International Journal of Innovative
Computing, Information and Control
Volume **9**, Number **3**, March **2013**

ICIC International ©2013 ISSN 1349-4198
pp. 1337–1355

COMMUNICATION-EFFICIENT TRACKING MODEL SELECTION METHODS FOR MULTI-MODEL BASED OBJECT TRACKING SENSOR NETWORKS

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Received January 2012; revised May 2012

Abstract. *The tracking technique is one of the most critical techniques in wireless sensor network applications. The methodology of most recently proposed tracking schemes is to predict the object locations based on a single object moving model, and periodically activate nearby sensors to monitor the target. In most real-world situations, a target moves with different movement patterns, and thus, accurately describing the movement of a target needs multiple moving models. Multi-model based Object Tracking Architecture (MOTA) is presented very recently to allow tracking irregularly moving objects by adopting different tracking models regarding movement properties of objects. However, MOTA only considered the framework of dynamically adopting tracking models in wireless sensor networks, but did not minimize the communication cost for data exchange among sensor nodes during monitoring objects. In this paper, we propose two communication-efficient tracking model selection strategies, called Bitmap Min-Max (BMM) Strategy and Aggregation-based Weighted Moving Average (AWMA) Strategy, to minimize the data transmitted in wireless sensor networks based on bitmap and aggregation techniques, respectively. We conduct a set of experiments to compare communication cost for the proposed methods. The results reveal that the proposed methods indeed efficiently minimize communication cost compared with the existing methods.*

Keywords: Object tracking sensor networks, Multi-model movement, Tracking architecture, Prediction, Simulation

1. **Introduction.** The location-based services play a significant role in the wireless sensor network applications [7, 17, 26], and are currently applied to many application fields, such as troops monitoring, wildlife habitat monitoring, and traffic control [8, 23]. For example, in the wildlife habitat monitoring application [3], a large group of sensors are deployed in the forest to monitor the wildlife periodically in order to understand the habits and customs of wildlife. Consequently, with the object tracking techniques over wireless sensor networks, scientists can observe the wildlife living behavior through merely connecting to Internet in the laboratory, instead of spending a great amount of hard working in an

outdoor and risky environment. Another object tracking application is the electronic military service. Thousands of sensor nodes are deoployed in the battle field so that these sensor nodes themselves can organize the ad hoc network for data communication. Each soldier equips a sensor node, thus, the object tracking technique can be used to monitor the movement of each soldier. In military activities, the commander can query the locations of troops through the object-tracking sensor network before making any decision. In addition, the commander can also know which soldiers do not achieve the scheduled progress. By the assistance of the object-tracking sensor network, the commander can even dynamically change the military strategy by only sending the new strategy to each soldier through the object-tracking sensor network. Other tracking applications in wireless sensor networks include patient monitoring in hospital management systems and so on.

To achieve the location-based services, the tracking system is one of the most critical fundamental component to retrieve the trajectory of target in the wireless sensor network [21]. Due to the significance of the location-based services, the location processing techniques are widely investigated from various research domains (e.g., hardware, network, system) in literature published recently. All these works are developed toward the location-based services, and we identified some current popular directions as follows according to domain aspects. On the hardware layer, certain signal processing methods are proposed for obtaining accuracy locations or efficiently tracking objects based on the hardware property [18, 20]. On the network layer, researchers addressed communication efficiency and distributed collaboration in tracking scenarios [15, 27]. On the system and data processing layer, many different software strategies are developed to improve the tracking performance with lower energy consumption, such as prediction techniques, sleep scheduling, model-based tracking [6, 11, 14, 24, 25]. Other additional tracking schemes proposed to monitor the target in the wireless sensor networks include [3, 10, 19, 21, 22, 25], and the rich literature manifests that the tracking applications vigorously grow and the tracking techniques are still inadequate to real applications in wireless sensor networks. Due to the unique properties of a wireless sensor network, such as the short communication range, scarce power, and limited hardware resources [1, 9], the tracking techniques in wireless sensor networks are widely discussed in the last decade. The tracking techniques can be also classified according to their tracking strategy. Next, we describe the evolution of the tracking techniques below and explain the relavance among the existing schemes. Then we will indicate the significance of our work investiaged in this paper.

Early tracking schemes adopted the continuous monitoring method that designated a group of sensors to constantly activate to monitor the target [3, 21]. Although continuous monitoring method can efficiently track the target, the continuous monitoring method has been proven to be an inefficient way for developing sensor applications [25], because constantly activating a group of the sensors would drain sensor energy rapidly. Thus, recent tracking schemes adopted the scheduled monitoring method to periodically activate a group of sensors to monitor the target based on a prediction mechanism [19, 25, 27]. However, the existing scheduled monitoring schemes based on the current prediction techniques are ineffective for a long-term object monitoring. The reason is that they pre-assume that the target always moves in a single moving model, but in most real world applications, the movement of a target for a long time might not be irregular, and cannot be accurately represented by only a movement model [4]. In order to monitor the irregular moving target for a long-term period, Chen and Liao [6] recently proposed a tracking framework, called Multi-model based Object Tracking Architecture (MOTA), to support the target monitoring with multiple movement patterns, the idea behind MOTA is to dynamically select the best tracking module to monitor the target among the equipped tracking modules according to different types of movement behavior. By intelligently switching between the multiple tracking modules, MOTA can reduce the probability of target loss, while monitoring targets for long-term periods.

The advance of MOTA is to add a new dimension on the research area of object-tracking sensor networks (OTSN) due to its multi-model architecture and operations on OTSN. The superior of the tracking performance is also shown in the related publication [6]. However, MOTA does not consider the optimization issue on the data communication over distributed sensor networks during monitoring objects. If an object has frequently moved across territory of sensor nodes, a node would send the large size data of the movement history to the next node for selecting a proper sensor node set to track the object. Hence, as time increases, more data size for the movement history is transmitted inside the sensor network than that in earlier time, and such extra energy consumption would shorten the service time of the sensor network. This motivates us to investigate the communication optimization issue in the multi-model object tracking architecture. Notice that the statistics of object movements are performed inside the sensor network, and moreover, the energy and the hardware resources are limited in a single node. Hence, only the short term of past movement history is collected, and the design of determining the next proper tracking model is not supposed to use algorithms with too high computation complexity.

In order to lend an impetus to the MOTA framework, the communication issue needs to be addressed to increase the practicability, because the communication component consumes most energy in a sensor application [1]. Analysing the workflow of MOTA (we will present the details in Section 3), the movement history is used to determine a proper tracking model in a sensor node. Hence, in this paper, we propose two communication-efficient tracking model selection strategies, called *Bitmap Min-Max (BMM) Strategy* and *Aggregation-based Weighted Moving Average (AWMA) Strategy*, to significantly reduce the data transmitted in wireless sensor networks. BMM is inspired by the compression theory, such as the bitmap techniques. The basic idea of BMM is that the maximal monitoring cost can be estimated from simply scanning the usage of recovery functions, instead of the complete history of monitoring costs. In BMM, the usages of recovery functions of each track model in the observed period are encoded as a bitmap structure, *recovery-function usage table*. When the monitoring task is handed over, only the bitmap structure is transmitted in OTSN. Thus, the communication data is greatly reduced. Contrast to BMM, AWMA is designed based on the concept of the aggregation technique. The basic idea of AWMA is to use the weighted moving average monitoring cost in the current period to represent the weighted moving average of historical monitoring costs for the next period. Therefore, the aggregation data size transmitted to next node for monitoring the object in the next period is minimized. After the presentation of the proposed strategies for reducing the communication cost, we further conduct a comprehensive set of experiments to compare the proposed methods against the existing methods on the communication cost. The results reveal the superior of BMM and AWMA, and show that the propsed methods indeed significantly reduce the communication cost by over 50% in most cases.

