Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 65 (2015) 778 – 786

Procedia Computer Science

International Conference on Communication, Management and Information Technology (ICCMIT 2015)

Data Mining and Fusion Techniques for WSNs as a Source of the Big Data

Mohamed Mostafa Fouad[a,b,e,f], Nour E. Oweis[b,e], Tarek Gaber[b,c,e,f], Maamoun Ahmed[d], Vaclav Snasel[b]

[a]Arab Academy for Science, Technology, and Maritime Transport, Cairo, EGYPT
[b]Faculty of Electrical Engineering and Computer Science, VSB-Technical University of Ostrava, Ostrava - Czech Republic
[c]Faculty of Computers and Informatics, Suez Canal University, Ismailia, Egypt
[d]Middle East University, Amman - Jordan
[e]IT4Innovations, VSB-Technical University of Ostrava, Ostrava - Czech Republic
[f]Scientific Research Group in Egypt (SRGE), http://www.egyptscience.net

Abstract

The wide adoption of the Wireless Senor Networks (WSNs) applications around the world has increased the amount of the sensor data which contribute to the complexity of Big Data. This has emerged the need to the use of in-network data processing techniques which are very crucial for the success of the big data framework. This article gives overview and discussion about the state-of-the-art of the data mining and data fusion techniques designed for the WSNs. It discusses how these techniques can prepare the sensor data inside the network (in-network) before any further processing as big data. This is very important for both of the WSNs and the big data framework. For the WSNs, the in-network pre-processing techniques could lead to saving in their limited resources. For the big data side, receiving a clean, non-redundant and relevant data would reduce the excessive data volume, thus an overload reduction will be obtained at the big data processing platforms and the discovery of values from these data will be accelerated.

Peer-review under responsibility of Universal Society for Applied Research
Keywords: Wireless Sensor Networks; Big Data; Data Mining; Data Fusion, Machine learning;

1. Introduction

A Wireless Sensor Network (WSN) is a wireless network which consists of a large number of nodes (small sensors) densely deployed either very close to a phenomenon (e.g. sensing humidity, pollution, monitoring bridge, etc.) or inside it. Most of the data, generated from the WSNs, are originally streaming data that represents either measurements or events happening over intervals of time. In some applications, this stream of data are continues and arrives at high speeds. This, consequently, has emerged the necessity to new techniques, platform, and tools to deal with this huge amount sensory data which is usually structured or unstructured. With the belief that the increase of using WSNs

E-mail address: mohamed.mostafa@vsb.cz (Mohamed Mostafa Fouad).

Peer-review under responsibility of Universal Society for Applied Research
doi:10.1016/j.procs.2015.09.023

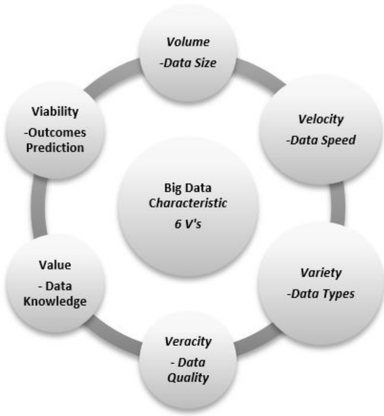

Fig. 1: The big data 6V's characteristics

in different applications, it is expected that the sensory data will also exponentially increase. This means that the standards data processing techniques may not be applicable for such situations. Therefore, to deal with the expected streamed data with high-volume and high-velocity along with the distributed computing characteristics of the WSN, the Big Data paradigm is the suitable solution for extracting, analyzing, visualizing, sharing, storing, and transferring this data.

The Big data is a cost-effective, and innovative forms used to describe the exponential growth and availability of structured and unstructured data for enhancing the processes of decision making[1]. There are a number of characteristics that distinguish the big data from traditional relational database management systems RDBMS. These characteristics can lies into six main descriptors called the 6V's[1,2]. Figure (1) summarizes these characteristics with briefly descriptions below[4]:

- **Volume**: This characteristic refers to the generation of high volume of data that requires huge storage space or consist of large number of records.
- **Velocity**: This denotes to the rate of data stream in unprecedented speed (or complex event processing) till the response to that data.
- **Variety**: This is a characteristic describing the multidimensional data fields that are collected from huge variety of sources with diversity formats.
- **Veracity**: This refers to cleaning biases, noise and abnormality in the big data.
- **Viability**: It means the combination of all relevant information to conduct various future predictions.
- **Value**: It is a characteristic describing the main objective of collecting such huge amount of data, i.e. finding relationships which either explicitly or hidden within the data in order to turn it to worthy value.

