IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 1 Issue 5, July 2014.
www.ijiset.com
ISSN 2348 – 7968

Information Fusion in WSNs: A Review

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Abstract

Wireless sensor networks produce a large amount of data that needs to be processed, delivered, and assessed according to the application objectives. The way these data are manipulated by the sensor nodes is a fundamental issue. Information fusion arises as a response to process data gathered by sensor nodes and benefits from their processing capability. This paper presents the state of- the-art related to information fusion and how it has been used in WSNs and sensor based systems in general. The common terminology used to describe information fusion and common classifications has also been discussed.

Keywords: *wireless sensor network, data, information, aggregation, fusion, multisensor etc.*

1. Introduction

A Wireless Sensor Network (WSN) is a special type of *ad hoc* network composed of a large number of nodes equipped with different sensor devices. This network is supported by technological advances in low power wireless communications along with silicon integration of various functionalities such as sensing, communication, and processing. WSNs are emerging as an important computer class based on a new computing platform and networking structure that will enable novel applications that are related to different areas such as environmental monitoring, industrial and manufacturing automation, health-care, and military. Commonly, wireless sensor networks have strong constraints regarding power resources and computational capacity.

A WSN may be designed with different objectives:

(1) It may be designed to gather and process data from the environment in order to have a better understanding of the behavior of the monitored entity.

(2) It may also be designed to monitor an environment for the occurrence of a set of possible events, so that the proper action may be taken whenever necessary. A fundamental issue in WSNs is the way the collected data is processed. In this context, information fusion arises as a discipline that is concerned with how data gathered by sensors can be processed to increase the relevance of such a mass of data. In a nutshell, information fusion can be defined as the combination of multiple sources to obtain improved information (cheaper, greater quality, or greater relevance).

Information fusion is commonly used in detection and classification tasks in different application domains, such as robotics and military applications. Lately, these mechanisms have been used in new applications such as intrusion detection and Denial of Service (DoS) detection. Within the WSN domain, simple aggregation techniques (e.g., *maximum*, *minimum*, and *average*) have been used to reduce the overall data traffic to save energy.

Additionally, information fusion techniques have been applied to WSNs to improve location estimates of sensor nodes, detect routing failures and collect link statistics for routing protocols.

2. Basic Fundamentals

Several different terms like data fusion, sensor fusion, and information fusion have been used to describe aspects of the fusion subject including theories, processes, systems, frameworks, tools, and methods. Consequently, there is terminology confusion. This section discusses common terms and factors that motivate and encourage the practical use of information fusion in WSNs.

The terminology related to systems, architectures, applications, methods, and theories about the fusion of data from multiple sources is not unified. Different terms have been adopted, usually associated with specific aspects that characterize the fusion. For example, Sensor/Multisensor Fusion is commonly used to specify that sensors provide the data being fused. Despite the philosophical issues about the difference between data and information, the terms Data Fusion and Information Fusion are usually accepted as overall terms.

Many definitions of data fusion have been provided through the years, most of them have been derived from military and remote sensing fields. In 1991, the data fusion work group of the Joint Directors of Laboratories (JDL) organized an effort to define a lexicon with some terms of reference for data fusion. They define data fusion as a "multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources." Klein [1993] generalized this definition, stating that data can be provided by a single source or by multiple sources.

Both definitions are general and can be applied in different fields, including remote sensing. Although they suggest the combination of data without specifying neither its importance nor its objective, the JDL data fusion model provided by the U.S. Department of Defense [1991] deals with quality improvement.

Hall and Llinas [1997] define data fusion as "the combination of data from multiple sensors, and related information provided by associated databases, to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone." Here, data fusion is performed with an objective: accuracy improvement.

However this definition is restricted to data provided by sensors; it does not foresee the use of data from a single source. Claiming that all previous definitions are focused on methods, means, and sensors, Wald [1999] changes the focus to the framework used to fuse data.

Wald states that "data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application." In addition, Wald considers data taken from the same source at different instants as distinct sources. The word "quality" is a loose term intentionally adopted to denote that the fused data is somehow more appropriate to the application than the original data. In particular for WSNs, data can be fused with at least two objectives: accuracy improvement and energy-saving.

