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HCBHRP-CS: Effective Routing Protocol for Multi-level Heterogeneous Wireless Sensor Networks

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Abstract

A wireless sensor network (WSN) consists of thousands of sensornodes with limited energy, memory, and computation capability. Theapplications of WSN in some extreme environment make sensor nodesdifficult to replace once they use up the resource. Hence, manyresearchers in this field focus on how to design a propertyrouting protocol to prolong the life span of the network. Theclassical hierarchical protocols such as CBHRP, WEEC and IMP-EELhave better performance in saving the energy consumption. However,the energy consumed for data aggregation among the nodes will makethe nodes that act as cluster heads too many times die early owingto the consumption of too much energy. In this paper, a heterogeneous clusterbased hierarchical routing protocol using compressing sensing(HCBHRP-CS) is proposed, which efficiently improves dataaggregation and therefore significantly reduce the energyconsumed in the process of sampling and transmission, and lowerthe wireless bandwidth required for communication under heterogeneousenvironment in WSNs. Simulations show that our improved protocol performsbetter than the CBHRP, WEEC and IMP-EEL.

Keywords: *Algorithm design and analysis, Base stations, Clustering algorithms, Compressive sensing, Energy efficiency, Head, Routing protocols, Heterogeneous Wireless sensor networks.*

1. Introduction

WSN consists of more than hundreds of small sensor nodes whichhave limited power, memory, and computational capabilities. Theapplication of the WSN involves many fields, such as the militarybattlefield, forest fire detection, and other extreme environments [1].WSNs can be classified into two types, namely homogeneous andheterogeneous sensor networks. In a homogeneous sensor networks,all sensor nodes are identical in terms of energy resource,computation and wireless communication capabilities. In heterogeneoussensor networks, typically, a large number of inexpensive nodes performsensing, while a few nodes having comparatively more energy performdata filtering, fusion and transport. This leads to theresearch on heterogeneous networks where two or moretypes of nodes are considered. One of the crucial challengesin the organization of the WSNs is energy efficiency and stabilitybecause battery capacities of sensor nodes are limited andreplacing them is impractical.Compressing sensing (CS) [2] is a new theory of sampling usedsuccessfully in many applications, including sensornetworks, digital image processing and analog-to-digital convertors. CS offers a new method of compression andcoding, in order to minimize storage and cost. This will result in extending the lifetime of the sensornetwork.The core operation of a WSN is to collect and process data at thenetwork nodes, and transmit the necessary data to the BS forfurther analysis and processing. Cluster-based Hierarchical Routing Protocol (CBHRP) [4]isan extension of the LEACH [5] protocol that is aself-organized cluster-based approach for continuous monitoring.In CBHRP, each cluster is managed by a set of cluster heads (CHs)is called head-set. The head-set members are responsible forcontrolling and management of the network. On rotation basis, ahead-set member receives data from the neighboring nodes andtransmits the aggregated results to the distant BS. In this paper,we improve CBHRP by proposing a new heterogeneous routing protocol using CS.We assume three types of nodes (normal, advanced and super), the energyconsumption of advanced is less than that of normal and the energyconsumption of super is less than that of advanced. The network is randomly dividedinto several clusters, each managed bya set of CHs called a head-set. Each member of the head-setcompresses the collected data using CS. Simulation results showthat our proposed protocol can compress data efficiently, reduceenergy consumption greatly and prolonging the lifetime and stabilityperiod of the whole network to a great extent. The remainder of the paper is organized as follows: related workis discussed in section 2. In section 3, we introduce theproposed system model. In section 4, we show the simulationresults of our protocol compared with CBHRP, WEEC and IMP-EELprotocols. And finally, conclusions are given in section 5.

