



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 3, March 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Energy-Efficient Solution in Wireless Sensor Networks using Amplify-and-Forward Compressed Sensing (AF-CS)

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ABSTRACT: Wireless Sensor Networks (WSNs) design is currently one of the most challenging topics in the field of wireless communications. In particular, WSNs are severely energy-constrained because they consist of many small, cheap and power limited nodes whose batteries cannot be recharged in most cases. Hence, the application of energy-efficient algorithms turns out to be crucial. Interestingly, sensor readings tend to be highly time correlated in many scenarios because of oversampling. Note that even sampling at the widely accepted Nyquist frequency, which is useful to capture the maximum possible variations in the signal of interest, there may be time windows where the signal fluctuates less and, in fact, this consideration applies to most detection and many monitoring scenarios. In some occasions the sensor readings are also space-correlated .

KEYWORDS: Wireless Sensor Networks (WSNs)

I. INTRODUCTION

Smart environments represent the next evolutionary development step in building, utilities, industrial, home, shipboard, and transportation systems automation. Like any sentient organism, the smart environment relies first and foremost on sensory data from the real world. Sensory data comes from multiple sensors of different modalities in distributed locations.

The smart environment needs information about its surroundings as well as about its internal workings; this is captured in biological systems by the distinction between exteroceptors and proprioceptors.

The sensing electronics measure ambient conditions related to the environment surrounding the sensor and transform them into an electric signal. Processing such a signal reveals some properties about objects located and/or events happening in the vicinity of the sensor. A large number of these disposable sensors can be networked in many applications that require unattended operations.

Each sensor node bases its decisions on its mission, the information it currently has, and its knowledge of its computing, communication, and energy resources. Each of these scattered sensor nodes has the capability to collect and route data either to other sensors or back to an external base station. A base-station may be a fixed node or a mobile node capable of connecting the sensor network to an existing communications infrastructure or to the Internet where a user can have access to the reported data.

Wireless communications have been extended to virtually all the possible scenarios and applications. Unfortunately, security risks are inherent in any wireless transmission. This is mainly because the communication channel is open to any intruder. Therefore, unauthorized entities may exploit this scenario in order to obtain confidential information, to corrupt the transmitted data, to degrade the network performance, etc.

II. LITERATURE SURVEY

1. J. E. Barcelo-Llado, A. Morell, and G. Seco-Granados,(May 2013) “Conditional downsampling for energy-efficient communications in wireless sensor networks,” *J. Adv. Signal Process.*, vol. 101, pp. 1–16

This paper deals with the power limitations in a wireless sensor network scenario. Concretely, we propose to use a conditional downsampling encoder (CDE) at the sensing nodes as an energy-efficient solution for the communication problem. It exploits the knowledge about the signal structure, which is assumed to be time-correlated, in order to decrease the sampling rate and hence to reduce the number of transmissions within the network. They analytically assess the performance of the CDE in terms of quadratic distortion, from which we derive closed-form expressions

when it is combined with one of the two decoders: the step decoder and the predictive decoder. Moreover, we propose two methodologies to design the CDE in order to guarantee a given coding rate. We also compare the CDE, both analytically and experimentally, with other classical decimator techniques, which are the deterministic downsampling encoder and the probabilistic downsampling encoder. Numerical simulation validates our analytical results. Moreover, we compare the obtained quadratic distortion and extract the conclusions of the capabilities of the studied encoding-decoding schemes.

2. Candes E.J and Tao T,(2007), “Optimization of the Amplify-and-Forward in a Wireless Sensor Network Using Compressed Sensing”,vol.34,pp-1124-1564

A novel compressed sensing technique applied to wireless sensor networks with a star topology. In particular, they propose an amplify-and-forward transmission scheme to achieve a distributed compressed sensing framework. The key idea is twofold; the first is to take advantage of time correlation properties present in most of the physical sensing scenarios and produce a sparse version of the measured signal. The second one is to perform random projections by means of the channel matrix that models the path among transmitters, relays and receivers.

3. S. Nikitaki and P. Tsakalides, (Aug. 2011), “Localization in wireless networks based on jointly compressed sensing,” in Proc. 19th Eur. Signal

Process. Conf., Barcelona, Spain, pp. 1–5

In orthogonal frequency-division multiplexing (OFDM) amplify-and-forward (AF) relay networks, in order to exploit diversity gains over frequency-selective fading channels, the receiver needs to acquire the knowledge of channel state information (CSI). In this article, based on the recent methodology of distributed compressed sensing (DCS), a novel channel estimation scheme is proposed. The joint sparsity model 2 (JSM-2) in DCS theory and simultaneous orthogonal matching pursuit (SOMP) are both introduced to improve the estimation performance and increase the spectral efficiency. Simulation results show that compared with current compressed sensing (CS) methods, the estimation error of our scheme is reduced dramatically in high SNR region while the pilot number is still kept small.

