An Objective based Classification of Aggregation Techniques for Wireless Sensor Networks

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Abstract.This paper presents a comprehensive survey of aggregation techniques that can be used in distributed manner to improve lifetime and energy conservation of wireless sensor networks. These techniques are designed to achieve some improvement objective e.g. reducing data size, minimizing transmission energy, enhancing accuracy etc. Main contribution of this work is proposal of a novel classification of such techniques based on the type of improvement they offer when applied to WSNs. We first review the meaning of term aggregation and then associate it with the proposed classes. Each class is presented with a brief literature review of example applications in WSN.

Keywords: Aggregation, wireless sensor networks, data fusion, energy conservation, accuracy

1 Introduction

Wireless Sensor Networks (WSNs) are adhoc networks comprising of resource constrained nodes, mostly of small size and low cost, with sensing and communication capabilities. The nodes collect sensor readings and communicate them to sink, mostly outside network, also known as Base Station (BS), via neighbouring nodes. BS processes the data to get conclusions about the state of sensed environment. WSN has been identified as one of the most important technologies of 21st century and has gained popularity due to their applications in social, environmental, military, medical, disaster relief, search and rescue domains.

The nature of WSN applications requires nodes to be small and cheap which sets limitations on the available resources and capacity of these nodes. However, irrespective of resource constraints the nodes are bound to handle and transmit large amount of sensed data. Hence, a number of optimization techniques are used to minimize energy consumption, improve bandwidth utilization and increase throughput.

Aggregation is one of the common methods used to improve network lifetime in WSNs. Aggregation is a term that has been defined in literature in a number of ways, sometimes synonymously with (data or sensor) fusion. Van Renesse [1] describes aggregation as "… programmable composition of the raw data into less voluminous refined data…". Similarly, it is stated as a combination of data from different sources to eliminate redundancy in [2]. Data fusion has also been defined as the combination of data from multiple sensors to achieve improved accuracy and inferences [3]. However, some researchers choose for a more generic connotation and express the output information of fusion process to be better in 'quality' [4] or 'some sense' [5]. The criteria of betterment may be qualitative or quantitative.

We share this generic view and define aggregation as a process which, when applied on a set of data, results in an output that is an improved representation of input. The improvements are suggested to be in the form of accuracy, completeness, relevance, reliability, energy conservation, efficiency etc. In sensor networks, the input may comprise of data sensed by one sensor, collected over a period, also called *temporal aggregation*, or from a number of sensors (of same or different dimensionalities), also called *spatial aggregation*.

The efficiency of aggregation depends on a number of factors including location of sources in the network, number of sources, network density, aggregation function, routing protocol and network load. The greatest gains in performance are achieved when sources are closer to each other but far from sink [6]. However, aggregation also brings in some tradeoffs. It needs to allow adequate number of readings to be accumulated which may result in delay at intermediate nodes. The second, more obvious factor that gets compromised is accuracy. The prepared abridged version of data evidently lacks precision when compared to raw data. However, careful selection of aggregation method suitable for the concerned application may help improve relevance of the result.

We note that the discovery of need of aggregation in WSN has led researchers to propose various ways of exploiting this useful technique ranging from the simplest functions of average, min, sum etc. to more sophisticated Bayesian inference and

Kalman filtering. However, only a little work could be found on consolidation of the solutions proposed in a variety of WSN application domains.

We aim to survey this large body of work and propose classification with a different perspective. We feel strong need of extracting the classification criteria from the very definition of the term aggregation and group aggregation methods based on the way they ‘improve the output’. We study the ways in which quality can be improved in WSN domain and the techniques that are used to achieve this. This survey will serve as a consolidated material for researchers requiring to know the state-of-the-art. It will also help designers of routing algorithms to select aggregation functions according to the requirements of their design. We believe that out of the minimal amount of reviews available in this emerging area, this paper presents a novel way of classification and is one of its own kind. Note that due to space limitations, some significant contributions had to be omitted and will be included in an extended version.

