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Compressive Sensing Path for Optimal Data Transmission in Underwater Acoustic Sensor Network

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ABSTRACT

The recent researchers have developed a range of techniques to decrease the power usage of underwater sensor networks. These methods include clustering, compressive sensing, and the implementation of a block diagonal matrix. By integrating the clustering process with either a block diagonal or compressive sensing matrix, a notable reduction in the energy needed for transmitting and receiving sensor data can be achieved. This outcome leads to an acceleration in the speed of data transmission and reception. To expedite the transfer of compressed sensing measurement data from the cluster head to the base station, a routing strategy that prioritizes the shortest viable path has been created. Additionally, the communication of compressive sensing outcomes within clusters is facilitated by making use of arbitrary directions. In summary, these techniques offer an efficient approach to optimize energy consumption and elevate the overall performance of underwater sensor networks.

1. Introduction

The use of underwater sensor networks (UASNs), has grown increasingly prevalent in a variety of settings, including those that are military as well as those that are civilian. The situation is analysed after the sensors, which are generally submerged, have been observed following their random distribution around the area that is within the range of their detection. In spite of the fact that they function most of the time without the need for routine maintenance or the utilisation of renewable energy sources, they are still able to carry out the duty that has been assigned to them [1].

The low-cost, low-power, and tiny devices are an absolute requirement for the operation of underwater sensor networks and their interaction with one another. During the entirety of the process of data collecting, preserving power in such networks has always been a key challenge. This is since it has a direct impact on the ability of the network to function over the course of time.

According to several studies that highlight the significance of this finding, keeping better track of data in underwater sensor networks consumes less power than was previously anticipated (UASNs).

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The process through which network sensors are placed in sensing hotspots is entirely arbitrary. The majority of the time, they are put to service in hazardous environments that do not have access to sources of electrical energy, nor do they receive routine maintenance. Because of the severe restrictions placed on the available energy, the network connection is forced to rely on extremely small and inexpensive equipment [2].

Compressive sensing (CS), is a novel method of data processing that was developed specifically for signals that are sparse or compressible. This approach offers to reconstruct all sensor readings from N nodes using just M = O(klogN/k). CS measurements gathered from the sensing area and communicated to the sink or base station because the sensor data in UASNs is spatially correlated (BS). This approach achieves this objective because the sensory input in UASNs is spatially associated with one another [3].

Sensory data is typically encoded as a k-sparse signal using the canonical basis or one of several alternative sparsifying bases, such as the discrete cosine transform (DCT) or the wavelet transform. This encoding method is utilised so that the data can be processed in a more efficient manner. Each CS measurement can be gathered either from all the sensing nodes in the network or from selected random nodes, and the decision of which approach to use is determined by the data collecting methods that are utilised in the network that employs CS. In recent years, a vast number of research projects about computer science and the collecting of data in UASNs have been carried out. These projects have been carried out all over the world.

Several routing methods, the most notable of which are gossip-based, random-walk, tree-based, and cluster-based systems, contribute, at least in part, to the ease with which sensor values can be transmitted to the BS. At the BS, we gather the CS data in the form of $Y_{M\times 1} = \Phi_{M\times N} \times {}_{N\times 1}$, where m is the measurement matrix (which is also known as the projection matrix), and X represents all the unknown values from all of the sensors. The data are collected in this format so that they can be analysed by the projection matrix. The underlying routing mechanisms are responsible for the variety in the final measurement matrices, which can be either sparse or rich in Gaussian coefficients. This variation is caused by the fact that the routing processes are buried under the surface.

In RW routing that uses CS, it is necessary to send out a predetermined number of RWs of a predetermined duration to collect sensor readings from randomly selected nodes. The length of these RWs is also predetermined. This is essential for UASNs since all sensors are dispersed at random over the sensing area in such networks. To CS recovery, the data gathered by each of the node sensors are consolidated into a single measurement of the CS before being sent to the BS. This is done before the data can be used to recover the CS. After then, this measurement is transmitted. During the process of CS recovery, several sensor nodes use a wide variety of distinct measurement matrices to collect data. Although it has been shown that random sparse measurement matrices are capable of just as much success as complete Gaussian ones in CS recovery methods, the RW routing that we recommend makes use of a sparse binary matrix.

