Event Detection through Differential Pattern Mining in Cyber-Physical Systems

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Abstract—Extracting knowledge from sensor data for various purposes has received a great deal of attention by the data mining community. For the purpose of event detection in cyber-physical systems (CPS), e.g., damage in building or aerospace vehicles from the continuous arriving data is challenging due to the detection quality. Traditional data mining schemes are used to reduce data that often use metrics, association rules, and binary values for frequent patterns as indicators for finding interesting knowledge about an event. However, these may not be directly applicable to the network due to certain constraints (communication, computation, bandwidth). We discover that, the indicators may not reveal meaningful information for event detection in practice. In this paper, we propose a comprehensive data mining framework for event detection in the CPS named `DPminer`, which functions in a distributed and parallel manner (data in a partitioned database processed by one or more sensor processors) and is able to extract a pattern of sensors that may have event information with a low communication cost. To achieve this, we introduce a new sensor behavioral pattern mining technique called *differential sensor pattern* (DSP) which considers different frequencies and values (non-binary) with a set of sensors, instead of traditional binary patterns. We present an algorithm for data preparation and then use a highly-compact data tree structure (called *DP-Tree*) for generating the DSP. An important tradeoff between the communication and computation costs for the event detection via data mining is made. Evaluation results show that `DPminer` can be very useful for networked sensing with a superior performance in terms of communication cost and event detection quality compared to existing data mining schemes.

Index Terms—Cyber-physical systems, wireless sensor, data mining, pattern mining, event detection, resource-efficiency

1 Introduction

CYBER-physical systems (CPS) have gained a lot of attention in both the public and the research communities, because they are expected to bring interactions between humans, environments, and machines to a new paradigm. With the capabilities of pervasive surveillance, the CPS have strong practical applications in many domains, e.g., structural health monitoring (SHM for short) for industrial machine or aerospace vehicles, chemical explosion, military surveillance, and smart grid [1]–[7].

In SHM applications, the characterizing feature of these systems is the interaction between physical processes governed by the laws of physics and an execution platform (i.e., cyber system) which comprises embedded software and hardware devices such as sensors, actuators, processors, and communication networks to interconnect them. The physical process involves the elements of structures and the physical conconnectivity between the elements of a structure. Any changes in elements, even micro-elements and their connectivity can be closely monitored by the cyber system. Such a change leads to further interaction in the cyber systems in terms computation, communications, etc. Thus, in an intended CPS, physical system aspects and cyber system aspects should be tightly combined. The wireless sensors in the CPS produce a huge volume of dynamic, geographically-distributed and heterogeneous data when deployed in these applications. The raw data, if accurately analyzed and transformed to usable information through data mining, can facilitate automatic and intelligent decision-making on specific events of interest (e.g., damage in aerospace vehicles, chemical explosion), while optimizing the resource efficiency of cyber systems. Hence, it is vital to develop methodologies to mine sensor data.

Recently, extracting knowledge from sensor data has received a great deal of attention in the data mining community [8]–[11]. Traditional data mining schemes focusing on association rules, frequent patterns, sequential patterns, clustering, and classification have been successfully used on sensor data. These mining schemes are usually centralized and computationally expensive, and they focus on disk-resident transactional data. A decent number of data mining algorithms have been developed with less computational complexity [8], [12]–[14], and the process of forming patterns and producing association rules is straightforward. Metrics, rules, binary patterns, and frequent patterns are often used as *indicators* to find interesting knowledge. They require excessive interactions and rule exchanges, leading to massive amounts of communication.

Through observation, we discover that many of the indicators do not reflect meaningful information of a physical event, particularly in those applications, including complex event detection like events in damage or cracks in struc-

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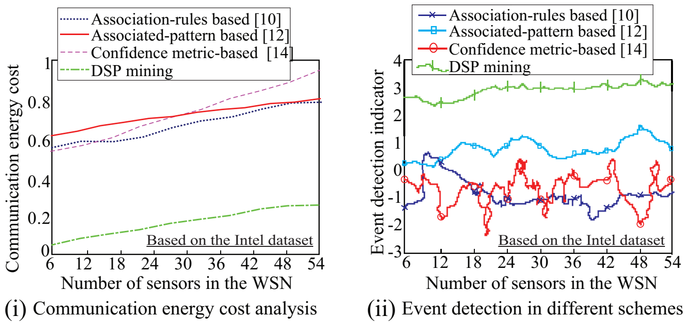


Fig. 1. Observation of the communication cost and event detection performance in WSN when applying data mining techniques.

tures (aerospace vehicles, nuclear plants, faults in industrial equipment, and so on) that urgently require preprocessed data for event detection once there is an event detection indicator. We select three types of data mining algorithms (associations rule based [10], associated-pattern based [12], and confidence metric-based [14]), and verify them with real datasets. We use Intel WSN real dataset [15] and mine these data with algorithms. We illustrate the outcome of the observation in Fig. 1. It depicts that the communication energy cost of a WSN with those algorithms is significantly high, while they often fail to detect an event. We find that, the binary frequency pattern does not exactly indicate moderate event intensity, as the intensity of an event occurence is analyzed by constant triggering or data. Thus, these algorithms are not directly applicable to the event detection due to resource constraints in networked systems (communication, computation, bandwidth).

In this paper, we present a comprehensive data mining framework for event detection in the WSN, named `DPminer`, which functions in a distributed and parallel manner (see Fig. 2) and is able to extract a pattern of sensors that may have event information by mining a **d**ifferential data **p**attern (with different frequencies and values in different datasets), with a low communication cost. The crucial thing is that `DPminer` can provide useful and interesting knowledge from sensor databases by considering non-binary frequencies and values of sensors in each tuple (similar to a "record" in a traditional database).

Each partition contains a set of data acquired at a time slot, which we call *Cases*. From *Cases*, a sensor mines different values/items and different rates of frequencies of these values, and puts in a database partition. Besides, the sensor maintains a *Controls* database/dataset that contains ranges of data (to compare with the data in *Cases*) and is defined by the event intensity in a specific application. Based on the event intensity, the sensor calculate a data pattern.

A cluster of sensors shares data patterns so that each sensor can calculate a sensor pattern. The sensors in a cluster coordinate with their cluster head (CH), and together, they develop a **d**ifferential data **p**attern tree structure, called *DP-Tree* in a distributed and parallel manner. The CH, along with its sensors, finds an initial *differential sensor pattern (DSP)* via the *DP-Tree*. After mining all initial DSPs, the CH provides a confirmed DSP that can ensure whether an event has occurred around some sensors or the cluster, even offering a value (e.g., $e_V > 1$) as the event indicator. (see Fig. 1(ii) for indicators in `DPminer` based on DSPs).

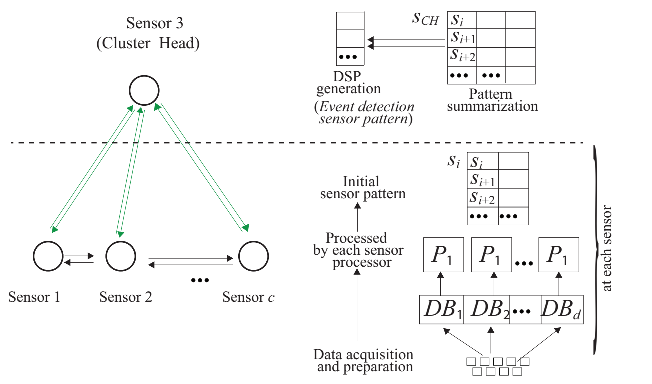


Fig. 2. The concept of `DPminer` showing interactions between sensors and their cluster head (CH) in generating a sensor pattern.

In `DPminer`, the sensors which are not in a DSP are dropped with their data from further pattern mining, thereby reducing the communication cost. Instead of finding binary frequent patterns, we find sensor patterns that come from the consideration of *different rates of frequencies and values* in the *Cases* and *Controls*. Generating such a DSP from a network can be very useful in a wide range of applications that require fine-grained monitoring.

The major contributions of this paper are four-fold:

- We define a new type of data pattern mining for sensors in the CPS, DSP, which discovers the sensors that contain event detection information. We design `DPminer` to generate the DSP for event detection.
- We propose a simplified "data preparation" algorithm, which is the first-stage data mining algorithm used to prepare data for a tree structure in a WSN.
- To generate a DSP, we devise a *DP-Tree* that is developed on a sensor partitioned database in such a way that data in each sub-database can be processed by one or more sensor processors in a distributed and parallel manner. A partitioning is also given.
- Finally, we validate `DPminer` in simulations on our real-data traces. We also consider other two sets of data traces to analyze the performance. We provide trade-off between sensor energy costs for communication and computation for event detection through sensor data mining in the CPS. We have found that `DPminer` achieves a superior performance in terms of both communication cost and detection quality compared to existing data mining schemes.

This paper is organized as follows. Section 2 reviews related work. We formulate our problem in Section 3. Section 4 explains the `DPminer` framework. Section 5 presents the data preparation algorithm. Section 6 develops *DP-Tree* and analysis, event detection, and database partitioning algorithm. Evaluation through simulations is conducted in Section 7. Finally, Section 8 concludes this paper.

2 Related Work

Big data mining from a WSN of the CPS is the process of extracting application-oriented event information or patterns with acceptable accuracy, which comes from a continuous and rapid flow of data streams. In the CPS, the data contains the physical system or event information. There are various data mining techniques and algorithms outlined in the literature, including frequent patterns, sequential patterns, clustering, and classification. They already address numerous issues in data mining including execution time, complexity, and rule or query processing needed to mine stored (static) and/or stream data [8]–[11], [14], [16]. Due to various constraints, a complete set of acquired data cannot be either stored or delivered in real-time. The data cannot be dropped due to guaranteeing monitoring quality.

