Correlation-Based Wireless Sensor Networks Performance: The Compressed Sensing Paradigm

Theofanis Xifilidis Kostas E. Psannis

Dept. of Applied Informatics, University of Macedonia, Thessaloniki, Greece

Abstract- In this paper, the performance of Wireless Sensor Networks (WSNs) operating for environmental monitoring is investigated. The performance metrics considered are normalized reconstruction error and energy estimation error. The temporal, spatial and spatiotemporal correlations are separately considered for the above metrics. The independent case and correlated cases for dense measurement cases along with the Compressed Sensing (CS) compressibility rule by selecting a subset of measurements for metric evaluation are thoroughly examined with extensive simulations and technical interpretations. Finally, applications of the proposed scheme are formulated in terms of topology and routing in fifth generation sensor networks and Internet of Things (IoT) deployment scenarios.

Keywords- Compressed Sensing, correlation, error, Wireless Sensor Networks

1. Introduction

WSNs [1] are the nowadays efficient solution for environmental monitoring quantities such as temperature, humidity, light and target tracking to representatively mention a few. WSNs consist of densely deployed sensors over the geographic area of interest and their task is to periodically monitor physical quantities or detect military targets in an area where they have been autonomously deployed.

Relative to the performance of WSNs, the main bottleneck that characterizes these networks is the limited energy for accomplishing the sensing, computation and communication tasks. This limitation stems from either the size and cost of the sensors introducing the limited stored energy or the infeasibility of recharging in inaccessible or hostile environments where the sensors have been deployed. In addition, the main challenges regarding design, deployment and efficient operation of WSNs are the ability to autonomously adapt to changes in topology, node failure or node battery depletion and reconfigure to continue operating even without the existence of a sink node or coordinator. Hence, the decentralized property remains a critical issue despite the advances in designing and deploying WSNs, as opposed to the centralized scenario where the computational issue is alleviated by the manner which assigns computational tasks to the sink or base station where the energy limitation does not hold as opposed to sensors. Moreover, the concept of mobility relative to nodes or multiple sinks in a network can extend the lifetime and compensate for holes in the network if properly designed taking synchronization into account. Finally, the heterogeneity of the network together with asymmetry which deals with unevenly dividing computation and communication of data through the network is another major challenge in state-of-the-art WSNs.

The concept of temporal, spatial and spatiotemporal correlation, as a means to optimize performance in terms of data gathering and processing, equivalent to redundant data is already a mature scientific area that promises to further boost network performance and reduce complexity of data reconstruction methods.

CS [2], [3], [4] is one of the most recent active scientific areas with two-fold optimization benefits: the alleviation of computation complexity and implementation complexity. It relies on dimensionality reduction of measurements enabling optimal data recovery/decoding by a small amount of linear projections. Noisy cases are also effectively treated and CS already exhibits effective algorithms regarding signal processing as well as optimization of wireless communications performance [5] with two related aspects: sparsity and compressibility. The former retains only nonzero measurements under the crucial assumption of nonzero measurements being a small fraction of initial dense measurements. The latter is a more quantitative aspect that retains the largest in magnitude measurements given a case specific threshold. Over the scientific progress made in the CS field, benefits introduced from signal processing emigrated to wireless communications performance. Integrated with temporal and spatial correlation as well as the spatiotemporal consideration CS provides more efficient data decoding and reconstruction as well as low complexity processing and useful information extraction.

2. Related work and contribution

WSNs have gathered significant research attention ever since their adoption and widespread deployment in a large scale manner. Relative to overall network design, an excellent survey [6] covering application specific requirements concerning WSN design and practical deployment including classification and analysis of WSN design issues and infrastructure. Another survey offering a holistic view of the main bottleneck of energy conservation in WSNs [7], includes a detailed taxonomy of energy saving methodologies such as data-driven approaches, duty-cycling, MAC protocols and mobility based viewpoints. The properties of temporal and spatial correlation have been extensively investigated verifying the benefits introduced by their consideration in WSN performance. Network self-management architecture is studied in [8] for power preservation by a temporal correlation aware sleep scheduling scheme jointly with quality of sensor observations. Spatial correlation addressed in a detailed work [9] integrates the relation of redundant data and spatial correlation together with an energy-aware consideration for packet delivery rate, active sensors and distortion. Another work [10] addresses the dense deployment case related to spatial correlation and redundancy in the same manner utilizing aggregation techniques to prolong lifetime and reduce communication overhead. Spatiotemporal correlation addressed in [11] describes performance optimization in terms of spatiotemporal coverage simplifying the relative NP-hard problem formulated. Moreover, a remarkable work [12] presents results of reduced reconstruction error along with robust prediction employing deep learning for predicting spatiotemporal signal in terms of sensor deployment optimization. Reduction of sampling and transmission rate relying on spatiotemporal correlation to significantly reduce energy consumption is investigated in [13].

CS has already been applied in WSNs [14]. Integrated with the spatiotemporal-based properties that realizes the optimal and low complexity of computations and implementation, it has been applied to numerous cases verifying its effectiveness as a reduced data reconstruction complexity methodology. Regarding CS-based temporal correlation, the paper [15] is representative exploiting CS sparsity with the latter correlation proposing algorithms that contribute to reducing energy consumption. CS is combined with spatial correlation in [16], the main contribution being joint sparsity model and energy efficient decoding and improved reconstruction error by applying spatial correlation aware algorithm. Moreover, the authors in [17] exploit CS sparsity of the covariance matrix aiming at providing the fusion center with compressed observations including noise variance uncertainty.

The combined effect of spatiotemporal correlation with CS is the main aspect for WSNs optimized performance, which is reflected by the fact that most of the publications exploit this joint spatiotemporal correlation. The authors in [18] propose a new scheme based on Kronecker CS and exploiting spatiotemporal correlation achieving improved results concerning the energy-performance tradeoff and reconstruction accuracy. Kronecker CS is also applied in [19] with the covariogram-based algorithm to exploit spatiotemporal correlation with the ability to adapt to signal correlation instead of a priori known value. Finally, [20] proposes a copula function scheme with CS to indicate superior performance against popular approaches such as classical or distributed CS schemes.

To the best of the authors' knowledge, this is the first work to consider temporal and spatial correlation property to optimize performance separately and jointly spatiotemporal correlation proposing a probabilistic scheme. The proposed scheme involves a vector x with mean values generated by multiple realizations of average values of sensor readings following a Gaussian distribution of zero mean and variance equal to the inverse of the number of readings forming the sum from which the average values are computed and consequently the realization elements of the vector. This vector is transformed by a matrix whose elements are produced in the same above way: sum of Gaussian zero mean same variance elements and realizations of dimension equal to matrix dimensionality. Finally, vector Y is also produced in the same way with same variance of the elements comprising the sum equal to the above and mean value depending on variance and the second moment either unit for temporal correlation case and inverse of number of realizations for the spatial correlation case. For the spatiotemporal case both assumptions are fairly considered for the distribution mean value calculation. Based on the mismatch between vector Y and the product of matrix Φ and vector x, the reconstruction error of the respective mean values Y and those of product Φ and vector x is estimated in the dense independent case, dense correlated case, and CS based case by considering the largest values based on compressibility error threshold. The error formulation is based on subtracting the values of the vector resulting from multiplication of matrix Φ and vector x from the values of the vector Y. The error considered is derived by division of the above difference from the vector Y values. It must be clearly noted that compressibility rule is the applicable CS related assumption, as opposed to sparsity. The reason is that channel gains do not practically take zero values. Instead, keeping the largest in magnitude cases is realistic in fading channel values and provides meaningful results. Considering the energy of each of the elements of the matrices the same dense independent, dense correlated and CS case based on compressibility rule, the mean values of energy estimation are considered for the above matrices, with the difference that the results now stem from sum of energies of the elements. The energy error is computed for each case. The results are interpreted in detail and applications to 5G WSNs and IoT network of the proposed scheme are provided.

3. System model and mathematical preliminaries

3.1 System model

This paper proposes a WSN model where the nodes are deployed in areas of equal distance defining the neighboring set of nodes and of areas of successively increasing distance thus enabling the determination of the area within which spatial correlation model can be applied. Instead of a square area or an area with the sink at the center of concentric circles, the tree based network is the most suitable model, as a compromise between centralized and in-network cases. It also enables the definition of a node neighborhood in a network where there is a bidirectional information exchange and the deployed nodes can be modeled by a set of vertices V representing the nodes and edges E, i.e. a graph G(V,E). A connected tree network is formed i.e. data flows are feasible between any pair of nodes. Moreover, the communication range is larger than maximum node distance. However, node interference stemming from the model considered is out of paper scope. As a complementary assumption, the network may be divided into clusters with each cluster consisting of cluster heads based on remaining battery energy or distance from the sink and nodes forwarding data to each respective cluster. Moreover, sampling rate is not quantified but considered large enough to achieve the temporal correlation as an assumption for the simulations conducted. Due to spatial correlation also assumed the neighboring nodes are considered to be d-hops away from the leaf nodes where d is successively increased as an integer as we move from the leaf nodes towards the sink. However, the consideration of the actual measured distance between nodes of a set or between nodes/clusters and sink is not quantified but assumed to be varying within a small range for a neighboring set of nodes and successively increasing as the transition from leaf nodes to sink takes place.

