Incomplete Feedback Data Recovery Scheme with Kalman Filter for Real-time Cyber-Physical Systems

Naushin Nower, Yasuo Tan and Yuto Lim
Japan Advanced Institute of Science and Technology (JAIST)
1-1 Asahidai, Nomi City, Ishikawa, 923-1292 Japan
Email:{naushin, ytan, ylim}@jaist.ac.jp

***Abstract*—Feedback data loss can severely degrade the overall system performance and as well as it can affect the control and computation of the cyber-physical systems (CPS) in the provision of real-time, efficient, dependable, safe, and secure operations of a wide range of emerging applications. In CPS applications, a wide range of data patterns are observed in different applications which make a great challenge in efficient and real-time recovery whenever the data is lost. In this paper, we propose a data recovery scheme called efficient temporal and spatial data recovery scheme with Kalman filter (ETSDR/KF) to ensure efficient and real-time recovery for any data patterns of CPS. In the proposed scheme, the data recovery ETSDR/KF algorithm is presented to recover incomplete feedback data. We identify the temporal model of the pattern using ARIMA model and consider the spatial effect of the neighbors as a data pre-processing step. However, the temporal model, generated from ARIMA has internal errors and the model parameters may not remain constant. Thus, to improve the accuracy of the estimated data, we incorporate a Kalman filter to reduce the error. Before that, we fix the window for Kalman filter to determine the proper process noise co-variance in online. Numerical results reveal that the proposed ETSDR/KF are very promising regardless of the increment percentage of missing data in terms quality of result (QoR).**

I. Introduction

Cyber-physical systems (CPS) are a collection of computational (cyber) and physical components that interact with each other to achieve a particular objective within a specific time frame. CPS enable the virtual world to interact with the physical world in order to monitor and control the intended parameter in real-time basis [1]. To facilitate the interactions between cyber world and the physical world, sensor networks will become a crucial ingredient of CPS due to the need for coupling geographically distributed computing devices with physical elements. In particular, CPS [2] requires the employed sensor networks to support real-time, efficient, dependable, safe, and secure operations. Among them, real-time and efficiency are the most critical criteria for ensuring CPS.

Since the CPS exploit the physical information collected by wireless sensor and actuator networks (WSANs), it also inherit the wireless contention problem of WSAN. This is a very challenging issue for control in real-time. Wireless channels have many adverse properties like path loss, fading, adjacent channel interference, node/link failure, etc. Besides these, wireless signal can be easily affected by noise, physical obstacles, node movement, environmental change and so on [3]-[4]. Because of this unpredictable and dynamic nature, sensing data loss is a common phenomenon, which makes hamper in controlling decision in real-time. In particular by using WSAN, the CPS with point-to-multipoint mode of communication cannot guarantee reliable and real-time. Thus, for point-multi-point CPS, feedback data must have to arrive on time, to make decision. In these cases, re-transmission cannot provide appropriate solution because of the unpredictable network behavior, which can cause high delay.

Moreover, the applicability of CPS is found in numerous time-critical applications including smart house to smart grid. Emerging applications of CPS include, medical devices and systems, aerospace systems, transportation vehicles and intelligent highways, defense systems, robotic systems, and so on [5]. In this wide spectrum of CPS applications, different data properties are observed, in terms of their shape, trend, variation and periodicity. Some series maintain stable stage, some show large variation in their evaluation and others exhibit repetition in their evolution [6]. In [7], we proposed a Efficient Spatial Data Recovery (ESDR) scheme that deals with stable or small variation of data pattern like temperature, humidity, moisture etc. In [6], we proposed different algorithms for different data patterns and mainly concentrate on the data patterns that has a large variation. To handle the data with large variation, we proposed a scheme called Efficient Temporal and Spatial Data Recovery (ETSDR) scheme by considering the nature. The first phase of our proposed scheme is to identify the temporal model for large variation of data using Auto Regressive Integrated Moving Average (ARIMA)[8] and to determine the spatial effects of neighbors in pre-processing step. In the next phase, which is real-time, the temporal model and spatial effect is used to recover data.

