Signal Reconstruction through Compressive Sensing and Principal Component Analysis in Wireless Sensor Networks

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Abstract
With the emergence of Wireless Sensor Networks (WSNs), Data Acquisition (DAQ) and signal reconstruction have been considered as the main area of interest in the IT research. In this paper, using an external server connected to the internet, the adaptive acquisition framework and WSN of signal reconstruction (AAR framework with D-PCA) along with the combination of the distilled sensing algorithms have been taken into account. Furthermore, for monitoring, Distributed Principal Component Analysis (D-PCA), data collection and signal reconstruction of WSNs are also considered. The results of the simulation show that using the adaptive algorithms of the Compressive Distilled Sensing in the signal sampling is more significant than the non-adaptive compressed Sensing algorithms. The former can solve the scalability problem and it also leads to the increase of the quality of signal sampling in WSNs. Moreover, by exploiting the algorithm of D-PCA for designing the Sparse Dictionary i.e. Ψ matrix in the server, the measurements with greater sparse have been transferred to the server which leads to a more exact reconstruction. In reconstructing the acquired signals, especially the sparse signals or signals with temporal correlation, the proposed framework in this work is very effective. The presented method decreased the number of samples and improved the signal reconstruction error smaller than 5 × 10-6.
Keywords:
Compressive sensing, compressive distilled sensing; distilledsensing:distributed principal component analysis; wireless sensor network

1. Introduction

The wireless sensor network is comprised of a great number of sensor nodes which are widely spread in an environment and it also collects information from the environment [1]. Data processing belongs to a large part of modern life. The favorite data usually have representations which are in the form of sparse in the main basis or the transformation basis. In general, the sparse has a significant role in sciences: For instance sparsity affects the estimates [2]. One of the important algorithms which is greatly effective in making sparsity structures is the principal components analysis algorithm [3] and this is particularly true with its distributed kind [4, 5]. Principal components analysis is a statistical analysis which selects a lower number of factors as the eigenvalues among the primal factors in order to omit some minor details.

In the traditional methods for sampling the data, all of the data are obtained firstly and then compressed. According to Donoho the problem with such processing is that: “Why these attempts are made to collect all the data while most of them will be discarded? Cannot we measure just the part which is not going to be discarded?” [6]. Instead, compressed sensing will do the same thing.

In the spite of attractions of compressed sensing method, this method has problems with the augmentation or existence of strong noise in the environment and losses required efficiency from accuracy and reduced in signal reconstruction error. This issue has made us to implement our proposed framework based on the adaptive compressive distilled sensing sampling method [7]. Our proposed framework has been presented in the two forms of the adaptive and non-adaptive in which the non-adaptive method compressed sensing of traditional theory [6] and has been used for sampling but in the other one, the distilled sensing [8] has been exploited in the compressed sensing.

To monitor and control all of the operations in the wireless sensor network through a server connected to the internet, an architecture framework has been designed and implemented. The overall architecture of our proposal consists of four blocks which are treated momentarily. However these blocks include:

Database: It is responsible for storing the measurements of the wireless sensor network.

The reconstruction signal and adaptive control block consists of two main modules:

b.1. Adaptive control module: It is responsible for transferring the measurement instruction and refining locations from which the measurements are collected. Other method of this analysis algorithm module is the principal distributed component which is the sparsity dictionary i.e. Ψ matrix (it is worth noting that signal values and sparsity dictionary are respectively located in Φ and Ψ matrices which are displayed by a change of the variable and like many of the articles, it is demonstrated in symbolic form as a matrix i.e. A. Thus the matrix of A equals $A = \Psi\ \Phi$) to redesign the next round of

Manuscript received June 5, 2017
Manuscript revised June 20, 2017

measurements.

b.2. Signal reconstruction module: It is responsible for reconstructing the signals presented in the database; the core of this module is the first order algorithm NESTA [9].

Transmission block: This block is responsible for wireless sensor network transmissions.

