En-Route Data Filtering Technique for Maximizing Wireless Sensor Network Lifetime

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***Abstract*—Today, we can witness wireless sensor networks (WSNs) in action almost everywhere. Their applications are ubiquitous covering environment, medical care, military, surveillance, etc. While the potential benefits of WSNs are real and significant, there remains two major challenges to fully realize this potential: big data collection and limited sensor energy. To overcome these problems, filtering techniques over data routed to the sink should be used in such a way that they do not discard useful information. In this paper, we propose a new filtering technique dedicated to periodic sensor applications. The first filter is applied at the sensor nodes and aims to reduce their raw data based on the Pearson coefficient metric. The second filter is applied at intermediate nodes, called aggregators. It uses K-nearest neighbor clustering algorithm in order to eliminate data redundancy collected by neighboring nodes. The evaluation of our technique is made based on experiments on telosB sensors. The obtained results show the relevance of our technique, in terms of energy consumption and data accuracy, compared to other proposed methods.**

***Keywords*—Wireless sensor networks, periodic applications, filtering techniques, Pearson coefficient, K-nearest neighbor algorithm, telosB motes.**

I. Introduction

During the last few years, wireless sensor networks (WSNs) have experienced explosive growth and have massively become a part of people's lives. These networks are consisting of a huge number of sensors deployed randomly in wide areas to provide low cost monitoring missions. The nodes are characterized by a small size (from cubic inches to cubic millimeters), can have multiple sensors on their board (such as for temperature, humidity, pressure, light, etc.), limited power supply and short range radio communication. Thanks to these smart sensors, a lot of real-world applications have been already deployed including environmental monitoring, medical care, military, agriculture and surveillance systems [1]. Additionally, data collected by sensor nodes are forwarded periodically to a specific access point (sink) for analyzing and decision purposes.

The problems in WSNs start from the data acquisition where a big amount of data about the monitored area should be collected for reliability purposes. Hence, what data to keep and what to discard become important in order to take the right decisions. In addition to big data collection problem, data transmission is another challenging task because of the energy-constrained nature of sensor networks. Indeed, transmitting data consumes most of the sensor energy which is mostly limited and not rechargeable, especially in unattended and hostile environments. Therefore, to avoid the above mentioned problems, filtering techniques have been introduced. Filters aim to remove large quantities of redundant data routed on the network, so as to minimize the amount of transmission and save energy.

In this paper, we propose a new filtering technique dedicated to periodic sensor applications. It aims to reduce the transmission of sensed data to the sink, while conserving data meaning and information integrity. Thus, it leads to reduce data transmission rate in the network then, optimizing network resource consumption. Our technique composed of two filters. The first filter is applied at the sensor nodes themselves and aims to reduce their big raw data based on the Pearson coefficient metric. The second filter is applied at intermediate nodes, called aggregators. Each aggregator has to eliminate data redundancy collected by neighboring nodes based on K-nearest neighbor clustering algorithm. The evaluation of our technique is made based on experiments on telosB sensors. The obtained results show the relevance of our technique, in terms of energy consumption and data accuracy, compared to other proposed methods.

The rest of the paper is organized as follows. Section II describes the periodic clustering architecture used in our network. Section III overviews various data reduction and filtering techniques existing in the literature for WSNs. in Section IV, we present the first data filtering proposed for the first level, e.g. sensor nodes, in our technique. Section V describes the second filter in our technique proposed for the aggregator level. Experimentations on real sensors are presented in Section VI. Finally, Section VII concludes our paper and gives some perspectives.

II. Our Network Architecture

In this section, we introduce the network architecture used in our technique. Our proposed filtering technique can be applied efficiently by assuming two main concepts for the network: cluster-based architecture and periodic data acquisition. In the next, we describe each of them in more details.