2. Related Work

In [5], Heinzelman et al. proposed LEACH (Low Energy AdaptiveClustering Hierarchy) protocol, which is considered as the basicenergy efficient hierarchical routing protocol. In the setup phaseof LEACH, each node decides whether to become a CH for the currentround, this decision is based on a predetermined fraction of nodesand the threshold$T(s)$as follows:

$$T(s) = \begin{cases} \frac{p_{opt}}{(1-p_{opt}\times(r \bmod (1/p_{opt})))} & if\ s \in G \\ 0 & otherwise \end{cases}, \quad (1)$$

where $p_{opt}$is the predetermined percentage of CHs, $r$is the count of current round, and$G$is the set of sensor nodes that have not been CHs in the last$1/p_{opt}$rounds. Using this threshold, each node will be a CH at some round within$1/p_{opt}$rounds. After$1/p_{opt}$rounds, all nodes are once again eligible to become CHs. Many protocols have been derived from LEACH with some modifications and applying advance routing techniques.In [4], Rashed et al. proposed CBHRP, an extension of LEACH. CBHRP introduced a head-set to control and manage clusters. CBHRP divided the network into a few real clusters that are managed by a virtual CH. In [6], Behboudi proposed a weighted energy efficient clustering algorithm (WEEC). WEEC is an improvement of LEACH. It takes into consideration the distance of the nodes to the BS as an important factor in CH selection phase and assigns a probability to each node which is analytically derived from the distance of the node to the BS. In [7], Madhav proposed an improved energy efficient LEACH (IMP-EEL) protocol. In IMP-EEL, the CHs are elected by a newly proposed energetic clustering probability based on the ratio between the residual energy of each node and the initial energy of the network. The node with high initial and residual energy has more chances to be the CHs than the low-energy node rotated in the epoch throughout the network.CS is a sampling theory, which leverages the compressibility of the signal to reduce the number of samples required for reconstruction. Under CS framework, any compressible signal $X \in \mathbb{R}^N$can be represented in the form of

$$X = \Psi\alpha, \qquad (2)$$

where$\Psi \in \mathbb{R}^{N\times N}$is the transform matrix and$\alpha$is the sparse representation of$X$. The measurements of$X$are$Y = \Phi\ X$,where$\Phi \in \mathbb{R}^{M\times N}$is a sampling matrix with far fewer rows thancolumns$(M \ll N)$. The measurements$Y \in \mathbb{R}^M$aremuch easier than the original networked data$X \in \mathbb{R}^N$to be stored, transmitted, and retrieved since$M \ll N$. Therefore, the measurements can be expressed as Eq. (3). If$A = \Phi\Psi$satisfies the restricted isometry property (RIP)[2] condition$M \le cK\log(N/K)$such that$c$ is a smallconstant with$c > 0$, the vectorαcan be accuratelyrecovered from$Y$as the unique solution of Eq. (4).

$$Y = \Phi\Psi\alpha, \qquad (3)$$

$$\hat{\alpha} = arg\, min_{\alpha} \|\alpha\|_1 \quad s.t. \quad Y = \Phi\Psi\alpha, \qquad (4)$$

The original networked data$X$may be sparse itself or can besparsified with a suitable transform such as Discrete CosineTransform or Discrete Wavelet transforms[8].Usually, the networkeddata vector$X$is sparse with a proper transformΨin Eq. (2).In WSNs, sampling matrix$\Phi$is usually pre-designed,i.e., each sensor locally draws$M$elements of the random projectionvectors by using its network address as the seed of a pseudorandomnumber generator.All the above protocols do not consider efficient datacompression. In this paper we improve CBHRP by consideringcompression of data using CS under heterogeneous environment in WSNs.Simulation shows that the proposed protocol achieves a longernetwork lifetime compared with CBHRP, WEEC and IMP-EEL.

3. System Model

In HCBHRP-CS, we have considered a heterogeneous network withthree types of nodes (normal, advanced and super).The battery power of advanced is more than that of normal and the batterypower of super is more than that of advanced.Each type has weighted election probability that determines the percentage ofCHs from each type. Super node has probability to become CHs morethan advanced and normal nodes and advanced node has probabilityto become CHs more than normal node.We have assumed the cluster head election is based onthe battery power and residual energy of the node.Our model relies on the following key assumptions regarding thefield and the sensor nodes:

1. Each node is assigned a unique ID to help identify one nodefrom other neighboring nodes,
2. Each SN is static and aware ofits own location. SNs can use location services to estimate their locations. For simplicity, weassume that every SN knows its location in space in terms of a(x, y) coordinate,
3. The CIR of each link between CH and anysensor is known at the BS,
4. A WSN consists of heterogeneous nodes in terms of nodeenergy.