Aggregation can be performed at sink having energy and computational resources in abundance. However, in-network data (sensor) fusion is found to be more effective in saving battery power by allowing partial aggregation at the nodes en route. The algorithms exploit spatial and/or temporal redundancy and can additionally lead to improved system performance in terms of congestion control, data accuracy and robustness. Hence, this work refers to in-network aggregation techniques unless stated otherwise.

The rest of the paper is structured in the following manner. Section II provides a brief overview of literature and motivation behind this work. We introduce the classification hierarchy in section III with details of techniques available in each class. Section IV concludes the paper.

2 Motivation And Related Work

There are a few survey papers available on aggregation techniques in WSN covering different aspects. A survey of protocols in WSN using aggregation and their impact on data latency, accuracy and energy consumption is presented in [7]. Protocols are classified with respect to the underlying network architecture and data flow pattern. However, little discussion could be found about the computation that each node performs on the data before it is sent out. Other papers also survey the routing protocols and couple aggregation with network structure and its formation [8]. The work of [9] and [10] were found to be closest to the ideas presented here. However, [9] groups the techniques in only two ways: 1) lossy and lossless, 2) duplicate sensitive and duplicate insensitive. [10] presents more comprehensive review but follows a different definition of data fusion (and aggregation) than considered here.

A body of research in literature has been dedicated to data centric routing protocols that employ services of an aggregator to transport data to sink in an efficient manner. One of the earliest proposals, also known as Directed Diffusion, is a query-based scheme and uses aggregation to reduce sensor data size while propagation to the requester. LEACH uses hierarchical dynamic clustering architecture and employs aggregation at cluster heads (CH) and reduces the amount of data being sent to the base station. TAG and COUGAR use tree structure routed at the Base station. Each node in the tree partially aggregates the data before forwarding to its parent node. This approach is improved further with respect to message loss tolerance in Synopsis Diffusion and Tributary-Delta by routing data through multiple paths. A detailed description of above mentioned protocols can be found in [9].

Significant amount of work has also been done to explore heterogeneity in these schemes suggesting that aggregation should be performed by only selected nodes to better utilize network resources [11]. Issues like how to select such nodes [12], whether these should be of different specification, whether the role should be rotated among all nodes, if yes, then when and how [12] etc. are still being addressed.

All the above mentioned protocols discuss the underlying infrastructure for efficient routing of the aggregated data but do not discuss the algorithm executed by the aggregator itself. Most of them refer to summarization as aggregation method.

This work is focused on the aggregation functions applied on the sensed data. We consider aggregator as a separate process at each node working on top of routing protocol (Fig. 1). It receives input from the routing layer, processes it and hands it back to the layer. Most of the routing protocols employing aggregation consider this process as a black box. We survey the techniques that can be implemented in that black box and hence, discuss the range of candidate algorithms to be executed by the aggregator.

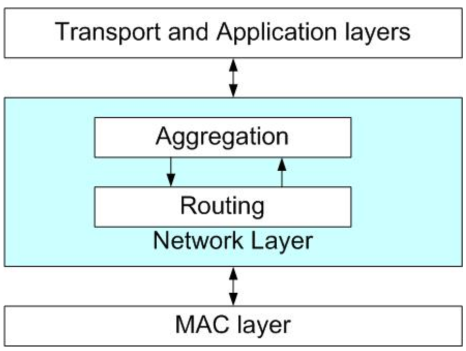

Fig. 1. Communication model for WSN incorporating aggregation

3 Classification

We present a classification of aggregation functions with respect to the purpose of their design. We note that various aggregation techniques are developed to achieve specific objectives e.g. reducing data size, improving reliability, accuracy or confidence of the information, minimizing transmission energy etc. Classification hierarchy is shown in figure 2. Definition of each class with brief overview of how it has been used in WSN is given in the subsections below. Note that data size reduction is a by-product of most of these functions.