A. Cluster-based Network

In our system, we assume that each set of sensor nodes send their collected data to an intermediate nodes, called aggregators. Each aggregator has an objective to clean data, using a specific filter defined later, coming from neighboring sensor nodes before sending them to the sink. The aggregators

can be defined prior to the network deployment and could have more power than normal sensor nodes, depending on the application requirements. Fig. 1 shows our sensor network architecture, where data transmission between sensor nodes and their appropriate aggregators is based on single-hop communication.

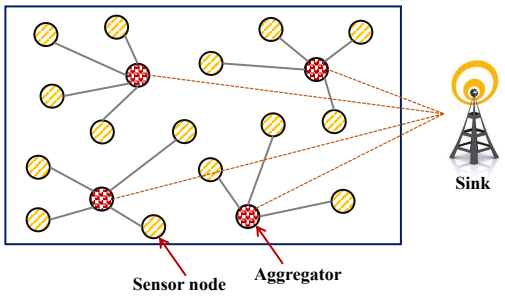
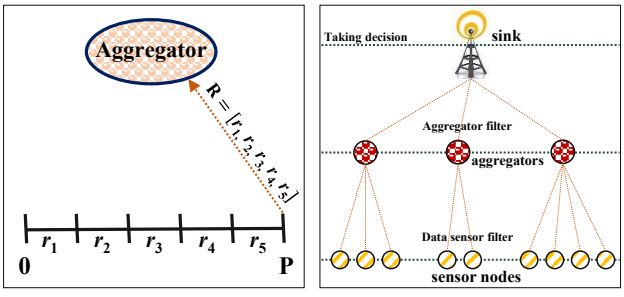


Fig. 1. Two-level data transmission architecture.

B. Periodic Data Acquisition Model

The main mission of WSNs is to forward data packets from event regions to the sink. Unfortunately, sensor nodes are energy-constrained and data transmission task consumes lots of the sensor energy comparing to data processing task. This means that the lifetime of the sensor will shorten if it forwards each sensed data sample to the sink. Hence, periodic data transmission model have been introduced in WSNs in order to reduce the amount of data collected thus, savings sensor energy.

In the periodic acquisition model, data are collected in a periodic basis where each period p is partitioned into time slots. At each slot t, each sensor node N_i captures a new reading r_i. At the end of the period p, N_i collects a vector of τ readings, e.g. $R_i^p=[r_1, r_2, \ldots, r_\tau]$, then it sends it to the sink (Fig. 2(a)). In our system, each sensor node sends periodically (period p) its data to the appropriate aggregator, which in turn sends it to the sink (Fig. 2(b)). Our technique defines two filters: the first one is applied at the sensor level and the second one is applied at the aggregator level.



(a) periodic data acquisition (b) data filtering scheme

Fig. 2. Periodic data filtering scheme.

III. Related Work

The huge amounts of data generated and transmitted by sensors result in increasing energy consumption in WSNs. Hence, a large number of filtering and reduction techniques have been proposed [2], [3], [4], [5] in order to eliminate redundant and meaningless data and consequently ensure energy-aware optimization in WSNs. In addition, filtering techniques can significantly reduce the amount of raw data to a size that helps decision makers to make a right decision, while conserving the important information. In the literature, we can find various data filtering approaches based on data compression, in-network processing or data prediction methods.

In [6], an adaptive filter based on the least mean squares (LMS) combined to a matrix completion is proposed. The authors aims to reduce to reduce the necessary readings transmitted from sensors to sink. The sensor nodes use LMS filter and Bernoulli probability to make a pattern based on which data are sent to the sink. the sink uses matrix completion algorithm to recover missed or lossy data. In [7], the authors propose two data filtering approaches to improve energy efficiency on the agricultural WSNs. The first one filters data collected at the sensor node using a simple moving average (SMA) method. The second approach is dedicated to nodes with one sensor board and it uses the Threshold Sensitive Energy Efficiency Sensor Network (TEEN) protocol. A positional prefix-suffix frequency filtering (PPSFF) is proposed in [8]. The objective of PPSFF is to reduce data delivery time by proposing a positional filtering that uses the indices of readings in a set and leads to meet limits of predefined similarity scores. The authors in [9] propose a data prediction algorithm based on the Kalman filter for air pollution monitoring sensor networks. The algorithm aims to reduce the uncertain data among the collected sensor readings, and adapt the sensor sampling rate based on the variation between the collected readings.