Although Wald's definition and terminology are well accepted by the Geo-science and Remote Sensing Society [2004], and officially adopted by the Data Fusion Server [2004], the term Multisensor Fusion has been used with the same meaning by other authors, such as Hall [1992], and Waltz and Llinas [1990]. Multisensor Integration is another term used in robotics/computer vision [Luo and Kay 1995] and industrial automation [Brokmann et al. 2001]. According to Luo et al. [2002], multisensor integration "is the synergistic use of information provided by multiple sensory devices to assist in the accomplishment of a task by a system; and multisensory fusion deals with the combination of different sources of sensory information into one representational format during any stage in the integration process."

Multisensor integration is a broader term than multisensor fusion. It makes explicit how the fused data is used by the whole system to interact with the environment.

However, it might suggest that only sensory data is used in the fusion and integration processes. This confusion of terms was highlighted by Dasarathy [1997] who adopted the term Information Fusion [Dasarathy 2001] stating that "in the context of its usage in the society, it encompasses the theory, techniques and tools created and applied to exploit the synergy in the information acquired from multiple sources in such a way that the resulting decision or action is somehow better (qualitatively or quantitatively, in terms of accuracy, robustness, etc.) than would be possible if any of these sources were used individually without such synergy exploitation." Possibly, this is the broadest definition embracing any type of source, knowledge, and resource used to fuse different pieces of information. The term Information Fusion and Dasarathy's definition are also adopted by the International Society of Information Fusion [2004]. Kokar et al. [1999] also use this term in a framework of formal logic and category theory where the structures representing the meaning of information (theories and models) are actually fused, while data is just processed and filtered through such structures.

The term Data Aggregation has become popular in the wireless sensor network community as a synonym for information fusion [Kalpakis et al. 2003; van Renesse 2003]. According to Cohen et al. [2001], "data aggregation comprises the collection of raw data from pervasive data sources, the flexible, programmable composition of the raw data into less voluminous refined data, and the timely delivery of the refined data to data consumers." By using 'refined data', accuracy improvement is suggested. However, as van Renesse [2003] defines, "aggregation is the ability to summarize," which means that the amount of data is reduced. For instance, by means of summarization functions, such as *maximum* and *average*, the volume of data being manipulated is reduced. However, for applications that require original and accurate measurements, such a summarization may represent an accuracy loss [Boulis et al. 2003a]. In fact, although many applications might be interested only in summarized data, we cannot always assert whether or not the summarized data is more accurate than the original data-set. For this reason, the use of data aggregation as an overall term should be avoided because it also refers to one instance of information fusion: summarization.

Here, we understand that both terms, data fusion and information fusion, can be used with the same meaning. Multisensor/sensor fusion is the subset that operates with sensory sources.

ISSN 2348 – 7968

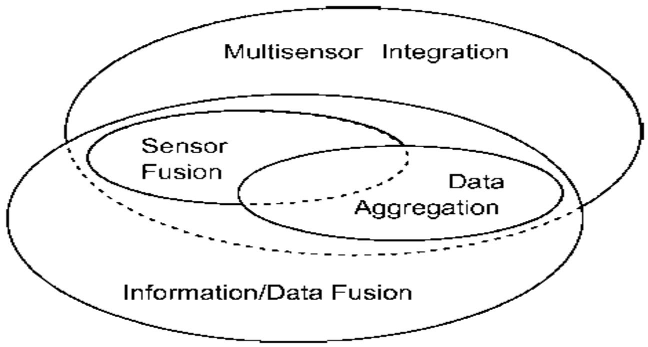

Fig.1 Relationship among the concepts of multisensor/sensor fusion, multisensor integration, data aggregation, data fusion and information fusion

Data aggregation defines another subset of information fusion that aims to reduce the data volume (typically, summarization), which can manipulate any type of data/information, including sensory data. On the other hand, multisensor integration is a slightly different term in the sense that it applies information fusion to make inferences using sensory devices and associated information (e.g., from database systems) to interact with the environment. Thus, multisensor/sensor fusion is fully contained in the intersection of multisensor integration and information/data fusion. Here, we chose to use information fusion as the overall term so that sensor and multisensor fusion can be considered as the subset of information fusion that handles data acquired by sensory devices. However, as data fusion is also accepted as an overall term, we reinforce Elmenreich's recommendation [Elmenreich 2002], which states that fusion of raw (or low level) data should be explicitly referred to as *raw data fusion* or *low level data fusion* to avoid confusion with the *data fusion* term used by the Geo-science and Remote Sensing Society [2004].

