International Journal for Scientific Research (IJSR)

IJSR

المجلة الدولية للبحوث العلمية

Vol. (3), No. (7) July 2024 الإصدار (3)، العدد (7)

Comparison between Kalman Filter and Adaptive Filter

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Abstract

This study contains a comparison between the two Kalman filter and adaptive filter has huge importance because of it is uses in different applications such as air navigation planes, satellites, cameras, motions, radar, stations. Adaptive filter has various Application as well and important in CCTV and microphones.

Keywords: Kalman Filter, Adaptive Filter, MATLAB.

Introduction

The introduction to this research, which is entitled a comparison between the way the filters work, namely the Kalman filter and the adaptive filter, which work on the method of filtering and filtering the frequently used radio signals. Our daily life is also used in some missiles and in monitoring stations, as it is used a lot in air navigation in military airports we studied in this research on making a comparison between filters in the way to purify the signal and we also studied the difference between the signals.

Kalman filters have been vital in the implementation of the navigation systems of U.S. Navy nuclear ballistic missile submarines, and in the guidance and navigation systems of cruise missiles such as the U.S. Navy's Tomahawk missile and the U.S. Air Force's Air Launched Cruise Missile. They are also used in the guidance and navigation systems of reusable launch vehicles and the attitude control and navigation systems of spacecraft which dock at the International Space Station.

This digital filter is sometimes called the Stratonovich–Kalman–Bucy filter because it is a special case of a more general, nonlinear filter developed somewhat earlier by the Soviet mathematician Ruslan Stratonovich. In fact, some of the special case linear filter's equations appeared in these papers by Stratonovich that were published before summer 1960, when Kalman met with Stratonovich during a conference in Moscow.

The Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. x ^ k ∣ k − 1 denotes the estimate of the system's state at time step k before the k-th measurement y_k has been taken into account; P k ∣ k − 1

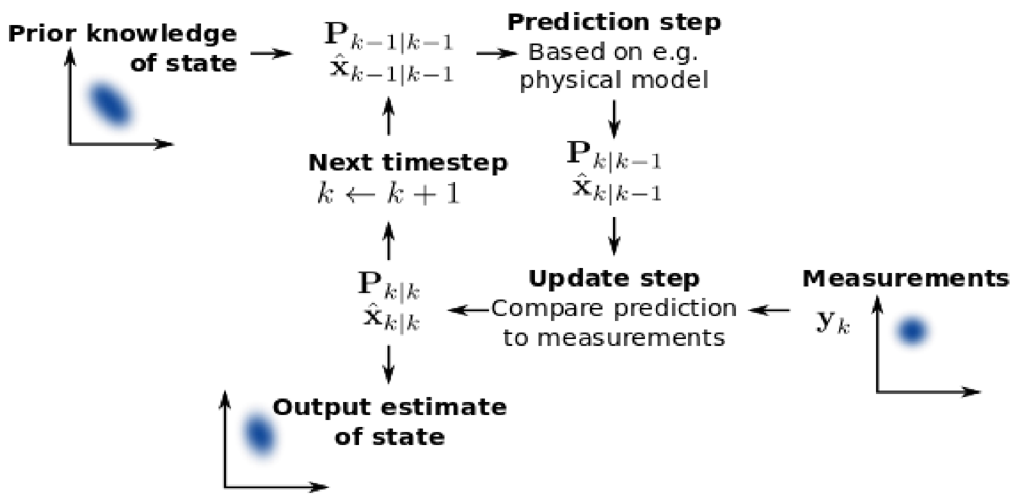


Figure (1): the corresponding uncertainty filters in the features and found the results for each signal

International Journal for Scientific Research, London Vol (3), No (7), 2024
https://doi.org/10.59992/IJSR.2024.v3n7p15 E-ISSN 2755-3418

Problem Definition

Our problem is provide needed military security requires to use the best filter to assure highest level of security, hence the need to compare between different filters is justified comparison between kalman filter and deal time adaptive filter will be done to grantee pure signal with lightest quality because of high importance of signal quality we need to use highly Efficient filter.

Research Objectives

The objectives of this research are to make a comparison between the filters in the way each filter.

Research Methodology

To use the MATLAB program in Kalman filter and the adaptive filter applications.

Background of the Study

We searched in this research to obtain a comparison between two-filter Kalman filter, the adaptive filter and we found the advantages of each filter in the method of purifying the original signal. We used MATLAB program in the practical application and obtained the results in our research.

Proposed Approach

Kalman Filter and Adaptive Filter

Kalman Filter

The Kalman filter uses a system's dynamic model (e.g., physical laws of motion), known control inputs to that system, and multiple sequential 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 only one measurement alone. As such, it is a common sensor fusion and data fusion algorithm.