The rest of the paper is organized as follows. In Section 2, we describe background and general tracking systems. In Section 3, we present the overview of multi-model based object tracking architecture. Then, we present two our proposed communication-efficient model selection strategies, i.e., BMM and AWMA, in Section 4. In Section 5, we conduct experiments to compare the performance of these two proposed model selection strategies. Finally, we conclude the paper in Section 6.

2. Background and Environment.

2.1. Sensor network. A sensor network consists of a large number of stationary sensors uniformly deployed in the interested environment. These sensors have sensing, computing and communication capabilities, and are well time-synchronized to achieve task cooperatively [1]. Each sensor has an unique sensor identification [19], and is aware of itself location through GPS [21], etc. With current localization techniques, the sensors can collaboratively compute locations of a moving object.

Most of today's sensors are able to switch between the active mode and the sleep mode for energy conservation [25]. Since a sensor consumes a much greater amount of energy in active mode than that in sleep mode, a sensor should stay in sleep mode as long as possible to prolong the lifetime of the sensor network. Thus, when the sensors are assigned with a task, the sensors would switch to active mode for completing the task. After the task is completed, the sensors switch to sleep mode for energy conservation. Notice that if nodes are in the sleep mode, they can be waked up through a wakeup radio [28]. Some more discussions about the energy conservation issue for the network layer can be found in our pervious work [12].

2.2. Generic tracking system. Figure 1 shows a generic tracking system which is organized by referring to existing tracking system [5, 19, 25]. A generic tracking system has three components, including targets, monitoring sensor set (MSS), and target location database (TLDB). The components are described as follows. *Targets* are moving objects monitored by the tracking system. The targets are equipped with actuators and have an unique identification (o_{id} in the figure), such that the tracking system can detect and recognize them. A *monitoring sensor set (MSS)* is a group of sensors used to collaboratively monitor a target and acquire the locations of the target. While the target moves out the region monitored by the MSS, the MSS members are re-arranged for continually monitoring the target. In order to avoid redundantly re-arranging the MSS members, the MSS head, called MSS leader, is elected by the MSS, and would re-arrange the next MSS members. The *target location database (TLDB)* is a centralized server that maintains the target locations, and can provide the sequential target locations or the target trajectory for spatio-temporal applications or location-based services. In TLDB, each target location is record in the form of $< o_{id}, o_t, o_{loc} >$, where o_{id} is the identification of the target, o_t is the timestamp, and the o_{loc} is the target location.

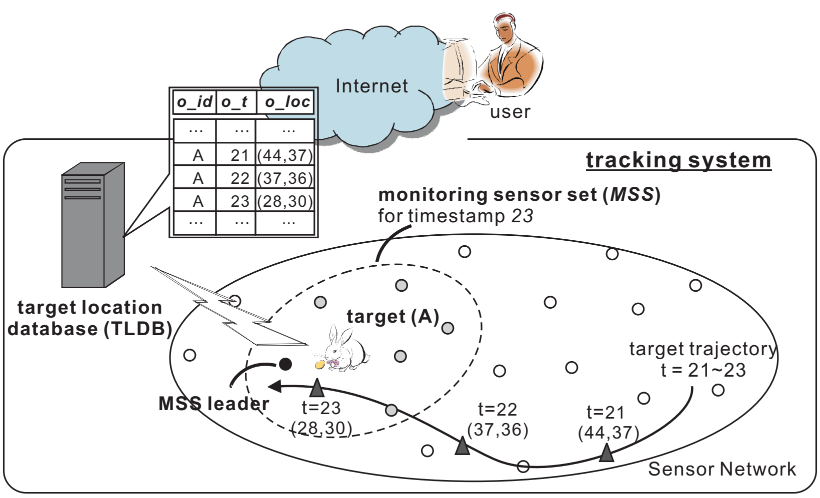


FIGURE 1. The generic tracking system

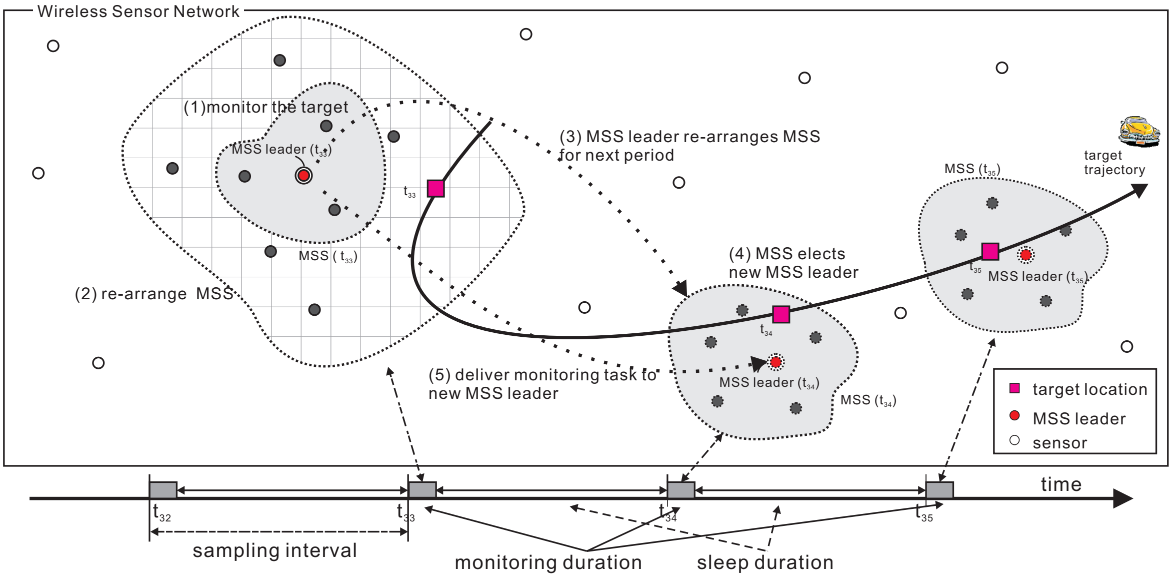


FIGURE 2. The target tracking process for a generic tracking system

Figure 2 illustrates the concept that a generic tracking system uses the MSS to periodically monitor the target. In order to reduce the energy consumption, the generic tracking system uses the MSS to periodically monitor the target, instead of monitoring the target all the time. The interval between the beginnings of two successive target monitoring tasks is called *sampling interval*, and each sampling interval is composed of a monitoring duration and a sleep duration (refer to the time axis in the figure). In the monitoring duration, all MSS members wake up to monitor the target collaboratively for retrieving the target (refer to (1) in the figure). If the MSS can monitor the target, the MSS leader obtains the target location and then reports it to TLDB. On the other hand, if the MSS cannot monitor the target, the MSS leader treats the case as a target loss. Then the MSS leader re-arranges the MSS by waking up alternative set of sensors to find the lost target (refer to (2) in the figure). If the lost target is still undetected, the MSS leader would iteratively re-arrange a different MSS to find the lost target until the lost target is found.

After the MSS reports the obtained target location to TLDB, the MSS leader would re-arranges the MSS and then the re-arranged MSS elect a new MSS leader for the next target monitoring (refer to (3) and (4) in the figure). Next, the new MSS would inform the original MSS to deliver the target monitoring task to the new MSS leader (refer to (5) in the figure), and the monitoring task in the current monitoring duration is finished. Lastly, the generic tracking system enters the sleep duration, that is, all MSS members switch to the sleep mode for energy conservation. The iteration of the monitoring duration and the sleep duration is repeated until the monitoring action is terminated.

