A Predictive Energy-Efficient Mechanism to Support Object-Tracking Sensor Networks

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ABSTRACT
In recent years, an increasing interest in deploying wireless sensor networks (WSNs) for real-life applications are have been found. However, before WSNs become a commodity, several challenging issues remain to be resolved. Object-tracking sensor network (OTSN)-based applications are widely viewed as being among the most interesting applications of WSNs. OTSN is mainly used to track certain objects in a monitored area and to report their location to the application's users. OTSNs are well known for their energy consumption when compared with other WSN applications. Here we propose a prediction based tracking technique using sequential patterns (PTSPs) designed to achieve significant reductions in the energy dissipated by the OTSNs while maintaining acceptable missing rate levels. PTSP is tested against basic tracking techniques to determine the appropriateness of PTSP under various circumstances. Experimental results have shown that PTSP outperforms all the other basic tracking techniques and exhibits significant amounts of savings in terms of the entire network's energy consumption.

Index terms
Data mining, object tracking, wireless sensor networks (WSNs).

1. INTRODUCTION
The sensor node is a very small device that represents the building blocks of the WSN. These nodes are being produced at a very low cost and yet with high levels of sophistication in terms of computing power, energy consumption savings, and multipurpose functionalities when compared with earlier generations of sensor nodes. WSNs are created by deploying a large number of sensor nodes in a certain area, which is usually called the *monitored region*, for monitoring purposes. These nodes are interconnected and are used together as a monitoring and reporting device to acquire specific types of data as desired by the application requirements. Object tracking, which is also called target tracking, is a major field of research in WSNs. The main task of an object tracking sensor network (OTSN) is to track a moving object and to report its latest location in the monitored area.

OTSN is considered one of the most energy-consuming applications of WSNs. Due to this fact, there is a necessity to develop energy-efficient techniques that adhere to the application requirements of an object-tracking system, which reduce the total energy consumption of the OTSN while maintaining a tolerable missing rate level. We propose the prediction-based tracking technique using sequential pattern (PTSP), which is an object tracking technique that revolves around the ability to predict the objects' future movements to track it with the minimum number of sensor nodes while keeping the other sensor nodes in the network in sleep mode. This would achieve my goal while significantly reducing the network's energy consumption.

The PTSP is based on the inherited patterns of the objects' movements in the network and the utilization of sequential patterns (a data-mining technique) to predict to which sensor node that the moving object will be heading next. Since the PTSP totally depends on prediction, it is possible to have some missing objects during the tracking process.

2. RELATED WORKS
Different classification techniques have been proposed in the literature for object tracking in WSNs. The naive scheme is considered a basic object-tracking technique, where all the sensors in the OTSN are kept active all the time, and therefore, each moving object in the network will be detected by the sensor nodes and reported to the base station every *T* milliseconds. The other schemes are explained as follows.

In the scheduled monitoring (SM) technique, all the sensor nodes in the network are allowed to stay in sleep mode; they change their status to active mode for a brief period of time where they start sensing their monitored area and report their findings to the base station, given that both the sensor nodes and the base station are well synchronized.

In the continuous monitoring (CM) technique differs the naive and schedule monitoring techniques; it does not involve all the sensor nodes in the OTSN network to track a moving object. The current active node will continue to monitor the moving object in its monitoring area until it leaves its coverage area and begins to enter a neighboring node detection area.

3. PREDICTION-BASED TRACKING TECHNIQUE USING SEQUENTIAL PATTERN FRAMEWORK
Assume that the sensor nodes are static and that the network topology, including the position of each sensor node in the network, is well known to the base station. In addition to that,

the communications between the sensor nodes in the network and base station will be based on single-hop communications.

The proposed PTSP is based on two stages: 1) sequential pattern generation and 2) object tracking and monitoring. In the sequential pattern generation stage, the prediction model is built based on a huge log of data collected from the sensor network and aggregated at the sink in a database, producing the inherited behavioral patterns of object movement in the monitored area. Based on these data, the sink will be able to generate the sequential patterns that will be deployed by the sink to the sensor nodes in the network.