This article gives an overview and discussion about a number of the state-of-art of two data processing techniques designed for WSNs. These technique were designed not only to enhance the performance of these networks but also improve the performance of the Big Data paradigm.

The rest of the paper is organized as follows. Section 2 discusses a brief introduction about the data types and sources of the Big Data. Section 3 describes challenges attached with wireless sensor networks. Sensory data processing techniques are discussed in section 4. Finally, Section 5 points out the concluding remarks.

2. Big Data Sources and Data Types

The first step in any big data framework is data generation, which is usually associated with cloud computing. This is because the analysis of large data sets in real-time required powerful platforms, which is usually provided by cloud service providers. In addition to cloud computing, there are other sources generating and technologies widen the big data such as: WSN, IoT, Social Networks, Search Engine, Biomedical, Mobile, NFC, etc.[3].

These different kind of big data sources produce various type of data. This leads to the heterogeneous problem of the Big Data. Therefore, to support the storage and the big data analysis, this data should be classified into either one of the following[2]:

- **Structured Data**: In this type, the data is represented in predefined format such as titled columns and rows. This type can be easily processed by traditional data processing tools (e.g. Relational databases, Files, etc.).
- **Semi-structured Data**: This is a type of the data structure which does not follow the relational databases format. However, it contains other markers, e.g. tags, which separate between semantic elements and impose hierarchies of records and fields within the data (e.g. E-mail, HTML, XML documents, etc.).
- **Unstructured Data**: It is a type of data which has no predefined data model nor organized in a predefined way (e.g. Text, video, audio, social media, etc.).

Among the main challenges of the big data analysis are the inconsistence and incompleteness of data. To address these challenges, so improving the quality of the data and its analysis results, a number of pre-processing techniques are required to remove noise, errors and reduces the data size. This article discuss two of these techniques, *the Data Mining* and *the Data Fusion*, from the perspective of their applications within WSN which is considered as a data-driven module of the big data.

3. Wireless Sensor Networks

Recently, the WSNs paradigm has been integrated as a subsystem in a number of modern applications. For example, the sensor based agriculture applications that collect accumulative information of a number of environmental parameters in order to react on different situation[5]. Moreover, WSNs are appropriate for time-sensitive applications; for instance, the traffic management and vehicular safety. That it could collaborate with another cloud tier to alert drivers about road anomalies through their smartphones in real-time[6,7].

Although, the WSN is an application-oriented network that its structure differs according to the application, its nodes sharing common functionalities: sensing, communication, and computation[8]. A node either participates as a source node or as a sink node; the source node are responsible for data acquisition and transmission through a multi-hop routing to the sink node at which the data where processed and delivered to the end-user. In view of the fact due to its small size, these nodes have a number of limitations that affect their performance, the network scalability and reliability[9].

4. Sensor Data

As a result of their limitations, traditional standard applies for data processing models (such as RDBMS) may not be applicable for WSN[10]. The sources of the sensor data is different form standard database in term of non-ending data streams that push immediately without any records of historical information. Even this challenge imposes the need for special design for data processing techniques in order to query, analyze and process WSNs data in multidimensional, multilevel, single-pass, and online manner.

The following subsections present two data processing techniques not only specially designed for WSNs but also will have their benefits over the high-volume and high-velocity big data such as: Data Mining, and Data Fusion.

4.1. Data Mining Over WSNs

The need for extracting knowledge from the sensor data, collected from WSNs, has become an important issue in real-time decision systems. However, the constrained resources of these networks along with its continuously streaming characteristics of sensed data make the traditional data mining techniques not applicable. In addition, the rapid change of the captured/monitored data requires the implementation of online-data mining algorithms in order to get a reasonable time response [11] or predictions as in [12].

The data mining algorithms could be generally classified into either a centralized or a distributed data processing (i.e. whether the mining process will be performed at the sink node or at the sensing nodes).