Looking into more details of particular data mining algorithms, in the recent decades, mining association rules have been used in transactional databases. Recently, they have been applied to data mining schemes in sensor networks. Mining the associations among sensor values that co-exist temporally in large-scaled the WSN and mining spatial temporal event patterns from sensor data are proposed in [14], [17]. A behavioral pattern named Target-based Association Rules (TARs) for point-of-coverage in the WSN which aims to discover the correlation among a set of targets monitored by a WSN and uses confidence metrics is proposed [14]. In TARs, every sensor maintains an additional flash memory that increases the deployment cost.

An interesting data mining technique in wireless ad hoc networks uses a tree-based structure called Positional Lexicographic Tree (MAR-PLT for short) to mine association rules [10]. It follows a FP-growth-like pattern growth mining technique, but the two database scanning requirements and the extra MAR-PLT update operations during mining limit efficient use of this technique in handling WSN data. Association rules-based growth trees do not show satisfactory performance in the WSN in terms of communication, as shown in Fig. 1(i).

In another work [9], generating context association rule over an online sensor/actuator transactional data stream is suggested. This is used to invoke proper operations of actuators relevant to values of the sensors. It organize frequent context itemsets over the current data steam, such that a set of frequently co-occurred sensors and actuators items is arranged. A data mining technique to generate association rules from WSN by using a prefix-tree called sensor pattern tree (SP-tree). Although SP-tree shows better performance than PLT [16], it still generates a large number of rules, many of which may not be useful enough, resulting in a significant communication cost and computation costs.

A method which captures association-like co-occurrences as well as temporal correlations (linked with such co-occurrences) is used to mine *associated patterns* from sensor data streams [12]. A regular frequent pattern is proposed to find frequent sensor patterns that occur after a certain interval in the sensor database. Most of these techniques consider a binary (0/1) occurrence of the patterns in the database. Binary value (0/1) is also used for frequent pattern association. Such a binary occurrence or pattern association may fail to detect events in practice. In addition, they still require significant communication costs in terms of excessive message transmission in the WSN.

A share-confidence framework and share-frequent sensor patterns (SFSPs) are proposed to identify share-frequent itemsets [18], [19]. The ShFSM (Fast Share Measure) algorithm used level closure property instead of downward property which to improve the past algorithms [20]. SFSPs has been proposed to facilitate a pattern growth mining technique to discover SFSPs from WSN data. But, both create too many candidates at each pass so it is computationally expensive.

Recently, applying machine learning algorithms for big data mining in CPS receives significant attention [1]–[3], [21], [22]. For example, cluster analysis is used to extract useful information and patterns from data generated from physical devices of a CPS. A density-based data stream clustering algorithm built on the multiple species flocking model for big data is considered [2]. FlockStream is based on a multi-agent system that uses a decentralized bottom-up self-organizing strategy to group similar data points. Another work discusses the challenges of a common big data-driven framework to support monitoring, anomaly detection, prognosis (degradation modeling), diagnosis, and control in CPS [3].

Most current data or pattern mining techniques are particularly suggested for transactional databases and require several scans to mine the frequent patterns. Thus, these existing algorithms may not efficiently mine sensor pattern from the sensor data stream. None of them analyzes event detection performance through the mining techniques. In particular event detection applications, structural health monitoring, industrial applications, intrusion detection in military applications that immediately require event detection indicators, with exact level of indication value. As shown in Fig. 1, binary indication may not reflect meaningful information of a physical event in the data mining algorithms: associations rule based [10], associated-pattern based [12], and confidence metric-based [14]). In terms of network performance (computation, communication), these algorithms are inefficient.

We observe that current data mining schemes using association rules, associated pattern, data clustering, and so on do not show satisfactory performance in terms of communication and event detection in sensors of the CPS. These issues have not been specifically addressed before. Our framework `DPminer` is an attempt to overcome these shortcomings while detecting an event through a DSP.

3 Differential Sensor Pattern Mining

In this section, we first describe the network aspect of the CPS. Then, we give a discussion on the event detection in the WSN of the CPS, regarding the cyber and physical aspects. Next, data mining technique is described. Finally, we define the problem of `DPminer`.

Let us consider a hierarchical WSN with a large set S of m sensors which is to be deployed for a particular monitoring application of the CPS, such as SHM, $S = \{s_1, s_2, \ldots, s_m\}$. The sensors are randomly deployed in the sensing area, and they are self-organized into clusters using a clustering algorithm [7], [23], [24]. The underlying principle of data mining in `DPminer` involves starting from simple in-network data mining at sensors (say data preparation) to fair regional complete pattern mining at intermediate sensors (e.g., cluster heads: CHs) and finally through to a global base station (BS).

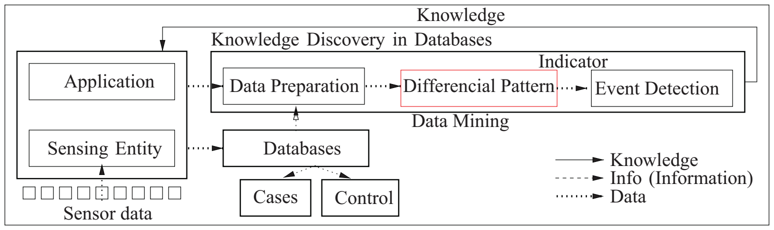


Fig. 3. The overall framework in which process of `DPminer` is involved in the CPS.

We give a representative example of how SHM system is a type of sensor network-based CPS system. It can be best observed that, commonly, "no change (e.g., damage event)" occurs in a physical structural system. Regarding this in the resource-constrained WSN, a large volume of data really does not always need to be transmitted to the BS. Instead, a pattern or a set of mined pattern transmissions may be interesting in the case of a "no change" state. However, if a change has occurred in the physical structural system, in addition to transmitting the set of patterns on the possible change, a sensor node may need to transmit all of its collected data towards an upstream node or the BS upon request. The nodes in the neighborhood may have additional interactions between them. For example, they need to communicate to the neighboring nodes in the region of the change and to further analyze the data for ensuing the state of the change. This indicates that *a change in the physical structural system* results in extensive communication and computation in the WSN system, especially between the sensor nodes in the region around the change. Therefore, the integration between both systems is a CPS. In such a system, a distributed pattern generation in a particular region of interest is essential so as to reduce the volume of data in the case of "no damage event." If there is a damage event at a part/section/span/region of the structure, a cluster of sensors around the region should operate for the event detection.

The overall data mining framework for the CPS is shown in Fig. 3. We assume that there can be different kinds of applications with different sensing entity and sensing modalities. Sensor devices collect data and put temporary in buffer for data preparation. Once data is prepared, data pattern are calculated for event detecting sensor pattern. From the patterns, an indicator is used to distinguish the event intensity. The complete process corresponds to sensor data mining.

We assume that the whole event detection time (Q_w) is divided into Q periods. Each period includes further q slots, i.e., $\{t_1, t_2, \ldots, t_q\}$ such that t_{k+1}-$t_k = \tau$, which is the length of each time slot. We assume that a sensor database DB can be partitioned into d sub-databases, i.e., $DB_1, DB_2, \ldots, DB_d$. One of the sub-databases (e.g., DB_1) of a sensor contains prepared data that is collected in period Q (refer to Fig. 4(i)). This arriving dataset is a large dataset which we call $Cases$. Other sub-databases are shared with the neighbors in a cluster.

Each wireless sensor mines both different values/items (V) and different frequencies (F) of these values from $Cases$ and determines a set of tuples within time slot t_k. Here, we maintain a $Controls$ database/dataset which contains the healthy data (for comparison with the data in $Cases$). The healthy data can also be said as reference data. If there is an event, each tuple may have frequent values with higher event intensity information (see Fig. 4(ii)). Some values can be distinguishable from other values. This can be determined through comparison with data in $Controls$. In $Cases$, a set of tuples denoted by $H_h(h = 1, 2 \ldots, n)$ is defined as a subset of data (frequencies and values) of a particular sub-database. From $Cases$, we first find a rate of frequencies (*rf*) and median values (*mv*) in H_h, a subset S_s of sensors, and DB_i. Then, we find the global values (*grf* and *gmv*) at each CH. We do not assume any user-driven threshold, percentage, or binary decision for pattern identification or frequency selection. Rather, we use a data pattern comparison with $Controls$.

TABLE 1
Symbol Definition

Symbol	Definition
D	Differential sensor patter (DSP)
F, V	data frequency, data value, respectively
rf & *mv*	rate of frequencies & median values, respectively
S_s	subset of sensors
H_h	set of tuple ($h = 1, 2 \ldots, n$)
$F_{t_k}(s_i, H_h)$	rate of frequencies in H_h of the ith sensor
$F_{t_k}(H_h)$	total frequencies in H_h
$F_{t_k}(H_h)_{rf}$	total rate of frequencies in H_h of a DB_i
$F_{t_k}(S_s, H_h)_{S_s}$	rate of frequencies in H_h of S_s
$F_{t_k}(S_s)_{rf}$	rate of frequencies in H_h of S_s in DB_i
$V_{t_k}(S_s)_{mv}$	median values in H_h of S_s in DB_i
$e_V >$	event indication based in on values
$e_F >$	event indication based in on frequencies

For SHM applications, data collection needs some particular models, for example finite element model (FEM) [25]. FEM is a numerical model for calculating the behavior and strength of structural mechanics, such as vibration and displacement in a building, bridge, or aircraft [25]. Via FEM, a complex structural model is simplified by breaking it down into small elements. When such an element hit and the external influence (force) is removed, it will vibrate at its natural frequency. The natural frequency is defined as the number of times a physical structural system will oscillate between its original position and its displaced position. An event such as damage or crack is a significant change to the geometric properties of the structural system, such as changes to captured frequencies. The data in Fig. 4 shows normalized frequencies from collected data.

