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Vehicle Tracking in Extreme Noisy Channel through Kalman Filter

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Abstract— Kalman Filter is one of the most important discoveries for a signal processing engineer. It uses a system's dynamics model (i.e., physical laws of motion), known control inputs to that system, and measurements (such as from sensors) to form an estimate of the system's varying quantities (its state) that is better than the estimate obtained by using any one measurement alone. This paper tries to estimate the correct position of a vehicle in an extreme noisy channel and compares it to the conventional filtering methods like running average etc. The paper presents threshold based technique along with Gaussian filtering to differentiate object from the background and estimates the two dimensional position of the vehicle.

Index Terms—Kalman Filter, Object Tracking, Gaussian, Particle Filter, Adaptive filter.

I. INTRODUCTION

It is important to first define Adaptive filtering. An adaptive filter is one that automatically adapts to time-varying properties of the communication channel. Kalman filter is also one kind of adaptive filter.

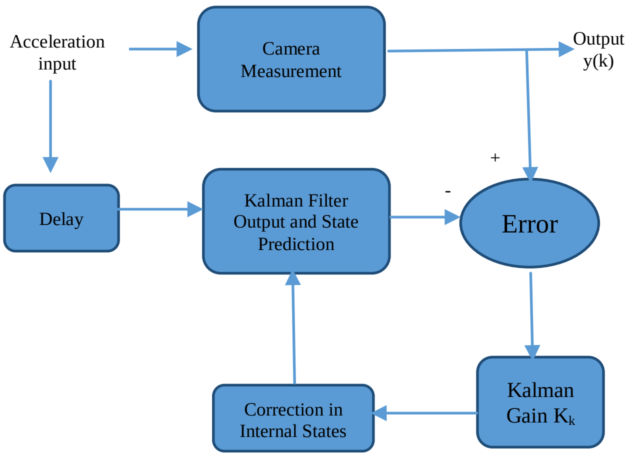

Figure 1: Overview of the Estimation Process

The Kalman filter provides estimates of the true values of measurements and simultaneously predict a future value, and provides the co variance estimate too. It uses linear equations to predict the state and is based on Bayesian model that also takes into account the control input which depends on system modelling. In this case, it will be acceleration of the vehicle.

The whole procedure is divided into three states:

1. Building a model
2. Determination of initial values and other parameters. Calculate initial value of state estimate and covariance matrices.
3. Looping between prediction and correction as shown in figure (1) to achieve closest estimate.

We can start with two basic equations of Kalman Filtering.

$$x_k = A * x_{k-1} + B * u_k + w_{k-1} \qquad (1)$$

$$z_k = H * x_k + v_k \qquad (2)$$

Equation (1) is a linear stochastic equation (the first one) where x_k is a linear combination of its previous value plus a control signal u_k and a process noise which depends on the variable parameters in a system. u_k is any driving factor for example acceleration.

Equation (2) tells that z_k which is any measurement value that is noisy and inaccurate is a linear combination of the signal value and the measurement noise. Both process noise w_k and measurement noise v_k are Gaussian in nature.

Matrices A, B and H are in general form matrices. These matrices depend on the system modelling are very crucial to the correct estimation. We can assume that most of the time, they do not change.

II. PLANNING ESTMATION PROCESS

It involves modelling different parameters according to the variables in the system.

A. Key Terms

The following terms are used in this document:

Posteriori: The future state calculation.
Covariance: measure of how much two random variables change together.
Gaussian Function: Used for filtering of the image to achieve smooth back grounds.
Hard Tracking: Tracking of vehicle in case of extreme noisy channel. It can some kind of continuous occlusion or high speed movement.
AOI: Area of Interest related to the center of mass of vehicle

B. Building a Model:

For Building a model, one should know all the variable parameters in the system. Along with it, prior knowledge of control input is required. In our case, we need to know the position of the vehicle. Our control input is acceleration and there is parameter of velocity that is varying. So in equation (1), P_x is linear combination of velocity and position of prior state and control input which is acceleration. It also has process noise that plays a significant role in state estimation.

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For this paper, we are considering noise as Gaussian.
For complete system modelling, we need to know the matrices A, B and process noise. Let us try to compute them in vehicular movement scenario. Our aim is to compute the 2-D position for vehicle but we will evaluate matrices for 1-D too.

The state variable which are important in this model are velocity and position.