History

The filter is named after Hungarian émigré Rudolf E. Kálmán, although Thorvald Nicolai Thiele and Peter Swerling developed a similar algorithm earlier. Richard S. Bucy of the University of Southern California contributed to the theory, leading to it sometimes being called the Kalman–Bucy filter. Stanley F. Schmidt is generally credited with developing the first implementation of a Kalman filter. He realized that the filter could be divided into two distinct parts, with one part for time periods between sensor outputs and another part for incorporating measurements. It was during a visit by Kálmán to the NASA Ames Research Center that Schmidt saw the applicability of Kálmán's ideas to the nonlinear problem of trajectory estimation for the Apollo program leading to its incorporation in the Apollo navigation computer. This Kalman filter was first described and partially developed in technical papers by Swerling (1958), Kalman (1960) and Kalman and Bucy (1961).

The Apollo computer used 2k of magnetic core RAM and 36k wire rope [...] The CPU was built from ICs [...]. Clock speed was under 100 kHz [...]. The fact that the MIT engineers were able to pack such good software (one of the very first applications of the Kalman filter) into such a tiny computer is truly remarkable.

In statistics and control theory, Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. The filter is named after Rudolf E. Kálmán, one of the primary developers of its theory.

Technical Description

The Kalman filter is an efficient recursive filter that estimates the internal state of a linear dynamic system from a series of noisy measurements. It is used in a wide range of engineering and econometric applications from radar and computer vision to estimation of structural macroeconomic models, and is an important topic in control theory and control systems engineering. Together with the linear-quadratic regulator (LQR), the Kalman filter solves the linear–quadratic–Gaussian control problem (LQG). The Kalman filter, the linear-quadratic regulator, and the linear–quadratic–Gaussian controller are solutions to what arguably are the most fundamental problems in control theory.

In most applications, the internal state is much larger (more degrees of freedom) than the few "observable" parameters which are measured. However, by combining a series of measurements, the Kalman filter can estimate the entire internal state.

In the Dempster–Shafer theory, each state equation or observation is considered a special case of a linear belief function and the Kalman filter is a special case of combining linear belief functions on a join-tree or Markov tree. Additional approaches include belief filters which use Bayes or evidential updates to the state equations.

A wide variety of Kalman filters have now been developed, from Kalman's original formulation, now called the "simple" Kalman filter, the Kalman–Bucy filter, Schmidt's "extended" filter, the information filter, and a variety of "square-root" filters that were developed by Bierman, Thornton, and many others. Perhaps the most commonly used type of very simple Kalman filter is the phase-locked loop, which is now ubiquitous in radios, especially frequency modulation (FM) radios, television sets, satellite communications receivers, outer space communications systems, and nearly any other electronic communications equipment.

Kalman filter deals effectively with the uncertainty due to noisy sensor data and to some extent also with random external factors. Kalman filter produces an estimate of the state of the system as an average of the system's predicted state and of the new measurement using a weighted average.

The Kalman Filter Equations

Many derivations of the Kalman filter exist in the literature; only results are provided in this equations shows a block diagram for the Kalman filter. The Kalman filter equations can be deduced from the filtering equation is

$$\underline{x}(n|n) = \underline{x}_s(n) = \underline{x}(n|n-1) + K(n)[\underline{y}(n) - \underline{G}\underline{x}(n|n-1)]$$

The measurement vector is

$$\underline{y}(n) = \underline{G}\underline{x}(n) + \underline{v}(n)$$

Where is zero mean white Gaussian noise with covariance RC

$$\mathfrak{R}_c = E\{\underline{y}(n) \ \ \underline{y}^t(n)\}$$

The gain (weights) vector is dynamically computed as

$$\underline{K}(n) = \underline{P}(n|n-1)\underline{G}^t[\underline{G}\underline{P}(n|n-1)\underline{G}^t + \mathfrak{R}_c]^{-1}$$

Where the measurement noise matrix P represents the predictor covariance matrix, and is equal to

$$\underline{P}(n+1|n) = E\{\underline{x}_s(n+1)\underline{x}^*{}_s(n)\} = \underline{\Phi}\underline{P}(n|n)\underline{\Phi}^t + \underline{Q}$$

Where $\underline{Q}$ is the covariance matrix for the input u?

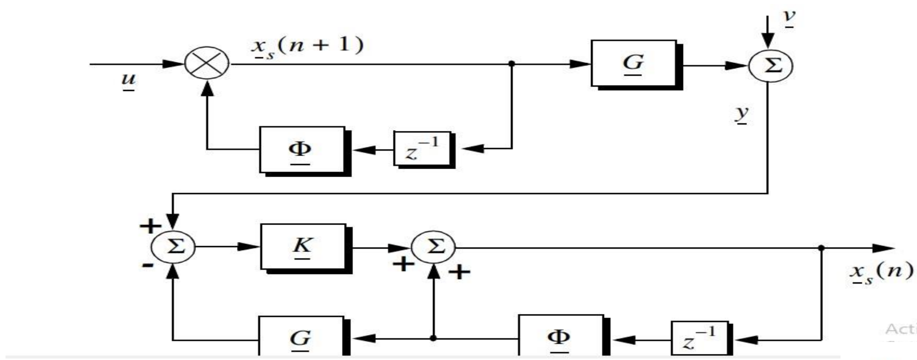
$$\underline{Q} = E\{\underline{u}(n) \ \ \underline{u}^t(n)\}$$

