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A Novel Enriched LASSO Based Compression Technique for Energy Efficient Wireless Sensor Networks

Anitha K[1], Jaison B[2], Nalini M[3], Shiny Irene D[4]

[1)] *Department of Computer Science and Engineering, Saveetha School of Engineering, Chennai, India*
Email: anithak.rameshr@gmail.com
[2)] *Department of Computer Science and Engineering, R.M.K Engineering College, Chennai, India*
Email: bjn.cse@rmkec.ac.in
[3)] *Department of Computer Science and Engineering, Saveetha School of Engineering, Chennai, India*
Email: nalinitptwin@gmail.com
[4)] *Department of Computer Science and Engineering, Saveetha School of Engineering, Chennai, India*
Email: dshinyirene@gmail.com

Abstract: The capability of transmission in Wireless sensor networks (WSN) is circumscribed due to the precincts in energy utilization, controlled resources of transmission devices and network components. Information compression is taken into account as the best option, because the major part of energy consumed is for transmission of information. Habitually Lossy compression is adopted, since WSN abides some error in the reconstructed signals subjected to some acceptable tolerance. Lasso based models have been ascertained their capability to effectually compress both multivariate and univariate data. Traditional Lasso considers ℓ1-norm regularization for learning in multi-dimensional data sets and assumes sparsity as model parameters. Lasso prominence on sparsity and deal with the correlation between the data points. However, model sparsity may be constricting and not essentially the foremost applicable assumption in several problem domains. To eliminate this limitation, an enriched lasso (MLasso) is proposed for compression bearing in mind both sparsity and correlation. In specific the strategy can select data that are having strong features to reconstruct the data and are less correlated between each other. Furthermore, an efficient Alternating Direction Method of Multipliers (ADMM) is adopted to resolve the ensuing sparse non-convex optimization problem. Extensive experiments on diverse datasets provides the proof that MLasso outperforms other similar algorithms for signal compression. Thus the proposed method ensures less energy consumption, decreases power loss and improves the operational life and reliability of network components.

Keywords: Multidimensional data, compression, energy efficiency, senor networks, lossy compression

1. INTRODUCTION

In current scenario, there is an immense development in usage of mobile technologies and remote sensing devices. Progresses in compact hardware and sensing devices aided to impart them into every object leading to Internet of Things (IoT) [1]. Large scale wireless sensor networks (WSNs) are employed to acquire and collect the data from different environments and objects. They are communicated to a data acquisition center for monitoring and surveillance. The application of WSNs embrace environmental monitoring [2], remote patient monitoring in healthcare [3], animal behavior classification [4], smart grid [5] and structural health monitoring for infrastructures [6].

The efficiency and the results of the applications depend on the amount of data and the acquisition speed of sensors. More data at high speed will help the application to perform efficiently. The same can be realized by higher sampling speed that ends up with large volume of raw data from sensors. Thus the network needs more energy for transmitting and huge memory for storage. Each battery supplying energy to the sensor nodes have limited stored energy and it is challenging to recharge or replace. As per Kimura and Latifi [7] each remote sensor consumes 80% of battery capacity for data transmission. The results presented by Barr and Asanovic [8] provides the evidence that the energy consumed by the network for transmitting a single bit of information is almost same as that required by the processing unit for performing thousands of computing operations. Also more energy consumption lead to more heating of sensor nodes and thus reduce the life. Thus it becomes a big challenge to manage equipment life, operate and maintain the data acquisition and storage systems in application scenarios.

The energy requirements can be regulated by adopting procedures at various sections of WSN protocol stack [9-12] by energy efficient routing [13] and battery saving media access control [14]. A packet forwarding protocol is presented by L. Zhang and Y. Zhang [15] and proved as energy efficient. The other approaches involved in improving the life of networks includes sample data reduction, battery replacement and data compression [16]. The perspective of this work given in this paper is to reduce transmission of data by introducing effective data compression.

In general there are two methods of data processing that will result in reduction [17] data aggregation and data approximation. Aggregation methods use statistical data such as minimum, maximum and average and effectively reduces the data size but fails to capture the important trends and changes in data required for arriving results. Data approximation is a model based method and will not disturb the actual information, if the data feed contains large amount of redundancy. Based on the method and purpose of application, the approximation method are categorized as time series analysis [18-20], data mining model [21], probabilistic model [22, 23] and data compression [24-26].

Data compression proves to be the more favourable technique that provides good data quality, best of system performance and significantly reduces the energy consumption of WSNs. Embracing data compression algorithm in data storage and transmission devours some energy to compute the compression but it will be much less than the energy required for storage and transmission.

In literature numerous algorithms and techniques have been offered and their capability to compress the time series data is proven and established. However many of them are derived and tested for compression of single variate sensor data such as temperature, relative humidity, etc. In-spite of vast applications of multivariate signals only few literature works are available addressing the issues in systems used to acquire, analyse and store multivariate signals.

The proposed work adopts an algorithm based on Lasso approximation, enriched lasso (MLasso) that can compress both multivariate and univariate sensor data. Lasso has proved itself very much suitable for multidimensional regression. Lasso assumes that there is no correlation in input data. But in WSNs, the data is captured using different sensor units in a node. These sensors will at the same time acquire many types of data, like sound intensity, acceleration, temperature, humidity, light intensity, and video. These data used to have certain correlation. Lasso happens to select only one feature among the correlated features and ends up in system underperformance [27]. This issue is addressed in the enriched lasso (MLasso) technique. In addition to discovering the correlation between the data, it also better discriminates similar data. This property of DLasso helps in achieving high reconstruction accuracy.