(1) **Matrices in 1-D vehicle movement**:

$$A = \begin{bmatrix} 1 & t \\ 0 & 1 \end{bmatrix} \quad (M1)$$

$$B = \begin{pmatrix} t^2/2 \\ t \end{pmatrix} \quad (M2)$$

A and B matrices can be easily computed by law of motion equations. As per equation (1), x is state estimation of position and velocity.

$$x = \begin{pmatrix} P_x \\ V_x \end{pmatrix} \quad (M3)$$

Where, P_x is position in x-axis and V_x is velocity in x-axis. The velocity and position of the vehicle are given equations (3) and (4) which helps in calculating value of A and B

$$P_t = P_{t-1} + V_{t-1} + \frac{1}{2} * u_t * t^2 \quad (3)$$

$$V_t = V_{t-1} + a_x * t \quad (4)$$

Relating equation (3) and (4) gives value of A and B matrices. Similarly, for measurement prediction matrix C, equation (2) can be used.

$$H = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad (M4)$$

H matrix only provides the position measurement and not the velocity. Hence the other term is zero in the above matrices.

The processing error w_k in equation (1) is given by covariance of position and velocity of the vehicle.

$$w_k = \begin{bmatrix} \sigma_p^2 & \sigma_p\sigma_v \\ \sigma_p\sigma_v & \sigma_v^2 \end{bmatrix} \quad (M5)$$

Covariance matrix is just a relationship between position and velocity and can be solved by taking time variable parts of equation (3) and (4).

$$w_k = \begin{bmatrix} t^4/4 & t^3/2 \\ t^3/2 & t^2 \end{bmatrix} \quad (M6)$$

(2) **Matrices in 2-D vehicle movement**:

The matrices calculated by using equation (1) – (4) are given below. In this case we will estimate x- axis as well as y-axis of the position of the vehicle.

$$x = \begin{bmatrix} P_x \\ V_x \\ P_y \\ V_y \end{bmatrix} \quad (M3)$$

$$A = \begin{bmatrix} 1 & 0 & t & 0 \\ 0 & 1 & 0 & t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (M7)$$

$$B = \begin{bmatrix} t^2/2 \\ t^2/2 \\ t \\ t \end{bmatrix} \quad (M8)$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (M9)$$

Where, P_x is position in x-axis and V_x is velocity in x-axis and P_y is position in y-axis and V_y is velocity in y-axis.

C. Prediction and Correction

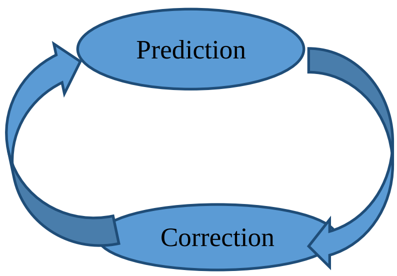

Figure 2: Prediction Correction Model

The prediction and correction cycle for vehicle location can be divided into time update and measurement update.

1. Time Update:

In time update state, we will be predicting position and covariance which will further be used in measurement stage. We will predict the covariance according to the following equation

$$P_K = A * P_{K-1} * A^T + Q \quad (5)$$

Where, Q = E_x is taken and we are supposing it as same as process noise.

2. Measurement Update:

Measurements are being done by a camera on road and represented by z_k . Considering equation (2) z_k has measurement noise so kalman gain factor K_k is used to reach the minimum error position state estimation.

$$x_K = x_{K-1} + K_k * (z_k - H * x_{k-1}) \quad (6)$$

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And K_k is given by following equation:

$$K_k = P_k * H^T * (H * P_k * H^T + R) \quad (7)$$

D. Iterations:

There is a continuous feedback process where estimations are done and passed to correction stage where kalman gain is calculated which is further used to correctly estimate vehicle's position.

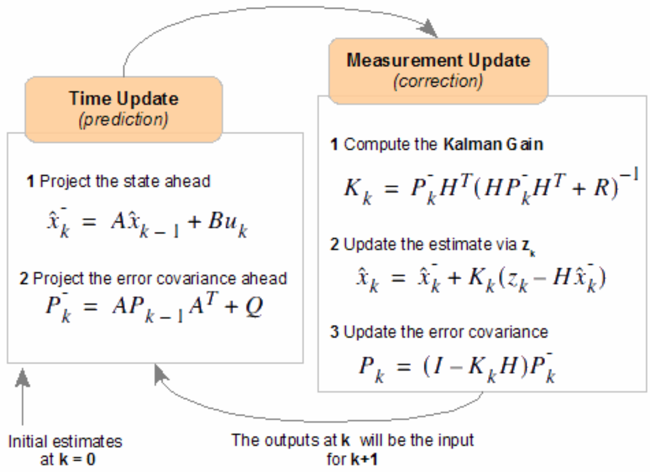

Figure 3: Iterative process of prediction and correction

III. MATLAB SIMULATIONS

The frames from the street cameras are taken and processed for back ground image that does not include car in the frames. Instead of real camera frames, we have considered frames from a famous game of the 90's Road Fighter. A mix of Gaussian filtering and binary threshold detection is followed to measure position of the vehicle.

