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Comparison and Evaluation of Image Filtering Models for Vehicle Tracking

Kamal Upreti, Arun Kumar, Nihar Ranjan Roy

Abstract – This paper represents a core comparative approach to design and analysis of a real-time based Vehicle Tracking System using Kalman filter and Complimentary filter. The proposed system is used to determine the current location of a target device in terms of UTC time , Data status, latitude, longitude, UTC date, Speed over ground in knots, Magnetic variation , Mode indicators and Checksum information by utilizing the sms features of GSM technology. An attempt is made to improve the accuracy in locating GPS receiver by filtering out the irregularities using Kalman filter. In this paper, we have also investigated the optimal position tracking means. Linear recursive filtering technique is used for estimating noise co-variance at current state (Q) and measurement errors (R) received from sensor noise measurement. The result obtained gives better accuracy with more consistency and provides better performance level as compared to the complementary filter.

Index Terms – GSM, GPS, noise co-variance, Kalman filter, measurement error, complementary filter.

1. Introduction

Positioning refers to the estimation of one's location by combining various sources of information [15]. There are number of monitoring technologies in existence. Traffic cameras are used for detecting and tracking current position of a vehicle. These cameras are not only used for simple applications such as counting cars ,checking car lane but also for more complex applications like tracking and analyzing position of a vehicle. Multiple object tracking is an important research topic in computer vision. It has the ability to deal with the single object difficulties such as changing latitudes, longitudes, magnetic variations, mode indicators, checksum and speed over ground in knots, velocity, time and background appearance.

The Kalman filter is a recursive predictive filter that is based on the use of state space techniques and recursive algorithms. It estimates the state of a dynamic system. This dynamic system can be distributed by noise, mostly assumed as white noise [12] . To improve the estimated state the kalman filter uses measurements that are related to the state but disturbed as well.

The Kalman filter consists of two steps:

Prediction problem: predicts location of an object being tracked in the next frame i.e identifying a region in which probability of finding region is very high.

Correction problem: identify predicted frame in the designated region.

A well known solution is Kalman filter, recursive predicts that is based on the use of state space techniques and recursive algorithms. It estimates the state of a dynamic system [5]. This dynamic system can be disturbed by some noise, mostly assumed as white noise. To improve the estimated state the Kalman filter uses measurements that are related to the state but disturbed as well[2]. In tracking system, two problems must be considered: prediction and correction.

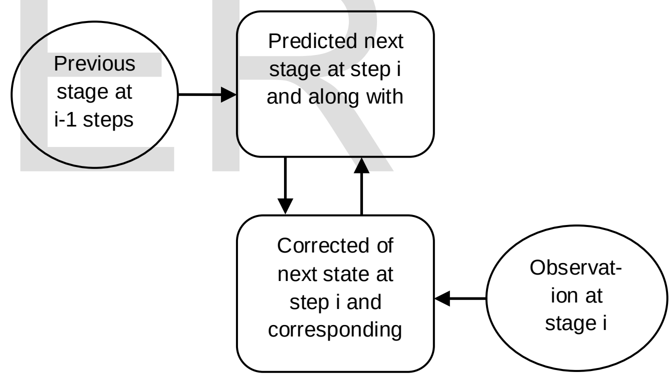

Figure 1: Diagram of Kalman filter

The correction problem is based on symmetric metric to compare current and previous frame of an object. Matching metrics in correction problem is important[1]. Tracking system is based on data association ,clustering, finding exact position of moving object when there is more than one valid sample.

2. System Overview

In this research, it is proposed to design an embedded system which is used for tracking and positioning of any vehicle by using GPS and GSM. The current design is an embedded application, which will continuously monitor a moving vehicle and report the status of the vehicle on demand. In this experimental setup, an AT89S52

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microcontroller is interfaced serially to a GSM modem and GPS receiver. A GSM modem is used to send the position of the vehicle from a remote place [1]. The GPS modem will continuously give the data i.e the latitude and longitude indicating the position of the vehicle.