Representation Block: It is responsible for displaying the reconstructed measurements in a dialogic context for the end user.

In the second section, the literature review is provided. In the third section, non-adaptive approach, adaptive approach, the principal component analysis algorithm and its distributed kind, NESTA algorithm and the theoretical stages of the reconstruction of the results from an adaptive framework of sampling signal are explained by NESTA algorithm. In the fourth section, all of the frameworks of adaptive framework of sampling signal and the proposed signal reconstruction are explained. In the fifth section, the results of the simulation which has been obtained by MATLAB software and frameworks under MATLAB, the l_1-Magic [10] and GPSR [11] will be explored. In the last section, the results and the solutions are provided for the future researches.

2. SecLiterature Review

The system Ebrahim and Assi[12] introduced the approach based on parallel projections on the basis of compressed sensing. They demonstrated that parallel approach can be effective in improving the consumed energy by decreasing the transmissions rate. However, this method in is non-adaptive and, as we will see in the last section of this paper, non-adaptive methods have weak performance in noisy contexts. In [13] solving the problem of data collection in WSNs with compressed sensing theory based on Random Walk approach has been considered. In this article a framework is proposed for collecting data with the random approach. It is worth noting that, the influence of ambient noise on the signal in its DAQ and reconstruction has been overlooked. In [14] a framework has been proposed for monitoring the wireless sensor network based on compressed sensing. In this article the samples are also made in the non-adaptive form and by a random matrix, besides at the round called the stage of training, the sensor nodes start to collect the data with the possibility equal to 1 which leads to the increase in the load of network as a result of decrease in the lifetime.

3. Data Acquisition Methods and Signal Reconstruction from Theoretical Viewpoint

3.1 Non-Adaptive Approach Based on Traditional Compressed Sensing

In this section, we deal with the general issue of reconstructing the sparse vector $x \in R^n$. Let us assume that x is simply described as the following Eq. (1).

$y = x + e$. (1)

Where $e \in R^n$ shows noise, x is regarded as sparse signal and all the non-zero components of x have the same value like $\mu > 0$. Support of x Eq. is shown in the form of $S = S(x) = support(x)$ which is a collection of all of the parameters in which x have non-zero components, for the noise quantity, we assume that $e \in \mathbb{R}^n$ represents a vector of additive Gaussian white noise; i.e. $e_j \overset{i.i.d}{\sim} \mathcal{N}(0,1), j = 1,2, \dots, n$ where i.i.d. stands for independent and identically distributed $\mathcal{N}(0,1)$ denotes the standard Gaussian distribution. The main goal in this work is to reconstruct support of x or to obtain an accurate estimation using the y noise data; here the support is shown as $\hat{S} = \hat{S}(y) = \hat{S}_{DS}$.

3.2 Adaptive Approach Based on Compressive Distilled Sensing

3.2.1. Distillation Sensing

We begin our discussion with Distillation Sensing (DS) by presenting a slightly generalized model of Eq. (1). Assume that we are able to collect measurements of x components in T observation steps; according to the model (1), we will have:

$y_{t,j} = x_j + \rho_{t,j}^{-1/2} e_{t,j}, j = 1,2, \dots, n,\ t = 1,2, \dots, T.$ (2)

Where the noise parameter is $e_{t,j}$ with the equal value of $i.i.d\ \mathcal{N}(0,1)$, t is the index related to the observing step and $p_{t,j}$ is the precision of non-negative parameters that can be selected for changing the noise variance at the current observation level. In other words, the variance of added noise related to the observing step $y_{t,j}$ equals $p_{t,j}^{-1}$. Thus, the highest value of $p_{t,j}$ is indicative of the greatest precision in observance. More specifically, the locations will be identified at the next steps which are related to the observations. They are strictly greater than zero meaning that I_2 satisfies the following Eq. $I_2 = \{j \in I_1 : y_t > 0\}$. For more information and observation of DS algorithm code see the work elsewhere [8, 15].