In this paper, we improve our previously proposed framework to a universal framework for data recovery scheme that can handle any type of data patterns. To do this, we utilized a pre-processing step that used to identify the nature of data using auto-correlation coefficient function (ACF) and then built a temporal model based on the analysis of ACF of the data. Besides this, the performance of the ETSDR real-time algorithm depends on the temporal model identification, more specifically on the parameter estimation and outliers detection of ARIMA model which always has some internal error. Moreover, previously it is also assumed that the estimated parameters of temporal model are constant throughout the series. But, in real-life CPS applications, the parameters may not remain constant and it is quite impossible to refine the parameter estimation in real-time.

In order to improve the accuracy and ensure real-time computation, in this paper we incorporate a Kalman filter (KF)

[9] to minimize the error from the estimated data of temporal model. In KF, state model and error co-variance act as key role of controlling the performance of KF. We get the state space model from ARIMA temporal model. Next, we need to determine the correct error covariance to get the best optimal performance of KF. In order to do that we determine a window to get the proper process noise co-variance. When the error co-variance is computed from the actual error of the measurement, satisfactory results are obtained without divergence of Kalman performance. Thus to get the proper error co-variance, we fix the window for KF whenever the original measurement is available.

The rest of the paper is organized as follows. Section 2 summarizes research background and state-of-the-art research works that are related to this paper. In Section 3, the proposed the data recovery scheme with Kalman filter is presented. We describe the simulation scenario and the evaluation parameters in Section 4. Simulation results and discussions are presented in Section 5. Section 6 concludes with conclusion and future works.

II. Research Background and Related Work

Data recovery is a part of most research and there exist several methods to handle this. Even though, there exist several methods, the recovery of data loss for CPS still poses an open problem because of its unique requirement. The whole recovery process for CPS must be held in real-time and need to maintain QoR. In this section, we discuss the requirements for CPS and the existing data recovery procedures for CPS.

We concentrate on the key issues of CPS: real-time and efficient. In CPS, the passage of time becomes a central feature to ensure real-time system, in fact, it is one of the important constraint distinguishing these systems from distributed computing in general. According to [10], "A real-time system must react to stimuli from the controlled object (or the operator) within time intervals dictated by its environment". Depending on the time constraints, there are two types of real time system: hard real-time and soft-real time as shown in Fig. 1. In a hard real-time system, the system must produces result before the deadline has expired. In a soft real-time system, an answer may still be useful for some time interval after the deadline has expired. CPS is intended to meet the hard real-time, such that the desired outcome is guaranteed within the specific deadline [11]. Depending on the particular environments and applications the deadline for hard real-time CPS may vary.

The another challenge for CPS is to maintain the QoR. QoR [11] is used to evaluate the outcome/result of a scheme or process. In this paper, the evaluation merits of accuracy such as root mean square error (RMSE), mean absolute error (MAE) and Integral of absolute error (IAE) are used. Among them, MAE provides the unbiased result in terms of accuracy [12]. To define the QoR, we use efficiency and execution time. The efficiency is defined as the improvement of the scheme with respect to the MAE in term of the percentage of missing data. Whereas, the execution time is defined as the elapsed time to produce a loss data of the scheme. In this paper, we define that the QoR is specified as an acceptable range of efficiency, i.e., above 80% and a deadline of execution time, i.e., below 1 millisecond. If a scheme does not achieve both said parameters, then the scheme cannot achieve its QoR.

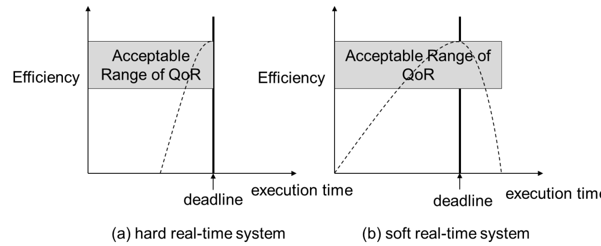

Fig. 1. Efficiency vs. execution time in (a) hard and (b) soft real-time systems

Xia, et al. [13] first proposed a solution for CPS over WSANs to cope with packet loss. They illustrate three prediction algorithms and provide a comparison between them. First algorithm based on the assumption that, the state of the physical system does not change during the last sampling period. The second algorithm computes a moving average of the previous m samples to restore the lost data. Thus it treats every previous measurement equally. In third algorithm, which is known as weighted prediction (WP), weighted average of all previous samples is taken to replace the missing one. Simulation result shows that third algorithm works well compared with others. All of their procedures are bound for specific situation where current data depends on the previous data or the combination of previous data but not for all conditions.