4.1.1. Centralized Sensors Data Mining Processing Approaches

In the centralized approaches, all sensors send their data to a centralized computing resources usually the sink node to be processed. Usually the centralized approach requires a high computational power with non-bounded energy sources. Following this approach, Halatchev and Gruenwald [13] have proposed a Data Stream Association Rule Mining (DSARM) framework for mining in a WSN. The framework uses the association rule data mining to identify the sensors' missing data through using the readings of other related sensors. Instead of generating a number of association rules between all sensors of a network, the DSARM only finds the relations between only two nodes.

Pan et al. [14] have proposed an enhanced version of the DSARM framework addressing the Halatchev's limitation of only focusing on the relation between a pair of sensors while ignoring the relation with other sensors. The enhanced DSARM makes use of Adaptive Multiple Regression (AMR) that reflects the spatial correlation of sensor data in the estimation of missing sensor's data. Since the sensed data could changes dynamically, the AMR can estimate the confidence level of the missing data through capturing the dynamic correlation of neighbors' sensed data and then selecting the optimal sample for regressing the appropriate coefficients of the estimation function.

One of the main current technologies that mainly depends on the WSN is the Internet of Things (IoT) paradigm. Based on this paradigm, there have been many sensor-based applications heavily utilize the World Wide Web (WWW), e.g. the Sensor Web [15,16] which are considered as another layer added to the WWW. Due to the heterogeneity between the types of sensors and the need to the interconnectivity to the Internet, the XML language provides the suitable solution to connect the sensors directly to the web applications [16]. To support mining for WSN-based applications (i.e. over the XML streams), there is a problem concerning the tree structure of the XML documents. To address this problem, Paik et al. [17] have proposed a reformulation of the association rules for XML streamed data. In this proposal, the mining within the XML scheme only requires one time scan over the streamed XML data. The main idea of the solution is that the association rules are used with the Label Projection Approach [18] to generate frequent XML tree items without any redundancy. As a result, the size of the stream data have been reduced to 37.5% of its original size.

For multiple data streams, Aghbari et al. [19] proposed the MG-join algorithm which used the Discrete Fourier transforms (DFTs) to reduce the dimensionality of streamed data into a few numbers of coefficients. Also, they used incremental methodology to update the streamed data. The main issue that the increase number of coefficients will affect the performance of the algorithm.

4.1.2. Distributed Sensors Data Mining Processing Approaches

In the distributed sensors data processing approach, each node uses its limited computing resources to perform the mining process. The main advantage of this approach is reducing the raw data streams to be delivered to the sink node. However, it may deplete the network resources in terms of memory footprint and energy consumptions. As for the sensor's memory footprint, the increased number of frequent patterns requires a large space of the memory as reported in [13,20]. For the energy consumption, each sensor node is energy-limited, so adding another task (i.e. data mining) will lead to more energy consumption. Following the distributed approach, a number of mining algorithms have been proposed address the footprint memory problem. In [21], the on-disk data structure (DSTable), which depends on the concept of the mining itemsets (items tend to co-occur), is capturing the important contents from streams of uncertain data and saving them onto the disk. Based on the user-defined minimum threshold, the DSTable is then used to determine the frequent items which are needed to build the Data Stream Projected trees (DSP-trees)[22] while ignoring the infrequent ones, thus saving nodes' memory.

Canzian et al.[23] have also proposed a system called Stream Mining Application (SMA) for distributed mining in WSN. The SMA uses a number of classifiers that distributed over a number of interconnected nodes and each classifier is trained to detect different high-level semantic features from a video stream acquired by a single surveillance camera. The input video is being filtered out through these classifiers to remove irrelevant data and keeping only data of interest to the final mining task. The main feature of this system is that data can be dynamically filtered in parallel manner, thus reducing the processing delay and increasing the detection accuracy.

For massive numbers of sensor nodes, Chunlin et al.[24] applied a distributed data mining based on the deep neural network (DNN). The principle of the DNN is a machine learning approach that divides the neural network into a number of hierarchical layers, as the division proposed here; within sensor nodes. Based on the fact that a sensor's data do not change in a short time, a random selections of 10% training had showed an optimized performance of the WSNs. The DNN improved the data mining over a WSN through extracting the internal representations of important raw data and ignores the redundant one.

