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Local Interpolated Compressive Sampling for Internet Traffic Reconstruction

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Abstract— **In this paper, we propose the integration of local interpolation on compressive sampling (CS) for application on internet traffic reconstruction. CS managed to solve the problem of missing Internet traffic but not in the case of extreme missing like Missing Elements at Random (MER) and Combine Missing Patterns (CMP). To overcome the problem is done by merging between local interpolations with CS. In this study conducted a comparison of local interpolation using correlation method and Euclidean norm and tested the effect of similarity parameters between rows and similarity between columns. The simulation results show that the incorporation of local interpolation can improve accuracy with insignificant time increaments, mainly on the addition of Euclidean norm technique.**

Keywords—local interpolation; compressive sampling; internet traffic matrix; correlation; Euclidean norm

I. INTRODUCTION

The problem of missing internet traffic becomes area that has been researched since 2006 by Roughan et all [1]. Roughan et al. explored the impact of six loss models, such as PureRandLoss, xxTimeRandLoss, xxElemRandLoss, xxElemSyncLoss, RowRandLoss, ColRandLoss on the performance of interpolation algorithms. They solved the problem by incorporating between spatio temporal CS using Sparsity Regularized Matrix Factorization (SRMF) and K-Nearest Neighbor (KNN) that performs superior for all loss models. In [2], Huibin et al. presented Self-Similarity and Temporal Compressive Sensing (SSTCS) algorithm for reconstructing lost traffic data consisting of Frequent Loss in Row (FLR), Successive Loss in Row (SLR), Frequent Loss in Column (FLC), Successive Loss in Column (SLC), Row Random Loss (RRL), Column Random Loss (CRL). This algorithm can retrieve the lost data with error less than 32% when data lost as much as 98%. In another research [3], the authors evaluated the effect of six missing patterns like as the missing problems on the actual network. The paper reported that CS reconstruction algorithms failed to recover the missing values for high loss, especially in the Missing Elements at Random (MER) and Combine Missing Patterns (CMP).

One of the simplest method for correcting the missing data is interpolation [1, 4, 5, 6]. It can solve the missing problems with small probability. The most recent work, since 2006, has introduced a new method known as Compressive Sensing (CS), which can improve the missing value in presence the available sample data [7, 8]. CS works with the following characteristics, ie sparse signal representation and Restricted Isometric Property (RIP) [9]. Sparse means signal with a few non-zero elements. Signals that are not sparse can be converted into sparse signals using the proper base transformation. Term that must be fulfilled in performing sparse signal recovery is RIP [10]. This property is almost orthonormal that acts as measurement matrix and applied to sparse vector.

In this paper, we proposed local interpolated compressive sampling to overcome the missing internet traffic. We first applied local interpolation which is focused on similarity property between rows and columns. We used two technique, such as correlation and Euclidean norm. We then combine its with CS reconstruction algorithms, such as Sparsity Regularized Singular Value Decomposition (SRSVD) [1]. l_1-norm optimization [11], Iteratively Reweighted Least Square (IRLS) [12], Orthogonal Matching Pursuit (OMP) [13].

II. THE PROPOSED METHODOLOGY

This section explains the proposed method of local interpolated compressive sampling for internet traffic reconstruction. The process of traffic matrix reconstruction in this research is shown in the Fig. 1. This proposed method is an extension of previous research in [3]. Traffic matrix data that used in our simulation is from Abilene network [14]. The data set is used previously in our research [3, 4]. The Abilene network is composed of 12×12 traffic flows connecting between nodes. Traffic flow is measured every 5 minutes. In one day, there are 288 measurements. In this study, the matrix represents that the row as a link between nodes and column as time measurements. The missing value is executed on TM matrix with probability p. After the missing process, were estimated based approach similarity between rows and columns using correlation and Euclidean norm. The CS process begins with a low-rank representation using SVD [15]. The next step is CS procedure of the low-rank matrix and mesurement matrix A. The compression result is returned as the original TM using CS reconstruction algorithms, consisting of SRSVD, SVDL1, IRLS, and OMP. The scaling process is purpose for obtaining an amplitude value proportional to the original value.

