PREDICTION BASED DATA REDUCTION AND CONTROLLED TRANSMISSION IN WIRELESS SENSOR NETWORK

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Abstract

Wireless sensor network is a network which includes sensing and routing via nodes mainly called sensors and sink to monitor physical and environment condition and having many protocols according of usage. Recently, Wireless Sensor Network(WSN) used in many areas like military, hospitals, biological equipments, environment monitoring etc. The limitation of WSN includes lifetime of network, Battery, Bandwidth, Energy, data redundancy and routing etc. In this study, we mainly focused on data redundancy and energy of sensor nodes. Data reduction is one of the data pre-processing techniques of data mining that can increase storage efficiency and reduce costs. Data reduction (DR) aims to remove unnecessary data while transmission. Wireless sensor networks have found many applications in detecting events such as security threats, natural hazards, or technical malfunctions. An essential requirement for event detection systems is the long lifetime of battery-powered sensor nodes. This study introduces a new method for prolonging the wireless sensor network's lifetime by reducing data transmissions between neighboring sensor nodes that cooperate in event detection.

Keywords: *WSN, Data Reduction, energy consumption.*

Introduction

WSN is an emerging technology that has wide range of potential applications including environment monitoring, surveillance, medical systems, robotic exploration, military etc. The individual nodes in a wireless sensor network (WSN) are inherently resource constrained: they have limited processing speed, storage capacity, and communication bandwidth. After the sensor nodes are deployed, they are responsible for self-organizing an appropriate network infrastructure often with multi-hop communication with them. Then the on-board sensors start collecting information of interest. WSN consist large number of distributed nodes that organized themselves into many multi-hop wireless network. Each mode equipped with one or more sensors, embedded processor and low power radios and is normally battery operated. A sensor node might vary in sizes and its cost. Generally, sensor node is a typical device that includes sensing (for data acquisition from environment), processing (for local data processing and storage) and communication.

The proposed transmission reduction method was implemented in a WSN for cargo monitoring during transportation. The considered WSN detects the instability of cargo boxes in a vehicle based on data collected from accelerometers and gyroscopes. This system is composed of a parent sensor node attached to the vehicle body and child sensor nodes inside the cargo boxes. The parent node detects events related to movements and tilts of the cargo boxes inside a car by taking into account the measurements of vibrations and angular velocities made for the cargo boxes and the body of the vehicle. This WSN was used as a testbed for the experimental assessment of the introduced transmission reduction method in a real-world scenario. During the experiments, the ability to extend the lifetime of the sensor nodes and the impact on the event detection accuracy of the proposed method were compared with those of state-of-the-art approaches.

The main contributions of this work are summarized as follows:

- A new method is presented for data transmission reduction in WSN where spatial events have to be detected based on data from neighboring sensor nodes. The method is based on predicting the possible errors of event detection that can be encountered when current sensor readings are not reported;
- The introduced method was implemented for event detection in a cargo monitoring system;
- Feasibility and effectiveness of the proposed method were experimentally verified using a prototype of WSN. The conducted experiments have involved in comparison with state-of-the-art approaches.

Data reduction systems in WSN

Data reduction systems have been deployed in many environments and scenarios to achieve conserve communication resources. Discrete fourier transforms (DFT) is a classic technique used to perform data reduction for temporally related data streams. Based on DFT, researchers have more recently developed an advanced method Discrete Wavelet Transform (DWT) to achieve data reduction. Also techniques such as, Singular Value Decomposition (SVD) based on traditional Principal Components Analysis (PCA) is an attractive data reduction technique because of its ability to provide optimal data reduction. Random projection of time series is another technique which has exhibited great promise and demonstrated good results since it can provide approximate answers with guaranteed bounds of errors. Stated below are some of the prominent data reduction schemes presented in the literature for WSN.

Data driven approaches can be classified according to problem they addressed.(i) Data acquisition mainly target to reduce energy spent by sensing subsystem.(ii) Data reduction used when unnecessary samples are used.(iii) In-network processing do data aggregation at intermediate node between sensor and sink.(iv) Data compression reduce amount of information sent by source nodes with encoding at sensor nodes and decoding at sink.(v) Data prediction predicts the value sensed by sensor nodes within specific error bound.

