Improving the localization accuracy of targets by using their spatial–temporal relationships in wireless sensor networks

Xiao Chen [a,*], Neil C. Rowe [b], Jie Wu [c], Kaiqi Xiong [d]

[a] *Department of Computer Science, Texas State University, San Marcos, TX 78666, United States*
[b] *Department of Computer Science, U.S. Naval Postgraduate School, Monterey, CA 93943, United States*
[c] *Department of Computer and Information Sciences, Temple University, Philadelphia, PA 19122, United States*
[d] *College of Computing and Information Sciences, Rochester Institute of Technology, Rochester, NY 14623, United States*

ABSTRACT

Due to the low cost and capabilities of sensors, wireless sensor networks (WSNs) are promising for military and civilian surveillance of people and vehicles. One important aspect of surveillance is target localization. A location can be estimated by collecting and analyzing sensing data on signal strength, time of arrival, time difference of arrival, or angle of arrival. However, this data is subject to measurement noise and is sensitive to environmental conditions, so its location estimates can be inaccurate. In this paper, we add a novel process to further improve the localization accuracy after the initial location estimates are obtained from some existing algorithm. Our idea is to exploit the consistency of the spatial–temporal relationships of the targets we track. Spatial relationships are the relative target locations in a group and temporal relationships are the locations of a target at different times. We first develop algorithms that improve location estimates using spatial and temporal relationships of targets separately, and then together. We prove mathematically that our methods improve the localization accuracy. Furthermore, we relax the condition that targets should strictly keep their relative positions in the group and also show that perfect time synchronization is not required. Simulations were also conducted to test the algorithms. They used initial target location estimates from existing signal-strength and time-of-arrival algorithms and implemented our own algorithms. The results confirmed improved localization accuracy, especially in the combined algorithms. Since our algorithms use the features of targets and not the underlying WSNs, they can be built on any localization algorithm whose results are not satisfactory.

© 2012 Elsevier Inc. All rights reserved.

1. Introduction

Wireless sensor networks (WSNs) are systems of small, low-powered networked sensing devices deployed over an area of interest to monitor interesting events and perform application-specific tasks in response to them. Typically, they monitor people and vehicles. Due to their low cost and capabilities, nonimaging sensors can avoid occlusion and confusion in depth, can violate the privacy less of those tracked, can be easier to conceal from adversary countermeasures, and can be distributed over large areas to provide uniform coverage [22]. WSNs have good potential in persistent pervasive surveillance in military and civilian contexts. A good present-day example is monitoring of a bridge for sabotage or explosive-device emplacement in Afghanistan: explosive devices rarely can be sensed directly, but sensors can be used to distinguish normal activity from suspicious loitering by tracking the positions of people and vehicles.

A fundamental problem addressed in surveillance is target localization. When a moving target enters a sensor network, it affects sensor readings by its properties such as temperature, sound, light, magnetism, and seismic vibration. Most of the existing localization algorithms for WSNs employ a centralized approach that requires all sensory data to be delivered to the central processor where the data are processed to locate a target by techniques such as signal strength [2,12,21], time of arrival or time difference of arrival [5,28], and angle of arrival [18,19]. However, the accuracy of these localization techniques is affected by measurement noise and environmental conditions [2,6], and often there is still room to improve the localization accuracy.

In this paper, we add an extra process to improve the localization accuracy after the initial location estimates are obtained from some existing localization algorithm. We tackle the problem from a new direction. Instead of taking more and better measurements and using more refinement processes in the WSNs, we exploit the *spatial–temporal relationships* of the targets

* Corresponding author.
E-mail addresses: xc10@txstate.edu (X. Chen), ncrowe@nps.edu (N.C. Rowe), jiewu@temple.edu (J. Wu), kxxics@rit.edu (K. Xiong).

being tracked. The spatial relationship of targets is defined as the relative locations of the targets within their group while the temporal relationship is defined as a target's locations at different times. To attain their goals, malicious people such as criminals and terrorists rarely act as individuals. They usually have a team of collaborators in actions such as explosive-device emplacement. Acting in a group can also confuse both manual and automated surveillance, especially if the members dress and behave similarly. In nature, fish swim in schools to avoid sharks, and birds fly in flocks to avoid hawks, to make it difficult for predators to track each individual. On the other hand, the co-location of the elements of group provides an extra condition to locate them better. Similarly, if we know a target's locations over time, we can better locate it. These observations motivate us to explore methods to improve the localization accuracy using spatial–temporal relationships of targets.