3.2.2. Distillation in Compressive Sensing

It is clear that adaptability in sampling can make considerable improvement in effective measurement of

SNR about the issue of sparse reconstruction. On the other hand, the number of the collected measurements by DS process [8] is absolutely greater than non-adaptive method. Since each component of the signal is measured at least once and some of the components might be measured T times meaning that every repetition of this process one time measurement is done, at the refinement step of DS algorithm(or in average) removes approximately half of the locations lacking signal components.

The observation model (2) can be written as follows:

$y_{t,j} = \rho_{t,j}^{1/2} x_j + e_{t,j}\ , j = 1,2, \ldots, n,\ t = 1,2, \ldots, T$(3)

Under the above formulation, the whole process of sampling can be effectively modeled by the matrix vector formulation $y = Ax + e$ where A (A = ΨΦ) is a matrix with the values of the signal. We provide our interpretation of resources measurement budget from the viewpoint of matrix A which is meant to state that the quantity1$\sum_{t,j} p_{t,y}$ is related to the limitation on all of the observation times and also the relevant quantity of this model encapsulates an inherent flexibility in the sampling process which inclines sensing of the resources towards the locations which have useful data [7, 15], in the main limitation formulation of $\sum_{t,j} p_{t,s}$, it is imposed on the measurement budget.

Now, let us explore the compressive distilled sensing algorithm. Every step of the algorithm is displayed with the index below $t = 1, 2, \ldots, \mathrm{T}$ .we calculate the measurements by $m_t \times n$t sampling matrix of A_t through the following method. It means for $u = 1,2, \ldots . m_t$ and $v \in \mathrm{I_t}$ ($\mathrm{I_t}$ is the same as set of promising locations), $-I(u, v)$th entry of A_t is independently obtained from the distribution $\mathcal{N}(0, \frac{\tau_t}{m_t})$ which$\tau_t = B_t/|I_t|$. Otherwise, the mentioned entry in $\mathrm{A_t}$matrix becomes equal to zero which means if $\mathrm{v} \in \mathrm{I_c}$, $\mathrm{I_c}$ is the total locations without signal components. For further information and observing the pseudo-code algorithm of DS see other works in the literature [7, 15].

3.3 Making Sparsity Matrix and Compressing by PCA and D-PCA

3.3.1. Compressing by PCA

Assume that $x_k \in \mathbb{R}^N$ is the measurement vector of our WSN in the time interval of k with n nodes. The measurements are based on fixed sampling rate in k discrete-time of $K = 1,2, \ldots . , K$ have been collected. Geometrically speaking, x_k is regarded as a location in $\mathbb{R}^N$ and by observing M-dimensional plan (where $M \ll N$), the best location in accordance with $x_k$is obtained in terms of its smallest Euclidean distance. Mean and covariance of $2x_{k3}$ are respectively displayed by $\hat{x}$ and $\hat{\sum}$ and is calculated easily by the following Eq. [16]:

$$\hat{x} = \frac{1}{k \sum_{k=1}^{K} x_k}, \widehat{\sum} = \frac{1}{k} \sum_{k=1}^{K} (x_k - \bar{x})(x_k - \bar{x})^T \quad (4)$$

Notice that in $Kyfan$ theorem, maximizing $\sum_{j=1}^{M} b_j^T \sum b_j$ is related to finding out the linear transformation $T: \mathbb{R}^N \rightarrow \mathbb{R}^M 4$ which guarantees the maximum data about the main signal $x_k \in \mathbb{R}^N$ should be maintained [3].