4. J. L. Paredes and G. R. Arce, (Jun. 2011), “Compressive sensing signal reconstruction by weighted median regression estimates,” *IEEE Trans. Signal Process.*, vol. 59, no. 6, pp. 2585–2601

A simple and robust algorithm for compressive sensing (CS) signal reconstruction based on the weighted median (WM) operator. The proposed approach addresses the reconstruction problem by solving a l_0 -regularized least absolute deviation (l_0 -LAD) regression problem with a tunable regularization parameter, being suitable for applications where the underlying contamination follows a statistical model with heavier-than-Gaussian tails. The solution to this regularized LAD regression problem is efficiently computed, under a coordinate descent framework, by an iterative algorithm that comprises two stages. In the first stage, an estimation of the sparse signal is found by recasting the reconstruction problem as a parameter location estimation for each entry in the sparse vector leading to the minimization of a sum of weighted absolute deviations. The solution to this one-dimensional minimization problem turns out to be the WM operator acting on a shifted-and-scaled version of the measurement samples with weights taken from the entries in the measurement matrix. The resultant estimated value is then passed to a second stage that identifies whether the corresponding entry is relevant or not. This stage is achieved by a hard threshold operator with adaptable thresholding parameter that is suitably tuned as the algorithm progresses. This two-stage operation, WM operator followed by a hard threshold operator, adds the desired robustness to the estimation of the sparse signal and, at the same time, ensures the sparsity of the solution. Extensive simulations demonstrate the reconstruction capability of the proposed approach under different noise models. We compare the performance of the proposed approach to those yielded by state-of-the-art CS reconstruction algorithms showing that our approach achieves a better performance for different noise distributions. In particular, as the distribution tails become heavier the performance gain achieved by the proposed approach increases significantly.

5. E. J. Candès and Y. Plan,(Nov. 2011), “A probabilistic and RIPless theory of compressed sensing,” *IEEE Trans. Inf. Theory*, vol. 57, pp.7235-7254

A simple and very general theory of compressive sensing. In this theory, the sensing mechanism simply selects sensing vectors independently at random from a probability distribution F ; it includes all models - e.g. Gaussian, frequency measurements - discussed in the literature, but also provides a framework for new measurement strategies as well. We prove that if the probability distribution F obeys a simple incoherence property and an isotropy property, one can faithfully recover approximately sparse signals from a minimal number of noisy measurements. The novelty is that our recovery results do not require the restricted isometric property (RIP) - they make use of a much weaker notion - or

a random model for the signal. As an example, the paper shows that a signal with s nonzero entries can be faithfully recovered from about $s \log n$ Fourier coefficients that are contaminated with noise.

6. P. Lioliou, M. Viberg, and M. Coldrey,(2012), “Efficient channel estimation techniques for amplify and forward relaying systems,” *IEEE Trans. Commun.*, vol. 60, pp. 3150–3155

A channel estimation scheme for Amplify-and-Forward (AF) relaying systems, using measurements at the destination only. A Least-Squares (LS) based channel estimation algorithm is developed, that provides the destination with full knowledge of all channel responses involved in the transmission. To investigate the algorithm performance, the Cramer-Rao lower bound (CRB) is analytically computed and compared with the asymptotic covariance of the proposed estimator. Since the existing estimator does not reach the CRB, we also propose and analyze an improved algorithm by taking into account the noise characteristics via weighted LS (WLS). The improved algorithm is asymptotically efficient, since it attains the CRB as the SNR tends to infinity.

III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

3.1.1 Amplify-and-Forward Compressed Sensing

A novel distributed compressed sensing transmission scheme, which is referred to as amplify-and-forward compressed sensing (AF-CS), in order to improve the existing tradeoff among reconstruction error, energy consumption, and resource utilization.

3.1.1.1 Compressed Sensing in WSNs

Compressed Sensing (CS) has been successfully applied in WSNs for localization, detection and in general for data collection, purposes in the recent years. In this paper we focus on data collection, which embraces monitoring but also some event detection applications, and our aim is to reduce the overall power consumption in the network. Motivated by the fact that radio transmission and reception is the main sink of energy (or at least a very important one) in the sensor nodes, we explore how to benefit from the compressed sensing theory in order to transmit as little as possible. To the best of the authors' knowledge, the most representative techniques in the literature that use compressed sensing for data collection purposes in WSNs have already been cited and suffer from two important drawbacks:

1. Either they assume impractical hypotheses about the sparsity of the signal of interest and/or
2. The resulting number of transmissions is high. Probably one of the most relevant works in the field of CS applied to WSNs that circumvents. Once R projections are available at the fusion center, it is able to recover an approximation of the original signal from its sparse representation with some bounded distortion.