The relationship between our algorithms and the existing ones is that our algorithms take the location estimates from the existing ones as inputs and apply the spatial–temporal relationships of targets to further improve the localization accuracy. In other words, our algorithms are built on the underlying existing localization algorithms, which we refer to as *baseline* algorithms. Our algorithms can be used if the location estimates from the baseline algorithms are not satisfactory. Thus, our algorithms do not incur extra communication cost except the computation cost. For the baseline localization algorithm that uses a centralized approach, the major cost comes from the communication between sensors and the central processor. To reduce the communication cost, a cluster-based hierarchical routing protocol [11,16] can be used: sensors are organized into clusters and cluster heads are selected. Routing is conducted by ordinary sensors first sending the sensory data to their cluster heads and then the cluster heads sending the data to the central processor. To the best of our knowledge, the idea to improve the localization accuracy using the spatial–temporal relationships of targets has not been discussed before besides our preliminary effort in [4]. A major advance in the current work is that we prove mathematically that our methods can further improve the localization accuracy. Another advance is the relaxation of the requirement for strict consistency of group positions and the necessity for perfect time synchronization. Still another advance is the results of the first good testing of the performance of our algorithms in simulations, now including data exploiting the time of arrival.

The main contributions of this paper are the following.

- We propose new methods to improve the localization accuracy using spatial–temporal relationships of targets, both separately and together.
- We prove mathematically that our methods can improve the localization accuracy.
- We relax the condition that group members should strictly keep their relative positions in the group and show that perfect time synchronization is not required.
- We validate the effectiveness of our methods with simulations.
- Because our methods use features related to targets themselves, and not those of WSNs, they can be used as an extra process to further improve the localization accuracy if the results from the existing algorithms are not satisfactory.

The remainder of this paper is organized as follows. Section 2 references the related work. Section 3 formulates the problem of using spatial–temporal relationships between targets to improve the localization accuracy. Sections 4–6 put forward methods to achieve that. Section 7 provides a theoretical analysis. Section 8 shows simulation results of the proposed approaches. Section 9 draws our conclusions.

2. Related work

Before a target can be localized, the locations of the sensors in WSNs should be identified. In the literature, there are many sensor localization algorithms for WSNs [3,7,10,17,20,25,26], so we ignore this problem here.

A target can be localized using many types of signal that it sends out: temperature, sound, light, magnetism, and seismic vibration. [1] lists different signals sent from an unarmed person, a soldier, and a vehicle. An unarmed person is likely to disrupt the environment thermally, seismically, acoustically, electrically, chemically, and optically. A soldier is more likely to be detected by a magnetic sensor because of the presence of metal on his/her body, e.g. a weapon. And a vehicle is likely to disrupt the environment thermally, seismically, acoustically, electrically, magnetically, chemically, and optically. Therefore a sensing modality can be determined based on the types of targets to be tracked.

The common localization techniques for nonimaging sensors are as follows.

- Signal strength [2,12,21]: Locations are estimated by comparing signal strengths at different locations, using a theoretical or empirical model to translate the signal strength into distance.
- Time of arrival/time difference of arrival [5,28]: Locations are estimated by comparing times of arrival of the signal or the time difference of arrivals at different locations. The propagation time can be directly translated into distance, based on the known signal propagation speed.
- Angle of arrival [18,19]: Locations are estimated by comparing relative angles of the signal at different locations.

There are also some existing papers on target tracking by data fusion. If we can obtain relatively independent estimates of the probability of a target at a location, we can combine the probability distributions by Bayesian, Dempster–Shafer, fuzzy, particle-filter, or other methods. Representative examples of this approach are [9,13,27,29]. Some works have considered the effects of groups of targets moving together [14,23,24]. But these target-tracking methods take better measurements and use more refinement processes in the WSNs. None of them has considered the spatial–temporal relationships of tracking targets. Also these methods are used to predict target locations or evaluate target correlations and not to improve the localization accuracy from estimated values.

