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ExtendedKalman Filter based Estimation for Speed Optimization

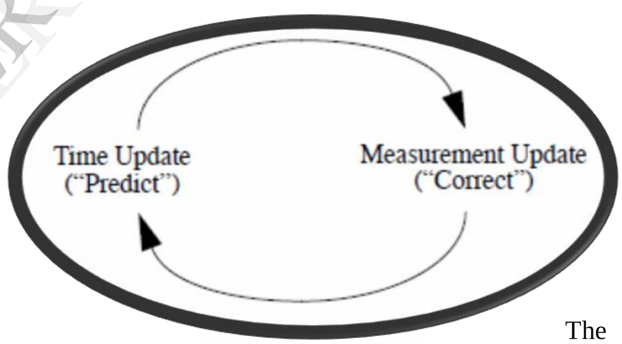
BhartiTiwari [1][M.TechscholarGyan Ganga College of Technology Jabalpur
PapiyaDutta [2][Asst.Prof& HOD GyanGanga CollegeofTechnology,Jabalpur,
NehaShrivastava[3] [Asst.prof, Gyan Ganga InstituteOfTechnology&Sciences,Jabalpur

Filters are used to achieve desired spectral characteristics of a signal, to reject unwanted signals, like noise or interferers, to reduce the bit rate in signal transmission, etc. The notion of making filters adaptive, i.e., to alter parameters (coefficients) of a filter according to some algorithm, tackles the problems that we might not in advance know, e.g., the characteristics of the signal, or of the unwanted signal, or of a systems influence on the signal that we like to compensate. Adaptive filters can adjust to unknown environment, and even track signal or system characteristics varying over time.LMS, RLS &Kalman are the popular adaptive filters methods for linear systems. Extended Kalman filter is a good choice when we needed adaptive filter in nonlinear Systems (e.g. OFDM). Available methods are quite good so we did not make any changes in the methods, we have improvised the adaption rate developing a unique combination of two Extended Kalman filter.

The purpose of this paper is to provide a practical introduction to the new affine combination of discrete Kalman filter. This introduction includes a description and some discussion of the basic discrete Kalman filter, a derivation, description and some discussion of the extended Kalman filter, and a results.

The Discrete Kalman Filter

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. Since the time of its introduction, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation. This is likely due in large part to advances in digital computing that made the use of the filter practical, but also to the relative simplicity and robust nature of the filter itself. Rarely do the conditions necessary for optimality actually exist, and yet the filter apparently works well for many applications in spite of this situation. 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 fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the 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 the a priori estimate to obtain an improved a posteriori estimate. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-correctoralgorithm for solving numerical problems as shown below in Figure



The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone

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The Kalman filter has numerous applications in technology. A common application is for guidance, navigation and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics.

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state; no additional past information is required.

Kalman filter formulation: In order to use the Kalman filter to estimate the internal state of a process given only a sequence of noisy observations, one must model the process in accordance with the framework of the Kalman filter. This means specifying the following matrices: $\mathbf{F}_k$, the state-transition model; $\mathbf{H}_k$, the observation model; $\mathbf{Q}_k$, the covariance of the process noise; $\mathbf{R}_k$, the covariance of the observation noise; and sometimes $\mathbf{B}_k$, the control-input model, for each time-step, k, as described below.

The Kalman filter model assumes the true state at time k is evolved from the state at $(k-1)$ according to

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k$$

where

- $\mathbf{F}_k$ is the state transition model which is applied to the previous state $\mathbf{x}_{k-1}$;
- $\mathbf{B}_k$ is the control-input model which is applied to the control vector $\mathbf{u}_k$;
- $\mathbf{w}_k$ is the process noise which is assumed to be drawn from a zero mean-multivariatenormaldistribution with covariance $\mathbf{Q}_k$.

$$\mathbf{w}_k \sim N(0, \mathbf{Q}_k)$$

At time k an observation (or measurement) $\mathbf{z}_k$ of the true state $\mathbf{x}_k$ is made according to

