputs to predict the most appropriate value of position and velocity of the object in different directions. Basically the idea behind using kalman is that GPS readings are already having very less noise as compared to accelerometer readings so using both of these sensors will result in more accurate values as compared to the values given by the individual sensor i.e. by using the values of both sensors in the kalman filter we will be able to get fused sensor readings which are more error free and we will also be able to calculate speed of the vehicle in a more accurate way. Also there may exist situations where the connection of mobile GPS with Satellite is lost or on higher altitude mobile GPS are not efficient, in these cases our kalman filter will be able to predict the speed of the vehicle using the previously entered GPS readings and current accelerometer readings. This will also help in improving the GPS of the mobile phone even in cases where GPS has lost the connection with the satellite. The 2D kalman filter that we will implement will mainly need the values of latitude and longitude in x, y coordinate system, Accelerometer readings rest every matrix will be programmed into the filter as per the systems noise and expected outputs.

IV. PROPOSED ARCHITECTURE

The proposed architecture involves taking input values from GPS and Accelerometer constantly at regular intervals of time and using those values in 2D-Kalman filter which will perform basic mathematical operations as per the equations and will give values of x, y and velocities of x and y which will be our required value. Also, the output of the state matrix i.e. x, y can be converted back to the latitude and longitude in order to reduce error in the values given by GPS. If we try to explain the proposed architecture in the form of a loop then the filter cyclically overrides the mean and the variance of the result.

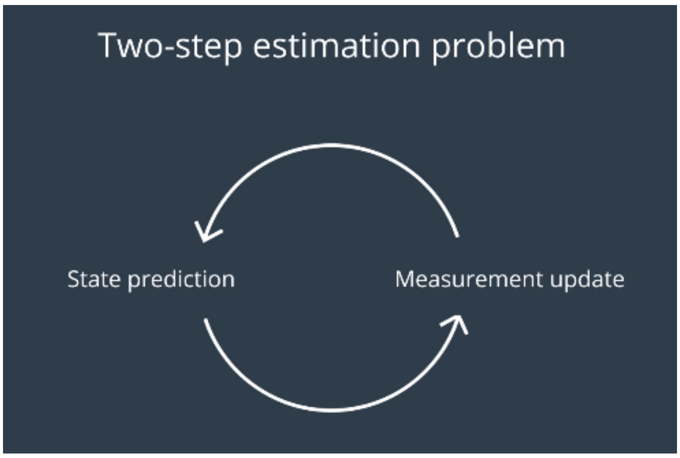

Fig.2 The loop that goes on and on.

The filter will always be confident on where it is, as long as the readings do not deviate too much from the predicted value.

A new measurement improves the estimate

Since the measured values (in update) fit relatively well to the predicted ones (by predict), the filter improves step by step to ensure that it is correct (normal distribution becomes narrower and higher), even though the values are noisy.

A. System State X

At the beginning we will have to initialize with an initial state. In one dimensional case the state was a vector.

$$x = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}$$

Initial State Matrix

If nothing is known, we can simply enter zero in the state matrix. If some boundary conditions are already known, they can be communicated to the filter. The choice of the following covariance matrix controls how fast the filter converges to the correct (measured) values.

B. Co-variance matrix P

An uncertainty must be given for the initial state. In the one-dimensional case, the variance was a vector, but now is the matrix of uncertainty for all states. Here is an example for all the four states.

$$P = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix}$$

The covariance matrix consists of uncertainty in the position and velocity in the x and y coordinates.

This matrix is most likely to be changed during the filter passes. It changes in both the predict and correct steps. The matrices can be initialized on the basis of the sensor accuracy. If the sensor is very accurate, small values should be used here. If the sensor is relatively inaccurate, large values should be used here to allow the filter to converge relatively quickly.

C. Dynamics matrix A

The core of the filter, however, is the following definition, which we should set up with great understanding of the physical context. This is not easy for many real problems. For our simple example (in-plane motion), the physics behind it comes from the smooth motion. for the state matrix shown above, the dynamics in matrix notation is as follows:

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The Dynamic matrix helps us in defining the equations for predicting the vehicle motion model.

This states "where" the state vector moves from one calculation step to the next within. This dynamic model is in our case the "constant velocity" model because it assumes that the velocity remains constant during a filter's calculation step(dt).

$$\begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}_{t+1} = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}_{t}$$

This is the prediction step for the state matrix.

This simply reflects the physical relationship for the uniform motion. A higher form would be the constant acceleration model, which would be a 6-D filter and still includes the accelerations in the state vector.