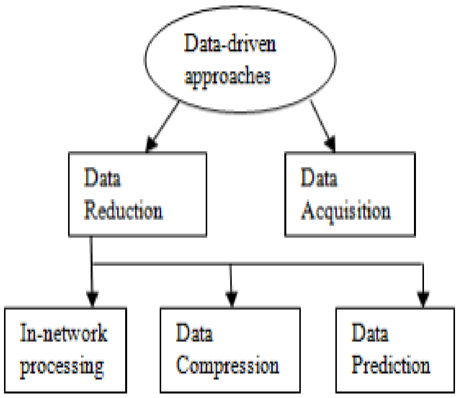

Figure 1: Data Driven Approach

Methodology

The objective of the conducted experiments was to test the proposed method on a real-world working event detection system. Our method was experimentally verified in a prototype WSN for cargo monitoring during transportation. The monitored events have included the movements of cargo boxes that are symptoms of improperly secured load in a vehicle. The objective of this monitoring system was the recognition of threats of possible damage to cargo and informs the users. The construction of the system was inspired by previous works on cargo monitoring in transportation and logistics systems. During experiments, the accuracy of event detection was analyzed, and measurements were performed to determine the energy consumption of sensor nodes and to evaluate their lifetime.

Results and Discussion

A dataset for our experiments was collected using the WSN prototype in a car traveling on urban roads in Sosnowiec, Poland. The routes were selected to cover many crossroads, roundabouts, and curves. When collecting data, we avoided traffic congestion and peak hours. Thus, the movements of unsecured packages in the car were very frequent. The data collection was conducted for three working days. A passenger in the car was controlling the situation by selectively holding and releasing packages for short time periods so that the released package was moving. We marked the events by registering the time when a given package was moving inside the car.

The first experiments were conducted to verify the possibility of detecting the events of interest and comparing the accuracy of cargo movement detection for various machine learning classification algorithms. The compared machine learning algorithms include: k-nearest neighbors (kNN), multilayer perceptron (MLP) which is a popular example of neural network probabilistic neural network (PNN), random tree (RT), and random forest (RF). All tests of the above-listed algorithms were performed using their implementations available in the Konstanz Information Miner (KNIME) and WEKA package. During the experiments, 60% of the collected data were used for training and 40% for testing. During the first part of the experiments, the reduction in data transmission was not performed; thus, all available data were taken into account. It means that the events were detected based on sensor readings from both the child and parent node. The results presented in below Figure 2 show that the collected data allow all the considered algorithms to detect the events of interest with a high level of accuracy. These results confirm that the elaborated WSN is useful for cargo monitoring during transportation.

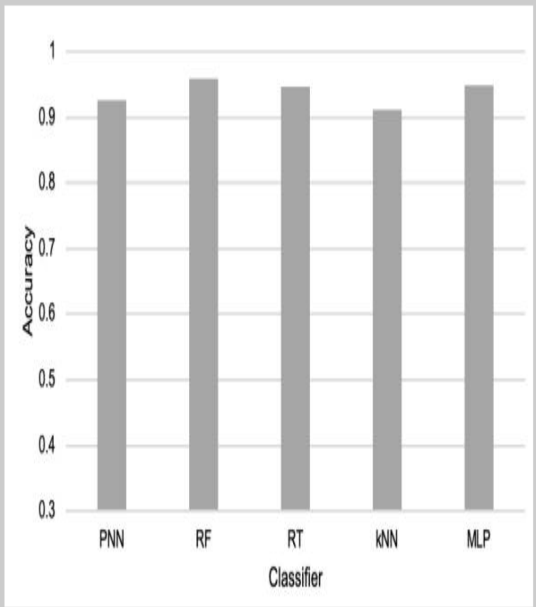

Figure 2: Accuracy of event detection for compared machine learning algorithms

The RF algorithm can be considered as an extended version of the RT method where a collection of decision trees is built. The RF algorithm creates decision trees using a random procedure. The construction of a decision tree involves the greedy selection of the best split point from the dataset at each step. By creating multiple trees with different samples of the training dataset, the RF algorithm introduces different views of the detection problem.

