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Sink attributes analysis for energy efficient operations of wireless sensor networks under randomly varying temporal and spatial aspects of query generation

Pramod Kumar [a,*], Ashvini Chaturvedi [b]

[a] Department of Electronics & Communication Engineering, Manipal Institute of Technology, Manipal 576104, India
[b] Center of Excellence – WSN division National Institute of Technology, Mangalore 575025, Karnataka, India

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ABSTRACT

Rapid advances and the development, compactness and economic viability; in IC technology, network hardware components and associated software have completely change the networking paradigm. The wireless sensor networks (WSNs) have also been not isolated from this unexpected changeover. This paper addresses three principal aspects that have been of interest in the WSN researcher community. These are investigating the suitable cluster formation scheme from some prominent scheme, incorporating the Spatio-temporal aspects of random query generation and subsequently model it using appropriate and extensively used probabilistic distribution functions, and exploring the importance of sink node(s) attributes towards much better energy profile of the WSN, as the energy consumption have been a vital component in deciding the overall network service conditions. The integration of these three aspects led to various case studies, which principally involves, uses of SKM, SFCM, DKM and DFCM as clustering schemes, uniform and Poisson probability mass functions uses to mathematically model the Spatio-temporal dependence of query distribution pattern, and the network surveillance by a single stationary sink, a moveable sink and four stationary sinks. The simulation results of various case studies are analyzed and compared.

1. Introduction

Wireless Sensor Networks (WSNs) architecture consists of large number of tiny sensor nodes typically in the order of several hundred or few thousands. These sensor nodes share the observed sensing attributes with each other or to an external base-station (BS)/sink node using multi-hop communication paradigm. Depending upon the applications, the sensor nodes are homogeneous/non-homogeneous and support multi-modality feature. Compared to other conventional networks, relatively higher densities of sensor nodes facilitate job of sensing with a reasonable accuracy over large geographical areas. Typically the sensor node architecture comprises of sensing, processing, transmission, mobilizer, position finding system, and power units (some of these components are optional like the mobilizer and position finding system). Usually, the sensor nodes are scatteredly deployed in a given surveillance area. Sensor nodes coordinate among themselves to produce high-quality information about the physical environment. Each of these scattered sensor nodes generate/relay the acquired data to other sensor nodes or to an external sink node(s). Sink nodes are stationary or mobile (relocation aspects) and connect the WSN to the outside world ubiquitously using internet gateway, thus the end users access the reported data [1].

In a majority of WSN architectures, sensor nodes possess limited resource of energy (battery), and thus the energy consumption must be dealt with proper care. In turn the lifetime of the WSN depends on the optimum utilization of resources and the routing strategy of packet transmissions. For a query based network, the network lifetime depends on the volume of query generated, inter-arrival time rate of query generation (frequency of query generation) and spatial distribution of query. In most of the WSN applications, the query generation/arrival pattern is discrete in nature; owing to it most of the time sensor nodes remain in sleep mode. Hence, the energy dissipation pattern is inherently discrete and if it is systematically scheduled among the neighboring nodes it would definitely leads to enhancement of the network lifetime. Several researchers have investigated the importance of

* Corresponding author. Tel.: +91 8202924821.
E-mail addresses: 79.pramod@gmail.com, p.kumar@manipal.edu (P. Kumar), chaturvediashvini@gmail.com (A. Chaturvedi).

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energy aspects in WSN environment, some of these are listed here.

Intanagonwiwat et al. proposed a data-centric energy efficient routing protocol using existing wireless local area network (WLAN) technologies [2]. Gharavi and Ban presented a cluster-based ad hoc routing scheme for a multi-hop wireless sensor network [3]. Kwon et al. reported an on-demand clustering mechanism, passive clustering to overcome limitations of limited scalability and inability to adapt high-density sensor distributions [4]. In a study proposed by Kumar and Gharavi; the important aspects of WSNs have been investigated primarily focused on distributed data compression and transmission, and collaborative signal processing. In a WSN; detection, classification, and tracking of targets require collaboration among sensor nodes. Distributed signal processing in a sensor network reduces the amount of communication required in the network, lowers the risk of network node failures, and prevents the fusion center from being overwhelmed by huge amount of raw data from sensors [5,6]. Chair and Varshney optimum fusion rules have been obtained under the conditional independence assumption [7,8]. Decision fusion with correlated observations has been investigated in [9–12]. Many findings on the problem of distributed detection with constrained system resources are reported in the literature [13–18].

Chamberland and Niu proposed frame work with a random number of sensors, a decision fusion rule that uses the total number of detections reported by local sensors as a statistic for hypothesis testing. Herein, the other reported observations indicate that the signal power attenuates as a function of the distance from the target, the number of sensors follows a Poisson distribution, and the locations of sensors follow a Uniform distribution within the region of interest (ROI) [19–21]. Wang et al. compared Poisson and Gaussian distribution of sensor nodes for object tracking in wireless sensor networks for randomly deployed sensor nodes [22]. Niu and Varshney presented a concept of region of interest ROI, in which the network architecture was a kind of ad-hoc network [21].