The corrector equation (covariance of the smoothed estimate) is

$$\underline{P}(n|n) = [\underline{I} - \underline{K}(n)\underline{G}]\underline{P}(n|n-1)$$

Finally, the Predictor Equation is

$$\underline{x}(n+1|n) = \underline{\Phi}\,\underline{x}(n|n)$$



αβγ

Figure (2): Structure of the Kalman filter

The Singer Kalman Filter

The Singer1 filter is a special case of the Kalman where the filter is governed by a specified target dynamic model whose acceleration is a random process with autocorrelation function given by

$$E\{\ddot{x}(t)\ \ddot{x}(t+t_1)\} = \sigma_a^2\ e^{-\frac{|t_1|}{\tau_m}}$$

Singer, R. A., Estimating Optimal Tracking Filter Performance for Manned

Maneuvering Targets, IEEE Transaction on aerospace and Electronics, Where τ_m is the correlation τ_m time of the acceleration due to target maneuver or atmospheric turbulence. The correlation time τ_m may vary from as low as 10 seconds for aggressive maneuvering to as large as 60 seconds for lazy maneuver cases.

Singer defined the random target acceleration model by a first order Markov process given by

$$\ddot{x}(n+1) = \rho_m \ \ddot{x}(n) + \sqrt{1-\rho_m^2} \ \sigma_m \ w(n)$$

Where is a zero mean, Gaussian random variable with unity variance, σ_m is the maneuver standard deviation, and the maneuvering correlation coefficient ρ_m is given by

$$\rho_m = e^{-\frac{T}{\tau_m}}$$

The continuous time domain system that corresponds to these conditions is as the Wiener-Kolmogorov whitening filter which is defined by the differential equation

$$\frac{d}{dt}v(t) = -\beta_m v(t) + w(t)$$

Where β_m is equal to the $1/\tau_m$. maneuvering variance using Singer's model is given by

$$\sigma_m^2 = \frac{A_{max}^2}{3}[1 + 4P_{max} - P_0]$$

A_{max} Is the maximum target acceleration with probability P_{max} and the term P_0 defines the probability that the target has no acceleration. The transition matrix that corresponds to the Singer filter is given by

$$\underline{\Phi} = \begin{bmatrix} 1 & T & \frac{1}{\beta_m^2}(-1 + \beta_m T + \rho_m) \\ 0 & 1 & \frac{1}{\beta_m}(1 - \rho_m) \\ 0 & 0 & \rho_m \end{bmatrix}$$

Note that when $T\beta_m = T/\tau_m$ is small (the target has constant acceleration), then Eq. (11.140) reduces to Eq. (11.114). Typically, the sampling interval is much less than the maneuver time constant; hence, Eq. (11.140) can be accurately replaced by its second order approximation. More precisely,

$$\underline{\Phi} = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T(1 - T/2\tau_m) \\ 0 & 0 & \rho_m \end{bmatrix}$$

The covariance matrix was derived by Singer, and it is equal to

$$\underline{C} = \frac{2\sigma_m^2}{\tau_m} \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix}$$

Where

$$C_{11} = \sigma_x^2 = \frac{1}{2\beta_m^5}\left[1 - e^{-2\beta_m T} + 2\beta_m T + \frac{2\beta_m^3 T^3}{3} - 2\beta_m^2 T^2 - 4\beta_m T e^{-\beta_m T}\right]$$

$$C_{12} = C_{21} = \frac{1}{2\beta_m^4}[e^{-2\beta_m T} + 1 - 2e^{-\beta_m T} + 2\beta_m T e^{-\beta_m T} - 2\beta_m T + \beta_m^2 T^2]$$

$$C_{13} = C_{31} = \frac{1}{2\beta_m^3}[1 - e^{-2\beta_m T} - 2\beta_m T e^{-\beta_m T}]$$

$$C_{22} = \frac{1}{2\beta_m^3}[4e^{-\beta_m T} - 3 - e^{-2\beta_m T} + 2\beta_m T]$$

Two limiting cases are of interest:

1. The short sampling interval case $(T \ll \tau_m)$,

$$\lim_{\beta_m T \to 0} \underline{C} = \frac{2\sigma_m^2}{\tau_m} \begin{bmatrix} T^5/20 & T^4/8 & T^3/6 \\ T^4/8 & T^3/3 & T^2/2 \\ T^3/6 & T^2/2 & T \end{bmatrix}$$

And the state transition matrix is computed from Eq. (11.141) as

$$\lim_{\beta_m T \to 0} \underline{\Phi} = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

Which is the same as the case for the $\alpha\beta\gamma$ filter (constant acceleration). 2. The long sampling interval ($T \gg \tau_m$). This condition represents the case when acceleration is a white noise process. The corresponding covariance and transition matrices are, respectively, given by

$$\lim_{\beta_m T \to \infty} \underline{C} = \sigma_m^2 \begin{bmatrix} \frac{2T^3\tau_m}{3} & T^2\tau_m & \tau_m^2 \\ T^2\tau_m & 2T\tau_m & \tau_m \\ \tau_m^2 & \tau_m & 1 \end{bmatrix}$$

$$\lim_{\beta_m T \to \infty} \underline{\Phi} = \begin{bmatrix} 1 & T & T\tau_m \\ 0 & 1 & \tau_m \\ 0 & 0 & 0 \end{bmatrix}$$