3.3.2. Compressing by D-PCA

PCA primal technique [3] is based on the linear transformation of sensor measurements. When the number of measurements is small, this linear transformation is effective, otherwise, it not only increases the computation time but also increases the consuming energy. The more the signal has sparsity, the more effective and precise the reconstruction can be [6]. Therefore, we use methods cited in to sparse the measured data framework and redesign its sparsity dictionary Ψ (which is shown here by $\hat{X}$ and in the text by $A = \Psi\Phi$) in the next round of our measurement. If y inputs are sufficiently correlated, the total eigenvalues of sparsity in the sparsity dictionary $\hat{X}$ can use compression matrix to compress M-dimensional measurements in the columns of Y to Q-dimension ($Q \ll Y$), which means $\hat{Z} = \hat{X}^h Y$. Now, the reconstruction of the signal can be done by implementing $\hat{X}$ as a decompression matrix which means $\mathrm{Y} = \hat{X}$.In terms of the minimum error squares criterion to the linear compression, the function of $\hat{X}$ is much better than Eq. of traditional PCA [4, 5].

If $\hat{X}$ is known, the coefficients of this matrix can be transferred to the nodes and it can be used in the future measurements of compression with X sparsity dictionary. To this end, the following block partition is defined [4]:

$$\hat{X} = \begin{bmatrix} \hat{X}_1 \\ \vdots \\ \hat{X}_K \end{bmatrix}. \quad (5)$$

Where $\hat{X}_k$ is a part of $\hat{X}$coefficients which are used iny_k. It means $\hat{X}^H y = \sum_{k \in K} \hat{X}_K^H y_K$, thus the node number of k can transmit the observations in Q-dimension to the M-dimension.

[1]This limitation is related to the total measurements which can be made it means that if we assume that $B(n)$is the measurement budget the mentioned limitation should satisfy the Eq. below $\sum_{t=1}^{T} \sum_{j=1}^{J} p_{t,j} \leq B(n)$.

[2] Mean and Covariance

3.4 Sparse Reconstruction Signal Algorithm of NESTA

NESTA [9] is a quick and strong first-order method which is developed to resolve the Basis-pursuit problems. The mentioned algorithm uses two methods of YuriiNesterov[17, 18], the first of which is idea of the accelerated convergence scheme for the first-order method. It provides optimal convergence rate for the issues of the mentioned class. The second idea is the smooth technique which is a substitution for the non-smooth technique of l_1 −norm.
NESTA primal algorithm solves the problem of Eq. 6, which is often known as the basis pursuit denoising (BDPN) [9]:
$(BP_\varepsilon)\ minimize\ ||x||_{l_1} subject\ to\ ||b - Ax||_{l_2} \leq \epsilon$ (6)
Parameter ϵ is normally small and is calculated in accordance with the estimation of the standard deviation error from every noise in the measurements. If ϵ was equal to zero, this problem was just an issue of the basis pursuit. The smoothed version of NESTA solves the l_1 −norm meaning that instead of solving the problem as follows,
$minimize\ ||\alpha||_{l_1}\ subject\ to\ x \in Q_p$, (7)
where$Q_p$is the primal feasible set as (8),
$Q_p = \{x: ||b - Ax||_{l_2} \leq \epsilon\}$, (8)
and solves it in the form of the following Eq.:
$minimize\ f_\mu(x) subject\ to\ x \in Q_p$. (9)
Where $f_\mu$the smoothed version of is l_1 −norm, which if μ is equal to zero, f_μ is exactly the same as l_1 −norm. It should be noted that in order to increase the accuracy, μ should be selected in a small number and for accelerating the performance one should choose a greater value ofμ .

