Multi-Sensor Data Fusion in Wireless Sensor Networks for Planetary Exploration

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***Abstract*— The SWIPE (Space Wireless Sensor Networks for Planetary Exploration) project uses Wireless Sensor Networks (WSN) to characterise the surface of the Moon. The envisaged scenario is that hundreds of small wireless sensor nodes dropped onto the Moon surface will collect scientific measurements. An ad-hoc WSN connecting these nodes will propagate the measurement data to sink nodes for uploading to a lunar orbiter and a subsequent transmission to Earth. The data gathered from the sensors will be processed using state-of-the-art data fusion techniques to overcome the restricted energy and bandwidth resources. In this paper, we first provide a short survey of classical data fusion techniques for WSNs. We then introduce data fusion architectures for the SWIPE project. Building on this, we propose data processing algorithms that enable energy conservation and processing efficiency in the proposed SWIPE architectures. The proposed algorithms are evaluated via a series of simulation models. The results show that the proposed algorithms can efficiently reduce the amount of the transmitted scientific data providing a good level of accuracy in the data reconstruction. Furthermore, they are able to correctly evaluate the node health status.**

Keywords—wireless sensor network; data fusion; planetary exploration;

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have been widely used to explore difficult-to-access areas on Earth. For example, they can be used to monitor physical or environmental conditions in uninhabited areas for the purposes of forest fire or natural event detections. Recently, some researchers are considering extending the concept of WSNs to space applications, for instance, detection of lunar water at very low temperatures of permanently dark regions on the moon [1, 2]. Bringing this technology to space enables several different advanced scenarios, such as planetary exploration using WSN [3], lunar water detection [4], etc.. Since WSNs are composed of a large number of sensor nodes and the nodes are deployed in different locations, they can monitor large geographical areas remotely, which could overcome the limitations of landers and rovers on planetary surfaces for carrying out in-situ measurements [4]. In general, each node has a processor, memory, sensors, a wireless communication module and a batteries power supply. However, maintenance of these nodes is a difficult task due to unfriendly and unattended environment, especially in the case of planetary exploration, where it is extremely difficult to access or replace dead nodes. Therefore, designing an energy efficient node architecture and data processing algorithms are a major concern for such WSNs. One efficient way to reduce the power consumption is to remove the redundant information using data fusion techniques. The reason is that the power consumption of a communication module is much higher than that of a data processing module [5]. Thus, through reducing the size of the data transmission, the overall energy consumption can be reduced significantly. In addition, as data fusion techniques combine data from different sensor sources, the physical phenomenon can be better understood. The fusing of multiple sensor signals also provides an efficient representation of the data.

The approach of the European Commission collaborative project SWIPE (Space Wireless Sensor networks for Planetary Exploration) project comes in line with this trend [3], and it proposes to bring an advanced terrestrial technology to space using innovative mission concepts. The SWIPE project will address not only the applicability of this technology in space WSNs, but it will also investigate new methods for data processing and fusion within WSNs. The SWIPE concept is depicted in Fig. 1.

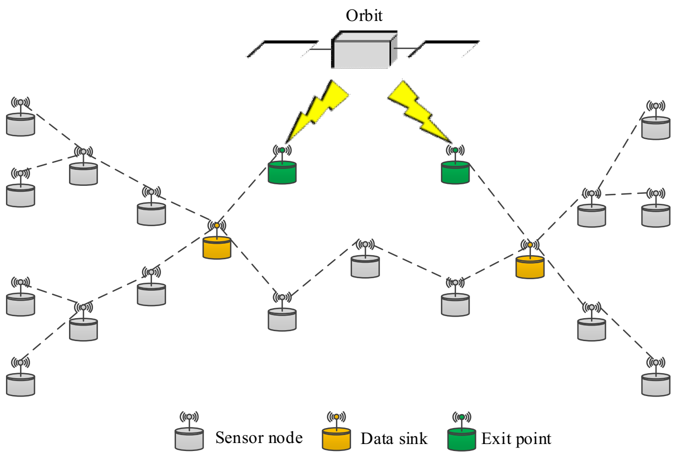

Fig. 1. SWIPE concept.

This paper presents the preliminary work done in the scope of the SWIPE project, focusing mainly on the data processing and fusion architectures design. The proposed data fusion architectures take into account the energy levels of the nodes

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extending the network lifetime as much as possible. In addition, the generated fused scientific and housekeeping data could help with reducing the redundancy of the raw data at node and network levels increasing the information density while preserving signal features.

This paper starts by reviewing the state of the art on data fusion techniques in WSNs. Proposed data fusion architectures for node and network levels data fusion tasks are introduced subsequently. This is followed by a series of simulation results. Finally conclusions are drawn.

II. RELATED WORK

Data fusion techniques process data obtained from various sources of a different nature, in order to improve the quality of the measured information for an intelligent system. Data fusion technology can be divided into three fusion levels, which are data level fusion, feature level fusion and decision level fusion. The data level fusion (data aggregation) aims to fuse the sensor raw data to reduce the redundant information. Feature level data fusion aims to extract features from the raw data to remove redundant information. Decision level data fusion (decision-making) aims to analyse feature information of the raw data and help the data fusion system to understand the working environment.