3. Problem formulation

We assume that sensor nodes are deployed over a two-dimensional area. They are responsible for tracking moving targets which intrude the monitored region. We further assume that targets move together in a group. When targets move in a group, their relative locations create the *spatial* relationships between them. And when a target moves along a constant direction with a constant speed, its *footsteps* in the trajectory, the locations of the target at different times, are *temporally* related.

The problem is formulated as follows: given the preliminary estimated locations of targets by some algorithm that treats the target locations as independent of one another and over time, is it possible to improve the localization accuracy further by exploiting the spatial relationships and temporal relationships of the targets? To avoid confusion, we denote a target's actual location as (x, y), the estimate of the position from some existing algorithm as (x^*, y^*), and the adjusted estimate after applying our methods as (x', y').
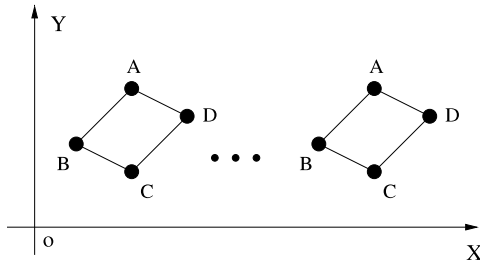
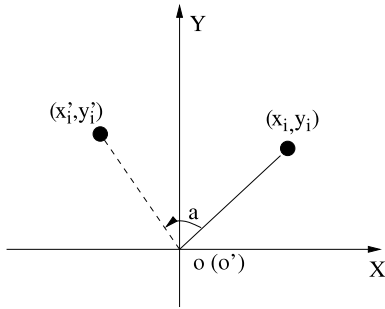**Fig. 1.** The four targets keep their configuration during movement.

Fig. 2. A target's location relative to the centroid of the group before and after movement.

4. Improving the localization accuracy by using spatial relationships

In this section, we put forward an algorithm which we refer to as *LAS* to improve the localization accuracy using the spatial relationships between targets.

Suppose that there are N targets $u_1, u_2, \ldots, u_N$ moving across a sensor field with their relative locations and apparent angles unchanged. For example, as shown in Fig. 1, we can imagine that four targets (A, B, C, and D) stay at the four vertexes of an iron frame. They do not change their relative positions during movement. At a certain time t, the estimated locations of these targets, calculated by some localization algorithm, are $(x_{u1}^*, y_{u1}^*), (x_{u2}^*, y_{u2}^*), \ldots, (x_{uN}^*, y_{uN}^*)$. Suppose initially that the relative position of a target $u_i (1 \leq i \leq N)$ to the group's centroid o, which is known, is (x_i, y_i). When the group moves to a certain location in the sensor field, the relative location of target u_i to the group's centroid o' is (x_i', y_i'). If we translate o' to o (see Fig. 2), the relationship between (x_i, y_i) and (x_i', y_i') can be expressed as

$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix} \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix}. \tag{1}$$

Here, α is a bearing after the group moves to a certain location, and r is an adjustment parameter.

From the estimated values, $(x_{u1}^*, y_{u1}^*), (x_{u2}^*, y_{u2}^*), \ldots, (x_{uN}^*, y_{uN}^*)$, we calculate the centroid o^* of the group and the relative position of each target (x_i^*, y_i^*) to their centroid o^* as follows:

$$\begin{cases} o_x^* = \dfrac{\sum_{i=1}^{N} x_{ui}^*}{N}, \\ o_y^* = \dfrac{\sum_{i=1}^{N} y_{ui}^*}{N}. \end{cases}$$
$$\begin{cases} x_i^* = x_{ui}^* - o_x^*, \\ y_i^* = y_{ui}^* - o_y^*. \end{cases}$$

We translate o^* to o' and we want to minimize the error term between our adjusted relative locations of all targets $(x_i', y_i')(1 \leq i \leq N)$ and the estimated relative locations by some localization algorithm of all targets $(x_i^*, y_i^*)(1 \leq i \leq N)$. Thus, we want to minimize the function

$$f(\alpha, r) = \sum_{i=1}^{N} [(x_i' - x_i^*)^2 + (y_i' - y_i^*)^2]. \tag{2}$$

To do that, apply Eq. (1):

$$f(\alpha, r) = \sum_{i=1}^{N} [(rx_i \cos\alpha - ry_i \sin\alpha - x_i^*)^2 + (rx_i \sin\alpha + ry_i \cos\alpha - y_i^*)^2].$$