HCBHRP-CS divides the network into a few real clusters. Eachcluster has a head-set that consists of several virtual CHs;however, only one head-set member is active at one time. Iterationconsists of two stages: an election phase and a data transferphase. At the beginning of election phase, a set of CHs are electedby using their weighted election probabilities. These CHs send a shortrange advertisement broadcast message. The sensor nodes receive theadvertisements and choose their CHs based on the signal strength ofthe advertisement messages. Each sensor node sends an acknowledgmentmessage to its CH. Moreover, in each iteration, the CHs choose a setof associate heads based on their weighted election probabilities andthe signal strength of the acknowledgments. A head-set consists of aCH and the associates. In the data transfer phase, the head-set member(CH) receives data from the neighboring nodes, compresses the collecteddata using CS aiming at improving the network lifetime and reducing thenetwork energy consumption, and then CH transmits the aggregated resultsto the distant BS. Finally, the BS decodes the networked data. Each datatransfer phase consists of several rounds. Each member of head-set becomesa CH once during a round. An epoch consists of several iterations.In one epoch, each sensor node becomes a member of head-set forone time. All the head-set members share the same time slot totransmit their frames. The above communication stages areillustrated in Figure 1.

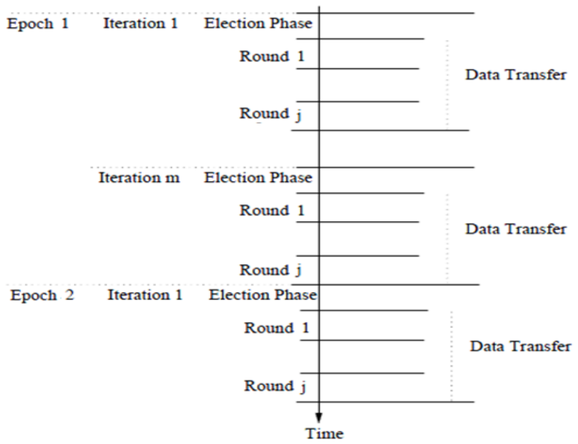

Figure 1: Communication Stages in HCBHRP-CS.

3.1. Radio Communication Model

We use the radio energy modelproposed in [5]. According to the radio energy dissipation model illustrated inFigure 2, in order toachieve an acceptable Signal-to-NoiseRatio (SNR) in transmitting a$L-$bit message over a distance d, the energy expended by the radio is given by Eq. (5), where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, ϵ_{fs} and ϵ_{mp} depend on the transmitter amplifier model we use, and d is the distance between thesender and the receiver. By equating the two expressions at$d = d_0$, we have$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$. To receive a L $-$bit message the radio expends $E_{Rx} = L.E_{elec}$.

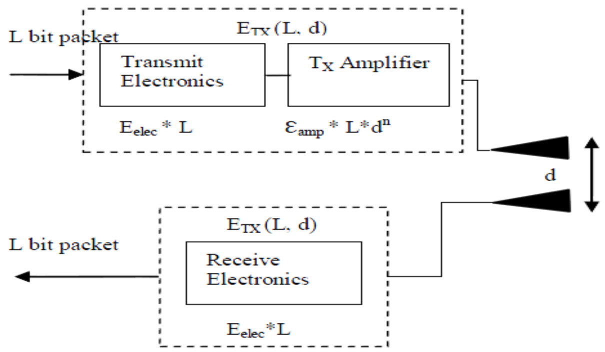

Figure 2: Radio Energy Dissipation Model.

$$E_{Tx}(L,d) = \begin{cases} L.E_{elec} + L.\epsilon_{fs}.d^2 & if\ d \le d_0 \\ L.E_{elec} + L.\epsilon_{mp}.d^4 & if\ d > d_0{}' \end{cases} \quad (5)$$

