Outlier Detection Using k-means Clustering and Lightweight Methods for Wireless Sensor Networks

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***Abstract*—Wireless Sensor Networks (WSNs) are susceptible to faults both in sensors and in communication. Information fusion techniques allow to extract precise information from a large amount of data. Detection, identification and treatment of outlier, in these techniques, is a key point. Outlier detection in WSNs is a challenge due to the low capacity of the nodes and low bandwidth of the network. This paper proposes a methodology that applies the clustering and lightweight statistics techniques for detection of outliers in WSNs. The assessment of the methodology involves a case study with temperature sensors in WSN nodes. The results show that this methodology is able to provide precise information, even in the presence of outliers.**

***Index Terms*—event detection, outlier detection, wireless sensor network, information fusion, monitoring applications.**

I. Introduction

Wireless Sensor Networks (WSNs) have emerged as an important area of research, integrating work related to the areas of communication and sensing. Furthermore, achieved developments also serve as a basic infrastructure for other research areas [1]. The usage scenarios of such networks are vast, including environmental monitoring applications, hospital, intelligent agriculture, oil refineries, among others.

A WSN is usually constituted of a large number of small nodes, which are used to monitor and collect environmental information and send them via wireless communication to a central point. Since the sensor devices are typically of low processing and battery capacity, reduced memory address space and with low-cost sensors [2], *outliers* (i.e. anomalous data) are eventually generated [3], which may introduce bias errors that need to be properly treated.

Outlier *detection* is not the only type of process that is usually involved in information fusion approaches. There is also the need to perform outlier *identification*, because there are two types of outliers [4], [5]. An anomalous data may be a spurious datapoint (e.g. due to a faulty sensor), or it may be an important event (e.g. the start of a forest fire). The type of treatment received by both outlier types is very different. Usually, spurious data are discarded, while relevant events are data that need receive the attention of the monitoring system.

Outlier detection – either of a relevant event, or of spurious data – is based on the same principle: detection of data that are significantly different to the rest of the observations or to the normal data pattern [3]. Furthermore, the identification process is generally based on the spatio-temporal correlation with data from neighbouring nodes. Roughly speaking, if there is evidence of a spatio-temporal correlation, it is assumed that the data correspond to a relevant event detection; otherwise, it is considered spurious data.

The main differences between spurious data detection and event detection lies in the fact that [4], [6], [7]: spurious data detection techniques usually are independent of the application semantics; while event detection techniques commonly exploit previous knowledge of the events that cause the anomalous data. Moreover, spurious data detection techniques aim to identify anomalous sensing through measurement comparisons; while event detection techniques try to detect events comparing the sensor readings with pre-defined patterns.

The importance of detection, identification and treatment of outliers in WSN is gaining prominence and, recently, many techniques have been developed for this purpose [4]. In this context, two major challenges to be overcome are (i) how to reduce the energy consumption of the sensors and (ii) how to handle large amounts of data. In this sense, *information fusion* (also referred to as *data fusion*) techniques can be applied in order to fuse data collected from sensors, eventually removing the outliers, when they are spurious data, making it possible to obtain more accurate information, while reducing the amount of data traffic [2], [8], [9].

This paper proposes a methodology to detect outliers in WSNs, consisting of the use of k-means clustering technique based on machine learning [10] together with statistical-based methods. An application of environmental monitoring with temperature sensors was used as case study to examine the proposed methodology. WSN nodes with radio compatible with IEEE 802.15.4 standard were deployed in a building. In this monitoring application, the sensor nodes operated with a duty-cycle of about 30s, and measurements were taken over a 24-hour period. The results showed that the using of the proposed methodology enabled better understanding of the monitored environment characteristics. This is achieved through an improved accuracy and reliability of monitored data.

This paper is organized as follows. In Section II, related work and methods used for detection and removal of outliers are briefly discussed. Section III introduces the problem statement. The proposed methodology, experiments and results are described in Section IV. Finally, in Section V, we present some

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final remarks.

II. BACKGROUND

A. Outliers Detection Techniques for WSNs

In the literature, there are several taxonomies for outlier detection techniques [3], [11] taking place from different perspectives. Here, we assumed the taxonomy from [4], developed specifically for WSNs, where techniques are categorized in: (i) statistical-based, (ii) neighborhood-based (iii) clustering-based, (iv) classification-based or (v) spectral decomposition-based.