Then the following partial derivatives should be equal to 0:

$$\begin{cases} \dfrac{\partial f(\alpha, r)}{\partial r} = 0, \\ \dfrac{\partial f(\alpha, r)}{\partial \alpha} = 0. \end{cases}$$

After solving the equations, α and r are as follows:

$$\begin{cases} \alpha = \arctan \dfrac{\sum_{i=1}^{N}(x_i y_i^* - x_i^* y_i)}{\sum_{i=1}^{N}(x_i x_i^* + y_i y_i^*)}, \\ r = \dfrac{\sum_{i=1}^{N}[(x_i x_i^* + y_i y_i^*)\cos\alpha + (x_i y_i^* - x_i^* y_i)\sin\alpha]}{\sum_{i=1}^{N}(x_i^2 + y_i^2)}. \end{cases}$$

Knowing α and r, the adjusted location of each target u_i relative to centroid o^* can be calculated according to Eq. (1). Thus, the location of target u_i can be adjusted to

$$\begin{bmatrix} x_{ui}' \\ y_{ui}' \end{bmatrix} = \begin{bmatrix} o_x^* \\ o_y^* \end{bmatrix} + \begin{bmatrix} x_i' \\ y_i' \end{bmatrix}$$
$$= \begin{bmatrix} o_x^* \\ o_y^* \end{bmatrix} + r \begin{bmatrix} x_i \cos\alpha - y_i \sin\alpha \\ x_i \sin\alpha + y_i \cos\alpha \end{bmatrix}. \tag{3}$$

From Eq. (3), the time complexity of improving the localization accuracy by using spatial relationships is $O(N)$.

5. Improving the localization accuracy by using temporal relationships

In this section, we improve the localization accuracy by looking at the footsteps of a single target over time. Suppose that we know that a target travels along a line with constant speed and direction, and that the estimated locations of this target by using some localization method from time 1 to T are $(x_1^*, y_1^*), (x_2^*, y_2^*), \ldots, (x_T^*, y_T^*)$. Here, time 1 may not be the time when the target starts moving. It can be any time during its movement that we start to observe. The problem is to adjust these estimated footsteps to make them closer to the actual locations. We explore methods under two sets of conditions: (1) the speed and direction of the target are known, and (2) the speed and direction of the target are unknown. We refer to the resulting algorithms as *LAT1* and *LAT2*, respectively.
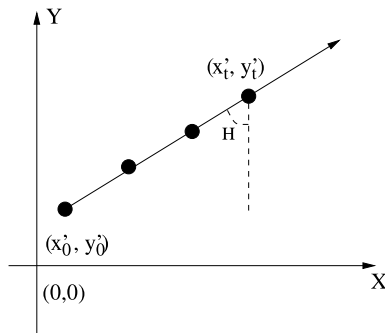
Fig. 3. A target's trajectory over a sensor field.

5.1. Speed and direction are known

Suppose that the speed of the target is v and that its bearing is H (see Fig. 3), and that the starting point of this target, which is unknown, is (x'_0, y'_0); then the location of this target at time $t(1 \le t \le T)$ should be

$$\begin{cases} x'_t = x'_0 + tv\sin(H) \\ y'_t = y'_0 + tv\cos(H). \end{cases} \tag{4}$$

Now, our task is to reduce the error term between the adjusted locations and the estimated locations. So we have to minimize the function

$$f(x'_0, y'_0) = \sum_{t=1}^{T} [(x'_t - x^*_t)^2 + (y'_t - y^*_t)^2]. \tag{5}$$

To do that, apply Eq. (4):

$$\begin{aligned} f(x'_0, y'_0) = \sum_{t=1}^{T} [&(x'_0 + tv\sin(H) - x^*_t)^2 \\ &+ (y'_0 + tv\cos(H) - y^*_t)^2]. \end{aligned}$$

Then the following partial derivatives should be equal to zero:

$$\begin{cases} \dfrac{\partial f(x'_0, y'_0)}{\partial x'_0} = 0, \\ \dfrac{\partial f(x'_0, y'_0)}{\partial y'_0} = 0. \end{cases}$$