Since the power budget of an embedded system is limited, reducing the total amount of data transmissions in the WSN will significantly improve the operating life of the WSN system. Recent research work [6-8], has shown that the use of data fusion technology can greatly reduce the total energy consumption of the WSNs.

Data generated from the same local sensor within a continuous period normally contain similar and redundant data information. Cooperative data fusion methodology could help with removing these types of redundant information. On the contrary, data collected from sensors, distributed in different locations, provide information related to their local environments. They will be fused with the local representative information to complement the data fusion process [9].

Most popular data fusion architectures for WSNs include centralized, decentralized and Joint Directors Laboratories architectures.

A. Centralized Data Fusion Architecture

The centralized architecture is the simplest architecture. All sensed data are transmitted to a centre node (data sink), and then the data sink fuses the collected data. In this architecture the centre node controls the whole network. The advantages of this architecture are that it is easy to implement and it is also easy to identify the faults of the nodes in the WSNs. The disadvantages are that the unbalanced energy consumption of the WSNs could break down the WSN in a particular area. Mhatre and Rosenberg [10] consider two types of nodes in the WSN system, type one are normal nodes and type two are high performance nodes, which could be used as a data sink in the WSNs. Their research has shown that the centralized data fusion architecture is suitable for small sized WSNs.

B. Decentarlized Data Fusion Architecture

The decentralized architecture is a widely used architecture in current WSN data fusion systems. In this architecture, there is no fixed fusion centre. Each node in this architecture can perform data fusion tasks based on the local observations and the information obtained from neighbour nodes. This architecture gives a good fault-tolerance performance. In addition, it can also save energy in WSN, as data are not reported to the centre. However, it is not the case in the Planetary Exploration Application, as the collected data need to be transmitted to an Earth control centre.

C. Joint Directors Laboratories (JDL)

This classical data fusion module is developed by the Joint Directors Laboratories data fusion group, established in 1986 [11]. The JDL data fusion architecture is a functionally oriented model. It is a two-layer hierarchical system. The input of this model is usually the extracted parameters of signal processing at the post-detection. The output of the data fusion process is a minimally ambiguous identification and characterization of individual entities. This system can be considered as a data-in-decision-out system.

This data fusion architecture is suitable for node-level data-aggregation system design. In this architecture, each node can fuse the sensor raw data before transmitting the node information. The advantage is that it could reduce the redundant transmitted data in the WSNs. The drawback of this architecture is that it cannot transmit all the raw data to the data sink. As a result of this, the node may lose some important information that might affect the data sink ability to perform a further analysis.

III. PROPOSED DATA FUSION ARCHITECTURES

According to the mission definition in [3], the input data types for data fusion tasks can be divided into the following two categories:

1) Scientific sensors' data: these data are generated by a set of scientific sensors: Radiation, Thermal, Illumination and Dust Deposition sensors. The sensors are scheduled to perform the measurements with different measurement frequencies.

2) Housekeeping data: these data are generated by the node internal monitoring sensors, providing values of parameters such as temperature, residual battery level, current voltage, on/off status etc. The sensors are scheduled to perform the measurements with the same frequency.

Since the measurement frequency of the housekeeping data is much higher than the scientific data, the amount of the generated data will be significantly more than the scientific data. On the other hand, the purposes of these types of data are also different. The scientific data is mainly used for fulfilling the mission objective, which necessitates that they are kept more informative and it is required that they are sent back to Earth. However, the housekeeping data is mainly used for monitoring the health status of each node by local node control management tasks or can be transmitted back to the base station for monitoring or debugging purposes. Thus, it is not necessary to send the original housekeeping data back on a continuous basis. The local decision information should be enough for monitoring purposes and the raw housekeeping data can be sent to the base station upon users' requests. The overall data processing/fusion architecture for a SWIPE node is shown in Fig. 2.

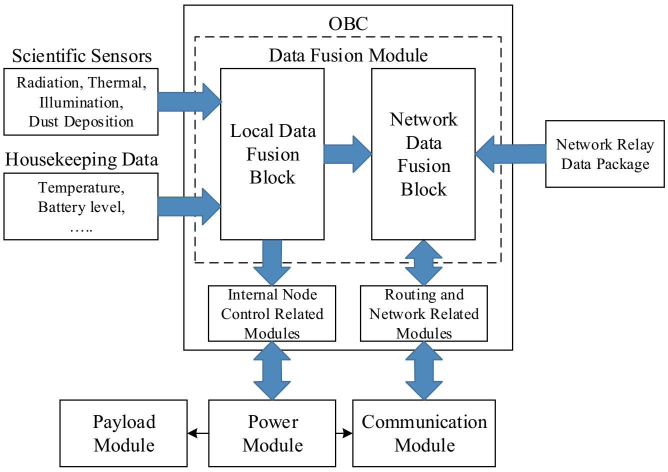

Fig. 2. Overall data processing/fusion architecture for a SWIPE node.