There are characteristics that influence the outlier detection in these techniques. Neighboring approaches, for example, usually present larger overhead than clustering approaches, as these former approaches are based on machine learning technique. Basically, clustering is a popular technique in data mining field that seek to group data with similarities in clusters, according to some predetermined criteria. Among the clustering techniques, the k-means is one of the simplest clustering algorithm, becoming appropriate to be used in WSN [10]. However, clustering approaches present challenges in network scalability [4].

Several work suggest statistical approaches as the most appropriate to deal with outliers in WSNs [4], [12], [6], [13]. Statistical-based techniques are stateless, lightweight and low resource demanding, when compared to other proposed solutions (e.g. nearest-neighbour-based and classification-based techniques). In statistical techniques, the information about the historic of data from each sensor is not considered in the detection. A reference model is used to analyse the last-obtained data sample before deciding on the significance, or not, of the data. Statistical-based techniques may, in turn, be classified as parametric or non-parametric; the difference between them lies in the presence of an *a priori* reference model. In the parametric approaches, the reference model is known at system design time. The simplest parametric approach is to assume a Gaussian model in which the underlying distribution of data is normal. On the other hand, in non-parametric approaches, there is no prior knowledge about data distribution. Frequently, the reference model is built at run-time through a history of previous executions (e.g. using *kernel regression* techniques [6]). The methods that were considered in this paper are discussed below.

Peirce's Criterion

The Peirce's Criterion is a statistical parametric method for outlier detection based on a normal distribution. According to [14], the Peirce method was described in 1852 as: "the proposed observations should be rejected when the probability of the system of errors obtained by retaining them is less than that of the system of errors obtained by their rejection multiplied by the probability of making so many, and no more, abnormal observations".

Briefly, the main goal of Peirce's Criterion is to generate error probabilities in the system, assuming n samples and k suspect values (i.e. doubtful measurements). The method begins with only one k suspect value, and compares the obtained mean with the normal distribution, to decide whether to reject or not the suspect value. In each round, the method increments the k value (the number of doubtful measurements) until no more data measurements need to be eliminated. It allows the detection of more than one outliers simultaneously.

Chauvenet's Criterion

The Chauvenet's criterion is other statistical parametric method for anomaly detection in a distribution. The criterion is based on the assumption that an arbitrary measurement may be rejected if the probability of obtaining the deviation for this average value is less than the inverse of twice the number of measurements [14].

Using a normal distribution average, samples that are no rejected are those that occupy the central range of the normal distribution curve with a probability equal to $1 - 1/2n$; where n is the number of samples. In this method, it is essential to observe the sample size, since this method must be avoided when the number of samples is very small.

Marzullo's Fault Tolerant Sensor Averaging (FTA)

This is a very simple method proposed by Marzullo [15] for sensor fusion. FTA divides the data sample into three groups and the data assumed as "anomalous" are deleted from the data sample. The basic idea is to order the samples and select a value $t = n/3$, where n is the sample size. Then, the extremes of the samples (the highest and lowest values of t) are excluded and the standard deviation and average are calculated. Note that FTA deletes two-thirds of the sample.

Elmenreich's Confidence-Weighted Averaging (CWA)

The method proposed by Elmenreich [16] correlates the sensor's confidence with the sensor's variance, i.e., the reliance on sensor data is inversely proportional to the sensor's data variance. Since the CWA uses the variances of each sensor as a metric for calculating the weight associated with the sensor (prioritising sensors with smaller variances), there is a problem when a malfunctioning sensor senses and sends repeatedly the same value. This situation generates variance values very close to zero. In this sense, this sensor should be assumed as faulty and have its weight assumed to be zero. It is important to note that CWA does not detect outliers. However, in practice, one can state that outliers are detected and removed or, at least, "partially removed", as they have their weight reduced in the average calculation.

CWA+FTA method

Elmereich [16] claims that the average value calculated by the CWA method may be conceived as a reference value. Moreover, according to the author, the CWA method may be improved by associating its results with other outlier treatment methods. In this sense, the association of CWA with the FTA method makes it possible to weigh the obtained sensor's value by the quality of the sensors and, subsequently, to detect and remove the remaining outliers through the FTA.