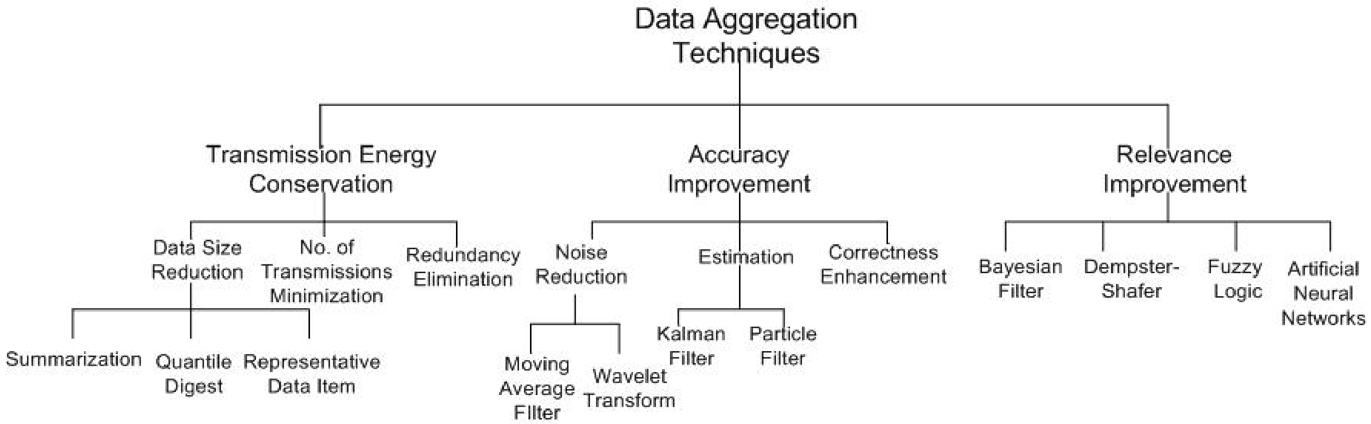

Fig. 2. Classification Hierarchy of Aggregation Techniques

3.1 Transmission Energy Conservation

This class encompasses algorithms that process incoming sensed data to save transmission power. We know that transmitting 1 bit consumes as much energy as processing about 1,000 instructions [13]. This class of techniques combines data sets so as to produce output that requires lesser energy for onward transmission. We divide this class in three sub-classes.

Data Size Reduction

This class represents a set of techniques that are particularly useful when the goal is to have the size of aggregated data, approximately equal to a single un-aggregated value. The following different types of methods are commonly used in WSN.

Summarization Techniques

Algorithms under this class attempt to find one single quantity extracted from the entire set of sensor readings. Most common functions such as average, min, max and count fall under this category. These operators possess some properties such as duplicate sensitivity, data loss tolerance etc. that need to be kept in mind while designing a system. A sophisticated algorithm to calculate simple average using partial sum and count values has been demonstrated in [14] for query-based systems. Similarly, an algorithm for reporting only the most frequently occurring items is proposed in [15]. Another work uses weighted average to merge data from proximate groups [16].

Quantile Digest

Quantile is the division of ordered data into some equal sized data subsets. Q-Digest dynamically partitions the data set aiming to have partitions of almost same size. An algorithm for calculating quantile, specially median, of values reported by multiple sensors, has been described in [17]. A Node is placed in q-digest:
If its count is not greater than n/k; and
If sum of counts of the node, its parent and siblings is greater than n/k.

Where n is the total number of readings and k is a compression factor. The algorithm also provides a confidence factor along with the median value. This work is an extension of [18] that responds to a quantile query keeping error within a certain bound.

Representative data items

This technique is used to find a relatively small number of parameters or variables that represent an entire class of data items. We restrict ourselves to two common methods of this subclass due to space limitations.