The GPS modem gives many parameters as the output, but only the NMEA (National Marine Electronics Association) data coming out is read and displayed on the LCD. The same data is sent to the mobile at the other end from where the position of the vehicle is demanded. An EEPROM is used to store the mobile number.

The hardware interfaces to microcontroller are GSM modem and GPS receiver. The design uses RS-232 protocol for serial communication between the modem and the microcontroller [2]. A serial driver IC is used for converting TTL voltage levels to RS -232 voltage levels. When request by user is sent to the number at the modem, the system automatically sends a reply to that mobile indicating the position of the vehicle in terms of latitude and longitude [1].

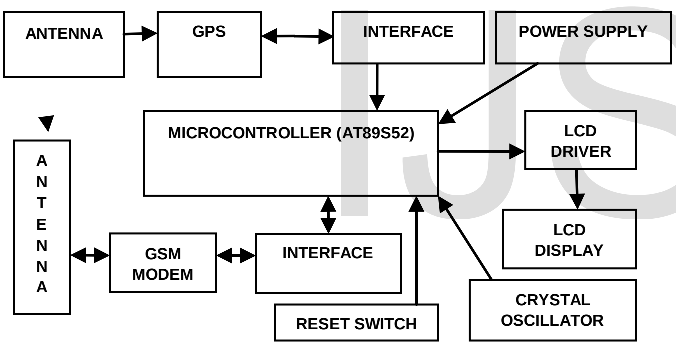

Figure 2: Overview of tracking system

3. KALMAN FILTER

The kalman filter, also known as linear quadratic estimation (LQE), a technique which uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies and produces estimates of unknown variables that tends to be more precise than those that would be based on a single measurement alone [3].

More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state.

The advantages of including kalman filter in the tracking process rate are:

I. It provides the best optimal location to search for next frame and to improve the error detection rate.

II. It reduces searching time of next frame, thus shortens the processing time.

III. The variance of the kalman filter innovations is smaller than variance of the deterministic innovations.

IV. It reduces phantom detection since image does not contain area of frame that exclude from the search.

For example, in a radar application, where one is interested in tracking a target, information about the location, speed and acceleration of the target is measured with a great deal of distorted signal by noise at any instance. The kalman filter exploits the dynamics of the target, which governs its time evolution, to remove the effects of the noise and get a good estimation of the location of the target at the present time (filtering), at a future time (prediction), or at a time in past (interpolation or smoothing).

The filter processes measurements to reduce a minimum error estimate of the system by utilizing the knowledge of the system, measurement dynamics and statistics of the system, noise measurement errors and initial condition information.

In addition, smoothing effect of the kalman filter will refine the tracking result from uncertainty of the noise [6]. It also helps to get exact location of the vehicle position where vehicles are not detected.

4. MATHEMATICAL FORMULATION OF KALMAN FILTERS

The Kalman filter addresses the general problem of trying to estimate the state x “Rn of a discrete –time controlled process that is governed by the linear stochastic difference equation as in equation.1.

$$X_K = A X_{K-1} + B U_K + W_{K-1} \quad ...(1)$$

With a measurement x “ R_n that is (as stated in equation 2)

$$Z_K = H X_K + V_K \quad …(2)$$

The random variables W_K and V_K represent the process and measurement noise (respectively). They are assumed to be independent (of each other), while with normal probability Distribution.

$$P (W) - N (0, Q) \quad …(3)$$

$$P (V) - N (0, R) \quad …(4)$$

The process noise covariance Q and measurement noise covariance R matrices (equations 3 and 4) might change with each other step or measurement, however here we assume they are constant. [5].

The n × n matrix A in the difference equation (1) relates the state at the current step K, in the absence of either a driving

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function or process noise. Note that in practice it might change with each time step, but here we assume it is constant.

The n × 1 matrix B relates the optional control input x “ R1 to the state x. The m × n matrix H in the measurement Equation (2) relates the state to the measurement Z_K. In practice, H might change with each time step or measurement, but here we assume it is constant.