Note that under the condition that $T \gg \tau_m$, the cross correlation terms and become very small. It follows that estimates of acceleration are no longer available, and thus a two state filter model can be used to replace the three state model. In this case,

$$\underline{C} = 2\sigma_m^2 \tau_m \begin{bmatrix} T^3/3 & T^2/2 \\ T^2/2 & T \end{bmatrix}$$

$$\underline{\Phi} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}$$

Relationship between Kalman and $\alpha\beta\gamma$ Filters

The relationship between the Kalman filter and the $\alpha\beta\gamma$ filters can be easily obtained by using the appropriate state transition matrix $\underline{\Phi}$, and gain vector K corresponding to the $\alpha\beta\gamma$

$$\begin{bmatrix} x(n|n) \\ \dot{x}(n|n) \\ \ddot{x}(n|n) \end{bmatrix} = \begin{bmatrix} x(n|n-1) \\ \dot{x}(n|n-1) \\ \ddot{x}(n|n-1) \end{bmatrix} + \begin{bmatrix} k_1(n) \\ k_2(n) \\ k_3(n) \end{bmatrix} [x_0(n) - x(n|n-1)]$$

$$x(n|n-1) = x_s(n-1) + T\ \dot{x}_s(n-1) + \frac{T^2}{2}\ \ddot{x}_s(n-1)$$

$$\dot{x}(n|n-1) = \dot{x}_s(n-1) + T\ \ddot{x}_s(n-1)$$

$$\ddot{x}(n|n-1) = \ddot{x}_s(n-1)$$

Comparing the previous three equations with the filter equations yields,

$$\begin{bmatrix} \alpha \\ \frac{\beta}{T} \\ \frac{\gamma}{T^2} \end{bmatrix} = \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix}$$

Additionally, the covariance matrix elements are related to the gain coefficients by

$$\begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} = \frac{1}{C_{11} + \sigma_v^2} \begin{bmatrix} C_{11} \\ C_{12} \\ C_{13} \end{bmatrix}$$

Indicates that the first gain coefficient depends on the estimation error variance to the total residual variance, while the other two gain coefficients are calculated through the covariances between the second and third states and the first observed state.

An Adaptive Filter

Is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm?

Because of the complexity of the optimization algorithms, almost all adaptive filters are digital filters.

Adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment

Type of Adaptive Filter

1- The least mean squares (LMS) filter.

2- The Recursive least squares (RLS) Filter.

Block diagram

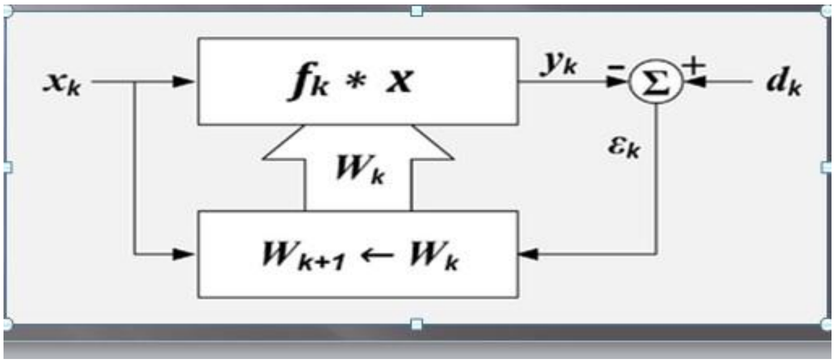


Figure (3)

Adaptive Filter, compact representation

k = sample number,

x = reference input,

d = desired input,

ε = error output,

f = filter impulse response,

Σ = summation,

Box=linear filter and adaption algorithm.

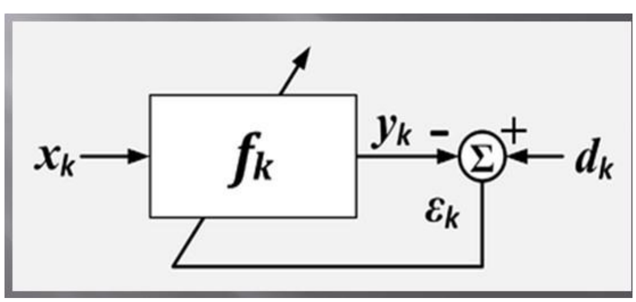


Figure (4): linear filter and adaption algorithm

There are two input signals to the adaptive filter:

K = represents the discrete sample number.

The filter is controlled by a set of = L+1 coefficients or weights.

$W_k = [w_{0k}, w_{1k}, . . ., w_{Lk}]$

Or vector of weights, which control the filter at sample time k.

Occurs as a result of adjustments computed at sample time k.

These changes will be applied after sample time k and before they are used at sample time k+1.