The measurement matrix will have one binary row that won't be used at all. This is because nodes only need to collect sensory input from a subset of the network rather than the complete thing. Over the time span of M iterations, each node gathers a sampling of data at random, which is represented by the equation $Y_{M\times 1} = \Phi_{M\times N} \times {}_{N\times 1}$. After that, these data are transmitted to the BS so that they can be incorporated into the CS recovery procedure.

The measurements of sensor data almost always have some form of spatial relationship, which causes the data to be naturally sparse on a level playing field. For the application of compressive sensing, it is helpful to use data that is already naturally sparse because this enables less data to be collected at a lower compression rate, which in turn results in less space being taken up by the compressed data. In summary, compressive sensing offers a fresh approach to the age-old problem of how to reproduce complete sensor readings using only the observations that are allowed by restricted compressive sensing. Compressive sensing offers a wide range of benefits, including this one. There is the potential for a considerable reduction in the total amount of power that is consumed by sensor networks.

The sparse random projections as the basis for a method of cooperative data sensing and compression. Because of this strategy, the sensors, which were already cooperating to get the intended outcomes, were not required to exert any more effort. By taking advantage of the spatial correlation of the data, the method can not only deliver great reconstruction accuracy for the detected field but also experience a significantly lower communication traffic burden when compared to conventional sampling algorithms that are used in underwater sensor networks [4]. This is possible because the method can take advantage of the spatial correlation of the data. This is conceivable since the method can make use of the spatial correlation that is present in the data. In the trials, the reconstruction accuracy and energy efficiency under different models of traffic movement are tested using data sets obtained from actual metropolitan environments in the real world [5, 6].

The fundamental goal of the adaptive CS-based sample scheduling method (ACS) for UASNs, which was created, is to obtain good sensing quality while yet retaining a low sample rate. to arrive at the optimal sample rate for each sampling window, the ACS considers not only the minimum required sample rate that is forecasted, but also the quality of the data that has been sensed. The implementation of ACS in cognitive sensor networks grants the networks the capability to carry out a variety of tasks, including the monitoring of their surroundings and the sensing of the spectrum [7, 8]. Compressed sensing as a more methodical answer to the problem. This suggestion comes highly recommended. It is possible to gradually restore the original data while still preserving the benefits of the NC-based approach, and the measurement and recovery strategy that we advocate is what makes all this possible [9, 10].

The combination of CS and RW to find ways to mitigate the negative effects that human activity has on the natural environment. It takes fewer CS measurements than the total number of sensor nodes in the network to reconstruct all the sensory data at the BS. A RW route with a duration that has been defined in advance is utilised so that each CS measurement can be obtained. The base station (BS) can gather random CS measurements for the purpose of CS recovery in one of two ways: either directly or through relaying through intermediary nodes. Both methods are described further below. to ensure that the networks use the least amount of energy possible, researchers are examining the best potential compromise that can be made between the sensor transmission range and the length of RWs. This is done to ensure that the networks can function properly [11, 12].

Using an asymmetric semi-homomorphic encryption approach and a sparse compressive matrix proposed a method for the secure collection of data that is based on compressive sensing. This method makes use of compressive matrices that are sparse. This was done to ensure the security of the information that was being collected (SeDC). To be more explicit, the asymmetric technique makes it easier to disseminate and handle secret keys [13, 14].

2. Proposed Methodology

This clustering and creation of compressive sensing measurements utilizing block diagonal metrics is made possible through the utilization of this compressive sensing technique, which then transmits these data to the base station either directly or over a series of hops. Because the compressive sensing measures can be distinct from one another depending on the sensors that are utilized in the network, it is essential for each cluster leader to have their own unique metric requirements.

In accordance with the principles underlying the concept of sensor networks, there are N sensors spread out over an LxL-sized region. It is necessary for the cluster head to receive the data from the sensor that is not physically positioned within the cluster head since that information is dependent on the distance that is being measured. The cluster heads are the ones in charge of the generation of compressed sensing data, which is subsequently delivered straight to the base station after it has been processed. The location of the base station can be moved to anywhere inside or outside of the sensing region at the user discretion.