The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the kalman filter into two groups: time update equations and measurement update equations as shown equations as in figure 3.Discrete kalman filter time update equations (5 & 6) are given as

$$X_{k^-} = A\,x_{k-1} + B\,u_k \quad \dots(5)$$

$$P_k = AP_{k-1}\,A^T + Q \quad \dots(6)$$

Time update equations project the state and covariance estimates forward from time step k-1 to step k. A and B are equations (1) , while Q is from equation (3). Initial conditions for the filter are discussed in the earlier references. Discrete kalman filter measurement update equations (7, 8& 9) are given below.

$$K_k = P_k\,H^T\,(H\,P^K\,H^T + R)^{-1} \quad \dots(7)$$

$$X_k = X_k^- + K^k\,(Z^k - H\,X_k^-) \quad \dots(8)$$

$$P_k = (I - K^k\,H)\,P_k \quad \dots(9)$$

The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain a priori estimates for the next time step. The measurement update equations are responsible for the feedback i.e for incorporating a new measurement into a priori estimate to obtain an improved a posteriori estimate [3]. The time update equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm for solving numerical problems.

The first task during the measurement update is to compute the kalman gain, K_k . The next step is to measure the process to obtain Z_k and then to generate a posteriori state estimate by incorporating the measurement as in equation (8). The final step is to obtain a posteriori error covariance estimate via equation (9).

After each time and measurement updates pair, the process repeated with the previous *a* posteriori estimates used to project or predicts the new *a* priori estimates. This recursive nature is one of the very appealing features of the Kalman filter – it makes practical implementation much more feasible than (for example) an implementation of a Wiener filter [15] which is designed to operate on all the data directly for each estimation. The kalman filter instead recursively conditions the estimate on all of the past measurements. Figure 3, offers a complete picture of the operation of the filter, combining the high –level equations 5 & 6.

It shows linearization requires the functions $f(x_{k-1},k-1)$ and $h(x_k, k)$ both be continuously differentiable . If the errors between the estimated state vector and the true state vector remain small, the linearization assumption is accurate. Higher order approximations have been derived but they typically involve significantly greater complexity while not usage outperforming the recursive kalman filter.[20].

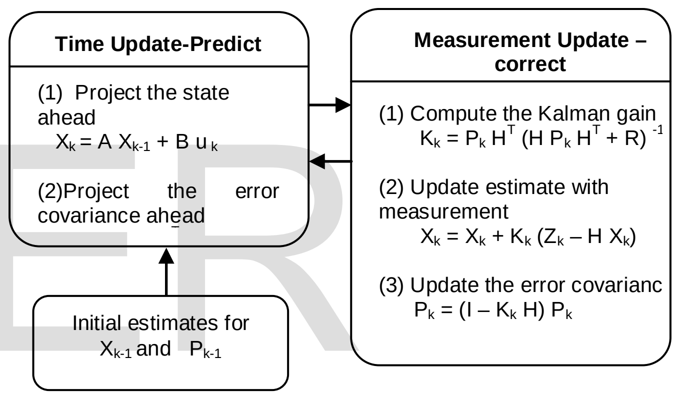

Figure 3: Parameters of kalman filter

5. Filter Parameters and Tuning

The kalman filter algorithm comprises of main four steps: Gain computation, state estimate update, covariance update and prediction. Matrix K is the gain that minimized a posteriori error covariance. The equation that needs to be minimized .

$$\hat{x}_{\bar{k}} = \hat{x}_{\bar{k}} + K(Z_k - H\hat{x}_k^{-})$$

$$e_k = x_k - \hat{x}_k$$

$$P_k = E\{e_k e_k^T\}$$

So, a posteriori estimate error covariance (P_k)

$$P_k = E\{e_k e_k{}^T\}$$

$$\frac{d}{dk}(P_k) = 0$$

One form of the result is

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}$$

- When the error covariance R approaches 0, the actual measurement Z_k is trusted more, while the predicted measurement X_k is trusted less.
- When a priori estimate error covariance approaches 0, the actual measurement Z_k, is trusted less, while the predicted measurement X_k is trusted more.