3. **Model Based Object Tracking.** In most real-world applications, the target could move with different moving patterns for different periods [16]. However, most existing tracking schemes in sensor networks [19, 25] monitor the target based on a single moving model, and thus, it is difficult to minimize the size of MSS (i.e., monitoring sensor set) for saving energy consumed for monitoring the target. In order to support multi-pattern movements of moving targets for a long period time, we proposed *Model-based Object Tracking Architecture (MOTA)* to monitor the target by dynamically adopting the most energy-effectively tracking module in every sampling time [6].

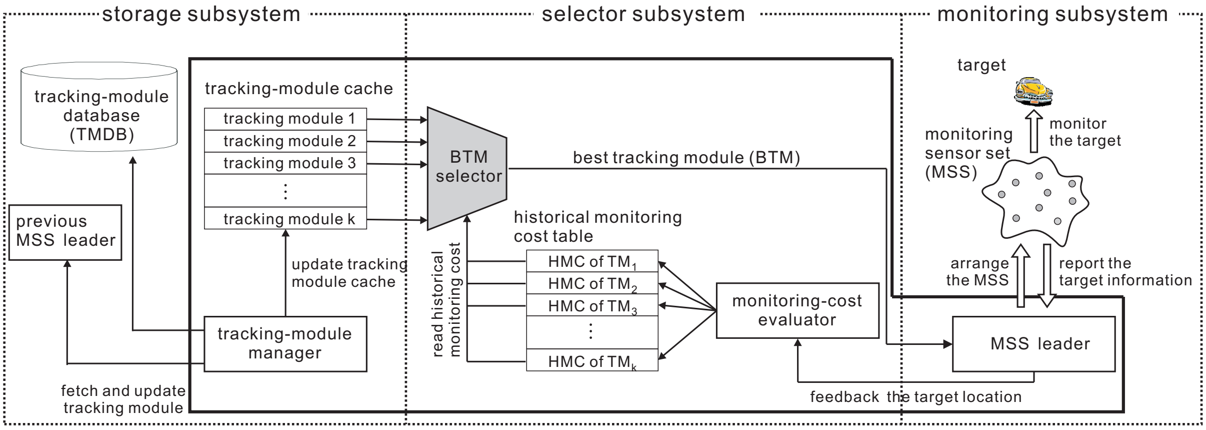


FIGURE 3. Model-based object tracking architecture [6]

MOTA consists of storage subsystem, selector subsystem, and monitoring subsystem, which is used to provide multiple tracking modules, dynamically selects the most energy-effectively tracking module, and applies the selected tracking module to monitor the target, respectively. Figure 3 illustrates the structure of MOTA. The kernel of the above three components of MOTA (referred to the solid bold line in the figure) is constructed in a MSS leader. Although three components are run on a MSS leader, most today's sensor devices can afford the needs of computation or energy consumption. For example, the data mining, complex query processing, and the data compression have been developed on recent sensor devices [19, 23, 26].

The first subsystem, *storage subsystem*, mainly provides the tracking modules for MOTA. The tracking-module cache stores predesigned tracking modules, which are the modulations of the existing tracking schemes. In order to be adaptable for small-storage sensors, the tracking-module cache can fetch and update tracking modules from the remote tracking-module database (TMDB) through the tracking-module manager. In this way, the tracking-module cache only needs to maintain the high-performance tracking modules. TMDB is a powerful server in the sensor network, and used to maintain all tracking modules. The tracking-module manager can periodically count the usage frequency of each tracking module for a sensor node, and then replace the less-used tracking modules as new ones from TMDB. The update period of the tracking-module manager can be adjusted by the administrator according to the interesting factors, such as energy consumption, network communication, or the sensor storage size.

The second subsystem, *selector subsystem*, is used to find out the most energy-effective tracking module, called *best tracking module (BTM)*. The BTM is delivered to the third subsystem, so that the MSS leader can monitor the target by following BTM. There are two components in this subsystem. The first component, called the *BTM selector*, is to find out BTM from Tracking-Module Cache. The basic idea of BTM Selector is to predict possibly best-performing tracking module in the future based on the performance statistics of each tracking module. In order to offer the past performance for the BTM Selector, the second component, called the *monitoring-cost evaluator*, would estimate the performance of tracking modules according to the movement of the moving target, and maintains the historical monitoring costs (i.e., HMC in the figure) for each tracking module in the historical monitoring cost table. Hence, the BTM selector can determine the best tracking module based on the historical monitoring cost table. The selector subsystem is the most unique and critical component for MOTA, because estimating monitoring cost of each tracking module and the selection strategy of the BTM selector are two key components

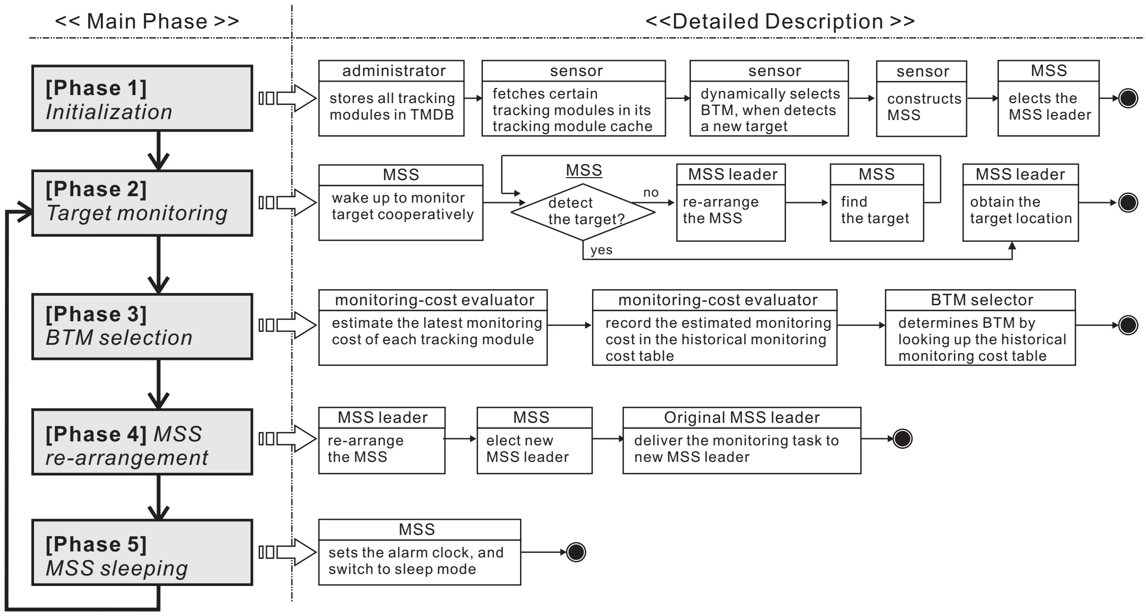


FIGURE 4. Flowchart of MOTA [6]

to differentiate MOTA from other existing tracking schemes that only support a single movement model.

The third subsystem, *monitoring subsystem*, is designed to command sensors to monitor the target. Similar to the generic tracking system mentioned in Section 2.2, MOTA uses MSS (i.e., monitoring sensor set) to cooperatively monitor the target in every monitoring duration for retrieving the target location or trajectory. In contrast to the generic tracking system, in MOTA, the MSS leader utilizes the BTM selected by the BTM selector to re-arrange the MSS. Since the optimal tracking module (BTM) is applied, MOTA would have high performance to track the target.