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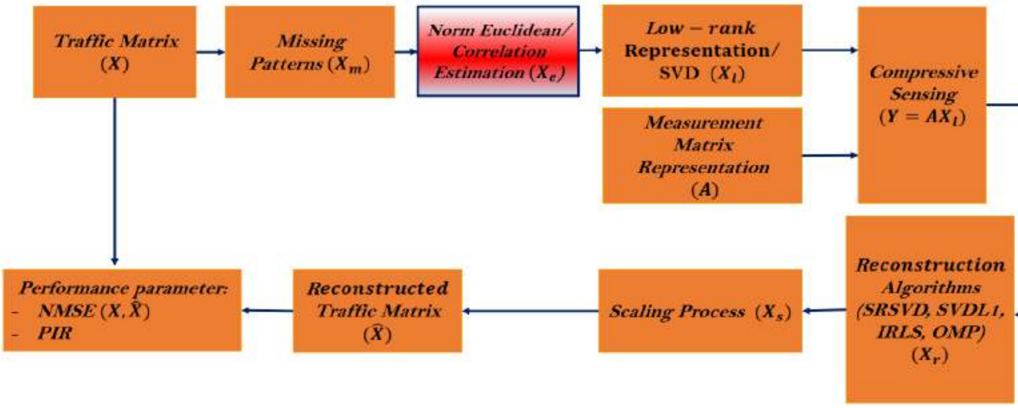


Fig. 1. The proposed method of local interpolated compressive sampling for internet traffic reconstruction

I. LOCAL INTERPOLATION

The interpolation solution is solved through a similarity approach between rows and columns to improve accuracy. If two rows/ columns show the similarity, then it can be assumed that one could be a great interpolant to another. We consider that the similarity of elements is influenced by the effect of the similarity between rows represented as α and the influence of similarities between columns expressed in β. We compare two methods to obtain the similarity, ie: correlation and Euclidean norm.

A. Correlation

Correlation uses the principle that the greater value of the correlation coefficient between rows / columns then the two rows / columns are similar. A traffic matrix of $\boldsymbol{X}$ sized $(i \times j)$ and missing elements at position $\boldsymbol{X_m}(\boldsymbol{m},\boldsymbol{n})$, then the correlation procedure on traffic matrix $\boldsymbol{X}$ are as follows:

Step 1) For the missing value in $\boldsymbol{X_m}(\boldsymbol{m},\boldsymbol{n})$, calculate the correlation coefficient between the row in the missing element $\boldsymbol{X_m}$ and the other row $\boldsymbol{X_i}$ with $i = 1,2,3,\ldots,i$ according to equation (1) below:

$$\rho(\boldsymbol{X_m},\boldsymbol{X_i}) = \frac{cov(\boldsymbol{X_m},\boldsymbol{X_i})}{\sqrt{cov(\boldsymbol{X_m},\boldsymbol{X_m})cov(\boldsymbol{X_i},\boldsymbol{X_i})}} \quad (1)$$

where $m \neq i$. Save the result in C_r

$$cov(\boldsymbol{X_m},\boldsymbol{X_i}) = \frac{1}{J-1}\sum_{j=1}^{J}\left((\boldsymbol{X_{m_j}} - \mu_{X_m})(\boldsymbol{X_{i_j}} - \mu_{X_i}\right) \quad (2)$$

$$\mu_X = \frac{1}{J}\sum_{j=1}^{J}\boldsymbol{X_j} \quad (3)$$

Step 2) Calculate the correlation between column of $\boldsymbol{X_n}$ with the other column of $\boldsymbol{X_j}$with $j = 1,2,3,\ldots,j$ and $n \neq j$ as in equation (1) and save the result in C_c.

Step 3) Find the maximum correlation coefficient in step 1 and 2

Step 4) Calculate the estimation results with correlation technique using equation (4)

$$\boldsymbol{X_e}(\boldsymbol{m},\boldsymbol{n}) = \alpha \ arg\,min_{\forall i, m\neq i}\, \rho(\boldsymbol{X_m},\boldsymbol{X_i}) + \beta\, arg\,min_{\forall j,\, n\neq j}\, \rho(\boldsymbol{X_n},\boldsymbol{X_j}) \quad (4)$$

where $0 \le \alpha \le 1,\ 0 \le \beta \le 1,\ \alpha + \beta = 1$

B. Euclidean Norm

The Euclidean norm approach states that the closer distance of the rows/ columns are, the two rows/ columns are similar. A traffic matrix size $\boldsymbol{X}$ $(i \times j)$ and missing elements at $\boldsymbol{X_m}(\boldsymbol{m},\boldsymbol{n})$, then the Euclidean norm steps on traffic matrix $\boldsymbol{X}$ are as follows:

