A Novel Approach for the Implementation of Kalman Filter for Level Estimation

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ABSTRACT
In this work a kalman filter is designed for estimating the level of a cylindrical tank and thus removing noise from the level sensor. The system is modeled as a first order system. The kalman filter is designed and is used to verify its effectiveness in level estimation. This work describes the Kalman Filter which is the most important algorithm for state estimation and noise cancellation in a level system. The real time implementation shows that the noise in the system is eliminated and estimation of level is done.
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Keywords
Kalman filter, Level system, Estimation, Noise cancellation technique

1. INTRODUCTION
The Kalman filter is an optimal estimator that can estimate the variables of a wide range of processes. Kalman filter also estimates the states of a linear system. The Kalman filter is theoretically attractive because apart from all possible filters, it is the one that minimizes the variance of the estimation error. Kalman filters are implemented in control systems because in order to control a process, it is required that an accurate estimate of the process variables.

Filtering is desirable in many situations in engineering and embedded systems. For example, many radio communication signals are corrupted with noise. A good filtering algorithm can be used to remove the noise from electromagnetic signals while retaining the useful information. Another example we can consider is power supply voltages. Filtering, the ability to selectively suppress or enhance particular parts of a signal is perhaps the most important tool for signal processing. The analog filter prototypes are the most common used method in order to transform analog to discrete time signals.

Least Squares estimation is particularly well suited to linear models because the estimated parameters can then be expressed mathematically in a closed form and turn out to be unbiased estimates of the true parameters. Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time.

In these methods, the higher order terms in the Taylor's expansion were neglected. Therefore estimation of distorted signals may occur incorrectly or take longer time to converge and even diverge.

In noise cancellation technique, various techniques are available. One of them is Bayesian filter. Bayesian filtering uses the available noisy observations to estimate the system state. A Bayesian filter uses prediction-correction technique. The time update model describes how the state updates from one time sample to the next. The measurement model describes how the observed data is related to the internal state of the system. This approach overcomes the major limitation of the adaptive filtering technique. Adaptive filtering is a commonly used method in biomedical signal processing in order to remove the unwanted recorded artifacts that contaminate the desired measured physiological signals. An adaptive filter will modify its filter coefficients according to a given optimization algorithm in order to remove the undesired noise from a recorded signal. The filter utilizes additional external sensors as a reference for the added noise with the assumption that the added artifact and the desired signal are uncorrelated. Thus the filter will remove all its artifacts from the recorded signals by using the reference to the artifact input. Thus, the choice of reference is of very important when utilizing the adaptive filter technique. The algorithm is very simple to implement and it doesn't requires any calibration but the requirement of a reference signal and additional sensors increases the hardware costs. The decision of adaptive algorithm is dependent on the computational resources available to the system in operation. The Bayesian filter technique does not require any reference to be used and additional sensors. The Bayesian filter is capable of operating online.

Kalman filter also operate on a prediction-correction technique. The Kalman filter has two layers of calculations; time update equations and measurement update equations and these equations require a prior knowledge of the process and measurement models. One of the main assumptions of the Kalman filter is that the initial uncertainty is Gaussian and that the system dynamics are linear functions of the state. As most systems are not strictly linear the other form of Kalman filter is used that is Extended Kalman Filter. The Kalman filter main advantage over other methods is in the computational efficiency of the algorithm due to its efficient use of matrix operations allowing for longer real-time artifact removal.

2. KALMAN FILTER
The kalman filter was developed by Rudolph Kalman, although Peter Swerling developed a very similar algorithm in1958.The filter is named after Kalman because he published his results in a more prestigious journal and his work was more general and complete. Sometimes the filter is referred to as the Kalmam-Bucy filter because of Richard Bucy's early work on the topic, conducted jointly with kalman [10].

The roots of the algorithm can betraced all the way back to the 18-year-old Karl Gauss's method of least squares in 1795.The kalman filter was developed to solve a specific problem like spacecraft navigation for the Apollo space program. From there on, the Kalman filter has found applications in hundreds of diverse areas, including all forms of navigation, nuclear power plant instrumentation, demographic modeling, and manufacturing, the detection of underground radioactivity and fuzzy logic and neural network training.