3.1.2 Sensing phase

Compressed sensing exploits sparsity to acquire high-dimensional signals represented in a low-dimensional subspace. A priori, physical phenomena are not necessarily sparse, but expected to be correlated in time and space. Thus, correlated signals may have a (pseudo)sparse representation if they are expressed in a proper basis. Wavelets are in general considered as a good candidate to construct the sparsity basis matrix, $\Psi \in \mathbb{C}^{S \times S}$. The main difficulty in projecting a signal onto a given wavelet basis is that this is a centralized problem.

In order to carry out this task, some central entity is needed to gather all the measurements (i.e., collect $x(n)$) and compute all the wavelet coefficients $\Psi x(n)$ (or at least the K most important). This is not a problem in centralized scenarios as image processing, but to do so in a distributed fashion is not straightforward and strong assumptions appear in the literature. In a WSN scenario, the computation of the transformed coefficients requires all the S sensing nodes to transmit their readings towards this central entity in order to get a sparse version of $x(n)$ afterwards. One can easily see that this approach is signaling intensive and highly energy consuming. In order to overcome this problem, one possible solution is to artificially create a sparse representation of $x(n)$ with only K loaded entries and to set the rest to zero. One can easily do that by substituting the linear transformation $\Psi x(n)$ by a non-linear downsampling encoder for each sensor.

In principle, this procedure is not ancient at all since we are drastically removing a huge amount of information about the vector $x(n)$, in particular $S-K$ of the total entries (remember that $K \ll S$). In order to counteract this effect, we propose to use a Conditional Downsampling Encoder (CDE), which benefits from the time correlation properties of the signal. In a WSN scenario, the computation of the transformed coefficients requires all the S sensing nodes to transmit their readings towards this central entity in order to get a sparse version of $x(n)$ afterwards.

The figure 3.1 shows the Sensing and Projection phase as given below.

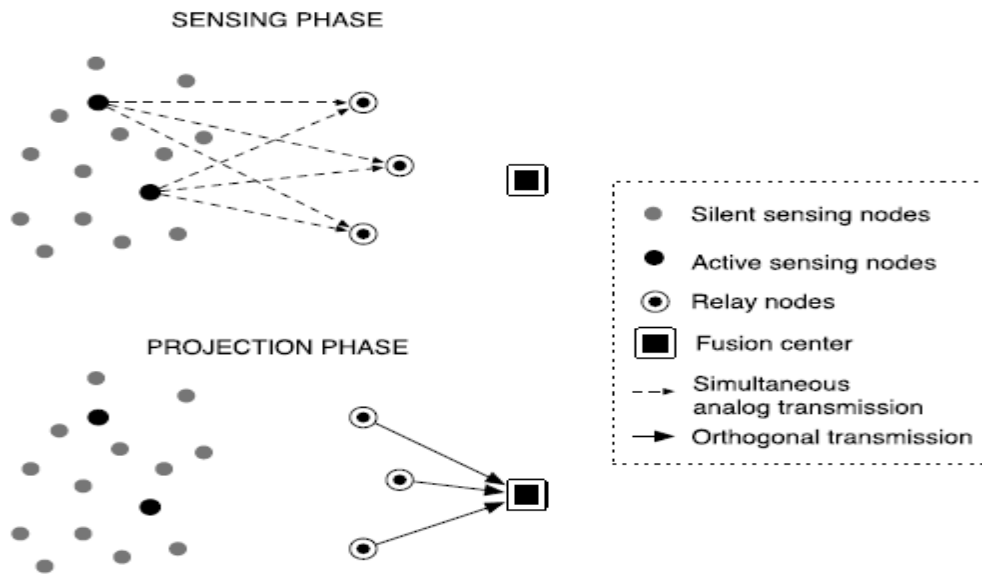


Figure 3.1 Sensing and Projection phase

3.1.3 Projection phase

Some existing CS-based techniques solve the problem of making projections by assuming a tree-based WSN and computing them in the gathering nodes. Others circulate the message from the source through the network and each node adds its contribution. Then, the message returns to the sink with all the contributions forming one projection. On the contrary, in each sensor sends its contribution $[\Psi]_{k,s} x_s(n)$ for $k = 1, \dots, K$, under the unfeasible assumption that the Then, the goal is to obtain a predictor $x_s(n)$ of each element of $\hat{x}(n)$ based on the N past readings of each sensor. This allows us to obtain a sparse version of $x(n)$, named $x_K(n)$, containing (on average) only the K most relevant readings with low distortion.