3.2 Mathematical preliminaries

The main mathematical tool involved in the investigation of this paper is the Gaussian distribution which is the most fundamental distribution in statistics of wireless communications. It is characterized by symmetry and, consequently, as non-skewed requires only the mean and variance parameters to be fully described.

The first tool utilized concerning the Gaussian distribution is the notion of independence between the random variables of a sum with the latter sum approaching a Gaussian distribution with a mean equal to the sum of the means, a generic property of a random variable sum, and the variance equal to the sum of variances of the variables comprising of the sum stemming from the notion of independence which cancels the covariance terms and leads to the above result. Proceeding to the correlated variables, the resulting sum of variables with equal pairwise correlation has the same mean equal to the sum of the means and a variance equal to the following formula:

$$\mathrm{var}(S) = N * \sigma^2 \left[1 + (\mathrm{N} - 1)\rho\right] \tag{1}$$

where σ^2 is the variance of each of the variables and ρ is the equal pairwise correlation. It is easily verified that in the independent scenario the second term in parenthesis is zero and the former result is verified. Additionally, the independent additive noise contaminating the sensor readings in both estimation and energy error derivations is also assumed Gaussian.

The next mathematical formulation is the statement of the estimation error of the means of the average values of the measured readings from each of the sensors in the neighborhood considered along with the estimation error of the mean value of the average values of the energy of the readings from each sensor. The problem is stated as follows:

$$Y=\Phi*x+e \tag{2}$$

where x is the vector of the mean values each resulting from the average values of the readings from the subset of sensors considered and Gaussian distribution of the sensor readings. The matrix Φ is the transformation matrix each element of which also represents mean values of average values of Gaussian distributed random numbers with same parameters. The vector Y is also Gaussian distributed with random values produced in the same manner but with a nonzero mean as opposed to vectors x and Φ. The remaining vector e is the mismatch between the measurement vector Y and transformed vector $\Phi*x$. The error is formed by considering the above mismatch divided by the respective values of vector Y, as stated in contribution part. In terms of error quantities, the aforementioned one constitutes the model mismatch already derived and the second consists of the additive Gaussian noise contaminating the sensor readings.

The nonzero means of the temporal and spatial separate cases are derived via the equation relating the first order moment i.e. mean, second order moment and variance of the assumed distribution. The mean is thus evaluated from the following equation:

$$mean=\sqrt{\mathrm{E}\left[x^2\right]-\sigma^2} \tag{3}$$

where the second order moment quantifies the power and σ^2 equals the variance. Given the latter two quantities inside the root the mean is accordingly calculated.

Finally, the case of error in energy estimation employs the (non-central) chi-square distribution with k degrees of freedom and s as the non-centrality parameter. However, analysis also resorts to a tight approximation of the latter chi-square distribution via Gaussian distribution as in [21]. The main reason for applying such a Gaussian approximation is that in such statistics the number of largest in magnitude elements preserved in the CS compressibility cases is quantified by a known formula, tackling the quantification for the non-central chi-square distribution case.

4. Algorithm formulations

This section derives two algorithms the first regarding reconstruction error estimation and the second energy error estimation for temporal, spatial and spatiotemporal cases including both noiseless and noisy cases in each separate case.

Algorithm 1 Reconstruction error estimation

1. **Input**: Temporal correlation casetemp, spatial correlation casespat, spatiotemporal correlation casespattemp. Number of readings in each sensor (temporal/spatial cases), number of sensing periods and power consumption for temporal case/number of sensors and power consumption for spatial case/equal number of sensing periods and sensors for spatiotemporal case. Additive Gaussian noise distribution as $N(0,1)$.

   For casetemp, noiseless case
2. Calculate mean and variance of each sensor reading.

   For the independence case
3. Calculate the encoded measurement vector Y, the transformation matrix Φ and vector x.
4. Estimate reconstruction error of means of average values of sensor readings (vector x), transformation matrix Φ and vector Y. Evaluate according to error magnitude and sign.

   For correlation case
5. Modify variance of sum according to correlation value and repeat step 3 and 4.

   For Compressed Sensing case
6. Determine correlation and sparsity ratio values, and repeat steps 3 and 4 for low and high sparsity ratio values.

   For casetemp, noisy case
7. Increase sensor reading variance by one and repeat steps 3-6.

   For casespat, noiseless case
8. Modify mean value of distribution of Y and repeat steps 3-6.

   For casespat, noisy case
9. Increase sensor reading variance by one and repeat steps 3-6.

   For casespattemp, noiseless case
10. Modify mean value of distribution of Y and repeat steps 3-6.

    For casespattemp, noisy case
11. Increase sensor reading variance by one and repeat steps 3-6.

    end

As indicated by the above algorithm all three correlation cases are included with the separate assumptions of noiseless and additive Gaussian noise in each case.

Algorithm 2 Energy error estimation

1. **Input**: Temporal correlation casetemp, spatial correlation casespat, spatiotemporal correlation casespattemp. Number of readings in each sensor (temporal/spatial/spatiotemporal cases), number of sensing periods and power consumption for temporal case/number of sensors and power

consumption for spatial case/equal number of sensing periods and sensors for spatiotemporal case. Additive Gaussian noise distribution as $N(0,1)$. Gaussian distribution approximation of non-central chi-square distribution.

For casetemp, noiseless case

2. Calculate mean and variance of each sensor reading.

3. Calculate degrees of freedom and non-centrality parameter of the (non-central) chi-square distribution modeling the sum of energies of the random variables.

4. Based on Gaussian approximation, calculate the encoded vector Y, transformation matrix Φ and vector x of mean values of average values of energies.

5. Estimate energy error and evaluate according to error magnitude and sign.

For correlation case

6. Modify non-centrality parameter according to correlation value and repeat step 3-5.

For Compressed Sensing case

7. Determine correlation and sparsity ratio values, modify non-centrality parameter and repeat steps 3-5 for low and high sparsity ratio values.

For casetemp, noisy case

8. Increase sensor reading variance by one, modify non-centrality parameter and repeat steps 2-7.

For casespat, noiseless case

9. Modify non-centrality parameter and repeat steps 2-7.

For casespat, noisy case

10. Increase sensor reading variance by one, modify non-centrality parameter and repeat steps 2-7.

For casespattemp, noiseless case

11. Modify non-centrality parameter and repeat steps 2-7.

For casespattemp, noisy case

12. Increase sensor reading variance by one, modify non-centrality parameter and repeat steps 2-7.

end

---

5. Simulation results

The simulations of this section were conducted using MATLAB software. They are divided in two subsections: the first presenting results of the reconstruction error of means of average values of vector Y relative to the product of measurement matrix Φ and vector x, i.e. the transformed, via matrix Φ, vector x and the second, energy estimation error of the means of average values of energy of the random variables.

5.1 Reconstruction error

Regarding vector Y, the mean value of each random variable of the sum that derives the average values is calculated based on Eq. (3) with unit power assumption as the value of the second order moment and a variance equal to 1/40 indicating 40 random variables in the sums of the vectors of eq.2. Finally, for each set of average values, a total of 30 realizations were generated representing 30 means of average values of 40 equivalent random variables comprising the sum. For the 30×30 vector Φ each variable in the sum was Gaussian distributed with zero mean and the above mentioned variance. The same Gaussian statistics also hold for vector x. For the CS case, the simulations were conducted introducing sparsity ratio from 0.1 to 0.9 with an increment of 0.1 along with considering correlation from 0.1 to 0.9 with the same increment of 0.1. The quantification of CS number of elements preserved is based on Gaussian statistics and is a function of the varying sparsity ratio considered. For all simulations conducted, the smallest integer greater than the decimal value resulting from the formula is considered for each case. Pairs were then made and the pair with the smallest estimation error was chosen for simulating the reconstruction error. A key final assumption regarding correlation is that all elements are equally pairwise correlated in temporal and spatial correlation cases. In the spatiotemporal case, the correlation value is equal between elements in the two groups as well as inside each temporal and spatial group.

5.1.1 Temporal correlation noiseless case

Based on the above valued parameters, the figure below depicts the reconstruction errors of the independence case by the blue curve, correlation case by the red curve and CS based cases with green curve representing the low sparsity ratio and magenta curve representing the high sparsity ratio. CS based cases retain only a subset of the 40 average values in each realization, as explained above. The value considered from each curve is the value at fifteenth realization which is indicative due to curve symmetry with respect to this realization.