From below Figure 3 shows the accuracy of event detection with the use of the RF algorithm for different numbers of trees. Based on this chart, it can be observed that when the number of trees is increased, the impact on recognition accuracy is not significant. This effect is especially visible when the number of trees is greater than 10 (the dotted line is almost flat). It should be noted here that the lower number of trees leads to the lower computational complexity of the detection procedure, which is desirable from the perspective of the implementation in sensor nodes.

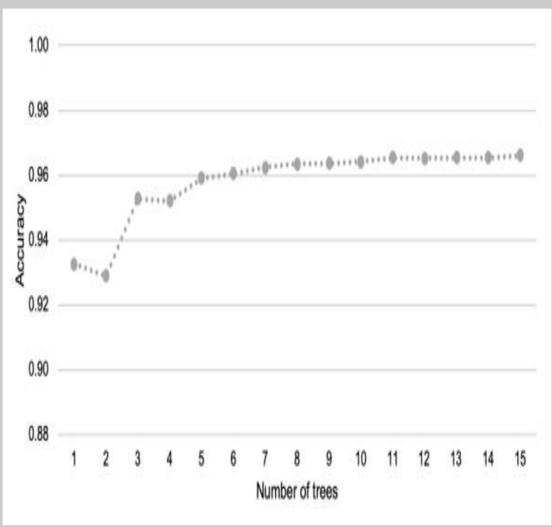

Figure 3: Accuracy of event detection for different numbers of trees

The second part of the experiments was devoted to the evaluation of the event-triggered approach. In this case, the child nodes detect events based on their own sensor readings. The amount of data transfers is reduced in this method since the child nodes send information to the parent node only when they detect movements of the packages. In order to detect the events, the same five machine learning algorithms were used, as in the previous experiments.

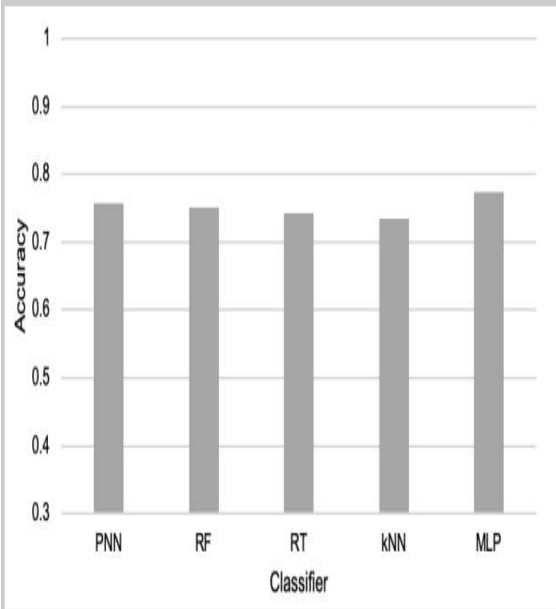

Figure 4: Accuracy of the parcel movement recognition for event-triggered approach

The results presented in Figure 5 show the dependency between event detection accuracy and transmission reduction. For all compared methods, the accuracy of event detection decreases when increasing the percentage of reduced transmissions. However, this decrease in accuracy is slowest in the case of the proposed method. Let us assume that we can accept an accuracy decrease by 10% as a cost of reducing data transmissions. Then, the proposed method allows us to eliminate almost 79% of data transmissions, while state-of-the-art methods achieve a transmission reduction of 65.3% for the naive model and 46.9% for the neural model.

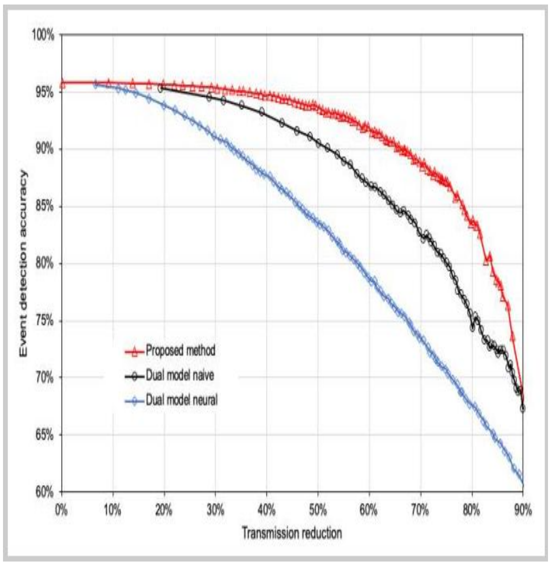

Figure 5: Event detection accuracy and transmission reduction for compared methods