Let $F_{t_k}(s_i, H_h)$ be the rate of frequencies in H_h of the ith sensor, i.e., the number of times a value is seen in t_k

of the ith sensor. For example, $A = 3$ in Fig. 4(v), i.e., a value within label A has been seen three times in H_h. Towards the DSP generation, we first need to define the rate of frequencies and the total values from a set of acquired data.

Definition 1 [$F_{t_k}(H_h)$]. The rate of frequencies in a set of tuple H_h represents the total frequencies in H_h; it is given by the following equation:

$$F_{t_k}(H_h) = \sum_{s_i \in H_h} F_{t_k}(s_i, H_h) \tag{1}$$

In Fig. 5, $F_{t_k}(H_1)$=$F_{t_k}(s_1, H_1)+F_{t_k}(s_3, H_1)+F_{t_k}(s_4, H_1)+F_{t_k}(s_6, H_1) + F_{t_k}(s_9, H_1) = 3 + 2 + 3 + 1 + 1 = 10$.

Definition 2 [$F_{t_k}(H_h)_{rf}$]. The total **r**ate of **f**requencies that carry event information in all tuples of a DB_i is given by the following equation:

$$F_{t_k}(H_h)_{rf} = \sum_{H_h \in DB_i} F_{t_k}(H_h) \tag{2}$$

In Fig. 5, $F_{t_k}(H_1)_{rf} = 10 + 13 + 16 + 8 + 12 + 16 = 75$.

Assume that a subset S_s of sensors is working in a cluster. Then, the following equation gives the rate of frequencies in H_h:

$$F_{t_k}(S_s, H_h)_{S_s} = \sum_{s_i \in S_s} F_{t_k}(s_i, H_h) \tag{3}$$

For example, $F_{t_k}((s_2, s_3, s_5), H_2)_{S_s} = 1 + 3 + 2 = 6$ in Fig. 5. We then calculate the rate of frequencies in all of tuples of S_s in DB_i as follows:

$$F_{t_k}(S_s)_{rf} = \sum_{S_i \in DB_i} F_{t_k}(S_s, H_h). \tag{4}$$

Similarly, the total **m**edian **v**alues in all of the tuples in a subset S_s of sensors in DB_i can be calculated by the following:

$$V_{t_k}(S_s)_{mv} = \sum_{H_h \in DB_i} V_{t_k}(S_s, H_h) \tag{5}$$

In Fig. 5, $V_{t_k}(s_2, s_3, H_h)_{mv} = V_{t_k}(s_2, s_3, H_2)_{mv} + V_{t_k}(s_2, s_3, H_6)_{mv} = (3.4 + 4.6) + (6.3 + 8.3) = 22.6$.

Once we have a subset S_s of sensors' frequencies and values in DB_i, we can find the DSP by ordering the sensors based on a differential data tree structure (called *DP-Tree*). This tree is structured by each sensor, but its structural process requires the participation of both the neighboring nodes and the CH node in a parallel and distributed manner. $V_{t_k}(S_s)_{mv}$ and $F_{t_k}(S_s)_{rf}$ are some possible criteria for developing a *DP-Tree* structure. Finally, a sensor pattern can be generalized via the *DP-Tree* using its step-by-step process.

Instead of finding a frequent sensor pattern (as is usually done in existing schemes), sensors found in DSP denoted by D come from the analysis of different frequencies and values in $Cases$ and $Controls$ of $\leftarrow S_s$. It is important to note that instead of just having a DSP, a simplified event indicator as a differentiation may also be calculated from the sensors in a DSP by the following:

$$e_V = \frac{V_{t_k}(S_s[Control])}{V_{t_k}(S_s)}, \quad e_F = \frac{F_{t_k}(S_s[Control])}{F_{t_k}(S_s)} \tag{6}$$

An event can be said to be present in the physical system environment if both $e_V > 1$ and $e_F > 1$. Otherwise, event information is said to be absent based on the collected sensor data.

A differential pattern D in DB_i can be defined by the differences between $Cases$ and $Controls$ datasets in terms of prepared data values and rates of frequencies obtained from all sets of tuples in DB_i, i.e., *diff*$(D, DB_i) = |\{H_s(H_h, S_s)|D \subseteq S_s\}|$. A pattern D is said to be a DSP if *diff*$(D, DB_i) \geq$ *min_diff*, where *min_diff* is a user-given minimum support parameter in percentage of DB_i size in terms of size (H_s) of tuples.

Our problem is to find a D of sensors (that may report an event of interest) by mining all sets of H_h of each sensor in a cluster in a distributed manner such that a CH can finally decide whether an event has occurred in the area and report to the BS. Our objectives are to reduce the communication cost of the sensor and to provide high-quality event detection.

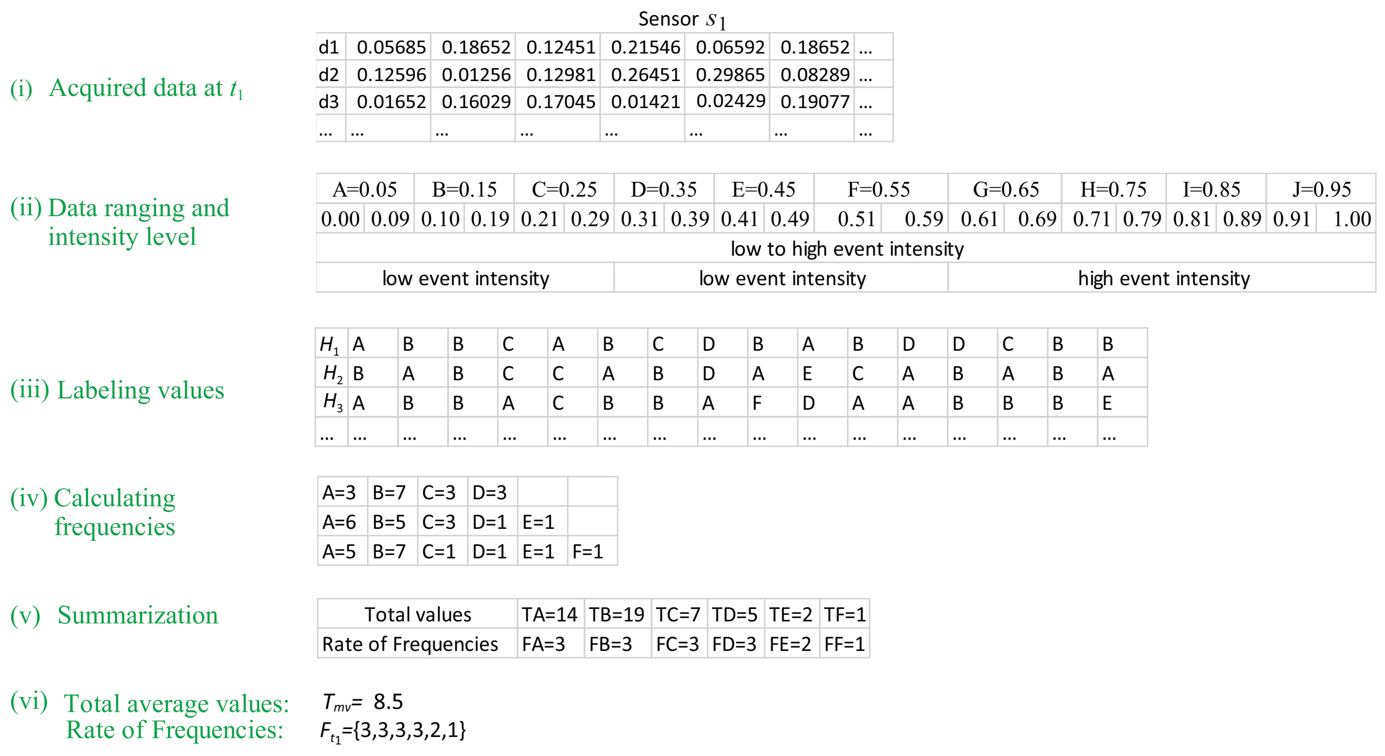
4 DPminer: A Distributed Data Mining Framework for Wireless Sensor in the CPS

In this section, we present the `DPminer` framework. It includes a step-by-step process for finding a differential sensor pattern (DSP) in a distributed and parallel manner. We also include necessary definitions.

To mine data parallelly in sensors means that mining tasks are performed concurrently in multiple processing nodes, a process referred to as "auto-palatalization." However, the term "distributed" is usually associated with data mining of geographically-distributed datasets and it is not concerned with computational scalability. In palatalization, the data can be partitioned into smaller subsets or sub-databases, and it is distributed to multiple processors [26].