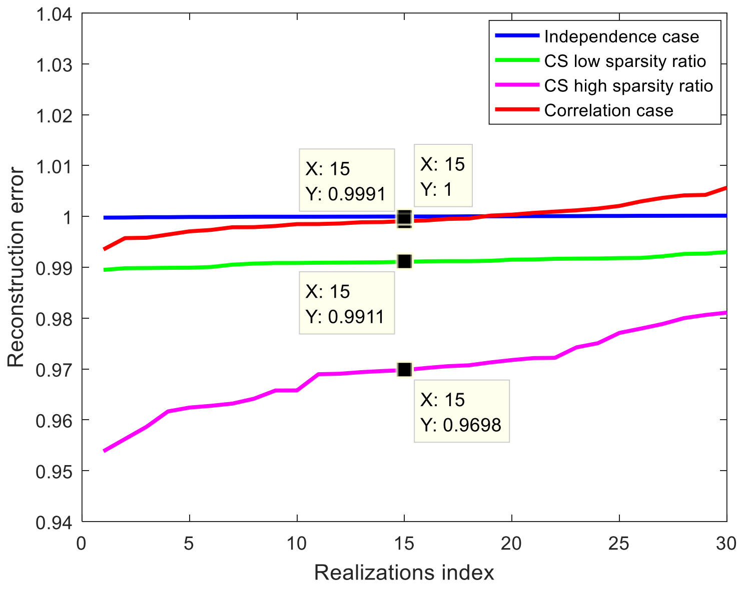


Fig.1 Reconstruction Error for temporal noiseless correlation case

As is apparent from the figure, the independence case performs the worst. The slightly lower error indicated by the correlation case dictates that in this case correlation introduces negligible benefit considered in case high data precision where mean value estimation error is measured up to fourth decimal digit. The first indication of error optimality for the CS case is displayed in the figure with the green curve representing the case of sparsity ratio equal to 0.1 and correlation equal to 0.1 and the magenta curve with sparsity ratio equal to 0.9 and correlation equal to 0.8. Thus, the crucial observation is the lower estimation error of the CS case with the lowest sparsity ratio i.e. the minimum fraction of mean values preserved and the low correlation complying with the requirement of incoherence of the values considered. Another interesting observation is the lower error assuming the largest sparsity ratio equal to 0.9 and correlation equal to 0.8. Hence, in the case where a small fraction of the elements is discarded the high value of correlation results in a further error improvement. Towards a clarified comment for this observation with a high correlation value but always in the CS regime, the effect of correlation is an even lower error compared to the error of the CS low sparsity ratio case.

5.1.2 Temporal correlation noisy case

This case includes additive Gaussian noise modeled as zero mean unit variance. The important observation in this step is that the variance of sensor readings of x or elements of matrices Φ and Y increase from a small decimal value to an increased value by one. This is due to $N(0,1)$ noise consideration and the independence assumption resulting to a variance of sum of independent variables equal to sum of variances of each of the variables in the sum. The effect of such an assumption is that the variance of variables representing the sum of readings or measurements are characterized by an order of magnitude larger variance and, as a consequence, the variance of the sums as well as average values and means is magnified, leading to a Gaussian distribution with a much wider bell curve. The relative figure for the temporal correlation noisy case is given below:

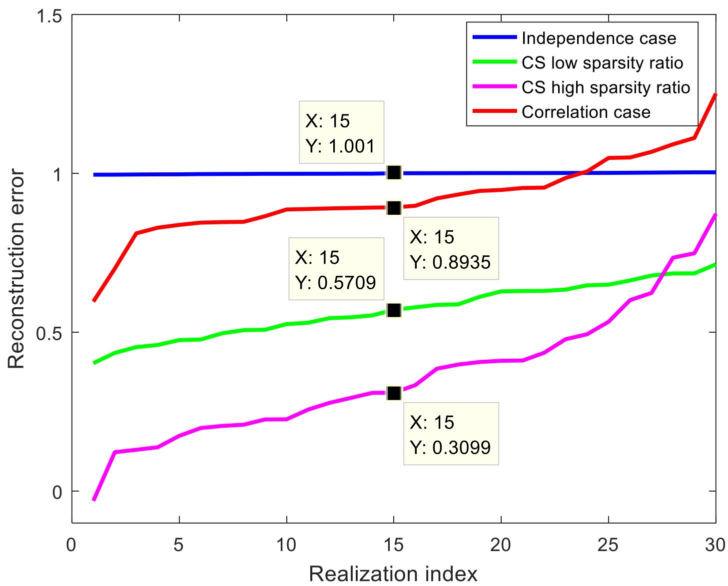


Fig.2 Reconstruction error for temporal noisy correlation case

The green curve assumes sparsity ratio equal to 0.1 and correlation equal to 0.3. CS based high sparsity ratio (magenta curve) assume sparsity ratio 0.9 and correlation equal to 0.8. Apart from the independence case, the other cases depict a lower error, significantly lower in the CS cases. This however, is contrary to the effect of increased error when noise contaminates the samples. For the above observation there is a straightforward explanation. The Gaussian curves of mean values of average values of sensor readings of x, elements of transformation matrix Φ and encoded measurements of Y are much wider in the noisy case. This is the reason why the Gaussian bell curves overlap. For matrix Y the curve is placed with respect to a positive nonzero mean while the curves of Φ and x are zero mean Gaussian distributed. In this case, they produce random variables in a wider value range and also overlap with each other. Indicatively, the error shifts towards lower values as a result of the random elements obtaining more distant values from the mean of the distribution with higher probability. In some cases, simulations indicated negative error values which verify the latter justification based on Gaussian bell curves overlap. The technical interpretation of the above is that the independent additive noise along with a larger uncertainty reflected by the significantly wide curves and the resulting overlap. By adjusting the correlation to a more general scenario where for each problem correlation value range is specified, the balance of achieving lower error can be obtained as opposed to the ideal case of independence. Returning to the simulation results, the CS based cases follow the same trend as in the noiseless case but with lower error magnitude.

5.1.3 Spatial correlation noiseless case

The main difference between the spatial case and the temporal case is the smaller nonzero mean of the Gaussian distribution modeling the encoded measurement vector Y. That is instead of unit power assumption in the temporal correlation case, the unit power is evenly spread to the 30 nodes defining the neighborhood of the network deployed. Thus, the second order moment in mean calculation formula is equal to 1/30. This assumption is essentially based on the concept of spreading particularly in the power metric, which spreads the energy budget to all nodes in a selected subset, hence a uniform allocation of available power. The variance of each variable of the sums remains the same as in previous cases. The figure for this case is given below:

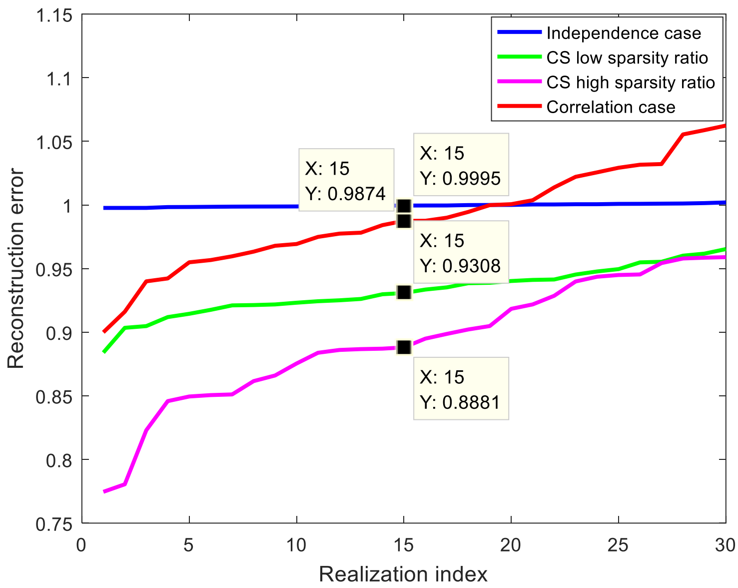


Fig.3 Reconstruction error for spatial noiseless correlation case

Relative to the temporal correlation noiseless case, the spatial case results in slightly lower errors for all cases. The CS optimality trend indicating lower errors also holds. The error for the green curve is based on 0.1 sparsity ratio and 0.3 correlation, while the magenta curves was based on 0.9 sparsity ratio and 0.8 correlation. The observations for the temporal also hold for this spatial noiseless case.