Thus, x'_0 and y'_0 can be found as

$$\begin{cases} x'_0 = \dfrac{1}{T} \sum_{t=1}^{T} x^*_t - \dfrac{T+1}{2} v\sin(H), \\ y'_0 = \dfrac{1}{T} \sum_{t=1}^{T} y^*_t - \dfrac{T+1}{2} v\cos(H). \end{cases} \tag{6}$$

Next, each estimated location (x^*_t, y^*_t) can be adjusted to (x'_t, y'_t) as follows:

$$\begin{bmatrix} x'_t \\ y'_t \end{bmatrix} = \begin{bmatrix} x'_0 + tv\sin(H) \\ y'_0 + tv\cos(H) \end{bmatrix}. \tag{7}$$

From Eq. (7), the time complexity of improving the localization accuracy by using temporal relationships when the speed and direction are known is $O(T)$.

5.2. Speed and direction are unknown

Suppose that the unknown speed of the target is v_x in the x direction and v_y in the y direction, and that the starting point of this target, which is also unknown, is (x'_0, y'_0); then the location of this target at time $t(1 \le t \le T)$ should be

$$\begin{cases} x'_t = x'_0 + tv_x \\ y'_t = y'_0 + tv_y. \end{cases} \tag{8}$$

Now, our task is to reduce the error term between the adjusted locations and the estimated locations. So we have to minimize the function

$$f(v_x, v_y, x'_0, y'_0) = \sum_{t=1}^{T} [(x'_t - x^*_t)^2 + (y'_t - y^*_t)^2]. \tag{9}$$

To do that, apply Eq. (8):

$$f(v_x, v_y, x'_0, y'_0) = \sum_{t=1}^{T} [(x'_0 + tv_x - x^*_t)^2 + (y'_0 + tv_y - y^*_t)^2].$$

Then the following partial derivatives should be equal to zero:

$$\begin{cases} \dfrac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial v_x} = 0, \\ \dfrac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial v_y} = 0, \\ \dfrac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial x'_0} = 0, \\ \dfrac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial y'_0} = 0. \end{cases}$$

Thus, v_x, v_y, x'_0, and y'_0 can be found as

$$\begin{cases} v_x = \dfrac{4 \sum\limits_{t=1}^{T} tx^*_t - 2(T+1) \sum\limits_{t=1}^{T} x^*_t}{4 \sum\limits_{t=1}^{T} t^2 - T(T+1)^2}, \\ v_y = \dfrac{4 \sum\limits_{t=1}^{T} ty^*_t - 2(T+1) \sum\limits_{t=1}^{T} y^*_t}{4 \sum\limits_{t=1}^{T} t^2 - T(T+1)^2}, \\ x'_0 = \dfrac{1}{T} \sum\limits_{t=1}^{T} x^*_t - \dfrac{T+1}{2} v_x, \\ y'_0 = \dfrac{1}{T} \sum\limits_{t=1}^{T} y^*_t - \dfrac{T+1}{2} v_y. \end{cases} \tag{10}$$

Next, each estimated location (x^*_t, y^*_t) can be adjusted to (x'_t, y'_t) as follows:

$$\begin{bmatrix} x'_t \\ y'_t \end{bmatrix} = \begin{bmatrix} x'_0 + tv_x \\ y'_0 + tv_y \end{bmatrix}. \tag{11}$$

From Eq. (11), the time complexity of improving the localization accuracy by using temporal relationships when the speed and direction are unknown is $O(T)$.

6. Improving the localization accuracy by combining the spatial and temporal relationships

In this section, we combine the spatial relationships with the temporal relationships. We do it in two different orders: (1) spatial

first and then temporal, and (2) temporal first and then spatial. We refer to the resulting algorithms as *LAST* and *LATS*, respectively.

6.1. Spatial first, temporal next

In the spatial first, temporal next combination, suppose that we know the estimated locations of all group members over the past T time points. We first use Eq. (3) to adjust their estimated locations using the spatial relationships in the group. After that, we apply Eq. (7) or Eq. (11) to adjust each target according to its footsteps in the past T time points.

6.2. Temporal first, spatial next

In the temporal first, spatial next combination, suppose that we know the estimated locations of all group members over the past T time points. We first use Eq. (7) or Eq. (11) to adjust each target according to its footsteps in the past T time points. After that, we apply Eq. (3) to adjust the locations of all the targets using the spatial relationships in the group.