Next, we present the operations of MOTA, and the flowchart is shown in Figure 4. The left-hand side of the figure shows the five main phases of MOTA, and the right-hand side describes the detailed description of each phase. In the detailed description, each rectangle includes the executor (on the top of the rectangle) and the corresponding operations. The first phase is the initialization for tracking target. While MOTA tracks the target, MOTA recursively follows the rest four phases to monitor the target.

The details of each phase are described as follows. Phase 1 is the *initialization phase*. In this phase, every sensor fetches certain tracking modules into its tracking-module cache from TMDB. In the case that a sensor detects a new target first time, the BTM is randomly selected from the tracking-module cache. Then, according to the selected BTM, the MSS is construed to start the tracking task, and the MSS leader is elected by MSS. Phase 2 is the *target monitoring phase*. At the beginning of the monitoring duration, nodes in MSS wake up to monitor the target cooperatively and retrieve the target location. If nodes in MSS detect the target, the MSS leader obtains the target location by employing any existing localization method, e.g., APIT, RADAR and AHLoS [13]. On the other hand, if the MSS cannot detect the target (that is, target loss), the MSS leader re-arranges the MSS by waking up alternative set of sensors to find the lost target. In case the lost target is still undetected, the MSS leader would iteratively re-arrange another different MSS to search for the lost target until the lost target is found.

Phase 3 is the *BTM selection phase*. This phase is used to select the best tracking model (BTM), such that MOTA can consume the minimal energy in the next monitoring duration. In this phase, the monitoring-cost evaluator first estimates the latest monitoring cost of each tracking module according to the newly-obtained target location, and then maintains the estimated results in the historical monitoring cost table. Lastly, the BTM selector determines the BTM by looking up the historical monitoring cost table. Phase 4 is the *MSS re-arrangement phase*. In this phase, the MSS leader re-arranges MSS by applying the selected BTM for the next target monitoring task. In addition, nodes in the re-arranged MSS also elect new MSS leader in order to avoid that the original MSS leader spends enormous communication cost on managing the re-arranged MSS. After the new MSS leader is elected, the original MSS leader delivers the target monitoring task to the new MSS leader. At the same time, the tracking modules in the tracking-module cache and the historical monitoring cost table are also delivered to new MSS leader for future statistics. Phase 5 is the *MSS sleeping phase*. Notice that after the above three phases (Phase 2-Phase 4), the monitoring task in current monitoring duration is finished and MOTA waits for the next monitoring task. Before the next monitoring, all members of the re-arranged MSS switch to the sleep mode for energy conservation.

4. **Communication-Efficient Model Selection Strategies.**

4.1. **Communication analysis of MOTA.**

After understanding the MOTA, we describe the impact of the tracking model design on the communication cost by analyzing the operation flow of MOTA. Reviewing the procedures of the MOTA by using Figure 4, we can observe that Phases 2-4 dominate the whole energy consumption because most life time of MOTA is the repetition of Phases 2-5[1]. We analyze the impact of communication to each phase as follows.

- The tasks of Phase 2 are on monitoring the target according to the adopted tracking model. Hence, the communication cost is determined by the behavior of predefined tracking modules. While MOTA adopts a tracking model, the related communication cost of tracking model is consumed. Minimizing such cost is outside of our paper scope, and hence, this topic is not discussed in this work.
- Phase 3 focuses on selecting the best tracking model by using the historical statistics sent from previous MSS leaders. This phase belongs to computation-intensive tasks. Different schemes are proposed and compared in [6].
- In Phase 4, the current MSS leader re-arranges the MSS, and hands over the monitoring task to the new MSS leader elected by nodes in the new MSS. Furthermore, the current MSS leader also delivers this historical statistics of target movement to the new MSS leader in order to perform the best model selection in Phase 3 of the next monitoring period. Hence, the historical statistics of target movement is necessary in MOTA. Notably, such data transmitting in the sensor network incurs a great amount of communication cost.
- Phase 5 is just to ask all members to enter the sleep mode, and this can even achieve by broadcasting one single message. Thus, the communication cost of Phase 5 is negligible.

From the above analysis to MOTA, we can see Phase 4 is the key stage to incur vast communication cost. This section will study how to minimize the data size of historical statistics based on characteristics of the model selection module in MOTA.

For tracking module controller, three module selection strategies (i.e., Greedy Strategy, Min-Max Strategy, and Weighted Moving Average Strategy) have been designed to choose

[1]Phase 1 is only called once in the beginning of the tracking procedure, and The phase do not incur too much energy. Therefore, the communication cost associated to the phase can be ignored in the discussion on minimizing total communication cost.

the best tracking module for minimizing the monitoring cost in the previous work [6]. In Greedy Strategy, no historical monitoring costs needs to be transmitted between sensors during the AS leaders handoff, because only the monitoring cost at the current timestamp is considered for the best tracking module selection, instead of the historical monitoring costs of each tracking module. However, for Min-Max Strategy and Weighted Moving Average Strategy, the historical monitoring cost table has to be transmitted between sensors during the AS leaders handoff. It is because that Min-Max Strategy and Weighted Moving Average Strategy consider not only the monitoring cost of each tracking module at the current timestamp, but also the historical monitoring costs in the past period for the tracking module selector. As a result, a large amount of communication cost could be incurred, and the service time of the sensor network would be shortened. In this section, Bitmap Min-Max Strategy and Aggregation-based Weighted Moving Average (AWMA) Strategy are proposed to minimize the size of the historical monitoring cost tables to reduce the communication cost for Min-Max Strategy and Weighted Moving Average Strategy, respectively. The reduction of communication cost would make the proposed strategies more feasible.

4.2. **Bitmap Min-Max (BMM) strategy.** In the previous design of Min-Max Strategy, the monitoring cost table has to be delivered between sensor nodes during the AS leader handoff, and tracking module selector then selects the best tracking module as one whose maximal monitoring cost is minimal among all tracking modules. Thus, we find that the monitoring cost in the above cost computation is dominated by the number of used recovery functions in dealing with target loss. The basic idea of Bitmap Min-Max (BMM) Strategy is that the maximal monitoring cost can be estimated from simply scanning the usage of recovery functions, instead of the complete history of monitoring costs. In other words, only the information about the number of used recovery functions for all tracking modules are required in this strategy. Thus, the bitmap structure, called *recovery-function usage table*, is designed to record whether the recovery functions of each tracking module are used in the observed period, for minimizing the size of the historical monitoring cost table. Then Bitmap Min-Max Strategy uses the maximal number of used recovery functions, which is determined by scanning the recovery-function usage table, to estimate the maximal monitoring cost at the next timestamp, and then selects the best tracking module.

Figure 5 shows the recovery-function usage table in the bitmap representation. The table is used to identify which recovery functions are used in each tracking module in the observed period. In the left-hand side of the figure, TMID refers to the identification (or ID) of each tracking module, and RID refers to the unique number assigned to each recovery function for each tracking module, where N_{RS^i} indicates the number of recovery functions for tracking module TM_i. The data in each cell indicates whether the tracking module uses the associated recovery function at the corresponding timestamp. If the k-th recovery function is used by tracking module TM_i to search for the lost target at timestamp $t - j$, the value of the associated cell is set to 1. Otherwise, the value of the associated cell is set to 0. Hence, with the content of the recovery-function usage table, BMM is aware of whether the recovery functions of each tracking module are used at each timestamp in the observed period.

After the recovery-function usage table has been established, the maximal monitoring cost of each tracking modules can be estimated by using the following four steps.