3.2. Optimal Number of Clusters

We assume that we have an area$A = R \times Rm^2$overwhich$N$nodes are uniformly distributed. For simplicity, weassume that the sink is located in the center of the field, andthe distance between any node to the sink or its CH is less thanor equal tod_0.Thus, energy consumed by a CH is estimated asfollows:

$$E_{CH} = \left(\frac{N}{C} - 1\right) Y.E_{elec} + \frac{N}{C} Y + Y.E_{elec} + Y\epsilon_{fs} d_{BS}^2, \quad (6)$$

where$C$is the number of clusters,$Y$is the compressed dataand$d_{BS}$is the average distance between CH and BS.The energy consumed by a non-CH node is given by:

$$E_{nonCH} = L.E_{elec} + L.\epsilon_{fs} d_{CH}^2, \quad (7)$$

where$d_{CH}$is the average distance between a clustermember and its CH. Assuming that the nodes areuniformly distributed, it can be shown that:

$$d_{CH}^2 = \int_{x=0}^{x_{max}} \int_{y=0}^{y_{max}} (x^2 + y^2)\rho(x,y)\,dxdy = \frac{R^2}{2\pi C}, \quad (8)$$

where $\rho(x, y)$ is the node distribution and R is the area of monitoring field. The energy dissipated in a cluster per round is given by:

$$E_{cluster} \approx E_{CH} + \frac{N}{C} E_{nonCH}, \quad (9)$$

The total energy dissipated in the network will be:

$$E_{tot} = Y(2NE_{elec} + \epsilon_{fs}(Cd_{BS}^2 + Nd_{CH}^2)), \quad (10)$$

By differentiating E_{tot} with respect to C and equating to zero, the optimal number of constructed clusters can be found:

$$C_{opt} = \sqrt{\frac{N}{2\pi}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \frac{R}{d_{BS}^2}, \quad (11)$$

The optimal probability of a node to become a CH p_{opt}, can be computed as follows:

$$p_{opt} = \frac{C_{opt}}{N}, \quad (12)$$

3.3. Cluster Head Election Phase

In HCBHRP-CS, we have assumed three types of sensornodes normal, advanced and super nodes. The energy exhaustion of batterysource is less in advanced and super nodes as comparedto normal nodes in the system. Let us assume E_0 is the initial energy of each normal sensor node, m is the fraction of advanced nodes among normal nodeswhich are equipped with α times more energy than thenormal nodes, and m_0 is the fraction of super nodesamong advanced nodes which are equipped with β timesmore energy than the normal nodes. Note a new heterogeneoussetting has no effect on the spatial density of thenetwork so the setting of p_{opt} does not change. On theother hand, due to heterogeneous nodes the net energy ofthe network is changed as the initial energy of each supernode become $E_0(1 + \beta)$ and each advanced node becomes $E_0(1 + \alpha)$. Therefore, the total (initial) energy ofthe new heterogeneous setting is given by Eq. (13):

$$Total\ Energy = \big(N.(1 - m).E_0 + N.m.(1 - m_0).E_0.(1 + \alpha) + N.m.m_0.E_0(1 + \beta)\big)$$

$$= N.E_0.(1 + m.(\alpha - m_0.(\alpha - \beta))), \quad (13)$$

Hence, the total energy of the system is increased by a factor of $\Big(1 + m.\big(\alpha - m_0.(\alpha - \beta)\big)\Big)$. In order to optimize the stable period of the system; the new epoch must become equal to $\left(\frac{1}{p_{opt}}\right).\Big(1 + m.\big(\alpha - m_0.(\alpha - \beta)\big)\Big)$ because the system has $m.(\alpha - m_0.(\alpha - \beta))$ times more energy. Virtually there are $N.\Big(1 + m.\big(\alpha - m_0.(\alpha - \beta)\big)\Big)$ nodes with energy equalto the initial energy of a normal node. In order to maintain theminimum energy consumption in each round within an epoch, the average number of CHs per round per epoch mustbe constant and equal to $N.p_{opt}$. In the heterogeneous scenariothe average number of CHs per round per epoch isequal toof $\left(1 + m.\left(\alpha - m_0.(\alpha - \beta)\right)\right).N.p_{nrm}$(because each virtual node has the initial energy of a normal node).Therefore, the weighed probabilities for normal, advanced and supernodes are, respectively:

$$p_{nrm} = \frac{p_{opt}}{1+m.(\alpha - m_0.(\alpha-\beta))}, \quad (14)$$

$$p_{adv} = \frac{p_{opt}}{1+m.(\alpha - m_0.(\alpha-\beta))} \times (1+\alpha), \quad (15)$$

$$p_{sup} = \frac{p_{opt}}{1+m.(\alpha - m_0.(\alpha-\beta))} \times (1+\beta), \quad (16)$$

In Eq. (1), we replace$p_{opt}$by the weighted probabilitiesto obtain the threshold that is used to elect the CH in each round.We define$T_{s_{nrm}}$ as the threshold for normal nodes, $T_{s_{adv}}$the threshold for advanced nodes and$T_{s_{sup}}$the threshold for super nodes.Thus, for normal advanced and supernodes, we have:

$$T_{s_{nrm}} = \begin{cases} \frac{p_{nrm}}{(1-p_{nrm}\times(r \bmod (1/p_{nrm})))} & if\ s_{nrm} \in G' \\ 0 & otherwise \end{cases}, \quad (17)$$

$$T_{s_{adv}} = \begin{cases} \frac{p_{adv}}{(1-p_{adv}\times(r \bmod (1/p_{adv})))} & if\ s_{adv} \in G'' \\ 0 & otherwise \end{cases}, \quad (18)$$

$$T_{s_{sup}} = \begin{cases} \frac{p_{sup}}{(1-p_{sup}\times(r \bmod (1/p_{sup})))} & if\ s_{sup} \in G''' \\ 0 & otherwise \end{cases}, \quad (19)$$

where$r$is the current round,$G'$is the set of normalnodes that have not become CHs within the last$1/p_{nrm}$rounds of the epoch, and$T_{s_{nrm}}$is the threshold applied toa population of$N.(1-m)$normal nodes.

3.4. Setup Phase

In this phase cluster formation takes place. For everytransmission round, node$s_i$calculates the probabilitythreshold$T(s_i)$and chooses random number between 0 and 1. Ifthe number is less than threshold $T(s_i)$, $s_i$becomes a CHduring the current round. The CHs then broadcast a short range advertisementmessage to the network and declare themselves as CHs.After this message, each regular node chooses its closest CH with the largest receivedsignal strength and then informs the CH by sending a join clusteracknowledgment message. If no message is broadcast from any CH, it makes itselfas CH. Furthermore, in each iteration, the CHs choose a setof associate heads based on their weighted election probabilities andthe signal strength of the acknowledgments. A head-set consists of aCH and the associates. The head-set member isresponsible for sending messages to the BS.The CH sets up a TDMA schedule and transmits it to thenodes in the cluster. After the TDMA schedule is known by all nodesin the cluster, the set up phase is completed and the next phasebegins.

3.5. Data Transmission Phase

Once the clusters are formed and the TDMA scheduleis fixed, the data transmission phase can begin.We consider$N$sensors randomly located in a field,each generating a data sample $x_j(j = 1, \dots, N)$tobe measured. The vector of data samples$X = [x_1, \dots, x_N]$ iscalled networked data, which will be transmitted to theBS. We use Discrete Cosine Transform (DCT) matrix as the sparsifyingtransform matrix and channel impulse response (CIR) matrix as the samplingmatrix.

