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Performance Evaluation of Data Loss Recovery Techniques using Compensated Closed Loop and Open Loop Kalman Filter

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***Abstract*—** State estimates play a dominant role in almost all fields of engineering and technology, unambiguously. It plays a great role in many physical systems, where system measurements are uncertain. Instead, there are the highest requirements for the development of powerful algorithms that can lead to limited evaluation errors when the loss of the package occurs at the exit of the system, say, e.g., Data loss is the major issue of control and different areas of engineering which degrade the efficiency of the system[1-2]. The minimum mean square formula is used to minimize the error that occurred. Kalman filter is an iterative process it predicts the system state and will update its state after each step. Kalman filter is mostly used in challenging problems of data loss to overcome the effects of loss therefore it updates after estimating the actual state, infrequently it is quite challenging if the input is lost for a known duration of time. Data loss in the systems states is quite challenging and degrade the efficiency of communication and control systems. The most dominant method for the recovery of lost samples in the case of estimating the state of the system are OLKF and CLKF[3-4]. The CCLKF utilize the 3 strategies, Normal Equation, LDA, and LGA, using AR model, ARMA, and ARMAX(Auto regressive moving average with exogenous input) If the input is lost for a known time The effective technique is AR(where only previous measurements are used), ARMA (previous measurements and moving average), ARMAX(modal has more parameters for executing data loss i.e input, the noise we consider its results is best) The accuracy of ARMAX must be higher than ARMA and AR Model but this technique is computationally expensive so there must be a trade-off between precision and simulation time In many systems the parameters increase the accuracy of the system increases but computational time also increase. Computation of this extra information bears an observable increase in Computational time. It will be verified after simulation that ARMAX will recover more efficiently as compared to AR and ARMA because the model parameter will increase in the case of (ARMAX) model (i.e exogenous input, noise, and regression to previous data) It is considered that ARMA model is Efficient as compere to AR but computationally expensive to overcome the problem of efficiency and computational time we will evaluate the linear prediction coefficients of ARMAX model and compere the results with AR, ARMA and ARMAX model using open-loop and compensated closed loop Kalman filter.

Keywords: KF(Kalmanfilter), AR (Autoregressive), ARMA(Auto-regressive moving Average), ARMAX (Auto-regressive moving average exogeneous).

I. Introduction

A lot of tools for state estimation perhaps the most familiar LTI system estimation Problem tool is KF. KF is an iterative mathematical process at first it finds the system state and updates to the next step based on Kalman gain it update its state until and unless track the original state of the system Major issue of loss of measurement in case of KF. The most dominant method for the recovery of lost samples in the case of estimating the state of the system are OLKF and CLKF. The CCLKF utilize the 3 strategies, Normal Equation, LDA, and LGA, using AR model, ARMA, and ARMAX(Auto regressive moving average with exogenous input) If the input is lost for a known time [7-8] The effective technique is AR(where only previous measurements are used), ARMA (previous measurements and moving average), ARMAX(modal has more parameters for executing data loss i.e input, the noise we consider its results is best) The accuracy of ARMAX must be higher than ARMA and AR Model but this technique is computationally expensive so there must be a trade-off between precision and simulation time[5-6].

II. Motivation and Objective of the Work

If the input to the Kalman filter lost (in figure 1) for some duration of time. It is challenging to recover the lost data efficiently for that CCLKF is tool to recover the lost data sevral approaches applied for data loss i.e Auto regressive and auto regressive moving average model but these stratagies are not efficient to enhace their efficiency and develop a robust algoretham for compensation of data loss i.e ARMAX model and compare its efficiency with the exixting techiniqe is the aim of this work [9-10].