The proposed algorithm in particular creates optimum predictions of multi variate data and thus achieves efficient energy utilization. To demonstrate the capability and suitability of the proposed algorithms in comparison with the competing algorithms available in literature, the system is evaluated and tested with benchmark data sets from different application domains. The experimental results of proposed system performed significantly better when tested with smooth multivariate data sets. This makes the system most suitable in applications such as behaviour monitoring. The work also includes development, optimizing and computing compression consuming less running time. In addition guidance for selection of parameters influencing the algorithm performance is also described.

The organization of this paper is as follows: In Section 2, a brief about the related work is given. The univariate and multivariate lasso compression algorithm and the methodology of implementation is proposed in Section 3. The description of real world publicly available data sets and the comparison of several compression algorithms available in literature is done in Section 4. Finally, section 5 briefs few concluding remarks.

2. RELATED WORK

In sensors that are intricate in long term real time monitoring, efficient consumption of energy is a conspicuous feature for their satisfactory performance. Several available compression algorithms are not directly malleable for sensor nodes. Only explicitly formulated and derived compression algorithms are appropriate and implemented for sensor nodes applications [28]. Multivariate data measured from one sensor node are correlated. Each original time series is not linear, however Deligiannakis [17] proposed an algorithm keeping base signal as an independent variable. Then the other series data is approximated using regression model. The base signal values are directly extracted from the actual sensor raw data and replaced during changes occur. The algorithm is more suitable for data having larger multivariate correlation. On the other hand the algorithm doesn't consider error constraints. RACE algorithm [24] is developed for data acquired from single sensor node. Few of the other techniques developed includes distributed source coding (DSC) [29], compressed sensing (CS) [30], distributed source modelling (DSM) [31] and distributed transform coding (DTC) [32].

There are other compression techniques grouped as temporal compression techniques classified as: lossless and lossy compression algorithms. They are characterized based on different principles. Data accuracy [8] is preserved in Lossless compression. This accuracy is preserved by eliminating redundant data during compression and decompression process. On the other hand, lossy compression techniques are derived to achieve better compression ratio at the cost of sacrificing the accuracy. A number of classic lossless compression methods have been derived and analysed. Few of the algorithms suitable and used in sensors is Sensor Lempel-Ziv-Welch (S-LZW) algorithm and a distinct variant of previous technique LSZ [33] made suitable for sensors. It is specially developed to storage and energy constraints in sensor networks. Lossless Entropy Compression (LEC) algorithm [33] is a lossless compression approach proved very efficient is based on traditional information encoding. The lossless compression techniques are not well suited for Sensor applications. In some cases they require large memory and in other cases their assumptions about entries of static dictionary are not appropriate.

Lossy compression relaxes the accuracy and accepts deviations from the original to reach the flexibility to achieve less energy consumption and reconstruction accuracy for higher compression ratio, in order this will increase the lifetime of wireless sensors. Schoell hammer has presented a less complex Lightweight Temporal Compression (LTC) technique. A small value of error is added with each reading, controlled by knob [34,35]. LTC technique is simple and less complex method and can be used for temporal data compression [36]. The performance of the algorithm decays for the fluctuating sensor readings. Piecewise Linear Approximation based scheme with less number of line segments (PLAMlis) algorithm exploits and estimates minimum variety of segments to approximate the given statistic. The error limit [37] is fixed during the compression process and the difference between any approximation value and its actual value is maintained less than the fixed limits.

The temporal lossy compression algorithms explained above are well suitable for slowly and gradually varying signals such as temperature and not for signals such as vibrations since they use piecewise linear representation of time series. Also LTC and PLAMlis are compression methods that are not effective for compression of multi-dimensional or multivariate time series. The work presented in this paper presents adoption of Enriched Lasso approximation algorithm for data compression. The algorithm is best suitable to compress both univariate and multivariate signals.

3. THE COMPRESSION ALGORITHM

Let the one dimensional signal be $y=(y_1, y_2, ...y_n)$ observed or sensed at times $t=(t_1, t_2, ...t_n)$ *where* $t_1 < t_2 < ... < t_n$. That is the signal y_i is measured at a time t_i, by the sensor. We can say that the reading of accelerometer y used to measure the acceleration of an equipment during a seismic test in the time duration $t_1 = 0s$ *and* $t_n = 30s$. It can be seen that the values measured by y will be varying during every time instant in a given time limit t, every values of y captured by the sensor in the time interval t should be acquired for monitoring and stored for further studies, analysis, modelling and development.

Furthermore, it can be for a sequence of instances the change in values of y can be of less significance. In this case, if the data read in during the time between t_p *and* t_q is such that $y_p = y_{p+1} = ... = y_q$ for some $p < q$. In this scenario, we could eliminate the data observed during the time p *and* q and store the reading $y = (...y_{p,} y_{q+1} ....)$ in the data base corresponding to instances $t = (...t_{p,} t_{q+1} ....)$. Thus data sensed in the time frame t_p *and* t_q is not varying vastly, we can be able to store the space required to store $|p-q|$ recorded sensor values and also the time stamps. Thus reducing the storage requirements also reduces the energy required for transmitting the data. In addition a very significant economic benefit in developing the sensor network can also be achieved.

In practical installations, the values read by the sensors may be with slight variations and will not be constant in a particular time period (t_p, t_q). In such cases, the size cannot be reduced just by eliminating the data, to compress the data that are varying continuously, an efficient algorithm derived from Lasso regularization [38] is presented. Previously Lasso approximation has been applied to order the features in a meaningful sequence in applications such as comparative prostate cancer analysis [39], genomic hybridization [40] and time-varying networks [41].

From the Literature it is evident that the basic Lasso-based algorithms assume restricted freedom among the variables, and their idea is to perform regression separately for each response vector rather than performing it jointly for all the response vectors. As a result they perform only data approximation and representation. Compression of signal y is attained by eradicating the small differences in the signal. The signal x a smoother approximation of signal y is computed by minimizing the differences between data at adjacent time intervals.