Choi, et al. [14] exploit an exponentially weighted moving average (EWMA) based value estimation algorithm to reduce the impact of packet loss. When some packets are randomly dropped in wireless network environment, the EWMA algorithm filters an abrupt increase or decrease by exponentially smoothing commands or data based on the past value profile. This method is only suitable, when the data series is an exponentially weighted combination of past data sets. But in real-life there is no guarantee that data will always maintain this combination. We believe that successful identification of data model and error reduction using KF can ensure accurate and timely recovery.

In the existing literature, there is no direction of data recovery based on data patterns. Thus, the recovery process without considering the nature can not provide a solution for all. To recover data accurately, we first need to understand the nature of the data and their spatial relationship with others. To achieve our motivation, we propose a data pre-processing stage, where the ACF is used to identify the nature of the data pattern and based on that property, then a model is built for real time recovery process.

III. Proposed Data Recovery with Kalman Filter based Scheme

In this section, we propose a data recovery framework for CPS. The designed data recovery framework contains two phases: i) Pre-processing and ii) Real-time processing. The universal framework for data recovery scheme is shown in Fig. 2.

A. Pre-processing

We analyzed the data series trend by analyzing it's ACF and then modeled it into ARIMA model. The ACF is a set

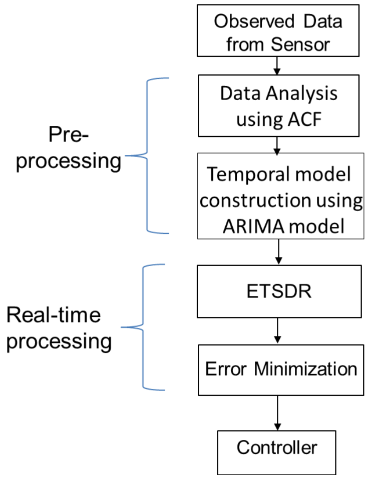

Fig. 2. Proposed data recovery framework for CPS

of correlation coefficients between the series and lags of itself over time [15]. The k-order auto-correlation coefficient of a data series $d_{s1}, d_{s2}, ..., d_{sn}$ of sensor s is defined as

$r_k = \frac{\sum_{i=1}^{n-k}(d_{si}-\bar{d_{si}})(d_{s(i+k)}-\bar{d_{si}})}{\sum_{i=1}^{n}(d_{si}-\bar{d_{si}})^2}$ where, r_k is the k-lag sample auto-correlation and $\bar{d_{si}}$ is the average of n observations. The ACF of small variation or stable data show almost straight line, on the other hand, data with the large variation show slow decaying in their ACF. Thus from the result of ACF, the data pattern can be identified. After identification of data pattern, the temporal model is built using ARIMA model. The details of temporal model construction is discussed in [6].

B. Real-time Processing (Proposed Data Recovery with Kalman Filter)

To deploy our proposed data recovery with Kalman filter based scheme, we propose a flowchart as depicted in Fig. 3(a). Here, the temporal model is used to compute the estimated data and the error is calculated, when there is an input measured data from the sensors. If there is no missing data, then the measured data is used as a feedback data. At the same time, error is computed from the measured data and model computed data to get the actual error for ensuring the better performance from the KF.

On the other hand, when there is a missing data, we utilize the model estimated data and apply KF on the model estimated data to make it more accurate. The KF has been used in a wide range of applications for error minimization. It is an efficient recursive filter that estimates the state of a process in a way that minimizes the mean of the squared error when the process and measurement models are accurate. We discuss the details of KF setting in the following subsection C.