In Fig. 2, the housekeeping and scientific data are processed separately in the data fusion module. The housekeeping data fusion is only focused on a decision level, where the current status of the node will be reported and stored inside the node. This information can be further used in other internal node modules (e.g. routing and power control modules) for a node behaviour management purpose. On the other hand, the scientific data are processed and fused in the data fusion module generating an output that only contains informative features. The purpose of this is to remove redundant information before data transmission.

In the following sections, the proposed data fusion architectures are discussed on the basis of their hierarchical structure (i.e. local and global data fusion/processing architectures).

A. *Local Data Fusion/Processing Architecture*

As mentioned in the previous sections, the purposes of processing scientific and housekeeping data are different. Thus, they are processed separately in the proposed local data/processing fusion architecture, shown in Fig. 3.

In Fig. 3, the scientific and housekeeping data are firstly pooled in the memory blocks RAM0 and RAM1 respectively, and then they are sent to different data processing modules. For scientific data, the data fusion/processing strategy uses both cooperative and complementary fusion methodologies. On the other hand, for the housekeeping data, a series of data fusion/processing algorithms can be applied to combine and analyse the information derived from different internal sensors. The output of the housekeeping data fusion module only contains the decision based on the current input information, which means that the size of the data will be reduced significantly. Eventually, the data will be stored in the

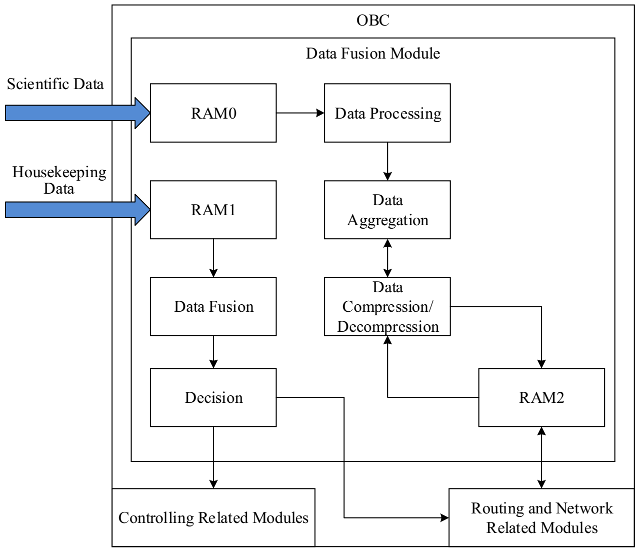

Fig. 3. Overall data processing/fusion block diagram for a regular node.

node, which can be retrieved and used by other node components to improve the performance of the management and control algorithms in the WSN. Details about the data fusion architecture for housekeeping data are shown in Fig. 4.

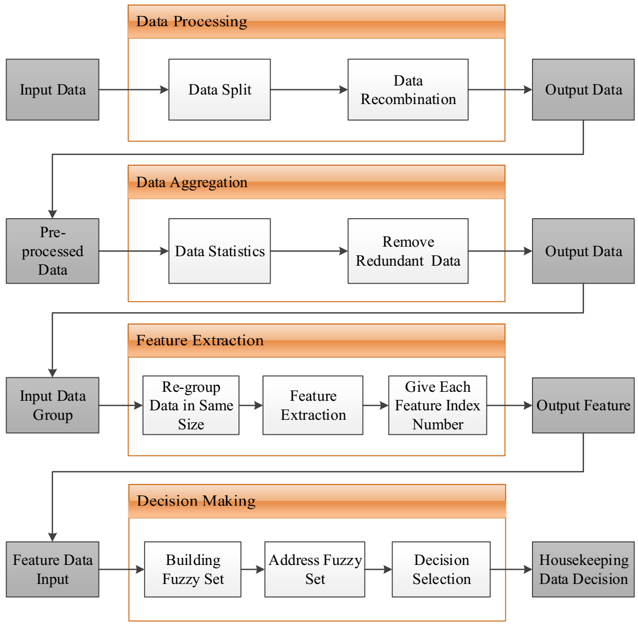

Fig. 4. Overall data fusion architecture for housekeeping data.

As illustrated in Fig. 4, the proposed housekeeping data fusion architecture is divided into four units: Data Processing, Data Aggregation, Feature Extraction and Decision Making Units. The Data Processing unit firstly regroups the raw data by their type and collection time tag (e.g. temperature and battery level). Subsequently, the Data Aggregation unit performs statistical analysis on the pre-processed data, which aims to remove the redundant raw data and calculate the data range. Based on the calculated data range, erroneous and redundant housekeeping data could be removed. After that, the data are firstly re-grouped in the same size, and then the features of each data group are extracted in the Feature Extraction unit. Eventually, in the Decision Making unit, a fuzzy set is built based on the features of the data group, which aims to analyse the features and output the decision values. The fuzzy logic decision making process uses likelihood ratio selection rules to assess a decision based on the input features.