5.1.4 Spatial correlation noisy case

Including the spatial nonzero mean of vector Y and the variance of each of the variables in the sum increased by one and magnified in the random sum variables the figure for this case is given below:

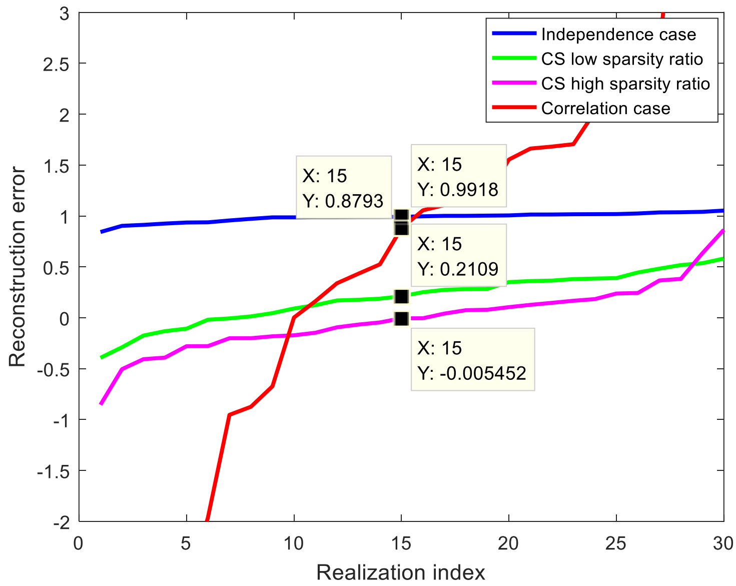


Fig.4 Reconstruction error for spatial noisy correlation case

The simulation results indicate smaller errors compared to the noiseless case and reduced error compared to the temporal correlation noisy case. Apart from the independence and correlated cases, the CS based cases indicate even lower errors, the green curve with parameters sparsity ratio 0.1 and correlation 0.3 and the magenta curve with high sparsity ratio 0.9 and correlation equal to 0.9 as well. Another observation is the increased fraction of errors with a negative sign. This is a direct result of the overlapping of the distribution curves which is now to a greater extent due to smaller nonzero mean of vector Y, i.e. smaller distance from zero mean distributions to the smaller nonzero mean. Regarding the errors from each curve, smaller errors are observed and as a distinction to other cases the magenta curve representing the high sparsity ratio CS case depicts an error which is practically zero i.e. the mismatch between encode measurement vector Y and product of matrices Φ and x is zero.

5.1.5 Spatiotemporal correlation noiseless case

The spatiotemporal is a combined case considering both the effects of temporal and spatial correlation. This is conducted by the consideration of 20 temporal correlation variables i.e. sampling periods and 20 spatial correlation variables i.e. number of neighboring nodes. The variances remain the same as are independent, correlation and CS based low and high sparsity ratio cases. The temporal and spatial variables are assumed to be correlated in each group but also correlated with the same value among each other for both groups. This is the reason why the variance of the sum of Gaussian distributed variables remains the same. The figure for the spatiotemporal noiseless case is thus given below:

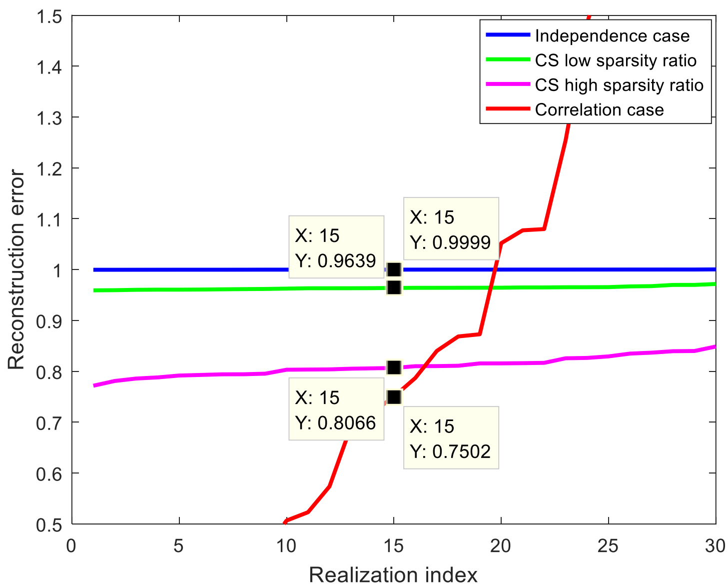


Fig.5 Reconstruction error for spatiotemporal noiseless correlation case

The simulation results for this case indicate some interesting findings. First of all, the independence case exhibits the same error value. On the other hand, the correlation case depicted by red curve indicates a more pronounced effect of smaller error by introducing correlation value of 0.9 as opposed to the previous case where small error reduction was observed. Concerning CS low sparsity ratio case, the sparsity ratio was taken equal to 0.2 and correlation value equal to 0.4. The value was lower than the temporal noiseless case and higher than the spatial noiseless case. In other words, it appears as produced by the joint contribution of temporal and spatial cases. A slightly greater sparsity ratio was assumed as well as slightly greater correlation. For the high sparsity ratio equal to 0.9 and correlation set to 0.8 the error was observed to be still lower than the low sparsity ratio as well as the previous noiseless cases.

5.1.6 Spatiotemporal correlation noisy case

For this case the assumptions of the previous noiseless case hold together with the increase of variance of the variables comprising the sum by one due to additive Gaussian $N(0,1)$ consideration. The figure with the simulation results is provided below:

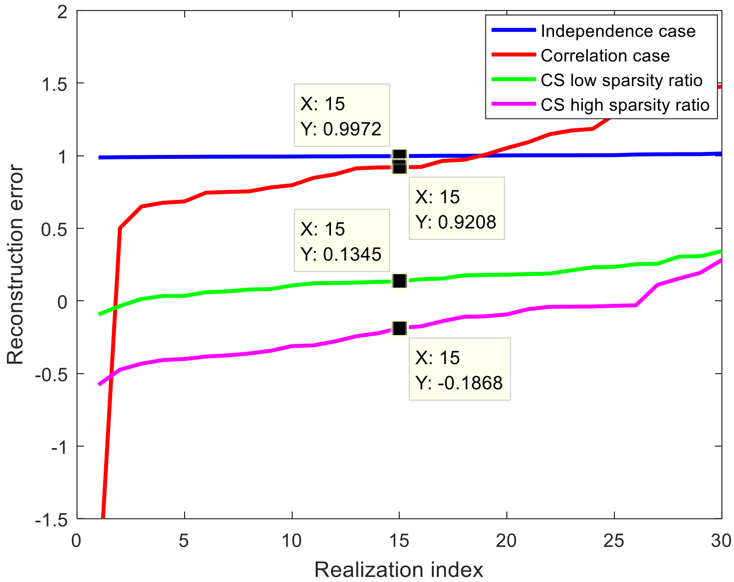


Fig.6 Reconstruction error for spatiotemporal noisy correlation case

The results of this section are those that display the most pronounced effect of applying CS principle with discarding large fraction of mean values. First of all, this is the case where the worst performing independence case exhibits a small reduction. The correlation case presents a slightly lower error. It is the CS cases, low and high sparsity ratios that indicate the lowest errors in each cases. For the green curve representing low sparsity ratio and for sparsity ratio set to 0.2 and correlation to 0.5 the error was found to be the lowest in all cases particularly in the noisy cases where the comparison is most meaningful according to aforementioned observations. Another crucial result is the negative signed error of the high sparsity ratio with sparsity ratio and correlation values both equal to 0.9. Considering the absolute value, the conclusion is the same being the lowest error together with the spatial noisy case. However, the negative sign indicates that the encoding vector Y underestimates the values produced by the product of the matrices Φ and x. Moreover, the results comply with the observation that the distance of the means of vector Y and the product of matrix Φ and vector x is between the respective values of the temporal and spatial cases, larger than the spatial case and smaller than the temporal case.

5.2 Energy estimation error

This section is devoted to the energy estimation error given the energy of each variable comprising the sum from which the average values and thus the means of the previous section were generated. Thus, the non-central chi-square distribution is used to model the sum of energies of the variables with specified degrees of freedom and non-centrality parameter as the distribution parameters.

Relative to the equivalent CS cases where only a fraction of the sums of energies of the respective variables are preserved the Gaussian modeled measurements are precisely modeled and there exists a standard formula for the number of larger measurements detained. However, the sums of energies of the respective chi-square distribution is not effectively quantified in the literature. In order to tackle this limitation, we employ an approximation of a non-central chi-square distribution with an accurate Gaussian distribution approximation as formulated in [21] in order to apply the aforementioned formula. All temporal, spatial and spatiotemporal cases both noiseless and noisy, are considered in this section as well.