7. Theoretical analysis

In this section, we first prove mathematically that our methods of using the spatial–temporal relationships of targets can improve the localization accuracy; then we relax the constraint that group members should strictly maintain their relative positions in the group, and show that perfect time synchronization is not required.

7.1. Theorem proving

To prove our results, we define the tracking error as $\sum_{i=1}^{N}(|ab|^2)$. $|ab|^2$ is the square of the distance from a target's estimated location/adjusted location a to its actual location b. We prove that the tracking error of the estimated values is greater or equal to the adjusted values: $\sum_{i=1}^{N}[(x_i^* - x_i)^2 + (y_i^* - y_i)^2] \geq \sum_{i=1}^{N}[(x_i' - x_i)^2 + (y_i' - y_i)^2]$.

Theorem 1. *Suppose that there are N targets, $u_1, u_2, \ldots, u_N$, moving coherently in a group and that the estimated locations of these targets, calculated by some localization algorithm, are $(x_{u1}^*, y_{u1}^*), (x_{u2}^*, y_{u2}^*), \ldots, (x_{uN}^*, y_{uN}^*)$. Then, if the targets keep their relative positions in the group, adjusting them by Eq. (3) improves the localization accuracy.*

Proof. Since (x_i, y_i), (x_i^*, y_i^*), and (x_i', y_i') are targets' relative positions to their centroids in the actual values, estimated values, and adjusted values, and o, o', and o^* are translated to the same point, it is equivalent to prove that

$$\sum_{i=1}^{N}[(x_i^* - x_i)^2 + (y_i^* - y_i)^2] \geq \sum_{i=1}^{N}[(x_i' - x_i)^2 + (y_i' - y_i)^2]. \quad (12)$$

From Eq. (2), $f(\alpha, r) = \sum_{i=1}^{N}[(x_i' - x_i^*)^2 + (y_i' - y_i^*)^2]$.
From $\frac{\partial f(\alpha, r)}{\partial \alpha} = 0$ and $\frac{\partial f(\alpha, r)}{\partial r} = 0$,

$$\sum_{i=1}^{N}[-(x_i' - x_i^*)y_i' + (y_i' - y_i^*)x_i'] = 0 \quad (13)$$

$$\sum_{i=1}^{N}[(x_i' - x_i^*)x_i' + (y_i' - y_i^*)y_i'] = 0. \quad (14)$$

Eq. (13) $\times \sin\alpha -$ Eq. (14) $\times \cos\alpha$,

$$\sum_{i=1}^{N}[(x_i' - x_i^*)x_i + (y_i' - y_i^*)y_i] = 0 \quad (15)$$

$$\sum_{i=1}^{N}[(x_i^* - x_i)^2 + (y_i^* - y_i)^2]$$

$$= \sum_{i=1}^{N}[(x_i^* - x_i')^2 + (x_i' - x_i)^2 + 2(x_i^* - x_i')(x_i' - x_i)$$

