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Continuous Time State Space Model of DC Motor using Kalman Filter

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ABSTRACT: In the research field of many applications Kalman Filter is very famous these days. Kalman Filter is used as a tool to estimate linear quadratic problems. In this paper we have shown the results using MATLAB tool. The results show that the mean error covariance y~yv due to measurement noise is demoted with the help of Kalman Filter. The estimation error covariance will be very small as compared to mean error covariance when Kalman Filter is used. Kalman Filter downgrade noise in DC motor also.

Keywords: Kalman Filter, DC motor, mean error covariance, estimation error covariance

I. INTRODUCTION

In 1960 Rudolph E Kalman write a paper about matter related to linear filtering of data separated to each other in this paper. He gave relating solutions to the problem. The name Kalman filter is flipped after him.

Kalman filter is basically used as a most effective answer to many chasing and data forecasting task and also in analysis of virtual motion. Kalman filter is used for estimating from noisy sensor proportions. Kalman filtering technique uses linear mean square error filtering that involves mathematical set of equations which implies an object known as predictor-corrector type optimal estimator. This introduces minimization in estimated error covariance with some speculated ways that are applied. The filter discussed in this paper is evolved as a mean square error minimizer. But an alternative is provided by making use of maximum likelihood statistics. Its objective is to educe the needful and relevant data from the signal and deduct the remaining data.

Its performance can be observed by making use of cost or loss function.

$y_k = a_k x_k + n_k$

y_k=observed signal is time controlled

a_k= gain

x_k= signal has knowledge about data

n_k= accretive noise

II. LITERATURE SURVEY

Dr. K Rameshbabu *et al* proposed a system. The authors used Kalman Filter for target tracking system and calculated the results. The result says that the output is 95% productive even in clangorous atmosphere (6).

B.L. Malleswari *et al* worked on the purpose of Kalman Filter in the modeling of GPS inaccuracy. A comparison of exactness is to call forth, correctness over with the Kalman filter usage is without doubt submit better results (7).

A.Uma Mageswari *et al* presented a non-segregated route to develop an effective estimator for scaling frequentness and harmonic factors of a time varying signal which is implemented in depleted SNR. This result in the Extended Kalman and Unscented Kalman filter diagnostics and a posterior implantation of the study to develop these filters.

Nathan Funk project observes the functions and various applications of the Kalman filter as a technique for visual tracking (8).

At the beginning, this filter is actionable in space navigations but later, it was applied in various upcoming fields. Simon acknowledged the applications of Kalman filter in instruments for particular purpose, relating to the makeover that occur in dynamic balance of population especially modeling in this case, frame, system of logic, and neural mesh training.

A. R. Reshma *et al* presented the impact of incipient pretension and proportions of inaccuracy in variance in the behavior of the filter. Reshma considered two models out of which model 1 assumed the target with invariable velocity and invariable course. In model 2, one can see it exhibit invariable velocity but diversifying course with a coordinated turn model.

Walter T. Higgins discusses the complementary filtering which is implemented in the manufacturing business that be in charge of flights for assessment while combining. This paper also shows the relationship between Kalman Filter and Complementary Filter.

Zs. Horváth discussed the state space evaluation for a valve of mechanical device controlled electrically using extended Kalman filter (EKF). A nominated actuator archetype consists of a Tustin's friction model with intense non-linearities. Therefore, it indicates a precise archetype for drawing the force that opposed relative motion in an electromechanical actuator valve.

III. PROBLEM FORMULATION

In the present work, a DC motor is considered as a case study. A DC Motor works on the functionality of conversion of electrical energy to mechanical energy and these electrical motors are of two type's i.e. DC & AC. Electrical motors consists of a stator and a rotor that operates with a mutual action between magnetic induction & flow of electricity to produce gyration speed and torque. DC motor operates from direct current. DC motor comprises of armature winding (one set of coils) and a stator (set of permanent magnets). When a voltage is applied to the coils, a torque is produced in the armature, resulting in motion as per following equation,

$T = K_t I$

Where, T=Motor torque, Kt=constant factor and I=Armature current.