4.2. Data Fusion Over WSNs

Data fusion is an important concept in both big data and WSNs. In the big data context, the fusion is achieved at the computational platform while in the WSNs context, the fusion is performed inside the network (i.e. in-network process). As one of the sources of the big data, it is preferable to achieve this in-network data fusion, so providing a unification of data representation and avoiding data explosion. Consequently, this will lead to saving the limited resources and capabilities of the WSNs.

A number of research proposals have been developed for in-network computing in the WSNs domain. An example of these proposal is the scheme of Madden et al.[25] that is considered the first step towards a generic in-network approach for collecting and computing sensor data. They introduce an SQL-style interface under the TinyOS operating system. This interface can be used to execute five basic SQL aggregates queries (COUNT, MIN, MAX, SUM, and AVERAGE) over ad-hoc sensor networks. The approach had led to noticeable power saving.

In general, as shown in Figure (2), data fusion in WSNs can be classified according to either the relation of the inputs sources or the data manipulation procedures (level of abstraction).

4.2.1. Fusion based on Input Sources Relation

The class, based on the relation of the inputs sources, can be further classified into three categories: Complementary, Redundant, and Cooperative data fusion as illustrated in figure (3)[26].

The complementary fusion is performed when source nodes obtain different pieces of data that need to be fused in order to complete the scene. In[27], the authors have followed this approach and proposed a system where a robotic boat was used to monitor the toxic cyanobacteria in a lake. The boat collects data from a number of points on a subpart of the lake for a final fusion process towards defining the toxicity rate. Another complementary-based solution was proposed in[28] to address the problem where there is no prior knowledge about sensing data errors and uncertainties in WSN. So, the authors have proposed a fuzzy-based data fusion approach for WSNs. This approach is applied over WSN based on clustering scheme, where each node transmits only the calculated result of the events. This calculation is based on weighting their data by using a fuzzy logic controller (FLC) rather than the entire fused data sent to the cluster head, and then to be transmitted to the sink node. The ability of sensor node to distinguish and aggregate only true values minimizes the node's energy consumption which consequently maximizes the network lifetime. The authors also showed that their fuzzy-based data fusion approach is robust in terms of node failure since it combines

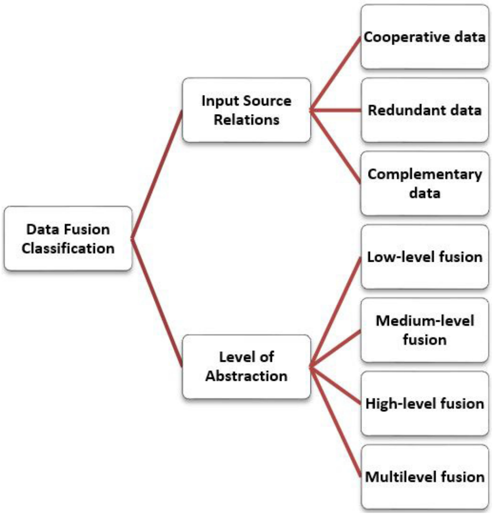

Fig. 2: Data Fusion Classifications within WSNs

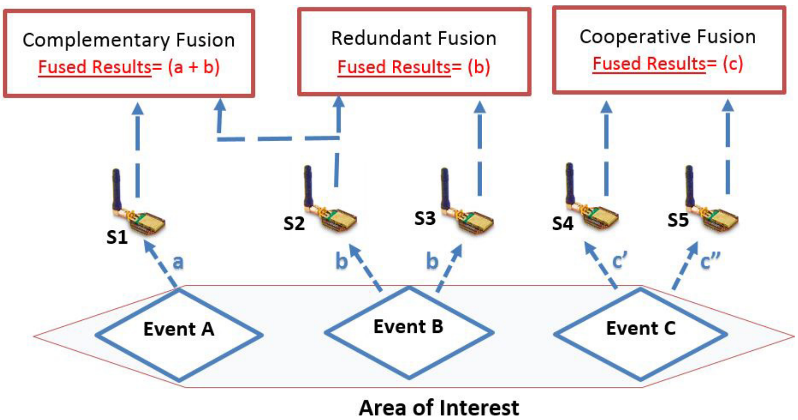

Fig. 3: Data Fusion Based on Relationships between Input Sources

the events of interest from other sensor nodes.