To consider the spatial effect, neighbor's model estimated data and neighbor's measured data is compared. Whenever the difference between two data crosses the spatial regressive threshold (SR_{th}), the spatial regression is considered. SR_{th} is the maximum tolerable error value as a threshold indicator to determine the spatial regression to be applied or not in the ETSDR algorithm. At the initialization step, SR_{th} is a predefined constant value in order to cope with the dynamic environmental changes (i.e., the disturbance effects). Since the temporal model is based only on the property of data series itself, but in real life, the sensor measurement can be effected by the surrounding environment factors. In the case of a missing data of a sensor, we utilize the temporal model to estimate the model computed data and at the same time we check all the one-hop neighbor's measurements to determine whether we should consider the spatial regression or not. To handle the spatial regression, we compare the neighbor's measured data and the neighbor's model computed data. In this paper, we define that e_i is the average error between all the one-hop neighbor's sensor of the measured data and the model computed data. If this e_i is greater the SR_{th}, the spatial regression is added to the model computed data. Otherwise, the only the model computed data is used as a feedback data.

C. Modeling of temporal model in Kalman filter

KF is based on a state-space approach in which a state equation models the dynamics of the data generation process with process error and an observation equation models the generated data with observation error. Thus, we need to convert our temporal model into a state-space approach that contains state and observation equations. The performance of KF depends on the proper modeling of these equations and error co-variances. The steps of KF for error reduction is depicted in Fig. 3(b).

The temporal pattern of the data is identified by ARIMA model in the pre-processing phase. An auto-regressive (AR) model is a simplified version of ARIMA model which describes linear stochastic process with large variation of data. The AR model of sensor s data series $d_{s1}, d_{s2}, ..., d_{sn}$ with order p is defined as follows

$$d_s n = c+\varphi_1 d_s(n-1)+\varphi_2 d_s(n-2)+...+\varphi_p d_s(n-p)+V_s n \tag{1}$$

where, p is the order of auto-regressive terms, $\varphi_1, \varphi_2, ...\varphi_p$ are the parameter of the model, c is a constant and $V_s n$ is error. The variables $\varphi_1, \varphi_2, ..., \varphi_p$ are the state-space model framework. From this, the state equation is formed as follows

$$\begin{bmatrix} d_s n \\ d_s(n-1) \end{bmatrix} = \begin{bmatrix} \varphi_1, \varphi_2, ..., \varphi_p \\ 1, 0, ..., 0 \end{bmatrix} \begin{bmatrix} d_s(n-1) \\ d_s(n-2) \\ ... \\ d_s(n-p) \end{bmatrix} + \begin{bmatrix} c \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} W_s(n-1) \tag{2}$$

where, $\begin{bmatrix} \varphi_1, \varphi_2, ..., \varphi_p \\ 1, 0, ..., 0 \end{bmatrix} = A$ is a state transition matrix and $W_s(n-1)$ is the process error. The observation equation is as follows.

$$y_s n = [1, 0, ..., 0] \begin{bmatrix} d_s n \\ d_s(n-1) \\ ... \\ d_s(n-p) \end{bmatrix} + V_s n \tag{3}$$

where, $H = [1, 0, ..., 0]$ is the observation matrix and $V_s n$ is the measurement error. Thus, from (1) and (2) we get the state

