Multiple Objects Device-Free Passive Tracking Using Wireless Sensor Networks

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***Abstract*—object tracking is a main application of wireless sensor networks (WSNs), and has been studied widely [4], [9]. In this work, we study multiple objects tracking problem using WSNs, in which we assume no equipment is carried by the object and the tracking procedure is passive. We first show that without carefully design, Received Signal Strength Indicator (RSSI) and Link Quality Indicator (LQI) are not as effective as claimed for passive detection through our testbed studies. We further propose to use light to track moving objects in WSNs. To our best knowledge, this is the first work to study multiple objects tracking using light sensors and general light sources. We propose a novel probabilistic tracking protocol to track multiple objects. We further design several efficient methods to compute some attributes of the moving objects (like heights, moving speeds etc.).**

I. Introduction

Wireless sensor networks (WSNs) have many successful applications such as health monitoring, environmental surveillance, localization and object tracking [11], [12]. With respect to tracking problems in WSN area, there are two main directions. One direction (*e.g.*, [1], [2]) is called device- based tracking. It assumes that the object being tracked carries some assistant advice(s) (*e.g.*, wireless sensor nodes, RFID, PDAs) such that the object can be easily detected by other assistant devices, like RFID reader or anchor sensor nodes. In contrast, the other direction assumes that the object being tracked is device-free, *i.e.*, the object carries no any assistant device and the tracking procedure is considered to be "passive". For example, considering a security monitoring scenario in a museum, clearly, it is impossible to equip some device for any intruder. In this paper, we study the passive (device-free) tracking problem using WSNs. We propose to detect and track multiple objects at an indoor environment using a group of light sensors with general light sources.

Our main contributions are as follows. Firstly, we conduct extensive experiments to test the validity of using Received Signal Strength (RSSI) and Link Quality Indicator (LQI) to detect moving object(s). Our results show that without careful design, both RSSI and LQI are not good indicators to detect the moving object. Secondly, to the best of our knowledge, this is the first work to use light sensors and general light sources to track multiple device-free objects. Thirdly, we propose a probabilistic tracking method to track multiple objects efficiently. Finally, we further discuss challenges in multiple objects tracking and propose some possible methods to improve the tracking accuracy.

The rest of the paper is organized as follows. We review related work in Section II. In Section III, we first define the problem and propose the main idea with a probabilistic approach to solve multiple objects tracking problem, then further propose some possible methods in order to improve the tracking accuracy of multiple objects tracking. We conclude our work in this paper in Section IV.

II. Related Work

The tracking problem is a fundamental research problem in many domains and has been widely studied recently [1], [9], [13], [16], [20]–[24]. For instance, in [1], Ahmed *et al*. studied the tracking problem by estimating and tracking an object based on the spatial differences of the object's signal strength detected by the monitoring sensors at different locations. In [2], the authors track one or more moving objects using RFID(s). Basically, all aforementioned methods aim at solving device-based tracking problem, which requires that the moving object(s) is(are) equipped with some equipment(s).

The other direction of tracking problem using WSNs is called Device-free tracking problem (DfP), first defined by Youssef *et al*., in [20]. They studied the feasibility of DfP and further discussed several research challenges regarding to the localization algorithms and infrastructure support. Tseng *et al*., [17] studied the object tracking problem by using a mobile agent (a wireless sensor node) which can follow the object by hopping from sensor to sensor. Some similar work was dong by Kung *et al*., in [10]. However, the work in [10], [17] assume that every sensor node has a sensing range and can detect the existence of an object accurately as long as the object falls into the sensing range of this sensor node, which is not realistic. Later, Zhang *et al*. [21], [22] and Yao *et al*., [19] proposed to use RF-based method to track transceiver-free objects. Their main idea is to detect objects based on Small-Scale Fading effect (SSF). Later, Moussa *et al*., [14] studied the performance of two DfP techniques, moving average (MA) and moving variance (MV) in a real environment. He *et al*., studied and designed VigilNet [9], a large-scale sensor network system consisting of 200 XSM motes which tracks, detects and classifies objects. Their main work concentrated on studying the tradeoff between the real-time performance and the energy consumption, and assumed that each wireless sensor can detect the existence of object with high probability when the object falls into the sensing range of the wireless node. In [5], Dutta *et al*. concentrated on the hardware design to save energy consumption, hence prolonged the life time of large scale wireless networks. The main idea of work in [8] by He *et al*., is to let wireless sensor nodes alternatively work and let several sensors work together to exclude false alarm such that the energy consumption is decreased. Das *et al*., [7] studied the problem to track moving objects using a smart sensor network. Their work was mainly based on two assumptions. One is that a sensor node is able to detect the existence of the moving object(s) when the objects falls in its sensing range. The other assumption is that the sensor has already learned the sensor reading to distance mapping. In [3], Arora *et al*. studied object detection and tracking problem using wireless sensor networks. By classifying the objects into three different classes, people, solider and vehicle, they concentrated on defining the system, environment, and fault models.