Using the idea above, we consider `DPminer` as a parallel and a distributed memory-shared data mining framework for event detection in the CPS. Regarding our network model, we consider the wireless sensor of CPS as a distributed system of m processing nodes denoted as $s_i, s_i \dots s_m$, that are collectively responsible for mining the whole prepared dataset. Each processing node is comprised of one or more processors, local memories, and limited resources, including energy. For memory sharing and processing the data on a share-basis, we also consider that a sensor database (DB) is horizontally divided into n non-overlapping partitions (where n is the number of neighboring nodes of sensor s_i). In that way, a processor of the ith sensor s_i processes almost an equal number of tuples (including different frequencies and values). Thus, we can have the DB in DB_1, DB_2,..., DB_d. We assume that each partition/sub-database is assigned to a sensor process, i.e., DB_i is assigned to sensor s_i. The example database where the dataset is split into several parts can be seen in Fig. 5; each is assigned to a processor (e.g., P_1). A simplified partitioning algorithm (Algorithm 3) is in Appendix A.

A CH can have some additional capacity besides its regular data mining tasks. It is responsible for performing extra sequential steps, and any of the processors can be allocated to do these tasks. This processor is called a CH/master processor P_{CH} while every other sensor's processor is called a local processor, $(P1, P_2, \dots, P_p)$. Each DB_i of DB is set as a local dataset for sensor s_i. Having subdatabases, the



(i) Acquired data at t_1

Sensor s_1

d1	0.05685	0.18652	0.12451	0.21546	0.06592	0.18652	...
d2	0.12596	0.01256	0.12981	0.26451	0.29865	0.08289	...
d3	0.01652	0.16029	0.17045	0.01421	0.02429	0.19077	...
...	...	...	...	...	...	...	...

(ii) Data ranging and intensity level

A=0.05		B=0.15		C=0.25		D=0.35		E=0.45		F=0.55		G=0.65		H=0.75		I=0.85		J=0.95	
0.00	0.09	0.10	0.19	0.21	0.29	0.31	0.39	0.41	0.49	0.51	0.59	0.61	0.69	0.71	0.79	0.81	0.89	0.91	1.00
low to high event intensity																			
low event intensity						low event intensity						high event intensity							

(iii) Labeling values

H_1	A	B	B	C	A	B	C	D	B	A	B	D	D	C	B	B
H_2	B	A	B	C	C	A	B	D	A	E	C	A	B	A	B	A
H_3	A	B	B	A	C	B	B	A	F	D	A	A	B	B	B	E
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

(iv) Calculating frequencies

A=3	B=7	C=3	D=3		
A=6	B=5	C=3	D=1	E=1	
A=5	B=7	C=1	D=1	E=1	F=1

(v) Summarization

Total values	TA=14	TB=19	TC=7	TD=5	TE=2	TF=1
Rate of Frequencies	FA=3	FB=3	FC=3	FD=3	FE=2	FF=1

(vi) Total average values: T_{mv}= 8.5
Rate of Frequencies: F_{t_1}={3,3,3,3,2,1}

Fig. 4. The process of data preparation from refined data in sensors of the CPS.

following key information is required to identify a DSP in a parallel and distributed environment.

Definition 3 [$F_{t_k}(S_s)_{lrf}$] The total rate of frequencies in all sets of tuples of a subset S_s of sensors that may carry event information denoted by $F_{t_k}(H_h)_{lrf}$ at t_k is the sum of frequencies in all the tuples of the **l**ocal partition of DB_i. It is given by the following:

$$F_{t_k}(S_s)_{lrf} = \sum_{S_s \subseteq H_h \in DB_i} F_{t_k}(H_h)_{lrf} \tag{7}$$

For example, $F_{t_k}(s_3, s_5, s_7)_{lrf}$= $F_{t_k}(H_2)_{lrf} = 13$, as shown in Fig. 5. This is because $\{s_3, s_5, s_7\}$ appears only in H_2 in the local partition P_1.

Definition 4 [$F_{t_k}(H_h)_{lmv}$] The total value in all sets of tuples of a subset S_s of sensors that may carry event information denoted by $F_{t_k}(H_h)_{lmv}$ at t_k is the the total median values in all the tuples of the local partition DB_i, and it is given by:

$$V_{t_k}(S_s)_{lmv} = \sum_{S_s \subseteq H_h \in P_i} V_{t_k}(H_h)_{lmv} \tag{8}$$

For example, $V_{t_k}(s_2, s_3, s_5, s_7, s_8)_{lmv}$= $F_{t_k}(H_2)_{lmv}$=40.4

Definition 5 [$F_{t_k}(S_s)_{grf}$] The total rate of frequencies in all sets of tuples S_s is the sum of frequencies in all the tuples of the global DB, and it is given by the following equation:

$$F_{t_k}(S_s)_{grf} = \sum_{S_s \subseteq H_h \in DB} F_{t_k}(H_h) \tag{9}$$

For example, $F_{t_k}(s_3, s_5, s_7)_{grf} = F_{t_k}(H_2) + F_{t_k}(H_{21}) + F_{t_k}(H_{22}) = 13 + 10 + 17 = 40$, as shown in Fig. 5. This is because $\{s_2, s_3, s_5, s_7, s_8\}$ appears only in H_2 in the ith local partition DB_i. Similarly, the total median value is $V_{t_k}(s_3, s_5, s_7)_{lmv} = V_{t_k}(H_2) + V_{t_k}(H_{21}) + V_{t_k}(H_{22}) = 40.4 + 39.9 + 67.3 = 147.6$.

For identifying a DSP in parallel and distributed sensors of the CPS, `DPminer` executes the following steps.

Step 1 Sensor s_i carries out “data preparation” based on its acquired data and puts the prepared data into its DB_i. Refer to Fig. 4 for acquired data that need to be prepared.

Step 2 Sensor s_i scans the local database DB_i only once, and it develops an initial local *DP-Tree* structure in lexicographic order of sensors [10]. It maintains *DP-Tree* locally and puts the values of $F_{t_k}(S_s)_{lrf}$ and $V_{t_k}(S_s)_{lmv}$ in ith sensor s_i's **h**eader **t**able dentoed by $s_i(SH)$. It then transmits it to the CH.

Step 3 The CH sensor s_{CH} maintains a global table $s_i(GSH)$ by accumulating all values of $F_{t_k}(S_s)_{lrf}$ and $V_{t_k}(S_s)_{lmv}$ available at local sensor node s_i and then broadcasts the $s_i(GSH)$ table to sensor s_i.

Step 4 s_i develops a *DP-Tree*, according to the descending order of $V_{t_k}(S_s)_{lmv}$. It then applies a compression method to locally reconstruct *DP-Tree*.

Step 5 Sensor s_i calculates initial DSP and then sends to the s_{CH}. This DSP can be an indicator of which are the subsets of sensors that have event information.

Step 6 Finally, s_{CH} receives all the initial DSPs from all sensors and mines them, generating a final DSP. This eventually tells whether there is an event or not, and the sensors which have the event information.

5 Data Preparation: The 1st Stage Data Mining

In this section, we present data preparation algorithm needed towards *DP-Tree* development for event detection. We provide an algorithm.

Acquired data from sensors often contains a large amount of redundancy, noise, and outliers for various reasons [8] separating out actual data from the acquired data is a rigorous task. In addition, sensor data is usually meaningless unless it is associated with the time and location of the information. There are various types of data extraction algorithms, cleaning methods, outlier detections, and data predictions that can help with this task using them, there is a risk of missing important data. Instead, in `DPminer` local data preparation is provided.

The idea behind the data preparation is to reduce additional data transmission and interactions by mining data, and therein, to reduce the communication cost. In the beginning of the system operation, in `DPminer`, the data preparation process diffuses the mining parameters from the BS to all nodes, and if there is a DSP, request the DSP as the event information (see Algorithm 1 for steps).

Algorithm 1: Network Interaction and Data Collection

```
The BS:
    Broadcast ($Q, Q_w, \tau$, clustering, DB partitioning,
            $min\_dif$)
    Upon receiving returned messages
      for each $t_k (t_k = 1$ to $\frac{Q_w}{\tau})$
        $I \leftarrow$ set sensors' identifiers within the same
            time slot
        $U \leftarrow (t_k, I)$
        Insert $(U, DB)$
Node $s_i$: (Upon receiving mining parameters)
    for each $i$th node $s_i$ of the CPS
      Communicate with the neighbors and organize
          into clusters
      $t_k = 1$
      $t \leftarrow$ current time $(t_c)$
      While $t_c \leq Q_w - t$
        If $(t_c \leq t + (t_k \times \tau))$
          Perform DB partitioning
          Acquire data and buffer
          Call Algorithm 2 at $t_k$ for data preparation
        else
          $t_k$++
```

These parameters include data collection period Q and t_k with slot length τ. Upon the returned message reception, the BS sets both its time slot and its time for data collection. This is highly important for synchronized data acquisition [27]. Once the sensor nodes receives the message, they start working.

Upon receiving the mining parameters, sensor s_i executes commands, including timing and clustering. It also sets its DB_i. We assume that data mining can be performed at each time slot (i.e., close to process as the data arrives). When a set of data is acquired, data preparation starts. Algorithm 2 is presented for data preparation and its corresponding illustration is shown in Fig. 4. After data acquisition, ith sensor node s_i stores the set of data into its DB_i: $Cases$ dataset. t_k is the ith time slot that the data is collected within a specific time period Q. s_i may have a large set of acquired data. A partial set of data can be seen in Fig. 4(i). Then, s_i performs a *proportion test* to refine the acquired data.