In the redundant fusion approach, if two source nodes share the same piece of data, the data is first ranked and fused into a high-quality single piece of data. So, this approach provide trustiness and reliability of sensed data. for example, the work, proposed in[29], that for ensuring a secure and an accurate data fusion, the Double Cluster Heads Model (DCHM) was proposed. A two cluster head are selected, per each cluster, and separately, each of them apply a Bayesian data fusion within the cluster. Then the in-cluster fusions are upload to the sink node to be used to compute the dissimilarity coefficient. Then a decision is been taken by the sink node to add the compromised nodes to a black-list. Therefore the use of fusion within WSNs is performs better than cryptography techniques that required higher processing power.

The third sub-class of the data fusion based on the relation of the inputs sources is the cooperative data fusion. This class is used when independent sources are fused their data to produce a new piece of data. This type of data fusion is suitable for the applications of the Body Sensor Networks (BSNs) which are currently enabling a number of humancentric applications specially e-Health and sports monitoring[30]. An example about the cooperative data fusion is the C-SPINE[31] which is a framework allowing data fusion from a number of Collaborative BSNs (CBSNs). The most significant features are selected from different sensors to be combines to provides a decision. The main advantage behind that framework is it consider the first reference model for addressing the collaboration between BSNs.

4.2.2. Fusion based on Level of Abstraction

In this class, data fusion can be further classified into four categories[26]: Low-level fusion, Medium- level fusion, High-level fusion, and Multilevel fusion. The Low-level fusion is a combination of a number of raw input data into a new and accurate raw data. An example of this sub-class is the work done in[32] where the fire disaster event can be detected by computing the data fusion collected from temperature sensors and humidity sensors.

Another two abstraction-based data fusion are the medium-level fusion (also, called feature/attribute fusion) and the High-level fusion (Symbol/decision level fusion). The former provides an abstraction map of all features and attributes of the entry data whereas the latter is a combination of symbols/decisions from different sensor sources to establish a single accurate symbol/decision. Cardarelli et al.[33] have suggested a multilevel fusion system which combines the medium-level and the high-level fusions in the automation of obstacle detection application. The main aim of this system is to optimize the data transmission time in which the medium-level features should include: ID, age, position, orientation, velocity and size of Automated Guided Vehicle, whereas the high-level decision fusion should include the classes of stationary and non-stationary objects. Using a heuristic based approach, the medium-level fusion is performed by collecting the velocity and the direction per each vehicle to recognize the occupational area of obstacles. The high-level fusion is also performed to classify different objects which is done based on (1) a number of patterns given to on-board multi-sensor systems and (2) the laser infrastructure-based perception systems.

5. Conclusions

The article has focused on the need to apply pre-processing techniques at the data collected from the WSNs (sensor data). Rather than transmitting amount of continues streaming data to big data storage, they should be an in-network pre-processing operations. WSNs's Data mining and data fusion techniques have been discussed. The data mining techniques are very important to reduce the unnecessary transmitted data to big data storage. The advantages and the limitation of centralized and distributed data mining techniques for WSNs have analyzed. Also, the data fusion techniques, ensuring the accuracy and trustiness of the collected data, and their sub-classes (i.e. abstraction-based and input sources relations-based) have been discussed and analyzed in terms of the energy consumptions and the limited resources of the WSNs. It is then concluded that as main sources of big data, it is vital for the sensor data to be in-network processed as this would prolong the WSNs lifetime and contribute to reduction of data volume of the big data, thus accelerating of the values discovery process from this big data.

6. Acknowledgment

This paper has been elaborated in the framework of the project New creative teams in priorities of scientific research, reg. no. CZ.1.07/2.3.00/30.0055, supported by Operational Programme Education for Competitiveness and co-financed by the European Social Fund and the state budget of the Czech Republic and supported by the IT4Innovations Centre of Excellence project (CZ.1.05/1.1.00/02.0070), funded by the European Regional Development Fund and the national budget of the Czech Republic via the Research and Development for Innovations Operational Programme.