III. Problem Formulation and Our Approaches

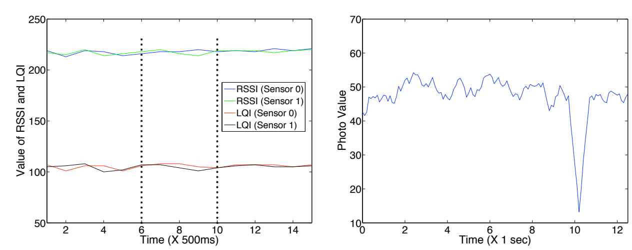
A. Problem Formulation

Given an indoor area, we want to track device-free moving objects inside this area using a wireless sensor network. Here, we assume that each wireless node is equipped with 1) one light sensor that can sense the level of light around it, and 2) at least one transceiver that can communicate with neighbor nodes such that all wireless nodes constitute a connected WSN. We assume that wireless sensors are placed in a 3D domain and the geometric positions of sensor nodes can be obtained easily when they are deployed. For simplicity, from now on we call the sampled light level of a wireless node as *photo* value of this sensor node.

Given the deployed WSN system, our goal is to track moving objects that appear in the service region efficiently and effectively. We are interested in obtaining a number of attributes of the moving objects, such as the moving speed, the height of the object (typically a human being) and further tracking the movements of multiple objects at the same time. The initial results obtained by our tracking system are expected to assist the surveillance cameras and human monitoring, hence reduce the overall cost for surveillance.

B. Finding Effective Detection Method

One of well-known techniques to detect (further track) some device-free object(s) is to use RSSI or LQI since the value of RSSI and LQI of a link connecing two wireless sensor nodes will be affected by the physical situation between these two nodes [15], [21]. However, RSSI and LQI of a wireless link depend on many aspects, like weather, temperature, hardware constraints and so on [6]. To verify the effect of using RSSI and LQI to detect moving object(s), we did extensive experiments at both indoor and outdoor environments. For example, we let two wireless TelosB nodes (with ID 0 and ID 1 respectively) continue sending packets (1 packet/ 200 millisec) to each other, and let an object (human being in our experiments) go through the link between two nodes. During the transmission, the receiver computes both RSSI and LQI value from the received packets in order to learn about the changing tendency of RSSI and LQI with the existence of some object. We repeat the above procedure using different transmission powers (for sender) and different Euclidean distance between the sender and the receiver. Disappointedly, our results showed that both RSSI and LQI are not good indicators for detecting the moving objects as we expected in both indoor and outdoor environment. For example, Fig. 1(a) shows the measured RSSI and LQI when the transmission power of the sender is level 5 and the distance between two nodes are 7 meters. As we can see, both RSSI and LQI do not change significantly when a person comes across the link between two nodes during time period from $x = 6$ to $x = 10$. We analyzed the possible reasons and found that both RSSI and LQI will not drop obviously due to signal refraction no matter whether there is some obstacle emerging in the middle of the wireless link or not. To confirm our conjecture, we redid our experiments with all the same test cases at an outdoor environment and got similar results. Hence, without carefully design, simply using RSSI and LQI to detect a moving object is not sufficient. Notice here, our claim is that without careful design, RSSI and LQI are not good indicators of the existence of some objects, rather than giving the total repudiation of RSSI and LQI.