Although the non-cluster heads are the ones who are tasked with determining how much the communication will cost, this is since the cluster heads are responsible for the production of the compressive sensing. to generate compressed sensing measures for usage within the cluster, the data from many sensors are merged. The command-and-control centre receives an immediate notification of the readings. The Eq. (1) can be used to calculate the total amount of power consumed [15]:

$$P_{total} = (P_{BS} + P_{intra-cluster}) \tag{1}$$

where $P_{intra-cluster}$ is intra-cluster consumption and P_{BS} is power consumption.

It is something that can be noted that the Pintra cluster plays a less significant function when the total number of clusters in the system decreases. This is something that can be seen. Pintracluster is computed with the assistance of the PSO model to reduce the amount of quality that is lost during the process of sending compressive sensing measurements from cluster heads to intermediate cluster heads and then to the base stations as Eq. (2).

$$P_{intra\text{-}cluster} = \left(\frac{N}{N_c} - 1\right)\frac{L^2}{2\pi} \tag{2}$$

This is done because a large amount of data is transferred during the process of sending compressive sensing measurements from cluster heads to intermediate cluster heads and then to the base stations. Large clusters often make use of a technique known as inter-cluster hop routing, which simply means hopping across clusters. Compressive sensing methods require less energy to transmit data as the number of cluster hops (CH) in each network rises. This is made possible by inter-cluster-hop routing.

After the clusters have been created with the assistance of the k-means algorithm, the focus of the inquiry that has been recommended will be on determining the path that is the most time and resource effective to travel from the hub to the base node. An algorithm known as PSO is utilized to successfully complete this task. To establishing a connection between the various cluster nodes and the roots of the base station, this approach makes use of a tree-like structure. It is a widely held belief that all of the nodes that comprise a cluster have the same transmission range (R), and that nodes that are able to communicate with one another and share data with one another are able to do so as long as they are within that range.

The newly created cluster heads are evaluated to make a decision regarding the transmission range that will be utilized. This makes use of a graph that is built on undirected geometry to connect each of the cluster unique nodes with one another in an efficient manner. G = (V,E), where V is the number of cluster heads and E is the set of edges by which they can communicate with one another.

The number of cluster heads is denoted by V, and E is the set of edges. The number of cluster heads is represented by the letter V, while the set of edges is marked by the letter E. Both the communication links that exist between cluster heads and the cluster heads themselves are subject to change depending on the circumstances.

Both the constrained variable, also known as the trip time tij, and the total cost cij are instances of components of a connection that have positive numerical values. The trip time tij is another name for the restricted variable. Integer programming is a method that is used for modelling the problem of determining the shortest route between the home station and the cluster leader while adhering to a set of constraints. This is accomplished by modelling the problem as a mathematical equation.

The PSO method can be used to figure out the route that will transfer data from sensors to nodes that are a part of a cluster in the most time and energy-effective manner. Creating a graph is the method used to accomplish this. All the nodes that comprise a cluster have the ability to communicate with one another and exchange information about the distance that separates each node from the base station thanks to the heads that are attached to each node. At first, the cluster will concentrate its activity inside the transmission range of the base station, which will be closer to it. The first thing that has to be done to figure out the maximum number of hops that can be used to transmit the data is going to be this. The value of Hops is initially set to 1, and during each iteration, the current state is communicated to any neighboring non-cluster heads that are located in the vicinity of the area.

The purpose of developing the PSO model is to find out which types of undirected sensor networks have the quickest routes to reach their final objectives. In this instance, the selection of the shortest path problem is the primary concentration, although the shortest path tree is of just a moderate degree of significance. If there are N nodes in the sensor network, then the path that leads to the sink with the shortest distance will have precisely one node in it. So, the procedure must continue to iterate until the shortest path tree has been built, connecting all of the nodes other than the final one (N-1). Using the PSO technique, it is possible to find a solution to the other challenge, which entails constructing the shortest path tree for a dynamic graph.