In case of using a dc motor we created continuous time state space model. For this, we have considered the state space model of dc motor which are given below,

$$A = \begin{bmatrix} 0 & -1 & 0.1 \\ 0 & -b/J & K/J \\ 0 & -K/L & -R/L \end{bmatrix} \quad ; \quad B = \begin{bmatrix} 0 \\ 0 \\ 1/L \end{bmatrix}$$

C = [1 0 0] ; D = [0]

Where,

J=A measure of the resistance of a body to angular acceleration

b=Motor viscid discordance constant

Ke=apparent strength that tends to move electricity

Kt=Motor twisting force

R=Electric resistance

H=Inductance possessed by device

Now with the following observed values of above constants,

J= 1 $kg.m^2$

b= 0.1 N.m.s

Ke= 0.01 V/rad/sec

Kt= 0.01 N.m/Amp

R= 1 ohm

L= 2 H

And we attained an output matrix having values representing the continuous time state space having some undesirable noise.

$$a = \begin{bmatrix} 0 & -1 & 0.1 \\ 0 & -0.1 & 0.01 \\ 0 & -0.005 & -0.5 \end{bmatrix} \quad ; \quad b = \begin{bmatrix} 0 \\ 0 \\ 0.5 \end{bmatrix}$$

c = [1 0 0] ; d = [0]

Therefore to overcome this flaw we designed the steady state Kalman filter whose optimal innovation gain comes out to be M =

0.0085

0.0008

-0.0399

IV. RESULT

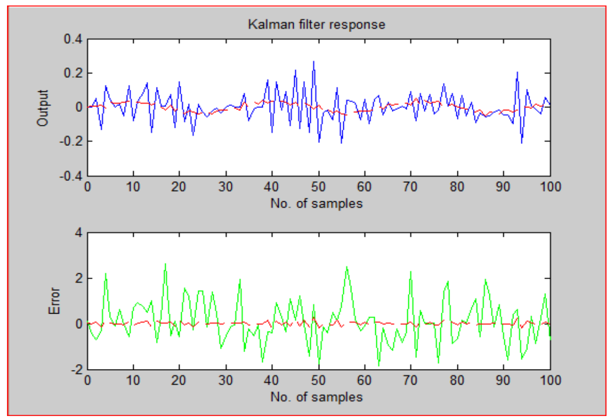

Fig. 1. Kalman Filter response output and error.

Second plot of the 1st figure indicates that the figured unwanted electronic signals procreate inaccuracy y~yv which is downgraded employing Kalman Filter.

During the evaluation the time diversifying filter conclude the output covariance and mark a graph of the output covariance to witness if the filter has stretched out to a condition that changes only negligibly over a specified time (as we would look forward with immobile input noise).

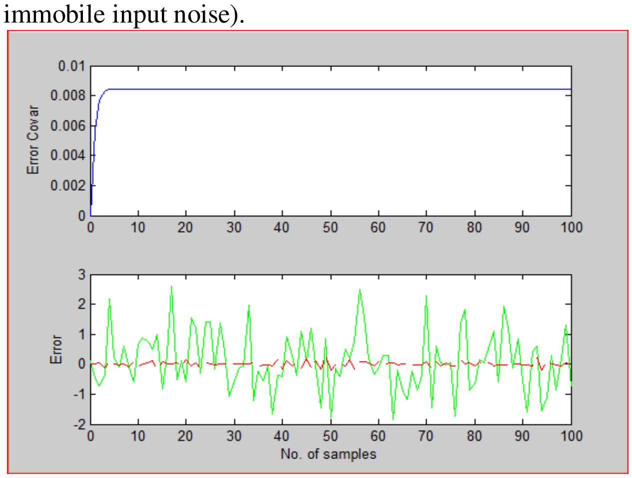

Fig. 2. Error covariance plot.

The covariance plot advocates that the output covariance did touch a condition that changes only negligibly over a specified time in about 8 specimens. Thence, the time diversifying filter has the identical interpretation similar to that of the steady state version.

V. CONCLUSION

We observed that we faced with an error so we made use of Kalman filter for noise reduction and in the result we can observe that the Kalman filter downgrade the inaccuracy in mean covariance y-yv (0.9871) due to figured unwanted electronic signals. And the estimation error covariance comes out to be a reduced version of mean error covariance (0.0077).

State space Kalman filter and final values of Kalman gain matrices synchronize.

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