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Author(s)	Nower, Naushin; Tan, Yasuo; Lim, Azman Osman
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Description	

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Japan Advanced Institute of Science and Technology

Efficient Spatial Data Recovery Scheme for Cyber-physical System

Naushin NOWER, Yasuo TAN and Azman Osman LIM
Japan Advanced Institute of Science and Technology
1-1 Asahidai, Nomi, Ishikawa, 923-1292 JAPAN
E-mail: {naushin, ytan, aolim}@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 System (CPS). Therefore, incomplete feedback makes a great challenge in any uncertain condition to maintain the real-time control of the CPS. In this paper, we propose a data recovery scheme, called Efficient Spatial Data Recovery (ESDR) scheme for CPS to minimize the error estimation and maximize the accuracy of the scheme. In this scheme, we also present an algorithm with Pearson Correlation Coefficient (PCC) to efficiently solve the long consecutive missing data. Numerical results reveal that the proposed ESDR scheme outperforms both WP and STI algorithms regardless of the increment percentage of missing data in terms of the root mean square error, mean absolute error and integral of absolute error.**

Keywords—data recovery scheme, spatial correlation, pearson correlation coefficient, cyber-physical system

I. Introduction

Cyber-physical system (CPS) is a new generation of communication, control, and computation that has received a great deal of attention recently [1]. CPS enables the virtual world to interact with the physical world in order to monitor and control the intended parameter in real-time basis. In CPS, technologies such as communication, control, computation, cognition and sensing converge to create new technologies for smarter society. The area of CPS represents the intersection of several systems trends, such as real-time embedded system, distributed systems, control system and networked wireless system.

To facilitate communications between cyber and the physical world, wireless sensor network (WSN) or more appropriate wireless sensor and actuator network (WSAN) is an essential ingredient of CPS. Traditional WSN is limited in their ability to monitor the physical world [2]. However, CPS achieves this requirement by facilitating the system to sense, interact and change the physical world in real-time by using feedback control loop. Fig. 1 shows the general block diagram of CPS. Since CPS uses WSNs to obtain the feedback measurement from sensors; it faces the wireless contention problem which makes the challenging issue to control in real-time. Wireless channels have many adverse properties like pathloss, 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]. Because of this unpredictable and dynamic nature, the sensing data loss is a common phenomenon, which makes hamper in controlling decision. Since, the applicability of CPS is found in numerous time-critical applications including smart house to smart grid, data loss makes the system unstable. Emerging applications of CPS include medical devices and systems, aerospace systems, transportation vehicles and intelligent highways, defense systems, robotic systems, process control, factory automation, building and environmental control, smart spaces, intelligent home and so on [4]. In all of these applications, CPS has to monitor and control the state of physical phenomenon in real-time. In particular, for time critical applications, feedback data must have to arrive on time, to make decision. In this case, retransmission cannot provide any solution because of delay. Thus for uninterrupted control, we need a data recovery scheme that can handle insufficient feedback control information. In this paper, our aim is to propose an highly Efficient Spatial Data Recovery (ESDR) scheme that deals with CPS. To do this, we design a framework structure for the control view of the CPS with our data recovery scheme. The designed framework incorporates the proposed ESDR scheme, which is based on the spatial correlation of neighboring sensors by using the Pearson correlation coefficient (PCC). One of our contributions is that the proposed ESDR scheme ensures timely data recovery because of minimum computation. Second, our proposed ESDR scheme is used to examine the smart home environment with CPS approach in order to maintain desired room temperature at different locations. Thus, the feedback measured room temperature is very important to keep the desired room temperature steadily at all the times.

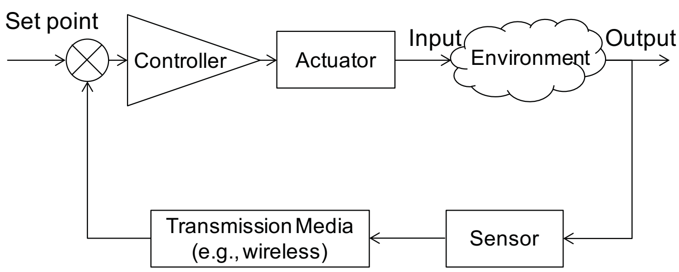

Fig. 1. General control view of cyber-physical system.