3. Why Information fusion?

WSNs are intended to be deployed in environments where sensors can be exposed to conditions that might interfere with their measurements. Such conditions include strong variations of temperature and pressure, electromagnetic noise, and radiation. Therefore, sensors' measurements may be imprecise (or even useless) in such scenarios. Even when environmental conditions are ideal, sensors may not provide perfect measurements. Essentially, a sensor is a measurement device, and an imprecision value is usually associated with its observation. Such imprecision represents the imperfections of the technology and methods used to measure a physical phenomenon or property. Failures are not an exception in WSNs.

For instance, consider a WSN that monitors a forest to detect an event, such as fire or the presence of an animal. Sensor nodes can be destroyed by fire, animals, or even human beings; they might present manufacturing problems; and they might stop working due to a lack of energy. Each node that becomes inoperable might compromise the overall perception and/or the communication capability of the network. Here, perception capability is equivalent to the exposure concept [Meguerdichian et al. 2001a; Megerian et al. 2002].

Both spatial and temporal coverage also pose limitations to WSNs. The sensing capability of a node is restricted to a limited region. For example, a thermometer in a room reports the temperature near the device but it might not fairly represent the overall temperature inside the room. Spatial coverage in WSNs [Meguerdichian et al. 2001b] has been explored in different scenarios, such as target tracking [Chakrabarty et al. 2002], node scheduling [Tian and Georganas 2002], and sensor placement [Dhillon et al. 2002]. Temporal coverage can be understood as the ability to fulfill the network purpose during its lifetime. For instance, in a WSN for event detection, temporal coverage aims at assuring that no relevant event will be missed because there was no sensor perceiving the region at the specific time the event occurred. Thus, temporal coverage depends on the sensor's sampling rate, communication delays, and the node's duty cycle (time when it is awake or asleep).

To overcome sensor failures, technological limitations, spatial, and temporal coverage problems, three properties must be ensured: *cooperation*, *redundancy*, and *complementarity* [Durrant-Whyte 1988; Luo et al. 2002]. Usually, a region of interest can only be fully covered by the use of several sensor nodes, each cooperating with a partial view of the scene; information fusion can be used to compose the complete view from the pieces provided by each node. Redundancy makes the WSN less vulnerable to failure of a single node, and overlapping measurements can be fused to obtain more accurate data; Rao [2001] shows how information fusion can perform at least as well as the best sensor. Complementarity can be achieved by using sensors that perceive different properties of the environment; information fusion can be used to combine complementary data so the resultant data allows inferences that might be not possible to be obtained from the individual measurements (e.g., angle and distance of an imminent threat can be fused to obtain its position).

Due to redundancy and cooperation properties, WSNs are often composed of a large number of sensor nodes posing a scalability challenge caused by potential collisions and transmissions of redundant data. Regarding the energy restrictions, communication should be reduced to increase the lifetime of the sensor nodes. Thus, information fusion is also important to reduce the overall communication load in the network, by avoiding the transmission of redundant messages. In addition, any task in the network that handles signals or needs to make inferences, can potentially use information fusion.

4. Limitations of Information Fusion

Information fusion should be considered as a critical step in designing a wireless sensor network. The reason is that it can be used to extend the network lifetime and is commonly used to fulfill application objectives, such as target tracking, event detection, and decision making. Hence, blundering information fusion may result in waste of resources and misleading assessments. Therefore, we must be aware of possible limitations of information fusion to avoid blundering situations.

Because of resource rationalization needs of WSNs, data processing is commonly implemented as in-network algorithms [Akyildiz et al. 2002; Intanagonwiwat et al. 2003; Madden et al. 2005]. Hence, whenever possible, information fusion should be performed in a distributed (in-network) fashion to extend the network lifetime. Nonetheless, we must be aware of the limitations of distributed implementations of information fusion.

In the early 1980s, Tenney and Sandell [1981] argued that, regarding the communication load, a centralized fusion system may outperform a distributed one. The reason is that centralized fusion has a global knowledge in the sense that all measured data is available, whereas distributed fusion is incremental and localized since it fuses measurements provided by a set of neighbor nodes and the result might be further fused by intermediate nodes until a sink node is reached. Such a drawback of decentralized fusion might often be present in WSNs wherein, due to resource limitations, distributed and localized algorithms are preferable to centralized ones. In addition, the lossy nature of wireless communication challenges information fusion because losses mean that input data may not be completely available.