At the end we note that under conditions where Q and R are constant, both the estimation error covariance P_k and the Kalman gain K_k will stabilize quickly and then remain constant [5].

The tuning is usually performed off-line, frequently with the help of another (distinct) Kalman filter in a process generally referred to as system identification, which is clearly stated in [19].

For example, in case of tracking the head of a user of a 3D virtual environment we might reduce the magnitude of Q_k if the user seems to be moving slowly, and increase the magnitude if the dynamics start changing rapidly. In such cases Q_k might be chosen to account for both uncertainties about the user's intentions and uncertainty in the model.

In that study using both synthetic and full-scale experimental data, we showed that the tuning improved the fitting of the data, and that more reliable predictions were obtained. Here we both present results from a study on the robustness of the methodology, using synthetic data, as well as some more results with full –scale experimental data. An alternative of using the ensemble Kalman filter to tune the model parameters is to use a least square approach. The least square approach is, however, more computationally demanding, and seems therefore not to be suitable to online tuning [21].

6. Complementary Filter

A pair of filters are called complementary filters if their transfer functions sum to one at all frequencies in a complex sense i.e phase is zero and the magnitude is one [17].In this hobbistic world, recently are emerging other filters, called as Complementary filter. It is a basic combination of noise measurement of two different approach –Low pass filter and high pass filter. It assumes that the noise in y is mostly high frequency, and noise in x is mostly low frequency [16].

If F(t) can be used as to high pass, then it filters out the noise of high frequency in y. If F(t) as low pass, [1-F(t)] isthe complement, i.e filter out noise of low frequency noise in x. In fact, they manage both high pass and low–pass filters simultaneously. The low pass filter filters high frequency signals such as accelerometer used in the case of vibration while low pass filter filters high frequency signals such as drift velocity used in gyroscope.

So, complementary filter does not consider any statistics for the noise corrupting the signals , and their filter is obtained by a simple analysis in the frequency domain.

A typical application of the complementary filter is to combine measurement of longitude, latitude and attitude to obtain an estimation of noise in a signal. It is a relevant approach to smoothening image or signal. So, combining these two filters to get good results in tracking position of vehicle with respect to latitude, longitude and altitude.

7. Results and Discussion

Using single frequency ML 300 GPS hand held Receiver: data is collected at different locations around Delhi, Noida and Meerut.

Figure 4- shows that comparative analysis of data collected at different locations on the basis of Longitude, Latitude and Altitude with and without using Kalman filter and complementary filter.

In addition, we have implemented a linear recursive filtering technique – Kalman filter which improves the system performance by filtering out irregularities such as noise and distortion level. This technique increases the performance level with more consistency as compared to the conventional vehicle tracking system.

It is shown in fig-4, that latitude mean error is 0.499299, longitude mean error is 0.102257 and altitude mean error is 0.950391 which is reduced by using Kalman filter.

- *Kamal Upreti is currently pursuing master's degree program in Computer Science Engineering from Galgotia University, India. E-mail: kamalupreti1989@gmail.com.*
- *Arun Kumar is Assistant Professor in Galgotia University of Computer Science Department, India.*
- *Nihar Ranjan Roy is Assistant Professor in Galgotia University of Computer Science Department, India.*

Figure 4: Comparative analysis between without filter, Kalman filter and complementary filter relative to longitude, latitude and altitude parameters.

8. Conclusion

On the basis of these techniques, we prepared a comparative analysis of data for different locations are suggesting accuracy through Kalman filter application is certainly yielding better results. It shows larger amount of variations in the signals due to noise co-variance which can be smoothened by using both kalman and complementary filtering technique.

According to our simulated results, Kalman filter technique is most widely used methods for tracking and estimation due to its simplicity, optimality, tractability and robustness. However the extensive application of this methodology i.e. smoothening the image or signal, but it has limitation that evaluating data in a robust domain creates some loss in the form of light, heat, white noise and redundancy of information through kalman filter.

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