Specifically, the CWA+FTA proposal consists of calculating the weighted average according to the CWA method, and subsequently removing two-thirds of the data according to the FTA method. At the end, an average is calculated from the remaining data.

B. Related work

Research on outlier detection in distributed environments using WSNs has been explored by various techniques, and their abilities of distinguishing between relevant events or spurious data have been analysed. Event detection can be used in various application scenarios in WSN. Thus, various techniques for detecting events are proposed and classified by [17], [18] and [19] in: threshold-based, pattern-based and learning-based. In the threshold-based approach, detection occurs when the sensor reading exceeds a predefined threshold value. The main advantage of this approach is that data can be locally processed in the node. However, threshold values alone are inaccurate and incapable of capturing spatio-temporal characteristics of events, which incurs high false alarm rates of monitoring applications [17]. The pattern-based approach detects events in data readings through spatio-temporal pattern matching techniques. An event is detected when a standard specified by the user instantly corresponds to a recent data node. The main limitation of this approach is the need for the event patterns set in advance. Then, event detection requires that the pattern matching technique be accurate for the application. On the other hand, the unsupervised machine learning-based approach is the unique technique that does not make use of prior information, applying instead probabilistic inference and graph theory to detect events. However, this technique usually incurs in large processing time overhead.

Another categorization of techniques for outlier detection is presented in [20]. In this paper we will discuss only the methods based on statistics, due to their lower consumption of computational resources and also because they not require prior information. These characteristics are adequate for WSN applications.

Targeting fire detection applications, Oladimeji [21] proposed a hybrid approach to event detection using k-means clustering technique and neural networks. Considering the differences, our proposed methodology applies the outlier detection method based on statistics and availability without prior information.

Mousive [22] applied probabilistic graphical models for event detection in WSN. This approach uses graph theory and probabilities to detect events. In order to detect outliers, a reference model was adopted with the classification of states made *a priori*. Regarding the differences, the method used to identify events proposed in our methodology uses the k-means clustering technique. As for the method for outlier detection, we apply statistical methods without prior knowledge of information.

Pei [19] proposed an approach for spatio-temporal event detections WSNs, through a hierarchical architecture. Clusters are formed by applying a Euclidean equation with variable signal strength and associated with the fusion of information to reduce communication overheads. Although both studies use the clustering technique method for the generation of groups, in our proposal there is a centralized detection and treatment.

III. Problem Statement

A. Experimental Setup and Network deployment

This section discusses adequate methods that may be used in the WSN outlier detection task. A WSN monitoring application was used to sense temperature in a building for a whole day. We used 15 sensors named by letters A to O. Figure 1 illustrates the sensor deployment scheme.

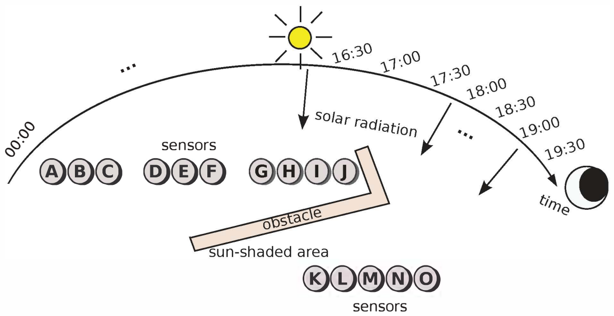

Figure 1. Sensor deployment scenario: Nodes A to J were deployed in the windows of a building. Nodes A to I were exposed to the sun most of the time, while sensors K to O were deployed close to the ground, staying mostly in the shade.

The sensor nodes were compliant with the IEEE 802.15.4 standard and the network was configured as a star topology. The sensors were stationary and homogeneous, all with the same hardware configuration as shown in Table I. One extra node (not shown in the Figure 1) played the role of network coordinator, synchronizing the other nodes, receiving and storing the sensed data.

Table I
Hardware description of sensor nodes.

Hardware	Description
Arduino Uno R3	Arduino open-hardware board that has a development environment based on C language.
Arduino XBee Shield and XBee radio	Component designed for the Arduino wireless communication, compliant with IEEE 802.15.4.
DHT 11 Sensor	Low-cost humidity and temperature sensor that allows temperature readings from 0C to 50C and humidity from 20 to 90%.