Step 1) For the missing value in $\boldsymbol{X_m}(\boldsymbol{m},\boldsymbol{n})$, calculate the Euclidean norm between the row in the missing element $\boldsymbol{X_m}$ and the other row $\boldsymbol{X_i}$ with $i = 1,2,3,\ldots,i$. The equation becomes:

$$d(\boldsymbol{X_m},\boldsymbol{X_i}) = \sqrt{\sum_{j=1}^{j}\left(\boldsymbol{X_{m_j}} - \boldsymbol{X_{i_j}}\right)^2} \quad (5)$$

where $m \neq i$. Save the result to D_r

Step 2) Calculate the Euclidean norm between column of $\boldsymbol{X_n}$ with the other column of $\boldsymbol{X_j}$ with $j = 1,2,3,\ldots,j$ and $n \neq j$ as in equation (6) and save the result in D_c.

$$d(\boldsymbol{X_n},\boldsymbol{X_j}) = \sqrt{\sum_{i=1}^{i}\left(\boldsymbol{X_{n_i}} - \boldsymbol{X_{j_i}}\right)^2} \quad (6)$$

Step 3) Find the minimum norm from step 1 and 2

Step 4) Calculate the estimation of Euclidean norm $\boldsymbol{X_e}(\boldsymbol{m},\boldsymbol{n})$ using the following equation (7)

$$\boldsymbol{X_e}(\boldsymbol{m},\boldsymbol{n}) = \alpha \ arg\,min_{\forall i, m\neq i}\, d(\boldsymbol{X_m},\boldsymbol{X_i}) + \beta\, arg\,min_{\forall j,\, n\neq j}\, d(\boldsymbol{X_n},\boldsymbol{X_j}) \quad (7)$$

where $0 \le \alpha \le 1,\ 0 \le \beta \le 1,\ \alpha + \beta = 1$

II. EXPERIMENTAL AND RESULTS

A. Missing Patterns

We use six missing patterns such as Missing Row Elements (MRE), Missing Column Elements (MCE), Missing Rows at Random (MRR), Missing Columns at Random (MCR), Missing Elements at Random (MER), and Combine Missing Patterns (CMP) [3]. The missing is done by making a zero value on TM. This process is create randomly with the probability of missing(ρ).

MRE is a missing pattern by selecting one row and eliminating some elements in the selected row. Whereas MCE is a missing that chooses single column in TM and omits some elements in the column chosen. The missing model that deletes rows randomly is MRR, whereas the column is MCR. MER is missing by removing random elements. CMP is a combination of all previous missing models.

B. Performance Parameter

The performance parameter used to calculate the accuracy of TM reconstructed is Normalized Mean Square Error (NMSE). The NMSE is Mean Square Error (MSE) between the original TM $\boldsymbol{X(i,j)}$ and the reconstructed TM $\boldsymbol{\hat{X}}(\boldsymbol{i,j})$ normalized by MSE of original TM, which is mathematically expressed in the following equations [16]:

$$NMSE\big(\boldsymbol{X(i,j)},\boldsymbol{\hat{X}}(\boldsymbol{i,j})\big) = \frac{MSE\ \big(\boldsymbol{X(i,j)},\boldsymbol{\hat{X}(i,j)}\big)}{MSE\ (X(i,j),0)} = \frac{\|\boldsymbol{X(i,j)} - \boldsymbol{\hat{X}}\ (\boldsymbol{i,j})\|_2^2}{\|\boldsymbol{X(i,j)}\|_2^2} \quad (8)$$

The other metric is Performance Improvement Ratio (PIR). The PIR denotes an increasing in a new approach to the old method. In this study, we used NMSE to calculate PIR, which is defined as follows [17]:

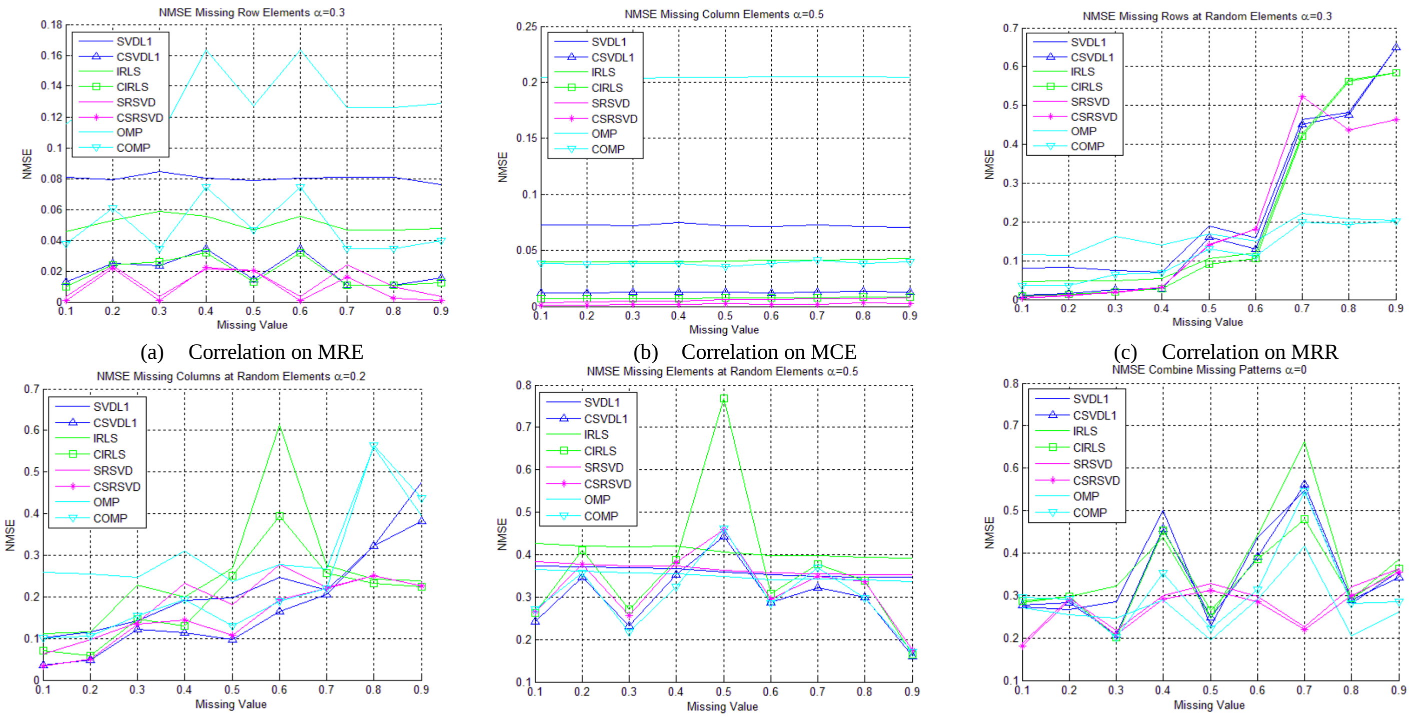
$$PIR = \frac{NMSE_l - NMSE_n}{NMSE_l} \quad (9)$$

where $NMSE_l$ denotes performance parameter from old algorithm, while the $NMSE_n$ states the performance of the proposed algorithm.

C. Proposed Reconstruction Algorithms

This work incorporates the local interpolation consisting of correlation and Euclidean norm technique with the CS methods (SRSVD, SVDL1, IRLS, and OMP) in order to improve its performance. A combination of correlation with CS reconstruction algorithms produces new methods called Correlation SRSVD (CSRSVD), Correlation SVDL1 (CSVDL1), Correlation IRLS (CIRLS), and Correlation OMP (COMP). While the enhance of Euclidean norm is named Euclidean SRSVD (ESRSVD), Euclidean SVDL1 (ESVDL1), Euclidean IRLS (EIRLS), and Euclidean OMP (EOMP).