As mentioned in the beginning of section III, the scientific data consist of various sensor data (i.e. Radiation, Thermal, Illumination and Dust Deposition sensors), and the aim of the research project is to continuously monitor the environmental parameters in a certain area, thus, each measured scientific data should be presented not only as detailed as possible, but also the redundancy of the raw data should be minimised as much as possible. Based on the above reasons, each type of sensor data should be processed separately. On the other hand, the data processing architecture should also be able to handle both local scientific data and network relayed data. The reason for that is because redundant information may be included in the network data package. Typically, close nodes would most likely produce similar information. Detailed data fusion architecture for the scientific data at node level is illustrated in Fig. 5.

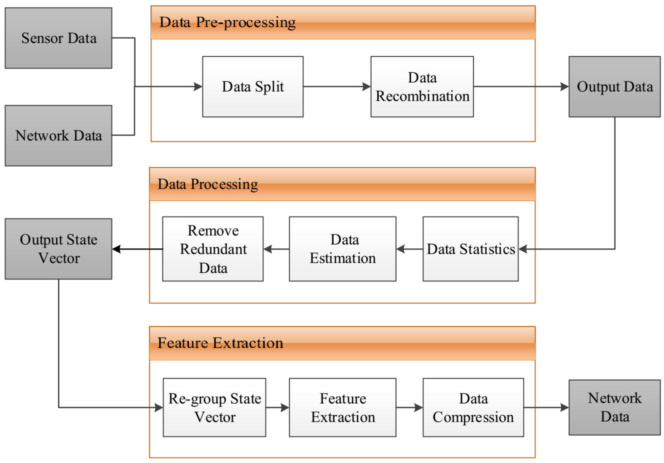

Fig. 5. Overall data fusion architecture for scientific data at node level.

As shown in Fig. 5, the node scientific data gathered by the sensor node and the network relayed data package are pre-processed in the Data Pre-processing unit, where the data are firstly regrouped by their type, collection time and origin. In the Data Processing unit, the data are statistical analysed and only relevant data information (i.e. data that are different from the previous data generated by the same sensor node) is reported to the next processing unit. In doing so, the sensor node should consume less energy when transmitting. The last processing unit is the Feature Extraction unit, where features are extracted from each type of sensor data and are compressed in a single data package to be sent to the network.

B. Global Data Fusion/Processing Architecture

The global data fusion/processing is mainly undertaken by the data sink node, which collects and processes data from all WSN nodes. The main difference between a data sink and a regular node is that the data sink node should have higher memory capacity than a regular node due to the requirement of storing all the data from other nodes. Besides processing scientific data from the network, the data sink also needs to process housekeeping data generated by its internal sensors. Fig. 6 shows the proposed global data fusion/processing architecture.

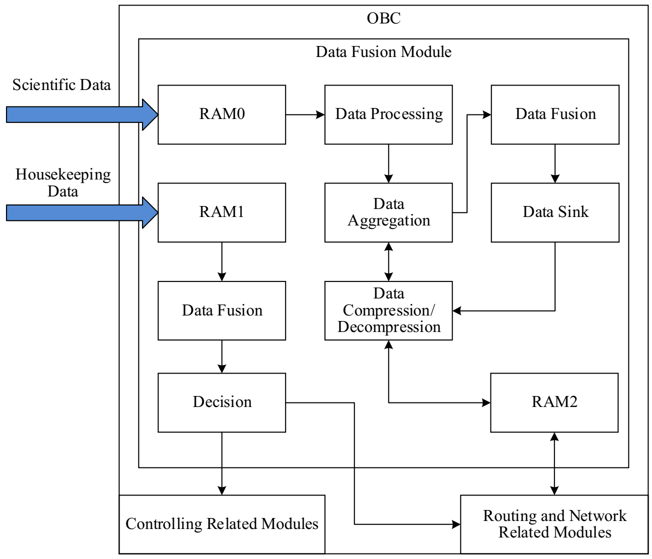

Fig. 6. Overall data processing/fusion block diagram for data sink node.

In Fig. 6, the global data processing/fusion architecture has almost the same internal components as the local one apart of the data fusion and sink blocks. As the data sink node has a global point of view of all the nodes, it should have the highest capacity to pool data from the network. Being the best place to perform the data fusion process, the data sink node will provide a representative fusion result for the entire measurement area. Details about the data fusion architecture at a network level are shown in Fig. 7.

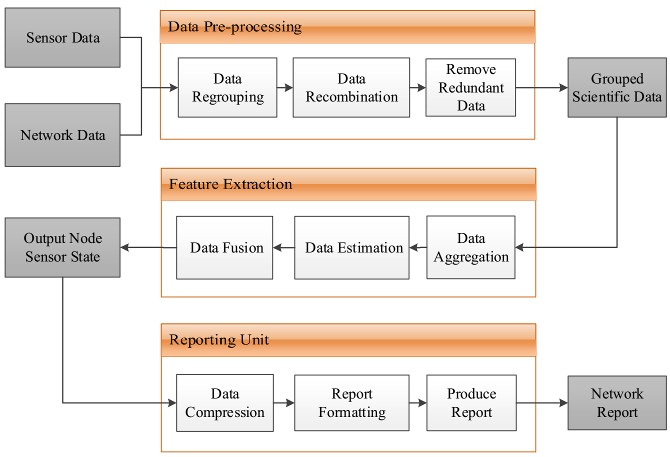

Fig. 7. Overall data fusion architecture for scientific data at network level.