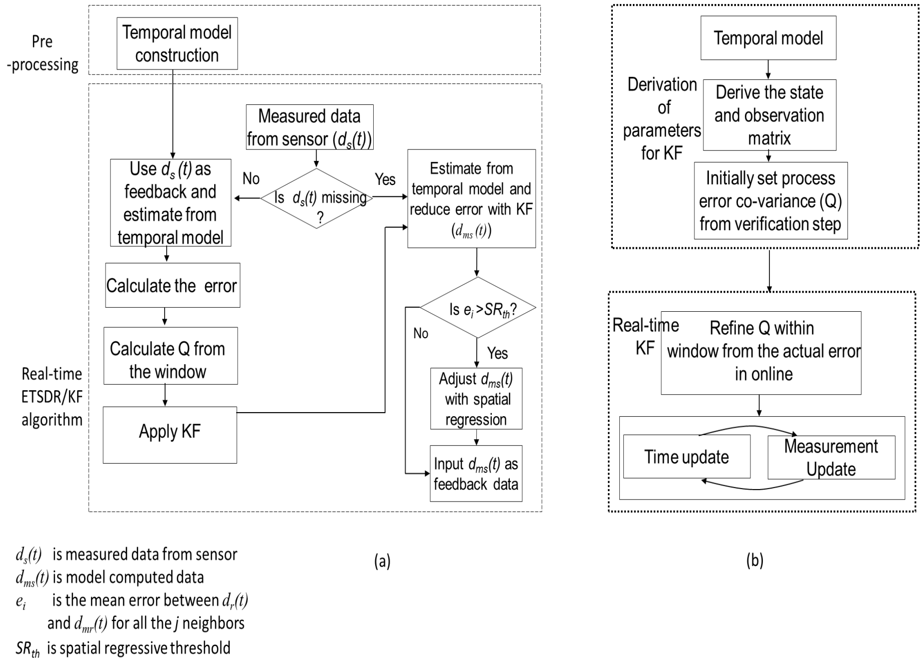

Fig. 3. (a) Flowchart of ETSDR/KF algorithm (b) Steps of KF for error reduction.

space model as follows

$$d_s n = A \sum_{i}^{p} d_s(n-i) + W_s(n-1) \quad (4)$$

$$y_s n = H d_s n + V_s n \quad (5)$$

Equation (4) represents a linear stochastic equation where, $d_s n$ is a linear combination of its previous value and a process error. Equation (5) indicates that any measurement value is a linear combination of the data value with the measurement error. From the temporal model, we derive the state transition matrix and observation matrix A and H and then left is to set the co-variances (Q) and (R) of process error ($W_s(n-1)$) and measurement error $V_s(n)$ respectively. We can derive the the state space model for MA and ARIMA temporal model by using the same process.

The KF requires that all of the error co-variances to be known exactly. Error co-variances in the KF play a key role in controlling the Kalman gain. At first, we choose the values of Q and R from the pre-processing stage during the temporal model verification step. Our main purpose is to minimize the error from the model, which is the process error $V_s n$. Thus, we need to set the co-variance Q of process error $V_s n$ properly. Since, we assume, the measurement noise is almost zero, we can set the R close to zero. Initially, we get the value of Q from the pre-processing step of model verification. In the real-time processing, whenever the sensor measured data is available, we get the actual error and the refine Q to be more appropriate. In order to do that, we define a window in which the value of Q will become stable. Before doing that, we assume that, there is no missing data within this window length, thus the actual error is used to converge to the stable value of Q. As long as the window length is higher, the more accurate Q can be achieved, but at the same time, the assumption become unrealistic. To

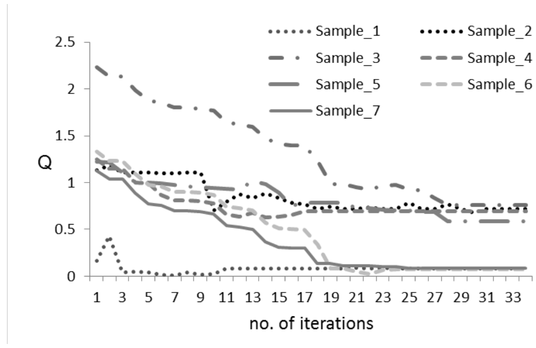

Fig. 4. Determination of window size for stable Q

determine the suitable window length, we have analyzed seven data series with 200 samples without any missing data and found that the Q becomes stable within window length 14.8 (on average). From this analysis, we fix the window length 15 to get the stable process noise co-variance in real-time without any missing data. We believe that, to utilize the window is easier, simple and requires less memory compare to training process.