(a) Indoor RSSI & LQI results (b) Photo value results.

Fig. 1. Changing tendency of RSSI, LQI and photo value when a moving person comes across.

After excluding using RSSI and LQI to detect an object, we found that a light sensor is very sensitive to the change of the light level of the environment around it especially at an indoor environment as long as we arrange the position of the light source and the light sensors carefully. We observe that when an object moves between a light source and a light sensor, it will affect the sensed photo value of the light sensor, especially when this light source is the only one or main light source to this sensor. In Fig. 1(b) we show the readings of a light sensor when the Euclidean distance between the light sensor and a general 40w lamp is 5 meters. As we can see, the photo value of a light sensor dropped obviously (from around 45 to less than 20) when one person came cross. Clearly, compared with RSSI and LQI, photo value of a light sensor node is more traceable when some object(s) come across. In addition, in order to be a valid light source for a light sensor, the Euclidean distance between the light source and the light sensor should be not too large depending on the illumination intensity of the light source. For example, when the Euclidean distance between the lamp (with 40w used in our experiment) and a light sensor is more than 12 meters, the light sensor cannot tell exactly whether there is an obstacle between it and the light source due to the light attenuation and hardware constraints.

C. Review of Computing Position, Height and Moving Speed of a Moving object

In one of our previous works [18], we studied the single object tracking problem and proposed some methods to compute the position, height and moving speed of the single object. Clearly, those methods can be used to distinguish different moving objects with different properties. We quickly review the main ideas as follows.

We first divide sensor nodes into groups and consider each group as a cluster. Next, we put two groups of sensors (face to face) on both sides of monitored area. Here, a group of sensors will be hanged in a vertical line at one side of the monitored area. In addition, we put one light source at each side such that the light source can irradiate the group of sensors at the other side of the monitored area. For simplicity, we assume the distance between two adjacent sensor nodes in the same group is same. Clearly, when an object goes across two group of sensor nodes, he/she will affect the readings of some sensors on both sides. See Fig. 2 for illustration. By computing the position of the rectangle containing the top point of the object, we can compute the position and height of the moving object with error bound, $\frac{d}{2}$ and $\frac{w}{2}$ [18]. Here d is the Euclidean distance between two adjacent sensors in the same group and w is the width of the monitored area. The error is caused by the fact that the sensor nodes were deployed discretely such that we may not find two lines ad and bc accurately.

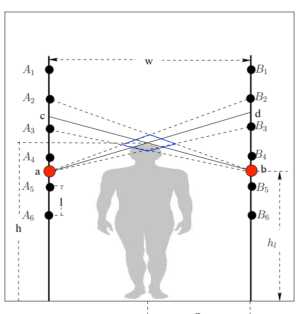


Fig. 2. Black nodes denote two group of sensors ($A_1 \cdot A_6$ and $B_1 \cdot B_6$) and two red nodes (a and b) are two light sources. The height of the person and the altitude of light sources are h and h_l respectively. The distance between the person and the right side wall is p. The distance between each two adjacent sensor nodes in the same group is d.

Considering that an object may choose an arbitrarily direction with different moving speeds, the main idea to compute

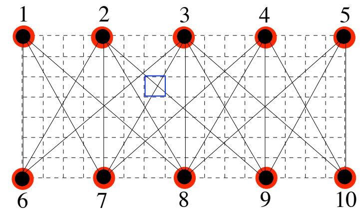


Fig. 3. A vertical view of partitioned area. Totally 10 (from 1 to 10) groups of sensors. Black (resp. Red) nodes denotes wireless sensors (resp. light sources). Solid lines denotes the possible links between light sensors and light sources. Slashed rectangles are partitioned cells.

the moving speed of a moving object is to compute the average moving speed of an object between two "catching points", at which the system can compute the height and position of the moving object.