The authors in [10] propose a supervised linear dimensionality (LDR) reduction technique to reduce the dimensionality of the original data to such that it is well-primed for Bayesian classification. This is done by sequentially constructing linear classifiers that minimise the Bayes error via a gradient descent procedure, under an assumption of normality. In [11], the authors builds a Spanish Inquisition Protocol (SIP) to reduce transmissions in a single-hop wireless sensor system dedicated to monitor temperature in a gas turbine engine application. SIP uses a state identification filter in order to select a subset of the collected data as well as it uses a weighted moving filter to increase the accuracy of the data predictions. In [12], the authors propose an energy-efficient compressed data reduction framework dedicated to underwater sensor network. The proposed technique is based on two layers: compressed sampling and data reduction. The first layer aims to select a subset of nodes to provide sampling while the full sampling is conducted in the second layer. The final goal of these layers is to minimize the total energy consumption of transmitting the data sensed by nodes. In [13], the authors propose a Sequential Lossless Entropy Compression (S-LEC) which organizes the alphabet of integer residues obtained from differential predictor into increased size groups. S-LEC codeword consists of two parts: the entropy code specifying the group and the binary code representing the index in the group. Compared to other compression schemes, S-LEC is characterized by its efficiency and highly robustness for diverse WSN data sets. Finally, the authors in [14] propose a prefix frequency filtering (PFF) technique based on clustering architecture of the network. Further to a local processing at the sensor node level, PFF

uses Jaccard similarity function to allow aggregator nodes to identify similarities between near sensor nodes at each period and integrates their sensed data into one record.

Although most of the proposed techniques allow efficient data reduction, however they present several disadvantages. First, they are very complex and require huge processing. Second, they need additional communication when initializing the proposed methods and detecting node failures. In this paper, we present a novel data filtering method that it is less complex and suitable for limited resources sensor nodes. Then, in order to evaluate our technique, we conducted a set of experiments on a real environment sensor networks based on telosB nodes.

IV. Sensor Data Filtering Model

Generally, data collected in the vector R contains very redundant readings mostly in the following cases: the observed zone changes slowly or the slot time between two collected readings is short. Hence, to reduce the size of vector R_i^p, we select a set of measures from R_i^p to send to the sink instead of the whole readings. Our proposed model is based on the Pearson coefficient which is introduced in the next section.

A. Pearson's Coefficient Metric

The coefficient of Pearson represents the degree of correlation between two data sets R_i and R_j. Given the interval $[-1, 1]$, a positive correlation is indicated when the Pearson coefficient is equal to 1, a no correlation is indicated when it is equal to 0, and -1 indicates a negative Pearson correlation. In our case, each sensor node is considered as a small database to record the variation of the observed zone where the sensor is deployed.

Indeed, the Pearson's coefficient between two sensor data sets is represented by the following equation:

$$\rho_{R_i,R_j} = \frac{n\sum r_i r_j - \sum r_i \sum r_j}{\sqrt{n\sum r_i^2 - (\sum r_i)^2}\sqrt{n\sum r_j^2 - (\sum r_j)^2}} \quad (1)$$

where $r_i \in R_i$, $r_j \in R_j$ and n is the number of readings in each of R_i or R_j.

Therefore, R_i and R_j are considered to be highly correlated (e.g. redundant) if and only if:

$$\rho_{R_i,R_j} < t_p \quad (2)$$

where t_p is a threshold determined by the application itself.