The KF algorithm involves two stages: Time update (prediction) and measurement update (correction). The time update equations are responsible for projecting forward (in time) the current state and error co-variance estimates to obtain the a previous estimates for the next time step.

$$\hat{d}_s n = A \sum_{i}^{p} \hat{d}_s(n-i) \quad (6)$$

$$\hat{P}_k = A \hat{P}_{k-1} A^T + Q \quad (7)$$

The measurement update equations are responsible for the

TABLE I. PSEUDO-CODE FOR EFFICIENT TEMPORAL AND SPATIAL DATA RECOVERY WITH KALMAN FILTER ALGORITHM

Algorithm: Efficient Temporal and Spatial Data Recovery with Kalman Filter (ETSDR/KF)

```
if d_s(t) = available then
  for each d_s(t) from the sensor s do
    Compute d_ms(t) from the temporal model
      Apply KF on d_ms(t) to reduce error
      end if
  end for
else
  for all one-hop neighbors, r of sensor s do
    if avg(abs(d_r(t) - d_mr(t))) > SR_th then
      d_e(t) <-- d_s(t) = KF(d_ms(t)) + spatial regression
    else
      d_e(t) <-- d_s(t) = d_ms(t)
    end if
  end for
end for
```

feedback of KF, it incorporates a new measurement into the a previous estimate to obtain a next improved estimate.

$$\hat{d}_s(n+1) = \hat{d}_s n + K_k(y_s n - H\hat{d}_s n) \quad (8)$$

$$P_k = (1 - K_k H)\hat{P}_k \quad (9)$$

where, K_k is a Kalman gain, which is defined as follows

$$K_k = \hat{P}_k H^T (H\hat{P}_k H^T + R)^{-1} \quad (10)$$

Table I describes the proposed ETSDR/KF algorithm, which is used to produce an estimated data from time to time.

IV. NUMERICAL SIMULATIONS

In this section, we conduct the simulation studies to evaluate our proposed ETSDR/KF scheme compared to the ETSDR algorithm [7], the WP algorithm [13] and the EWMA algorithm [14]. In this simulation the data with large variation is considered, which is more difficult to recover when data is lost. We create a small scenario for simulation that can resemble to smart grid applications for energy consumption control in smart community. We assume a community with five houses, where each sensor (e.g., smart meter) in a house measures the energy consumption and communicates with the controller, that placed in a cloud for computing the energy demand and supply in real-time manner. The value of created energies (e.g., solar panel, fuel cell, or electric vehicle, wind energy, etc) from different houses may or may not linearly correlate with other houses as a spatial correlation. In our simulation environment, five sensors and one controller are considered. We generate data with large variation data series using MATLAB simulator and assign it to the five sensors. We assume that the one-hop sensors are linearly co-related. Moreover, to make the scenario more realistic we add some disturbance effects at the certain period of time. We use SR_{th} [7] as 1.09 to cope with the spatial effect. We construct the temporal model from the generated data by following the steps in [7]. We identify the temporal model as $d(n) = 0.11 * d(n-1) - 0.96 * d(n-2)$ which is a AR(2) model. From this model, we get the matrix $A = [.11 - .96]$ and use $H = [1, 0]$ for Kalman filtering. Since, our goal is to reduce the error form the model and we assume that there is almost no measurement error, thus we set the value of R as $= 1e-3$. In order to determine the process error we utilize the window with length (15) and the value of Q converges from 2.009 and become stable at 0.5.

Based on the generated data, we investigate the performance of our proposed scheme using a MATLAB. In this simulation, we assume that the single sensor produces a missing sensed data when it transmits its packet to the base station. We randomly delete the data according to the percentage of missing data from the original set and recover them using the aforementioned data recovery algorithms. We use the root mean square error (RMSE), the mean absolute error (MAE) and the integral of absolute error (IAE) to evaluate the performance of the said algorithms. The RMSE of an algorithm estimation with respect to the estimated value, d_e is defined as the square root of the mean squared error as written as $RMSE = \sqrt{\frac{\sum_{n=1}^{N}(d_s(n)-d_e(n))^2}{N}}$ where d_s is original measured value. The MAE is another statistical measurement that used to measure how close the estimated values are to the measured values. The MAE is given by $MAE = \frac{1}{N}\sum_{n=1}^{N}|d_e(n) - d_s(n)|$. On the other hand, the IAE is a widely used performance metric in control community, which is recorded to measure the performance of the control application. The IAE is calculated as follows $IAE = \int_0^t |d_e(t) - d_s(t)|\, dt$ where, t denotes total simulation time. In general, the larger the IAE values imply the worse the performance of the control algorithm.