The input signals are defined as follows:

$d_k = g_k + u_k + v_k$

$x_k = g_k' + u_k' + v_k'$

Where:

g = the desired signal,

g' = a signal that is correlated with the desired signal g

u = an undesired signal that is added to g, but not correlated with g or g'

u' = a signal that is correlated with the undesired signal u, but not correlated with g or g',

v = an undesired signal (typically random noise) not correlated with g, g', u, u' or v',

v' = an undesired signal (typically random noise) not correlated with g, g', u, u' or v.

https://doi.org/10.59992/IJSR.2024.v3n7p15
E-ISSN 2755-3418

Tapped Delay Line FIR Filter

If the variable filter has a tapped delay line Finite Impulse Response (FIR) structure, then the impulse response is equal to the filter coefficients. The output of the filter is given by

$$y_k = \sum_{l=0}^{L} w_{lk} \; x(k-l) = \hat{g}_k + \hat{u}_k + \hat{v}_k$$

Where

w_{lk}

Ideal Case

In the ideal case $v \equiv 0$, $v' \equiv 0$, $g' \equiv 0$. All the undesired signals in d_k are represented by u_k.

x_k consists entirely of a signal correlated with the undesired signal in u

The output of the variable filter in the ideal case is

$y_k = \hat{u}_k$

The error signal or cost function is the difference between d_k and y_k

$\epsilon_k = d_k - y_k = g_k + u_k - \hat{u}_k$. The desired signal gk passes through without being changed.

The error signal ϵ_k is minimized in the mean square sense when $[u_k - \hat{u}_k]$ is minimized. In other words, $\hat{u}_k$ is the best mean square estimate of uk. In the ideal case, $u_k = \hat{u}_k$ and $\epsilon_k = g_k$, and all that is left after the subtraction is g which is the unchanged desired signal with all undesired signals removed. Signal components in the reference input in some situations, the reference input x_k includes components of the desired signal. This means $g' \neq 0$. Perfect cancelation of the undesired interference is not possible in the case, but improvement of the signal to interference ratio is possible. The output will b $\epsilon_k = d_k - y_k = g_k - \hat{g}_k + u_k - \hat{u}_k$. The desired signal will be modified (usually decreased).The output signal to interference ratio has a simple formula referred to as power inversion.

ρ o u t (z) = 1 ρ r e f (z).

Where

ρ o u t (z) = output signal to interference ratio.

ρ r e f (z) = reference signal to interference ratio.

This formula means that the output signal to interference ratio at a particular frequency is the reciprocal of the reference signal to interference ratio.

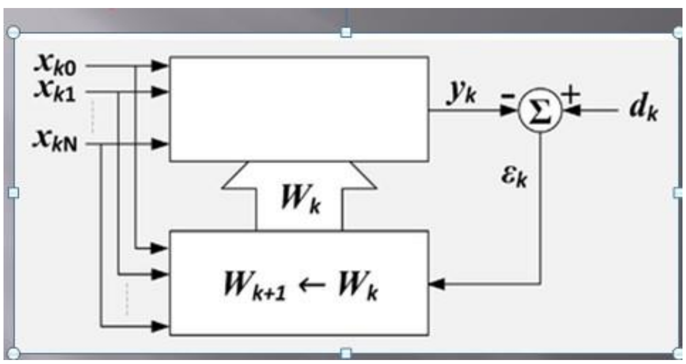


Figure (5): Adaptive linear combiner

Adaptive linear combiner showing the combiner and the adaption process. k = sample number, n=input variable index, x = reference inputs, d = desired input, W = set of filter coefficients, ε = error output, Σ = summation, upper box=linear combiner, lower box=adaption algorithm.

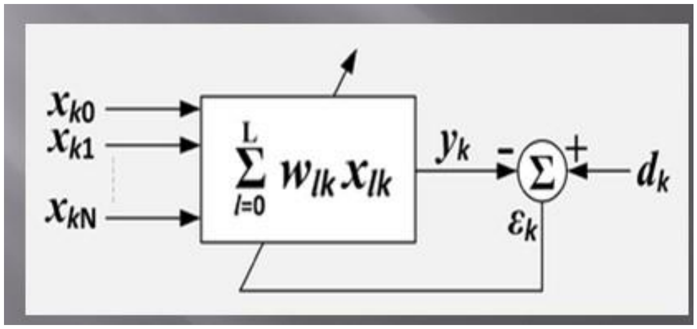


Figure (6): Adaptive algorithm.

Adaptive linear combiner, compact representation.

k = sample number,

n=input variable index,

x = reference inputs,

d = desired input,

ε = error output,

Σ = summation.

The adaptive linear combiner (ALC) resembles the adaptive tapped delay line FIR filter except that there is no assumed relationship between the X values. If the X values were from the outputs of a tapped delay line, then the combination of tapped delay line and ALC would comprise an adaptive filter. However, the X values could be the values of an array of pixels. Or they could be the outputs of multiple tapped delay lines. The ALC finds use as an adaptive beam former for arrays of hydrophones or antennas.

$y_k = \sum_{l=0}^{L} w_{lk} x_{lk} = W_k^T x_k$

Where w_{lk} refers to the l 'th weight at k'th time.