B. Sensor Filtering Algorithm

This section shows the algorithm used to reduce the vector of readings collected by each sensor at each period. Algorithm 1 allows each sensor to find the minimum number of readings that represent R_i^p by applying iteratively the Pearson's coefficient metric. The main idea behind this algorithm is to divide R_i^p into equal subvectors by applying Pearson's coefficient until the subvectors are highly correlated. This can be made by using the function $divide$ which divides a vector of readings into two equal subvectors. Therefore, the process starts by considering that the readings in R_i^p are not correlated (lines 4-7). Then, R_i^p is divided into two subvectors, e.g. $R_{i_1}^p$ and $R_{i_2}^p$ (line 9), and the correlation between them is calculated (line 10). If the correlation is less than the threshold of Pearson's coefficient (line 10) then, the initial vector R_i^p is a final vector of readings. Therefore, the final vector $V_{R_i^p}$ contains the mean value of the readings as well as the weight of the mean value (lines 11-13). The weight of the mean value indicates the number of readings represented by the mean value (line 12). Otherwise, e.g. the correlation meets the threshold, we again divide the subvector into two equal vectors and w restart the process over the readings in the new subvectors (line 16).

Algorithm 1 Sensor Filtering Algorithm.

Require: Reading vector: $R_i^p = [r_1, r_2, \ldots, r_\tau]$.
Ensure: Vector of representative readings of R_i^p: $V_{R_i^p}$.
1: $V_{R_i^p} \leftarrow \emptyset$
2: $V' \leftarrow \emptyset$ // a temporary set of reading vectors
3: $R_1^p \leftarrow \emptyset$
4: **for** each set reading $r_i \in R_i^p$ **do**
5: $R_1^p \leftarrow R_1^p \cup \{r_i\}$
6: **end for**
7: $V' \leftarrow V' \cup \{R_1^p\}$
8: **repeat**
9: $\{R_{i_1}^p, R_{i_2}^p\} \leftarrow Divide(R_i^p)$
10: **if** $\rho_{R_{i_1}^p, R_{i_2}^p} < t_p$ **then**
11: find the mean value, $\overline{r}_i$, of readings in R_i^p
12: $wgt(\overline{r}_i) = R_i^p.length$
13: $V_{R_i^p} \leftarrow V_{R_i^p} \cup \{\overline{r}_i, wgt(\overline{r}_i)\}$
14: remove R_i^p from V'
15: **else**
16: $V' \leftarrow V' \cup \{R_{i_1}^p\} \cup \{R_{i_2}^p\}$
17: **end if**
18: **until** no reading vector $R_i^p \in V'$
19: return $V_{R_i^p}$

After applying Algorithm 1, each sensor will send a vector of representative readings $V_{R_i^p}$=$[\overline{r}_1, \overline{r}_2, \ldots, \overline{r}_k]$ to its proper aggregator, where $k \leq \tau$.

V. Aggregator Filtering Model

At the end of each period, each aggregator will receive a set of representative data sets coming from its sensor nodes. At this level, we propose a second filter allows each aggregator to eliminate redundancy, resulted from temporal correlation between sensed data, among representative sets before sending them to the sink. Our proposed filter is based on data clustering approach. Data clustering is a data classification technique aims to group object having similar dimensions with each other in order to simplify their processing. In this paper, we are interested in K-nearest neighboring (KNN) algorithm adapted to Euclidean distance. In the next section, we explain in more details KNN algorithm as a second filter to clean data at the aggregator level.

A. K-Nearest Neighboring Algorithm

K-nearest neighbors (KNN) [15] is one of the top 10 data mining algorithms used for classification and regression. It is

considered as a non-parametric test that does not assume any hypothesis about the normality of the data. KNN algorithm has lots of applications ranging from business[16] and medical [17] to classification of web text [18]. The input of KNN algorithm consists of the entire training dataset. Subsequently, in order to search the similarities of a new data instance, KNN algorithm calculates the distance between the new data instance and all datasets in the training dataset. Then, it returns the K-most similar instances that having the minimum distance to the new instance.