3.4.1. NESTA Sparse Signal Reconstruction Algorithm

As mentioned in [7, 15] one can reconstruct the compressed signal which is the result of measurement vector of y and sampling matrix of A with various algorithms such as LASSO [19] or other sparse signal reconstruction algorithms [20]. Here, we are eager to resolve the convex optimization problem by the first-order and precise algorithm of NESTA [9]. To understand the reconstruction process, we can model the measurement model (3) by the standard and known sampling matrix equation:
$y = Ax + e$,(10)
Where x is assumed to be sparse, A is the sampling matrix of vector or measurement, y is the measurement vector in T time and e is the same as added noise to the signal in nosed contexts. Now, according to Model 10, the support set for the minimization of l_1 −norm can be solved through the following Eq.:
$\hat{x} = {}_{subject\ to\ ||y_t - A_t x||_{l_2} \leq \varepsilon}^{minimize\ ||x||_{l_1}}$. (11)
LASSO algorithm can be solved as:
$\hat{x} = argmin_{z \in \mathbb{R}^n} ||y_t - A_t Z||_2^2 + \lambda ||Z||_1$. (12)
As mentioned above, the smoothed version of NESTA solves $l_1 -$ norm, instead of solving through the minimization Eq. 11 in the following form below:
$minimize\ ||x||_{l_1} s.t\ \ x \in Q_p$, (13)
Where $Q_p$is the same as the primal feasible set:
$Q_p = \{x: ||y_t - A_t x||_{l_2} \leq \varepsilon$, (14)
and it is solved as:
$minimize\ f_\mu(x)\ s.t\ \ x \in Q_p$. (15)
Where$f_\mu(x)$ is the smoothed version of l_1 −norm. With regard to the Eq. $\min_{x \in Q_p} f(x)$ in [18], the problem of Eq. 10 can be rewritten for reconstructing by the NESTA algorithm as:
$\min_{x \in Q_p} ||x||_{l_1}$, (16)
Where Q_p is in the sampling interval of convex Tand $x \in \mathbb{R}^n$ one sparse vector with only Qeffective ($Q \ll M$) element for reconstructing. The ε is related to noise in matrix y_t measurements in noisy environments and $A$is equal with $p_{t,j}^{1/2}$ and is the sample matrix of our framework. In NESTA, $||x||_{l_1}$in the form of a maximizing problem can be rewritten as:
$||x||_{l_1} = \max_{u \in Q_d} \langle u, x \rangle$, (17)
Where $Q_d \subseteq \mathbb{R}^n$ is the same as $l_\infty$and is defined as:
$Q_d = \{u: ||u||_\infty \leq 1\}$, (18)
Thus, $||x||_{l_1}$ function with regard to Eq. 9 is estimated as:
$||x||_{l_1} \simeq f_\mu(x) = \max_{u \in Q_d} \{ \langle u, s \rangle - \frac{\mu}{2} ||u||_{l_2}^2 \}$, (19)
It is shown that the function $\nabla f_\mu(x)$ is a Lipschitz function [9]. As a result, NESTA method solves the Eq.:
$min_{x \in Q_p'} max_{u \in Q_d} \{\langle u, x \rangle - \frac{u}{2} ||u||_{l_2}\}$. (20)
Now, Eq. (13) can be solved through Nesterov minimization algorithm in a linear time by sequential evaluation of the elements of u. In fact, the supporting set which we display as $\hat{S}_{DS}$ is calculated as below:
$\hat{S}_{DS} = argmax_{u \in Q_d} \{\langle u, x \rangle - \frac{u}{2} ||u||_2^2\}$ (21)
Now the supporting set can be defined as below:
$\hat{S}_{DS} = \{j \in I_t, \hat{x}_j > 0\}$.(22)

4. Adaptive Framework of Data Acquisition and Reconstructing Wireless Sensor of Network Signal

The proposed framework or namely adaptive framework for data acquisition and reconstruction signal in wireless sensor network with distributed PCA is abbreviated as AAR-Framework with D-PCA by combining the distributed component analysis and is comprised of four main parts: database, signal reconstructing block including two main modules i.e. adaptive control module and signal reconstructing module, transmission block and representation block.