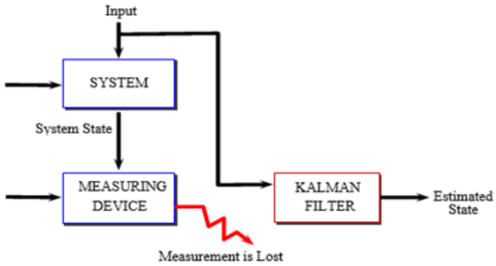

Figure 1. shows the loss of input

III. Overview of Existing Models

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

A. *Open loop kalman filter(OLKF)*

In OLKF the only prediction step takes place and the update step is skipped and Kalman gain will zero KF starts its prediction during the lossy period, in this case, no update step happens [11] open-loop case due to the absence of feedback Kalman updating is not possible so it relay on prediction step only so it is speedy and easy to track the data but chances of error in case of OLE is maximum during the loss period. Employing an OLE approach, however, it is impossible to achieve measurement update no available data due to because of lost samples Units.

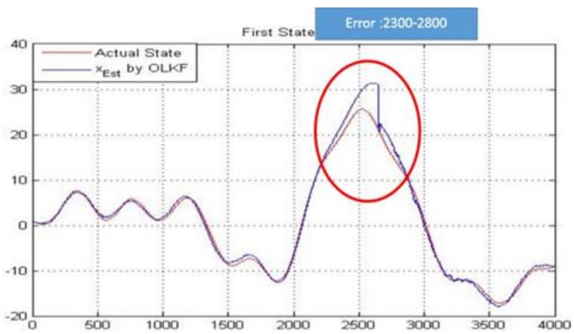

Figure 2. Open loop kalman filter during loss of measurment

B. *Compensated Closed loop kalman Filter (CCLKF)*

When data is lost for a certain period of time, the open-loop Kalman gain is zero, and the Kalman filter is unable to track the precise state of the system in order to counteract the open-loop effect. The auto regressive, auto regressive moving average, and ARMAX are the approaches used by the CCLKF to alleviate the weakness caused by the OLKF.[7][8].

i. ARMA MODEL

The ARMA is a previous model that combines autoregressive and moving average techniques. Throughout this framework, the concept autoregressive refers to using the system's prior estimation $c_{\mathrm{k-m}}$ and the concept moving average refers to using the input $u_{\mathrm{k-m}}$ and also compensating for the loss measurement. Experiments have shown that ARMA is superior to AR but is more computationally intensive.

$$\hat{c}(k) = \sum_{m=1}^{p} A_m\, c_{\mathrm{k-m}} + \sum_{m=1}^{p} B_m\, u_{\mathrm{k-m}} \qquad (1)$$

Am and Bm are the model parameters which is calculated in [13][14] the result shows in Fig.3.

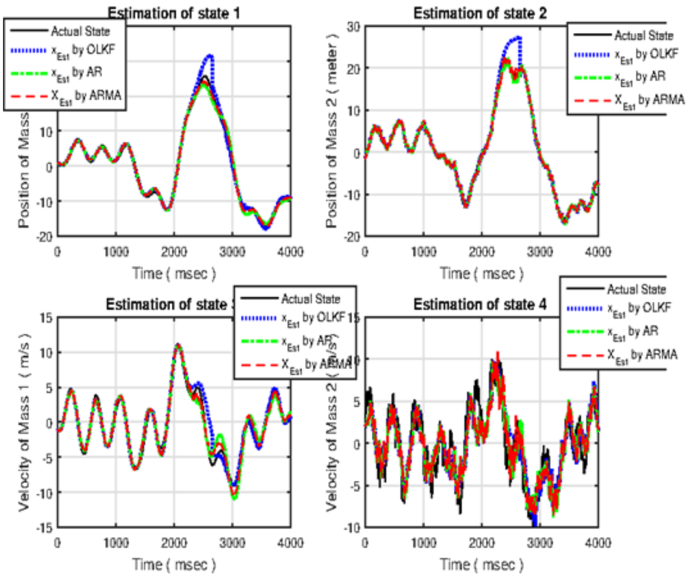

Figure 3. AR ARMA and OLKF during loss

The Figure 3 illustrates the simulation result of AR,ARMA and OLKF black line is the actual state of system green and red dased line AR and ARMA model respectively, the dotted blue color is for Open loop Kalman filter estimation It shows that ARMA model estimate accurately as compare to OLE and AR model.