Another issue regarding information fusion is that, intuitively, one might believe that in fusion processes, the more data the better, since the additional data should add knowledge (e.g., to support decisions or filter embedded noise). However, as Dasarathy [2000] shows, when the amount of additional incorrect data is greater than the amount of additional correct data, the overall performance of the fusion process can be reduced.

5. Classifying Information Fusion

Information fusion can be categorized based on several aspects. Relationships among the input data may be used to segregate information fusion into classes (e.g., cooperative, redundant, and complementary data). Also, the abstraction level of the manipulated data during the fusion process (measurement, signal, feature, decision) can be used to distinguish among fusion processes. Another common classification consists in making explicit the abstraction level of the input and output of a fusion process. These common classifications of information fusion are explored in this section.

5.1 Classification based on relationship among the sources

According to the relationship among the sources, information fusion can be classified as complementary, redundant, or cooperative [Durrant-Whyte 1988]. Thus, according to the relationship among sources, information fusion can be:

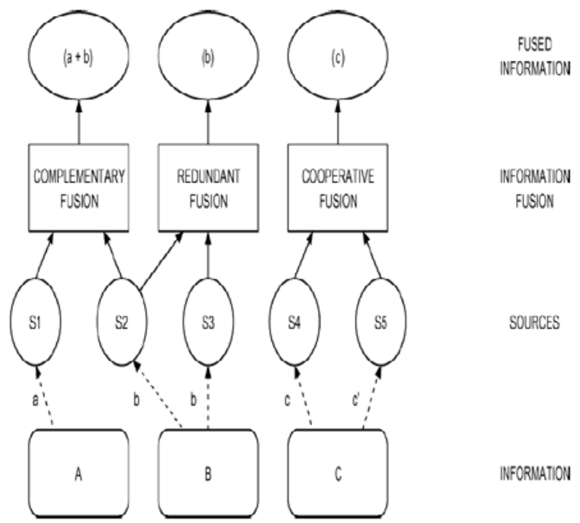

Fig. 2 Types of information fusion based on the relationship among the sources.

Complementary. When information provided by the sources represents different portions of a broader scene, information fusion can be applied to obtain a piece of information that is more completing (broader). In Fig. 2, sources S1 and S2 provide different pieces of information, a and b, respectively, that are fused to achieve a broader information, denoted by (a+b), composed of non redundant pieces a and b that refer to different parts of the environment (e.g., temperature of west and east sides of the monitored area).

Redundant. If two or more independent sources provide the same piece of information, these pieces can be fused to increase the associated confidence. Sources S2 and S3 in Fig. 2 provide the same information, b, which is fused to obtain more accurate information, (b).

Cooperative. Two independent sources are cooperative when the information provided by them is fused into new information (usually more complex than the original data) that, from the application perspective, better represents the reality. Sources S4 and S5, in Fig. 2, provide different information, c and c_, that are fused into (c), which better describes the scene compared to c and c_ individually.

Complementary fusion searches for completeness by compounding new information from different pieces. An example of complementary fusion consists in fusing data from sensor nodes (e.g., a sample from the sensor field) into a feature map that describes the whole sensor field hence broader information.

Redundant fusion might be used to increase the reliability, accuracy, and confidence of the information. In WSNs, redundant fusion can provide high quality information and prevent sensor nodes from transmitting redundant information.

A classical example of cooperative fusion is the computation of a target location based on angle and distance information. Cooperative fusion should be carefully applied since the resultant data is subject to the inaccuracies and imperfections of all participating sources.

5.2 Classification based on levels of abstraction

Luo et al. [2002] use four levels of abstraction to classify information fusion: signal, pixel, feature, and symbol. Signal level fusion deals with single or multidimensional signals from sensors. It can be used in real-time applications or as an intermediate step for further fusions. Pixel level fusion operates on images and can be used to enhance image-processing tasks. Feature level fusion deals with features or attributes extracted from signals or images, such as shape and speed. In symbol level fusion, information is a symbol that represents a decision, and it is also referred to as decision level. Typically, the feature and symbol fusions are used in object recognition tasks. Such a classification presents some drawbacks and is not suitable for all information fusion applications.

First, both signals and images are considered raw data usually provided by sensors, so they might be included in the same class. Second, raw data may not be only from sensors, since information fusion systems might also fuse data provided by databases or human interaction. Third, it suggests that a fusion process cannot deal with all levels simultaneously.