D. Our Probabilistic Approach for Single Object Tracking

Before we introduce the main ideas of tracking multiple objects, we take solve the simpler case first when only one object exists. Our main idea is to partition the monitored area into cells and assign probabilities to different cells based on the collected data such that for any time slot, the cell with highest probability will be considered the position of the moving object. See Fig. 3 for illustration. As we can see, each cell could be gone through by one or more links between a light sensor and a light source. For instance, the cell (blue rectangle) in Fig. 3 is gone through by link $(2, 9)$ and $(3, 7)$. After partitioning, we assign different probabilities to different cells by collecting enough readings of sensors. For instance, if there are some nodes from group $2, 3, 7, 9$ reporting "catching" event to the base station, it is more possible that the moving object is in the blue cell since all other cells being crossed by link $(2, 9)$ has smaller probability to cause the readings of sensors (in group 3 and 7) to change. For simplicity, we say that a link (a, b) is "active" at time slot t if there are sensors from both group a and group b reporting "catching" events at time slot t. Noticing that, there are some cells that are not crossed by any link, *i.e.*, these cells are in blind area in which a moving object cannot be detected. We can increase the number of sensor nodes to eliminate such "blind" cells in order to increase the tracking accuracy of our system.

Based on the partition, we proposed the main idea of computing the trajectory of a moving object as follows. At the beginning, when no object exists, all cells have the same probability 0. Given any time t, if only two groups of sensor report "catching" events, then we use method (in Sec. III-C) to compute the location (and height etc.) of the object. Otherwise, when there exist multiple links at time slot t, *i.e.*, there could be more than one potential possible position where the object could be. For each cell c and each link l, if l crosses cell c and l is active, we increase the probability that cell c contains the moving object. Next, we pick the center of the cell with the highest probability as the position of the moving object.

Sometimes, two different cell may have the same highest probability. Through experiments we found that the main reason for two different cell have the same highest probability is due to the moving object's occupying two cells at the same time, in other words, these two cells are adjacent. In such case, we merge two cells into a big cell and consider the gravity center as the most possible position for the moving object. When two cells which are not adjacent to each other have the same highest probability (although this seldom happens according to our experimental results), we consider the cell which is closer to the position of the moving object at previous time slot has higher probability. The reason for us to do this is because we consider the moving object has regular moving speed, like the walking speed of a normal person. Since the average sample rate for a sensor is around 100 milliseconds and we consider the time period of a single time slot is 500 milliseconds, it is more possible that the cell which is closer to the position of previous time slot has higher probability. Actually, when the above assumption about the constraints of moving speed is not true, we can randomly pick up the center of one of two cells as the location of the moving object since we can continue to refine the position of the moving object by future readings of sensors. See Alg. 1 for details.

Algorithm 1 Computing position of an object at time slot t

Input: Given all the readings collected by the base station at time slot t, all cells in set $\mathcal{C}$