Indeed, distance functions are one of the most similarity measures used in KNN algorithm to search the K-nearest neighbors for a dataset. However, there are huge number of distance functions used in the literature like Euclidean, Cosine, Hamming, Manhattan and so on [19]. The suitable distance method can be chosen based on the characteristics of the studied data; for instance, if the studied variables have different types (like age, height, etc.) then the Manhattan distance is the most suitable; if the studied data can be categorized or have a binary type, the Hamming distance is more suitable. For real-valued data, e.g. similar in type (all measured temperature or humidity), the most popular distance measure is the Euclidean distance.

B. Euclidean Distance

Computing the distance between a set and all sets in the training datasets is a fundamental process when applying KNN algorithm. In this paper, we are interested in the Euclidean distance that is widely studied and used in different domains. In mathematics, the Euclidean distance is the ordinary distance, e.g. straight line distance, between two points, sets or objects. Let us consider two data sets, R_i and R_j, then the Euclidean distance (E_d) between them can be calculated as follows:

$$E_d(R_i, R_j) = \sqrt{\sum (r_i - r_j)^2}, \tag{3}$$

where $r_i \in R_i$ and $r_j \in R_j$.

However, the weights of the mean values used at the sensor level makes the computation of the Euclidean distance is not a trivial task. In order to overcome this challenge, we must transform each set of representative readings $V_{R_i^p}$ to a vector as follows:

$$v_{R_i^p} = \big[\underbrace{\overline{r}_1, \ldots, \overline{r}_1}_{wgt(\overline{r}_1) \text{ times}}, \underbrace{\overline{r}_2, \ldots, \overline{r}_2}_{wgt(\overline{r}_2) \text{ times}}, \ldots, \underbrace{\overline{r}_k, \ldots, \overline{r}_k}_{wgt(\overline{r}_k) \text{ times}} \big]. \tag{4}$$

Then, the Euclidean distance between any two representative readings $V_{R_i^p}$ and $V_{R_j^p}$ is calculated based on their readings vectors $v_{R_i^p}$ and $v_{R_j^p}$.

C. Selection of K

The selection of the value of K parameter is very crucial in the KNN algorithm, which is a user-defined constant. In general, the classification will be more accurate when the value of K increases. Heuristic techniques are one of the approaches used to select the proper value of K which is determined by the experts. Another way for the selection of K is by experimenting different values of K (e.g. values from 1 to 20) and see which works best for our problem, i.e. the most accurate results. Indeed, the optimal value of K for many studied applications varied in the interval $[3, 10]$.

D. KNN Adopted to Euclidean Distance

Algorithm 2 describes the process of KNN algorithm to search the top K similar datasets for a new dataset given as an input for the algorithm. The process starts by computing the Euclidean distance between the new dataset and every dataset in the training set R^p (line 3). Thus, a dataset is added to the final list of top K similar sets of the new set if the list is not yet full (line 4) or its distance to the new dataset is less than the maximum of an existing distance (line 7-10).

Algorithm 2 KNN Adopted to Euclidean Distance Algorithm.

Require: List of datasets $R^p = \{R_1^p, R_2^p, \ldots, R_n^p\}$, new dataset R_j^p, K.
Ensure: List of top K similar datasets to R_j^p: $TopK_{R_j^p}$.

```
1: TopK_{R_j^p} ← ∅
2: for each dataset R_i^p ∈ R^p do
3:    compute distance = E_d(R_i^p, R_j^p)
4:    if TopK_{R_j^p}.length < K then
5:       TopK_{R_j^p} ← TopK_{R_j^p} ∪ {(R_j^p, R_i^p, distance)}
6:    else
7:       find R_l^p ∈ TopK_{R_i^p} corresponding to the maximum
         distance with R_j^p
8:       if E_d(R_l^p, R_j^p) > E_d(R_i^p, R_j^p) then
9:          replace R_l^p by R_i^p
10:      end if
11:   end if
12: end for
13: return TopK_{R_j^p}
```

E. Redundant Sets Reduction at the Aggregator

In this section, we show how to integrate the KNN algorithm at the aggregator level in order to search, then eliminate, redundant datasets sent from the sensor nodes at the end of each period (Algorithm 3). First, the aggregator identifies the top K similar sets for each dataset sent by a sensor (lines 3-5) using Algorithm 2. It aims to find the top K sensors that generate similar data, in terms of temporal correlation, to every sensor in the network. Therefore, data transmission size sent to the sink node will be decreased. Lastly, the aggregator deletes pairs of similar datasets containing either $V_{R_i^p}$ or $V_{R_j^p}$ from the pair set (i.e. dont check again) (line 8).