5.2.1 Temporal noiseless energy estimation error case

This subsection presents simulation results regarding temporal correlation of the variables of which the means of average values of sum of energies are modeled through Eq. (2). Hence, this case vector e represents the energy estimation mismatch. As in the previous section, the independence case, correlation case and CS based low and high sparsity ratio cases are also included in simulations conducted. The related figure for this case is given below:

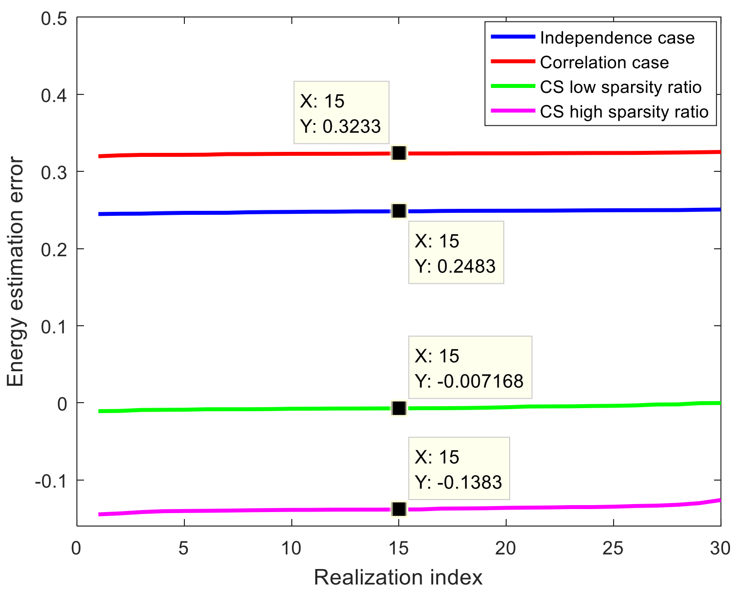


Fig.7 Energy estimation error for temporal noiseless correlation case

It can be deduced from the figure that independence case performs better than the correlation case as apparent from the blue and red curves respectively. The same observation is present in the CS based cases. Considering the absolute value, low sparsity ratio 0.4 and correlation equal to 0.7 achieves a smaller error than CS case with sparsity ratio equal to 0.9 and correlation equal to 0.2. Also interesting is the observation that the high sparsity ratio requires more energy samples to be preserved due to higher sparsity ratio and higher correlation value. On the contrary, the higher sparsity ratio equal to 0.9 is paired with correlation value equal to 0.2. However, the negative sign of the errors in the CS based cases is equal important to the magnitude of these errors. It indicates that the vector Y is smaller in value to the elements of the product of matrix Φ and vector x. This result indicates that the representation by Y is lossy, thus the energy represented by Y is a portion of the energy of the transformed, via matrix Φ, vector x. The above is interpreted by the overlapping of the related Gaussian bell-shaped curves.

5.2.2 Temporal noisy energy estimation error case

In this subsection, the variance is modified as in all above noisy cases, which in this subsection modifies the non-centrality parameter of the related non-central chi-square distribution. The figure for this temporal noisy case is given below:

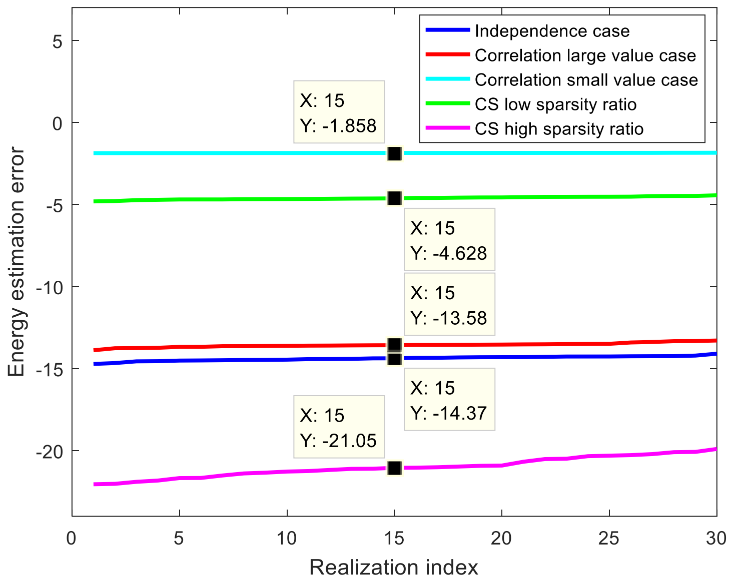


Fig.8 Energy estimation error for temporal noisy correlation case

The increase in variance in this noisy case as in the above results in a decrease of the non-centrality parameter but to an increase of the variance of the approximating Gaussian distribution and as a consequence, increased overlapping. This justifies the negative sign of the energy estimation errors in all the cases considered in this subsection. Contrary to the previous cases and due to the negative signed results correlation value with value of 0.9 performs slightly better than the independence case. More importantly, an observation holding also for the temporal noiseless case is that the decrease in correlation value leads to smaller error as shown from the cyan colored curve for correlation value. Thus, for decreasing correlation value from 0.1 to zero leads to a successively decreasing error improvement. As a result, with the independence case depicted by the blue curve, assuming a nonzero value of correlation always leads to improved performance. Finally, the CS high sparsity ratio with sparsity ratio equal to 0.4 presents a smaller error than the high sparsity ratio with a value of 0.9. A remark concerning these cases is stated: for both cases the correlation was assumed to be 0.1. This stems from the fact that in all cases investigated for the pair of sparsity ratio with the lowest error, increasing error was assumed in absolute value with a negative sign as the correlation increased. With the largest error equal to one in the zero correlation case the smallest error was observed for the minimum correlation equal to 0.1. As the slope of the curve was observed steeper for larger errors, the value of correlation for minimum error shifted towards the zero value with decreasing distance with respect to the slope becoming steeper. A concluding remark is that the measurement vector Y is a lossy procedure as evident from the negative sign of all the errors.

5.2.3 Spatial noiseless energy estimation error case

In this case the mean of the variables comprising the sum is modified in the manner of spreading power among 30 neighboring nodes as in the spatial correlation cases already analyzed. The related figure is given below:

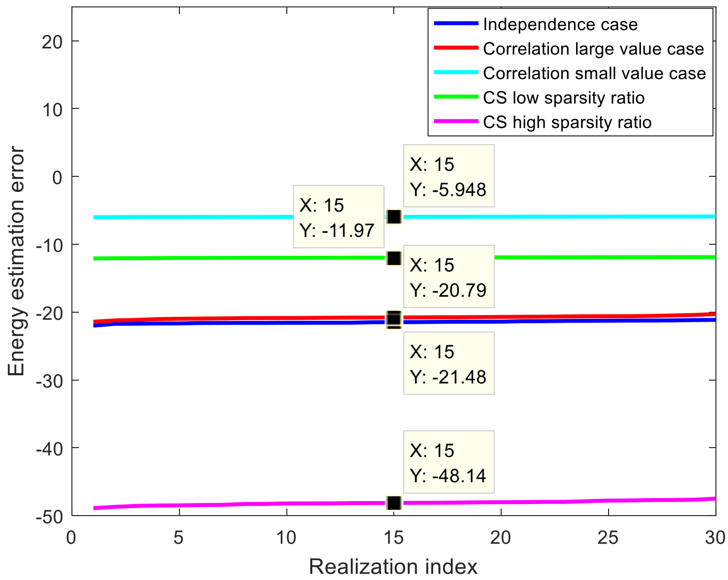


Fig.9 Energy estimation error for spatial noiseless correlation case

The main observation for this case is the negative values of all errors that result from the overlapping of the approximating Gaussian distributions. The independence case and correlation case with value equal to 0.9 achieve errors with negligible difference. As in the previous subsection, correlation value 0.1 results in smaller error. The CS case with sparsity ratio 0.4 and correlation as low as 0.1 satisfying incoherence requirement performs significantly better than CS with sparsity ratio as high as 0.9. The small correlation value i.e. cyan curve achieves a lower error than the CS low sparsity ratio displayed by green curve. In summary, the main observation of this subsection is the large negative value of all errors, hence, representation of the transformed, via matrix Φ, vector x by the vector Y results in significant energy loss and thus is not efficient.