1. Database: This component is the mediator between all the blocks which receive their required data from this component. Every measurement in this component is described by three fields first of which is Sensor ID: that is the characteristic of the sensor that transmitted the data. Signal Value: it measures the values by the sensor with the specified in the ID field. Capture Time: it shows discrete time sample $t = 1,2,\dots,T$.
2. Signal reconstructing block and adaptive control
   2.1 Adaptive control module: This module is responsible for synchronizingDAQ process with regard to the refinement step output related to compressive distilled sensing algorithm. The observation step with $y_t = A_t x + e_t$ is the start of sampling step in which the order of starting the measurements is transferred and the measurements are calculated by the output resulted from the refinement step. As a result, it causes the practiced samples to become potentially having non-zero components of the signal. Thus, the refining step is implemented which divides the locations in the measurement step into two independent sets that are used in the the next round of iteration(in observation step), The theoretical expression of the module is done as below:

$$\underbrace{y_1, y_2, \dots, y_{t+1}}_{Observation}, \underbrace{I_1, I_2, \dots, I_{t+1}}_{Refinement} \qquad (23)$$

The set of locations equals with $\{I_t\}_{t=1}^{T}$ and the observations is $\{y_t, A_t\}_{t=1}^{T}$. One of the other responsibilities of this module is redesigning sparse dictionary. The coefficients of sparsity dictionary are calculated by the main distributed component analysis signal. Then, the sparsity dictionary is redesigned and transferred to the sensor nodes along with the promising locations. In Figure 1, a scheme of adaptive control module design is displayed:

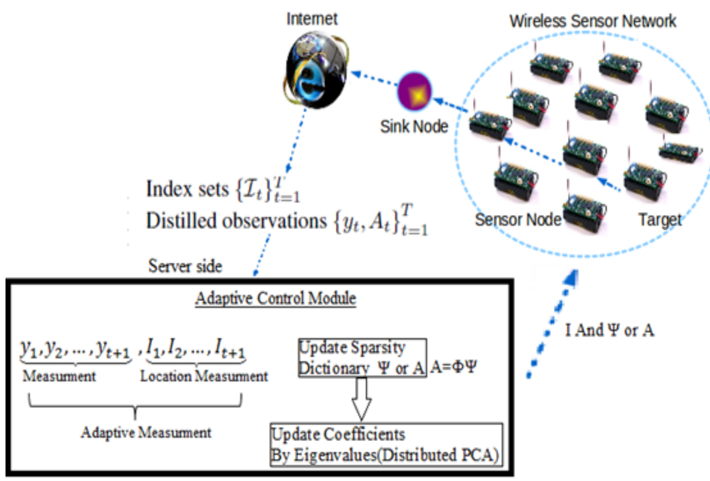

Fig. 1Adaptive control module

   2.2. Signal reconstructing module: It is responsible for reconstructing the main by the measurements within the database in every refining step which is shown by the index $t = 1,2,\dots,T$.. The measurements are calculated by A_t matrix which is a $m_t * n$ matrix. The output of compressive distilled sensing algorithm or $\{y_t, A_t\}_{t=1}^{T}$ is the optimization NESTA reconstruction algorithm.
3. Transmission block: It is the enter and exit gate of the frameworks messages which consists of adaptive control module messages for the next period of DAQ and the sensing network data to transmit to the database.
4. Representation Block: The reconstructed data of WSNs are shown to the end user in an interactive environment.

5. Results and Discussions

In order to analyze the AAR Framework with D-PCA, by applying the changes, the package of $l_1 - Magic$[10] of GPSR software is used [11]. In the present analysis, the proposed framework is compared with two WNS-Control and Non-adaptive frameworks [14] with regard to precision, the amount of reconstruction error and the locations from which the samples are taken. It is worth noting that in these analyses to have a better glance at the efficacy of our framework, three main indices are used:

i. Mean squared error index (MSE) [21]: This index is used for determining the amount of reconstruction error proportionate to the signal scale:

$$MSE = \left(\frac{1}{n}\right) ||\hat{s} - x||_2^2 \quad (24)$$

ii. False discovery proportion index (FDP) [15]: Non-zero signal components are located in some of these locations while it is not the case:

$$FDP(\hat{S}) = \frac{|\hat{S} \setminus S|}{|\hat{S}|} \quad (25)$$

iii. Non-discovery proportion index (NDP) [15]: A special situation including non-zero signal components, while this is not true:

$$NDP(\hat{S}) = \frac{|S \setminus \hat{S}|}{|S|} \quad (26)$$

The analysis under the different signal scales which are generally displayed by n are taken into consideration for $n = 2^{12}, 2^{13}, \ldots, 2^{22}$. A summary of applying parameters are shown in Table 1:

Table 1.Simulation Parameters.