Proportion Test. As part of the data preparation algorithm, we perform a proportion test [28] (i.e., to check whether the collected data is within a given range or not). We then configure a simplified dataset $Controls$. It includes (i) a set of ranges to classify the acquired data in order to find frequencies and simplified values and (ii) a set of tuples with different frequencies and values defined/collected that can be defined by the healthy data (when there is no event in an application). The ranges are set between 0.01 and 1. Note that these ranges can be different for different applications due to the nature of sensor data, their special characteristics, as well as the intensity of an event required in a particular application. Note that, without mining all of sensor s_i's data, there is no guarantee whether there is an event or not. In `DPminer`, a set of tuples (H_h) is defined as value and frequency combinations of different dataset. The key goal by defining this is to find data patterns that may not have a significant frequency and value differences in $Cases$ and $Controls$.

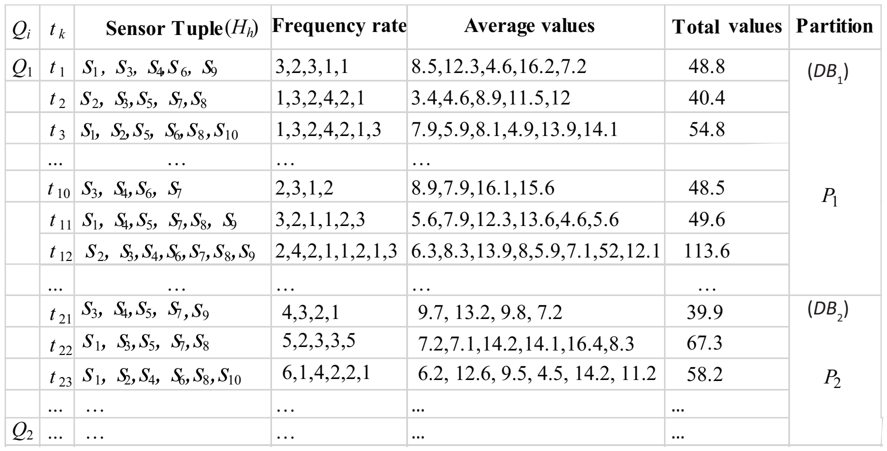
Through the proportion test, a significant amount of unnecessary, irregular, or null data (i.e., the data having no relation to event information, not indicate the data in $Controls$) can be reduced. Although the proportion test helps to reduce irregular data, we still need redundant/duplicate data for event detection so do not skip them. The proportion test establishes a data pattern by comparing close frequencies and values between $Cases$ and $Controls$ ($H_{in} : \pi_{Case} = \pi_{Control}$ vs $H_{out} : \pi_{Case} \neq \pi_{Control}$, where H_{in} and H_{out} denote the frequencies and values that are 'in' the range and 'out' of the range, respectively) in between $Cases$ and $Controls$). We denote the frequencies in the union of $Cases$ and $Controls$ by π. In the following equation, p_{Case}, $p_{Control}$, and p are estimates of π_{Case}, $\pi_{Control}$ and π, respectively. Then, we have,

$$z = \frac{p_{case} - p_{control}}{\sqrt{p(1-p)(\frac{1}{\pi_{case}} + \frac{1}{\pi_{control}})}}. \tag{10}$$

Under the null hypothesis of no difference in values, the square of the statistic z^2 follows the *Pearson's chi-squared test* [29]. In Fig. 4(iii), we have the label for the data for sets of tuples H_h. Based on this tuple set, every sensor calculates the total values and frequencies that are used in the *DP-Tree* development, as shown in Figs. 6(v) and 6(vi) .

Algorithm 2. Data Preparation and Summarization

```
for each node $s_i$
  Acquired data // e.g., step (i) in Fig. 4
  Pass the acquired data through the ProportionTest
  Classify and label all the data according to the ranges
        (see step (ii) and step (ii) in Fig. 4
  Calculate frequency and value set
```



Q_i	t_k	Sensor Tuple(H_h)	Frequency rate	Average values	Total values	Partition
Q_1	t_1	S_1, S_3, S_4,S_6, S_9	3,2,3,1,1	8.5,12.3,4.6,16.2,7.2	48.8	(DB_1)
	t_2	S_2, S_3,S_5, S_7,S_8	1,3,2,4,2,1	3.4,4.6,8.9,11.5,12	40.4	
	t_3	S_1, S_2,S_5, S_6,S_8,S_{10}	1,3,2,4,2,1,3	7.9,5.9,8.1,4.9,13.9,14.1	54.8	
	...	…	…	…		
	t_{10}	S_3, S_4,S_6, S_7	2,3,1,2	8.9,7.9,16.1,15.6	48.5	P_1
	t_{11}	S_1, S_4,S_5, S_7,S_8, S_9	3,2,1,1,2,3	5.6,7.9,12.3,13.6,4.6,5.6	49.6	
	t_{12}	S_2, S_3,S_4,S_6,S_7,S_8,S_9	2,4,2,1,1,2,1,3	6.3,8.3,13.9,8,5.9,7.1,52,12.1	113.6	
	...	…	…	…	…	
	t_{21}	S_3, S_4,S_5, S_7,S_9	4,3,2,1	9.7, 13.2, 9.8, 7.2	39.9	(DB_2)
	t_{22}	S_1, S_3,S_5, S_7,S_8	5,2,3,3,5	7.2,7.1,14.2,14.1,16.4,8.3	67.3	
	t_{23}	S_1, S_2,S_4, S_6,S_8,S_{10}	6,1,4,2,2,1	6.2, 12.6, 9.5, 4.5, 14.2, 11.2	58.2	P_2
	...	…	…	...	...	
Q_2	...	…	…	...	...	

Fig. 5. A sensor DB with sensor data values, sensor tuples, and each DB partition corresponding to a processor.

Make a summary of the total frequencies and values

After the data preparation, we can begin the second stage of the mining process which we call DSP mining process, each sensor represents itself with different data frequencies and values (instead of '0/1' values). Next section will illustrate the pattern mining sensors to store and mine the data.

6 DSP Mining Through *DP-Tree* Development

This section studies data mining in sensors of the CPS through *DP-Tree* development, and generates a differential sensor pattern (DSP), and shows the event detection through the DSP.

6.1 DP-Tree Development

We devise a data mining tree structure (called *DP-Tree*) on a partitioned database DB_i for generating a DSP. Each s_i maintains a *DP-Tree* to mine the pattern. The tree structure is composed of two segments: insertion segment and restructuring segment. Insertion segment arranges local DB_i contents into the tree, while restructuring segment restructures the tree into descending order.

6.1.1 Insertion Segment

We consider DB_i as shown in Fig. 5. We also consider that s_i can have two or more processors P_1 and P_2. In Fig. 5, the rows corresponding to P_1 mean that these rows are within DB_1. If s_i first has only one process, and the parts of its data (if any remain) may be processed by another processor of its own, or a neighboring sensor which is free of tasks at the time slot. ith DB_i is assigned to the ith respective processor, as shown in Fig. 5. s_i develops the insertion segment of *DP-Tree* in parallel.

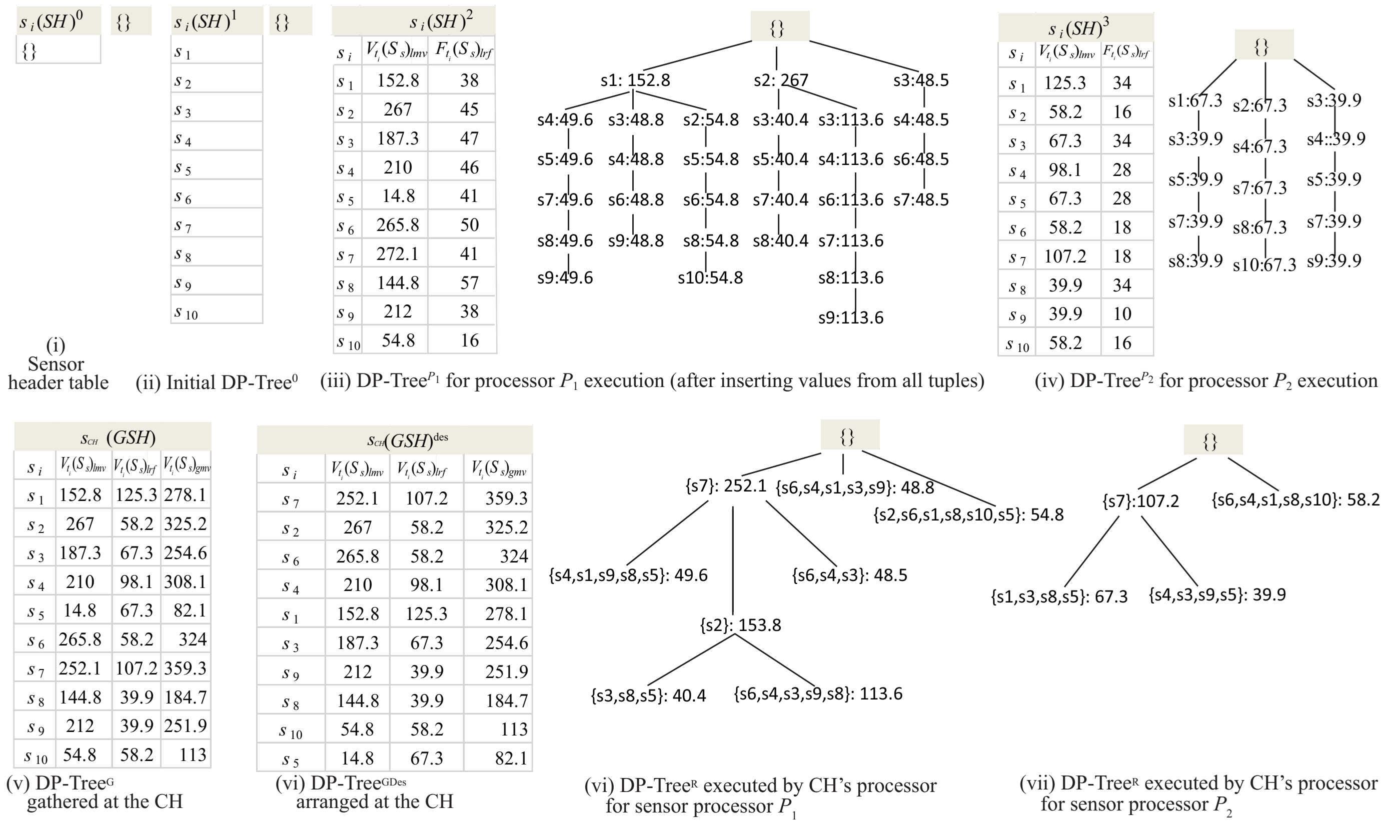
To illustrate the details of the tree structural process, we depict a part of the data from database DB in Fig. 6. It shows that ith sensor's sub-database (DB_1) that is processed by ith sensor processor P_1. Consider the *DP-Tree* having q tuples for a set of sensors (which are mainly neighbors). *DP-Tree* is executed by each sensor but the data can be shared and processed by other sensors. This implies that all the partitions of DB are processed by different processors. Particularly, all of the *DP-Trees* are executed in parallel. The step-by-step development processes of *DP-Tree* (with the corresponding representation in Fig. 6) is as follows.