IV. Proposed Model

This work aims to eliminate the adverse effects arising in communication and control system engineering it has been the most difficult challenge which attracts researchers to mitigate the adverse effects due to loss of measurements.

The most enhanced version of data loss has been targeted. ARMAX (auto regressive moving average with exogenous) model. In this work, it has been aimed that the replacement of ARMA with the ARMAX and to evaluate the performance based on computational time and steady-state error to implement ARMAX the aim is to calculate the model parameters efficiently.

A. *Mathimathical modeling of ARMAX*

This work is aimed to present the compensation of data loss in the case of the ARMAX model. The target of this work is to compute the LPC optimally and combine it with the KF to solve the challenging problem of data loss The main theme of this work is to replace AR and ARMA with ARMAX and evaluate the performance based on computational time and error.

$$\widehat{z_k} = \sum_{i=1}^{p} \alpha_i z_{k-i} + \sum_{j=1}^{q} \beta_j u_{k-i} + \sum_{k=1}^{r} \gamma_l d_{k-l} \quad (2)$$

$$e_k = z_k - \widehat{z_k} \quad (3)$$

where J is the cost function and using the knowledge of LPC, one can obtain the

$$J = E\left[z_k - \sum_{i=1}^{p} \alpha_i z_{k-i} - \sum_{j=1}^{q} \beta_j u_{k-i} - \sum_{k=1}^{r} \gamma_l d_{k-l}\right]^2 \quad (4)$$

To find $\alpha_j, \beta_j, \gamma_j$ using partial differential equations

$$\frac{\partial J}{\partial \alpha_j} = 2E\left[z_k - \sum_{j=1}^{p} \alpha_i z_{k-j} - \sum_{j=1}^{q} \beta_j u_{k-j} - \sum_{j=1}^{r} \gamma_l d_{k-j}\right] z_{k-i} \quad (5)$$

$$r_1 := E(z_k z_{k-i}) \quad R_1 = E\sum_{i=1}^{p} z_{k-i} z_{k-i}) \quad R_2 := \left(E\sum_{j=1}^{q} z_{k-i} z_{k-i}\right)$$

$$R_3 := E\sum_{k=1}^{r} 1\, d_{k-l} z_{k-i})]$$

$$r_1 = \alpha_j R_1 + \beta_j R_2 + \gamma_l R_3 \quad (6)$$

$$\frac{\partial J}{\partial \beta_j} = 2E\left[z_k - \sum_{j=1}^{p} \alpha_i z_{k-j} - \sum_{j=1}^{q} \beta_j u_{k-j} - \sum_{j=1}^{r} \gamma_l d_{k-j}\right] u_{k-i}$$

$$r_2 := E(z_k u_{k-i}) \quad R_4 = E\sum_{i=1}^{p} z_{k-i} z_{k-i})$$

$$R_5 := \left(E\sum_{j=1}^{q} z_{k-i} z_{k-i}\right)$$

$$R_6 := E\sum_{k=1}^{r} 1\, d_{k-l} z_{k-i})]$$

$$r_2 = \alpha_j R_4 + \beta_j R_5 + \gamma_l R_6 \quad (7)$$

$$\frac{\partial J}{\partial \gamma_j} = 2E\left[z_k - \sum_{j=1}^{p} \alpha_i z_{k-j} - \sum_{j=1}^{q} \beta_j u_{k-j} - \sum_{j=1}^{r} \gamma_l d_{k-j}\right] d_{k-i}$$

$$r_3 := E(z_k d_{k-i}) \quad R_7 = E\sum_{i=1}^{p} z_{k-i}$$

$$R_8 := \left(E\sum_{j=1}^{q} z_{k-i} z_{k-i}\right) \quad R_9 := E\sum_{k=1}^{r} 1\, d_{k-l} z_{k-i})]$$

$$r_3 = \alpha_j R_7 + \beta_j R_8 + \gamma_l R_9 \quad (8)$$

solving eq 6 7 and 8 the value of model parameters(α_i, β_j *and* γ_l) can be found optimally

$$\gamma_j = [N_5 N_3 - N_4 N_1][N_5 N_2 - N_6 N_1]^{-1}$$

$$\alpha_j = [n_3 N_7 - n_1 N_8][n_3 N_9 - n_2 N_8)]^{-1}$$

$$\beta_j = [n_2 N_7 - n_1 N_9][n_2 N_8 - n_3 N_9]^{-1}$$

Where N_n and n_n are the function of correlation matrix of R_n and r_n detail calculation [15-16]