Output: The position of the moving objects.

```
Obtain all active links based on all readings collected by the base
    station, assume the active link set is ℒ.
if Only one active link exists then
    Compute and return the position by our method proposed in
    Sec. III-C
else
    for each cell c ∈ 𝒞 do
        for each active link l ∈ ℒ do
            if l goes through cell c, increase the probability of cell
            c to contain the moving object
    while any two cells c1 and c2 have the same highest proba-
    bility do
        If c1 and c2 are adjacent to each other, merge c1 and c2 into
        big cell c12, 𝒞 = 𝒞 ⋃ c12 \ {c1, c2}; Otherwise, increase
        the probability of the cell which is closer to the position of
        object at time slot t − 1.
    Return the position of the (gravity) center of the cell with the
    highest probability
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E. Main Idea for Multiple Objects Tracking

When multiple objects exists at the same time, we have to distinguish different object first before we can track each of them. Remembering that a wireless node is able to tell whether there is an object exiting along the line between it and some light source. In this sense, our multiple objects tracking problem can be modeled as a binary tracking problem, under which each sensor node has a sensing range such that it can report "yes" or "not" anytime to the question whether there is some object within its sensing range with some probability. Since the object is not a point and has some volume, the sensing range of a light sensor node will be some area, rather than the combination of some line(s).

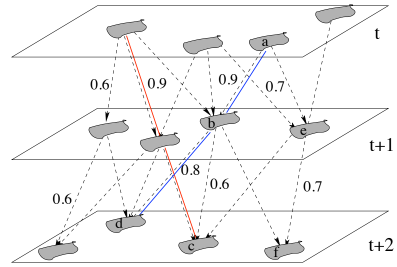
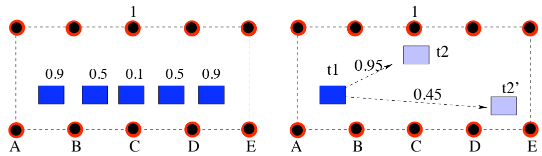


Fig. 4. Two possible paths (blue and red) for two objects with highest probabilities. From up to bottom, there are 3 snapshots of time t, $t+1$ and $t+2$ respectively.

We consider a centralized model in which a tracker node collects the information gathered by all the sensors over a certain interval of time, and processes the collected data to estimate the trajectories.

Since an object may exist at different places with different probabilities, the probabilities for it to move from one place to another place are different as well due to some moving speed constraints. Our main idea is to compute m moving trajectories with highest probability for totally m objects. See the example shown in Fig. 4 for illustration. In this example, for each time slot t, $t+1$ and $t+2$, there are multiple possible places with different probabilities for each of two objects. In addition, the probabilities for an object from one place at time slot t to another place at next time slot $t+1$ may be also different based on the speed constraints. The number besides a directed link denotes the probability by which an object will move from one possible area to next possible area. For example, the probability for an object (staying in area a at time t_1) to move to area b (resp. c) at time t_2 is 0.9 (resp. 0.7). For these two objects, we compute two paths with highest probabilities. The blue and red path are computed possible paths for two objects with highest probabilities. Here, we can compute the possible path either under the constraints that the average probability for two computed paths is highest or maximizing the minimum probability among all resultant paths.

PRELIMINARY APPROACHES: We first propose to analyze the sequence of events at the base station to assign different probabilities for all possible places where the object could be at some time slot t based on the observation that the movement of the object is continuous. Remembering that each wireless node will report "catching" event to the base station with the time stamp when it catches some object, the base station is able to remove much noise and assign different probability to all possible places (where the object could be) based on the collection information during some time slot. For example, in Fig. 5(a), we show a case when it is the first time that the reading of light sensor 1 is affected, which may be caused by any light source from A, B, C, D, E. When the base station check the sequence of all events and found that it is the first time that the reading of light sensor is affected, it is more possible that the object goes through the leftmost or rightmost line since the moving object will come into the monitored area



(a) (b)

Fig. 5. Different probabilities (a) for current places based on the sequence of events. (b) for the next move based on the speed constraints.

from either left side or right side before it reach the middle of the monitored area. Hence the probability for the five possible positions (lines) decreases from two ends to the middle. In addition, by checking the time stamps of events reported by other wireless nodes will further remove such noise and assign different probabilities to different places for the same time slot.

Secondly, we observed that the moving speed of the object being tracked is limited generally, *e.g.*. the moving speed of a person is usually less than 10 meters/sec. Under this observation, the probabilities for an object move from one place at time slot t to some other places at time slot $t+1$ are also different. See Fig. 5(b) for illustration. For example, assume the object is at place $t1$ at time slot t and there are two possible place $t2$ and $t2'$ at the next time slot. Based on the speed constraints, the probabilities for an object moving from $t1$ to either $t2$ or $t2'$ are different (for example, could be 0.95 and 0.45 respectively). There are some other information helpful to remove noise and assign probability, like the moving directions and computed heights, etc., we leave these as our possible future work.

IV. Conclusion

In this paper, we studied passive multiple objects tracking problem. We first showed that counting on RSSI and LQI to do passive tracking is a little bit overestimated and proposed to use light sensors to do passive tracking. We proposed several algorithms to study the moving patterns of objects efficiently. Based on showing our main algorithm in single object tracking using light sensors and light sources, we further proposed our probabilistic method to track multiple objects at the same time.

There are several interesting remaining issues. When multiple objects are close enough, it is hard to distinguish them using light sensors. Even counting multiple objects in this case is difficult. We found that it is possible to do counting when we can carefully arrange the position of light sources and sensors. One of our next steps is to improve our approach for counting and then tracking multiple moving objects efficiently using light sensors, further do real testbed experiments.

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