This will allow the sensor nodes to predict the future movements of a moving object in their detection area. In the second stage, the actual tracking of moving objects starts. It includes the model of *activation mechanism*, which entails the use of the sequential patterns to predict which node(s) should be activated to continually keep tracking of the moving object.

3.1. Sequential Patterns

It can be viewed as a new data mining approach that standardizes the framework for splitting a new task into several sub-tasks under any part of category like aggregation or composition. The following provide its various highlighted definitions.

3.1.1. Definition 1

Let S represent the set of sensors in a certain WSN. The list $L = [(s1, t1), (s2, t2), (s3, t3), \ldots, (sm, tm)]$ denotes a list that contains the pairing of each sensor detection (represented by its corresponding sensor ID) and its equivalent time of detection, where $si \in S$ and $t_i \le ti{+}1$ for all $1 \le i < m$.

The pair (si, ti) represents the detection of a certain event by the sensor si, which took place at time ti. $O(L) = [s1, s2, s3, \ldots, sm]$ represents the list of sensors shown in L, except that it was chronologically ordered based on the time of detection recorded by each sensor. O called the list's sequential pattern.

3.1.2. Definition 2

The pattern $O=[s1, s2, s3, \ldots, sm]$ is considered a sub pattern of the pattern $O\_ =[s\_1, s\_2, s\_3, \ldots, s\_n]$. This can be interpreted as $O\_O\_$, if $m \le n$, and a list of incremental integers exists as $i1, i2, i3, \ldots, im$, where $1 \le i1 < i2 < \cdot\ \cdot\ \cdot < im \le n$, and $sk = s\_\ ik$ for $k=1, 2, .., m$. Thus, O is designated as the "sub pattern," whereas $O\_$ is called the "super pattern".

3.1.3. Definition 3

Let DS be a database of sensor lists. The support of the pattern O in DS is defined by the number of lists in DS, where the sequential pattern O represents a sub pattern of the lists' sequential patterns. Thus, $Support(O) = |\{L \in DS | O\ \_\ O(L)\}|$.

3.2. Sequential Tri-Sensor Patterns

Tri-sensor patterns can be represented as [*Source Sensor, Current Sensor, Destination Sensor*]. This represents the chronological ordering of the sensors' detection of a certain moving object in the network.

Therefore, the *source sensor* represents the sensor ID of the sensor, which detected a particular moving object *o* before it moved to the next sensor designated as the *current sensor*; later on, the object *o* moves to the next sensor denoted by *destination sensor*. In order to evaluate the statistical significance of a certain tri-sensor pattern, I had to calculate the *confidence*, in addition to its support, of each particular tri-sensor pattern.

3.3. Movement Pattern Acquisition

The proposed scheme relies on deploying the WSN and simply turning it on for the whole time to record movement patterns collected from sensors (basically the naive technique). As every object moves, its movement path and the sequence of sensors detecting it get recorded into a database. Each tuple in the database will contain the object ID and the ID of the sensor that detects this object, along with the time of detection.

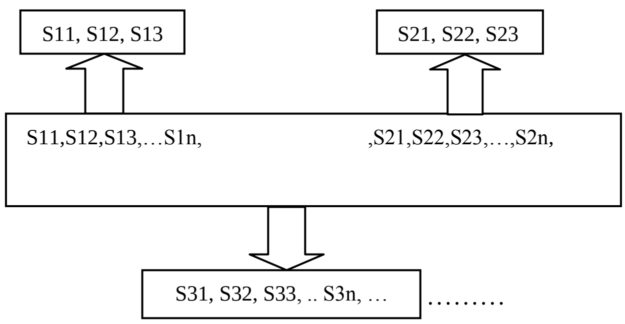
A pattern simply records the *source sensor* of a certain object (the sensor where the object used to be before moving toward the current sensor), the *current sensor*, and the sensor the object travelled to next, which is also called the *destination sensor*. These tri-sensor patterns are generated in an overlapping manner where the *Current Sensor* becomes the *Source Sensor* and the *Destination Sensor* becomes the *Current Sensor*, whereas the *Destination Sensor* will be the next sensor in the sequence. Table I shows the complete details for each sensor that tracks or detects object movement.