The rest of the paper is organized as follows. Section II summarizes some state-of-the-art research works that is related to this paper. In Section III, the proposed ESDR scheme with its algorithm is presented. We describe the experimental scenario and the evaluation parameters in Section IV. Simulation results and discussions are presented in Section V. Section VI concludes with conclusion and future works.

II. Related Work

Missing data recovery is a part of most research and there exist several methods to handle this. Although there exists several methods, but 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 invisible to the outside world.

Missing data is a well-studied subject in statistics. Little and Rubin provide an introduction to statistical missing data imputation techniques, such as Least Squares Estimates, Bartlett's ANCOVA and likelihood-based approaches in [5]. Maximum Likelihood (ML), Multiple Imputation (MI) and Expectation Maximization (EM) are widely used method for missing data imputation. ML [6] calculates the likelihood function for given set of data, which is a hypothetical probability that uses past event with known outcome. Then, by using iterative steps, ML makes the likelihood function maximum. EM [7] also uses iterative step to maximize the likelihood function but here, model depends on unobserved or latent variables. Based on mean and covariance matrix of multivariate normal distribution, expectation (E) step initializes the expected values for latent variables. Maximization (M) step plugs the expected values into the log-likelihood function and maximizes the log-likelihood function by repeating the E and M steps. However initialization step directly impact the performance of EM based imputation. On the other hand, in MI [8], missing data are filled by m different times to generate m complete data sets. Generated m data sets are analyzed by standard procedure and then combined for inference. But these well known techniques for missing data imputation are not suitable for WSNs, due to their high space and/or time complexities.

Imputation methods based on machine learning are sophisticated procedures that use a predictive model to estimate values. These approaches model the missing data estimation based on information available in the data set. If the observed data contain useful information then, imputation procedure maintains high precision [9]. Multi-layer Perceptron (MLP), Self Organizing Map (SOM), k-Nearest Neighbors (k-NN) are examples of imputation techniques based on learning. MLP is multi-layer computational unit which is connected by feed-forward way. It estimates the missing data by training an MLP to learn incomplete data by using complete data [10]. On the other hand, in SOM, a set of nodes is organized in 2D grid, where each node has a specific position and weight. The weight is initialized by iterative training steps, and then it is used to estimate missing data [11]. Both of this methods require all data to trained and estimate the missing value. But in k-NN [12], to impute missing data, only k nearest neighbor's data is considered. These techniques are used in WSN to impute data but for real time CPS, these are not suitable.

Compressed sensing (CS) [13] is widely used scheme for signal processing to acquire and reconstruct a signal, based on underdetermined linear systems. This takes advantage of the signal's sparseness or compressibility in some domain, allowing the entire signal to be determined from relatively few measurements. The main difference between the missing data recovery problem and the conventional CS is that in the conventional CS, the sampling scheme can be determined by the users, and usually random linear projections are preferred, while in the missing data recovery problem the sampling matrix cannot be controlled by the user since it is determined by the missing events, e.g., locations of missing nodes in the network which is completely uncertain [14].

Guo, et al. [15] design an algorithm considering spatial-temporal correlations of sensor nodes, which is more suitable with WSNs due to nature of WSNs. Their algorithm first checks if a neighbor sensor node is within the missing sensor's sensing range. Then the observation from the neighbor is used for filling in the missing values. This generates a spatially correlated replacement. If there are multiple neighbors within the sensor's range and they do not have the same readings, the majority reading is chosen. But in real life, there is no guarantee that all the sensors within one hop neighbor are spatially and temporally correlated.

In the existing literature, there are other two ways to investigate the spatial correlation for missing data recovery, which is inverse distance weighted averaging (IDWA) [16] and Kriging [17]. The IDWA, which is relatively fast and easy to compute, is one of the most widely used methods for computing spatial interpolation [16]. Assuming the spatial correlation in adjacent sensors is uniform, IDWA tries to estimate the values of missing data in the form of some linear combination of neighboring sensor's data. The weights for the linear combination only depend on the distance between the sensors. The weight is higher for the sensor which is situated in large distance compare to the close one. Thus, IDWA will work well if the values of missing sensors are expected to be similar to values of the neighboring sensors. However, this assumption affects the estimation accuracy in many practical situations, where a physical phenomenon varies rather than uniformly increasing or decreasing in magnitude. The averaging process in IDWA has the tendency to smoothen the data, which is not suitable for the situation when data change fast in the area of interest.