5.2.4 Spatial noisy energy estimation error case

As already stated, variance of the variables comprising the sum is increased by one due to unit variance additive Gaussian noise. The related figure for this case is given below:

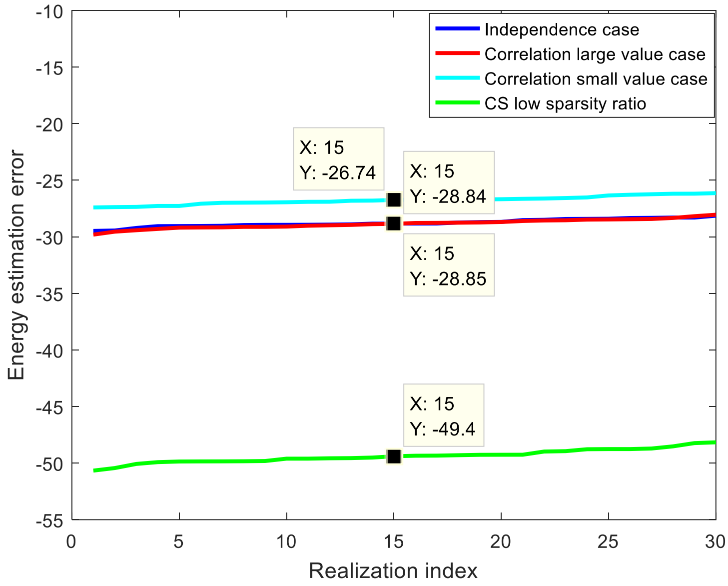


Fig.10 Energy estimation error for spatial noisy correlation case

The results from this subsection indicate same energy estimation error for independence and correlation case with value equal to 0.9. As in previous subsection, correlation with value of 0.1 exhibits smaller error. The CS case with sparsity ratio 0.4 and correlation value equal to 0.1 performs significantly worse than the other cases. Finally, the CS case with high sparsity ratio equal to 0.9 was found to exhibit a much larger error and was not displayed in the figure due to large magnitude of the related error. As a concluding remark, the errors indicate that the representation of transformed, via matrix Φ, vector x product by vector Y is highly inefficient for the spatial noisy case incurring energy loss from the encoding procedure.

5.2.5 Spatiotemporal noiseless energy estimation error case

In this subsection, the number of sampling periods and number of neighboring nodes are both equal to 20, as already stated in the previous spatiotemporal cases. The figure for the spatiotemporal noiseless energy error estimation is given below:

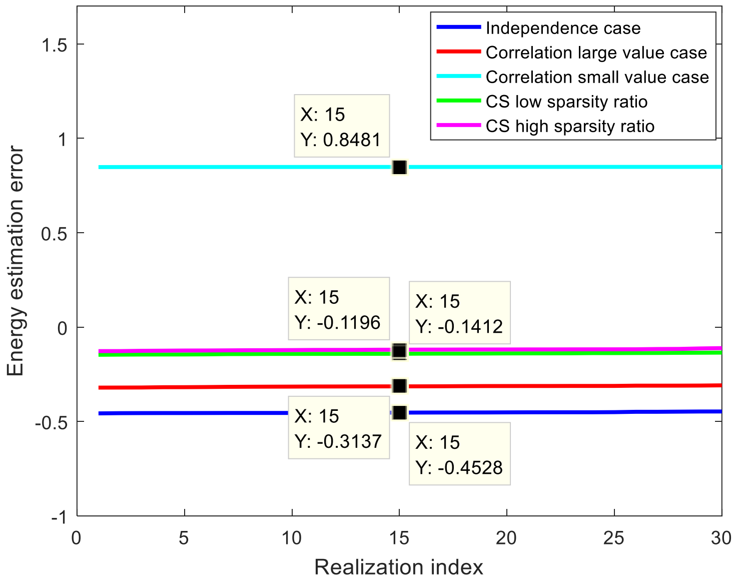


Fig.11 Energy estimation error for spatiotemporal noiseless correlation case

The figure from this section displays the CS based cases achieving the smallest error negative signed indicating a negligible energy loss by the encoding performed. The worst performing case is the correlation case with the value 0.1 (cyan curve). The independence case follows in terms of error magnitude and the correlation case with a value of 0.9 follows. The important observation is that the results of this subsection represent slightly larger errors compared to the temporal noiseless case and much smaller errors than the spatial noiseless case. Hence, the spatiotemporal results appear to stem from a «weighted» contribution of the separate temporal and spatial noiseless, with the temporal contributing the most as in slightly smaller error than the spatiotemporal noiseless case investigated in this subsection.

5.2.6 Spatiotemporal noisy energy estimation error case

This last subsection of the energy estimation error case involves the increase of variables' variance by one due to unit variance additive Gaussian noise. The figure depicting the results of this subsection is the following:

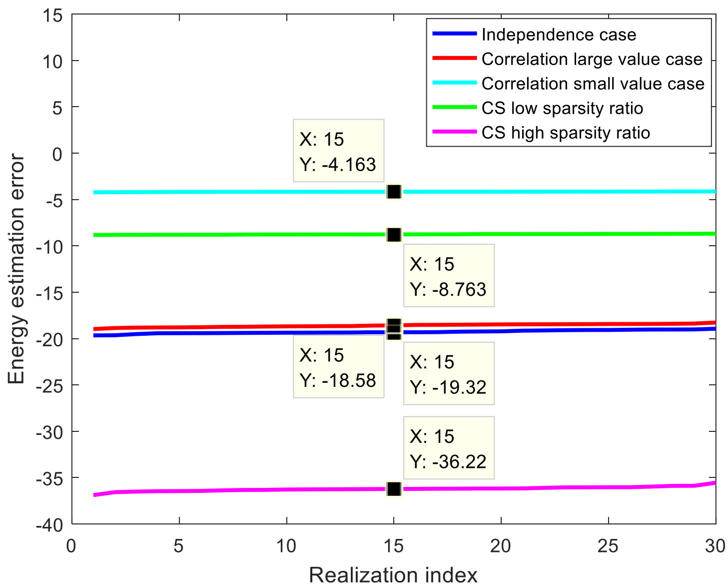


Fig.12 Energy estimation error for spatiotemporal noisy correlation case

Both of main observations in the noisy cases hold for this spatiotemporal noisy case as well. First, it is the significant loss in energy as a result of energy error between vector Y and transformed, via matrix Φ, vector x leading to the conclusion that the result of such representation is highly inefficient in terms of energy preservation. The second comes from comparing the previous noisy cases showing the same trend of weighted contribution, mainly from the temporal noisy case and less from the spatial noisy correlation case. Independence case performs almost as well as correlation case with value of 0.9. Correlation with low value of 0.1 presents a smaller in absolute value error. CS case with sparsity ratio equal to 0.4 follows in terms of energy estimation error achieved. Finally, CS case with sparsity ratio of 0.9 leads to high representation inefficiency.

5.3 Overall results interpretations

The independence case, being an impractical model, performs worse in all cases of means reconstruction error, hence, introducing a maximum possible correlation according to the specific application yields optimal reconstruction error. Regarding the CS cases, the case of low ratio achieves correlation with a small correlation value which fits into the incoherence principle of CS theory, based on which the reconstruction procedure is optimally conducted. Moreover, the assumption of high sparsity ratio i.e. equivalent in less variables/samples discarded approaching the dense scenario, results in small errors as well when assuming a high correlation value. This conveys that large correlation is indeed optimal producing smaller errors as correlation value increases. Summarizing, the reconstruction error evaluations are not bounded for all cases investigated. This is evident from the value range of errors for the respective cases. Regarding the noise assumed to be Gaussian, $N(0,1)$, the key assumption leading to a different result than the effect of noise leading to higher uncertainty and thus higher reconstruction error is that of independence. The quantification of the results are however, dependent to the assumptions related to the simulations conducted mainly, the distance of the nonzero mean of vector Y from zero value stemming from the unit power of the temporal cases and the even spreading of this power to the defined set of the 30 nodes in the neighboring nodes of a node in the network for spatial correlation. The increase in variance of each variable in the sum is magnified in the generated sum of such variables. Consequently, the curves overlap and the range of values that appear as random numbers generated for a specified probability increases. This is the reason for lower values of errors as well as negative errors. The negative sign in the mean reconstruction error is present in the noisy cases and has the meaning of underestimating the value of the transformed via matrix Φ, vector x.

Regarding energy estimation error, the crucial observation is that the correlation in the dense measurement case results in increased error compared to the independence case in the temporal noiseless correlation case, contrary to the former reconstruction error case. In the cases with negative signed errors, particularly noisy cases, the results stem from the aforementioned effect of Gaussian bell curves overlapping. In other words, the larger values of the product of matrix Φ and vector x subtracted from smaller values of vector Y, are the reason for the latter observation. This is due to increased probability of values of each distribution that are such that the negative signed errors result. This result can be mitigated in a practical scenario where noise correlation must be included as a prerequisite. A concluding remark regarding CS cases is that in energy estimation error cases a shift towards larger sparsity ratios has been observed for achieving minimum errors in the figures. The correlation value of 0.1 is assumed as a minimum correlation for simulations conducted in the cases where the minimum errors are observed between zero value and 0.1. Hence, the minimum correlation in a practical application can achieve an arbitrarily low energy estimation error.