References

1. Ding, Guoru, Qihui Wu, Jinlong Wang, and Yu-Dong Yao. "Big Spectrum Data: The New Resource for Cognitive Wireless Networking.", arXiv preprint arXiv:1404.6508, 2014.

2. Chen, CL Philip, and Chun-Yang Zhang. "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data.", Information Sciences, vol. 275, pp. 314-347, 2014.
3. Chen, Min, Shiwen Mao, Yin Zhang, and Victor CM Leung. "Big Data Generation and Acquisition." In Big Data, Springer International Publishing, pp. 19-32, 2014.
4. Wamba, Samuel Fosso, Shahriar Akter, Andrew Edwards, Geoffrey Chopin, and Denis Gnanzou. "How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study." International Journal of Production Economics, 2015.
5. Abbasi, Abu Zafar, Noman Islam, and Zubair Ahmed Shaikh. "A review of wireless sensors and networks' applications in agriculture." Computer Standards and Interfaces, vol. 36, no. 2, pp. 263-270, 2014.
6. Hu, Xiping, Xitong Li, Edith C-H. Ngai, Jidi Zhao, Victor CM Leung, and Panos Nasiopoulos. "Health Drive: Mobile Healthcare Onboard Vehicles to Promote Safe Driving." in the Proc. of Hawaii International Conference on System Sciences (HICSS), 2015.
7. Mohamed, Adham, Mohamed Mostafa M. Fouad, Esraa Elhariri, Nashwa El-Bendary, Hossam M. Zawbaa, Mohamed Tahoun, and Aboul Ella Hassanien. "RoadMonitor: An intelligent road surface condition monitoring system." In Intelligent Systems, Springer International Publishing, pp. 377-387, 2015.
8. Tarek, Gaber, and Aboul Ella Hassanien. "An Overview of Self-Protection and Self-Healing in Wireless Sensor Networks." In Bio-inspiring Cyber Security and Cloud Services: Trends and Innovations, Springer Berlin Heidelberg, pp. 185-202, 2014.
9. Fouad, Mohamed Mostafa M., and Aboul Ella Hassanien. "Key Pre-distribution Techniques for WSN Security Services." In Bio-inspiring Cyber Security and Cloud Services: Trends and Innovations, Springer Berlin Heidelberg, pp. 265-283, 2014.
10. Madden, Samuel, and Michael J. Franklin. "Fjording the stream: An architecture for queries over streaming sensor data." In Proceedings of the 18th International Conference on Data Engineering, IEEE, pp. 555-566, 2002.
11. Mahmood, Azhar, Ke Shi, Shaheen Khatoon, and Mi Xiao. "Data mining techniques for wireless sensor networks: A survey." International Journal of Distributed Sensor Networks, vol. 2013, Article ID 406316, 2013.
12. Yao, Dezhong, Chen Yu, Hai Jin, and Qiang Ding. "Human mobility synthesis using matrix and tensor factorizations." Information Fusion, vol. 23, pp. 25-32, 2015.
13. Gruenwald, Le, and Mihail Halatchev. "Estimating missing values in related sensor data streams." In Proceedings of the 11th International Conference Management of Data (COMAD'05), 2005.
14. Pan, Liqiang, Huijun Gao, Hong Gao, and Yong Liu. "A Spatial Correlation Based Adaptive Missing Data Estimation Algorithm in Wireless Sensor Networks." International Journal of Wireless Information Networks, vol. 21, no. 4, pp. 280-289, 2014.
15. Botts, Mike, George Percivall, Carl Reed, and John Davidson. "OGC sensor web enablement: Overview and high level architecture." In GeoSensor networks, Springer Berlin Heidelberg, pp. 175-190, 2008.
16. Broring, Arne, Johannes Echterhoff, Simon Jirka, Ingo Simonis, Thomas Everding, Christoph Stasch, Steve Liang, and Rob Lemmens. "New generation sensor web enablement." Sensors, vol. 11, no. 3, pp. 2652-2699, 2011.
17. Paik, Juryon, Junghyun Nam, Ung Mo Kim, and Dongho Won. "Association Rule Extraction from XML Stream Data for Wireless Sensor Networks." Sensors, vol. 14, no. 7, pp. 12937-12957, 2014.