1. First, BMM determines which recovery function is used in each tracking module for the target monitoring at timestamp t, and then updates the number of recovery functions in the recovery-function usage table.

TMID	RID	Observed period			
		t-1(1_{op}-1)	. . .	t-1	t
1	1	1	⋮	0	0
	2	1		0	0
	⋮	⋮		⋮	⋮
	N_R^1	0		0	0
2	1	0	⋮	1	1
	2	0		0	1
	⋮	⋮		⋮	⋮
	N_R^2	0		0	0
⋮					
N_{TM}	1	1	⋮	1	1
	2	1		0	1
	⋮	⋮		⋮	⋮
	$N_R^{N_{TM}}$	0		0	0

FIGURE 5. The recovery function employment table in the bitmap represent for Bitmap Min-Max strategy

2. After the recovery-function usage table has been updated, BMM scans the recovery-function usage table to determine the maximal count, n_r^i, of used recovery functions for each tracking module, TM_i, $i = 1 \cdots N_{TM}$, in the observed period.
3. Then, BMM applies the maximal count, n_r^i, of used recovery functions to estimate the amount of monitoring cost at the next timestamp for each tracking module.
4. Finally, BMM selects the best tracking module as the module whose maximal monitoring cost is minimal among all tracking modules at the next timestamp.

Figure 6 shows an example where the Bitmap Min-Max Strategy and Min-Max Strategy select the best tracking module from TM_1 and TM_2 at timestamp 45, and the length of observed period is set to 10 monitoring time units. Each of tracking modules, TM_1 and TM_2, has two recovery functions in this example. Notice that the best tracking module selected by Min-Max strategy [6] is TM_2, because TM_1 has less monitoring cost than TM_1 as shown in the figure. BMM selects the best module as follows. First, BMM looks up whether any target lost is occurred at timestamp 44. BMM discovers that TM_1 incurs target lost and finds back the target by using one recovery function; TM_2 does not incur any target lost. Thus, BMM records the situation at timestamp 44 for TM_1 by $L_{44}^1[0] = 1$ (true) and $L_{44}^1[1] = 0$ (flase). Next, according to the array elements from L_{35}^1 to L_{44}^1 and ones from L_{35}^2 to L_{44}^2, BMM knows there is at most one recovery function (i.e., $n_r^1 = 1$) used in TM_1 from timestamps 35 to 44; and no recovery function (i.e., $n_r^2 = 0$) is used in TM_2 during the same period. Then, BMM can estimate monitoring cost for TM_1 and TM_2 at timestamp 45 are 13.503 and 6.832, respectively. Hence, BMM selects TM_2 as the best tracking module due to the less monitoring cost ($6.832 < 13.503$). We can also find that the decision of BMM is the same as that of Min-Max strategy.

4.3. **Aggregat-based weighted moving average (AWMA) strategy.** In the design of previous Weighted Moving Average Strategy [6], the historical monitoring cost table has to be transmitted between sensors (i.e., AS leaders), and the tracking module selector then selects the best tracking module. We observed that the weighted moving average monitoring cost (computed from historical monitoring costs) is an aggregated result of the historical monitoring costs. Thus, the basic idea of Aggregated-based Moving Average

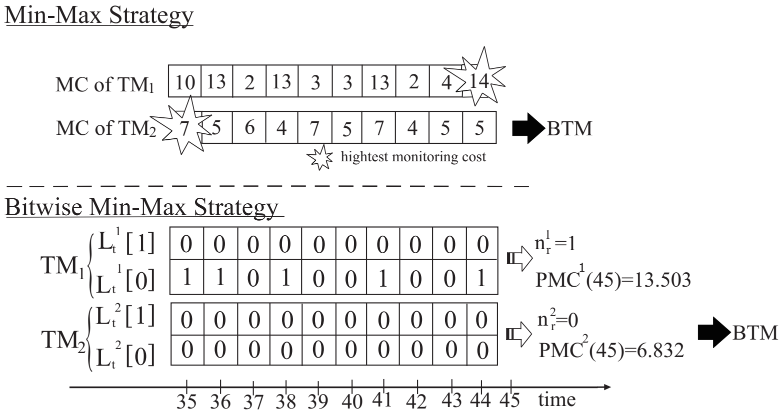


FIGURE 6. The recovery function employment table in the bitmap represent for Bitmap Min-Max strategy

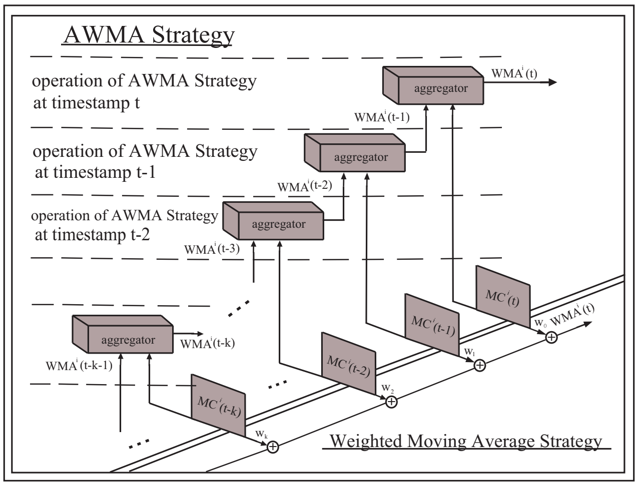


FIGURE 7. Illustration of Aggregat-based weighted moving average (AWMA) strategy

(AWMA) Strategy is to aggregate the weighted moving average monitoring data at the current timestamp, and the aggregated data with only small amount of data size will be used in the next timestamp. The overview of AWMA Strategy is shown in Figure 7. At timestamp $(t-1)$, the aggregator calculates the weighted moving average monitoring cost $MC_i^{WMA}(t-1)$ for timestamps before $(t-1)$. Then, at timestamp t, the weighted moving average monitoring cost $MC_i^{WMA}(t-1)$ (calculated at timestamp $(t-1)$) is represented as the weighted moving average of the historical monitoring cost. Thus, the aggregator calculates the weighted moving average monitoring cost $MC_i^{WMA}(t)$ by using the historical weighted moving average monitoring cost $MC_i^{WMA}(t-1)$ and the monitoring cost $MC_i(t)$ at timestamp t. In this way, only the monitoring data at the current timestamp t and the aggregated weighted moving average monitoring data evaluated at the last timestamp $(t-1)$ are required for the monitoring cost evaluation. Hence, only the aggregated data of moving average monitoring for all tracking modules is required to be transmitted between sensors in AWMA, instead of the complete history of monitoring costs of all tracking modules required in WMA. Therefore, the communication cost required in AWMA is much less than that in WMA.

In order to represent that the significance of historical moving average monitoring data within aggregation results is degraded as increasing time, the weighted values for evaluating the weighted average monitoring cost can be expressed as the following forms of the geometric sequences:

$$\begin{aligned} w_1 &= w_0 \times r \\ w_2 &= w_1 \times r = w_0 \times r^2 \\ &\vdots \\ w_k &= w_{k-1} \times r = w_0 \times r^k \end{aligned}$$

where w_0 is the weighted value for monitoring cost at the current timestamp t, w_k is the weighted value for the monitoring cost at the timestamp $(t-k)$, and r is the common ratio of the weighted value. Thus, the weighted value w_k of the monitoring cost at timestamp $(t-k)$ is that r times as much as the weighted value w_{k-1} of the monitoring cost at timestamp $(t-k+1)$.