Step 1 The *DP-Tree* is initialized with developing ith sensor s_i's header table, denoted as $s_i(SH)^0$. Initially, it is empty (having a 'null' value), as shown in Fig. 6(i). This is because, the table for the tree is made empty after a period of event detection operation. However, the sensor pattern tuples can be kept for further analysis with additional space adjustment.

Step 2 In table $s_i(SH)^1$ as shown in Fig. 6(ii), the rows are allocated for the neighboring nodes. This is arranged according to the lexicographic order of sensor identifiers (i.e., $s_1 > s_2 >, \ldots, s_m$. Here, '$>$' implies the order of sensor ranks). The table is built by inserting every tuple into the DB_i one after another (see [10] for the lexicographic order). See Fig. 6(ii) for sensor ordering.

Step 3 All the tuples in each ith DB_i are inserted into the respective *DP-Trees*, following the sensor order. As shown in Fig. 6(iii) and Fig. 6(iv), the lmv values of $V_{t_k}(H_h)_{lmv}$ and the lrf values of $F_{t_k}(H_h)_{lrf}$ are calculated (refer to Fig. 5 for example prepared data) and inserted into tables $s_i(SH)^2$ and $s_i(SH)^3$, respectively. These are processed by processor P_1 and P_2, respectively. In Fig. 6, it is seen that $s_i(SH)^2$ and $s_i(SH)^3$ are complete representations of sensors DB_i, and $s_i(SH)^2$, and $s_i(SH)^3$ are constructed by lmv and lrf. Note that, only the lmv values are shown in the tree.

Step 4 After the insertion segment ends, the restructuring segment begins. The goal of these segments is to achieve a highly compact *DP-Tree*, which will utilize less memory and facilitate a fast data mining process. The processor P_{CH} of a corresponding CH calculates the $V_{t_k}(H_h)_{gmv}$



$s_i(SH)^0$
{}

$s_i(SH)^1$
s_1
s_2
s_3
s_4
s_5
s_6
s_7
s_8
s_9
s_{10}

$s_i(SH)^2$		
s_i	$V_{t_i}(S_s)_{lmv}$	$F_{t_i}(S_s)_{lrf}$
s_1	152.8	38
s_2	267	45
s_3	187.3	47
s_4	210	46
s_5	14.8	41
s_6	265.8	50
s_7	272.1	41
s_8	144.8	57
s_9	212	38
s_{10}	54.8	16

$s_i(SH)^3$		
s_i	$V_{t_i}(S_s)_{lmv}$	$F_{t_i}(S_s)_{lrf}$
s_1	125.3	34
s_2	58.2	16
s_3	67.3	34
s_4	98.1	28
s_5	67.3	28
s_6	58.2	18
s_7	107.2	18
s_8	39.9	34
s_9	39.9	10
s_{10}	58.2	16

(i) Sensor header table (ii) Initial DP-Tree^0 (iii) DP-Tree^{P_1} for processor P_1 execution (after inserting values from all tuples) (iv) DP-Tree^{P_2} for processor P_2 execution

$s_{CH}(GSH)$			
s_i	$V_{t_i}(S_s)_{lmv}$	$V_{t_i}(S_s)_{lrf}$	$V_{t_i}(S_s)_{gmv}$
s_1	152.8	125.3	278.1
s_2	267	58.2	325.2
s_3	187.3	67.3	254.6
s_4	210	98.1	308.1
s_5	14.8	67.3	82.1
s_6	265.8	58.2	324
s_7	252.1	107.2	359.3
s_8	144.8	39.9	184.7
s_9	212	39.9	251.9
s_{10}	54.8	58.2	113

$s_{CH}(GSH)^{des}$			
s_i	$V_{t_i}(S_s)_{lmv}$	$V_{t_i}(S_s)_{lrf}$	$V_{t_i}(S_s)_{gmv}$
s_7	252.1	107.2	359.3
s_2	267	58.2	325.2
s_6	265.8	58.2	324
s_4	210	98.1	308.1
s_1	152.8	125.3	278.1
s_3	187.3	67.3	254.6
s_9	212	39.9	251.9
s_8	144.8	39.9	184.7
s_{10}	54.8	58.2	113
s_5	14.8	67.3	82.1

(v) DP-Tree^G gathered at the CH (vi) DP-Tree^{GDes} arranged at the CH (vi) DP-Tree^R executed by CH's processor for sensor processor P_1 (vii) DP-Tree^R executed by CH's processor for sensor processor P_2

Fig. 6. Distributed and parallel development of *DP-Tree* in sensors of the CPS.

and $F_{t_k}(H_h)_{grf}$ values for each sensor processor which is available at each sensor's table $s_i(SH)^3$. This is a relatively small sequential step and s_{CH} performs this task. Table $s_{CH}(GSH)$ contains these values.

Step 5 When P_{CH} finishes the calculation of all $V_{t_k}(H_h)_{gmv}$ and $F_{t_k}(H_h)_{grf}$ values, it then sorts the sensors in table $s_i(GSH)$ according to the descending order of gmv values (called $s_i(GSH)^{des}$) as shown in Fig. 6(vi).

Step 6 CH sensor i_{CH} then broadcasts $s_i(GSH)^{des}$ to all of its sensors so that each sensor processor P_i facilitates restructuring as well as mining phases. s_i is enabled to *merge sort* to put the tree structure according to $V_{t_k}(H_h)_{gmv}$. For restructuring $s_i(GSH)^{des}$ to have the *DP-Tree*, a branch sorting method (BSM) is used [30]. BSM uses the merge sort to sort every path of the prefix tree. This approach first removes the unsorted paths, then sorts all the paths, and finally reinserts them into the tree. At this stage, a computationally inexpensive but effective compression process is employed. This puts the sensors with the same values of $V_{t_k}(H_h)_{mv}$ in each branch of the tree and merges them to a single node. The final *DP-Tree*, after restructuring and compression, is shown in Fig. 6(vii), after having changed from Fig. 6(i) to 6(ii) and from Fig. 6(vi) to 6(vii), respectively. Due to space limitations, we ignore further analysis of the mining process by the *DP-Tree*.

Based on the two segments of tree structure above, s_i first generates an initial DSP. If there is no event detected, DSP can be empty, i.e., $D = \{\}$. ith sensor then forwards the DSP to its CH. The CH receives all such patterns from sensors, mines the patterns, and then finally generates a DSP that may convey event information. If the system user wishes, the CH can be enabled to provide a value as an event indicator, which can be calculated by the combination e_V and e_F. If $(e_V + e_F) > 1$, an event has occurred around those sensors in the DSP. The reason is that whenever an event happens, both values and frequencies should be more than 1. The CH forwards the final sensor pattern after making association between all the pattern received from the sensors. In the case of the presence of an event, the CH may request the sensors , which are in the DSP, for the data, which are in the DSP.