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

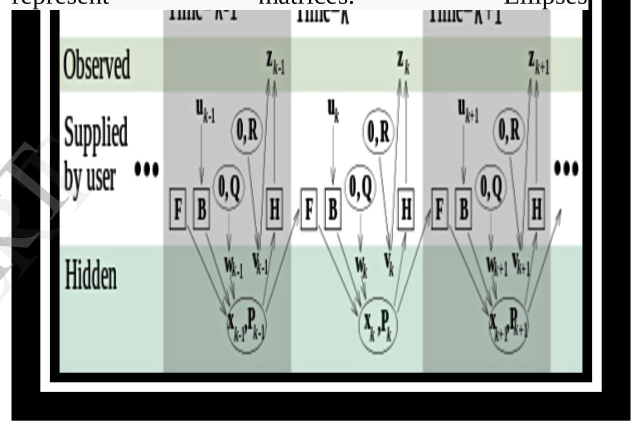
Where $\mathbf{H}_k$ is the observation model which maps the true state space into the observed space and $\mathbf{v}_k$ is the observation noise which is assumed to be zero mean Gaussian white noise with covariance $\mathbf{R}_k$.

$$\mathbf{v}_k \sim N(0, \mathbf{R}_k)$$

The initial state, and the noise vectors at each step $\{\mathbf{x}_0, \mathbf{w}_1, ..., \mathbf{w}_k, \mathbf{v}_1 ... \mathbf{v}_k\}$ are all assumed

to be mutually independent.

Figure above is the Model of Kalman filter. Squares represent matrices. Ellipses



represent multivariatenormaldistributions (with the mean and covariance matrix enclosed). Unenclosed values are vectors. In the simple case, the various matrices are constant with time, and thus the subscripts are dropped, but the Kalman filter allows any of them to change each time step.

Extended Kalman filter: In the extendedKalman filter, the state transition and observation models need not be linear functions of the state but may instead be differentiable functions.

$$\boldsymbol{x}_k = f(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}) + \boldsymbol{w}_{k-1}$$

$$\boldsymbol{z}_k = h(\boldsymbol{x}_k) + \boldsymbol{v}_k$$

Where $\mathbf{w}_k$ and $\mathbf{v}_k$ are the process and observation noises which are both assumed to be zero mean multivariate Gaussian noises with covariance $\mathbf{Q}_k$ and $\mathbf{R}_k$ respectively.

The function *f* can be used to compute the predicted state from the previous estimate and similarly the function *h* can be used to compute the predicted measurement from the predicted state. However, *f* and *h* cannot be applied to the covariance directly. Instead a matrix of partial derivatives (the Jacobian) is computed.

At each time step, the Jacobian is evaluated with current predicted states. These matrices can be used in the Kalman filter equations. This process essentially linearizes the non-linear function around the current estimate.

Predict

Predicted state estimate

$$\hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_{k-1})$$

Predicted covariance estimate

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1|k-1}\boldsymbol{F}_{k-1}^{\top} + \boldsymbol{Q}_{k-1}$$

Update

Innovation or measurement residual

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k|k-1})$$

Innovation or covariance residual

$$\boldsymbol{S}_k = \boldsymbol{H}_k\boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\top} + \boldsymbol{R}_k$$

Near-optimal Kalman gain

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\top}\boldsymbol{S}_k^{-1}$$

Update state estimate

Updated $\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\tilde{\boldsymbol{y}}_k$

covariance estimate

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k|k-1}$$

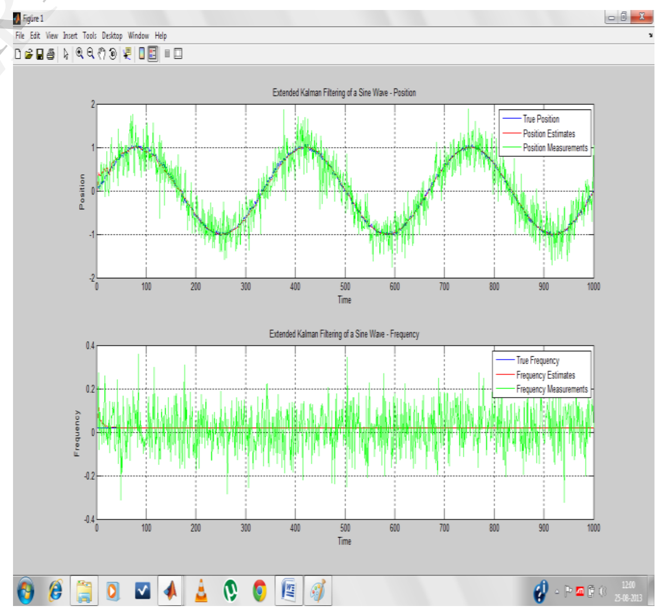
Where the state transition and observation matrices are defined to be the following Jacobeans