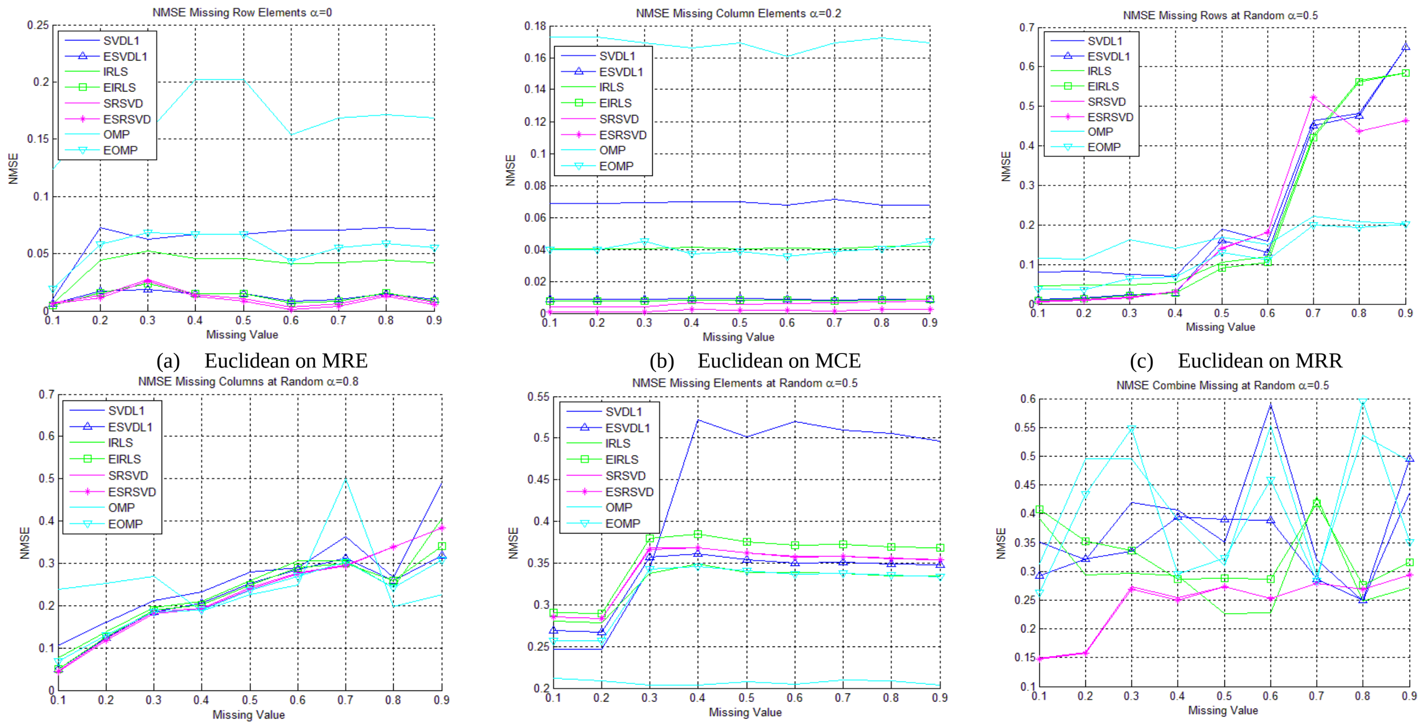
Fig. 2 and Fig. 3 show the relationship between NMSE and the probability of missing on different missing types and α parameter. The X-axis is missing value and the Y-axis is the NMSE. This test describes the effect of missing value on the reconstruction result.



(a) Correlation on MRE (b) Correlation on MCE (c) Correlation on MRR

(d) Correlation on MCR (e) Correlation on MER (f) Correlation on CMP

Fig. 2. NMSE and missing value relationship in different missing patterns using correlation technique



(a) Euclidean on MRE (b) Euclidean on MCE (c) Euclidean on MRR

(d) Euclidean on MCR (e) Euclidean on MER (f) Euclidean on CMP

Fig. 3. NMSE and missing value relationship in different missing patterns using Euclidean norm technique

Fig. 2. (a) shows NMSE on MRE pattern with α parameter 0.3. All proposed algorithms can improve accuracy with NMSE results <0.08. The increasing of missing probabilities has no effect on NMSE. Because missing elements only occur on one row so that the number of available samples is still quite a lot. In missing probability 0.9 on one row is equal with 0.6% missing from the total number of matrix elements. Fig. 3. (a) expresses NMSE on MRE missing pattern with α parameter 0. All proposed algorithms can improve accuracy with NMSE results <0.07. EOMP shows the largest NMSE decline, followed by ESVDL1 and EIRLS. While the ESRSVD decrease in NMSE is not significant.