Principle component analysis is a statistical technique used to convert a large set of highly correlated observations into a smaller set of uncorrelated values called principle components. This approach is used in [19] to find a small number of readings that represent large data sets in an accurate manner. Moreover, it has been demonstrated that good approximation of sensor measurements can be obtained by relying on few principle components [20]. This work also proposes supervised and unsupervised compression techniques that differ in accuracy and resultant message size

Pattern coding is used when sensor readings can be grouped into classes and assigned concise codes. Sensors send these codes instead of actual readings to higher level aggregator (parent or CH) and achieve reduced transmission size [21]. CH may suppress duplicate codes and second phase may involve retrieving actual data values, if required.

Number of Transmissions Minimization

This class of algorithms repackages the received set of either temporal or spatial data into one packet to avoid multiple transmissions without information loss (lossless aggregation). Unlike most algorithms in Data Size Reduction class above, the output packets are of variable length depending on number of input packets used for concatenation. The data packets can be divided into payload and header fields. This scheme attempts to reduce header overhead only. It has been shown that energy saving is more effective for small payload size [22]. This class can also be used by address-centric routing protocols as it can work on network layer packets and send results to MAC layer for onward transmission. It is mostly employed when either the network is under-loaded, as it does not help much in congestion control or when higher granularity of data is required at sink. [23] demonstrates the use of aggregation by concatenation to solve consensus in WSN.

Redundancy Elimination

This class of algorithms exploits the simple fact that data sensed by nodes in close proximity is highly correlated. Hence, transmission energy is saved by identifying and discarding spatially redundant data. The simplest form of this technique is duplicate suppression[6], [21], [16] where only one copy among the duplicates received from multiple sensors is forwarded to higher level node. Data redundancy has serious impact on correctness of information in protocols which use duplicate sensitive functions like count, sum, average for computation of final result. OPAG[24] uses multi-path routing for reliable dissemination but prevents data from being aggregated more than once by letting each node choose its aggregator and pad the message with aggregator ID. This ensures that only the nominated nodes aggregate the encapsulated data whereas others will merely forward the redundant copies.

3.2 Accuracy Improvement

Algorithms in this class deals with data with the objective that the aggregate data has lesser impurities and higher precision. Aggregators analyse the data set, look for associations and/or anomalies, relate it with the history and produce data that has better accuracy. This class is divided into three classes given below.

Noise Reduction

Algorithms in WSNs process data that is prone to distortions and noise due to hardware transient faults and deployment in rough environments. Hence, noise removal techniques are applied to pre-process the sensed data before it can be used any further. These are temporal aggregation techniques that work on some predefined bounds to remove noise or unwanted spiky values in sensor readings. These algorithms work on a set of data collected over a period of time, the length of which has significant impact on the performance. Bigger window size produces smoother output but results in higher aggregation latency. Hence, an optimal value needs to be chosen according to application requirements. Two types of noise reduction techniques were found to be commonly used in WSN.

Moving Average Filter

It is a relatively simple technique to remove noise from digital signal streams in time domain. Simple arithmetic mean of a number (window size) of last sensor readings is calculated to produce each point in the output signal. This technique is demonstrated to effectively filter unwanted signal from the observations of magnetic, acoustic and thermal sensors in [25]. To ensure realistic filtering, the bound (threshold) is adjusted over time with respect to maximum signal strength of the observation.

Wavelet Transforms

Wavelets are much more complex in functionality than Fourier Transforms and provide resolution at particular time and frequency, which makes them more suitable for wireless sensor networks. Signals can be easily categorized by observing their behavior e.g. discontinuities or peaks. A number of variations with advanced features like compression [26], multi-resolution features for reproduction of signal [27], fast computation of coefficients [28] etc. have been used in WSN to smoothen input data streams.

Estimation

Estimation theory is about approximating unknown parameters based on the measured data. It uses law of probability to compute state of various field properties e.g. temperature, humidity, target location, object velocity etc. Improvement in accuracy is dependent on the knowledge of noise and probability distribution of the measured data. This section discusses two estimation methods commonly used in WSN known as Kalman Filtering and Particle Filtering. These techniques have been widely used in WSN for applications like aerospace and marine navigation, target tracking and target localization.