Figure (4) describes the whole process of converging to area of interest in the image i.e. vehicle's center of mass. The road camera will collect 1000 images without any vehicle to differentiate background from vehicle. 1000 images are taken to average out the back ground as back ground will remain same for most of the time and there can surely be some noise that can affect the final results.

Figure (5) is the result of averaging 1000 image frames and converting to double format for processing in Mat lab.

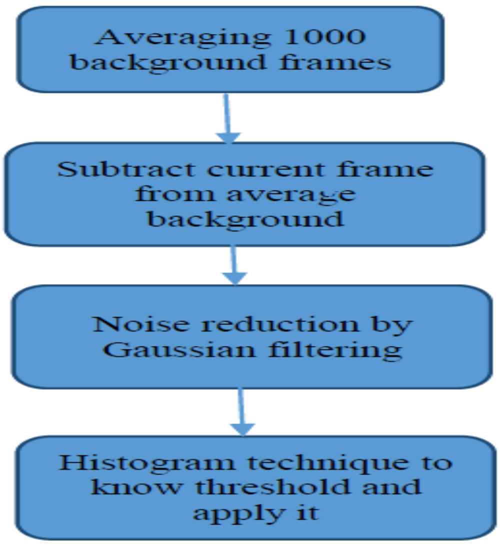

Figure 4: Image processing Technique

Gaussian filter is convolved with the background subtracted image. Gaussian filter has H-size of 20 and sigma of 10.

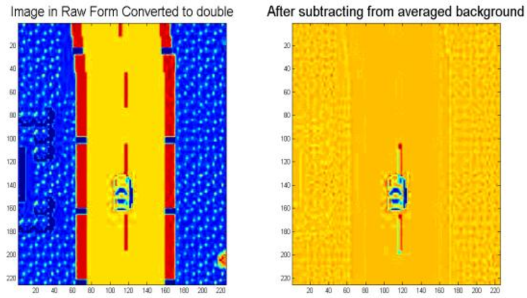

Figure 5: Subtracted raw image of Vehicle

Figure (5) also shows the subtracted view of the vehicle on the road. All the back ground has turned yellow but there are still irregularities which can be removed by simple Gaussian filtering. The vehicle can be seen in green color.

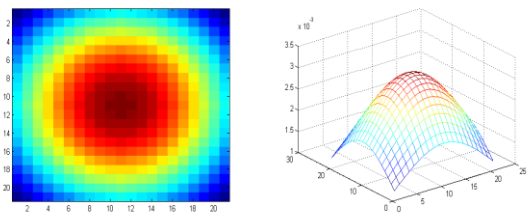

Figure 6: Gaussian Filter used

Figure (6) shows the properties of the Gaussian filter used to remove the irregularities in the image. If we see Figure 7(a), it clearly shows that Gaussian filter has removed all the white noise from the image. To refine it more, we can put a threshold and filter all the values that are there above that threshold value. In figure 7(b), it can be seen that most points of interest have a value higher than 4000.

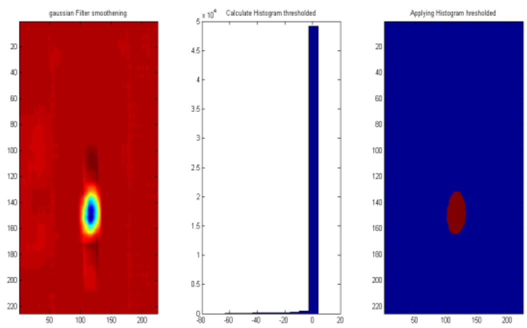

Figure 7: (a) Gaussian Filter smoothening (b) Calculate Histogram threshold (c) Applying Histogram threshold

The dot in figure 7(c) shows the center of mass of the vehicle and it is input to kalman filter prediction stage. Value of E_x is kept high to simulate extreme noise scenario. Let us first see the actual trajectory of vehicle movement given to its changing velocity.

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Let us first try to evaluate vehicle position in low noise scenario and compare its performance with moving average filter. In this case, both process noise and measurement noise are on lower side. The results of the simulation are depicted in following figures.

