www.ijiarec.com

ISSN:2348-2079

Volume-5 Issue-2

International Journal of Intellectual Advancements and Research in Engineering Computations

Lifetime enhancement using apkf algorithm for large scale wsn

1. Ms. Suguna Angamuthu MCA., MPhil., ME., Associate Professor

2. Ms. S. Kaviya, UG Scholar, 3. Ms. S. Suvitha, UG Scholar, 4. Ms. N. Saranya UG Scholar

Department of MCA, Nandha Engineering College, (Autonomous), Erode-52.

sugunaangamuthu@gmail.com, kaviyashanmugasundaram@gmail.com

Abstract - This work combines an efficient prediction model with a Kalman filter (PKF) to reduce the communication cost in Wireless Sensor Networks (WSNs) with a guaranteed data quality. The hardware accelerator requires fewer resources than previous approaches, while achieving higher energy reductions. Exhaustive experimental results based on datasets from a real WSN application confirm the advantages of the proposed mechanism. Energy efficiency is a primary concern for wireless sensor networks (WSNs).This work uses a predictor combined with a Kalman filter (KF) to reduce the communication energy cost for cluster-based WSNs. The technique, called PKF, is suitable for typical WSN applications with adjustable data quality and tens of pico joule computation cost. However, it is challenging to precisely quantify its underlying process from a mathematical point of view.

Keyword - wireless sensor networks, data compression, energy efficiency, adaptive mechanism.

1. INTRODUCTION

WSNs consist of a large number of self-organized sensor nodes, which are usually battery driven and are not rechargeable. In order to monitor the physical world for as long as a few months or even decades, the reduction of the energy consumption is a key problem. Typically, transmitting a single bit consumes over 1000 times more energy than a single 32-bit computation. The energy exhausted during the radio start up is 10-100 times greater than the actual transmission energy. Consequently, reducing the communication cost via proper data processing is the vitally necessary.

Several researches focus on communication cost reduction by forwarding an approximation of aggregates at the source node or predicting the source value at the sink node. In these schemas, the achievements for data accuracy and the complexity are not always satisfactory. An interesting approach to reduce communication overhead is the use of dual KFs. A common application is for outlier detection to stop unnecessary data transmitting KF-based data fusion is one of the most significant approaches to overcome sensor failures and spatial coverage problems. The main contribution of this work is a schema to reduce the communication cost within clusters of WSNs. It keeps the advantages of the KF approaches, while overcoming their complexity and data accuracy issues. In comparison with the previous result: ***a)*** The hardware accelerator requires fewer resources; ***b)*** The communication cost is significantly reduced under the same data quality conditions. The paper is organized as follows overview the basic knowledge of KF. The subjects are the proposed approach and the complexity comparison presents the simulation results. Gain is calculated by to update the *a priori* estimation. As indicated above, to compute the estimation for the current state, only the current measurement and the estimated state from the previous time step are needed. This is low complexity and the storage economization advantages make KF very suitable for resource constrained WSNs.

1. Proposed Approach

The architecture of the motes is evolving from the standard RF-Frontend plus microcontroller to a more sophisticated and capable SoCs including dedicated hardware accelerators and IPs. Compared with the traditional solution, this new architecture reduces over 98% energy consumption. This work focuses on an algorithm for a HA to reduce communication cost in those advanced WSN SoCs. We assume sensor nodes have already formed sets of clusters, according to a certain clustering algorithm, like Directed Diffusion, LEACH or CAG. Data packets are firstly forwarded from leaf nodes to cluster heads, and then the aggregated data are transmitted by a one-hop or multi-hop procedure to the sink node.

Clusters based WSN topology
Following the process of KF in, a simple prediction model is proposed. Next we combine this prediction model with the KF, namely our PKF approach, to reduce the communication cost and guarantee the data quality within clusters.

ADAPTIVE PREDICTION APPROACH

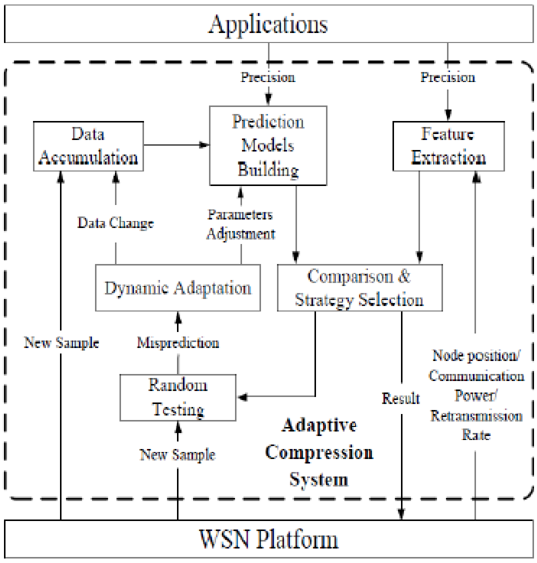


Fig.4(Framework of adaptive compression system)