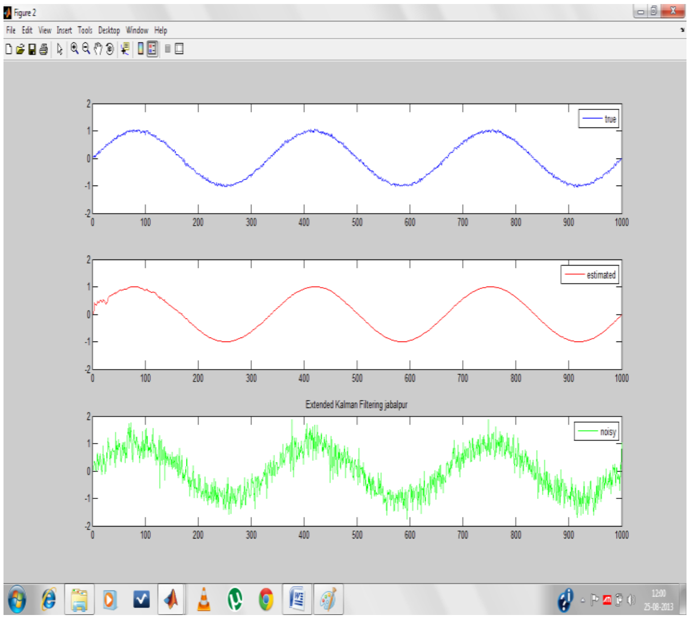
$$\boldsymbol{H}_k = \left.\frac{\partial h}{\partial \boldsymbol{x}}\right|_{\hat{\boldsymbol{x}}_{k|k-1}} \quad \boldsymbol{F}_{k-1} = \left.\frac{\partial f}{\partial \boldsymbol{x}}\right|_{\hat{\boldsymbol{x}}_{k-1|k-1},\boldsymbol{u}_{k-1}}$$

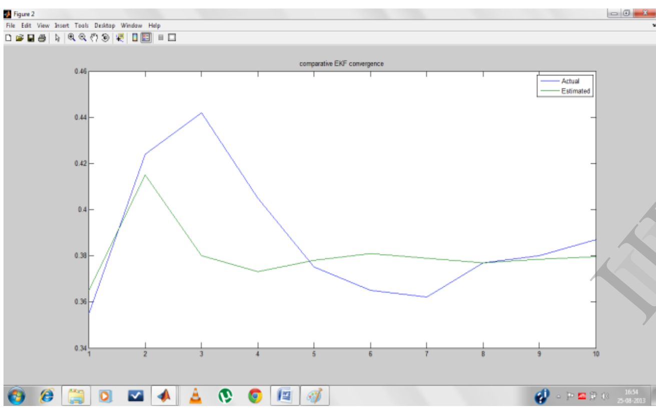
Conclusion

In this thesis work we were able to effectively mathematically model of new design of Extended Kalman Filter which is an affine combination of two Extended Kalman Filter & reduce the white noise in non linier system. There are applications like fast time varying channels in many military such as guided missiles and even in satellite launch vehicles or commercial applications like 4G data communication
For these type of application we needed fast adaptive non-linear filter which can adapt unknown system as soon as possible, our proposed design have very fast converging rate which allows the very fast adaption of unknown filter. The work functions mainly in the time domain and this allows us to implement the design of ref increase SNR.

Result







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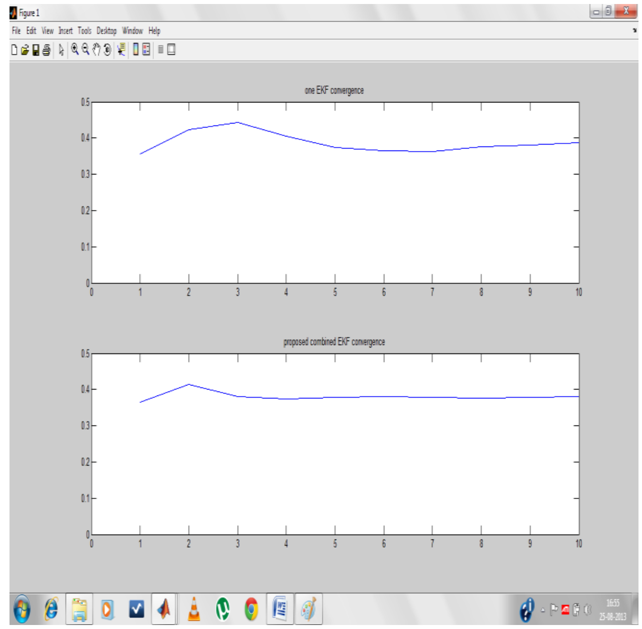

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