Many algorithms have been proposed and much improvement has been established in the basic Lasso, but the achieved response may not be the optimum. The lasso based algorithms considers the correlations between the data points and computes an approximate signal x of signal y. The Lasso algorithm performs well if the sensor data has less variance and its performance decays with increased variance between the data points in sensor data set. To improve and achieve a generalized results, it is necessary to consider the correlation between the data points in the data set and correlation between data points and response. In view of above mentioned issues in existing Lasso-type approximation methods, an enhanced lasso (referred to as MLasso) is proposed for data compression.

This algorithm not only discovers the correlations between the data points and the response, in addition also discriminates similar data points. This characteristics of the algorithm differentiates the proposed algorithm from the rest of Lasso based algorithms. The proposed MLasso method uses a novel graph regularizer on the data points which simultaneously considers the 'response-data point correlation' and the 'data point-data point correlation' in the data. In this work alternating direction method of multipliers (ADMM) is employed to optimize the MLasso algorithm method and does the data compression effectively.

3.1. Lossy Compression for sensor signal

To achieve the requirement of compressing an original signal, it shall be sparse in some possibly transformed domain. Compressive sampling Theory or compressed sensing developed for data transmission has become an active investigation area. The basis of this theory is that the true data can be represented using reduced samples and the same shall be recoverable from this samples with an allowed error bound. On this basis the true sensor signal β can be recuperated from approximated fewer samples of signal derived by the solution of the problem:

$$\min_{\beta} \|W\beta\|_1 \tag{1}$$

$$\text{subject to } \phi\beta = y$$

Where the original signal β is a $p \times 1$ matrix to be compressed and compression theorem W is a $p \times p$ known matrix. The $n \times p$ sensing matrix Φ, contains in rows, n bases for the measurements needed to be sampled from the sensed signal. The general choice to initialize Φ is n randomly generated data points. Finally $n \times 1$ vector y will contain the sampled data points from the original signal β such that $n < p$.

The data acquired by the sensor in the field may contain noise. Considering the measurements in practical cases the problem given in (1) is generally rewritten as:

$$\min_{\beta} \|W\beta\|_1 \tag{2}$$

$$\text{subject to } \|y - \phi\beta\|_2^2 \le \varepsilon$$

Where ε represents the noise in the measured signal. As mentioned in (2) the l_1 norm of β under the compression transform W is minimized, such that reconstructed signal β^* from n measurements of y (compressed signal) of true signal shall be consistent.

The optimization problem in eq. (2) with constraints shall be rewritten in the following form:

$$\min_{\beta} \|y - \phi\beta\|_2^2 + \lambda \|W\beta\|_1 \tag{3}$$

The values of ε in eq. (2) and λ in eq. (3) can be determined empirically. The eq. (3) can be found that it is similar to the Lasso eq. (4)

$$\min_{\alpha,\beta} \|y - 1\alpha - X\beta\|_2^2 + \lambda \|\beta\|_1 \tag{4}$$

A main difference between eq. (3) and eq. (4) is the compression transform W available in the second term of eq. (4) called penalty term.

3.2. Enriched Lasso for Data Compression

Since the introduction of lasso l_1 regularization has been adopted for learning in high-dimensional databases. Extending Lasso eq. (4), the learning compressible models can be formulated as follows:

$$\min_{\alpha,\beta} L(y, 1\alpha + X\beta) + \lambda \|W\beta\|_1 \tag{5}$$

The proposed data compression method is motivated by the objective to support the selected samples to correlate more with the reconstructed signal due to low redundancy between them. Therefore, Equations eq.4 and eq.6, are combined and propose the MLasso method for data compression and formulated as:

$$\min_{\beta} \|y - \phi\beta\|_2^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \beta^T S \beta \tag{6}$$

where $\lambda_1, \lambda_2 \geq 0$ are tuning parameters. Note that $\beta^T S \beta$ is a non-convex constrain. Our MLasso disparities with previous Lasso-type data compression methods, which use convex methods and which may be suboptimal in terms of the accuracy. Here, the proposed MLasso method enforces stricter non-convex constrictions, i.e., 'data point-response correlations' and 'data point-data point correlations', in locating the optimal regression β. Once the solution β of Eq.7 is obtained, the selected samples can be easily recuperated.

3.2.1 Learning Compressible Models

Let X is a $n \times p$ matrix with constant p, $Y = X\beta + \varepsilon$ is the sensed data with noise. The Lasso refers to:

$$\min \|Y - \beta X\|_2^2 \text{ such that } \|\beta\|_1 \leq L \tag{7}$$

and in Lagrangian it becomes

$$\min \frac{1}{2n} \|Y - \beta X\|_2^2 + \lambda_n \|\beta\|_n \tag{8}$$

The proposed MLasso algorithm solve the non-convex problem in eq. (7) by using alternating direction method of multipliers (ADMM). The concept of ADMM approach is to bifurcate a very complicated problem into a set of simpler and solvable problems. The best features of augmented Lagrangian methods and dual decomposition are combined to solve the constrained optimization problem [42]. By introducing an auxiliary variable γ into the objective function Eq.7, the problem solved by ADMM takes the following form:

$$\min_{\beta} f(\beta) + g(\gamma) = \frac{1}{2} \|y^T - \beta^T X\|_2^2 + \lambda_1 \|\gamma\|_1 - \lambda_2 \beta^T S \beta \tag{9}$$

$$subject\ to\ \beta-\gamma=0$$

which is found as same as the problem in Eq.(7) and γ in the eq. (8) shall be considered as a proxy for β . The augmented Lagrangian associated with the constrained problem in eq. (8) is given by

$$L(\beta,\gamma,z)=\frac{1}{2}(y^T-\beta^T X)_2^2-\lambda_2\beta^T S\beta+\lambda_1\|\gamma\|_1+(\beta-\gamma,z)+\frac{\rho}{2}\|\beta-\gamma\|_2^2 \tag{10}$$