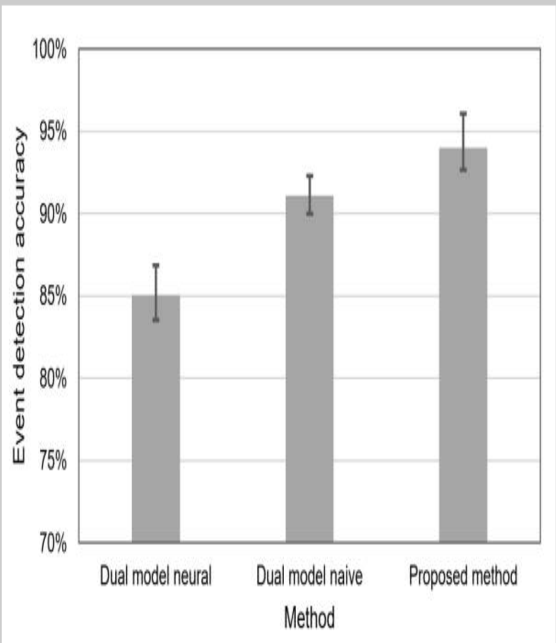

Figure 6: Accuracy of event detection for the compared methods when the WSN lifetime equals 120 h

Figure 7 compares the accuracy of event detection, which was obtained in a situation when the lifetime of WSN was equal to 120 h. In this case, the dual prediction based on the neural model allows us to detect the events of interest with an average accuracy of 85.1%. When using the dual prediction with the naive model, we achieved the average accuracy of 91.1%. The highest event detection accuracy (94% on average) was observed for the proposed method.

As it already explained earlier in this section, we applied the RF algorithm to detect events in our experiments since this classifier achieved the best results during the preliminary tests. Additional experiments were performed to compare the performance of RF with RT and MLP algorithms when detecting events with the use of the reduced data. For the considered scenarios, 60% of the data transmissions were reduced. The results of these experiments are presented in Figure 8. They show that the RF classifier also has a higher event detection accuracy than RT and MLP for reduced data. The superiority of the RF classifier was observed for all the three considered transmission reduction methods.

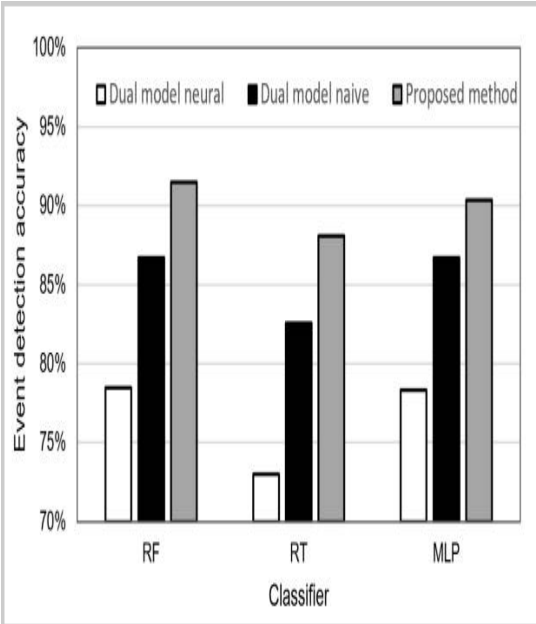

Figure 7: Accuracy of event detection with the use of different classifiers for the compared transmission reduction method

Conclusion

The method presented in this paper reduces the number of data transmissions between neighboring sensor nodes that detect spatial events based on shared sensor readings. As a result of transmission reduction, the lifetime of WSN is prolonged. Moreover, the lower number of data transmissions leads to a reduced probability of collisions and delays in transmitting the data from sensor nodes. According to the proposed method, the child sensor node has to determine a set of possible sensor readings of the parent node to decide whether data transmission can be skipped. The set of possible sensor readings is determined with the use of a percentile tracking algorithm and represented by intervals. This means that all sensor readings in the interval are considered equally possible.

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