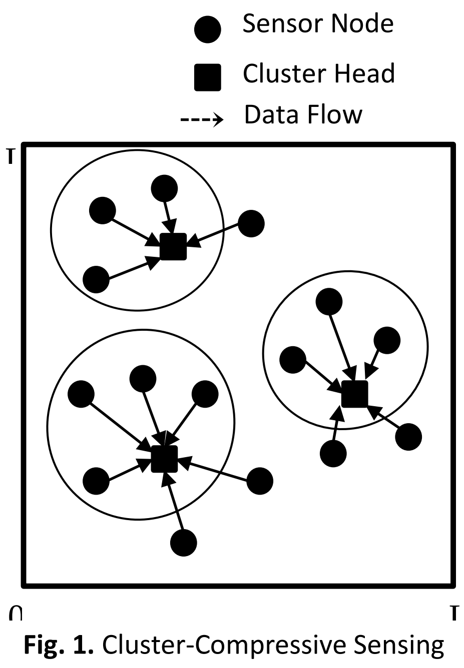


Fig. 1. Cluster-Compressive Sensing

Figure 1 illustrates how the suggested procedure is segmented into three distinct stages that can be followed in any order.

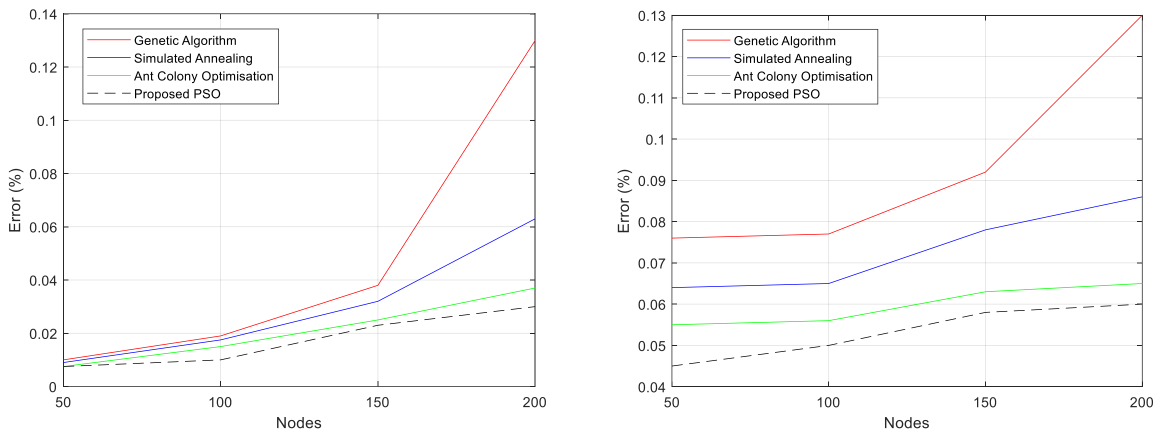
- While working with digraphs, the challenge of finding the path with the shortest distance between two points is tackled in the first phase, which makes use of a generalised PSO model. During this stage, any additional issues that may have sprung up are also addressed and resolved.
- In the second step, we make some modifications to the generalised PSO model so that it can manage the complications of optimising a network that has many sinks. This allows the model to produce more accurate results.

In the third stage, the newly acquired information is used in the process of reconstructing the shortest path tree. Modifications to the link weight provide the fundamental basis for the flow of the link network to be redirected in the desired direction.

3. Results and Discussion

In this section of the essay, we will present a comprehensive study of the method that has been proposed. This method will be evaluated by putting it through its paces using a variety of different databases. This considers both the signals that have not been sorted and those that have been sorted, we are able to arrive at the conclusions that we are looking for. The data collecting process is handled by the sensors that are a member of the square sensing network.

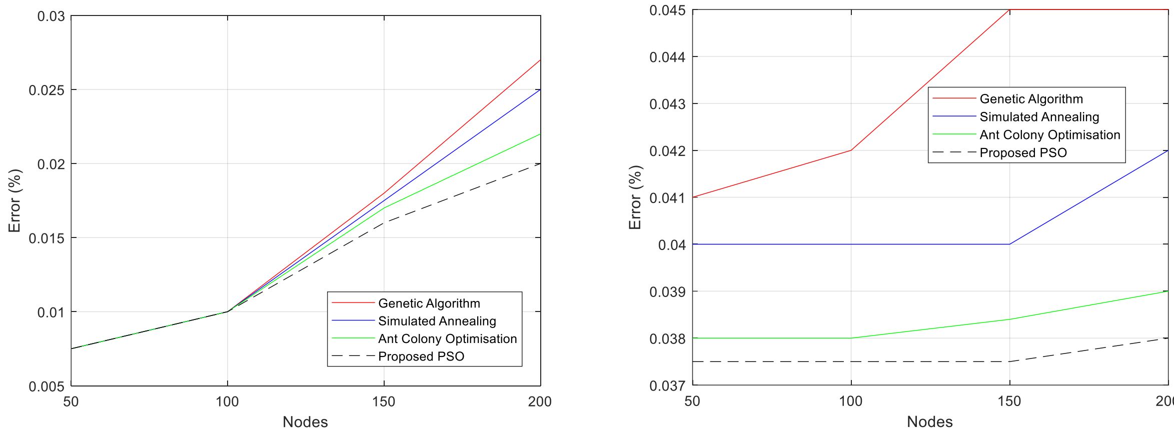
Not only can the availability of such data at varying k values influence the reconstruction error that takes place at the base station, but it can also influence the cost that is incurred when sending data from the cluster head to the base station. Both effects can be caused by the availability of such data.