V. SIMULATION RESULTS AND DISCUSSION

In this section, we present our simulation results and make some discussions on the performance of algorithms based on QoR that is efficiency and execution time. The aim of this simulation is to examine the potential of the proposed algorithm in coping with the data missing for the CPS application. The percentage of missing data is varied from 10% to 60% in steps of 10%.

Fig. 5(a) depicts the RMSE comparison among data recovery algorithms for data with large variation. As the percentage of data missing increases, the proposed ETSDR/KF always shows better performance that is compared to the ETSDR and other two algorithms. The reason for this improvement over ETSDR is because ETSDR/KF reduces the model generated error using Kalman filter. On the other hand, WP and EWMA algorithm always use the same combinations of previous measurement. In addition, they do not consider the effect from the neighbors. Through this simulation, we can observe that this problem also can be found at the EWMA algorithm. Both WP and EWMA algorithm use the fixed combination of previous measurements only.

The MAE comparison among four data recovery algorithms is shown in Fig. 5(b). We can see that the ETSDR/KF outperforms the ETSDR, the WP algorithm and the EWMA algorithm. Besides that, the proposed scheme with Kalman filter can steadily maintain a small value of MAE regardless of the increment of missing data because of accurate setting of process error co-variance through the window. This also means that the distance between the real measured data and estimated data of the proposed scheme is always stable.

In Fig. 5(c), the accumulated IAE comparison of all the data recovery algorithms is plotted. The simulation results

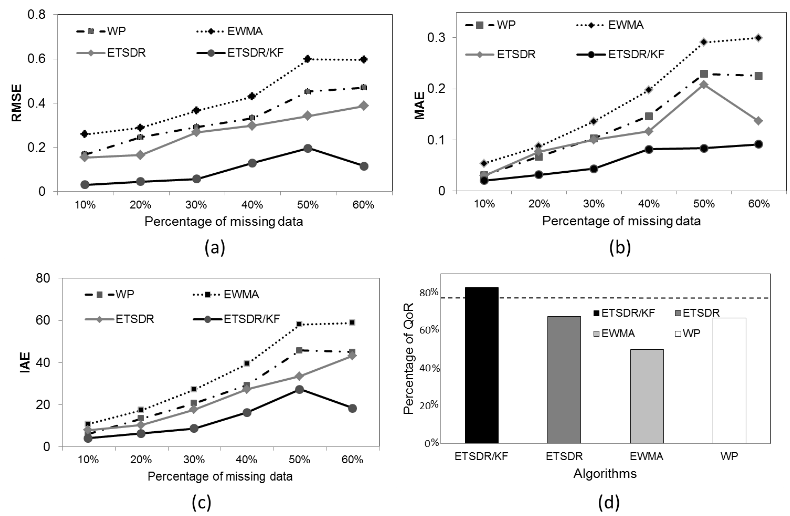

Fig. 5. Comparison of (a) RMSE (b) MAE and (c) IAE of all the data recovery algorithms as the percentage of missing data changes from 10% to 60% and (d) average percentage of QoR of algorithms for 10% to 60% missing data

demonstrate that the proposed scheme with Kalman filter outperforms the others. We believe that, this for properly incorporating the Kalman filter with ETSDR algorithm.

To measure the execution time of the all the said online algorithms, we use the computer with the Intel Core i7 3.0 GHz processor and the 8 GB memory to run each algorithm 10 times. The average execution time of each algorithm is given in Table II, which shows that all of the said algorithms can meet the deadline.