As depicted in Fig. 7, the network level data processing architecture is similar to the node level data processing one in Fig. 5, where the data are firstly regrouped by their type, collection time and origin in the Data Pre-processing unit. The aim of these operations is to remove non-relevant information by statistical analysis. In the feature extraction unit, a complementary data fusion based approach is used to fuse data from different nodes together with the local representative information to complement the data fusion process. On the other hand, if there is an incompleteness of sensor data from a particular location, a pre-specified estimation model could resolve this problem by supplying an estimated value. The last processing unit is the Reporting unit, where various reports of the measurements could be produced based on users' requests. Although the measurements are performed continuously, the Reporting unit only reports the relevant data, which means that the sink node only sends reports to the exit point node if it differs from the last transmitted data information. By doing this, the exit point node would gather exactly the same information as with the classical approach (e.g. the nodes continuously transmit their information regardless of the data relevancy [12]) while receiving less reports and thus less energy required.

IV. MODELLING AND EVALUATION RESULTS

In this section, we evaluate the efficiency of the data fusion/processing architectures for the local housekeeping and scientific data proposed in sec. III. A set of simulation models have been developed in order to validate the analytical results. A series of scientific and housekeeping data fusion algorithms were also implemented in MATLAB as a proof of concept prior to hardware implementation. In the following sub-sections, we will first introduce the testing data set, and then will present the results of implementing the proposed data fusion algorithms for housekeeping and scientific data accordingly.

A. Testing Data Set

Since the same temperature sensors are used to collect housekeeping and scientific data, and there is no direct relationship between the temperature data and the other scientific sensors data, the evaluation uses temperature sensor data as an example.

1) Temperature data: several platinum temperature sensors [13] will be used to measure the thermal changes on lunar surface and the internal environment of the node in the SWIPE project. The transfer function that relates temperature and voltage measured is given as follows:

$$V_{temp} = \frac{5R_0(1+aT+bT^2+c(T-100)T^3)}{R_0(1+aT+bT^2+c(T-100)T^3)+1000} \quad (1)$$

where T is the measurement temperature in *°C*, V_{temp} is the corresponding measurement voltage in *V*, R_0 = 1000 Ω, *a*, *b and c* are the coefficients of the equation, which are equal to 3.9083×10^{-3}, -5.775×10^{-7} and -4.183×10^{-12} respectively.

We use a standard Sine wave (0°-180°) as our temperature model, where 1080 temperature data are sampled (as shown in Fig. 8 (a)). The measurement temperature range in the test case is between 0°C to 70°C. In order to simulate real sensor measurements, an 8% Gaussian random noise signal is also added to the original signal. In total, 10 different data sample sets are generated to form the scientific testing database. On the other hand, each housekeeping data set has 5400 temperature data samples, and there are 10 different data sample sets included in the housekeeping testing database (as illustrated in Fig. 8 (b)). Equation (1) is used to convert temperature to corresponding voltage values.

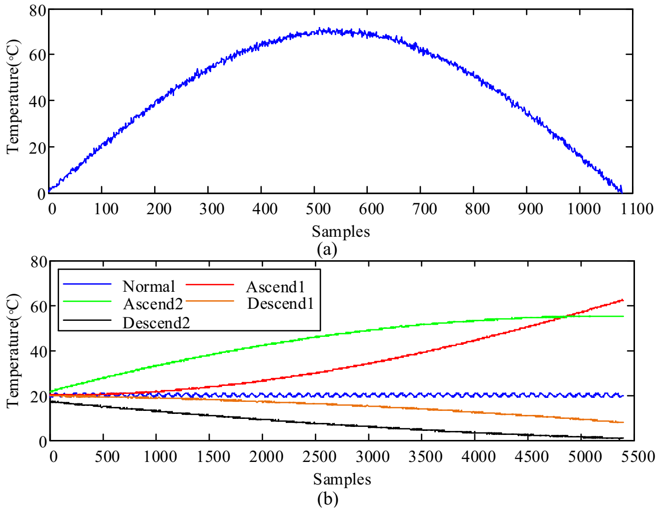

Fig. 8. Scientific and housekeeping temperature data samples. (a) Scientific data samples; (b) Housekeeping data samples.

2) Battery data: rechargeable lithium-ion battery will be used in the SWIPE project [14]. The discharge and charge characteristics diagrams at 0.5 A are given as follows:

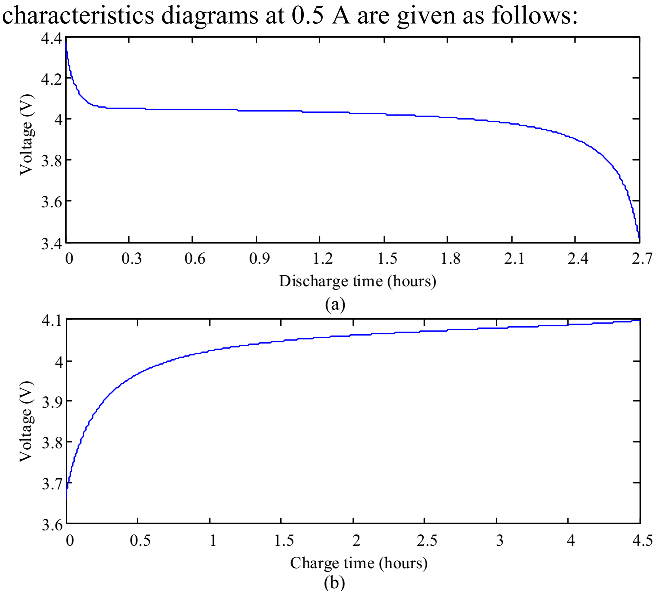

Fig. 9. Used battery discharge and charge characteristics diagrams at 0.5 A. (a) Discharge characteristic; (b) Charge characteristic.

We assume that the State of charge (SOC) of the battery is initialised at 100%. When its state of charge decreases to 5%, the battery starts to recharge itself until it is full. After that, the battery periodically performs the same operations. We sample the data every minute until 5400 samples, the total sampling time per data set is approximately equivalent to 90 hours of measurements.

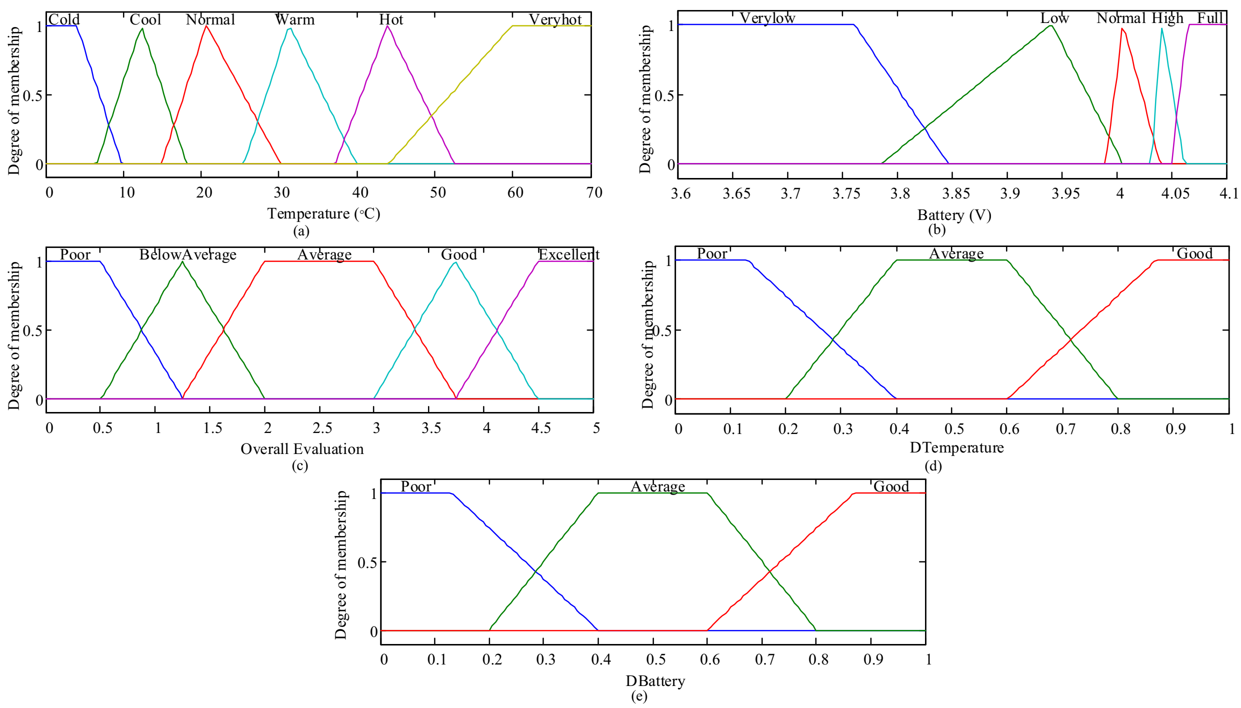

Fig. 10. Membership functions for the inputs and outputs of the proposed FIS. (a) Temperature input; (b) Battery input; (c) Node overall evolution output; (d) Temperature status output; (e) Battery status output.

3) Analogue-to-digital converter (ADC): a 12-bit ADC is used to convert the voltage measurements to digital values. The dynamic range selected for the ADC is 5V.

We use the transfer function of the ADC to convert the temperature and battery voltage samples to the corresponding digital values.

B. Housekeeping Data Fusion

The proposed housekeeping data fusion algorithm is based on a Fuzzy Inference System (FIS) [15]. The FIS has two inputs: temperature and battery voltage, and three outputs: overall node, temperature and battery health status evaluations. The used membership functions for the input and output variables are shown in Fig. 10.

The proposed FIS aims to provide an overall evaluation of the internal status of the node (i.e. temperature and battery status), and this information would further be used in the WSN routing algorithms [16] or the node internal control module. Since the FIS could provide a quantization evaluation of the node status, it could help the routing algorithm to achieve more accurate decision making and predict potential threats. Fig. 11 shows the testing results using the proposed FIS to analyse the one of the housekeeping testing data set.