The Kalman Filter (KF) is the best possible, optimal, estimator for a large class of systems with uncertainty and a very effective estimator for an even larger class. it is one of the most well-known and often-used tools for so called stochastic state estimation from noisy sensor measurements. Under certain assumptions, the KF is an optimal, recursive data processing or filter algorithm [7].

- The KF is optimal, because it can be shown that, under certain assumptions; the KF is optimal with respect to virtually any criterion that makes sense for example the mean squared error. Kalman filter assumes a multivariate Gaussian distribution [5]. One of the reasons the filter performs optimally is because it uses all available information that it gets. It does not matter about the accuracy it just an overall best estimate of a state, i.e., the values of the variables of interest. The KF is recursive, which brings the useful property that not all data needs to be kept in storage and re-processed every time when for example a new measurement arrives.
- The KF is a data processing algorithm or filter, which is useful for the reason that only knowledge about system inputs and outputs is available for estimation purposes. A filter tries to obtain an optimal estimate of variables from data coming from a noisy environment.

The filter also supports in the estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown. Mathematically, the filter estimates the states of a linear system. The gain, noise covariance and prediction covariance are assumed initially. Using these values, the Kalman gain has been calculated and it predicts the estimated value to update the co variances. The estimates produced by this method make the true values equal to the original measurements. Figure 1 shows the concept of kalman filter

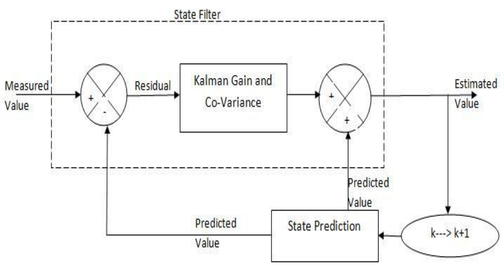

Figure1:Concept of kalman filter

The Kalman filter uses a system's dynamics model, 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. As such, it is a common sensor fusion algorithm.

2.1. The Kalman Filter Algorithm

The Kalman Filter is a state estimator which produces an optimal estimate in the sense that the mean value of the sum of the estimation errors gets a minimal value. The Kalman Filter gives the following sum of squared errors:

$E[e_x^T(k)\, e_x(k)] = E[e_{x1}^2(k) + \ldots\ldots\ldots + e_{xn}^2(k)]$

a minimal value. Here,

$e_x(k) = x_{est}(x) - x(k)$

is the estimation error vector. (The Kaman Filter estimate is sometimes denoted the "least mean-square estimate".) This assumes actually that the model is linear, so it is not fully correct for nonlinear models. It is assumed the that the system for which the states are to be estimated is excited by random ("white") disturbances (or process noise) and that the measurements (there must be at least one real measurement in a Kalman Filter) contain random ("white") measurement noise.

The Kalman Filter has many applications, e.g. in dynamic positioning of ships where the Kalman Filter estimates the position and the speed of the vessel and also environmental forces. These estimates are used in the positional control system of the ship. The Kalman Filter is also used in soft-sensor systems used for supervision, in fault-detection systems, and in Model-based Predictive Controllers (MPCs) which is an important type of model-based controllers.

The Kalman Filter algorithm was originally developed for systems assumed to be represented with a linear state-space model. However, in many applications the system model is nonlinear. Furthermore the linear model is just a special case of a nonlinear model. Therefore, I have decided to present the Kalman Filter for nonlinear models, but comments are given about the linear case. The Kalman Filter for nonlinear models is denoted the Extended Kalman Filter because it is an extended use of the original Kalman Filter. However, for simplicity we can just denote it the Kalman Filter, dropping "extended" in the name. The Kalman Filter will be presented without derivation.

2.2. Kalman Filter State Estimation

1. This step is the initial step, and the operations here are executed only once. Assume that the initial guess of the state is xinit. The initial value xp(0) of the predicted state estimate xp (which is calculated continuously as described below) is set equal to this initial value:

Initial state estimate

$xp(0) = xinit$

2. Calculate the predicted measurement estimate from the predicted state estimate:

Predicted measurement estimate:

$yp(k) = g\,[xp(k)]$

3. Calculate the so-called innovation process or variable – it is actually the measurement estimate error – as the difference between the measurement y(k) and the predicted measurement $y_p(k)$:

Innovation variable:

$e(k) = y(k) - y_p(k)$

4. Calculate the corrected state estimate $x_c(k)$ by adding the corrective term Ke(k) to the predicted state estimate $x_p(k)$:

Corrected state estimate:

$$x_c(k) = x_p(k) + Ke(k)$$

Here, K is the Kalman Filter gain. The calculation of K is described below.

