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A Compressed Sensing Method for Wireless Sensor Networks with Evolution Model Based on KH-SVM

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Abstract : *Wireless sensor networks are able to provide crucial and real time information in many scenarios of crisis response and management. Sensor node localization is one of research hotspots in the applications of wireless sensor networks (WSNs) field. A localization algorithm based on improved Support Vector Machine (SVM) for WSNs is proposed in this paper. SVM classification accuracy is the key to the localization accuracy. The selection of parameters is the important factor that influences the performance of SVM. Therefore, this paper proposes a parameter optimization algorithm based on Krill-herd algorithm (KH-SVM). The experimental results show that KH-SVM algorithm has better searching optimization ability compared with other optimization algorithms. In order to improve the fault tolerance against both random attacks and deliberate attacks for wireless sensor networks, this paper proposes a evolution model.We present an efficient seismic data sensing scheme in wireless sensor networks based on the promising compressed sensing technology to mitigate wireless communication load, data processing and caching complexity on nodes.*
Keywords: *Compressed Sensing, Wireless Sensor Networks, Evolution Model, SVM,Krill-herd.*

I. Introduction

Wireless sensor network is a multi hop self-organizing wireless communication network system by deploying a large number of cheap micro sensor nodes in the monitoring region. Its purpose is to perceive, gather and process the information detected by the tiny sensors in the coverage area, and send the useful information to the observers and control centers [1]. Localization is the key to many WSN applications, such as network management, environmental monitoring, target tracking and routing. WSN node localization technology has gained wide attention and become one research hotpot of WSN.In another case, the volcano monitoring and studies are very important for crisis response and management, which require focusing on the high data rates and high data precision [2]. Wireless sensor networks (WSN) are suitable to accomplish these tasks. Generally, WSN contain many tiny sensor nodes, and these nodes not only perform data sensing but also fulfil network transmission. Normally a node comprise a microcontroller unit, a sensor or several sensors, and a wireless transceiver. WSN owns the distributed sensing capabilities taken advantage of a large number of nodes and the easy deployment which supported by the wireless networks, and these lead to efficient data acquirement[3].Sensor nodes are normally powered by limited capacity batteries. For saving energy, generally nodes switch their wireless transceivers off in time and essentially become disconnected from the network. In this dynamic environment, it is a major challenge to support real time communication while minimizing the energy consumption [4]. The energy-efficient operation of WSN, however, provides longer lifetimes and better feasibility obviously.

Wireless sensor networks (WSNs) are usually made up of hundreds even thousands of distributed sensor nodes by self-organized and multi-hop manner, which can be used to perceive, collect, process and transmit the information of the sensed objects, and send them to the owner of the networks[5]. WSNs can cover a wide range of application domains such as environmental monitoring, traffic control, health care, etc., since they can be easily deployed and self-organized [6]. It will cause the overall network connectivity and coverage decline, even lead to the connected network topology segmentation when the wireless sensor network node runs out of energy, encounters hardware fault, or external intrusion. Therefore, how to improve the fault tolerance of the networks is a very important concern in the study of wireless sensor networks.

Recently, there has been considerable interest in exhibiting the topological structure, function and dynamical properties of many real world networks such as the World Wide Web, social networks, biological networks and scientific collaboration networks [7]. Wireless sensor networks, which can be described as a special case, belong to the category of complex networks, so many researchers use complex networks theory to solve the fault tolerance of the wireless sensor networks [8]. Authors in Ref. [9] improve the cluster generation algorithm in DEEG protocol and construct a high fault-tolerant wireless sensor networks evolution model by combining cluster head evolution mechanism with preference connection. Authors in Ref. [10] not only construct an energy efficient BA model through inter-cluster topology evolution, but also propose an immune strategy based on random walk[11], which makes the model have the good robustness.