Table I: Objects Movement Log

Time	Sensor ID	Object ID
00:00	S3	OBJ 1
00:00	S9	OBJ 4
00:01	S4	OBJ 2
00:02	S12	OBJ 3
00:02	S6	OBJ 1
....	...	....

The generation of tri-sensor patterns as per sequential pattern model is depicted in the following figure.

Fig 1: TRI-SENSOR PATTERN GENERATION



This demonstrates how the tri-sensor patterns are generated in an overlapping manner from the sequence of detections by the sensor nodes in OTSN for a particular moving object. Here, the sink of first cycle has sensor nodes containing IDs like (S11, S12, S13… S1n) generate tri-sensor pattern (S11, S12, and S13) as Source Sensor, Current Sensor, and Destination Sensor respectively.

Table II: TRISENSOR PATTERN GENERATION FROM THE SEQUENCE OF DETECTIONS BY SENSOR NODES FOR EACH OBJECT

Object ID	Sensor Detection Sequence	Tri-Sensor Patterns Generated
Obj 1	S1,S2,S3,S4...	[S1,S2,S3], [S2,S3,S4],....
Obj 2	S21,S23,S25,S29...	[S21,S23,S25], [S23,S25,S29], ...
Obj 3	S32,S35,S37,S46, S48...	[S32,S35,S37], [S35,S37,S46], [S37,S46,S48],..
....	....	.....

As the patterns accumulate, we can find the most repeated patterns and draw conclusions there. For example, if we found that the pattern *S*1, *S*2, *S*3 too frequently occurs, this is that, if an object is at S2, coming from S1, then, mostly, it will head to S3.

TABLE III: AGGREGATING TRISENSOR PATTERNS BASED ON THEIR OCCURRENCE

Source Sensor	Current Sensor	Destination Sensor	Occurrence
S11	S23	S44	182
S12	S22	S52	132
S31	S41	S65	4080
S41	S51	S73	2400
S51	S62	S93	4896
S61	S83	S97	16

By applying simple mathematics (i.e., Factorial for two turn on/off sensor nodes and percentage for ratio of number of turn-on nodes to turn-off nodes), the confidence value is measured.

TABLE IV: SEQUENTIAL PATTERNS GENERATED FROM TRISENSOR PATTERNS' FREQUENCY OF OCCURRENCE

Source Sensor	Current Sensor	Destination Sensor	Confidence
S11	S23	S44	85.7%
S12	S22	S52	83.3%
S31	S41	S65	82.4%
S41	S51	S73	87.5%
S51	S62	S93	83.3%
S61	S83	S97	93.75%

Therefore, the higher the confidence value, the better the chance of predicting the next sensor node. While running the technique, we should also keep updating these patterns as new objects move. This makes our scheme adaptive to changing movement patterns, which we refer to as "active learning".The sensor nodes which are in active as well as in sleep mode (turn on / off while sensing) at their detection area, the actual tracking movement is predicted. The current sensor will utilize the embedded sequential patterns to decide which destination sensor it will activate. Also, it predicts the objects' future movements to track it with the minimum number of sensor nodes while keeping the other sensor nodes in the network in sleep mode.The sequential patterns generated in Table IV can also be represented using the implication form, which can be shown as follows:

[*S*11, *S*23] => *S44*, *Conf* = 85.7%
[*S*12, *S*22] => *S*52, *Conf* = 83.3%
[*S*31, *S*41] => *S*65, *Conf* = 82.4%
[*S*41, *S*51] => *S*73, *Conf* = 87.5%
[*S*51, *S*62] => *S*93, *Conf* = 83.3%
[*S*61, *S*83] => *S*97, *Conf* = 93.75%.