LMS Algorithm

Main article: Least mean squares filter

If the variable filter has a tapped delay line FIR structure, then the LMS update algorithm is especially simple. Typically, after each sample, the coefficients of the FIR filter are adjusted as follows:

For $l = 0 \ldots L$

$w_{l,k+1} = w_{lk} + 2\mu\ \epsilon_k\ x_{k-l}$

μ is called the convergence factor.

The LMS algorithm does not require that the X values have any particular relationship; therefor it can be used to adapt a linear combiner as well as an FIR filter. In this case the update formula is written as:

$w_{l,k+1} = w_{lk} + 2\mu\ \epsilon_k\ x_{lk}$

The effect of the LMS algorithm is at each time, k, to make a small change in each weight. The direction of the change is such that it would decrease the error if it had been applied at time k. The magnitude of the change in each weight depends on μ, the associated X value and the error at time k. The weights making the largest contribution to the output, y k, are changed the most. If the error is zero, then there should be no change in the weights. If the associated value of X is zero, then changing the weight makes no difference, so it is not changed.

Convergence

μ controls how fast and how well the algorithm converges to the optimum filter coefficients. If μ is too large, the algorithm will not converge. If μ is too small the algorithm converges slowly and may not be able to track changing conditions. If μ is large but not too large to prevent convergence, the algorithm reaches steady state rapidly but continuously overshoots the optimum weight vector. Sometimes, μ is made large at first for rapid convergence and then decreased to minimize overshoot.

Widrow and Stearns state in 1985 that they have no knowledge of a proof that the LMS algorithm will converge in all cases. However under certain assumptions about stationarity and independence it can be shown that the algorithm will converge if

$0 < \mu < 1 \sigma 2$

Where

$\sigma 2 = \sum l = 0 L \sigma l 2$ = sum of all input power

σl is the RMS value of the l 'th input

In the case of the tapped delay line filter, each input has the same RMS value because they are simply the same values delayed. In this case the total power is

$\sigma 2 = (L + 1) \sigma 0 2$

Where

$\sigma 0$ { is the RMS value of $x k$, the input stream.

This Ieads to a normalized LMS Algorithm

$w l , k + 1 = w l k + (2 \mu \sigma \sigma 2) \epsilon k \quad x k - l$

In which case the convergence criteria becomes: $0 < \mu \sigma < 1$

Applying the Proposed Approach

Applications and the Advantages

The Applications Kalman Filter

The Kalman filter has numerous applications in technology. A common application is for guidance, navigation, and control of vehicles, particularly aircraft, spacecraft and dynamically positioned ships. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. Kalman filters also are one of the main topics in the field of robotic motion planning and control, and they are sometimes included in trajectory optimization. The Kalman filter also works for modeling the central nervous system's control of movement. Due to the time delay between issuing motor commands and receiving sensory feedback, use of the Kalman filter supports a realistic model for making estimates of the current state of the motor system and issuing updated commands.

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. The algorithm is recursive. It can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required.

Using a Kalman filter does not assume that the errors are Gaussian. However, the filter yields the exact conditional probability estimate in the special case that all errors are Gaussian.

Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on nonlinear systems. The underlying model is a hidden Markov model where the state space of the latent variables is continuous and all latent and observed variables have Gaussian distributions. Also, Kalman filter has been successfully used in multi-sensor fusion, and distributed sensor networks to develop distributed or consensus Kalman filter

The Calculation

The Kalman filter uses a system's dynamic model (e.g., physical laws of motion), known control inputs to that system, and multiple sequential 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 only one measurement alone. As such, it is a common sensor fusion and data fusion algorithm.

Noisy sensor data, approximations in the equations that describe the system evolution, and external factors that are not accounted for all place limits on how well it is possible to determine the system's state. The Kalman filter deals effectively with the uncertainty due to noisy sensor data and, to some extent, with random external factors. The Kalman filter produces an estimate of the state of the system as an average of the system's predicted state and of the new measurement using a weighted average. The purpose of the weights is that values with better (i.e., smaller) estimated uncertainty are "trusted" more. The weights are calculated from the covariance, a measure of the estimated uncertainty of the prediction of the system's state. The result of the weighted average is a new state estimate that lies between the predicted and measured state, and has a better estimated uncertainty than either alone. This process is repeated at every time step, with the new estimate and its covariance informing the prediction used in the following iteration. This means that Kalman filter works recursively and requires only the last "best guess", rather than the entire history, of a system's state to calculate a new state.

The relative certainty of the measurements and current state estimate is an important consideration, and it is common to discuss the response of the filter in terms of the Kalman filter's gain. The Kalman gain is the relative weight given to the measurements and current state estimate, and can be "tuned" to achieve a particular performance. With a high gain, the filter places more weight on the most recent measurements, and thus follows them more responsively. With a low gain, the filter follows the model predictions more closely. At the extremes, a high gain close to one will result in a more jumpy estimated trajectory, while a low gain close to zero will smooth out noise but decrease the responsiveness.