6.2 Computation and Communication Tradeoff

6.2.1 *The computation cost in the sensor of the CPS*

Initially, sensor s_i has tasks of data preparation, including data acquisition. Let c_{cr}, c_{in}, $c_{F_{t_k}}$, and $c_{V_{t_k}}$ be the computation costs of data cross-checking with data in $Controls$ through the ProportionTest, refined data insertion, total frequencies, and values computations. Then, the total computation cost for data preparation is $C_{dp} = c_{cr} + c_{in} + c_{F_{t_k}} + c_{V_{t_k}}$. We have DB_i of sensor s_i. Let V and F be the total number of values and frequencies in DB_i respectively. Assume that the average computation costs to scan one tuple from DB_i and to insert it into the *DP-Tree* are c_S and c_I, respectively. Therefore, the total cost to scan all tuples from DB_i and insert them into the *DP-Tree* is $C_c = V \times F \times (c_S + c_I)$. The total cost for the CH is $C_h = c_{GSH} + c^{des}_{GSH} + c_{mine}$ for tasks in tables $s_{CH}(GSH)$ and $s_{CH}(GSH)$ and in DSP mining. $C_a = c_m + c_{BSM} + c_{P_i}$ is the extra computation cost required for merge sort c_m, BSM sort (c_{BSM}), and initial sensor pattern generation (c_{P_i}). The total computation cost for *DP-Tree* and the DSP generation is given by:

$$C_T = C_{dp} + C_c + C_h + C_a \tag{11}$$

The communication cost in the sensor of the CPS. Recall that *DP-Tree* in `DP-miner` functions in a cluster. We first find cluster-wise energy costs for communication. Assume a cluster denoted by S_c contains a total of n_i sensors. Then, the total energy in a cluster, denoted by $cost(S_c)$, is given by the following:

$$cost(S_c) = X \cdot e_T + (n_i - 1) X \cdot e_R + (n_i - 1) \frac{n_t}{2} (e_T + e_R) \tag{12}$$

where e_T and e_R are the energy costs for transmitting and receiving X data and n_t is time length. The first two terms at the right side of (12) are , respectively, the energy costs required when a CH broadcasts its time data to its sensors or the BS, and when all the sensors receive the broadcasts, respectively. The last term is the energy consumption when the $(n_i - 1)$ sensors in the cluster transmit back their response (including connection establishment), table data transmission, sensor pattern transmission, and all data transmission if it is in the DSP; a CH may receive the request for data transmission.

From (12), we can get $cost(n_i) = cost(S_c)$, indicating that the energy consumption of a cluster is only associated with n_i sensors in a cluster. When m sensors are partitioned into equal-sized clusters of size l, then the number of clusters $isz = m/l$. The optimal cluster size [23] can be obtained by looking for l that minimizes the *average energy cost per node*, defined thusly:

$$Cost(s_i) = \frac{z.cost(l)}{m} + \frac{1 - l/m}{l - 1} \kappa \tag{13}$$

where κ is a constraint on the overlapping sensor nodes in the cluster [23].

The right side of (13) indicates that, in terms of wireless communication, partitioning sensor network into large-sized clusters is preferred when e_T is greater than an available transmission energy indicator, while generating small-sized clusters is better if otherwise.

7 Performance Evaluation

7.1 Methodology

We evaluate the performance of `DPMiner` and its *DP-Tree* development for a DSP generation. The objective of the evaluation is to verify its ability in terms of communication and computation cost, and the quality of event detection. We conduct an extensive set of simulations and then highlight the main characteristics that enable for the mining process using *DP-Tree*.

We consider two sets of large datasets for the evaluation, and we evaluate the performance of `DPminer` in heterogeneous sensors in the CPS. The first dataset containing real sensor data is from the Intel Berkeley Research Lab [15] and has been widely used [10]. This consists of tuples from 54 sensors and 84600 time slots (one month). The second *dataset (available online)* we used is collected by an SHM system deployed on the Guangzhou National TV tower (GNTVT) [31]–[34]. It consists of a set of 800 wired acceleration sensors data, collected in 273000 time slots. The dataset consists of vibration signals collected from a sophisticated SHM system. However, to see the DSP mining performance in sensors of the CPS, we have conducted simulations seriously considering WSN aspects, commutation, communication, event detection. We consider the GNTVT SHM dataset in the 200-sensor case.

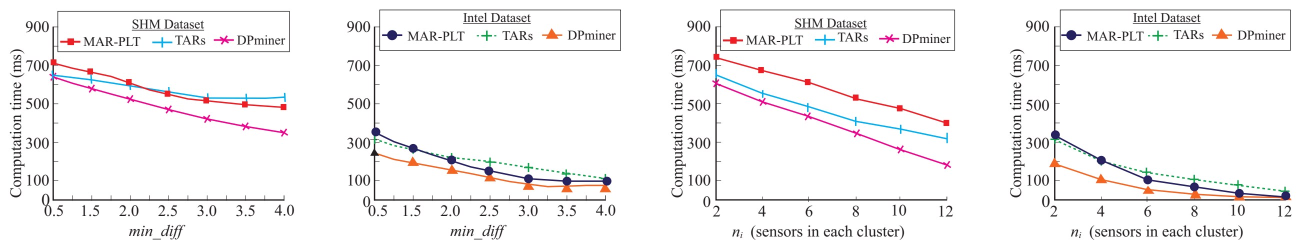
Considering recent advancements of the CPS, as modeled before, we consider that some sensors could have greater memory and more processors than others. Each DB is distributed among the sensors, and the processor in the node has complete access to its portion of the database. Simulations are performed with Omnet++ simulation tool within a $50m \times 500m$ rectangular field, taking into account the SHM environment, e.g., a high-rise building, bridge, aircraft, etc. The hardware constants for the processor and transceiver are from the Intel Xscale PXA271. The Imote2 uses a CC2420 radio chip for wireless communication. We model each sensor with six discrete power levels in the interval {-10dBm, 0dB}, considering the Imote2s power settings, which is tuned within the IEEE 802.15.4. We adopt similar configurations from an improved log-normal path loss model [35] and a synchronized data collection method [28] only for data forwarding. For the sake of convenience, we normalize the communication cost and computation cost from 0% to 100%.

For observing the presence of an event, we consider the GNTVT SHM dataset and give different levels of event injection (damage information) at different sensor locations (by modifying the input signal randomly in the data sets of (5-10)th sensors, (41-45)th sensors, (90-95)th sensors, and (170-175)th sensors). For comparison, we consider two other sensor network data mining schemes: MAR-PLT [10] and TARs [14]. The main reason of choosing them is that the similarity in terms sensor data mining or pattern mining and the hints for event information.

7.2 Performance Results

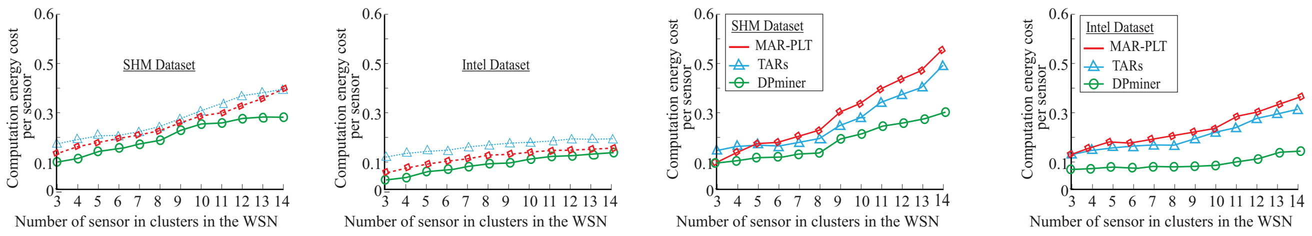
7.2.1 Computation Cost

In the first set of simulations, we observe the average computation time in generating a DSP in `DPminer`. We gather the time for two data set computations in sensors of CPS. The total computation time is composed of the time for data preparation, *DP-Tree* development (including data insertion, tree restructuring, delay in data broadcasting/receiving between the CH and sensors), and finally, DSP generation. The results for the two data sets at their respective min diff parameter settings (defined in Section III) are in Figs. 7(i) and 7(ii). We vary the *min_diff* parameter from 1.0 to 4.0. It



(i) Computation time vs. *min_diff* (ii) Computation time vs. *min_diff* (iii) Computation time vs. n_i (iv) Computation time vs. n_i

Fig. 7. Average computation time in different network data mining schemes for executing to the GNTVT SHM dataset and Intel dataset: (i) and (ii) computation time vs. *min_diff*; (iii) and (iv) computation time vs. n_i.



(i) Computation energy in DPminer (ii) Computation energy in DPminer (iii) Computation energy in different schemes (iv) Computation energy in different schemes

Fig. 8. Computation cost in data mining in the sensor: (i) and (ii) in `DPminer`; (ii) and (iv) comparison between `DPminer`, MAR-PLT, and TARs.

shows the average computation time for the three schemes. It is found that the computation time in `DPminer` is a little lower compared to that of MAR-PLT and TARs.

We note that the computational load is almost equally distributed among all the processors in a cluster for the two data sets. In Figs. 7(iii) and 7(iii), it is evident that the computation time decreases when the number of processors increases in each cluster. In the simulations, the number of processors in developing the *DP-Tree* distributedly and parallely in a cluster is varied for each dataset in different simulations. Importantly, we found that the rate of decreases is faster in `DPminer` than the rates found in MAR-PLT and TAR.

7.2.2 Energy Cost of the sensor in the CPS for DSP Mining

Recall that the performance of different data mining schemes in terms of the c energy cost and event detection is shown in Fig. 1, which is achieved by using the Intel dataset.

First we discuss results of the computation cost achieved by using the SHM dataset and Intel Dataset. The energy cost of the sensor for computation in `DPminer` is shown in Figs. 8(i) and 8(ii) for the both datasets. We can see computing SHM dataset need additional computation cost in `DPminer`. Comparison between `DPminer` and other schemes for the two datasets can be in Figs. 8(iii) and 8(iv), respectively. These show that the computation energy cost for data mining is much lower compared to other schemes

Next, we discuss the results of communication cost achieved by using the SHM dataset and Intel Dataset. The energy cost of the sensor for communication in `DPminer` is shown in Figs. 8(i) and Fig. 8(ii). Based on parameters for sensors and clusters, we demonstrate the communication energy cost for various cluster sizes, when the transmission power e_T is set from $e_T = 1e_R$ to $e_T = 6e_R$. This is because the communication cost dominates the energy cost in a wireless sensor. We normalize the energy cost usage between 0 to 100%.