The Figure 3.2: CDE-PD transmission shows as given below,

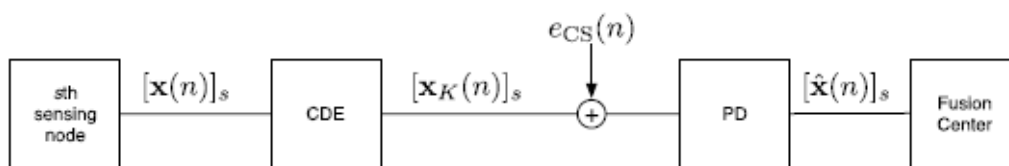


Figure 3.2: CDE-PD transmission

The parameters K and R have a direct influence on the distortion level at the AF-CS decoding stage. The higher the value of K , the lower the distortion at the PD. At the same time, a sufficiently large value of R ensures zero distortion at the CSD. On the other hand, K and R also influence the number of transmissions. In order to adjust both K and R , we define the cost function $v(\beta)$ as,

$$v(\beta) = \beta D_{AF-CS} + (1 - \beta)E \quad (3.1)$$

where E is the energy consumption modeled as the number of transmissions normalized by the total number of sensors, Recall that the distortion of the AF-CS decoder can be modeled as $D_{AF-CS} = DPD$ if CCS holds. Thus, this problem can be solved very fast because DPD depends only on K . Once K^* is obtained, the lowest value of R that satisfies CCS is computed.

A direct consequence of the CS principle, that is, the signal can be accurately recovered from a small amount of the total data. On the contrary, for high values of K and R , the proposed CS scheme performs inefficiently due to either a wrong signal recovery or a higher energy consumption or both.

To evaluate the robustness of the techniques in terms of D_{sim} AF-CS against thermal noise and for different values of R . We observe that AF-CS outperforms clearly CWS for low values of SNR (below 5dB). However, both techniques perform similarly for high values of SNR. The performance of the AF-CS scheme to two reference systems in the WSN

1. The Classical Approach (CA) where the group of S sensing nodes transmit their measurements directly to the fusion node each time slot.
2. The Compressive Wireless Sensing (CWS).

Energy consumption E measures the energy consumption in comparison to a standard star-topology WSN (in terms of the number of transmissions). For a fair comparison among all considered schemes, Assume that they all have the same duration and transmission power in mean. In the evaluated strategies, In addition, the relay nodes retransmit the computed R projections to the fusion center.

- $E = 1$ for the case of CA. All S sensors transmit their readings to the fusion center.
- $E = R$ for CWS. All S sensors transmit using the same resource to the fusion center to perform one projection. This process is repeated R times.
- $E = R+K S$ for AF-CS. The nodes in the subset $K(n)$ broadcast their messages towards the R relays, involving K transmissions.

3.2.4 Methodology

1. They extend our previous algorithm scheme in, analyzing it from a physical layer secrecy point of view. We find out that not only it is efficient in terms of energy and channel uses but also secure against passive eavesdropping.
2. They present a design condition for the required number of eavesdropping nodes to guarantee exact reconstruction with high probability.
3. They compare our proposed AF-CS with CWS and we find out that AF-CS dramatically increases the protection against eavesdropping at physical layer.

- A set E (of cardinality E) of malicious and passive eavesdropping nodes.

According to the CS nomenclature, K also corresponds to the number of non-zero elements of the transmitted vector $x(n) \in \mathbb{R}^S$, and R is the number of measurements used in the reconstruction process at the fusion center, i.e., the number of rows of the sensing matrix, $\Phi \in \mathbb{R}^{R \times S}$, where typically $K < R < S$. On the contrary, the eavesdroppers use E measurements to try to decode the signal, i.e., the number of rows of the sensing matrix, $\tilde{\Phi} \in \mathbb{R}^{E \times S}$, used by the eavesdroppers.

The fusion center has perfect channel information of all the links between a node in $K(n)$ and a node in R . One possibility is to estimate the channel matrix previously during a training phase at the network setup. On the other hand, the nodes in E do not have the channel information between the nodes in $K(n)$ and R . Instead, the eavesdroppers have a degraded version of the channel matrix of all the links between $K(n)$ and E . The fusion center knows the second order statistics of the signal of interest. The covariance matrix can also be estimated during an initial training phase. Thus the eavesdroppers do not have full access to this information.

IV. WIRELESS SENSOR NETWORKS

Wireless Sensor Networks (WSNs) consist of small nodes with sensing, computation, and wireless communications capabilities. Many routing, power management, and data dissemination protocols have been specifically designed for WSNs where energy awareness is an essential design issue. Due to recent technological advances, the manufacturing of small and low cost sensors became technically and economically feasible.