Fig. 2. (b) describes the NMSE value of the MCE pattern with α parameter 0.5, while Fig. 3. (b) at α parameter 0.2. The amount of missing probability has no effect on NMSE, this is because the missing probability of 0.9 on one column is identical to 0.3% missing of whole elements matrix. The reconstruction algorithm applied to the missing MCE pattern always yields the best accuracy compared to the other missing techniques. The simulation results show the NMSE value less than 0.05 on all the proposed algorithms.

Fig. 2. (c) indicates the NMSE on MRR pattern with α parameter 0.3, whereas Fig. 3. (c) with α parameter 0.5. The NMSE value increases with increasing the probability of missing. The proposed algorithm can only slightly lower the value of NMSE, especially in CSRSVD and ESRSVD. While COMP and EOMP show the best performance.

Fig. 2. (d) describes NMSE on MCR pattern with α parameter 0.5, while Fig. 3. (d) at α parameter 0.8. In this model, the NMSE value is proportional to the probability of missing. All proposed algorithms succeeded in decreasing the NMSE, except on COMP and EOMP. Its produce poor performance due to an increase in NMSE value when the probability of lost traffic starts from 0.8.

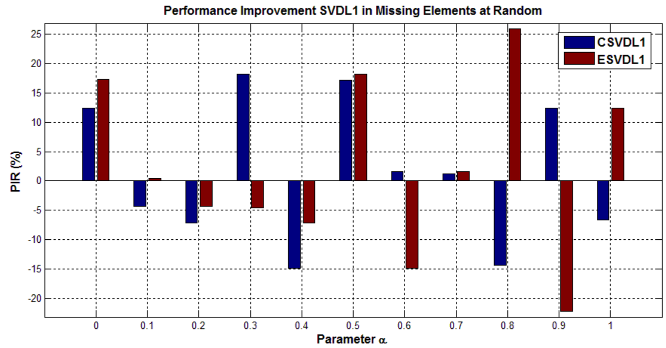
Fig. 2. (e) and Fig. 3. (e) illustrate the NMSE on MER pattern with α parameter 0.5. In Fig. 2. (e), some conditions suggest that the proposed algorithm decreases the performance of the accuracy results, as shown in the probability of missing 0.5. This is due to the random nature of the missing traffic elements so that existing traffic does not have a high correlation with each other to predict the values of missing elements. In Fig. 3 (e) shows that only ESRSVD decreases NMSE even though the decrease is very low. The other proposed algorithms can not work well. This is greatly influenced by the random way of missing elements so that the present elements in the matrix may have bit of similarity. Therefore, the new algorithm is difficult to get the closest distance between matrix elements.

Fig. 2. (f) shows NMSE on CMP pattern with α parameter 0, while Fig. 3. (f) at α parameter 0.5. In Fig. 2 (f) indicates that significant decrease occurs in CIRLS. In Fig. 3. (f) shows that the proposed algorithms do not work well where some tests are able to decrease NMSE, and some actually increase NMSE. It is because the CMP is a combination of some missing randomly chosen, such as missing rows, missing columns, and missing elements, then the probability of a certain missing can result in intersection between missing processes so that the amount of missing becomes less or even vice versa. COMP and EOMP are not suitable for CMP missing model.

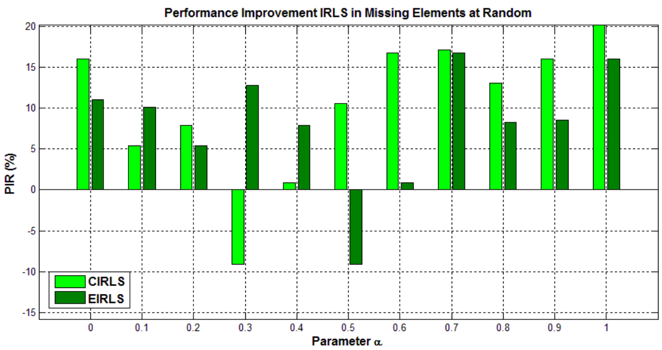
D. Similarity Parameter

The similarity parameter that used are two, namely the similarity between rows (α) and similarities between columns (β). The similarity between rows implies the relationships that occur between links, while the similarity between columns refers to the relationship between time. The experiments were performed 10 times and the average performance improvement result shown in Fig. 4. The results are presented only in the case of missing MER.