As it can be seen from Fig. 11(a), the FIS 'battery status output' is periodically changing following the battery discharge and recharge cycles, as result of this, the FIS 'overall evaluation output' is also changing in the same pattern. Since the temperature input in Fig. 11(b) is increasing, the FIS 'temperature status output' remains at a lower status once the node is overheating. Although the used membership transfer functions are all linear functions, the outputs curves are still relatively smooth, which means that the proposed FIS provides a good accuracy. On the other hand, the use of the linear membership transfer functions could also help with reducing the computational cost when the FIS is deployed in an embedded WSN node.

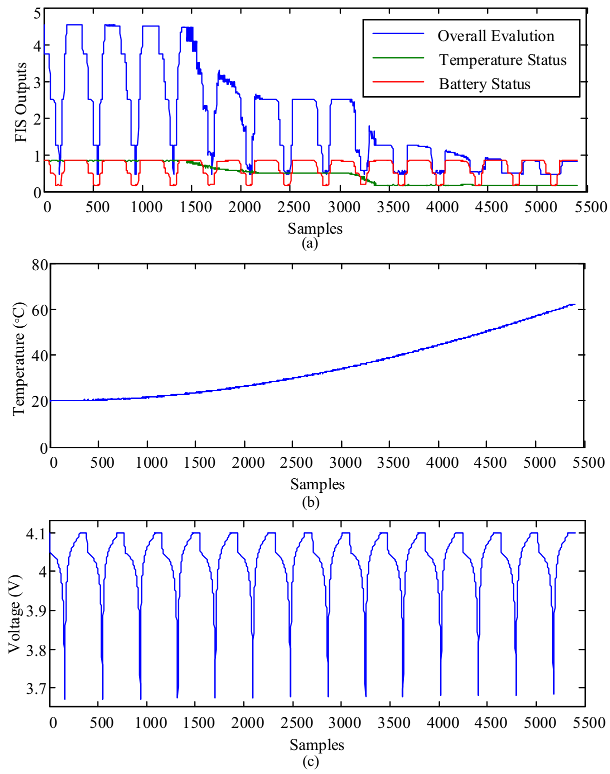

Fig. 11. Testing results of the proposed FIS. (a) FIS outputs; (b) Temperature inputs; (c) Battery voltage inputs.

C. Scientific Data Fusion

Four different statistical approaches were applied to fusing the scientific data [17]. The approaches to data fusion are: Arithmetic Mean (AM), Standard Deviation (SD), Standard Deviation with Sign (SDS), and Arithmetic Mean with Variation (AMV).

We first divide the original data signal into different fusion units, where each fusion unit has the same number of data samples n, and then we let S_i denote the i^{th} fusion unit in the original signal.

1) Arithmetic Mean (AM): the basic idea of this approach is to calculate the arithmetic mean of each fusion unit, and then using the mean values to estimate the rest of the data in each fusion unit. Finally, the original signal can be reconstructed by the estimated values. The arithmetic mean of the i^{th} fusion unit can be calculated by:

$$\mu_i = \frac{1}{n}\sum_{x=1}^{n} S_i(x) \tag{2}$$

where $S_i(x)$ is the x^{th} original element in fusion unit S_i, n is the total number of samples in the fusion unit.

In order to reconstruct the original signal, we first use the mean values of every fusion units to calculate the differences between each adjoining fusion units. Each reconstructed element within the two fusion units can then be calculated by:

$$S_i^{'}(x) = \mu_i + \frac{x(\mu_i - \mu_{i+1})}{n-1} \tag{3}$$

where $S_i^{'}(x)$ is the x^{th} reconstructed element in the i^{th} fusion unit, $x \in \{1, 2, \ldots, n\text{-}1\}$.

The main benefit of this approach is that only a mean value of each fusion unit is needed for the data reconstruction, which will reduce the amount of data transmission to $1/n$ of the original amount.

2) Standard Deviation (SD): this approach is similar to the previous one; the main difference being that the reconstructed elements are chosen from a set of random values with a normal distribution. An SD value at the i^{th} fusion unit can be calculated by:

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{x=1}^{n}(S_i(x) - \mu_i)^2} \tag{4}$$

where $S_i(x)$ is the x^{th} original element in fusion unit S_i, n is the total number of samples in the fusion unit, and μ_i is the arithmetic mean of all the elements in the fusion unit.

We first generate a set of random values $S_i'(x)$ with a normal distribution, where $(\mu_i - \sigma_i) \le S_i'(x) \le (\mu_i + \sigma_i)$ and $1 \le x \le n$. After that, we directly assign these data to each reconstructed elements in the fusion unit.

Comparing with the first approach, the second approach requires both mean value and SD value of each fusion unit to reconstruct the original signal, which means the amount of data transmission is $2/n$ of the original data amount.

3) Standard Deviation with Sign (SDS): this approach is an extension of the second approach. Instead of using completely random values, a sign of the difference between the original element and the mean value of the fusion unit is recorded. The sign is used to narrow down the range of the random value generation.