V. CASE STUDY OF MASS SPRING DAMPER SYSTEM

A case study of mass spring damper system shown in Figure 4 is executed the system dynamics is calculated by using mass spring damper system is evaluated [12-14]

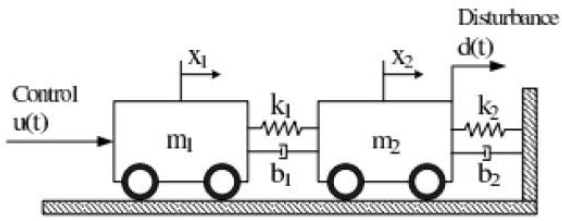

Figure 4. Mass Spring Damper Syste

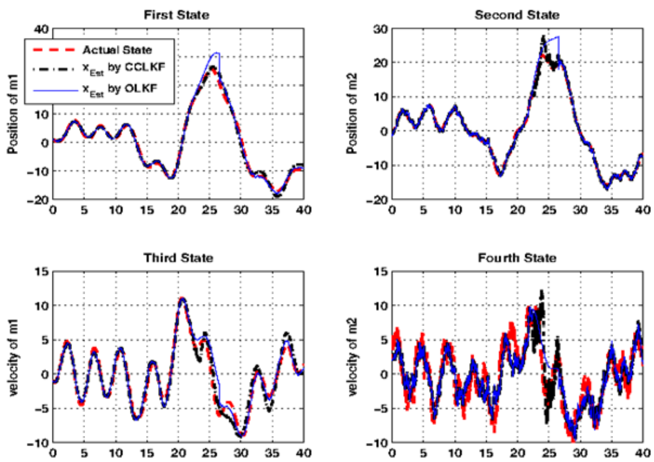

Figure 5: Simulation results of ARMAX Model for position and velosity of mass m_1 and m_2

The Figure 5 illustratrs the actual state red dashed line and black is for the ARMAX model which track the exact states more efficiently the lossy region is from 21 to 28 along time axis

A) Performance Evaluation Of Data Loss Recovery Methods

In this section a case study of mass spring damper system has been executed OLKF and closed loop Kalman filter technique for data loss recovery has evaluated from the following below Figures 6, 7, 8, 9. it is concluded that ARMAX model recover data more effectively as comphere to the other techniques.

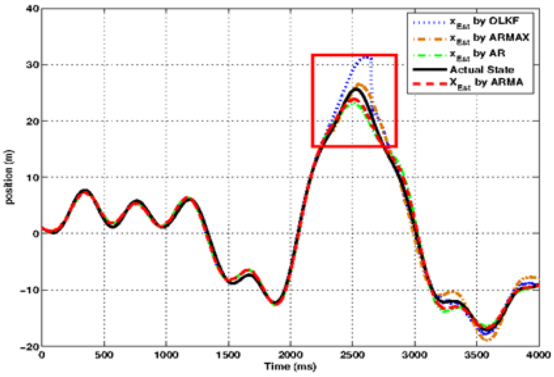

Figure 6. Combine result of system state 1 (OLKF, AR, ARMA, and ARMAX)