Index	Value
Sampling scale signal(or signal length)	$n = 2^{12}, 2^{13}, \ldots, 2^{22}$
Noise	0-25 dB
Sparsity level (non-zero samples)	5-1024
Number of experiment's turn	1000

Figure 2 displays ascatter plot of FDP and NDP values with the mean value of 1000 trials from both AAR-Framework with D-PCA and non-adaptive. The experiments are related to signal with the length of $n = 2^{22}$and 128 non-zero existence within the range of $\mu > 0$ and $SNR = 20dB$.

As shown in Fig. 2, the error performance of non-adaptive process with regard to

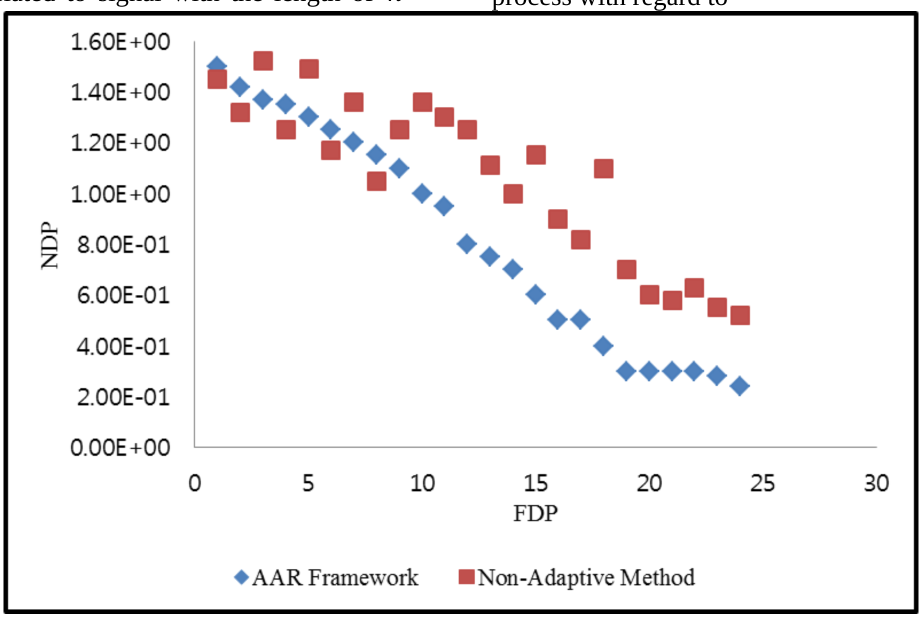

Fig. 2NDP and PDF spread charts (scatter plot) for the adaptive framework AAR-Framework with D-PCA and non-adaptive algorithm

Expansion of the dimensions decreases in a great extant while the performance of the adaptive framework is the same to a great extent. In Figure 3, we used the MSE criterion to estimate the reconstruction signal error with regard to the different amounts of noise in the environmentswithin the interval $e = [5 - 25]dB$ and the fixed signal length of $n = 2^{22}$ with the same reconstructed signal algorithms (NESTA). It is observed that the reconstruction error of our proposed framework when confronted by the strong noise $SNR > 20dB$ and a signal of very great scale due to exploiting the distributed principal component analysis algorithm in redesigning the sparsity dictionary is under the certainthreshold of 10^{-6}.