A Wireless Sensor Network (WSN) contains hundreds or thousands of these sensor nodes. These sensors have the ability to communicate either among each other or directly to an external base-station (BS). A greater number of sensors allows for sensing over larger geographical regions with greater accuracy.

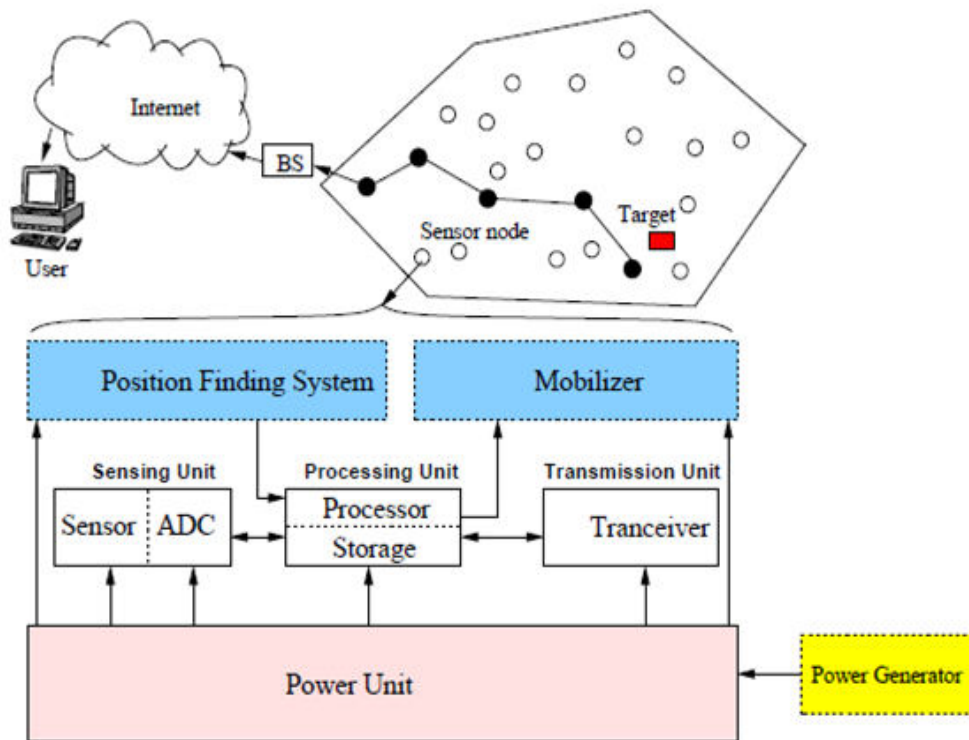


Figure 4.1 : The schematic diagram of sensor node

Figure 1 shows the schematic diagram of sensor node components. Basically, each sensor node comprises sensing, processing, transmission, mobilize, position finding system, and power units (some of these components are optional like the mobilize). The same figure shows the communication architecture of a WSN. Sensor nodes are usually scattered in a sensor field, which is an area where the sensor nodes are deployed. Sensor nodes coordinate among themselves to produce high-quality information about the physical environment.

Networking unattended sensor nodes may have profound effect on the efficiency of many military and civil applications such as target field imaging, intrusion detection, weather monitoring, security and tactical surveillance, distributed computing, detecting ambient conditions such as temperature, movement, sound, light or the presence of certain objects, inventory control, and disaster management. Deployment of a sensor network in these applications can be in random fashion (e.g., dropped from an airplane) or can be planted manually (e.g., fire alarm sensors in a facility). For example, in a disaster management application, a large number of sensors can be dropped from a helicopter. Networking these sensors can assist rescue operations by locating survivors, identifying risky areas, and making the rescue team more aware of the overall situation in the disaster area.

The figure shows the complexity of wireless sensor networks, which generally consist of a data acquisition network and a data distribution network, monitored and controlled by a management center. The plethora of available technologies makes even the selection of components difficult, let alone the design of a consistent, reliable, robust overall system.