5. Calculate the predicted state estimate for the next time step, x_p (k + 1), using the present state estimate x_c (k) and the known input u(k) in process model:

Predicted state estimate:

$$x_p(k + 1) = f\,[x_c(k), u(k)]$$

2.4. Flowchart Of Kalman Filter

Figure2.4shows the flowchart of kalman filter

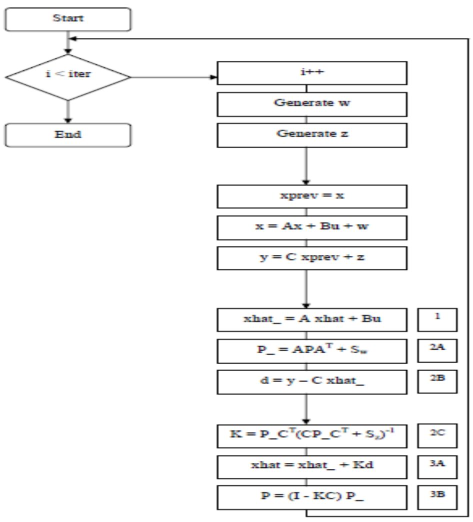

Figure 2.4 Flowchart for the Concept of Kalman Filter

Initially, the noise covariance and prediction covariance are assumed. The Kalman gain is calculated then the innovation error is been calculated. Using Kalman gain obtained and initialized noise covariance the priori covariance estimate is done. The priori estimate is performed using the Kalman gain, innovation vector and initial state of the system. The new system is formed by updating the posterior estimate and posterior covariance estimate. The settling point is been checked- if yes the settling point remains the same otherwise the state is increased and cycle is again repeated until the settling point is reached.

3. SYSTEM DESCRIPTION

3.1 Level Process Description

The level control of a process is a common control system found in process industries. When processes are complex, or their controls require high degree of performance quality, finding a control algorithm may be an complicated mathematical problem, due to non-existence of reliable models that explain the process dynamics suitably. Moreover, there are many process in which operator is necessary, even in a low level control loop. The proper controller must control the level control. The objective of the controller in the level control is to maintain a level set point values dynamically. The mainframe is a metallic structure mounted on four castor wheels for system mobility with facility to lock the systems in a desired place using the castor wheel brakes.

Inevitably the mainframe is organized as two racks and control panel. While the bottom rack houses the reservoir tanks, solenoid valve, motor and piping. The upper rack houses differential pressure transmitter, I/P converter, control valves, process tank and cabinet. The front panel of cabinet holds the process schematic, pressure gauges and the electrical and pneumatic terminations. The right end of the cabinet holds the pressure regulator. The O/P of the pressure transmitters current to pressure converter one terminated in the front panel. The block diagram representation of the entire process will be as shown in the below Figure 3.

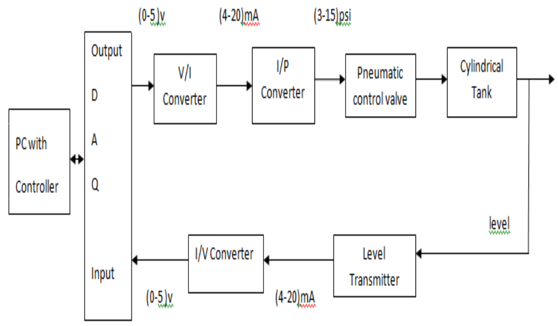

Figure 3 block diagram of level process system

4. SYSTEM MODELLING

The empirical method of identifying the system is the most modern method. Empirical models use data gathered from experiments to define the mathematical model of a system. A step change in the input to a process produces a response, which is called process reaction curve .A variety of empirical modelling methods exists. One method for developing models uses system identification methods. System identification methods use measured data to create difference equation which are used for representations that model the data.

In general terms, the time constant (τ), describes how fast the process variable (PV) moves in response to a change in the controlled output (CO). the time constant must be positive and it must have units of time. Most often it has units of minutes or seconds. Step test data implies that the process is in manual mode (open loop) and initially at steady state.