Assume the current timestamp is t. The weighted moving average monitoring cost evaluated at the last timestamp $(t-1)$ can be expressed as

$$\begin{aligned} &MC_i^{WMA}(t-1) \\ &= w_0 \times MC_i(t-1) + w_1 \times MC_i(t-2) + \cdots + w_{k-1} \times MC_i(t-k) + \cdots \\ &= w_0 \times MC_i(t-1) + w_0 \times r \times MC_i(t-2) + \cdots + w_0 \times r^{k-1} \times MC_i(t-k) \end{aligned}$$

Note that $r > 0$, we can multiply r to both sides of the equation as follows to compute the result of next timestamp.

$$\begin{aligned} &MC_i^{WMA}(t-1) \times r \\ &= w_0 \times r \times MC_i(t-1) + w_0 \times r^2 \times MC_i(t-2) + \cdots + w_0 \times r^k \times MC_i(t-k) + \cdots \end{aligned}$$

Then, we obtained the weighted moving average monitoring cost evaluated at the last timestamp t, which can be expressed as:

$$\begin{aligned} &MC_i^{WMA}(t) \\ &= w_0 \times MC_i(t) + w_1 \times MC_i(t-1) + \cdots + w_k \times MC_i(t-k) + \cdots \\ &= w_0 \times MC_i(t) + w_0 \times r \times MC_i(t-1) + \cdots + w_0 \times r^k \times MC_i(t-k) + \cdots \\ &= w_0 \times MC_i(t) + r \times MC_i^{WMA}(t-1) \end{aligned}$$

where $MC_i(t)$ is the amount of monitoring cost of the i-th tracking module TM_i at timestamp t and $MC_i^{WMA}(t)$ is the weighted moving average monitoring cost of the i-th tracking module TM_i at timestamp t. Thus, the weighted moving average monitoring cost of the i-th tracking module TM_i at timestamp t can be calculated by weighted summing the monitoring cost at timestamp t and the weighted moving average monitoring cost evaluated at timestamp $(t-1)$. Hence, we obtain the following equation:

$$\begin{aligned} &WMAMC_i(t) = \sum_{i=0}^{n} w_i \times MC_i(t-i) \\ &= w_0 \times MC_i(t) + w_1 \times MC_i(t-1) + w_2 \times MC_i(t-2) + \cdots + w_k \times MC_i(t-k) + \cdots \\ &= w_0 \times MC_i(t) + w_0 \times r \times MC_i(t-1) + w_0 \times r^2 \times MC_i(t-2) + \cdots + \\ &\qquad w_0 \times r^k \times MC_i(t-k) + \cdots \end{aligned}$$

$$
\begin{aligned}
&= w_0 \times MC_i(t) + r \times \bigg(w_0 \times MC_i(t-1) + w_0 \times r \times MC_i(t-2) + \cdots + \\
&\qquad w_0 \times r^{k-1} \times MC_i(t-k) + \cdots \bigg) \\
&= w_0 \times MC_i(t) + r \times WMAMC_i(t-1)
\end{aligned}
$$

Notice that, the sum of weighted values has to be 1, because the weighted moving average monitoring cost is a weighted average of monitoring costs in the past. Thus, the common ratio of the weighted value r can be derived as follows:

$$
\begin{aligned}
&\sum_{i=0}^{n} w_i = 1 \\
&\Rightarrow w_0 + w_0 \times r + w_0 \times r^2 + \cdots + w_0 \times r^k + \cdots = 1
\end{aligned}
$$

By applying the concept of Maclaurin series [29], we can obtain

$$
\begin{aligned}
&w_0 + w_0 \times r + w_0 \times r^2 + \cdots + w_0 \times r^k + \cdots = 1 \\
&\Rightarrow \frac{w_0}{1-r} = 1 \\
&\Rightarrow r = 1 - w_0
\end{aligned}
$$

5. **Performance Evaluation.** In this section, we conduct a comprehensive set of experiments on comparison of MOTA to the related tracking systems and performance of proposed model selection methods. Before discussing the experiment results, we describe the simulation settings used in the simulation.

5.1. **Simulation model.** In our simulation, we deploy 10000 nodes with square topology in a $1000 \times 1000\text{m}^2$ sensor network [5, 21, 23], and the distance between two neighboring nodes is 10m. The nodes have the ability to obtain the target location and the sensing rate in our experiment is $1/sec$, i.e., the tracking system generates the target location every second [5, 25]. With each sensor node, the sensing range and the radio range are set to 10m. The maximum size of a packet (that a sensor delivers once) is 100 bytes [27]. The energy consumptions for monitoring the target, transmitting a packet, and receiving a packet are $383.3mW$, $771.1mW$ and $751.6mW$, respectively [20]. Additionally, the shortest path multi-hop routing algorithm [20] is applied to transmit messages between sensors. To model the moving patterns of the target, four moving models, including Random Direction Mobility Model, City Section Mobility Model, Random Waypoint Model, and Random Walk model [2], are used to generate target trajectories. Each time, the selected moving model is adopted for 300 seconds. That is, the simulator changes the target movement behavior every 300 seconds.

5.2. **Comparisons of tracking systems.** Our first experiment studies the performance of MOTA and other four tracking schemes (i.e., PES, HTM, DCTC and Frisbee [3, 19, 25, 27]), and the results are depicted in Figure 8. In the experiment, we vary the time duration of a moving pattern. From the figure, we can see that MOTA activates the least number of MSS members among all related schemes, and the total energy consumption of other four tracking schemes is $2 \sim 26$ times greater than that of MOTA. Such result shows that our proposed MOTA successfully avoids more target losses than other schemes. The reason is that MOTA dynamically adopts the most adequate tracking module while monitoring the target in each time unit. Moreover, the results also imply that the monitoring-cost evaluator of MOTA is able to accurately estimate the needed cost of tracking modules,

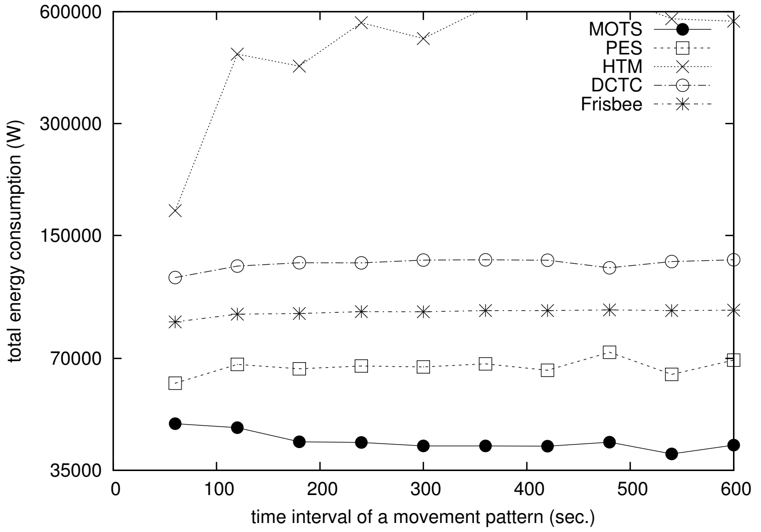


Figure 8. Comparison of various tracking systems

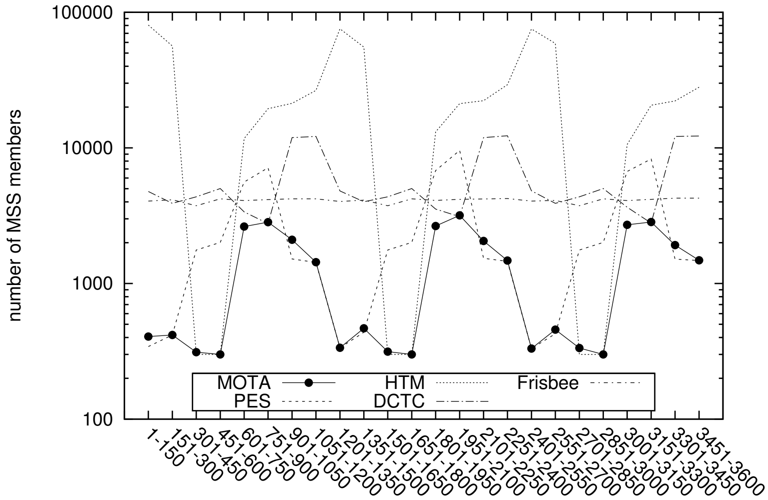


Figure 9. Performance trace of MOTA and related tracking systems

and thus, the selection strategy can employ the high-quality cost evaluation results to select the adequate tracking module.