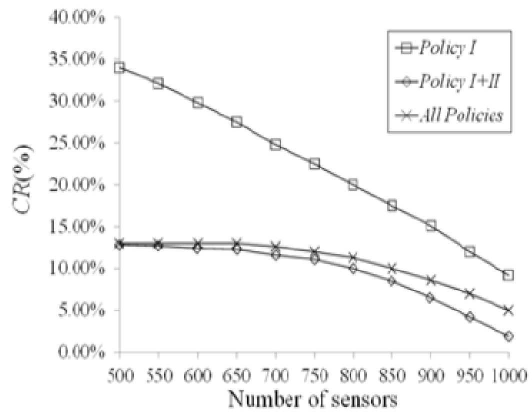
Accurate prediction of compression ratio and execution time is an important part of ensuring the correct selection of strategy. Thus, an adaptive mechanism is introduced into our proposed system. This mechanism requires fewer samples to build the prediction models, which makes on-line modelling. The beginning of the adaptive mechanism uses an initial sample step with a given range. Once a new sample is ready for verification, the compression ratio and execution time are both measured. The comparison then determines whether the difference between the predicted value and the real one exceeds a preset error bound. If the prediction error is large, the information including the compression ratio and time overhead are recorded for the new model. Even if the initial models are somewhat inaccurate, they will be adjusted adaptively to the best results.

1. Experimental Results

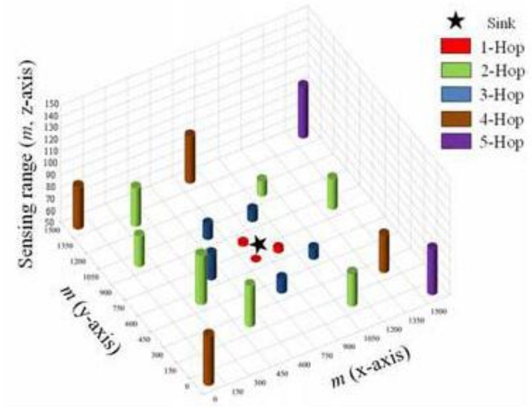
A. Analysis of Adaptive mechanism with PKF

set an initial sample step (*step*)
set an allowable step range [*step min*, *step max*]
if (sample is awaiting verification) **then**
measure *CR* and *TMCU*
if ((|prediction error of *CR*|>=error bound)
or (|prediction error of *TMCU* |>=error bound)) **then**
record compression ratio and time overhead for the sample
if (*step* == *step max*) **then**
rebuild the models with the recorded samples
reset *step*
else
decrease *step*
end if
else
decrease *step* until *step max*
end if

In a cluster, each leaf node runs a KF and the KF-based prediction model. The cluster head synchronously executes all of these prediction models, in order to regenerate the optimal values of leaf nodes in the whole cluster. When this predicted error (calculated by leaf nodes) exceeds the bounded limitation, the current optimal value is transmitted to the cluster head. In order to reduce noise presented in the raw data, a KF is installed in the leaf node A to obtain the optimal values as described based on the *a priori* estimate model of the KF in the leaf node A, the simple prediction model in Giving an initial value, this model can work recursively. Following our example, there are 13 leaf nodes in the cluster 1. If the HAH executes Dual KF, it needs 234 additions, 494 multiplications and 13 divisions. Using our PKF, no division is required. Only 13 multiplications are needed in PKF-Constant. Even in PKF-Linear, the number of multiplications and additions are at least nine times less than Dual KF.



The comparison of the overlapping ratio which indicates the contribution of each phase designed in *SRA* mechanism. The proposed *SRA* approach mainly consists of three phases, including *WVD-C*, *OR*, and *INL* phases.



The sink is located at the center of *M*.

B.ESTIMATION

SIMULATION PARAMETERS

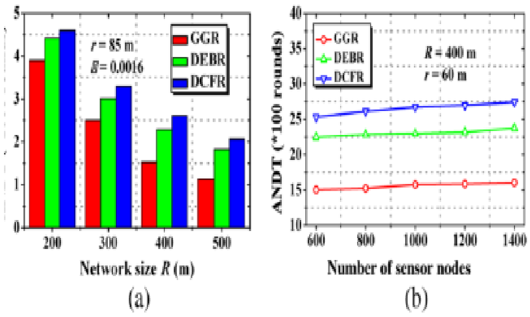
Parameter	Value
Number of nodes	100
Network Grid	500×500m2
Channel BW	1 Mbps
Size of data packet	500 bytes
Initial energy of nodes	1J

1. Further Discussions

In this section, we further discuss the significance of our analytical results and apply them to the WSN routing design to mitigate energy hole problem and improve sensor network lifetime. Our analytical results and observations are instructive and useful for WSN deployment, design, and optimization.

1) It has been proposed that we can balance the energy consumption of the network by non-uniform node deployment. Since the energy hole boundary can be estimated, the location of the hotspot can also be derived to guide the non-uniform node deployment. Moreover, after the network deployment, we can reevaluate the network lifetime by the proposed analytical model.