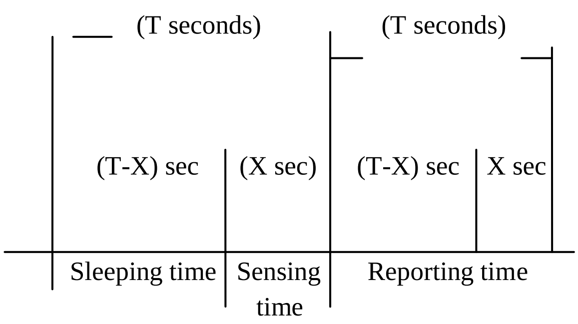
3.4. Deployment of Sensor Nodes

Here, all generated sensor sequential patterns are embedded to their respective sensor nodes, which resemble the second and final step in building the prediction model of our tracking technique. However, these sequential patterns will be continuously evaluated and updated to maintain a high level of accuracy in terms of our technique's prediction abilities.

3.5. Object Tracking and Monitoring - (Sensor Node Activation Mechanism):

After the completion of the first stage of the PTSP, i.e., sequential pattern generation, the second stage, in which the object tracking and monitoring starts. The key objective of this stage is to keep in sleep mode, for the longest possible period, any sensor node that has no object moving in its detection area, thus saving its energy.
Moreover, in the case of a moving object in the vicinity of a certain sensor node, this sensor node will not be awake all the time. It ought to switch to sleep mode as long as possible while not impairing the tracking process; this sensor node will be called the *current sensor*. The current sensor switches to active mode for *X* ms, and during this time, the current sensor senses its detection area. It reports the findings to the base station by the end of *X*, which also matches the end of *T* (the time period between reports).

Fig 2: Demonstrating the relation between *X*, *T*, and (*T* − *X*).



The last action the current sensor performs before switching to sleep mode is predicting the location of the moving object during the ($T - X$) *ms* and sending a message to the destination sensors to wake up after the ($T - X$). The current sensor will utilize the embedded sequential patterns to decide which destination sensor it will activate.

The decision to apply sequential pattern(s) on a particular sensor is based on the minimum confidence level required by the application, which would be required from any sequential pattern before it could be used to predict the future movements of a moving object. Here, the reporting time is measured by setting activation time at the destination sensor.
Therefore, if the application sets the minimum confidence level at 70%, then any sequential pattern with a confidence level lower than 70% will not be executed. Both the current sensor and the destination sensors will activate after the passing of $(T - X)$ ms and start tracking the moving object.

4. EXPERIMENTAL RESULT

Energy consumption analysis is the best preferred metric, in which all active and sleep mode sensor nodes are utilized in order to predict a next sensor node while tracking an object.

Energy Consumption Analysis

In this experiment, I have tested and compared PTSP to the other basic tracking schemes, i.e., Scheduled Monitoring (SM) and Continuous Monitoring (CM). Mean while, naive technique includes the new arrangement of sensor nodes in a clustered region in which they get refreshed.