Figure 9 shows the summary results of every experiment rounds, and the behavior of each tracking scheme is hard to observe. Hence, we deeply trace each tracking scheme (MOTA and other four schemes), and clearly show their performance for different periods in Figure 9. In the experiment, time interval of changing moving patterns in the target movement is set to 300 sec. and the total number of MSS members is counted every 150 sec. From the results, we can see each of four schemes (PES, HTM, DCTC and Frisbee) can perform best in some time units, but none of the four schemes always performs best all the time. This is because the target would change its movement behavior and this incurs different impacts on each of them. For the conservative scheme (e.g., DCTC), it activates more nodes to monitor the target, but has a lower impact on target losses while the target changes its movment behavior. On the contrary, for the aggressive scheme (e.g., PES), it activates less nodes to monitor the target, but pays more penalty while the target changes its movment behavior. For the mining-based scheme (e.g., HTM), it performs best only when the target movement follows the scheme's expection. Compared with these four schemes, MOTA successfully selected the best tracking module, and dynamically applies the adequate tracking module to monitor the target. Hence, MOTA achieves the least number of sensor nodes in most time. This figure also demonstrates the performance difference of each scheme in the above result of Figure 8. Hence, for a long-term monitoring task or monitoring an irregularly movement behavior, MOTA can greatly reduce the number of sensor nodes and energy consumption than other related tracking schemes.

5.3. **Study of communication cost BMM improved.** Figure 10 shows the amount of energy consumption in MSS-leader hand-off for Min-Max Strategy and BMM Strategy. From the figure, we see that BMM Strategy greatly reduces the amount of energy consumption for MSS-leader handoff of Min-Max Strategy. The reasons for the results are explained as follows. For BMM Strategy, the historical monitoring cost table merely contains the bitmap structure to maintain the related information (i.e., the data size is around 108 bits or 13.5 bytes). Thus, only one packet is needed for BMM Strategy to transmit between new MSS leader and original MSS leader. On the contrary, for Min-Max Strategy, four packets are required according to its data structures of historical monitoring cost table and target velocity information (288 bits for historical monitoring cost table and 32 bits for target velocity information). As a result, compared with Min-Max Strategy, BMM Strategy consumes 25% energy in MSS-leader handoff.

5.4. **Study of communication cost AWMA improved.** Figure 11 shows the amount of energy consumption in MSS-leader hand-off for AWMA strategy and WMA strategy. Observing the figure, it is clear that AWMA Strategy greatly reduces the amount of energy consumption in MSS-leader handoff against WMA strategy. By using the aggregation technique, AWMA Strategy aggregates the monitoring history for each tracking module, so that the size of historical monitoring cost table is merely around 32 bytes. Hence, similar to BMM Strategy, only one packet is required under AWMA Strategy to transmit between new MSS leader and original MSS leader. On the contrary, under Weighted Moving Average Strategy, the size of historical monitoring cost table is around 928 byte. Compared with Weighted Moving Average Strategy, AWMA Strategy consumes only 10%

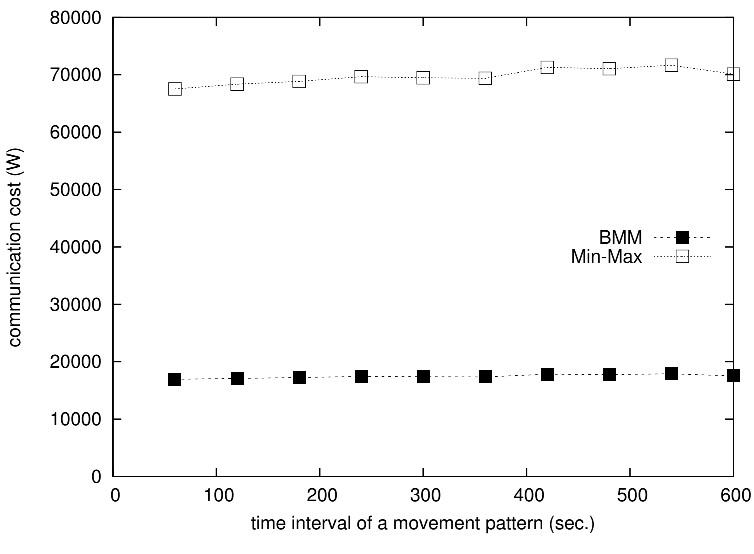


Figure 10. Comparison of communication cost between BMM and Min-Max strategies

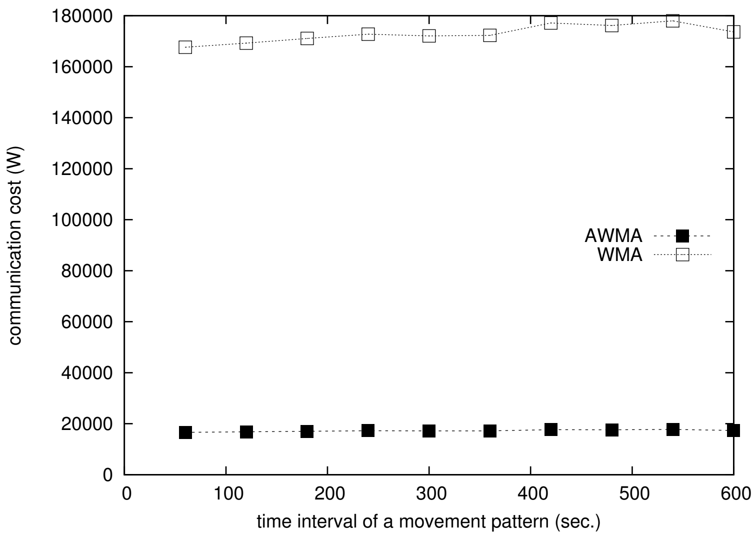
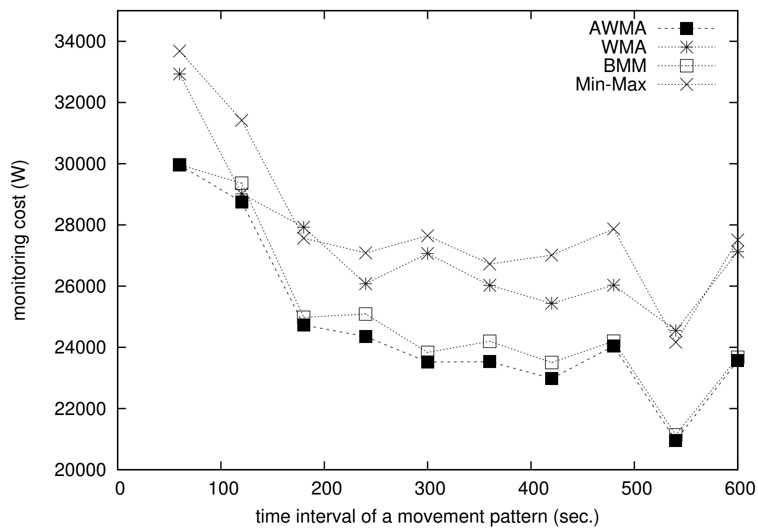