Here ρ is a positive penalty factor and z is a Lagrange multiplier corresponding to the equality constraint $\beta=\gamma$. The objective function in eq. (7) is simplified by decoupling the function by introducing an additional variable γ and a constraint $\beta-\gamma=0$. The original eq. (6) is solved by iteratively minimizing $L(\beta,\gamma,z)$ over β and γ , and then z is updated. The learning rule adopted is as given below:

$$\beta^{i+1}=\arg\ \min_{\beta\in R^d} L(\beta,\gamma^k,z^k) \tag{11}$$

$$\frac{\partial}{\partial\beta}=\frac{\partial}{\partial\beta}\left[\frac{1}{2}(y^T-\beta^T X)_2^2-\lambda_2\beta^T S\beta+\lambda_1\|\gamma\|_1+(\beta-\gamma,z)+\frac{\rho}{2}\|\beta-\gamma\|_2^2\right]=0$$

$$Xy+XX^T\beta-2\lambda S\beta+z^k+\rho(\beta-\gamma^k)=0$$

$$Xy-XX^T\beta+2\lambda S\beta-z^k-\rho(\beta-\gamma^k)=0$$

$$Xy-z^k+\rho\gamma^k=XX^T\beta-2\lambda S\beta+\rho\beta$$

$$\beta^{k+1}=(XX^T-2\lambda S+\rho I)^{-1}Xy-z^k+\rho\gamma^k$$

$$\gamma^{k+1}=\arg\ \min_{\beta\in R^d} L(\beta^{k+1},\gamma,z^k) \tag{12}$$

By applying β_i^{k+1} and the multipliers $z_i^k, i=1,2......d$ are fixed in the Lagrangian, the minimization problem of $\gamma_i^{k+1}, i=1,2......d$ is:

$$\min_{\gamma_i}=[\lambda_i\sum_{i=1}^{d}|\gamma_i|_1-\sum_{i=1}^{d}\left(\gamma_i.z_i^k\right)+\frac{\rho}{2}\sum_{i=1}^{d}\left(\beta_i^{k+1}-\gamma_i\right)^2] \tag{13}$$

Derivative of equation with respect to γ_i and equating it to zero, we get:

$$\frac{\partial\lambda_i|\gamma_i|}{\partial\gamma_i}-z_i^k+\rho(\gamma_i-\beta_i^{k+1})=0$$

$$\frac{\partial\lambda_i|\gamma_i|}{\partial\gamma_i}=z_i^k-\rho(\gamma_i-\beta_i^{k+1})$$

$$\gamma^{i+1}=\begin{cases}\frac{1}{\rho}\left(z_i^k+\rho\beta_i^{k+1}-\lambda_i\right) & if\ \ z_i^k+\rho\beta_i^{k+1}>\lambda_i\\ \frac{1}{\rho}\left(z_i^k+\rho\beta_i^{k+1}+\lambda_i\right) & if\ \ z_i^k+\rho\beta_i^{k+1}<-\lambda_i\\ 0 & z_i^k+\rho\beta_i^{k+1}\in[-\lambda_i,\lambda]\end{cases} \tag{14}$$

$$z_i^{k+1}=z_i^k+\rho(\beta_i^{k+1}-\gamma_i^{k+1}) \tag{15}$$

The learning algorithm is considered converged and stops if the primal and dual residuals meets the predefined stopping criterion mentioned as absolute tolerance and relative tolerance. The penalty parameter ρ affects the primal and dual residuals, and hence affects the termination of the algorithm. A large ρ tends to produce small primal residuals, but increases the dual residuals. A fixed $\rho = 0$ is commonly used. But there are some schemes for varying the penalty parameter which achieve better convergence.

4. EXPERIMENTAL RESULTS

In this section, we brief and report the results to illustrate the performance of Lasso approximation algorithm on both multivariate and univariate datasets. We implemented both Algorithms in JAVA with eclipse as front end. All experiments were performed on a HP with an Intel Processor with access to 5GB of RAM.

4.1. Experimental Data

The compression capability of MLasso algorithm is verified with datasets provided by Sensor Scope in collaboration with HES-SO, Clim-Arbes project and Microphone provided by CMU.

Sensor Scope:

The real time data is collected using a small sensor network [26]. The data collection consists of 1472 recordings of Temperature and humidity sampled at 2 seconds. It is noticed that the recorded values of humidity is higher than the recorded temperature values. The recorded values are smooth i.e. there will not be any sudden changes. The data is represented as FN_T (Temperature) and FN_H (Humidity).

Microphone (CMU):

The dataset contains 2887 data sampled at an interval of 4-9 seconds done at CMU Room NSH 4622. The univariate data is discontinuous or non-smooth due to presence of lot of noise and surges. The dataset is denoted as SC_M.

Mobile Health (MHEALTH):

Among the several multivariate data sets available for public, the Mobile Health (MHEALTH) three dimensional data set from UCI Machine learning repository [25] is the first of its kind. The dataset comprises of 483840 data with a sampling rate of 0.02 second. The collection contains body motion and vibrant signs from ten volunteers while performing twelve physical activities using Shimmer wearable sensors. The multiple sensors used measures the motion experienced by the body parts namely acceleration, the rate of turn and the magnetic field orientation. From the MHEALTH data set, two-lead ECG (MH_ECG), three-axis acceleration of right wrist (MH_AR), three-axis acceleration of left ankle (MH_AL), and three-axis magnet data (MH_MG) are selected for experimentation.