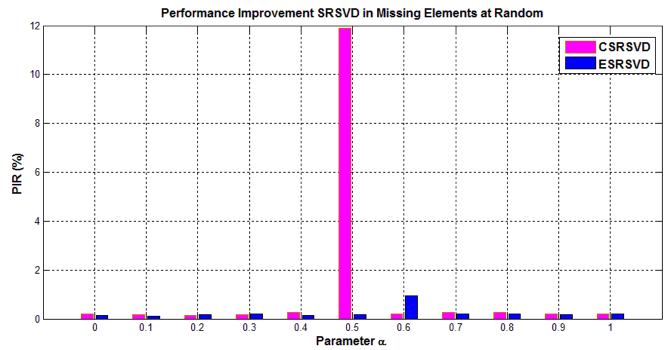
Performance improvements at all parameter α occur in CSRSVD and ESRSVD, although the increase is very small, ie less than 12% in CSRSVD and less than 1% in ESRSVD. While on the other algorithms, performance improvement is strongly influenced by correlation factor between row and column. In CIRLS and EIRLS, 90% of the experiments show performance improvement, and the highest performance occurs at $\alpha = 1$ and $\beta = 0$ on CIRLS, it indicates that accuracy is only affected by correlation between rows. On EIRLS, the best performance occurs at $\alpha = 0.7$ and $\beta = 0.3$. In CSVDL1, 60% of the experiments showed the highest performance improvement with $\alpha = 0.3$ and $\beta = 0.7$, this illustrates that the correlation between columns is more important than the correlation between rows at the time of reconstruction. ESVDL1, 60% of the experiments showed the highest performance improvement occurred at $\alpha = 0.8$ and $\beta = 0.2$ On COMP, 20% of the experiments increased, and the maximum performance occurred at $\alpha = \beta = 0.5$. While EOMP, 10% experiments increased, and maximum performance occurred at $\alpha = 0.4$ and $\beta = 0.6$.



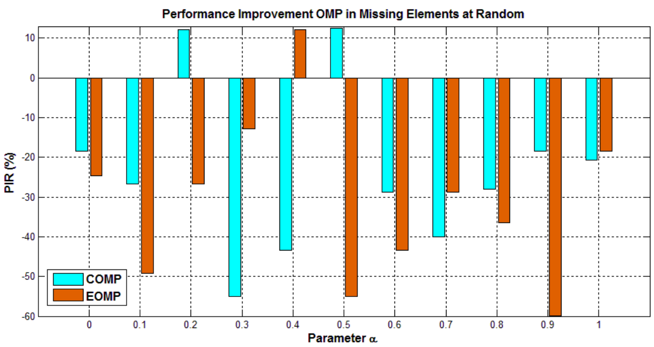
(a) SVDL1



(b) IRLS



(c) SVDL1



(d) IRLS

(a)

Fig. 2. The influence of parameter $\boldsymbol{\alpha}$ on the MER missing pattern in the proposed algorithms (a) SVDL1, (b) IRLS, (c) SRSVD, (d) OMP

E. Running Time

The running time testing aims to determine the effect of time that occurs due to the addition of local interpolation. Table I shows the experimental results that performed on MRE case with probability missing 50%, parameter $\alpha = 0$ and $\beta = 1$. The addition of correlation techniques led to an increase in average running time of 9.83 seconds compared to the original algorithm. Whereas in addition to the euclidean norm technique, the addition of running time has no significant effect. The average running time is about 0.4 seconds.

TABLE I. RUNNING TIME FOR RECONSTRUCTION ALGORITHMS

Reconstruction Algorithms	**Running Time (second)**		
	Original Technique	***Combination Correlation***	***Enhanced Euclidean Norm***
SVDL1	23.2259	33.1651	23.2712
IRLS	1.735798	11.91579	2.03541
SRSVD	0.870585	10.29429	1.503879
OMP	0.868778	10.64318	1.45948

III. CONCLUSIONS

Enhance norm Euclidean and Combination of Correlation on CS reconstruction algorithm (SVDL1, IRLS, SRSVD, OMP) can improve accuracy in case of lost traffic MRE and MCE. ESRSVD and CSRSVD do not provide significant performance improvements since SRSVD has been able to work well in TM reconstruction. EIRLS and CIRLS can provide significant performance improvements even though NMSE values still need to be fixed. EOMP and COMP are not suitable for performance improvements, especially in lost MCR, MER, and CMP traffic patterns. The addition of local interpolation results the increased of running time. The time required for the correlation process is longer than the time of the euclidean norm process.

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