Figure 11. Comparison of communication cost between AWMA and WMA strategies

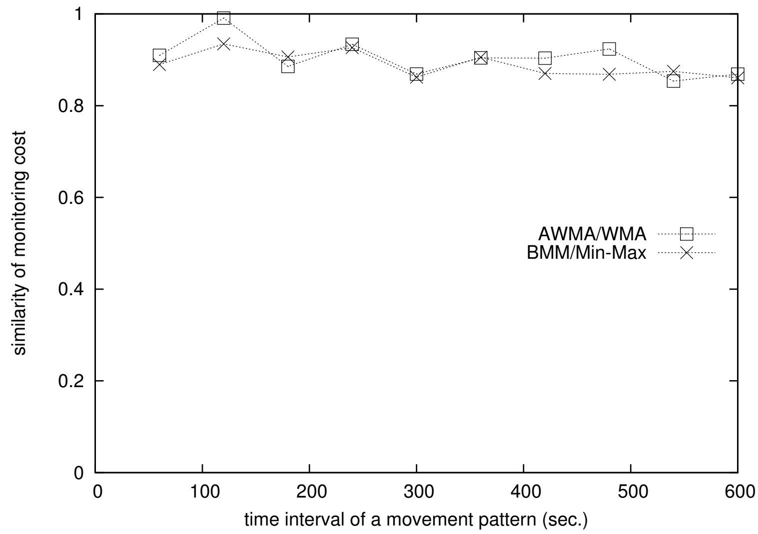
energy in MSS-leader handoff. Although the curve trend of this figure is similar to that of BMM, the benefit comes from different designs (i.e., bitmap structure versus aggregation technique). Thus, application designers can adopt a suitable solution between AWMA and BMM according to their needs.

5.5. **Monitoring performance of BMM and AWMA.** In intuition, communication cost and the monitoring performance is a tradeoff in object tracking schemes of wireless sensor networks. Thus, we design the experiment to observe how much the monitoring performance is decreased, and the results are depicted in Figure 12. Figure 12(a) shows the monitoring cost of Min-Max Strategy, BMM, WMA, and AWMA. As we can see, BMM and AWMA perform very similar to Min-Max strategy and WMA, respectively. In addition, AWMA and WMA have lower monitoring cost than BMM and Min-Max. Such trends are similar to the previous work [6] which can increase validity of experiment results. In addition, the trend of each curve decreases with the horizontal axis. This is because the longer time interval of a movement pattern indicates the objects move more regular, and each model selection strategy needs not frequently change tracking models in MOTA. Hence, the monitoring cost decreases as increasing time interval of a movement pattern.

In order to ensure that BMM and AWMA have the same degree of monitoring performance to Min-Max Strategy and WMA respectively, we examine the degree of similarity of monitoring cost between BMM and Min-Max Strategy, and so do between AWMA and WMA. Figure 12(b) shows the result of this examination. The degree of similarity of monitoring cost between BMM and Min-Max Strategy is equal to the ratio of monitoring cost of BMM to the monitoring cost of Min-Max Strategy; similarly, the degree of similarity between AWMA and WMA is the ratio of monitoring cost of AWMA to monitoring cost of WMA. As shown in Figure 12(b), the degree of similarity of BMM/Min-Max and the degree of AWMA/WMA reaches over 90% in most cases. The results indicates that BMM and AWMA have almost equivalently well monitoring performance in comparison to Min-Max and WMA, respectively, while these two strategies adopt additional techniques to reduce the data size of the historical monitoring cost table. Therefore, the designs of the two strategies do not heavily hurt the monitoring performance while reducing communication cost.



(a) monitoring cost



(b) monitoring-cost ratio of strategies

FIGURE 12. Monitoring performance of BMM and AWMA

5.6. **Comparisons of total energy consumption.** The last experiment is to study the comparisons of total energy cost for related strategies, and the results are shown in Figure 13. From the figure, we can see that AWMA and BMM need less than 50000 Watt in most cases, while the existing tracking selection methods (Greedy, Min-Max, WMA) need more than 100000 Watt. This shows the designs of AWMA and BMM are more superior to the related methods. In addition, we found a model selection method which varies with different movement behaviors (e.g., Greedy) is unreliable for real applications, because it may incur the performance crash out of administrators' expectation and then exhausts the energy of wireless sensor networks. AWMA and BMM do not vary with time interval of a movement pattern. This property indicates that AWMA and BMM can be applied to wide spectrums of movement behaviors. Hence, the two strategies are practical in most applications.

6. **Conclusions.** Tracking irregularly moving objects for long-term period in wireless sensor networks is a critical technique in many sensor applications. In the very recent

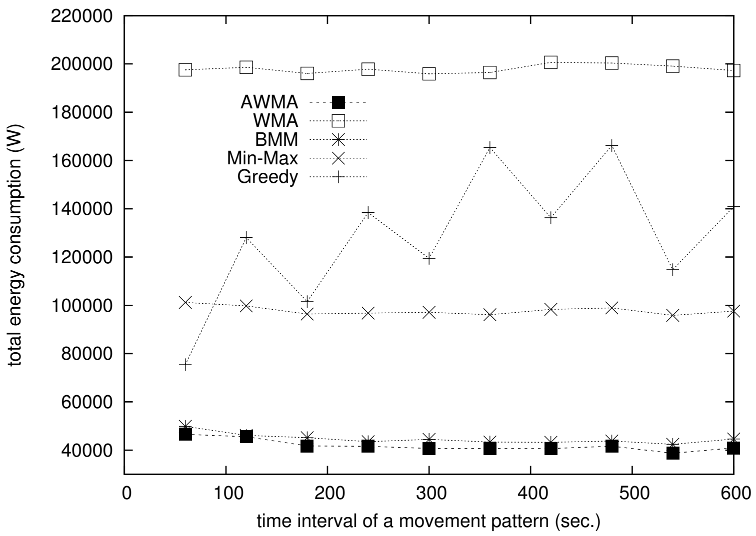


FIGURE 13. Comparisons of total energy consumption for various strategies

literature, the multi-model based object tracking architecture (MOTA) has been shown its outstanding performance in [6]. However, MOTA does not give solutions about how to design communication-efficient tracking models in the related literature. In this paper, we propose Bitmap Min-Max (BMM) Strategy and Aggregation-based Weighted Moving Average (AWMA) Strategy to energy-effectively monitor moving targets for long-term period. Based on the fact that a target moves with different patterns in most cases, MOTA is designed to equip with the multiple tracking modules and dynamically select the most adequate tracking module to monitor the target, and our proposed BMM and AWMA can assist MOTA to greatly reduce communication cost in the wireless sensor network. The experimental results reveal that BMM and AWMA successfully reduce communication cost compared to the existing methods, and the improvements are over 50% in most cases. Our future work is to design complex tracking modules which could combine artificial intelligence or data mining techniques. The complex tracking modules can be used to describe more complex target movements. Hence, the frequency of retrieving new tracking modules from the central server to sensor nodes (e.g., MSS leaders) will be reduced, and thus, this will incur the decrease of communication cost further.

Acknowledgment. This work was partially supported by National Science Council of Taiwan and National Cheng Kung University under grants NSC100-2221-E-006-267-MY2, NSC 99-2221-E-218-035 and D101-13103.

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