Despite the monitoring occurred in a continuous interval of 24 hours, the values presented here represent only the time interval between 16:30 to 19:30. The choice of this time interval is due to temperature variation obtained from some sensors by exposure to the Sun, while others remain in the shade. It is also important to note that, although the sensors are sampled at a frequency of about 30s, for ease of understanding and for convenience, throughout this paper the results were analyzed and are presented in periods of 30 minutes.

B. Analyzing a scenario with a faulty sensor among 10 nodes

In order to provide context to the problem statement, in this experiment, we consider only the first 10 sensor nodes, named by letters A to J. The K to O sensors were disregarded and assumed, in this configuration, as non-existent. In this sense, the sensor J was used as a source of outliers, due to the fact that it mostly delivered discordant values when compared to the other sensor values (Figure 2). This occurred because sensor J remained much of the time in the shade, while other sensors were exposed to the Sun.

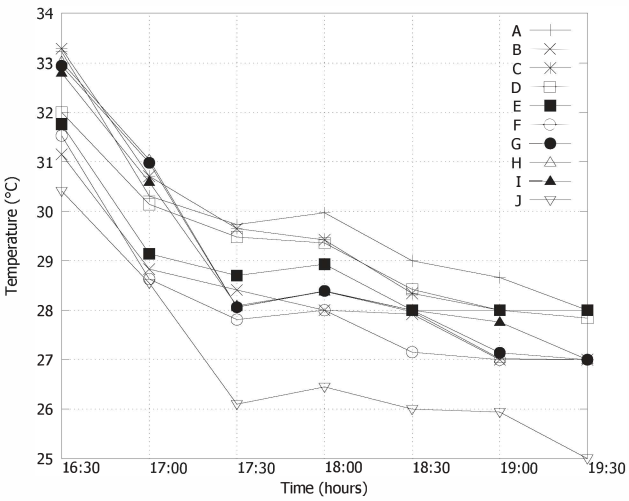

Figure 2. Values of temperature from the sensor nodes.

The main goal of the analysis of this scenario with 10 nodes is to assess the five statistical methods of outlier detection presented in Section II: Peirce, Chauvenet, FTA, CWA and CWA+FTA. Table II shows the outlier detection results. Each time the sensor J was detected as an outlier, the table shows the letter "Y"; otherwise it presents the letter "N".

Table II
OUTLIER DETECTION (Y= DETECTED; N= OTHERWISE).

Time	Chauvenet	Peirce	FTA	CWA+FTA
16:30	N	N	Y	Y
17:00	N	N	Y	Y
17:30	Y	Y	Y	Y
18:00	Y	Y	Y	Y
18:30	Y	Y	Y	Y
19:00	Y	Y	Y	Y
19:30	Y	Y	Y	Y

The results obtained in this scenario showed that the Criterion of Chauvenet had, on average, the same behaviour as the Criterion of Peirce, detecting correctly outliers in 71% of measurements. However, only FTA and CWA+FTA techniques detected properly data from sensor node J as an outlier, during all the monitored period.

C. Analyzing the complete scenario with 15 nodes

It is important to note that the scenario described in the previous section constitutes a particular case of this complete scenario with 15 nodes. In this complete scenario, node J is accompanied by other nodes that sit around nearby on the ground, staying in the shade for most of the analyzed time period. The main purpose of this scenario analysis is to point out the need for clustering techniques along other statistical outlier detection techniques. Here, only the techniques that had the best performance in the previous section are now analysed: CWA, FTA and CWA+FTA. Additionally, for comparison purpose, a simple arithmetic average and the Elmereich's CWA are also presented.

Figure 3 presents the obtained average of each method (in degrees Celsius), after removing the values assumed as outliers. In the simple average calculation, there is no outlier removal; on the other hand, the CWA method improves the simple arithmetic average by reducing the weight of the outliers, weighting the obtained values in accordance to the inverse of their variances.

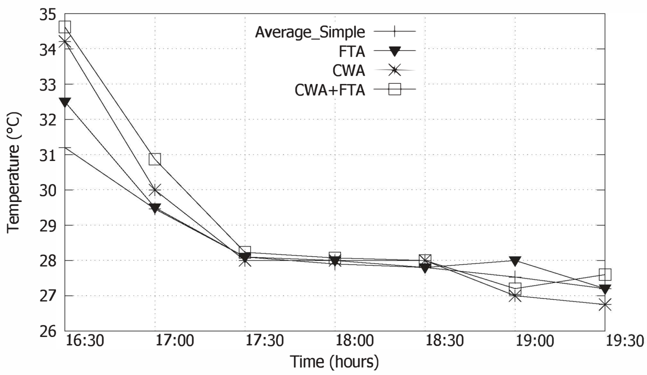

Figure 3. Information fusion techniques comparison.