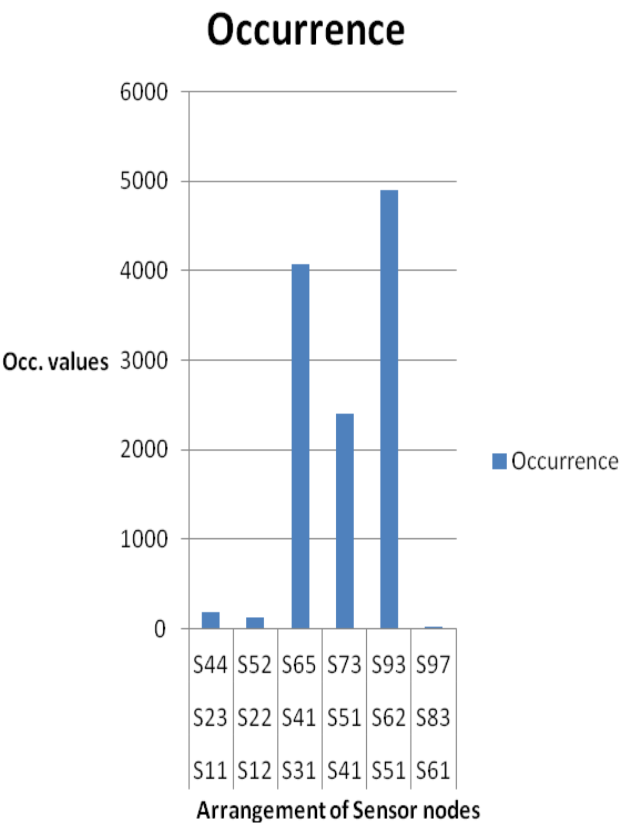


Fig 3: Graphical representation showing tri-sensor patterns' occurrence values

Here, both active and sleep mode duration of sensor nodes, the actual tracking movement is predicted. This is achieved by allocating all possible occurrences of tri-sensor patterns. As we run our technique, we should also keep updating these patterns as new objects move. This makes our scheme adaptive to changing movement patterns, which we refer to as "active learning".
In the case of CM and PTSP, the increase in the number of objects means an increase in the number of active sensor nodes and, thus we have higher energy consumption levels.

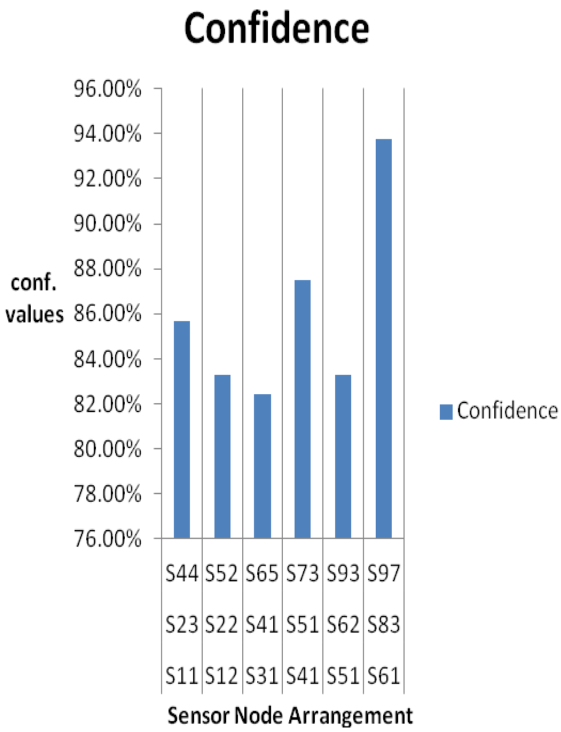


Fig 4: Graphical representation showing tri-sensor patterns' confidence values

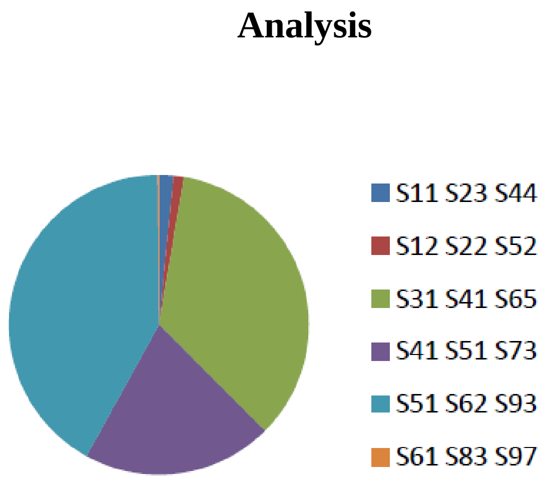


Fig 5: Energy Consumption Analysis for each tri-sensor pattern

By the above mentioned graph, the confidence values are set which promotes above 70%. Therefore, there is chance for predicting next sensor right. It shows the range of tri-sensor patterns for its highest confidence value.

5. CONCLUSION AND FUTURE WORK:

A method for proposing an energy- efficient PTSP, which implements a novel based approach in its prediction mechanism. PTSP utilizes the sensor sequential patterns to produce accurate predictions of the future movements of a certain object. These sequential patterns are continuously evaluated and updated to provide the prediction mechanism with the latest and most accurate predictions. Also the simulation of the proposed tracking scheme (PTSP) is done, along with two basic tracking schemes in which they are outperformed for comparison purposes.

From among these, PTSP is a best approach for supporting object tracking sensor networks and hence it increases the lifetime of a network by more energy consumption. The energy consumption for the radio component will be the subject of our future research.

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