CRAWDAD:

The second multivariate data set contains the three axis acceleration readings (CJ_A) of vehicles. The data set is collected by the motion of different vehicles using the mobile phone of its drivers. The collection contains 16060 data sampled at 0.0625 second intervals.

In addition to the above dataset the third multivariate data set is provided by Samuel Madden et al. (http://db.csail.mit.edu/labdata/labdata.html). The data set contains 2.30 million data and were collected by 54 Mica2Dot nodes at the same time. Four attribute data humidity, temperature, voltage and light intensity were collected from each node. Each real number such as sampling data, wavelet coefficient, regression coefficient, which is stored in Mica2nodes, needs 2 bytes for storage. 2 bytes are enough for storing an integer such as start number start and the count number length of data..

To understand the effectiveness of the proposed algorithm, the results achieved are compared with the below mentioned well-established algorithms available in literature:

- Lightweight Temporal Compression (LTC), is a low-complexity piecewise linear approximations lossy compression algorithm. It fits the consecutive measurements as a straight line within the desired error margin. The greater compression ratio is obtained, while the larger error bound is given.
- Piecewise Linear Approximation with Minimum number of Line Segments (PLAMlis), takes an n-length sequence of measurements and finds the minimum number of line segments required to represent the sequence within an error bound.
- Lasso : Compression of signal y is achieved by removing the small differences between the data points in the signal. The signal x a smoother approximation of signal y is computed by minimizing the differences between data at adjacent time intervals

4.2. Performance Evaluation

4.2.1. Correlation length

For a discrete time series $x(n)$ with n = 1, 2. . . , N, μ_x is the mean and σ_x^2 is the variance the correlation length of $x(n)$ can be defined as the smallest value n^* subjected to the autocorrelation function of signal is lesser than a threshold ∂ (predefined).

The autocorrelation function is given by:

$$\rho_x(n) = \frac{E[(x(m) - \mu_x)(x(m+n) - \mu_x)}{\sigma_x^2} \tag{16}$$

$$\text{and } n^* = \arg\min_{n>0}\{\rho_x(n) < \delta\} \tag{17}$$

4.2.1. Compression Ratio (η)

If the time series $x(n)$ with n = 1, 2. . . , N, needs $N_b(x)$ bits to store and its compressed version $\hat{x}(n)$ needs $N_b(\hat{x})$ bits to store then η is estimated using:

$$\eta = \frac{N_b(\hat{x})}{N_b(x)} \tag{18}$$

4.2.2. Total Energy Consumption

The total energy consumed is the sum of energy needed to compress the signal and to transmit the compressed signal expressed in joule. The number of operations (*addition, subtractions, divisions, multiplications and comparisons*) required for compression is estimated and mapped into number of clock cycles and then to energy consumption. Energy required for transmission and receiving the data depends on the energy consumed by equipment to transmit a bit of data and number of bits.

4.2.3. Total Error

If the compressed signal $\hat{x}(n)$ is reconstructed to its original form and is given by $y(n)$. The error is the difference between the reconstructed and original signal. The total error is calculated using:

$$Error = \sum_{i=0}^{N} \left(x(i) - \hat{x}(i) \right)^2 \tag{19}$$

4.4. Experimental Results

To evaluate the proposed algorithm, the synthetic signals of correlation length n^* with lengths {1, 10, 20, 50 . . . 500} time slots are used to test the system. ∂ = 0.05 have been adopted for the results presented in this paper. Additionally, a Gaussian noise with standard deviation σ_{noise} = 0.04 has been included in the signal. Acceptable tolerance in error between actual signal and reconstructed signal has been set to $\varepsilon = \xi\sigma_{noise}$ where $\xi \geq 0$. The same signal $x(n)$ has been used for all the compression methods for each simulation run and value of n^*.

The plot in Fig. 1 between provides the Compression Ratio achieved for different correlation lengths n^* for four compression methods. Form these results, it can be found that compression performance of all the four methods are poor for small values of n^* and improves with the increased correlation length. This ensures that the correlation length n^* is a key factor that decides the performances of the algorithm. The energy required for compression is presented in Fig. 2. We can achieve better compression values for higher values of n^*. The same is not true in the case of energy consumption among all scheme.

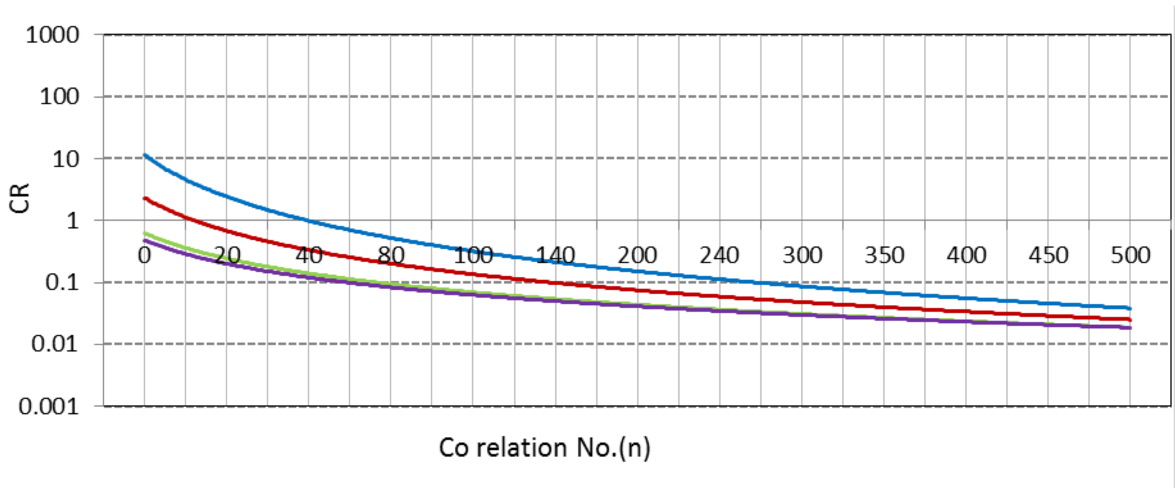


Fig. 1. Illustration of changes in Compression ratio for various Correlation length for Univariate data.