D. Process noise co-varience matrix Q

As the movement of the vehicle (in the sense of a superimposed, normally distributed noise) may also be distributed, this is where the process noise co-varience matrix is introduced. This matrix tells us about the filter, and how the system state can "jump" from one step to the next. Imagine the vehicle that drives autonomously. It can be distributed by a gust of wind or road bumps, which has a force effect. A speed change by the driver is also an acceleration that acts on the vehicle. If an accelerometer now affects the system state, then the physical dependencies for it is Q. The matrix is co-variance matrix containing the following elements:

$$Q = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\dot{x}} & \sigma_{x\dot{y}} \\ \sigma_{yx} & \sigma_y^2 & \sigma_{y\dot{x}} & \sigma_{y\dot{y}} \\ \sigma_{\dot{x}x} & \sigma_{\dot{x}y} & \sigma_{\dot{x}}^2 & \sigma_{\dot{y}\dot{x}} \\ \sigma_{\dot{y}x} & \sigma_{\dot{y}y} & \sigma_{\dot{x}\dot{y}} & \sigma_{\dot{y}}^2 \end{bmatrix}$$

The process noise co-varience matrix consists of the error caused in the process.

It is easy to calculate by placing the vector and then multiplying it by the assumed standard deviation for the acceleration.

$$Q = G \cdot G^T \cdot \sigma_\alpha^2$$

$$G = [0.5\Delta t^2 \quad 0.5\Delta t^2 \quad \Delta t \quad \Delta t]^T$$

The Equations to set the Q matrix appropriately.

E. Control Matrix B and Control Input u

External control variables (eg: steering, braking, acceleration, etc.) are possible via the control matrix. The u matrix will contain the robotic input of the system which could be the instantaneous acceleration or the distance traveled by the system from an IMU or an odometer sensor.

F. Measuring matrix H

The filter must also be told what is measured and how it relates to the state vector. In the example of the vehicle, the car enters a tunnel with only position measured at first point, only the speed is measured! The values can be measured directly with the factor 1.0 (i.e. the velocity is measured directly in the correct unit), which is why only 1.0 is set to the appropriate position.

$$H = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The H-matrix.

G. Measurement noise covariance matrix R

As in the one-dimensional case the variance, a measurement uncertainty must also be stated here.

$$R = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$$

The R Matrix

This measurement uncertainty indicates how much one trusts the measured values of the sensors. Since we measure the position and the velocity , this is a 2 × 2 matrix. If the sensor is very accurate, small values should be used here. If the sensor is relatively inaccurate, large values should be used here.

H. Unit matrix I

Last but not least, a unit matrix is necessary, which would be used to simplify the kalman equations.

I. Filtering step Prediction / Predict

This part of the Kalman filter now dares to predict the state of the system in the future. In addition, under certain conditions, a state can be calculated with it which cannot be measured, but in our case exactly what we need. We cannot measure the position of the vehicle because the GPS of the navigation device has no reception in a tunnel or region where GPS readings are not accurate. By initializing the state vector with a position and measuring the velocity, however, the dynamics can still be used to make an optimal prediction about the position.

$$X_{t+1} = A * x_t$$

Next state matrix

The covariance must also be recalculated. Uncertainty about the state of the system increases in the predicted step, as we have seen in the one dimension case. In the multidimensional case, the measurement uncertainty is added, so the uncertainty becomes larger and larger.

$$P=A\cdot\ P\cdot\ A'+Q$$

The Kalman filter has made a prediction statement about the expected system state in the future or in the upcoming time-step. The filter will now be measuring / correcting and checking whether the prediction of the system state fits well with the new measurements.

The covariance chosen to be smaller by the filter illustrates the certainty, if not, then something is wrong, which makes the filter more uncertain.

J. Filter Step Measure / Correct

From the sensors come current measured values, with which an innovation factor (y) is obtained by using the measurements, the state vector with the measuring matrix.

$$y=Z-(H\cdot\ x)$$

Then it looks at which variance can be further calculated. For this, the uncertainty and the measurement matrix and the measurement uncertainty required.

$$S=(H\cdot\ P\cdot\ H'+R)$$

This determines the so-called Kalman gain. It states whether the readings or system dynamics should be more familiar.

$$K= P\cdot\ H'S$$

The Kalman Gain will decrease if the readings match the predicted system state. If the measured values say otherwise, the elements of matrix K become Larger.

This information is used to update the system state.

$$x = x + (K\cdot\ y)$$

And also determined a new co-variance for the upcoming predict step.

$$P= P- (K\cdot\ H.P)$$

which is,

$$P= (I- (K\cdot\ H)) \cdot\ P$$

Now it's back to the step prediction.

This filter runs permanently as long as measured values come in. It can also be an open loop, so only the prediction step will be executed if no measurements are available. Then the uncertainty gets bigger and bigger.

The Basic Process of Kalman filter will be applied in between a time loop that will take values of x, y coordinates from the device (converted from Latitude and Longitude taken from GPS) and Acceleration from accelerometer and update the values in state matrix and control variable matrix in regular order which will reduce the deviation as the kalman filter will constantly be working on the values measured by device rather than its on prediction. this will give us the required output in terms of velocity of the vehicle in x, y direction with new values of x,y coordinates, this will perform two functions for us, firstly, calculating the velocity of vehicle will become easier and secondly the values of x,y can be converted into latitude and longitude to keep the values of GPS regularly in check reducing the error.

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