3.5.1. DCT Basis

We use Discrete Cosine Transform (DCT) to sparsify thenetworked data$X$. Once the BSknows the locations of all sensor nodes, DCT basis can becomputed. DCT replaces the 2-D set of measurements with a set oftransform coefficients that, for piecewise smooth fields, aresparser than the original data as in Eq. (20),where$S \in \mathbb{R}^N$ is the transform coefficient vectorwhich contains$K$ ($K \ll N$)nonzero, and$D$ is the DCT basis.

$$X = DS, \tag{20}$$

3.5.2. CIR Basis

At each cluster, a head-set member CH receives data from theneighboring nodes, compresses the collected data using CS andtransmits the aggregated results to the distant BS. The receivedsignal vector at CH can be written as Eq. (21),where$G$the CIR matrix is whose component can be written asEq. (22).

$$y = GX = GDS, \tag{21}$$

$$G[m, n] = d_{m,n}^{-\gamma} |h_{m,n}|. \tag{22}$$

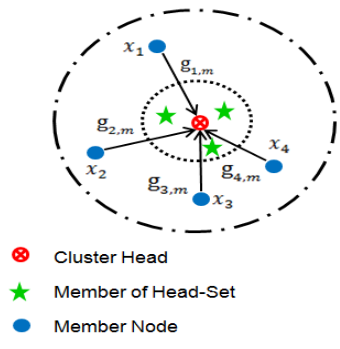

Figure 4: Transmission in Clusters.

where$d_{m,n}$ is the distance between the m^{th} CH and the n^{th} sensor node. γis the propagation loss factor which is 2 for free space and takes on other values for different media [8]. $h_{m,n}$is the Rayleigh fading coefficient modeled as complex Gaussian noise with zero mean and unit variance [8]. Nsensor nodes transmit their samples to M CHs. Subsequently CHs transmitmeasurements Y to the BS independently. Finally, the BS decodes the networked data X from Y using for example the basis pursuit solver in Sparselab toolbox of Matlab [9].

4. Simulation Results

In this section, the analysis of the proposed HCBHRP-CSprotocol is carried out using MATLAB to evaluate the energyconsumption and maximize the lifetime of the sensor network.We describe the simulation environment, performance metricsand experimental results.The simulation parameters are summarized in the following table(Table 1):

Table 1: Simulation Parameters.

Description	Parameters	Values
Number of nodes	N	1000
Proportion of advanced nodes	m	0.2
Proportion of super nodes among advanced nodes	m_0	0.3
Energy factor for advanced nodes	α	3
Energy factor for super nodes	β	1.5
Initial energy level of normal nodes	E_0	$0.5\,J$
Location of the BS	BS	(50,50)
Data packet size	L	$4000\ bit$
Network area	$R \times R$	$100\ m^2$
Transmit amplifier if $d_{BS} \leq d_0$	ϵ_{fs}	$10\ PJ/(bit * m^2)$
Transmit amplifier if $d_{BS} \geq d_0$	ϵ_{mp}	$0.0013\ PJ/(bit * m^4)$
Number of nonzero coefficients	K	10
Number of measurements	M	50
Propagation loss factor	γ	2

4.1.Performance Metrics and Experimental Results

Here, we present the performance results and the comparison of the proposed protocol with other existing protocols.The evaluation of performance metrics demonstrate the improvement and strength features of the proposed protocolcompared with CBHRP, WEEC and IMP-EEL protocols.

4.1.1. Energy Consumption

Figure 5 illustrates the difference of the energy consumed per round in the proposed, CBHRP,WEEC, and IMP-EEL protocols.It shows that WEEC achieves better performance compared with CBHRP,whereas WEEC considers the distance of the nodes to the BSas an important factor in CH selection to reduce the energydissipated in each round. Also, IMP-EEL performs better than WEEC; the reasonis IMP-EEL selects more energetic CHs during every round.It is obvious that the energy consumption of the proposed scheme is much lowerthan that of CBHRP, WEEC and IMP-EEL. This is because HCBHRP-CS uses residual energyof nodes in electing CHs; nodehaving higher residual energy has greater chances to be a CH,therefore, the energy efficiency is enhanced.Besides, HCBHRP-CS efficiently compresses data and at the same timeguarantees fast data compression which is an important issue in WSNs due to the scareresources of sensor node.Consequent to this compression, the total network energy consumption isminimized compared with CBHRP, WEEC and IMP-EEL.