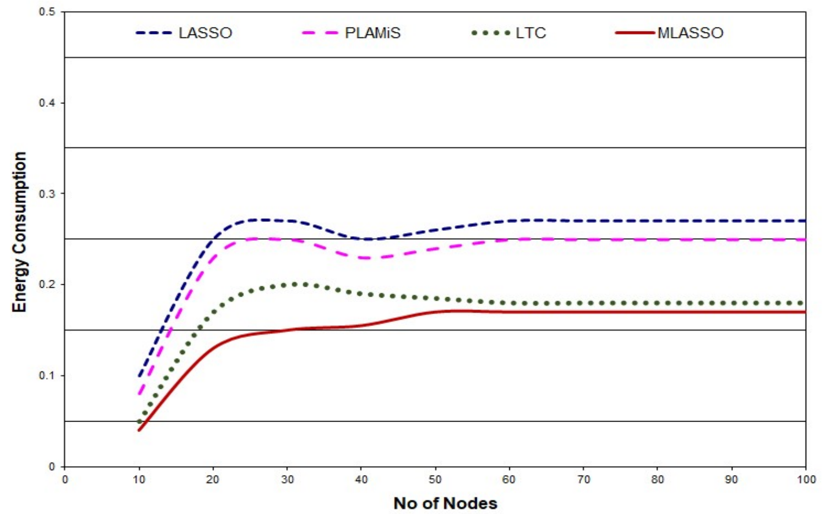
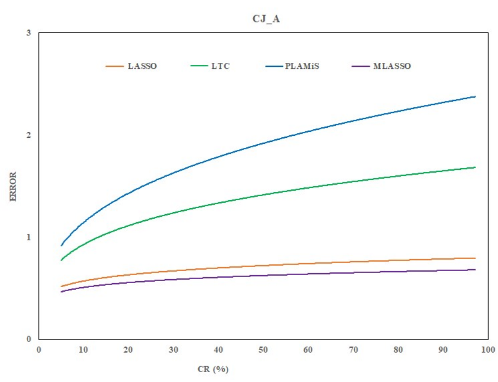
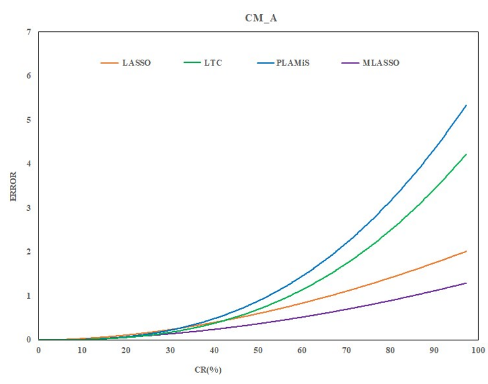


Fig. 2. Compression ratio vs Energy consumption for compression methods for fixed $\varepsilon = 4\sigma_{noise}$

We shall look at the dependence of energy required for compression on correlation length n^*. The energy consumption depends on the operational model of a particular algorithm adopted for compression. In case of LTC, the input signal $x(n)$ is incrementally, initially starts the first sample and including one sample at a time. Thus correlation length n^* has weak influence on the consumed energy. PLAMLiS divides and reiterates based on the correlation length and thus the method performs lesser iterations if the correlation length increases. Thus the number of operations required decreases, consequently decreasing the energy consumption. For LASSO and MLASSO, the energy requirements increases during the addition of new sample to the model. The error tolerances have to be verified after updating the model. Thus energy consumption by these models rises with increased correlation length of the input time series.

In general the reconstruction error increases with the increased compressed ratio. A method can be considered as superior if it compresses the dataset and if the reconstructed dataset from the compressed data is most similar(less reconstruction error) to the original dataset. In order to explore the capabilities of the methods in compressing the signals, error of the reconstructed signals from signals of different compression ratios are presented in **Fig.3.** It can be found that the reconstructed signal from the compressed data using MLasso is more similar to the original signal(less error). Also it can be observed that the proposed method for compression provides generalized performance for data of different types. The error remains almost same for a range of compression ratio.