Kalman filter

It is a mathematical model used to estimate the state of a process with minimal mean of the squared error. It works in two steps: prediction of current state (based on previous state estimate and its covariance) and updating estimate of current state (based on first step prediction and new measurement). Kalman filtering is well-suited to the resource constrained WSN as it does not rely on the entire history of information.

Kalman filters have been effectively used to predict data routes in mobile sensor networks by choosing paths with high delivery probability based on favorable movement patterns and available resources [29]. A move from the centralized approach was proposed in [30] for WSN applications like tracking target [31] and reaching consensus [32]. This involved decomposing the filter into a number of distributed filters and associating them with consensus filters to get better estimates by incorporating readings of neighboring nodes.

In unreliable communication channels, effect of communication delays and information loss cannot be ignored. Kalman filter has been used in such a scenario to calculate threshold on the arrival rate of a reading, catering for affected intermittent arrivals [33].

Particle Filter

It is a nonlinear filter that performs estimation using sequential Monte Carlo methods to approximate probability density function of target state. The main idea is to represent the required posterior density functions by a set of random samples (particles) with associated weights and to compute estimates based on these. Its operation can also be divided into two phases similar to the ones of Kalman filter. However, it outperforms traditional Kalman filtering due to its ability to incorporate Non-Guassian noise and detect targets with variable levels of intensity. Most popular applications have been target tracking and object localization.

Distributed particle filter (PF) has been used to track moving target in [34] and [35] while keeping communication overhead to minimum. Advancements have also been proposed to cater for multi-modal sensor data [36], simultaneous detection and tracking of mobile target [37] and imperfect nature of the communication channel between sensors and fusion center [38].

Correctness/Reliability Enhancement

WSN nodes often find their applications in harsh and vulnerable conditions where nodes are susceptible to failures and sensed data may suffer transmission losses, inconsistencies and errors. This necessitates incorporation of a mechanism which can identify and discard spurious values to improve correctness of results. Specialized aggregation methods are designed that involves rounds of communication between neighboring nodes for sharing their observations to reach consensus on detection of the event of interest [39-41]. Each node makes use of spatial redundancy present in the network and updates its decision based on majority votes. As can be easily imagined, such techniques incur accuracy-energy conservation tradeoff and conserve less energy when higher accuracy is needed. Similar trend can be observed for aggregation latency.

Another type of algorithms in this class attempts to improve reliability by using trust model. Each node assigns trust rating to its neighbours on the basis of past records and accordingly decides to consider/ignore neighbour's observations [42].

3.3 Relevance Improvement (Inference)

This class of algorithms process data to draw some conclusion about system state based on some known and true set of parameter readings. These techniques build better understanding of the event/situation under observation and conjecture its state based on correlated low level data collected from the network. The result is of more relevance to the employing application and helps decide upon necessary actions. The methods discussed here are more complex than most of the previous classes. They are widely used in WSNs for target tracking, localization and event detection applications. We discuss four mechanisms in this class below.

Bayesian Filtering

It is the process of making inferences about a hypothesis from some evidence (in the form of measured data) using famous Bayes' probability model. An interesting WSN application of this technique is detection of faulty measurements using estimate of sensors' true reading given the neighbours' readings[43]. It has also been used to conserve energy by allowing a subset of nodes to sleep [44]. The missing data is then inferred at sink from the observed data of 'awake' nodes and prior probability distribution of the field being sensed. A multi-sensor fusion scheme using Bayesian inference for target detection is proposed in [45], wherein target's position and velocity is conjectured by combining multiple sensors' observations and prior information of target's position

Dempster-Shafer Inference

The Dempster-Shafer method is known as the theory of belief functions. Unlike Bayesian method, it does not need probabilities to be assigned to unknown propositions a priori. Degree of belief is obtained by combining available evidence from different sources. Dempster-Shafer Inference method has been used in [46] to achieve better battlefield picture fusing uncertain information in Airborne Sensor Networks. Each sensor gives a list of target types with different confidence levels which are then fused to classify the target types. Another application has been demonstrated in [47] to detect real-time events. Evidence of a sub event is reported in both temporal and spatial spectrum. Aggregator uses confidence function to calculate degree of belief which is incorporated in the final decision at sink. Furthermore, it has also been used to analyze data traffic for detection of failed aggregator nodes [48]. Greater decay in traffic indicates failure and activates topology rebuilding.