TABLE II. EXECUTION TIME IN UNIT OF SECONDS

Algorithms			
ETSDR/KF	ETSDR [7]	WP [13]	EWMA [14]
1.5565e-04	1.0263e-06	2.7368e-06	2.0526e-06

To illustrate the QoR of all the algorithms, we depicted one more graph in Fig. 5(d) which shows the average MAE of all said algorithms from 10% to 60% missing data. It is easily observed that only ETSDR/KF can achieve more then 80% in terms of QoR. On the other hand, none of the others can achieve 80% efficiency. Although ETSDR/KF requires higher execution time compare to other three, but it still maintain the deadline. Thus ETSDR/KF maintains QoR in terms of efficiency and deadline compare to the others.

VI. CONCLUDING REMARKS

In this paper, we have proposed a data recovery with KF based scheme for any type of data of CPS. Since, data series with large variation is more difficult to estimate than the others, we incorporate Kalman filter to improve the accuracy in estimation. However, the same scheme can be applicable to the data with small variation also. Our simulation results reveal that the proposed ETSDR/KF scheme is very beneficial and outperforms the ETSDR, the WP and the EWMA algorithms regardless of the increment of missing data. Moreover, further research will focus on examining the real communication environment to ensure the performance of real-time execution of ETSDR/KF scheme.

REFERENCES

[1] Edward, A.L.: Cyber physical systems: Design challenges. IEEE Symp. on Object Oriented Real-Time Distributed Computing, 363–369 (2008)

[2] Xia, F., Mukherjee, T., Zhang, Y., Song, Y.: Sensor Networks for High-Confidence Cyber-Physical Systems. Int. J. of Distributed Sensor Networks Volume 2011 (2011).

[3] Wu,F.J., Kao, Y.F., and Tsenq, Y.C.: From wireless sensor networks towards cyber physical systems. J. Pervasive and Mobile Comp. 7(4), 397–413 (2011)

[4] Martincic, F. and Schwiebert, L.: Introduction to wireless sensor networking, Handbook of Sensor Networks-Algorithms and Architectures, John Wiley Sons, New York, USA, 2005.

[5] Edward, A.L.: CPS foundations. ACM/IEEE Design Automation Conf. (DAC) 737–742 (2010)

[6] Nower, N., Yasuo, T. and Lim, A.O.: Efficient Spatial Data Recovery Scheme for Cyber-physical systems, IEEE Int. Conf. on Cyber-Physical Systems, Networks, and Application, pp.9297, Taipei, Taiwan, August 2013.

[7] Nower, N., Yasuo, T. and Lim, A.O.: Traffic Pattern based Data Recovery Scheme for Cyber-physical System, IEICE Trans. on Fundamental E97-A(9), 1926–1936 (2014).

[8] Box, G., Jenkins, G. Reinsel, G.: Time Series Analysis: Forecasting and Control, 4th edn., NJ: Wiley, 47–92(2008)

[9] Welch, G., Bishop, G.: An introduction to the Kalman filter. (1995).

[10] Laplante, P.A.: Real-time systems design and analysis An Engineers Handboook. 2nd ed. IEEE Press, Piscataway, NJ, USA, http://www.ieee.org, 1997.

[11] Kremer, U.: Cyber-Physical Systems: A case for soft real-time.

[12] C.J. Wilmott and K. Matsuura, "Advantages of the mean absolute error (MAE) over root means square (RMSE) in assessing average model performance," Climate Research, vol.30, pp.79–82, 2005.

[13] Xia, F., Kong, X. and Xu,Z.: Cyber-physical control over wireless sensor and actuator networks with packet loss. Wireless networking based control, Springer, 85–102(2011)

[14] Choi, R.H., Lee, S.C., Lee, D.H. Lee, and Yoo, J.: WiP abstract: Packet loss compensation for cyber-physical control systems. IEEE/ACM Int. Conf. on Cyber-Physical Systems (ICCPS) 205(2012)

[15] B.L. Bowerman, R.T. O' Connell, Forecasting and Time Series: An Applied Approach, China Machine Press, Beijing, 2003.