(a) (b)

Fig. 2. Figure (a) Reconstruction Error (b) Normalized Reconstruction Error

As in Figure 2(a) and (b), the reconstruction error at the base station has a propensity to grow either when the total number of clusters in the data set grows or when the total number of coefficients that are communicated to the base station decreases. Both scenarios are shown to have a negative impact on the accuracy of the reconstruction.



(a) (b)

Fig. 3. Figure (a) Average Reconstruction Error for Sorted Signal (b) Average Reconstruction Error for Unsorted Signal

The reconstruction of sensor values at the base station can be shown in Figure 3, which demonstrates how diverse and noisy data can be employed. This illustrates one of many potential outcomes. Compressive sensing allows for the reconstruction of the initial sensor signal with a significantly reduced degree of error when more measurements are obtained than with traditional sensing methods. The same pattern can be seen in Figure 4(a), which indicates that the tendency for the reconstruction error to grow can be seen when DCT compression is done in an environment that is noisy. The number of sensor readings that are obtained results in a rise in the error rate, which is proportional to the number of readings shown in Figure 4(b).

This study aims to propose a method for the efficient collecting of data that makes use of adaptive multi-hop routing in conjunction with block-wise compression. This method will be presented as the result of this investigation. The natural signals are related to one another in space, which causes the readings from the sensors to have a sparse distribution as a result. Compressive sensing may now be utilised in a manner that results in a data collection process that is more efficient. In contrast to the studies that came before it, this one take use of clustered networks and compressive sensing in its data collection. This indicates that each node in the network is responsible for communicating its observations to the cluster head node. To recover the sensing, cluster heads must first be formed from the measurements received through the use of compressive sensing. Once these cluster heads have been produced, they must then be sent to the base station with multi-hop routing.

It has been demonstrated that the PSO algorithm is capable of significantly lowering the amount of infectious data transfer while simultaneously improving energy efficiency through compressive sensing performance in optimal clustering. This ability of the PSO algorithm to achieve these two goals simultaneously has been referred to as optimal clustering. Because of this method, the network can consume significantly less energy than it would have in any other scenario.

According to the research, one factor that contributes to determining the optimal size for the cluster is having a signal that is relatively weak. When actual sensor readings are used within a cluster, using the discrete cosine transform (DCT) as a sparse basis for clustered compressive sensing enables larger clusters to be deployed with decreased power consumption. This is made possible by employing the DCT as a sparse basis for clustered compressive sensing. The utilisation of DCT as a sparse foundation enables this to become a reality. This approach demonstrates that the one supplied is more trustworthy, effective, and efficient than the customary way things are done, as compared to the typical method.

4. Conclusion

A cluster-based compressive sensing strategy that makes use of an amoeba model has been presented as a potential choice that can bring the clustering procedure to a successful conclusion. After that, the data is sent over a multi-hop network by way of a cluster head that is located at the geographic center of the network. The size of each cluster is used as a basis for estimating the size of the block that corresponds to it in the block diagonal matrix. This is done by comparing the size of each cluster to the size of the block. power consumption in underwater sensor networks that are structured around compressive sensing while considering the impact that data sparsity has on the efficiency of the underlying sensing algorithm.

Power consumption in underwater sensor networks that are structured around compressive sensing. When the base station is situated in the precise geographic middle of the area that is being sensed, the system functions at the utmost level of effectiveness that it is capable of. The study generates the optimal number of clusters required to accomplish the goal of achieving minimal UASN power consumption if you follow this technique.

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