Kriging is another way to estimate the missing samples using the combination of available measurements. It defines a semi-variogram by calculating the spatial correlation between sensors. From the semi variogram, the weight for the linear combination is determined. As a result, these weights vary spatially and depend on the correlation [17]. Assuming the historical variogram is known and can approximately represent the current variogram, missing samples are estimated based on the historical variogram function. However, the spatial interpolation may not be right if the semi-variogram varies a lot in the temporal dimension [14].

Besides these, many researchers combine Genetic Algorithm (GA) with Artificial Neural Network (ANN) [18], GA with Bayes algorithm [9] and many more to estimate the missing value.

Xia, et al. [19] first propose a solution for CPS over WSANs to cope with packet loss. They illustrate three prediction algorithms and show 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. So, previous sample is used to replace the missing value. 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 weighted average of all previous samples is taken to replace the missing one. Simulation result shows that third algorithm works well compared with others.

Choi, et al. [20] exploit an Exponentially Weighted Moving Average (EWMA) based value estimation algorithm to reduce the impact of packet. 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.

III. EFFICIENT SPATIAL DATA RECOVERY SCHEME

In this section, we propose a data recovery scheme for CPS, called efficient spatial data recovery (ESDR) scheme. Before we propose this scheme, we identify the nature of missing data. There are three types of missing data [7]; missing not at random (MNAR), missing at random (MAR), and missing completely at random (MCAR). In MNAR, the data are missing because of its own observation data. In MAR, the data are missing because of the data is depending on other variables. In MCAR, the data are missing because of unpredictable circumstances, e.g., the sending packet of a sensor is loss due to the radio link quality is poor. In this research, we design that our ESDR scheme is to mitigate the problem of MCAR. Fig. 2 shows that the control view of CPS with our proposed ESDR scheme.

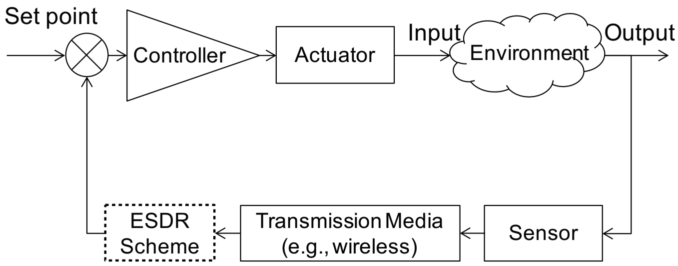

Fig. 2. Proposed data recovery scheme for control view of CPS.

To deploy our proposed ESDR scheme, we propose a flowchart with the ESDR scheme for CPS as depicted in Fig. 3. The following assumptions have been considered. First, the estimated data can be computed in a short time. Second, the historical dataset is available to perform the ESDR scheme. Third, the error offset of the measured data and estimated data is initially computed and known. Fourth, the maximum number of consecutive missing data (C) is fixed at initialization stage. prior set. The parameter C is also used for terminating the entire system to indicate the estimated data cannot be produced anymore because of the long consecutive missing data.

In the flowchart, the ESDR scheme will compute the estimated data when there is an input measured data from the sensors. When there is no missing data, the data offset error is computed and the measured data is used as a feedback data. When there is a missing data, the consecutive missing data is evaluated and the estimated data is used as a feedback data.