VI. Experimental Results

In this section, we show the relevance of our proposed technique after performing experiments on real sensor nodes deployed in our laboratory. We used Crossbow telosb motes in order to collect data about the zone. Twenty motes have been deployed in our laboratory where each of one monitors temperature data. The motes send their collected data to a sink [1] node of type SG1000 [20]. SG1000 is connected to a laptop machine in order to retrieve and make statistics over the collected data. Due to the limited bandwidth of telosB, the

[1] in our experiments, the sink plays the role of an aggregator.

Algorithm 3 Selecting Final Sets Algorithm.

Require: List of representative reading sets $V_{R^p} = \{V_{R_1^p}, V_{R_2^p}, \ldots, V_{R_n^p}\}$, K.
Ensure: List of sent reading sets at period p: V_{L^p}.

```
V_{L^p} ← ∅
topk ← ∅
for each set V_{R_i^p} ∈ V_{R^p} do
    topk ← topk ∪ KNN(V_{R^p} − {V_{R_i^p}}, V_{R_i^p})
end for
for each pair of sets(V_{R_i^p}, V_{R_j^p}) ∈ topk do
    V_{L^p} ← V_{L^p} ∪ {V_{R_i^p}} // or V_{L^p} ← V_{L^p} ∪ {V_{R_j^p}}
    Remove all pairs of sets containing one of the two sets V_{R_i^p} and V_{R_j^p}
end for
return V_{L^p}
```

period size is set in our experiments to 50 readings where each mote takes a new reading of temperature every 30 seconds. Figure 3 shows the distribution of motes inside the laboratory. Motes are ranged from 1 and 20 respectively while the ID of SG1000 is set to 0. The effectiveness of our technique at the sensor level is tested and compared to a data compression technique (S-LEC) proposed in [13].

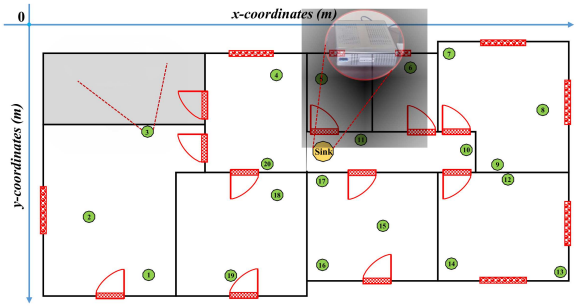


Fig. 3. Distribution of motes in our lab.

Our technique, S-LEC and naïve approach are implemented on the motes as shown in Table I:

Technique	mote IDs
our technique	1, 5, 6, 7, 9, 12, 13, 15, 19, 20
S-LEC	3, 8, 11, 14, 16, 18
naïve	2, 4, 10, 17

TABLE I. TECHNIQUES IMPLEMENTED ON THE MOTES.

Finally, it must be noticed that all methods were implemented on the motes based on the nesC language [21], i.e. the standard programming language of tinyOS [22], while a Java code was implemented on the laptop machine to retrieve data from the sink node.

A. Filtering Ratio at each Mote

As mentioned before, the Pearson coefficient allows each sensor node to minimize the size of its sensed data by removing similar readings. Figure 4 shows the average number of temperature readings sent by each mote along the days of deployment, using our technique and S-LEC. The obtained results show that our data filtering model allows motes to significantly reduce its data transmission compared those operating with S-LEC technique. Subsequently, each mote can reduce up to 50% the temperature readings sent to SG1000.