As a new sampling method, compressive sensing can keep the original structure of signals by attaining the non-adaptive linear projections. Even without reconstructing signals for CS method, compressed sensing still can solve more and more signal processing problems given incoherent measurements. Furthermore, for most compressive signal processing application such as detection, estimation and classification, the number of measurements may even be lower than that necessary for signal reconstruction.A recent publications offer many schemes for obtaining sparse solutions of underdetermined systems of linear equations. Popular methods have been developed from many aspects: minimization, matching pursuit method, iterative thresholding methods,subspace methods, convex regularization and nonconvex optimization.Compressed sensing has the characteristic that it can gather the compressed data directly and get more information from less data. For this reason, people use it in many applications that the cost of signal acquisition is too expensive to be afforded, either because state-of- the-art samplers cannot obtain such high sampling rates required by Shannon/Nyquist sampling theorem, such as radar three-dimensional signal and video images, and so on. Recently, compressed sensing has been extensively applied in the seismic field. Yao utilizes CS to address seismic sources during the rupture of the 2011 Tohoku-Oki Mw9.0 earthquake in Japan from teleseismic P waves recorded by an array of stations in the United States [12]. Herrmann applies CS in exploration seismology [13]. However they don't apply the compressed sensing method to wireless sensor networks in the seismic field. It can improve energy efficiency for applying compressed sensing into wireless sensor networks obviously [14].

II. Evolution Model Of Wsns

The stochastic network is more resistant to deliberate attacks for its relatively uncertain characteristics. Therefore, FTEM takes the node residual energy and its communication radius as constraints, and reduces the proportion of nodes with high degree by introducing random edges connections. The generation of a network is as follows:

The initial network contains m0 nodes.Growth of topology. At each time step, we add a new node to the network and connect it to the nodes that are already present. Connection with preference or random follows the rules below:

The new node chooses random connection with the probability of p. It arbitrarily chooses m (m<m0) nodes in the existing local-world network to connect.The new node chooses preference connection with the probability of 1-p. The probability that the node i connects to the new node is pi. The value of pi is related to the residual energy (f(Ei)) and the degree (ki) of the node i, and its value is expressed as:

$$p_i = f(E_i)k_i \,/\, \sum_{j \in Local} f(E_j)k_j \tag{1}$$

It shows that the greater the product of the residual energy and the degree of the node i is, the greater the possibility that it is selected to be connected to the new node. Furthermore, we get the probability that the new node is connected to the node i of the network

$$\prod_i = \frac{p}{m_0 + t} + (1 - p)\frac{f(E_i)k_i}{\sum_{j \in Local} f(E_j)k_j} \tag{2}$$

The detailed descriptions of the parameters used in the above formulas are shown as table 1.

Table.1. Parameter table.

Parameter	Description
m0	the number of nodes in the initial network
m	the number of edges of the newly joined node
ki	the degree of node i
Ei	the residual energy of node i
πi	probability of newly joined node connected to node i
L	the total number of the nodes of the local-world of the newly joined node
n	the total number of nodes in the network

III. Compressed Sensing Method

Using Wireless Sensor Network, we can gather and transmit the earthquake observing data of the seismic region, as well as the volcano activity. The purpose of WSN is collaborating sensing, collecting relevant information of the objects monitored within the network coverage, and transferring the gathered data to gateway by the communication of short-range wireless multi-hop networks for analysis and processing by users. Since the sensor nodes usually have limited computing ability and power supply, a primary goal of data gathering is to collect the sensed data at required accuracy with the least energy consumption. The architecture of WSN for monitoring seismic activity is shown as Fig. 2. There are three types of WSN nodes in the system: seism monitoring nodes, sound monitoring nodes and picture nodes. Seism monitoring nodes utilize the seismometer to collect the seismic information. Picture nodes take a photograph of the scene, and the sound monitoring nodes capture the sound signal. These nodes transmit the data to the sink node. The sink node equips a satellite transceiver, and transfers the collected data to a server through the satellite, satellite station, and intranet network. Therefore with the satellite link, we can keep up the communication even under the huge disaster.