It is possible to observe that, as the simple average uses all data values in the calculation, the outliers may harm the results. The difference in values between the FTA method and the simple average reached up to 1,3^{o}C; and the difference between the CWA+FTA method and the simple average reached up to 3,4^{o}C. Table III shows the differences among methods, compared to the simple average; while Table IV shows the difference between FTA and CWA+FTA method.

Table III
DIFFERENCES OF THE METHODS COMPARED TO SIMPLE AVERAGE.

	CWA		FTA		CWA+FTA	
Time	^{o}C	%	^{o}C	%	^{o}C	%
16:30	3,0	9,6	1,3	4,2	3,4	11
17:00	1,4	4,7	0,0	0,1	1,4	4,8
17:30	0,1	0,4	0,0	0,0	0,1	0,5
18:00	0,3	1,2	0,1	0,4	0,2	0,6
18:30	0,3	1,2	0,0	0,0	0,2	0,7
19:00	0,0	0,3	0,5	1,7	0,3	1,2
19:30	0,6	2,4	0,0	0,0	0,4	1,5

In the calculations, the FTA method identifies and removes the outliers in all samples, obtaining a temperature variation of up to 1,3^{o}C, which represents a difference of 4,2%. The CWA+FTA method obtained a temperature variation of up to 3,4^{o}C, which represents a difference of 11%. Comparing the FTA with FTA+CWA methods, the difference between

Table IV
DIFFERENCE BETWEEN FTA AND CWA+FTA METHODS.

Time	Difference	
16:30	2,1°C	6,8%
17:00	1,4°C	4,7%
17:30	0,1°C	0,5%
18:00	0,1°C	0,3%
18:30	0,2°C	0,7%
19:00	0,8°C	2,9%
19:30	0,4°C	1,5%

Table V
GROUPING SENSORS INTO CLUSTERS.

Time	Cluster I	Cluster II
16:30	A,B,C,D,E,F,G,H,I,J	k,l,m,n,o
17:00	A,B,C,D,E,G,H,I	F,J, k,l,m,n,o
17:30	A,C,D,E,G,H,I	B,F,J, k,l,m,n,o
18:00	A,C,D,E	B,F,G,H,I,J, k,l,m,n,o
18:30	A,B,C,D,E,F,G,H,I,	J, k,l,m,n,o
19:00	A,B,C,D,E,G,I,	F,H,J, k,l,m,n,o
19:30	A,C,D,E,	B,F,G,H,I,J, k,l,m,n,o

temperatures was up to 2,1°C or 6,8%, as shown in Table IV.

IV. OUTLIER DETECTION METHODOLOGY

A. Proposed methodology

In the previous section, the significant differences between results of distinct techniques could be attributed to false outlier detection. Attempting to obtain a single average in the previous scenario is not an appropriate approach. It is clear that, in the described application, over certain periods of time, there are two averages: the average of the nodes that receive direct light from the Sun, and the other of the nodes that are in the shade.

In this paper we propose a methodology to be applied in the detection of outliers in WSNs. Basically, we propose a simple two-step procedure:

(i) the use of clustering identification;
(ii) followed by a statistical-based method.

There are several clustering techniques. Here, we applied the k-means technique [10] that is a simple and unsupervised data mining algorithm, because it performs analysis and classifies numerical data automatically. The Elmenreich's CWA is the method selected to be used to average the results. Both techniques are lightweight being adequate to be used in WSN. An assessment using this methodology with two steps is presented in the following section.

B. Assessing the proposal: clustering nodes through k-means technique and averaging data with CWA method

In the experiments, we defined two clusters. For clarity, in Table V, the capital letters represent the sensor deployed in the windows of the building; and the lower case letters represent the sensors deployed close to the ground, staying in the shade most of the time. Using the k-means, the data with higher temperatures have been automatically grouped into Cluster I; while the data with lower temperatures have been migrated to Cluster II. At 16:30, all sensor nodes in the windows stayed in Cluster I, while nodes close to the ground stayed in Cluster II. With the passage of time, changes in the elements of the clusters can be observed.