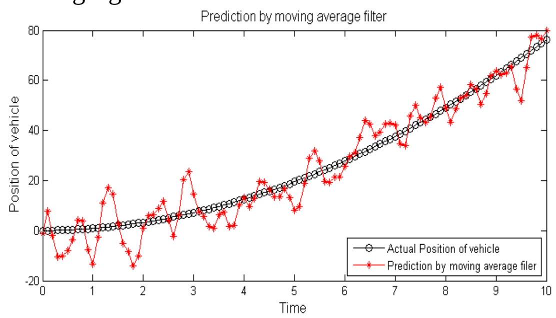

Figure 8: Performance with Moving average filter

If we observe in Figure (8) the red line is moving average filter estimation and it is not able to properly predict the correct position. At places, where velocity suddenly changes, the error in measurement is extremely high.

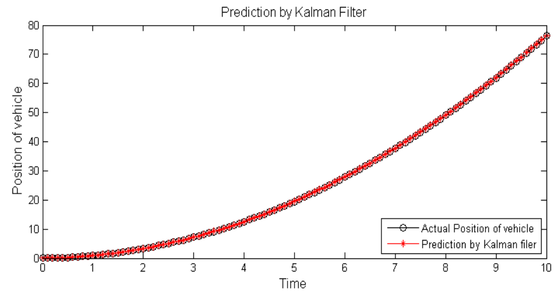

Figure 9: Performance with Kalman filter

In Figure (9) the red line is Kalman filter estimation and it is able to accurately predict the correct position even places where velocity suddenly changes, nearly zero error is observed. Now, let us try to evaluate extreme noisy situations and compare the working of two filters.

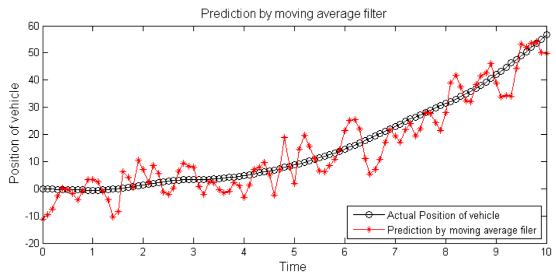

Figure 10: Performance with Moving average filter

Again, in extreme noisy situations moving average filter has just gone for a toss and erroneous predictions are done if we compare to actual position in black line in figure (10).

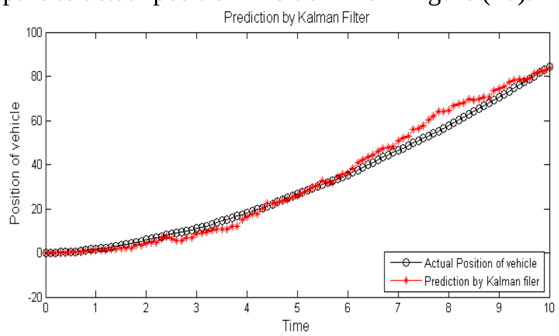

Figure 11: Performance with Kalman filter

In Figure (11) the red line representing Kalman filter estimation is at some places giving an error but considering these are extremely noisy situations, this error is expected but most of the time, Kalman filter is able to estimate nearly accurate position of the vehicle.

The results above show that the Kalman Filter algorithm converges to the position estimate. Here, we displayed the first the results taken over 10 seconds of interval and we clearly see the signs of convergence. If we broaden our measurement period, more accurate results can be achieved.

IV. ASSUMPTIONS

We have assumed white Gaussian noise for measurement as well as process equations. Results may significantly change if there is non-Gaussian noise but in most of the real time scenarios, only Gaussian noise exists. Secondly we have considered non-bursty noise. Kalman filter gain can be affected if there is bursty noise in some scenario. Moreover, advanced filters like extended kalman filter and unscented kalman filter can be used to achieve higher accuracy. Nevertheless; it is one of the most common data fusion filtering techniques present today and its importance can be felt from the fact that it was even used in Apollo Moon mission.

V. CONCLUSION & FUTURE WORK

The kalman filter predicts the very accurate positioning of the vehicle. It can be very useful in cases when vehicle is moving with high speed or occluded by some physical object. The plan is to extend the working to three dimensional tracking where we will track the position of air drones etc. and track multiple vehicle at the same time. In the end, I am grateful to Prof. Prakhar Priyadarshi, BVCOE New Delhi for their constant help throughout the whole project.

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AUTHORS PROFILE

Rahul Sharma, B.Tech in Electronics and Communication Engineering from GGSIPU in 2011 with Honors. Having 4 years of experience in different fields like signal processing and wireless. Has worked in LTE telecom domain developing full eNodeB solutions for macro, micro and femto cells.