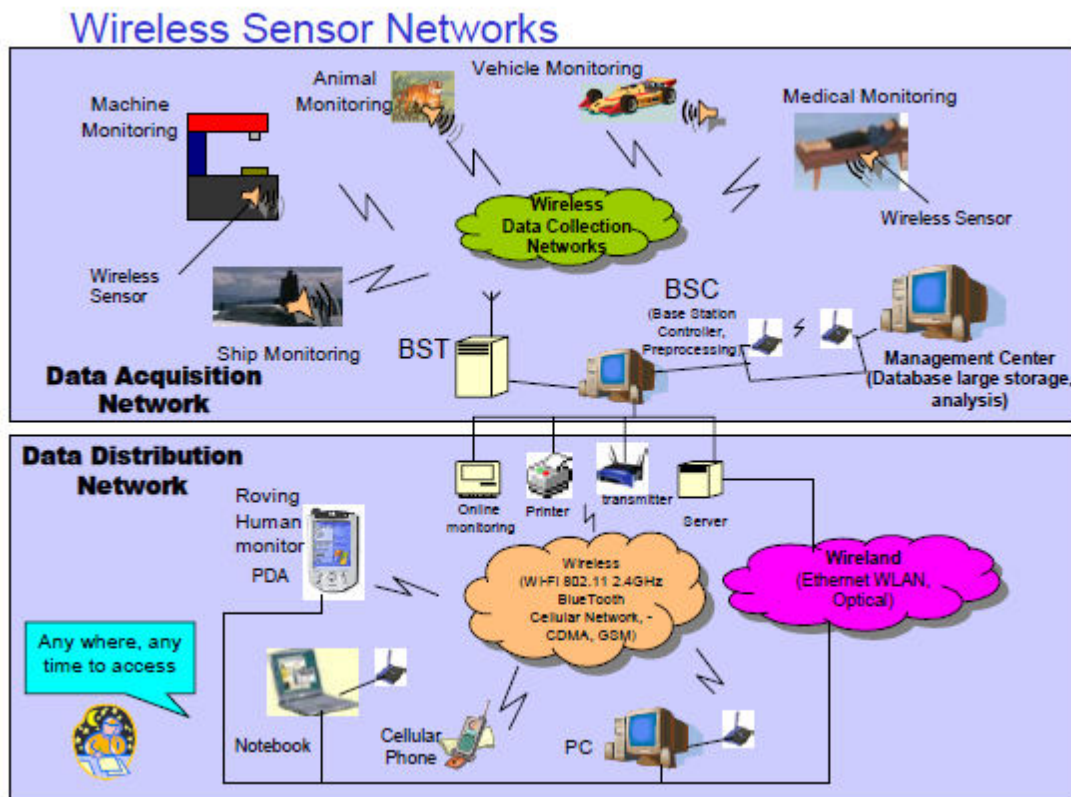


Figure 4.2 : Study of wireless Network

4.2. COMMUNICATION NETWORKS

The study of communication networks can encompass several years at the college or university level. To understand and be able to implement sensor networks, however, several basic primary concepts are sufficient.

4.2.1. Network Topology

The basic issue in communication networks is the transmission of messages to achieve a prescribed message throughput (Quantity of Service) and Quality of Service (QoS). QoS can be specified in terms of message delay, message due dates, bit error rates, packet loss, economic cost of transmission, transmission power, etc. Depending on QoS, the installation environment, economic considerations, and the application, one of several basic network topologies may be used.

A communication network is composed of nodes, each of which has computing power and can transmit and receive messages over communication links, wireless or cabled. The basic network topologies are shown in the figure and include fully connected, mesh, star, ring, tree, bus. A single network may consist of several interconnected subnets of different topologies. Networks are further classified as Local Area Networks (LAN), e.g. inside one building or Wide Area Networks (WAN), e.g. between buildings.

SENSORS

Sensors are hardware devices that produce a measurable response to a change in a physical condition like temperature or pressure. Sensors measure physical data of the parameter to be monitored. The continual analog signal produced by the sensors is digitized by an analog-to-digital converter and sent to controllers for further processing. A sensor node should be small in size, consume extremely low energy, operate in high volumetric densities, be autonomous and operate unattended, and be adaptive to the environment.

WSN Applications

WSN applications can be classified into two categories: monitoring and tracking (see Fig. 1.4). Monitoring applications include indoor/outdoor environmental monitoring, health and wellness monitoring, power monitoring, inventory location monitoring, factory and process automation, and seismic and structural monitoring. Tracking applications

include tracking objects, animals, humans, and vehicles. While there are many different applications, below we describe a few example applications that have been deployed and tested in the real environment.