2) The paper presents a guideline for selecting optimal network parameters to improve network lifetime or performance. It has been demonstrated that different transmission radii lead to different network lifetime, which is useful to select an optimal r for a given network.



Model (a) denotes the energy consumption model adopted in this paper, while Model (b) denotes the model without energy consumption in idle listening. Besides, since the energy consumption for idle listening is relatively large, it motivates us to design an energy- efficient sleep scheduling algorithm for the sensor nodes to further reduce the energy consumption and improve the network lifetime. 3) Although geographic routing has inherent advantages to be applied into large scale WSNs, its negative influence on energy efficiency and network lifetime cannot be neglected. From our analysis, there is more than 93% energy left when the network is partitioned by the energy hole. Thus, our work should be helpful to provide navigation for designing an energy-efficient routing protocol.

In the following two sections, we intend to illustrate the significance of the proposed analytical results in guiding the WSN design and optimization. We take the routing design for instance to discuss how to improve the network lifetime, including both FNDT and ANDT, by designing an energy-efficient routing based on our analytical results. Energy-Efficient Routing Design

Based on Lifetime Analytical Results According to our analytical results, since the nodes near the sink should forward the data from upstream nodes, the unbalanced energy consumption and energy hole problem cannot be avoided in a uniformly deployed data-gathering WSN.

However, it is still possible to mitigate the unbalanced energy consumption of the sensor nodes and improve the network life- time by designing an energy-aware routing scheme. The main idea of most existing energy aware routing solutions is to select the next hop based on the residual energy to avoid premature death in hotspot. Therefore, energy consumption balance should be considered from two aspects, nodal residual energy and energy consumption rate. Since the cost function-based routing has the inherent advantages in scalability and has been extensively studied for energy efficiency, our routing scheme concentrates on the cost function design. At first, an optimal energy cost function should map small changes in nodal residual energy to large changes in the value of the function. Such a function can rise sharply the cost of a routing path whose residual energy is low and off- set the cost reserving by path length reduction (if any exists), forcing nodes to select the route with more residual energy. Second, the energy consumption rate of nodes should be taken into consideration in cost function design. As the nodes in hotspots generally have higher energy consumption rate than other nodes, the energy can be further balanced by introducing this factor into the cost function. Based on the two principles, the double cost function-based routing (DCFR) scheme can be designed as follows. For the sensor node i, its neighbouring sensor nodes whose distances to the sink are smaller than is constitute the candidate node.

CONCLUSION

In this paper, we have reduced the communication rate by decreasing the unwanted sensor processing and analyzed an analytic model to estimate the traffic load, energy consumption, and lifetime of sensor nodes in a data-gathering clustered WSN. The sensor gets used our simulation results demonstrate that the proposed analytic model can estimate the network lifetime and energy hole evolution process within an error rate smaller than 5%. The improved routing scheme based on our analytical results can efficiently balance the energy consumption and prolong the network lifetime. In our future work, we will extend the lifetime analysis into energy harvesting WSNs. It is very challenging to analyze and optimize the network lifetime under the continuous and unstable energy supply.

REFERENCE

[1] Shan, S., Mohammed, A, Sutharshan, R, Christopher, L , Marimuthu, and P. Labelled Data Collection for Anomaly Detection in Wireless Sensor Networks. In Proceedings of the Sixth International Conference on Intelligent Sensors, Sensor Networks and Information Processing, Brisbane, Australia, December, 2010.

[2] Y. Huang, W. Yu, and A. Garcia-Ortiz, "PKF: A communication cost reduction schema based on Kalman filter and data prediction for wireless sensor networks," in *Proc. 26th IEEE Int. Syst. Chip Conf.*, Erlangen, Germany, Sep. 2013, pp. 73–78.

[3] C. Wang, H. Ma, Y. He, and S. Xiong, "Adaptive Approximate Data Collection for Wireless Sensor Networks," IEEE T Parallel Distrib Syst, vol. 23, no. 6, pp. 1004–1016, 2012.

[4] C. Y. Chang, C. Y. Lin, C. T. Chang, and W. C. Chu, "An Energy-Balanced Swept-Coverage Mechanism for Mobile WSNs," *Springer Journal of Wireless Networks*, vol.19, no. 5, pp. 871-889, Jul.2013.

[5] S. Li, L. D. Xu, and X. Wang, "Compressed sensing signal and data acquisition in wireless sensor networks and Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2177–2186, Nov. 2013.

[6] Y. Pei and M.W. Mutka, "Stars: Static relays for remote sensing in multirobot real-time search and monitoring," *IEEE Trans. Parallel Distrib.Syst.*, vol. 24, no. 10, pp. 2079–2089, Oct.
2013.

[7] Y. Gu, F. Ren, Y. Ji, and J. Li, "The evolution of sink mobility management in wireless sensor networks: A survey," *IEEE Commun. Surv. Tuts*, doi: 10.1109/COMST.2015.2388779, Jan. 2015.