The seismic information which is collected by the nodes of wireless sensor networks is a kind of consecutive variables. Consecutive values are obtained from the monitoring point with each data is very significant. However this produces a heavy burden for the tiny node of WSN. With the benefits of the rapid development of information and communication technology, considering the above mentioned problems, applying compressive sensing method in wireless sensor networks is a promising technology.

Compressed sensing is a novel methodology of information acquisition, a method of sampling and reconstruction based on sparse signal representation, based on measurement matrix and approximation theory. This method was first presented by David L. Donoho, Emmanuel J. Candès, and Terence Tao respectively, and published nearly at the same time in 2006 [6][7]. According to the compressed sensing theory, as long as the signal is sparse or compressive in some basis, much lower sampling rate than the Nyquist sampling theorem can be enough to gain structure information of the signal and exactly reconstruct the signal through reconstruction algorithm. Thus a great significance is brought to data transmission, storing and processing. According to the sparsity requirement of CS, fortunately many signals in practice such as wireless sensor networks, image signal and medical signals are compressible signals and can be compressed in convenient basis such as Wavelet or Fourier basis.

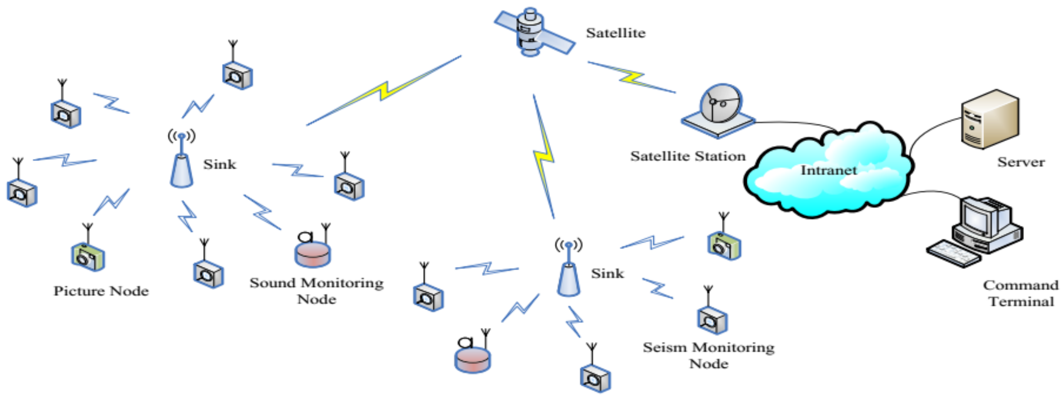

Figure 1. Architecture of WSN for monitoring seismic activity

IV. Localization Based On SVM

It is assumed that we randomly deployed a wireless sensor network with n nodes { S1 , S 2 , S3 , … , SN } in a 2D geographic area [0, D]2 (D > 0). The communication range of each node is same. In the WSN, k nodes are beacon nodes which know their own location; other N-k nodes are nonbeacon nodes which need to estimate their location. We divide the 2D area into M X M square cells. X-dimension is divided into M parts, Y-dimension is also divided into M parts. Each cell can be seen as one class. So, x-coordinate has M = 2m classes cxi , and the y-coordinate has M = 2m classes cyi . Each node resides in a cell, so it is assumed that each node exists in class [cxi, cyi] in 2D area.In other words, respectively each node exists in [(i－1)D / M, iD / M] X [(j－1)D / M, jD / M] unit.

The connectivity information would be gathered by beacon nodes from the WSN and would be sent to the head node (sink node or base station) where the SVM algorithm is running. The node Ni's true coordinates is (xi , yi). The vector Hi = <h(Ni , N1), h(Ni , N2), h(Ni, Nk)> is taken as feature vector of SVM to classify node Ni , where h(Ni , Nj) denotes the the shortest path hop-count between nodes Ni and Nj. All beacons' feature vectors {H i } (i = 1→k) are composed of training sample set. Radial Basis Function can be chosen to be the kernel function as shown in Equation (1). The SVM will build a model by training. This built model would be broadcasted to all the nodes even they are beacons or not. Each nonbeacon node is classified into one unit by this SVM model. And then, the center of each unit with (x_i , y_i) is used as the predicted position.