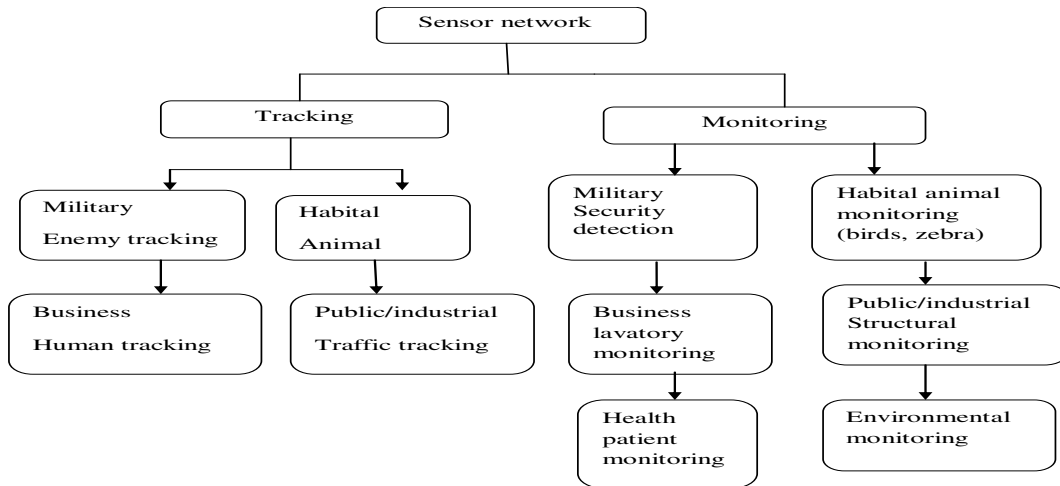
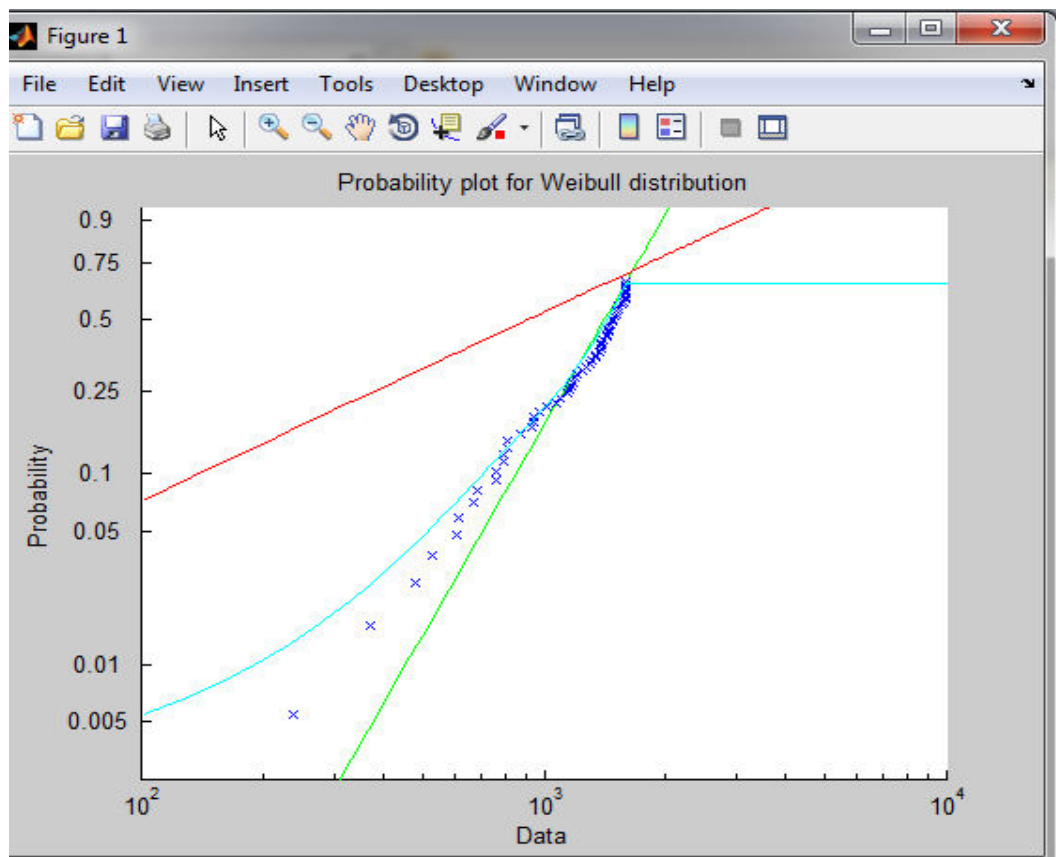
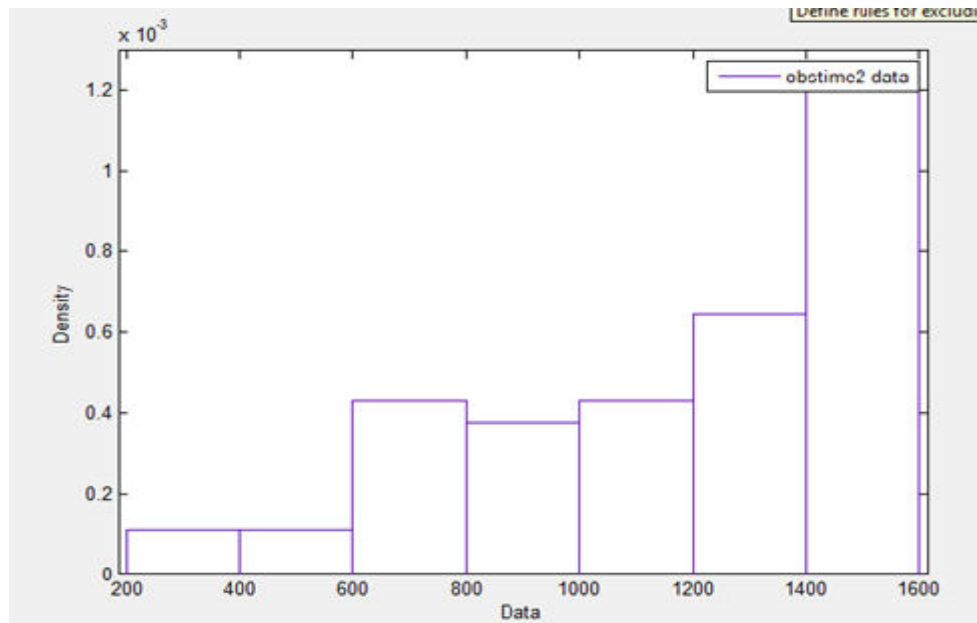