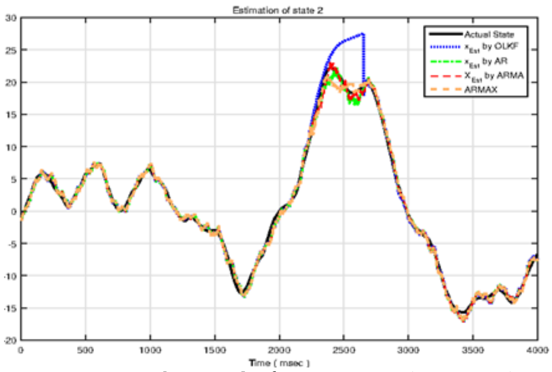

Figure 7. Combine result of system state 2 (OLKF, AR)

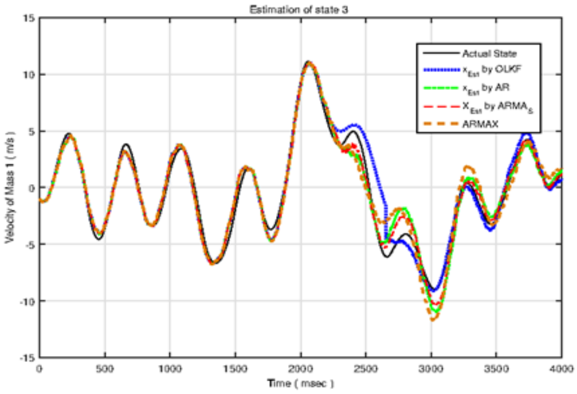

Figure 8. Combine result of system state 3 (OLKF, AR, ARMA, and ARMAX)

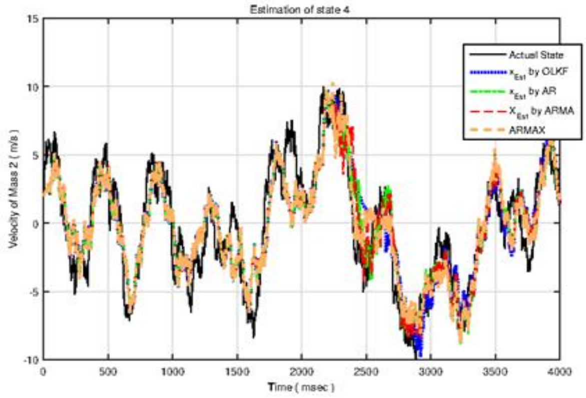

Figure 9. Combine result of system state 4 (OLKF, AR, ARMA, and ARMAX)

B) Error Analysis Data Loss Recovery Techniques

Figure 10 show the error analysis of AR, ARMA, and ARMAX, and OLKF it has been shown that the error of ARMAX is small and is much more efficient as compere to AR and ARMA.

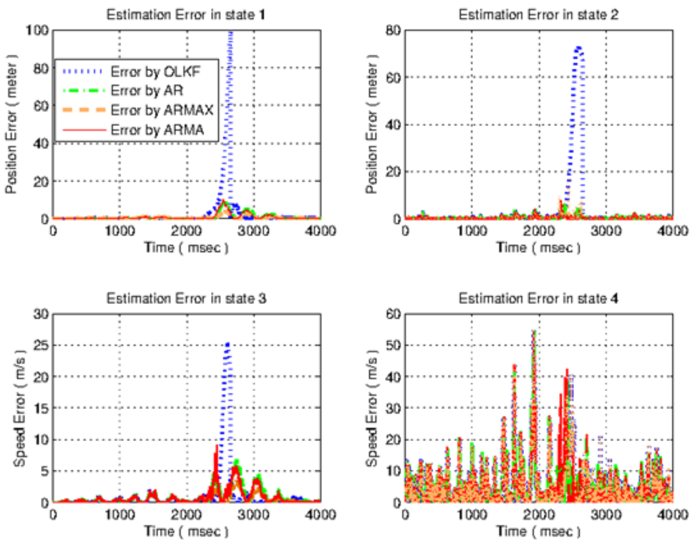

Figure 10. Error Analysis of data loss recovery techniques

The above Figure 10 illustrates error analysis of OLKF and CCLKF error of blue(OLKF) dotted line diverge the error of ARMAX model is smallest and seems more efficient in comparsion with other methods.

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