When performing the actual calculations for the filter (as discussed below), the state estimate and covariances are coded into matrices to handle the multiple dimensions involved in a single set of calculations. This allows for a representation of linear relationships between different state variables (such as position, velocity, and acceleration) in any of the transition models or covariances.

Example of Application

As an example application, consider the problem of determining the precise location of a truck. The truck can be equipped with a GPS unit that provides an estimate of the position within a few meters.

The GPS estimate is likely to be noisy; readings 'jump around' rapidly, though remaining within a few meters of the real position. In addition, since the truck is expected to follow the laws of physics, its position can also be estimated by integrating its velocity over time, determined by keeping track of wheel revolutions and the angle of the steering wheel. This is a technique known as dead reckoning.

Typically, the dead reckoning will provide a very smooth estimate of the truck's position, but it will drift over time as small errors accumulate.

In this example, the Kalman filter can be thought of as operating in two distinct phases: predict and update. In the prediction phase, the truck's old position will be modified according to the physical laws of motion (the dynamic or "state transition" model). Not only will a new position estimate be calculated, but also a new covariance will be calculated as well. Perhaps the covariance is proportional to the speed of the truck because we are more uncertain about the accuracy of the dead reckoning position estimate at high speeds but very certain about the position estimate at low speeds. Next, in the update phase, a measurement of the truck's position is taken from the GPS unit.

Along with this measurement comes some amount of uncertainty, and its covariance relative to that of the prediction from the previous phase determines how much the new measurement will affect the updated prediction. Ideally, as the dead reckoning estimates tend to drift away from the real position, the GPS measurement should pull the position estimate back towards the real position but not disturb it to the point of becoming noisy and rapidly jumping

The Advantages Kalman Filter

1. The gain coefficients are computed dynamically. This means that the same filter can be used for a variety of maneuvering target environments.
2. The Kalman filter gain computation adapts to varying detection histories, including missed detections
3. The Kalman filter provides an accurate measure of the covariance matrix. This allows for better implementation of the gating and association processes.
4. The Kalman filter makes it possible to partially compensate for the effects of miss-correlation and miss-association
5. Kálmán's ideas to the nonlinear problem of trajectory estimation for the Apollo program leading to its incorporation in the Apollo navigation computer.

Application of Adaptive Filters

Adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment.

Example of Application

A fast food restaurant has a drive-up window. Before getting to the window, customers place their order by speaking into a microphone. The microphone also picks up noise from the engine and the environment. This microphone provides the primary signal. The signal power from the customer's voice and the noise power from the engine are equal. It is difficult for the employees in the restaurant to understand the customer. To reduce the amount of interference in the primary microphone, a second microphone is located where it is intended to pick up sounds from the engine.

It also picks up the customer's voice. This microphone is the source of the reference signal. In this case, the engine noise is 50 times more powerful than the customer's voice. Once the canceler has converged, the primary signal to interference ratio will be improved from 1:1 to 50:1

The Advantages of Adaptive Filters

1- They could be the outputs of multiple tapped delay lines. The Adaptive linear combiner (ALC) finds use as an adaptive beam former for arrays of hydrophones or antennas. y k = ∑ l = 0 L w l k x l k = W k T x k

Where w l k refers to the l 'th weight at k'th time.

2- Linear filter.

3- The filter Real Time,

4- The noise = zero.

Results and Discussion

The Result of Different Kalman Filter and Adaptive Filter

International Journal for Scientific Research (IJSR)
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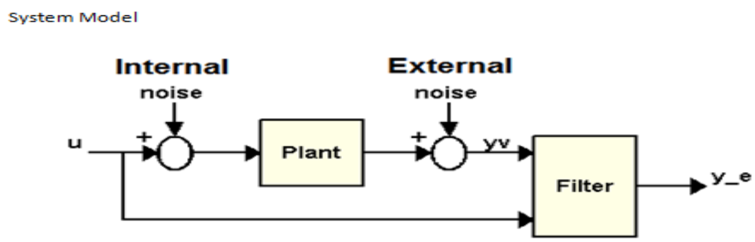
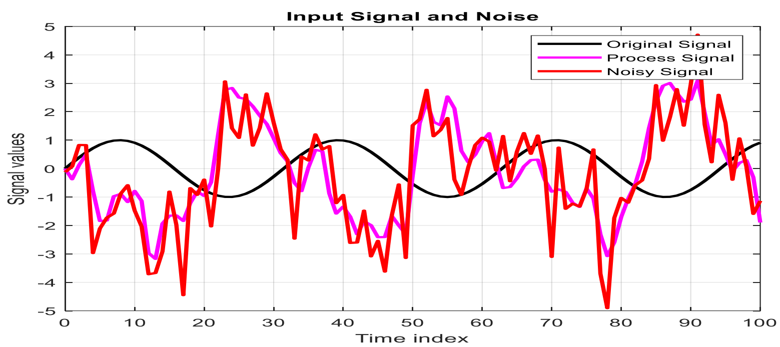


Figure (7)