Fuzzy Logic

Fuzzy logic has been used for inference since 1964, for making decision in situations when the inputs are impure or conventional boolean solutions cannot be applied. Such inputs are fuzzified using a certain membership function. The outputs of these functions are supplied to an inference engine, which then generates fuzzified output, based on some output membership function. Generally, it is left to the application to obtain crisp output if required.

Due to the complexity of fuzzy engine, majority of the work available in literature performs inference task at the sink [49]. However, greater benefits can be achieved if the engine is implemented in a distributed manner over the nodes. A relevant example uses cluster heads to host inference engine to fuse collected data and identify the event [50]. Fuzzy logic is often used in conjunction with Artificial Neural Networks.

Artificial Neural Networks

Artificial Neural Networks (ANN) are used to extract patterns and detect trends that are too complex to be noticed by either humans or conventional computer techniques. Massive parallelism of very simple basic units called neurons, analogous to the large number of sensors, has gained attention of scientists working on WSNs. The network is divided into connected layers of neurons, each producing outputs based on weighted sum of inputs and bias. Error at the final output is used to dynamically adjust interconnection weights.

Initial training is needed for supervised ANNs and is mostly performed at the sink after which the weights and thresholds of each layer are sent to the corresponding nodes. Aggregation scheme of [51] uses CHs as hidden and output layer neurons and cluster members as input layer neurons. The task of CHs is to send the data that represents features of the sensed raw data to the sink, thereby reducing number of transmissions and removing redundant information.

ANN can easily be used to fuse multi-sensor data and can be extended with fuzzy and/or wavelet layers to perform more complex computations. For example, a 12 layered fuzzy NN to fuse four dimensional sensor readings for deducing fire emergency can be found in [52]. Similarly, In [53] a sensor net has been proposed that identifies intrusions using an unsupervised ANN based on fuzzy adaptive resonance theory (ART). Wavelets are also used here for preprocessing data.

3.4 Miscellaneous

Depending on the nature of application, nodes of WSN may be distributed on large scale, deployed at vulnerable locations to monitor environment and track targets. Wagner brought community's attention to adding security and resilience to data aggregation for WSN environments [54]. He commented that results of simple and widely used aggregation functions like average, sum, maximum etc. can easily be compromised in the presence of even a single tampered sensor node. Since then techniques have been proposed to improve robustness and security of various aggregation functions against malicious attacks. Protocols proposing secure computation of these simple functions have also been proposed [55]. Security and fault-tolerance are two vital attributes of WSN that have attracted considerable research. To avoid presenting a partial view on work present on these important features, they have been considered out of scope for this paper.

Another aggregation technique that is considered important in a number of applications is correlation. Correlation is being used for a number of high-level tasks e.g. improving resilience, diagnosing anomalies to improve sensor data accuracy, analyze anomalous data to minimize false positives and alleviate effect of inserted data etc. This technique cannot be discussed in its entirety due to space limitations.

4 Conclusion

Aggregation has been increasingly used in WSNs as an effective way of improving network lifetime. In-network aggregation is particularly used in data centric protocols due to evidence of significant gains in energy conservation. It covers a multitude of algorithms varying in complexity and level of operation ranging from simple summarization techniques to complex inference mechanisms. The survey presented in this paper indicates that selection of a technique is majorly influenced by the concerned WSN application domain and specification of the problem for which the WSN is deployed. We believe that the classification of these techniques with respect to type of improvements they offer will assist this selection. This is an on-going work and preparation of a more comprehensive classification in the form of a journal paper is underway.

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