4.1.2. Iteration Time

The estimated time for one iteration with respect to the network diameterconsidering the percentage of head-set size is shown in Figure 6.It is obvious that our proposedprotocol outperforms CBHRP, WEEC, and IMP-EEL.Whereas, in the proposed protocol the extension of the network service duration isbecause HCBHRP-CS efficiently compresses data using CS and every sensor node independentlyelects itself as a CH based on its weightedelection probability and also treat each heterogeneous node discriminatorilyin terms of energy discrepancy.Therefore, HCBHRP-CS would extend the estimated time for one iteration,and consequently the battery lifetime would be extending to more than current lifetime.The iteration time is proportional to the initialenergy and the network diameter found in this figure.The network will be alive for a longest period of timewith initial energy when the head-set size is 50% of the cluster size.However, it is more or less with respect to the head-set size.

4.1.3. Number of Frames

Figure 7 shows the number of frames transmitted per iteration in the proposed,CBHRP, WEEC, and IMP-EEL protocols. It is clear that proposed protocol outperforms existing protocolsbecause HCBHRP-CS has three types of nodes (normal, advanced and super), whereasthe super nodes become CHs more than both the advanced and normal nodes.The advanced nodes take up the role of CH more frequentlythan the normal nodes. Moreover, using CS would optimize energy usage toreduce storage space and energy consumption.Also, it is shown that when the head-set size increases, there are more controland management sensor nodes.As a result, the iteration can last for a longer time,which is also consistent with the results shown in Figure 6.Consequently, the data collecting nodes can be used for a longer period of time.Our results show that the proposed protocolprovides a more systematic approach of transmitting a higher numberof data frames in contrast to CBHRP, WEEC, and IMP-EEL.

4.1.4. Stability

The stability period is the time interval from the startof network operation until the death of the first alive node,which is crucial for many applications where the feedback fromthe sensor network must be reliable.In terms of the length of the stability period, by varyingm, m_0, α and β, we show that the stability of our HCBHRP-CS protocolexceeds existing protocols.Figure 8 shows the network stability when the firstnode dies. We observe that the stable period of HCBHRP-CSis extended in comparison with CBHRP, WEEC, and IMP-EEL protocols.The reason is HCBHRP-CS efficiently compresses data and uses head-setinstead of only one CH within a cluster, besides morepowerful sensor nodes act as CHs for morenumber of rounds, therefore, stabilityperiod of HCBHRP-CS is enhanced which is the main requirement for thelifetime of the WSN.