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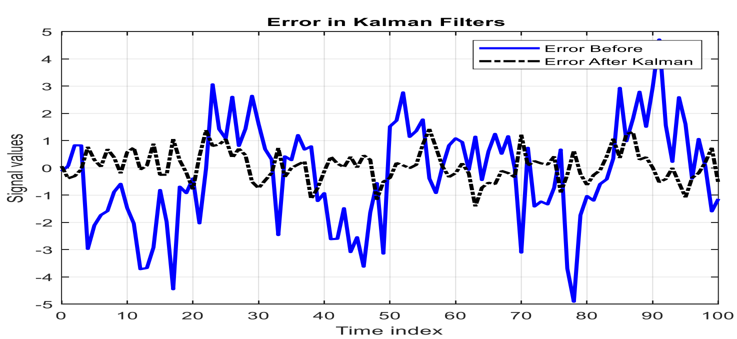

Figure (9)

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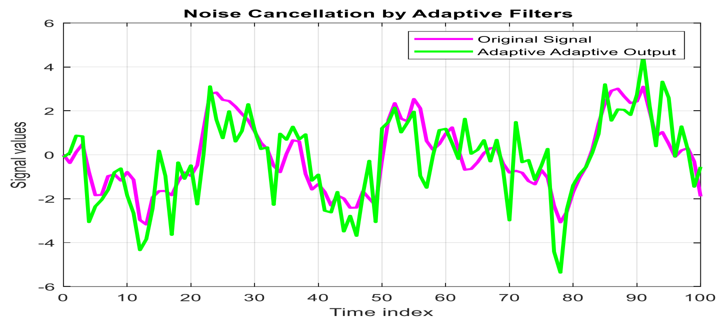

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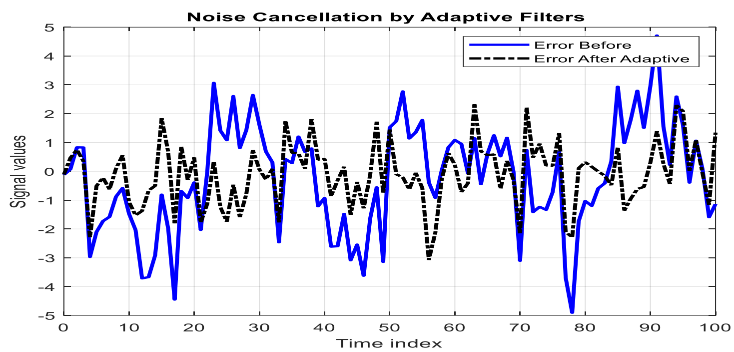

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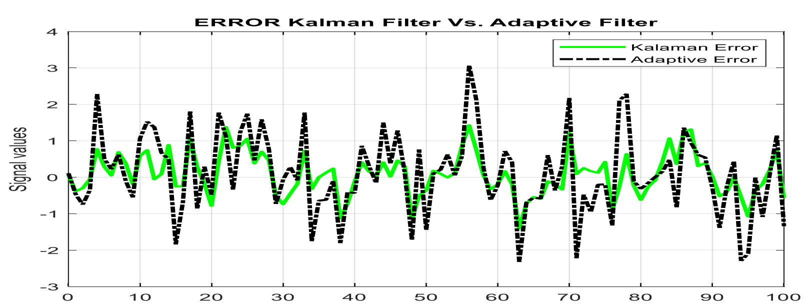

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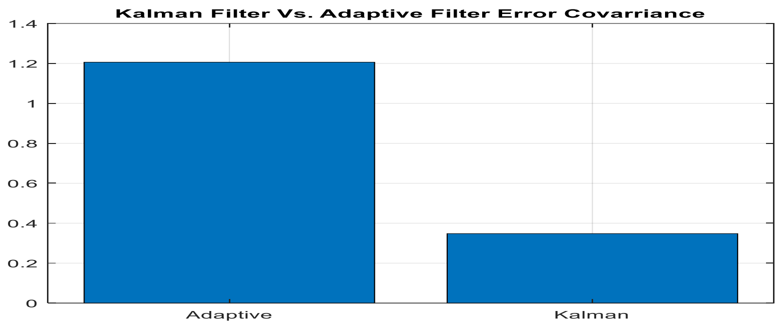

Figure (13)

Conclusions

In a Kalman Filter you assume a model for your system and a model for your error and the filter estimates the dynamic states of the model, which change as a function of time. On the other hand, with adaptive control you assume a model, but define some parameters of the model that are unknown.

The Kalman filter is a linear estimator that minimizes the mean squared error as long as the target dynamics are modeled accurately.

All other recursive filters, such as the and the Benedict-Bordner filters are special cases of the general solution provided by the Kalman filter for the mean squared estimation problem.

After comparison between kalman filter and real time adaptive filter we got the result of demonstrates that, the best filter to be use and provide the required military protection for the country is kalman filter because of it is high efficiency.

Future Work

The Kalman Filter predicts the future system state based on past estimations.

https://doi.org/10.59992/IJSR.2024.v3n7p15
E-ISSN 2755-3418

For instance, imagine you want to predict the future position of a moving object based on noisy sensor data. The Kalman filter will help refine those readings and provide a more accurate forecast of the object's future state.

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