Figure 4.4:sensor application

A dense deployment of sensors to detect and measure the time of arrival of muzzle blasts and shock waves from a shot. Sensors route their measurements to a base station (e.g., a laptop or PDA).

V. EXPREMENTAL RESULT





5.2.2 Neural Network Toolbox Applications

It would be impossible to cover the total range of applications for which neural networks have provided outstanding solutions. This topic describe only a few of the applications in function fitting, pattern recognition, clustering, and time series analysis. The following table provides an idea of the diversity of applications for which neural networks provide state-of-the-art solutions.

Industry	Business Applications
Aerospace	High-performance aircraft autopilot, flight path simulation, aircraft control systems, autopilot enhancements, aircraft component simulation, and aircraft component fault detection.
Automotive	Automobile automatic guidance system, and warranty activity analysis.
Banking	Check and other document reading and credit application evaluation.
Defense	Weapon steering, target tracking, object discrimination, facial recognition, new kinds of sensors, sonar, radar and image signal processing including data compression, feature extraction and noise suppression, and signal/image identification
Electronics	Code sequence prediction, integrated circuit chip layout, process control, chip failure analysis, machine vision, voice synthesis, and nonlinear modelling.
Entertainment	Animation, special effects, and market forecasting.
Financial	Real estate appraisal, loan advising, mortgage screening, corporate bond rating, credit-line use analysis, credit card activity tracking, portfolio trading program, corporate financial analysis, and currency price prediction.
Industrial	Prediction of industrial processes, such as the output gases of furnaces, replacing complex and costly equipment used for this purpose in the past.
Robotics	Trajectory control, forklift robot, manipulator controllers, and vision systems
Securities	Market analysis, automatic bond rating, and stock trading advisory systems



Industry	Business Applications
Speech	Speech recognition, speech compression, vowel classification, and text-to-speech synthesis
Telecommunications	Image and data compression, automated information services, real-time translation of spoken language, and customer payment processing systems

Table5.1 Neural Network Toolbox Application

VI. CONCLUSION AND FUTURE WORK

In existing system, they introduced a distributed solution for a compressed sensing implementation in a Wireless Sensor Network scenario, which is referred to as Amplify-and-Forward Compressed Sensing (AF-CS). In particular, it presents an energy-efficient design for a star-topology sensor network based on an Amplify-and-Forward configuration. First, the sensing nodes exploit inner time correlation in order to reduce the number of transmissions, only keeping as active nodes the K sensors with the most unpredictable readings. In such a way, we distributedly transform the vector of interest $x(n)$ in a K-sparse approximation $x_K(n)$. Second, the relay nodes receive random projections formed from the linear combination of the K readings of the active sensors, each one multiplied by its channel gain. In order to do so, the active nodes transmit time-synchronized. Thus, the number of channel uses may be drastically reduced. The relay nodes retransmit the received random projections to the fusion center. A design criteria based on a cost function that controls the existing trade-off between the energy consumption and the signal distortion.

FUTURE WORK:

The main contributions of our proposed scheme in front of other CS techniques in the literature are listed as:

1. AF-CS presents a practical and distributed scheme that does not require some unrealistic assumptions of other schemes in the literature
2. AF-CS focuses on the minimization of the number of transmissions and not only the transmitted power. This approach is proved to be way more realistic and more suitable for energy-constrained scenarios as WSNs.
3. AF-CS reduces drastically the number of channel uses in front of classical schemes and at the same time maintain similar number of channel uses than other distributed CS techniques.

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