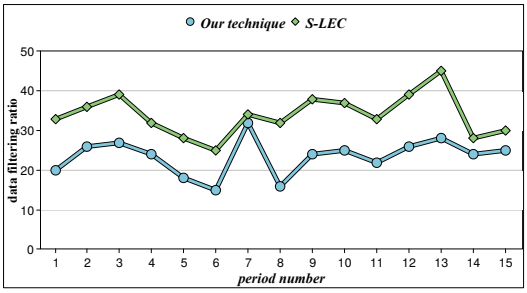


Fig. 4. Filtering ratio at each mote during periods, $\tau = 50, t_p = 0.5$.

B. Filtering Set Ratio at the Sink

In Figure 5, we show the average number of remaining sets after applying KNN algorithm at the sink node, when varying K values to 3, 4 and 5 respectively. The obtained results show that KNN can significantly eliminate redundant data sets generated by neighboring sensors compared to naïve approach, e.g. without any filtering technique. Subsequently, we observe that KNN can reduce up to 85% of the whole received sets at the sink. These results confirm that the clustering is a very efficient approach in terms of eliminating redundant data and providing useful information to the enduser, comparing to other existing approaches. We can also observe that KNN eliminates more sets when K increases; this is because, the temporally correlation between each sensor and it neighboring nodes will increases thus, KNN will consider then eliminate more datasets.

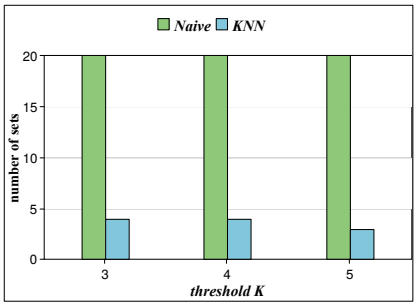


Fig. 5. Filtering set ratio after applying KNN at the sink, $\tau = 50, t_p = 0.5$.

C. Data Accuracy

Data accuracy is a main metric that should be studied in WSNs. In our experiments, data accuracy has been calculated by divided the number of loss readings after applying KNN algorithm over the whole readings collected by the naïve sensors. Figure 6 shows the results of data accuracy of KNN compared to S-LEC technique, when varying the threshold K.

The obtained results are highly dependent on the number of remaining sets after applying KNN (see results of Figure 5); more the number of remaining sets thus less of readings are lost. Indeed, we observe that both techniques give important results regarding the accuracy of the collected data where the integrity of the information is highly conserved for the end user. Subsequently, we notice that KNN algorithm gives the best results of data accuracy when K is small, e.g. ≤ 4, whilst the information is more conserved using S-LEC when K increases, e.g. > 4.

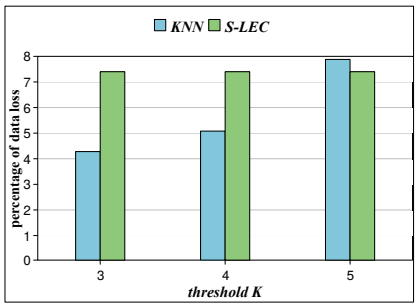


Fig. 6. Percentage of data loss, $\tau = 50, t_p = 0.5$.

VII. Conclusion and Future Work

Wireless sensor networks (WSNs) will play an important role in future internet by collecting surrounding conditions and environment information. Thus, designing new filtering techniques will become essential in order to eliminate meaningless/redundant raw data and make such networks operated as long as possible. This paper proposed energy-efficient filtering technique dedicated to periodic sensor applications. The first filter uses Pearson coefficient metric and aims to reduce the raw data collected by the sensors. The second filter allows aggregator nodes to eliminate redundant data collected by neighboring nodes using K-nearest neighbor clustering algorithm. Or technique has been evaluated based on both simulation and experiments on real telosB sensors. The results obtained with our technique showed significant energy savings and high accurate data collection compared to existing approaches.

Many future directions for our work can be traced. First, we plan to let aggregators in our technique be able to adjust the sampling rate of the sensors based on the redundancy level with their neighboring nodes. Second, we seek to try another data clustering methods at the aggregator level, like decision trees and neural networks.

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