With the increase of sensors in clusters, the communication cost decreases slowly at first; then, it increases speedily. Some observations are as follows: when the number of sensors (n_i) in a cluster is small to medium (e.g, 3 to 6), the sensors have low communication tasks for *DP-Tree* development; when n_i is medium to high (e.g, 6 or more), there are high communication tasks for *DP-Tree* development. The comparison of different schemes in terms of communication energy cost can be seen in Figs. 8(iii) and 8(iV). We find that `DPminer` consumes a lower amount of energy than either MAR-PLT and TARs. MAR-PLT requires higher energy cost for communication than TARs. Both MAR-PLT and TARs apply a lot of association rules between sensors and interactions, and the tree development process in them requires a significant communication cost in each step (which is not investigated in their works).

In an observation, we find that both the computation and communication energy costs are steady at first and then gradually increase when the size of *DP-Tree* increases. With similar computation energy costs, `DPminer` significantly reduces the communication energy cost in data mining compared to both MAR-PLT and TARs.

The computation cost decreases slowly, and but communication cost speedily. Some reason are because the computation tasks of DB_i is performed in parallely and distributedly in more number of processors so that the computation time and cost decreases, but the data transmission in the cluster increases. With the increase of e_T , the cluster size is increased but does not go unbounded considering the energy cost of the *DP-Tree* for a large cluster.

7.2.3 Performance on the Event Detection

Finally, we report an interesting result about event detection performance in `DPminer` regarding the situations of event detection in AR-PLT and TARs. Recall that we have provided event information injection into some of the sensors' data. Corresponding clusters containing these sensors should have a DSP, by which the detection indicator based

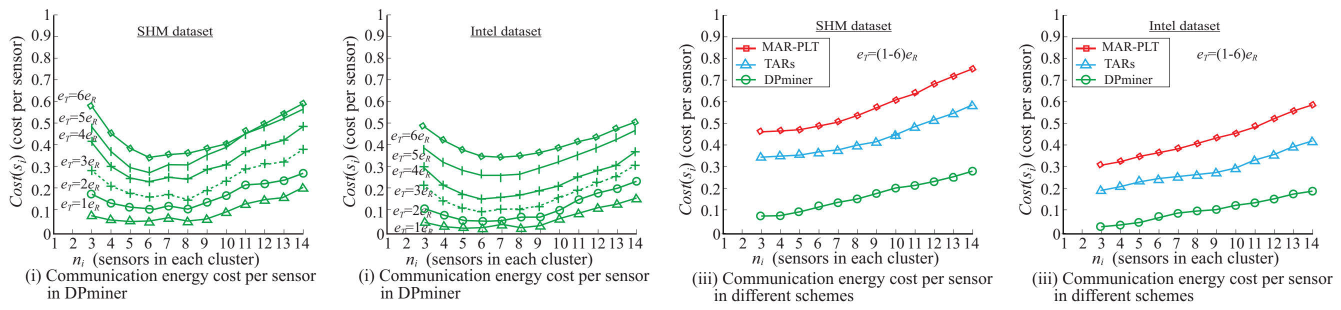


Fig. 9. Performance of the communication cost.

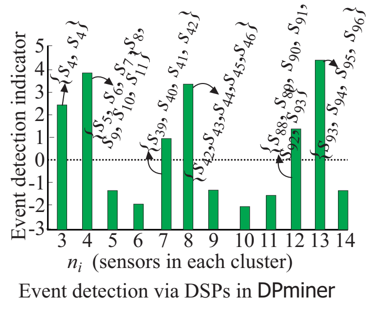


Fig. 10. Performance of the event detection through differential pattern mining in `DPminer`.

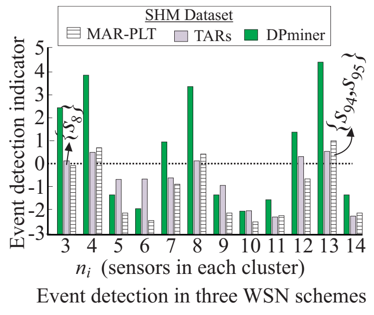


Fig. 11. Performance of the event detection through differential pattern mining in different schemes.

on e_V and e_T is calculated. Fig. 10 shows the performance on the event detection in different clusters in `DPminer`. Here, a detection indicator is calculated by average values of $(e_V + e_F)$ in different time slots within a given period of time in the wireless sensor of the CPS. We find the indicator cluster-wise since the *DP-Tree* is developed between sensors in each cluster in a distributed and parallel manner. Different values are found as detection indicators (which is different from binary 0/1 value) in each of the cluster, which is calculated from sensors in the differential sensor pattern (pattern is shown in Fig. 10.

As shown in Fig. 11, we can see that the sensors around clusters 3, 4, 8, 12, and 13 have DSPs and detection indicators with values larger than 2 in `DPminer`, while AR-PLT and TAR almost fail to detect the event. The TARs has a detection indicator in clusters 4 and 13, but indicators are less than 1. AR-PLT achieves a slightly better performance (in clusters 4, 8, and 13) than the TARs achieves. Some of the possible reasons are figured out here. The same transactional related association rules are used in the event detection, which do not reflect the actual event detection. The sensors have low event information, but they might be rejected by binary-based association rules ("0" for 0.49, while "1" for 0.51). If there is an acquired data value less than 0.5 (e.g., 0.46), both AR-PLT and TAR detect it as a binary "0" value (i.e., there is no event), which is the wrong detection. However, this low event intensity is also crucial for various applications, including SHM, industrial equipment monitoring, etc.

8 Conclusion

In this paper, we have proposed `DPminer`, a comprehensive data mining framework for wireless sensors in the CPS which functions in a distributed and parallel manner and is able to extract a pattern of sensors that have event information. Towards the event detection, we have presented a differential sensor pattern mining technique considering actual data. In the technique, we have not modified the actual data for the pattern generation. It is a unique mining framework which works on sensing actual values and providing important values as outputs (rather than "0/1" binary decision) for event detection. `DPminer` hints that if an application user wishes to have further analysis on the event, such outputs can be crucial. Thus, it can be useful for many CPS applications. We have validated that with a lower or similar computational time in generating a sensor pattern for event detection, `DPminer` can significantly reduce the energy for computation and communication in the CPS. Applying the differential sensor mining technique with a machine-learning approach and in big data environments will be our future work.

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Algorithm 3: Sensor Database Partition

```
Input: A set of wireless sensors with their database
Output: Each sensor with a partitioned database
  Sort $m$ sensor nodes according to $c_j$ descending order
  Sort $d$ partitions according $r_i$ descending order
    for $i = 1$ to $d$
      for $j = 1$ to $d[i].length$
        $m[i][j] \leftarrow d[i]m[j]$
```

Appendix A
Sensor Database Partitioning

We consider using heterogeneous sensors in the CPS, and share the processor tasks and partitioning the sensor database to balance the processing load on the sensors. We adjust the *DP-Tree* in such the CPS where the loads are distributed among the nodes in the system by the *knapsack problem* based resource-aware load balancing technique [36], [37]. The load balancing problem is a multiple knapsacks problem where each processor represents a knapsack and the overall processing capacity is defined by the number of the available processors. In our case, the WSN model has m nodes, where each node represents a knapsack and there are d partitions of datasets/database DB that need to be assigned to them where each partition is taken as a knapsack item. An important issue in the load balancing problem can be to minimize the overall parallel computation time. The problem thus becomes a minimization problem.

Let $[c_j^{CPU} c_j^{MEM}]$ be the capacity of the jth node and $j = \{1, 2, \ldots m\}$ and $[r_j^{CPU} c_{rj}^{MEM}]$ be the resource requirements of the ith partition and $i \in \{1, 2, \ldots d\}$. t_{ij} is the computation time for the ith partition in the jth node and x_{ij} is $\{0, 1\}$ variable that indicates whether partition DB_i is set into m_j. Then, we formulate the partition setting problem as a multi-knapsack problem with an objective of minimizing the total computation time, by setting a partition in the available sensor node as follows:

$$\min \sum_{i=1}^{d} \sum_{j=1}^{m} x_{ij} t_{ij} \tag{14}$$

$$s.t \sum_{i=1}^{d} r_i^{CPU} \cdot x_{ij} \leq c_j^{CPU}, \sum_{i=1}^{d} r_i^{MEM} \cdot x_{ij} \leq c_j^{MEM} \tag{15}$$

$$\sum_{j-1}^{N} x_{ij} = 1 \tag{16}$$

The first constraint (14) guarantees that the filling of knapsack j does not surplus its corresponding capacity c_j, and the second constraint (15) guarantees that each partition is allocated to one and only one of the sensor nodes. This is an NP-hard problem. To solve this problem, we apply the heuristic from [36] for the Virtual machines (VMs) placement in the cloud systems through emulated VM migration. In the method, a VM is directly placed to the best physical machine (PM), as long as PM has enough capacity. Otherwise, a migration-based placement technique is used, which migrates another VM from the current PM to accommodate the new VM.

Our partition setting method is similar to direct VM placement. We study the partition placement problem under the off-line scenario, where we know the information about the incoming partitions set a priori (i.e., partitions resource demand). We set one partition in one node according to the resource requirements (i.e., CPU, memory) of the partition. The pseudo-code for partition placement is shown in Algorithm 3. This type of resource-aware load distribution ensures minimum computation time, and thus optimizes the overall WSN system performance. After receiving load (partition), each sensor node develops the *DP-Tree* for a DSP generation.

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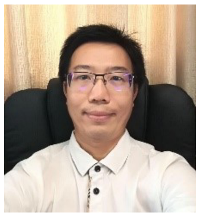

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