The transfer function models are required only for the simulation studies of the controller design. Here we are controlling the level (H) of the tank by manipulating the flow rate (Q). The most commonly used model to describe the dynamics of the industrial level process is general First Order plus Time Delay Process (FOPTD). And the FOPTD model structure is given in equation (4.1)

$$G(s) = \frac{K}{\tau s + 1} e^{-\theta ds} \qquad (4.1)$$

Θd – Time delay

Kp – Process gain

τ - Time constant

Here the process of interest is approximated by a First Order plus Time Delay Process. The time delay or dead time approximation can be done in several methods; some methods are discussed below:

1. The simplest approximation method is taking the first two terms of Taylor series expansion of the Laplace transfer function of the dead time element.

$$e^{-\tau_d s} \cong 1 - \tau_d s \qquad (4.2)$$

2. The pade approximation

$$e^{-\tau_d s} = \frac{e^{\frac{-\tau_d s}{2}}}{e^{\frac{\tau_d s}{2}}} \cong \frac{1 - \frac{\tau_d s}{2}}{1 + \frac{\tau_d s}{2}} \qquad (4.3)$$

3. The crude approximation

$$e^{-\tau_d s} \cong \frac{1}{1 + \tau_d s} \qquad (4.4)$$

Thus by approximating the dead time by any of the above mentioned methods, we can conclude that a First Order plus Time Delay Process can be approximated as a higher order process. The transfer function parameters of the process are obtained by doing the step test. That is at a fixed inlet flow rate the system is allowed to reach the steady state. After that a step increment in the input flow rate is given, and various readings are noted till the process becomes stable. Steps to find transfer function are:

1. Note down the Initial Steady State (I.S.S) value of the process variable (PV).
2. Give a noticeable change in the input at time (t1) and the time delay (L).
3. Observe the change in the process variable and note down the New Steady State (N.S.S) value.
4. Find out the total change in PV,ΔPV=N.S.S – I.S.S
5. Compute the value (ΔPV*.632) + I.S.S
6. Note down the time (t2) corresponding to (ΔPV*0.632) + I.S.S value.
7. Then the time constant (τ) can be calculated as τ=t2-t1
8 The process gin (Kp) is ΔPV/ΔV, where ΔV is the change in input in Volts

The transfer function of the tank is computed as,

$$G(s) = \frac{2.075 e^{-25s}}{769s + 1}$$

The state space parameters obtained for the tank is
A = -0.0013
B = 0.0625
C = 0.0432
D = 0
Thus the state space equation is,
$\dot{x}$ = -0.0013 x(t) + 0.0625 u(t)
y = 0.0432 x(t)

5. SOFTWARE IMPLEMENTATION

5.1 Simulation in matlab

The process identification has been done to obtain the state transition matrix, the process noise covariance matrix and the measurement matrix. The process model under consideration has been chosen is very simple, and consequently the Kalman filter does a good job in rejecting the process and measurement noise to generate a very good estimate of the process output.

The algorithm of Kalman filter was written in M-File Matlab programming.It shows how the filter works, generate some input data and random noise and compare the filtered response y_e with the true response y and measured response yv. The function KALMAN to design a steady-state Kalman filter and this determines the optimal steady-state filter gain M based on the process noise covariance Q and the sensor noise covariance R. Figure5.1 shows the kalman filter response for a steady state. The first plot shows the true response *y* (dashed line) and the filtered output y_e (solid line). The second plot compares the measurement error (dash-dot) and the estimation error (solid).

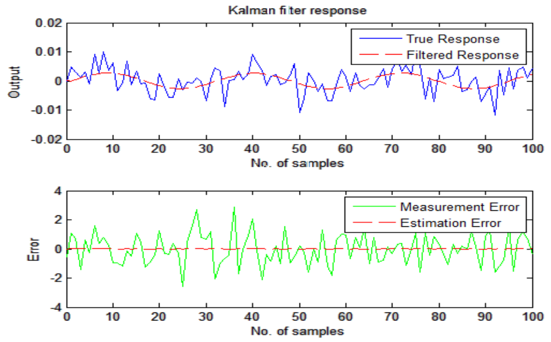

Figure5.1:Kalman filter response for a steady state

This plot shows that the noise level has been significantly reduced. This can also be confirmed by the following error computations.