6. Effects in topology and routing of Wireless Sensor Network design

Regarding network topology, the optimal definition of d-hop network topology is the set of concentric circles of increasing radius the value of which increases as the distance to cluster head and finally sink decreases. Thus considering the known topology of the nodes arranged in circles, at the center of which the sink is located, the optimal model would be a node the neighborhood of which is defined by a circle. This pattern should be the basis for constructing the wireless sensor network. Given that the flexibility of choosing a geometrical shape for the network comes along with a sub-optimal coverage of the respective area, the tree model should be chosen as a balance between area coverage and circular symmetry. The above is based on the geometrical property that covering the entire circular area with a given shape does not lead to an optimal coverage. Hence, the tree network assumed also has a direct impact to performance of proposed scheme. The aforementioned flexibility is further supported by the redundancy given the similar mean values generated by each sensor being a parent node of at least one leaf node. The results from the energy estimation error require the joint spatiotemporal consideration as the model for spatial correlation is significantly lossy as indicated from the simulations above. The redundancy of mean values as a data aggregation function would also contribute to the fault tolerance in the network topology, an extreme case of which could be compensated by selected subset of nodes mobility. The latter could also benefit from applying a randomized model as deterministic ones include cases where they could fail to cover network holes. On the contrary, randomization scheme could provide the optimal route and set of locations needed for the mobile node to attend to ensure network coverage and connectivity. Finally, the flexibility provided by the emerging redundancy could also aid the feasibility of dynamic change of network topology either deemed necessary by node failure or energy depletion or by enabling autonomous network operation promoting the property of decentralization i.e. operation without the need or with limited need of sinks or infrastructure. Considering that this paper introduces a probabilistic assessment of mean value reconstruction error and energy estimation error the above randomized scheme could be integrated in terms of correlation and CS compressibility rule with the scheme of minimizing energy consumption, delay and bandwidth constrained resources.

The routing of the model proposed by the analysis of this paper is the critical aspect that verifies the temporal/spatial/spatiotemporal correlation based redundancy as the similarity of the mean values formulated in the respective vectors. Initiating from a localized computation scheme in the d-hop neighborhood and shifting the mean calculations towards the sink in order to reach representative, on the basis of not receiving abnormal readings as samples from the nodes, values of the means generated is the first stage. Due to redundancy the merit of values calculated initially localized, expands to the entire network. Hence, nodes in each neighborhood gradually gain knowledge of these representative values and the required computations for updating the mean values generated tend to continuously decrease This reduces the necessity for shifting heavy computational load to the sink. Hence, the proposed network operation supports a fully decentralized scheme where rare values updating is locally performed without the need for more computation efficient coordinator sinks. In summary, the fact that redundancy is a consequence of the fact that sensor readings are not rapidly altered with respect to past values and also neighboring nodes, the decreasing necessity for heavy computations from the sink results in this decentralized property mentioned that is therefore achievable. The above also have an impact of reducing energy consumption despite the lossy characteristic of the proposed scheme which suggests an inherent loss that can be considered as granted despite the energy efficiency of the scheme.

7. Application to 5G Wireless Sensor Networks

The WSNs and the design and characteristics of 5G system technology [22] share some common features and challenges. There is a vast range of design and performance issues that are investigated in detail and attempts to optimize them considering constraints that further define and formulate the application specific problem are made.

The main bottleneck in 5G networks is energy efficiency as a prerequisite for network lifetime longevity and effective operation. Energy harvesting techniques introduced in 5G networks are not proven sufficient to address the energy depletion issue of sensor nodes. Thus, alternative techniques must be applied such as duty cycling where sophisticated schemes for scheduling sleep intervals of sensors that do not sense or transmit and assumed idle are employed. Techniques for coordinating active and inactive sensors continue to receive intense scientific attention.

Scalability versus effective area coverage is a major issue. The impact of this paper analysis highlights the correlated data that provide flexibility and tolerance to node failures. Hence, effective scalability of the network is a portion of the actual one.

Another issue regards the bidirectional information exchange assumption that is crucial for realizing the benefits of correlation and representative mean values, as already stated due to the fact that the initial heavy computation load requires communication with sink, which gradually becomes unnecessary and decentralized network operation further establishes, as stated above.

Interference mitigation is another crucial issue common to WSNs as in 5G systems. Together with a set of directional antennas that comply with the direction of information exchange through the network, i.e. with an optimal sensor selection scheme, interference can be mitigated not by decreasing transmission power but by alternative techniques such as coding which further benefits from correlation. Distributed transform Coding can be applied in a post correlation learning stage. Correlation control is also essential in order to compensate for the reconstruction error of mean values with a significant value or for the energy estimation error with a small value. The above balance can be found according to the application considered. Network capacity expansion is also a major issue in 5G sensor networks. The redundancy of data must be drastically reduced towards achieving diversity of the data in the network in order to increase capacity in a case of heterogeneous network or by the former mention diversity in a portioned into segments network. Privacy and security is also a bottleneck that must be dealt with in order to ensure exchanged data integrity. The probabilistic scheme of this paper enables the selection of nearby sensors that are less prone to overhearing in order to establish a safe route from the leaf nodes to the sink. Relative to 5G WSNs infrastructure handoff management can be applied in an area not covered or in a case of an autonomous network reorganization to cover network holes. The concept that handoff is required comes along with exchanging information in a dynamic topology or a case of energy depletion or node failure. Finally, QoS consideration as a constraint for optimization of network performance remains an insufficiently addressed issue for numerous practical applications. The proposed scheme can be considered as a means of localizing the QoS requirement and gradually covering the entire network. To conclude, bandwidth allocation and latency bounds on optimized performance pose an application dependent issue as well. Latency in environmental monitoring is clearly not an issue contrary to cases such as disaster event detection, healthcare smart networks or military target tracking. Hence, the proposed scheme is not highly dependent on synchronization and delay mitigation even in the heterogeneous network case.

The final remarks concern the 5G Internet-of-Things (IoT) networks [23], [24], which is an additional step in terms of increased smart nodes scalability. Energy efficiency is directly applied as a prerequisite in IoT networks as well. Thus, research for addressing these issue also impacts the latter networks. Moreover, the issue of heavy traffic load also emerges as a result of increased smart node density in the coverage area. The main assumption when facing the IoT infrastructure and implementation is the high heterogeneity, location awareness, effective routing schemes and high data processing complexity. The proposed probabilistic scheme can be applied always considering the different types of data collected in each densely deployed area. The last aspect that is considered is the cost of deploying such networks, the drastic reduction of which can only be realized by the joint contribution of many technologies such as node design, antenna design as well as low power and consequently cost of sensing nodes.

8. Conclusions and future work

In this paper, a probabilistic scheme based on Gaussian distribution is proposed based on the calculation of reconstruction error of mean values of average values of Gaussian elements as well as energy estimation error considering the sum of energies of the respective elements. The dense independent, dense correlated and CS based cases are included, considering both low and high sparsity ratios for performance evaluation. The results are technically justified and application to 5G WSNs and IoT scenario are derived.

As future research directions, the l_0 CS based problem formulation and convex relaxation for solvability of the initial problem via l_1 norm or a greedy algorithm as an alternative can be considered and compared to the proposed probabilistic scheme in terms of error magnitude and optimized performance. The related metrics can also be jointly considered. The extension to additive noise and fading for addressing the communication of nodes in the network and the effect of spatiotemporal correlation is a feasible direction to be investigated. Relative to WSNs design, dynamic topology with CS problem constraints along with efficient routing are possible research directions. Finally, cross-layer optimization is a promising aspect under the CS compressibility rule and combined consideration of system parameters to be jointly optimized.

Declarations

To be used for non-life science journals Not applicable

Funding The authors state that there was no funding about this work.

Conflicts of interest There are no potential conflicts of interest financial or non-financial

Research involving human and animal rights Not applicable

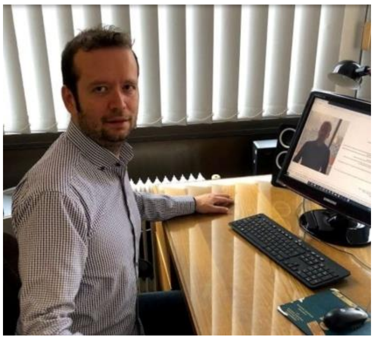
References

1. Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: Wireless Sensor Networks: a survey. Comput. Netw. **38**(4), 393-422 (2002)
2. Donoho, D.L.: Compressed Sensing. IEEE Trans. Inf. Theory. **52**(4), 1289-1306 (2006)
3. Rani, M., Dhok, S.B., Deshmukh, R.B.: A Systematic Review of Compressive Sensing: Concepts, Implementations and Applications. IEEE Access. **6**, 4875-4894 (2018)
4. Eldar, Y., Kutyniok, G.: Compressed Sensing: Theory and Applications, Cambridge University Press (2012)
5. Choi, J.W., Shim, B., Ding, Y., Rao, B., Kim, D.I.: Compressed Sensing for Wireless Communications: Useful Tips and Tricks. IEEE Comm. Surveys and Tutorials. **19**(3), 1527-1550 (2017)
6. Yick, J., Mukherjee, B., Ghosal, D.: Wireless sensor network survey. Comput. Netw. **52**(12), 2292-2330 (2008)
7. Anastasi, G., Conti, M., Di Francesco, M., Passarella, A.: Energy conservation in wireless sensor networks: A survey. Ad Hoc Netw. **7**(3), 537-568 (2009)