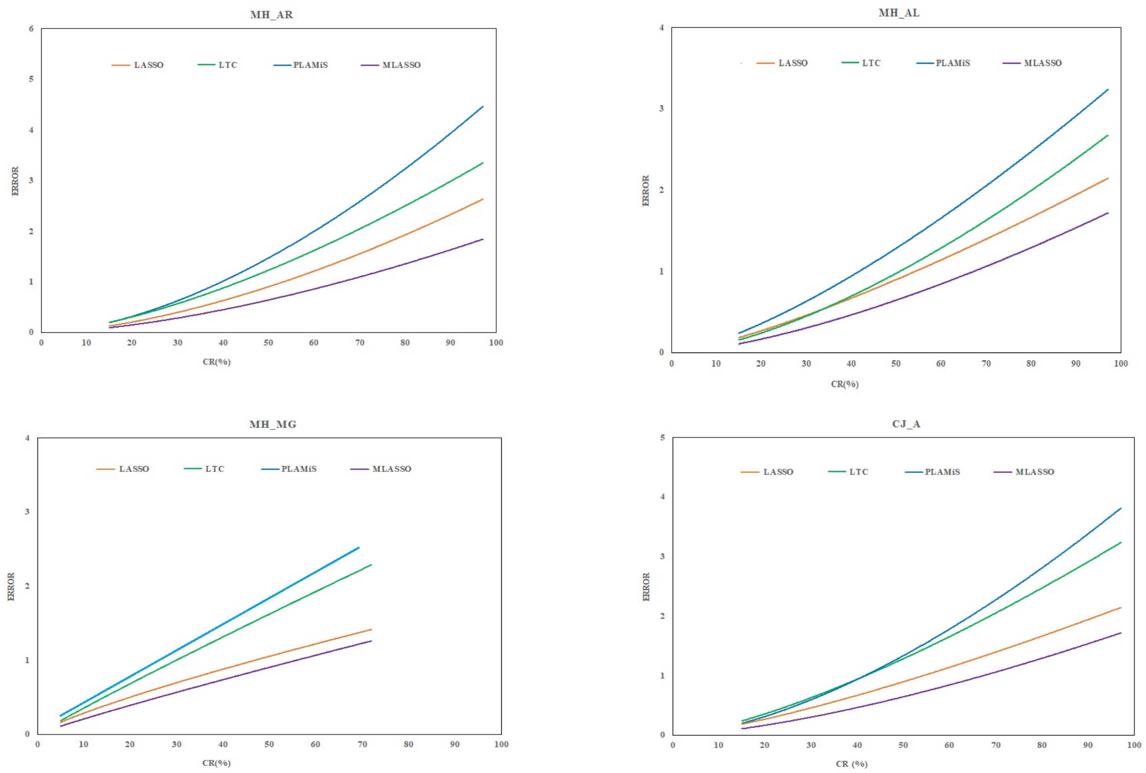


Fig. 3. The change in error at different Compression ratio for different datasets

This performance of the proposed Lasso based method MLasso allows to adopt the method to compress signals with more variance between the signal samples. Also by adopting the method it is possible to compress the signal to very smaller sizes, since the original signal can be reconstructed using small error. The plots in Fig.4 shows the total energy gain for different correlation lengths. The total energy gain, defined as the ratio between the energy spent for transmission in the case with no compression and the total energy spent for compression and transmission using the selected compression techniques.

The proposed method MLasso, produces the highest energy gain. In WSN scenario the total energy is highly contributed by the energy required for computations required for compression. Thus, lightweight methods, LTC and PLAMLiS, also performs better. In the case of UWN, the energy required for computations of compression is negligible compared to transmission energy requirements. In this scenario, MLasso, whose performance is the best will support more for energy savings. In this case energy savings by methods such as LTC, is limited.

It can be noted that till now the compression ratio has been considered as a parameter to evaluate the system performance. And the compression ratio depends on error tolerance $\varepsilon = \xi\sigma_{noise}$, so the compression algorithm takes ξ as an input from the user. The relative error ξ can be related with the compression ratio. Here we relate mathematically ξ as a function of compression ratio. In the same way N_c can also be expressed with respect to compression ratio. These relationships have been derived.

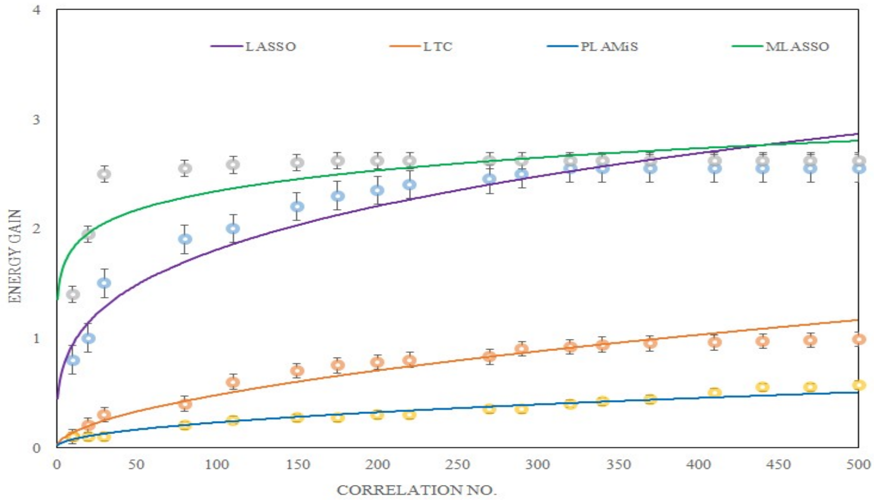


Fig. 4. Energy Gain vs Correlation Length

through synthetic signals, extensive simulations and numerical fitting. The relative error tolerance can be related to compression ration through the following formulae:

$$\xi(n^*,\eta) = \begin{cases} \dfrac{p1\eta^2 + p2\eta + p3}{\eta + q1} & Lasso \\ \dfrac{p1\eta^4 + p2\eta^3 + p3\eta^2 + p4\eta + p5}{\eta + q1} & MLasso \end{cases} \tag{20}$$

The fitting parameters p1, p2, p3, p4, p5 and q1 depends on the correlation length. The fitting formulae are validated against the CARWAD dataset. The temperature and humidity values in the dataset are utilized for validation. The experimental relationships of Eq. (14) for MLasso and Lasso are provided in Fig. 5(a) and 5(b). The plot with marks provide the performance obtained to compress temperature and humidity dataset using Lasso and MLasso. From these plots, it can be noted that the numerical fittings obtained with the synthetic signals also suitable for representing the signals from datasets. It can be also observed for decreasing values of n^*, the shape of the curves related to ξ and compression ratio remain similar but shifts towards the right. Lastly, it is noticed that the influence of n^* on the performance is mainly noticeable at lesser values of n^*, and for correlation lengths larger than 100, the plots be likely to converge.