18. Paik, Juryon, Joochang Lee, Junghyun Nam, and Ung-Mo Kim. "Mining maximally common substructures from XML trees with lists-based pattern-growth method." In International Conference on Computational Intelligence and Security, IEEE, pp. 209-213, 2007.
19. Aghbari, Zaher Al, Ibrahim Kamel, and Thuraya Awad. "On clustering large number of data streams." Intelligent Data Analysis, vol. 16, no. 1, pp. 69-91, 2012.
20. Troiano, Luigi, and Giacomo Scibelli. "A time-efficient breadth-first level-wise lattice-traversal algorithm to discover rare itemsets." Data Mining and Knowledge Discovery, vol. 28, no. 3, pp. 773-807, 2014.
21. Cameron, Juan J., Alfredo Cuzzocrea, Fan Jiang, and Carson K. Leung. "Mining frequent itemsets from sparse data streams in limited memory environments." In Web-Age Information Management, Springer Berlin Heidelberg, pp. 51-57, 2013.
22. Leung, Carson Kai-Sang, and Dale A. Brajczuk. "Efficient mining of frequent itemsets from data streams." In Sharing Data, Information and Knowledge, Springer, Heidelberg, pp. 2-14, 2008.
23. Canzian, Luca, and Mihaela van der Schaar. "Real-time stream mining: online knowledge extraction using classifier networks." IEEE Network Magazine-Special Issue on Networking for Big Data, 2015.
24. Li, Chunlin, Xiaofu Xie, Yuejiang Huang, Hong Wang, and Changxi Niu. "Distributed Data Mining Based on Deep Neural Network for Wireless Sensor Network." International Journal of Distributed Sensor Networks, Article ID 157453, 2014.
25. Madden, Samuel, Robert Szewczyk, Michael J. Franklin, and David Culler. "Supporting aggregate queries over ad-hoc wireless sensor networks." In Proceedings Fourth IEEE Workshop on Mobile Computing Systems and Applications, IEEE, pp. 49-58, 2002.
26. Abdelgawad, Ahmed, and Magdy Bayoumi. "Data Fusion in WSN." In Resource-Aware Data Fusion Algorithms for Wireless Sensor Networks, Springer US, pp. 17-35, 2012.
27. Hitz, Gregory, Alkis Gotovos, Franccois Pomerleau, Marie-Eve Garneau, Cedric Pradalier, Andreas Krause, and Roland Y. Siegwart. "Fully autonomous focused exploration for robotic environmental monitoring." In IEEE International Conference on Robotics and Automation, pp. 2658-2664, 2014.
28. Izadi, Davood, Jemal H. Abawajy, Sara Ghanavati, and Tutut Herawan. "A Data Fusion Method in Wireless Sensor Networks." Sensors, vol. 15, no. 2 (2015): 2964-2979.
29. Fu, Jun-Song, and Yun Liu. "Double Cluster Heads Model for Secure and Accurate Data Fusion in Wireless Sensor Networks." Sensors 15, no. 1, pp. 2021-2040 2015.
30. Hung, Kevin, C. C. Lee, and Sheung-On Choy. "Ubiquitous Health Monitoring: Integration of Wearable Sensors, Novel Sensing Techniques, and Body Sensor Networks." In Mobile Health, Springer International Publishing, pp. 319-342, 2015.
31. Fortino, Giancarlo, Stefano Galzarano, Raffaele Gravina, and Wenfeng Li. "A framework for collaborative computing and multi-sensor data fusion in body sensor networks." Information Fusion, vol. 22, pp. 50-70, 2015.
32. Zou, Pinghui, and Yun Liu. "An Efficient Data Fusion Approach for Event Detection in Heterogeneous Wireless Sensor Networks." In International Journal of Applied Mathematics and Information Sciences, vol. 9, no. 1, pp. 517-526, 2015.

33. Cardarelli, Elena, Lorenzo Sabattini, Cristian Secchi, and Cesare Fantuzzi. "Multisensor data fusion for obstacle detection in automated factory logistics." In IEEE International Conference on Intelligent Computer Communication and Processing, pp. 221-226, 2014.