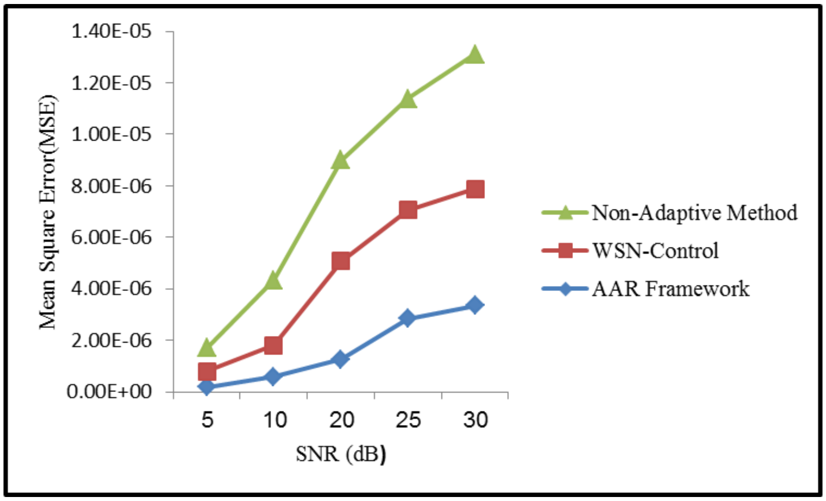

Fig. 3Examining the amount of signal reconstruction error with MSE signal

In Figure 4, the signal length of $n = 2^{10}$, the number of components of non-zero main signal within the range of $k = [5 - 600]$ (sparsity level) and noise level are considered as equal to$25dB$. The results show that non-adaptive method recognizes a lower number of non-zero components of the main signal along with the increase in the amount of signal scale which causes impairment in reconstructing process and loss of much of signal data.

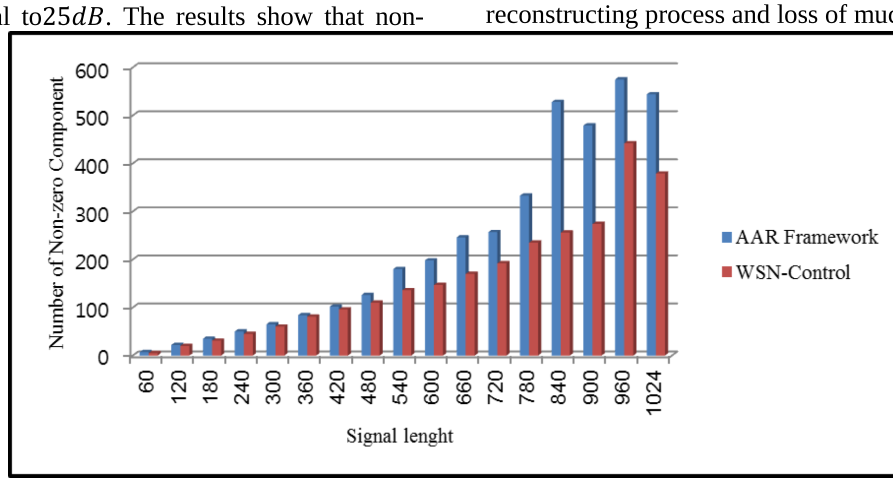

Fig. 4The number of adaptive non-zero components of the main signal

6. Conclusions

AAR framework with D-PCA was proposed for monitoring and acquisition wireless sensor network. In this framework, distilled sensing theory for DAQ of wireless sensor network in adaptive form is exploited, disturbed principal component analysis algorithm for redesigning sparsity dictionary Ψ (or A) and signal reconstruction algorithm of NESTA. The results of simulation showed that the proposed method has been scalable and due to the improvement of signal reconstruction error, it lead into the precision and increase in the sampling quality.

Moreover, according to redesigning of the sparsity dictionary through distributed principal component analysis algorithm, firstly the transmission rate in the network has decreased which leads to the increase in the life time of the wireless sensor network. Secondly, sparsity dictionary also in each period of implementation is redesigned effectively. Our future work is allocated to changing the refining step in the compressive distilled sensing algorithm for sampling the signals with the positive and negative amplitude.

Introduction should argue the case for the study, outlining only essential background, and should not include the findings or the conclusions. It should not be a review of the subject area, but should finish with a clear statement of the question being addressed.

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