V. SVM PARAMETERS OPTIMIZATION Based On Krill-Herd (KH-SVM)

The SVM classification accuracy is an important factor to the localization accuracy, however, choice of parameters of the kernel function and penalty parameters is one key to classification accuracy. N-folded cross-verification is the best compromise method for evaluating parameters between computational cost and reliable parameter estimation. It can avoid the overfitting, so it is called unbiased estimate of the generalization error. In this paper, the result of N-folded cross-verification is used to evaluate the performance of parameters optimization algorithm. SVM parameters selection problem based on n-folded cross-verification can be taken as multi-peak value optimization. Many works have introduced some optimization algorithm to solve this problem such as Particle Swarm Optimization (PSO-SVM) and Genetic Algorithm (GA-SVM) (Ranaee et al., 2011; Cao, 2015; Liu, 2015; Huo and Zhao, 2016).

According to foraging behavioral characteristic of kill herding, Amir Hossein Gandomi and Amir Hossein Alavi put forward a novel intelligent optimization algorithm which is named Krill-herd (KH), in 2012 (Gandomi and Alavi, 2012). The KH algorithm simulates the herding behavior of krill individuals. “This method gets global and local optimum through the induced motion, foraging motion and physical diffusion” (Lari and Abadeh, 2015; Gandomi and Alavi, 2012). The related works have proved that it has excellent global optimization, rapid convergence and can avoid prematurity. So, this paper applied the KH algorithm to solve SVM parameters selection problem.

In the KH algorithm, krill density and distance from the food are taken as the objective function, and the value of objective function is taken as fitness. According to fitness, each krill constantly changes the position to reach around the global optima. For the optimization problem, the solution space is the arbitrary dimension.

SVM parameters selection problem based on n-folded cross-verification can be taken as multi-peak value optimization. The krill-herd algorithm is introduced into solving this optimization problem which named KH-SVM. The main steps of SVM parameters selection by krill-herd algorithm are as follows:

Step 1: First, SVM model is constructed. The most important step is decision of kernel function, and then number of parameter can be confirmed. In this paper, Radial Basis Function is chosen to be the kernel function. So, two parameters need to be selected. One is kernel function parameters γ, the other one is error penalty C.

Step 2: Create initial population randomly. The vector of [γ, C] is taken as position of a kill. The value of γ is between1 and 10000. The value of C is between 0.0001 and 1. 30 krill are selected randomly as initial population in this paper.

Step 3: Fitness function and KH algorithm parameters are determined.

Step 4: Calculate the fitness of each kill. The best kill and the worst kill are selected.

Step 5: Simulation of Kill behavior, including: induced motion, foraging motion and physical diffusion. And then implement the crossover and mutation.

Step 6: Update the position of each kill.

Step 7: GO to step 4 until the stop condition is reached.

VI. Simulation And Analysis

We randomly selected three simulation results to be shown as Fig. 2, Figure. 3 and Figure. 4 when the number of nodes is 500, the beacon population is 20%, 25% and 30% in the square-shape network. The communication range is 10m. The * represents positions of beacon nodes, the Δ represents the positions of real non-beacon nodes, and the ○ represents the estimated positions of non-beacon nodes.