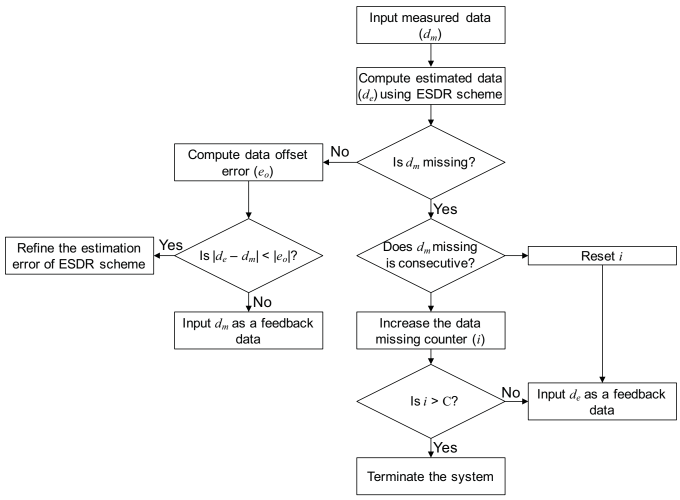

Fig. 3. Proposed flowchart with ESDR scheme for CPS.

As far as we are concerned, most of the spatial correlation for data recovery scheme is focusing on the data correlation that based on the difference between the nearest neighbor. In our ESDR scheme, we consider the most spatial correlation among the neighboring sensors based on the Pearson correlation coefficient (PCC) [22]. In PCC, if an environment is highly correlated in space, then the spatial information can be used to estimate missing data and the estimation function can achieve a high accuracy. PCC is a common measure of the linear correlation between two random variables i and j. It reflects the degree of association between two variables. Therefore, the PCC (ρ) in between two random variables i and j can be computed as follows

$$\rho_{ij} = \frac{\sum_{w=1}^{W}\left(i(w)-\bar{i}\right)\left(j(w)-\bar{j}\right)}{\sqrt{\sum_{w=1}^{W}\left(i(w)-\bar{i}\right)^2}\sqrt{\sum_{w=1}^{W}\left(j(w)-\bar{j}\right)^2}} \tag{1}$$

where W is the window size of the sample dataset.

Table I shows the association degree of the ρ. The range from -1.0 to 1.0 shows that the ρ has a degree of correlation. The negative value of ρ indicates the negative linear relationship, whereas the positive value of ρ indicates the positive linear relationship.

TABLE I. CORRELATION DEGREE OF PEARSON CORRELATION COEFFICIENT

No Correlation		$0.1 > \rho > -0.1$ and $1.0 > \rho$ and $\rho < -1.0$
Correlation Degree	Small	$0.1 \le \rho < 0.3$ and $-0.1 \ge \rho > -0.3$
	Medium	$0.3 \le \rho \le 0.5$ and $-0.3 \ge \rho \ge -0.5$
	Large	$0.5 < \rho \le 1.0$ and $-0.5 > \rho \ge -1.0$

Note: ρ is a correlation coefficient value.

Fig. 4 describes the ESDR algorithm, which is used to produce an estimated data from time to time. In this algorithm, we assume that the threshold value of estimation counter (c_{th}) is used to optimize the estimation function of the algorithm. Once the ESDR algorithm cannot use the PCC, we recommend that the estimated data is produced based on the nearest neighbor data. When the number of estimation counter for the corresponding of sensor k (c_k) is above the threshold value, the new corresponding of sensor will be computed again. To maintain high accuracy in estimation, we select the value of ρ is in between 0.5 to 1.0.

Algorithm: Efficient Spatial Data Recovery (ESDR)

if $c_k = 0$ **then**
  for each input sensor d_i **do**
    for all sensors d_j within one-hop neighbor of d_i **do**
      Compute ρ_{ij} with the specified window size, W
      if $0.5 < |\rho_{ij}| \le 1.0$ **then**
        $k \leftarrow \text{argmax}\{|\rho_{ij}|\}$; $c_k \leftarrow 1$
      end if
    end for
  end for
else if $c_k > c_{th}$ **then**
  $c_k \leftarrow 0$
else
  Compute ρ_{ik} with the specified window size, W
  if $0.5 < |\rho_{ik}| \le 1.0$ **then**
    $d_e(t) \leftarrow d_i(t) = d_k(t) + [d_i(t-1) - d_k(t-1)]$
  else
    $k \leftarrow \text{argmin}\{distance_{ij}\}$
    $d_e(t) \leftarrow d_i(t) = d_k(t) + [d_i(t-1) - d_k(t-1)]$
    $c_k \leftarrow c_k + 1$
  end if
end if

Fig. 4. Pseudo code for ESDR algorithm.