The k-means technique requires the user to define the number of clusters explicitly. Although initially two clusters were defined, results in Table V indicate that there should be effectively just one cluster after 19:00. Notably, after 19:00, some nodes exchange randomly between the clusters until the next day, when the Sun reappears again (time period not shown). For this reason, the remainder of this section discusses only the periods between 16:30-18:30, when the formation of two clusters is clear. As can be seen in Table VI, with the temperature variation over time, the average values of clusters I e II presented differences of up to 5,1°C, at 16:30 when the sunlight was intense. In this sense, the use of clusters generated better results for the detection of outliers, and improved the precision of the obtained average values.

Table VI
DIFFERENCE BETWEEN TEMPERATURE OF CLUSTERS USING K-MEANS.

Time	Cluster I	Cluster II	Difference
16:30	32,9°C	27,8°C	5,1°C
17:00	31,0°C	27,7°C	3,3°C
17:30	29,4°C	27,4°C	2,0°C
18:00	29,3°C	27,5°C	1,8°C
18:30	28,3°C	26,8°C	1,5°C

The k-means calculates a simple average in each cluster, without dealing with outliers. On the other hand, as previously stated, the CWA method weights the outliers, reducing their impacts on average, thus improving the precision. In this sense, the CWA method could also be applied in each cluster defined by the k-means. The results of this approach are presented in Table VII. The difference of the obtained averages for the different clusters reached the significant value of up to 7.0°C. The Table VIII shows the difference between the obtained values using k-means (as a simple average) and the CWA method into each cluster. The difference of the averages for the different clusters was up to 1,3°C.

Table VII
DIFFERENCE BETWEEN CLUSTERS USING CWA METHOD.

Time	Cluster I	Cluster II	Difference
16:30	34,2°C	27,2°C	7,0°C
17:00	31,5°C	29,0°C	2,5°C
17:30	29,4°C	27,2°C	2,1°C
18:00	29,1°C	27,1°C	2,0°C
18:30	28,4°C	26,0°C	2,4°C

The k-means used as a clusterization technique provided a better understanding about the specificities of the sensed environment. Taking as example the 16:30 sample, without using any clustering approach and instead using a simple average, the value was 31,2°C; and using the CWA method, the average was 34,2°C (Figure 3). However, for this particular scenario, it is correct to say that there are two averages, as shown in the "clusterized" CWA results (Table VII): 34.2^{o}C for nodes in Cluster I (exposed to the sun) and 27.2^{o}C for nodes in Cluster II (that stayed in the shade).

Table VIII
DIFFERENCE VALUES BETWEEN THE SIMPLE AVERAGE AND CWA IN EACH CLUSTER.

Time	Cluster I	Cluster II
16:30	1,3^{o}C	0,6^{o}C
17:00	0,5^{o}C	1,3^{o}C
17:30	0,1^{o}C	0,1^{o}C
18:00	0,2^{o}C	0,3^{o}C
18:30	0,1^{o}C	0,8^{o}C

V. CONCLUSION

Wireless sensor networks present several hardware and software constraints. Moreover, they are generally deployed in harsh environments aiming to monitor some critical system. Thus, information fusion techniques enhance the precision of collected and transmitted data. In this context, lightweight static techniques for outlier detection in WSNs was assessed in this paper and a simple methodology based on two steps was proposed. The low overhead, scalability and stateless characteristics of lightweight outlier detection techniques are crucial characteristics for WSNs.

Our experiments showed the importance of outlier detection in a monitoring area. The source and nature of outliers should guide the selection of the outlier detection technique. Among the evaluated methods, CWA obtained good results. Sensor clustering was performed based on the k-means algorithm; in this way, sensors that present similar readings were clustered. Thus, we achieved a better precision in outlier detection.

The testbed shows that the original deployment scheme was maintained by k-means (nodes exposed to the Sun and nodes in the shade were placed in separated clusters). However, during the monitoring, cluster formation changed according to the environmental characteristics. Clustering techniques detect important sensing results that are not detected in just one cluster. Therefore, we conclude that clustering is an important tool to maximise outlier detection in lightweight techniques.

As a future work, we propose to test other outlier detection techniques for WSN applications, specifically we intend to find alternatives for the k-means technique.

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