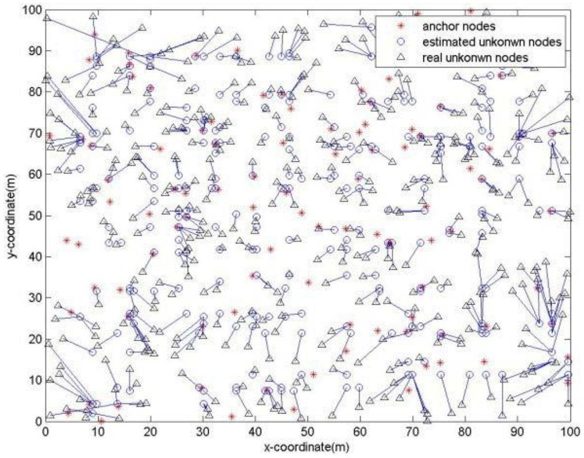

Figure. 2 The estimation result of 20% beacon nodes in square-shape network.

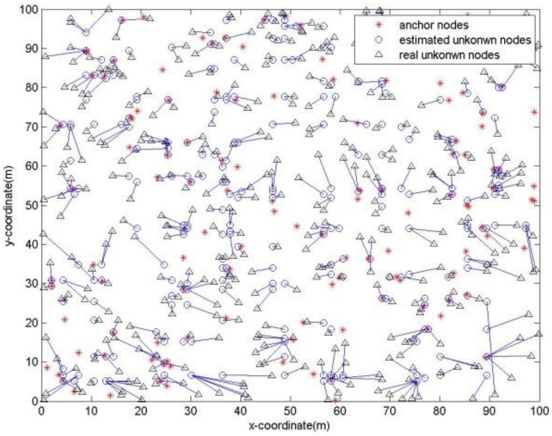

Figure 3. The estimation result of 25% beacon nodes in square-shape network.

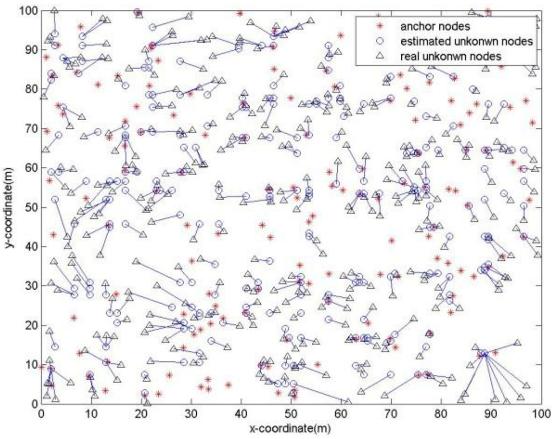

Figure 4.The Estimation Result of 30% Beacon Nodes in square-shape network

VII. Conclusion

In this paper, we present the compressed sensing based seismic data sensing scheme in wireless sensor networks. With the flexibility and easy deployment of WSN, we can monitor the earthquake or volcanic eruptions which aren't feasible with traditional instrumentation. However the high data volume is a challenge for tiny WSN nodes. So we present the promising compressed sensing technology to mitigate wireless communication load, data processing and caching complexity on nodes. We analyze the energy consumption with CS method and without CS, and compressed sensing based WSN can reduce the energy cost obviously. Fault tolerance of wireless sensor networks not only reflects good invulnerability against stochastic networks, but also reflects good invulnerability against deliberate attacks. Based on the researches on the existing fault-tolerance of wireless sensor networks, this paper uses complex network theory to construct the fault-tolerant evolution model. In the construction of evolution model, both preference connection and random connection are introduced on the basis of considering the degree of nodes, residual energy and transmission radius. The introduction of preference connection guarantees that the wireless sensor networks keep the characteristics of scale-free network. The introduction of random connection reduces the ratio he high degree nodes, which makes the generated network have certain stochastic network characteristics. we propose a distributed localization algorithm in wireless sensor networks based on KH-SVM. The proposed localization algorithm transforms the location estimation problem into multi-class problem, and binary SVM classification is used to solve the multi-class. So, it is suitable for WSNs that do not require pairwise distance measurements and special assisting devices. The SVM classification accuracy is the key to the localization accuracy. The selection of parameters is the important factor that influences the performance of SVM.Therefore, we proposed a parameters optimization algorithm based on Krill-herd algorithm (KH-SVM).

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