In fact, information fusion deals with three levels of data abstraction: measurement, feature, and decision. Thus, according to the abstraction level of the manipulated data, information fusion can be classified into four categories:

Low-Level Fusion. Also referred to as *signal (measurement) level fusion*. Raw data are provided as inputs, combined into new piece of data that is more accurate (reduced noise) than the individual inputs. Polastre et al. [2004] provide an example of low-level fusion by applying a moving average filter to estimate ambient noise and determine whether or not the communication channel is clear.

Medium-Level Fusion. Attributes or features of an entity (e.g., shape, texture, position) are fused to obtain a feature map that may be used for other tasks (e.g., segmentation or detection of an object). This type of fusion is also known as *feature/attribute level fusion*. Examples of this type of information fusion include estimation of fields or feature maps and energy maps.

High-Level Fusion. Also known as *symbol* or *decision level fusion*. It takes decisions or symbolic representations as input and combines them to obtain a more confident and/or a global decision. An example of high-level fusion is the Bayesian approach for binary event detection proposed by Krishnamachari and Iyengar [2004], which detects and corrects measurement faults.

Multilevel Fusion. When the fusion process encompasses data of different abstraction levels—when both input and output of fusion can be of any level (e.g., a measurement is fused with a feature to provide a decision)—multilevel fusion takes place. Nakamura et al. [2005b] provide an example of multilevel fusion by applying the Dempster-Shafer theory to decide about node failures based on traffic decay features.

Although the first three levels of fusion are specified by Iyengar et al. [2001], they do not specify Multilevel Fusion. Typically, only the first three categories of fusion (low, medium, and high level) are considered, usually with the terms *pixel/measurement*, *feature*, and *decision fusion* [Pohl and van Genderen 1998]. However, such a categorization does not foresee the fusion of information of different levels of abstraction at the same time.

5.3 Classification based on Input and Output

Another well-known classification that considers the abstraction level is provided by Dasarathy [1997], in which information fusion processes are categorized based on the abstraction level of the input and output information. Dasarathy identifies five categories:

Data In–Data Out (DAI-DAO). In this class, information fusion deals with raw data and the result is also raw data, possibly more accurate or reliable.

Data In–Feature Out (DAI-FEO). Information fusion uses raw data from sources to extract features or attributes that describe an entity. Here, "entity" means any object, situation, or world abstraction.

Feature In–Feature Out (FEI-FEO). FEI-FEO fusion works on a set of features to improve/refine a feature, or extract new ones.

Feature In–Decision Out (FEI-DEO). In this class, information fusion takes a set of features of an entity generating a symbolic representation or a decision.

Decision In–Decision Out (DEI-DEO) Decisions can be fused in order to obtain new decisions or give emphasis on previous ones.

Compared to the classification presented in Section B, this classification can be seen as an extension of the previous one but with a finer granularity, where DAI-DAO corresponds to Low Level Fusion, FEI-FEO to Medium Level Fusion, DEI-DEO to High Level Fusion, and DAI-FEO and FEI-DEO are included in Multilevel Fusion. Contextualizing the examples in Section 3.2, Polastre et al. [2004] use DAI-DAO fusion for ambient noise estimation through a moving average filter; Singh et al. [2006] use FEIFEO fusion for building feature maps that geographically describe a sensed parameter such as temperature; Luo et al. [2006] use DEI-DEO fusion for binary event detection by fusing several single detections (sensor reports) to decide about an actual event detection; and Nakamura et al. [2005b] apply FEI-DEO fusion when they fuse features describing the traffic decay to infer about node failures.

The main contribution of Dasarathy's classification is that it specifies the abstraction level of both input and output of a fusion process, avoiding possible ambiguities. However, it does not allow in the same process, the fusion, for instance, of features and signals to refine a given feature or provide a decision.

4. Conclusions

This paper presents the background about information fusion, such as: What is information fusion? (2) Why should a designer use it? In simple words, Information fusion is the set of resources used to combine multiple sources such that the result is in some sense better than the individual inputs. Information fusion should be used to improve the performance of a task by understanding the current situation, and supporting decisions. The provided background supports the design of fusion-based solutions for different levels of applications in a WSN, such as internal tasks (e.g., data routing) and system applications (e.g., target detection). However, there are some limitations regarding the methods and the architectures that should be considered.

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