IV. NUMERICAL STUDIES

In this section, we conduct the simulation studies to evaluate our proposed ESDR scheme compared to the weighted prediction (WP) algorithm [19] and the spatial temporal imputation (STI) approach [15]. First, we conduct an experiment of WSN with four sensors and one base station as illustrated in Fig. 5. In this experiment, all the sensors forward their data to reach the base station in single radio hop through the simplest spanning tree topology routing protocol. We assign that all the sensors transmit their sensed temperature in every five seconds. We collect the information for one hour. We also ensure that all the sensors and the base station are located at the same height without any obstacle or object is placed in between them when the experiment is conducted in the indoor environment.

Based on the collected information from the experiment, we investigate the performance of our proposed scheme using a MATLAB. In this simulation, we assume that the Sensor_2 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), Mean Absolute Error (MAE) and Integral of Absolute Error (IAE) to evaluate the performance of the said algorithms.

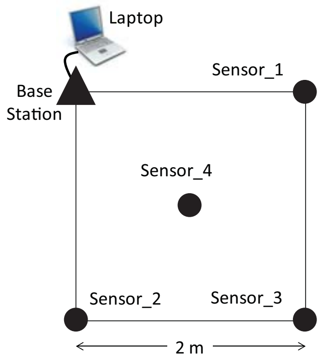

Fig. 5. Network topology of the WSN experiment for room temperature control in the smart home environment.

The RMSE is a frequently used measure of the difference between values estimated by an algorithm and the values actually measured from the real environment. 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

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}\left(d_m(n) - d_e(n)\right)^2}{N}} \tag{2}$$

where d_m 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

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|d_e(n) - d_m(n)\right| \tag{3}$$

The MAE measures the average magnitude of the errors in a data set, without considering their direction. It is also an average of the absolute error, $e = |d_e - d_m|$. In other words, it measures the accuracy for the continuous variables. The MAE and the RMSE can be used together to analyze the variation in the errors of the dataset. The RMSE will always be larger or equal to the MAE. The greater difference between them, the greater the variance in the individual errors in the sample [23].

If the RMSE is equal to the MAE, then all the errors are the same magnitude. In [23], Wilmott, et al. indicate that the MAE is the most natural and unambiguous measure of average error magnitude.

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

$$IAE = \int_0^t \left| d_e(t) - d_m(t) \right| dt \quad (4)$$

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 Discussions

In this section, we present our simulation results and make some discussions on the performance of algorithms. The aim of this simulation is to examine the potential of the proposed ESDR scheme in coping with the data missing for the CPS application. In our ESDR scheme, we measure the PCC in between the sensors from time to time by specified the window size (W) is ten data samples. We use the most correlated value of ρ to recover the missing data of Sensor_2. We realize that not all the sensors within one-hop neighbor are spatially correlated with each other. In our simulation, we investigate the impact of increasing percentage of missing data on the data recovery algorithm performance. The percentage of missing data is varied from 30% to 60% in steps of 10%.

Fig. 6 depicts the RMSE comparison among three data recovery algorithms. As the percentage of data missing increases, the proposed algorithm always shows better performance that is compared to the existing two algorithms. At the 40% data missing, the proposed ESDR scheme performs slightly better than the WP algorithm. At the 60% data missing, the proposed ESDR scheme reduces almost half of the RMSE than the WP algorithm. The reason for this dramatic improvement is because the WP algorithm cannot cope with the long consecutive missing data. Through this simulation, we can observe that this problem also can be found at the STI algorithm.

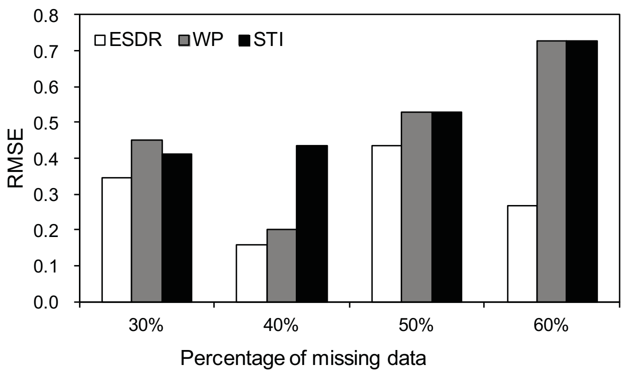

Fig. 6. The comparison of RMSE of all the data recovery algorithms as the percentage of missing data changes from 30% to 60%.