8. Das, S.N., Misra, S., Wolfinger, B.E., Obaidat, M.S.: Temporal-Correlation-Aware Dynamic Self-Management of Wireless Sensor Networks. IEEE Trans. Industr. Informatics. **12**(6), 2127-2138 (2016)
9. Shah, G.A., Bozyigit, M.: Exploiting Energy-aware Spatial Correlation in Wireless Sensor Networks. In: 2007 Second International Conference Communications Systems Software and Middleware, pp.1-6. IEEE (2007)
10. Maivizhi, R., Yogesh, P.: Spatial Correlation based Data Redundancy Elimination for Data Aggregation in Wireless Sensor Networks. In: 2020 International Conference on Innovative Trends in Information Technology (ICITIIT), pp. 1-5. IEEE (2020)
11. Liu, C., Cao, G.: Spatial-Temporal Coverage Optimization in Wireless Sensor Networks. IEEE Trans. on Mobile Comput. **10**(4), 465-478 (2011)
12. Chen, J., Li, T., Wang, J., Silva, C.D.w.: WSN Sampling Optimization for Signal Reconstruction Using Spatiotemporal Autoencoder. IEEE Sensors Journal. **20**(23), 14290-14301 (2020)
13. Tayeh, G.B., Makhoul, A., Perera, C., Demerjian, J.: A Spatial-Temporal Correlation Approach for Data Reduction in Cluster-Based Sensor Networks. IEEE Access. **7**, 50669-50680 (2019)
14. Kumar, G., Baskaran, K., Blessing, R., Lydia, M.: A Comprehensive Review on the Impact of Compressed Sensing in Wireless Sensor Networks. J. on Smart Sensing Intell. Syst. **9**(2), 818-844 (2016)
15. Alwakeel, A.S., Abdelkader, M.F., Seddik, K.G., Ghuniem, A.: Exploiting Temporal Correlation of Sparse Signals in Wireless Sensor Networks. In: 2014 79th Vehicular Technology Conference (VTC Spring), pp.1-6. IEEE (2014)
16. Hu, H., Yang, Z.: Spatial-Correlation Based Distributed Compressed Sensing in Wireless Sensor Networks. In: 2010 Sixth International Conference on Wireless Communications Networking and Mobile Computing (WiCOM), pp.1-4. IEEE (2010)
17. Wimalajeewa, T., Varshney, P.K.: Robust detection of random events with spatially correlated data in wireless sensor networks via distributed compressive sensing. In: 2017 Seventh International Workshop on Computational Advances in Multi-Sensor Adaptive Processing(CAMSAP), pp.1-5. IEEE (2017)
18. Zhang, C., Li, O., Tong, X., Ke, K., Li, M.: Spatiotemporal Data Gathering Based on Compressive Sensing in WSNs. IEEE Wirel. Comm. Lett. **8**(4), 1252-1255 (2019)
19. Hooshmand, M., Rossi, M., Zordan, D., Zorzi, M.: Covariogram-Based Compressive Sensing for Environmental Wireless Sensor Networks. IEEE Sensors J. **16**(6), 1716-1729 (2016)
20. Deligiannis, N., Mota, J.F.C., Zimos, E., Rodrigues, M.R.D.: Heterogeneous Networked Data Recovery From Compressive Measurements Using a Copula Prior. IEEE Trans. Comm. **65**(12), 5333-5347 (2017)
21. Seri, R.: A Tight Bound on the Distance Between a Noncentral Chi Square and a Normal Distribution. IEEE Comm. Lett. **19**(11), 1877-1880 (2015)
22. Agiwal, M., Roy, A., Saxena, N.: Next Generation 5G Wireless Networks: A Comprehensive Survey. IEEE Comm. Surveys and Tutorials. **18**(3), 1617-1655 (2016)

23. Shafique, K., Khawaja, B.A., Sabir, F., Qazi, S., Mustaqim, M.: Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios. IEEE Access. **8**, 23022-23040 (2020)
24. Xiao, S., Li, T., Yan, Y. Zhuang, J.: Compressed sensing in wireless sensor networks under complex conditions on Internet of Things. Cluster Comput. **22**, 14145-14155 (2019)

Theofanis Xifilidis received the Diploma of Electrical and Computer Engineering from the Aristotle University of Thessaloniki, Greece. He received his Master's Degree of Electronics and Radioelectrology from the Physics Department Aristotle University of Thessaloniki, Greece. He is currently pursuing his P.H.D. in the Department of Applied Informatics, University of Macedonia, Thessaloniki, Greece. His research interests include Applied Mathematics, Compressive Sensing, Signal Processing, Information theory, wireless communication systems and MIMO wireless technology.



Konstantinos E. Psannis was born and raised in Thessaloniki, Greece. He is currently Associate Professor in Communications Systems and Networking at the Department of Applied Informatics, School of Information Sciences, University of Macedonia, Greece, Director of Mobility2net Research & Development & Consulting JP-EU Lab, member of the EU-JAPAN Centre for Industrial Cooperation and Visiting Consultant Professor, Graduate School of Engineering, Nagoya Institute of Technology, Nagoya 466-8555, Japan. Konstantinos received a degree in Physics, Faculty of Sciences, from Aristotle University of Thessaloniki, Greece, and the Ph.D. degree from the School of Engineering and Design, Department of Electronic and Computer Engineering of Brunel University, London, UK. From 2001 to 2002 he was awarded the British Chevening scholarship. The Chevening Scholarships are the UK government's global scholarship programme, funded by the Foreign and Commonwealth Office (FCO) and partner organisations. The programme makes awards to outstanding scholars with leadership potential from around the world to study at universities in the UK. Dr. Psannis' research spans a wide range of Digital Media Communications, media coding/synchronization and transport over a variety of networks, both from the theoretical as well as the practical points of view. His recent work has been directed toward the demanding digital signals and systems problems arising from the various areas of ubiquitous Big Data/AI-IoT/Clouds and communications. This work is supported by research grants and contracts from various government organisations. Dr. Psannis has participated in joint research works funded by Grant-in-Aid for Scientific Research, Japan Society for the Promotion of Science (JSPS), KAKENHI Grant, The Telecommunications Advancement Foundation, International Information Science

Foundation, as a Principal Investigator and Visiting Consultant Professor in Nagoya Institute of Technology, Japan. Konstantinos E. Psannis was invited to speak on the EU-Japan Co-ordinated Call Preparatory meeting, Green & Content Centric Networking (CCN), organized by European Commission (EC) and National Institute of Information and Communications Technology (NICT)/Ministry of Internal Affairs and Communications (MIC), Japan (in the context of the upcoming ICT Work Programme 2013) and International Telecommunication Union. (ITU-founded in 1865), SG13 meeting on DAN/CCN, Berlin, July 2012, amongst other invited speakers. Konstantinos received a joint-research Award from the Institute of Electronics, Information and Communication Engineers, Japan, Technical Committee on Communication Quality, July 2009 and joint-research Encouraging Prize from the IEICE Technical Committee on Communication Systems (CS), July 2011. Dr. Psannis has more than 70 publications in international scientific journals and more than 100 publications in international conferences, 20 Book Chapters and 11 Technical Reports. Professor K.E. Psannis has more than 3800 citations (h-index 27, i10-index 56). Professor Konstantinos has several highly cited papers powered by Web of Science - Clarivate. Dr. Psannis supervises three post-doc students and eight PhD students. Prof. Konstantinos E. Psannis is serving as an Associate Editor for IEEE Access and IEEE Communications Letters. He is Lead Associate Editor for the Special Issue on Roadmap to 5G: rising to the challenge, IEEE Access, 2019. He is a Guest Editor for the Special Issue on Compressive Sensing-Based IoT Applications, Sensors, 2020. He is a Guest Editor for the Special Issue on Advances in Baseband Signal Processing, Circuit Designs, and Communications, Information, 2020. He is a Lead Guest Editor for the Special Issue on Artificial Intelligence for Cloud Based Big Data Analytics, Big Data Research, 2020. He is TPC Co-Chair at the International Conference on Computer Communications and the Internet (ICCCI 2020), Nagoya Institute of Technology Japan, ICCCI 2020, June 26-29 at Nagoya, Japan, and will be held in 2021 June 25-27, at Nagoya, [http://iccci.org/] and Conference Chair at the World Symposium on Communications Engineering held at University of Macedonia, Thessaloniki, Greece, October 9-11, 2020 and to be held at University of Macedonia, November 25-28, 2021, Thessaloniki, Greece (WSCE 2021 - http://wsce.org/). Professor Konstantinos E. Psannis has been included in the list of Top 2% influential researchers globally (prepared by Scientists from Stanford University USA), October 2020 (https://lnkd.in/dhSwdgB) and October 2021 (https://lnkd.in/gCk8FAxu).