Measurement Error = y-yv;
Estimation Error = y-ye;

After computation we get the measurement error as 2.8728 and the estimation error as 0.0083.Thus from these values we can say that the error has been reduced after using the kalman filter.

5.2.1Simple Kalman Filter Implementation In LabVIEW

The algorithm of simple Kalman filter was implemented in LabVIEW. The desired value was set and a number was randomly generated to produce a measured signal. The covariance was set and the program was executed. The front panel of the algorithm is shown below in the Figure 5.2. The estimated value for the measured value was close to the value of the desired value. In the Figure 5.2, the desired value was 2 and the measured value was 5. The obtained estimated value was 2.05708.

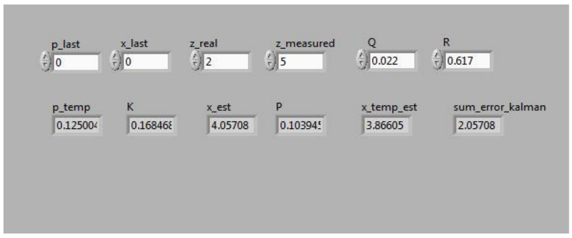

Figure5.2 Simple kalman filter implementation

5.2.2. Implementation of Kalman Filter for Various Signal Type In LabVIEW

The algorithm of Kalman filter was implemented for various signal type in LabVIEW. A sine wave and a noisy sine wave was generated and applied to the algorithm. Figure5.3 shows the implementation of kalman filter for sine signal.

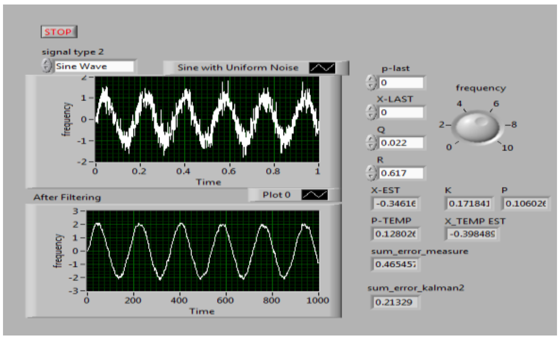

Figure 5.3 Implementation of kalman filter for sine signal

5.2.2 Kalman Filter Implementation In Lab VIEW For Level Estimation

Figure 5.2.2 shows the front panel of a lab VIEW simulator of a level estimator.In this simulation the outflow is varied and the Kalman filter estimates the correct steady state value.

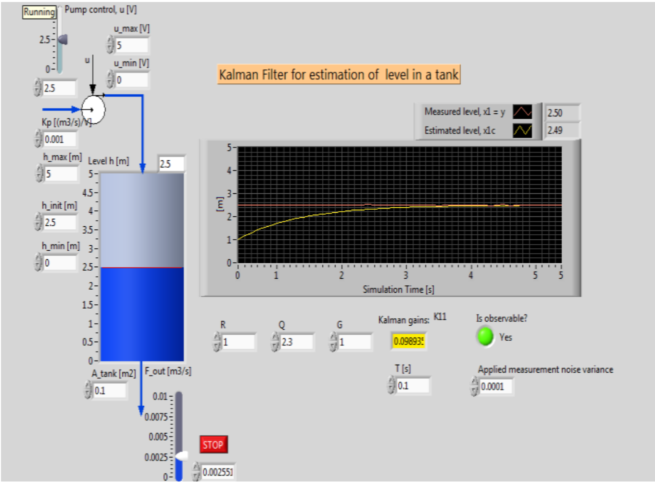

Figure 5.2.2 Front panel of simulator of level estimator

6. CONCLUSION

The system identification of the spherical tank using emperical method was done and the piecewise transfer function was obtained in real time and hence the system was studied. The controllers parameters for an integer order system was obtained using Ziegler Nichols method and the simulation was done using Matlab Simulink. matlab The algorithm of kalman filter was written in M-file matlab programming and the effectiveness of the algorithm for the plant was verified. And from performance values and from the graph it can be viewed that the error is reduced to a certain value.

For future work this project can be extended to do in the real time implementation.

7. REFERENCES

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