It was also found that the computational cost N_c depends linearly on compression ratio and the correlation length (n^*) and can be expressed as in eq.(15):

$$N_c(n^*,CR) = \alpha(CR) + \gamma n^* + \beta \tag{21}$$

From the experiments it is ensured that N_c more depends on compression ratio and less on correlation length. Hence eq.(15) takes a simple form as in eq.(16)

$$N_c(CR) = \alpha(CR) + \beta \tag{22}$$

Fig. 6 provides the results of eq. (16). The results ensure results obtained for experimental signals against the results obtained on real world signals.

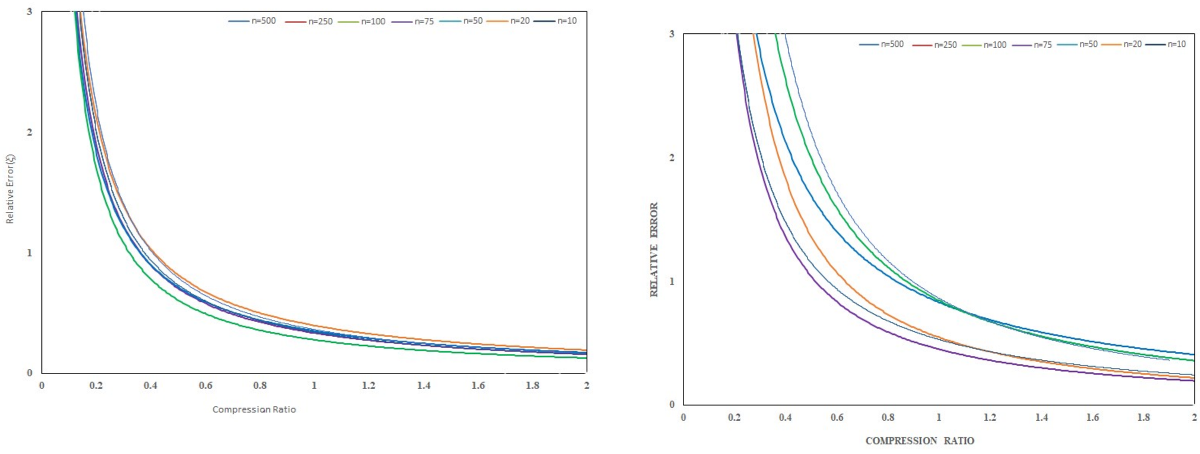


Fig. 5. Relationship between compression ratio and Fitting functions $\xi(n^*,\eta)$ for MLasso and lasso

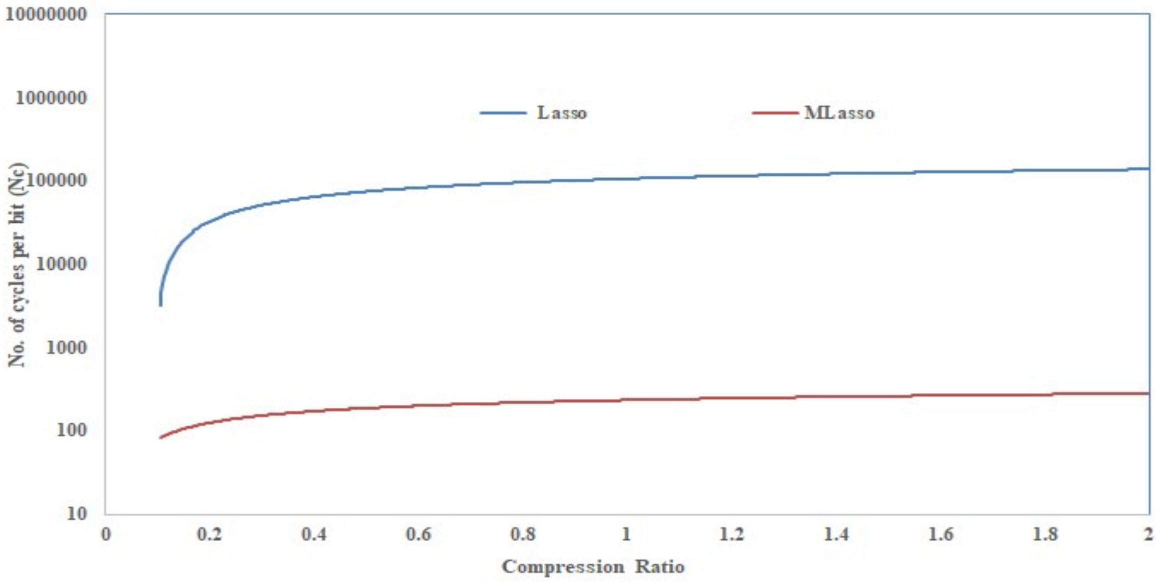


Fig. 6. Relationship between compression ratio and No. of Cycles per bit

5. CONCLUSION

In this paper we have systematically compared the Lasso and a MLasso compression algorithms for saving the energy in sensor networking. The intension was to explore the better method for energy savings are possible depending on the statistics of sensor algorithm, performance of compression and the type of hardware used to construct the network. The results in the paper reveal that there is considerable energy savings when signal compression is done by using Lasso based algorithms, since they need lesser computational cost. But it can be noticed that in the case of underwater transmission of data more energy shall be required and in these case algorithms that can produce higher compression performance will be more suitable. At the end formulas for parameters that are suitable for Lasso based compression methods that relates computational requirements, reconstruction error and compression ratio are derived and tested with real world datasets. The usefulness of proposed algorithm is assessed using these test results.

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