Anand and Lampe in reported work improved the reliability of the detection/estimation of hidden data of WSN. The localized hidden data are defined by a hidden Markov model (HMM). The propagated probability mass function is also observed by using Gibbs sampler (GS) [23]. Xinxin et al. have addressed energy-efficient data gathering issues in WSNs; an energy aware probability-based clustering algorithm (EPC). It has high scalability and flexibility for large scale WSNs [24]. Liu et al. presented an event detection application of WSN and work mainly comprises of a multiple event detection scheme using compressed sensing (CS). Three algorithms of CS are used in the proposed scheme to manifest the associated merits of detection probability over the traditional decentralized detection methods using Bayesian approach [25].

Xu et al. proposed Bayesian Compressive Sensing (BCS) theory with hierarchical Bayesian analysis model to investigate the process of wideband spectrum detection and data fusion for Cognitive Wireless Sensor Network (C-WSN) [26]. Mousavi et al. proposed a Spatio-temporal event detection algorithm. The algorithm provides a probabilistic graphical model (PGMs) of WSNs. The algorithm incorporates the Markov chains in temporal dependency and Markov random fields' theory in the spatial dependency of sensors in a distributed fashion [27]. Christian et al. presented the Spatio-temporal indexing problem that includes a benchmark for the performance evaluation and comparison of Spatio-temporal indexes [28]. Al Naymat et al. presented the performance of spatial indexing structures which drastically deteriorates in a high dimensional space. On dimensionality reduction, another reported methodology comprises of a preprocessing strategy which involves a random projection to reduce the transformed space [29].

Yang et al. presented uses of microbial fuel cells (MFCs) as renewable energy source to support environmental monitoring. The paper reports mathematical models for optimal duty-cycling that minimizes the probe packet reception time [30]. Sun et al. presented a primate-inspired mobility model for intermittently connected mobile networks. To overcome some of the inherent drawbacks of the proposed model a scheme called primate-inspired adaptive routing protocol (PARP) is presented [31]. Recently, Huang et al. proposed a cross-layer routing design for cognitive radio networks (CRNs) with two primary objectives, (i) to reduce the average cumulative end-to-end delay of all flows and (ii) to increase the packet delivery ratio [32].

In this paper, uses of the four different cluster formation schemes is investigated when query generation and its spatial distribution pattern are approximated by two types of probability mass function (PMF) models. To improve the lifetime of a WSN, the limited energy resource to be used precisely and the routing protocol must be devised dynamically in proportion to the energy reserve status. With this motivation, we present four different schemes for clusters formation while adopting different query generation patterns. In this paper, we presumed that in a given surveillance area (SA), the query spatial distribution follows the uniform and Poisson PMF pattern. On deploying all the four clustering scheme; WSN performance is evaluated on the basis of following measures (i) Residual energy status (RES) estimation for all the network nodes, (ii) Average residual energy status (ARES) estimation of entire network nodes; periodically and on attaining predetermined target lifetime of WSN, (iii) Critical residual energy status (CRES) estimation with progressive time; in terms of percentage of network nodes that attain set threshold energy level. These performance measures are analyzed and compared for all the four clustering schemes. The paper is organized as follows; the location addressing scheme is described in Section 2, probabilistic models of query generation are described in Sections 3 and 4, the simulation results are presented and discussed in Sections 5 and 6 concludes the paper, while appendix includes the details of network parameters used during simulation exercise.

2. Geographical location addressing scheme

For the given surveillance area (SA); its dimensions along x and y axes are resolved into smaller units (grids) of dimension using n_x and n_y bits for x and y segments, respectively. SA geometry may be of square/rectangular shape. In this work, square shape SA is considered. For the chosen SA; uniform resolution along x and y axes results in $n_x = n_y$ i.e., the same number of bits are required to transform the x and y distance measures into binary encoded frame, and we refer it as Binary Location Index (BLI). In a BLI with uniform resolution either n_x or n_y can be treated as Most Significant Bits Segment (MSBS) or Least Significant Bits Segment (LSBS) and vice-versa. Thus, on selecting n_x as LSBS and n_y as MSBS corresponding BLI is shown in Fig. 1.

The exact location, EL, of a cell can be decoded from the BLI as [22]:

$$\mathrm{EL} = (\mathrm{BL})_x + (\mathrm{BL})_y \tag{1}$$

$$\text{where,} \quad (\mathrm{BL})_x = n_x 2_x^{n-1} + \cdots + n_2 2^1 + n_1 2^0 \tag{2}$$

$$(\mathrm{BL})_y = n_y 2_y^{n-1} + \cdots + n_2 2^1 + n_1 2^0 \tag{3}$$

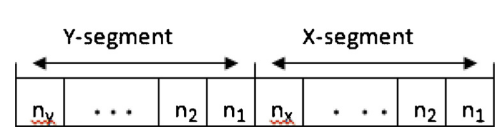

Fig. 1. BLI for square shape SA.