The MAE comparison among three data recovery algorithms is shown in Fig. 7. We can see that the proposed ESDR scheme outperforms the WP algorithm and the STI algorithm. Besides that, the proposed ESDR scheme can steadily maintain a small value of MAE regardless of the increment of missing data. This also means that the distance between the real measured data and estimated data of the proposed ESDR scheme is always stable. As a result, the proposed ESDR scheme can estimate a better value to recover the missing data. Simulation results reveal that the average MAE of the proposed ESDR scheme is about two times smaller than the WP algorithm and the STI algorithm.

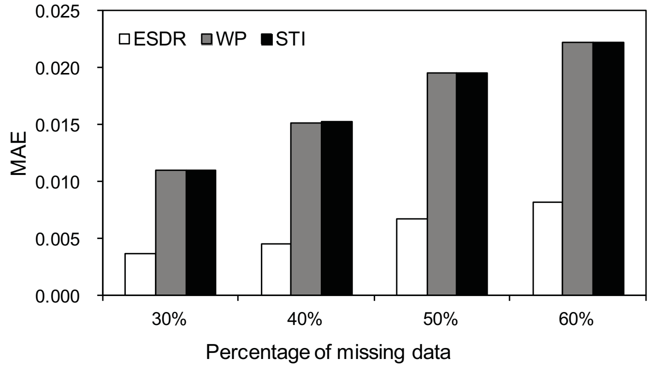

Fig. 7. The comparison of MAE of all the data recovery algorithms as the percentage of missing data changes from 30% to 60%.

In Fig. 8, the accumulated IAE comparison of all the data recovery algorithms is plotted. The simulation results demonstrate that the proposed ESDR scheme outperforms the WP algorithm and the STI algorithm. This is because of the error of the estimation function in the proposed ESDR scheme is minimized by using the PCC approach. The IAE values of the proposed ESDR scheme are 2.4 and 5.3 at the 30% and the 60% data missing, respectively. The average IAE of the WP and STI algorithms is about 3.5 times larger than the proposed ESDR scheme.

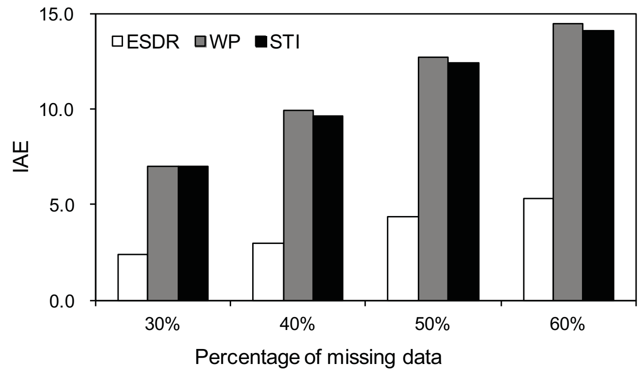

Fig. 8. The accumulated IAE comparison of all the data recovery algorithms as the percentage of missing data changes from 30% to 60%.

VI. CONCLUSION

In this paper, we have presented new data recovery scheme, called ESDR scheme to ensure a very low error in estimating the missing data. In this research work, we also identified that the nearest one-hop neighbor sensor is not always spatially correlated with the missing input sensor. Our simulation results reveals that the proposed ESDR scheme is very beneficial and outperforms the WP and STI algorithms regardless of the increment of missing data. At the preliminary stage, our research works are very encouraging and we will focus on finding the fine-tuned of window size (*W*). Further research is required to investigate a proper estimator with a good estimation algorithm and develop an refinement scheme for the offset error to improve the accuracy of the proposed ESDR scheme. Besides that, a future work will focus on examining the real-time missing data using the proposed ESDR scheme.

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