For example, if an original element is less than the mean, the sign of this element will be marked as '-', then the random value will be generated within the range of $(\mu_i - \sigma_i, \mu_i)$. Using the same principle, if the sign is '+', then the range of generation is $(\mu_i, \mu_i + \sigma_i)$.

Comparing with the second approach, apart from the mean value and SD value of each fusion unit, it also needs a sign bit to reconstruct the original signal, which means the amount of data transmission is $(1/12+2/n)$ of the original data size.

4) Arithmetic Mean with Variation (AMV): the idea of this appoach is to use the mean value and the difference between each element and the mean to reconstruct the original signal. Thus, the reconstructed signal can then be calculated by:

$$S_i^{'}(x) = \mu_i + d_x \tag{5}$$

where $d_x = S_i(x) - \mu_i$, $x \in \{1, 2, \ldots, n\}$.

Comparing with the previous three approaches, this approach should have the highest accuracy, as the exact variations between the original data and the mean are recorded. However, it needs $(n+3)/3n$ of the original data size (e.g. the size of d_x is 1/3rd of the original size).

In order to evaluate the performances of the data fusion algorithms, we have implemented them in MATLAB, and tested them using the same scientific database. We first reconstruct each data set using the proposed approaches with different sizes of the fusion unit, and then calculate the average correlation coefficients between the reconstructed and the original signals. The results of this modelling experiment are shown in Fig. 12 (a). Apart of examining the accuracies, we also calculate the ratios of the actual data transmission amount and the original data amount for the four appoaches with different fusion unit sizes. The achieved results are shown in Fig. 12 (b).

As illustrated in Fig. 12, all four approaches have shown a good performance on the reconstruction of the original signal. The AMV approach achieves the best accuracy in reconstructing the original signal, but it requires the largest amount of data transmission. Although the AM approach also has the second-highest accuracy, it has the smallest data transmission size. As long as the size of the fusion unit is increasing, the accuracies of the AM, SD and SDS approaches are all decreasing accordingly, whereas the results of the AMV approach are constant. Meanwhile, the ratios of the actual data transmission amount and the original data amount are also decreasing, but they are decreasing slowly when the size of fusion unit is greater than 120 samples. Overall, the AM approach is particularly suitable for processing of a continuous signal that has similar values over a short period of time, which is the case of fusing scientific temperature data, hence, the AM approach could be one of the suitable candidates for the SWIPE project.

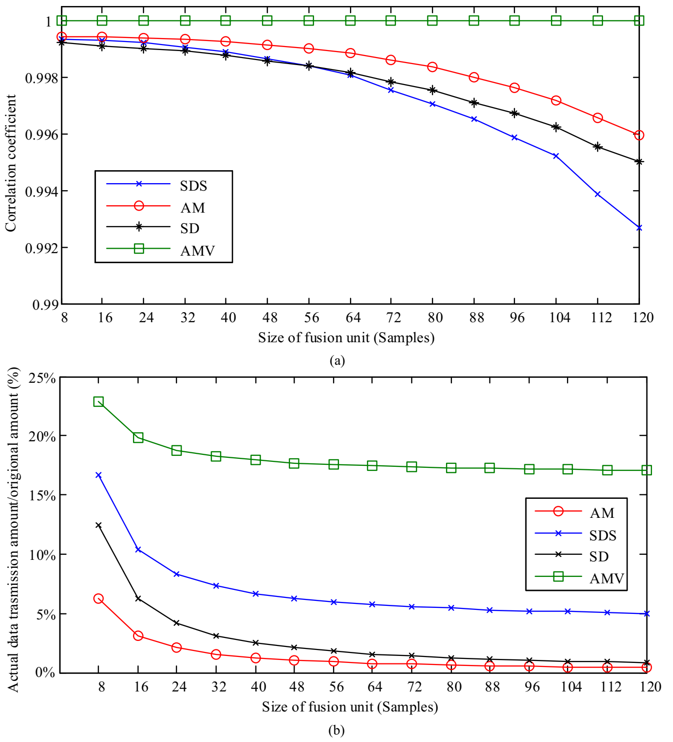

Fig. 12. Simulation results of the AM, SD, SDS, and AMV approaches. (a) Correlation coefficients; (b) ratios of the actual data transmission amount and the original data amount.

V. Conclusion

This work has focused on studying the benefits using data fusion techniques in the SWIPE project. A preliminary set of hybrid data fusion architectures for the SWIPE project are firstly introduced. A fuzzy logic based data fusion algorithm to infer the health status of a node is proposed. In addition a data fusion algorithm to fuse the scientific data is proposed which is based on a set of statistic rules. The obtained simulation results show that the health status of a node can be evaluated efficiently using the proposed housekeeping data fusion algorithm. Using the proposed scientific data fusion algorithms, the amount of the temperature data transmission can be significantly reduced with almost 100% of accuracy in the reconstruction of the original signal, which further verify the efficiency of the proposed data fusion/processing architectures for both, the local housekeeping and scientific data. Future research directions will be to consider the data fusion architectures and algorithms in conjunction with other types of scientific and network data, which could further reduce the transmission of the redundant information by propagating the data.

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