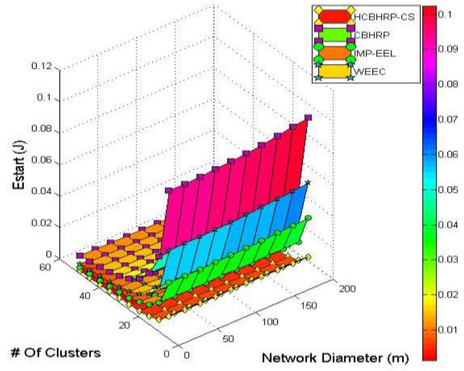

Figure 5: Energy Consumption

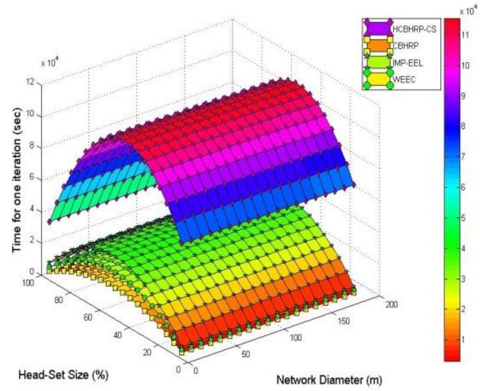

Figure 6: Time for Iteration

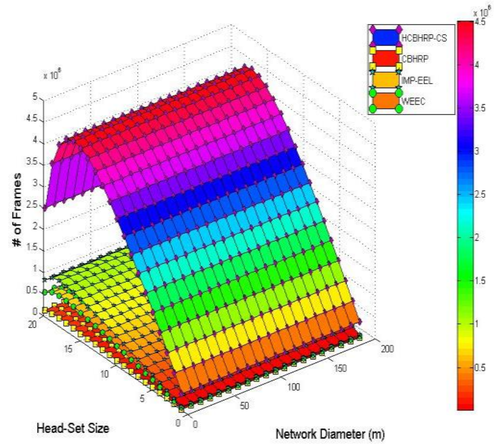

Figure 7: Number of Frames Transmitted per Iteration

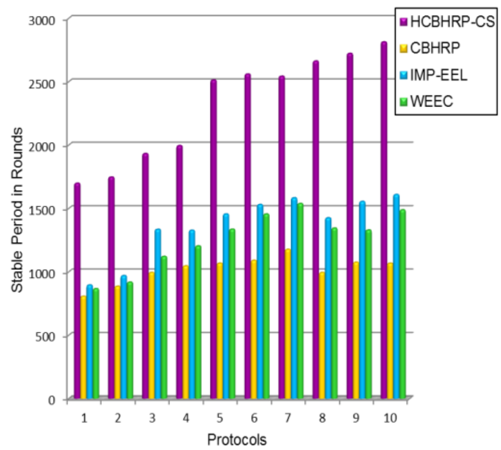

Figure 8: Network Stability

5. Conclusion

In this paper, we propose a compressive sensing (CS) enhancementfor the CBHRP protocol under heterogeneous environment.CS measurements are obtained via clusterheads. Discrete Cosine Transform (DCT) is used as the sparsifyingmatrix and channel impulse response (CIR) matrix is used as thesampling matrix. Using head-set concepts within a heterogeneousthree-tier node setting in a clustering algorithmic approach,nodes elect themselves as cluster heads based on their energy levels,retaining more uniformly distributed energy among sensor nodes.The simulation results show that our method decreases the energyconsumption and therefore, prolongs the network lifetime andstability period and increases the number of frames transmittedper iteration compared with CBHRP, WEEC and IMP-EEL protocols.

References

[1] J. Li and H. Gao, "Research advances in wireless sensor networks," *Journal of Computer ResearchandAdvances*, vol. 45, no. 1, pp. 1-15, 2008.

[2] Candés, E. J. and M. B. Wakin, "An introduction to compressive sampling", *IEEE Signal Process. Mag.*, Vol. 25, No. 2, pp. 21-30, 2008.

[3] ZhuangXiaoyan, Wang Houjun and Dai Zhijian, "Wireless sensor networks based on compressed sensing," in 3^{rd}*IEEE International Conference on Computer Science and Information Technology (ICCSIT2010), Chengdu*, pp. 90-92, 2010.

[4] M. G. Rashed, M. HasnatKabir, Muhammad Sajjadur Rahim, and ShaikhEnayetUllah, "Cluster Based Hierarchical Routing Protocol For Wireless Sensor Network," *International Journal of Computer and Network Security*, Vol. 2, No. 5, May 2010.

[5] W. Heinzelman, A. Chandrakasan and H. Balakrishnan, "Energy-efficient Communication Protocol for Wireless Microsensor Networks", *Proceedings of* 3^{rd}*Hawaii International Conference on System Sciences*, 2000.

[6] N. Behboudi and A. Abhari., "A Weighted Energy Efficient Clustering (WEEC) for Wireless Sensor Networks," *Seventh International Conference on Mobile Ad-hoc and Sensor Networks (MSN)*, pp.146-151, 2011.

[7] T. V. Madhav and N. V. S. N. Sarma, "Energy Efficient Routing Protocol with Improved Clustering Strategies for HomogeneousWireless Sensor Networks," *International Journal of Computer Applications*, 0975 8887, Vol. 38, No. 8, January 2012.

[8] M. Jia, L. Husheng, and H. Zhu, "Sparse event detection in wireless sensor networks using compressive sensing," 3^{rd}*Annu.Conf. Information Sciences and Systems*, pp. 181-185, 2009.

[9] D. Donoho, V. Stodden and Y. Tsaig, Available at http://sparselab.stanford.edu/.