$$+ (y_i^* - y_i')^2 + (y_i' - y_i)^2 + 2(y_i^* - y_i')(y_i' - y_i)]$$

Apply Eq. (14),

$$= \sum_{i=1}^{N}[(x_i^* - x_i')^2 + (x_i' - x_i)^2 - 2(x_i^* - x_i')x_i$$

$$+ (y_i^* - y_i')^2 + (y_i' - y_i)^2 - 2(y_i^* - y_i')y_i]$$

$$= \sum_{i=1}^{N}[(x_i' - x_i)^2 + (x_i^* - x_i')(x_i^* - x_i' - 2x_i)$$

$$+ (y_i' - y_i)^2 + (y_i^* - y_i')(y_i^* - y_i' - 2y_i)]$$

Apply Eq. (14),

$$= \sum_{i=1}^{N}[(x_i' - x_i)^2 + (x_i^* - x_i')(x_i^* - 2x_i)$$

$$+ (y_i' - y_i)^2 + (y_i^* - y_i')(y_i^* - 2y_i)]$$

Apply Eq. (15),

$$= \sum_{i=1}^{N}[(x_i' - x_i)^2 + (x_i^* - x_i')x_i^*$$

$$+ (y_i' - y_i)^2 + (y_i^* - y_i')y_i^*]$$

Apply Eq. (14),

$$= \sum_{i=1}^{N}[(x_i' - x_i)^2 + (x_i^* - x_i')(x_i^* - x_i')$$

$$+ (y_i' - y_i)^2 + (y_i^* - y_i')(y_i^* - y_i')]$$

$$= \sum_{i=1}^{N}[(x_i' - x_i)^2 + (x_i^* - x_i')^2$$

$$+ (y_i' - y_i)^2 + (y_i^* - y_i')^2]$$

$$\geq \sum_{i=1}^{N}[(x_i' - x_i)^2 + (y_i' - y_i)^2].$$

Thus proves the theorem. □

Theorem 2. *When the speed and the direction of a target are known, given the estimated locations of the target over T time points calculated by some localization algorithm $(x_1^*, y_1^*), (x_2^*, y_2^*), \ldots, (x_T^*, y_T^*)$, adjusting them by Eq. (7) improves the localization accuracy.*

Proof. Proving this theorem is equivalent to proving that

$$\sum_{t=1}^{T}[(x_t^* - x_t)^2 + (y_t^* - y_t)^2] \geq \sum_{t=1}^{T}[(x_t' - x_t)^2 + (y_t' - y_t)^2]. \quad (16)$$

From Eq. (5), $f(x_0', y_0') = \sum_{t=1}^{T}[(x_t' - x_t^*)^2 + (y_t' - y_t^*)^2]$.

From $\frac{\partial f(x'_0, y'_0)}{\partial x'_0} = 0$ and $\frac{\partial f(x'_0, y'_0)}{\partial y'_0} = 0$,

$$\begin{cases} 2\sum_{t=1}^{T}(x'_t - x^*_t) = 0, \\ 2\sum_{t=1}^{T}(y'_t - y^*_t) = 0. \end{cases}$$

So,

$$\begin{cases} \sum_{t=1}^{T}x'_t = \sum_{t=1}^{T}x^*_t, \\ \sum_{t=1}^{T}y'_t = \sum_{t=1}^{T}y^*_t. \end{cases} \tag{17}$$

If a target is moving with a certain speed v and a bearing H, the actual location of the target (x_t, y_t) at time t is

$$\begin{cases} x_t = x_0 + tv\sin(H) \\ y_t = y_0 + tv\cos(H) \end{cases} \tag{18}$$

$$\sum_{t=1}^{T}[(x^*_t - x_t)^2 + (y^*_t - y_t)^2]$$

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (x^*_t - x'_t)^2 + 2(x^*_t - x'_t)(x'_t - x_t)$$

$$+ (y'_t - y_t)^2 + (y^*_t - y'_t)^2 + 2(y^*_t - y'_t)(y'_t - y_t)]$$

Apply Eq. (18),

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (x^*_t - x'_t)^2$$

$$+ 2(x^*_t - x'_t)(x'_t - x_0 - tv\sin(H))$$

$$+ (y'_t - y_t)^2 + (y^*_t - y'_t)^2$$

$$+ 2(y^*_t - y'_t)(y'_t - y_0 - tv\cos(H))]$$

Expand and apply Eq. (17),

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T}(x^*_t)^2 - 2v\sin(H)\sum_{t=1}^{T}tx^*_t - \sum_{t=1}^{T}(x'_t)^2$$

$$+ 2v\sin(H)\sum_{t=1}^{T}tx'_t$$

$$+ \sum_{t=1}^{T}(y^*_t)^2 - 2v\cos(H)\sum_{t=1}^{T}ty^*_t - \sum_{t=1}^{T}(y'_t)^2$$

$$+ 2v\cos(H)\sum_{t=1}^{T}ty'_t$$

Apply Eq. (4),

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T}(x^*_t)^2 - 2v\sin(H)\sum_{t=1}^{T}tx^*_t$$

$$- \sum_{t=1}^{T}(x'_0 + tv\sin(H))^2 + 2v\sin(H)\sum_{t=1}^{T}t(x'_0 + tv\sin(H))$$

$$+ \sum_{t=1}^{T}(y^*_t)^2 - 2v\cos(H)\sum_{t=1}^{T}ty^*_t$$

$$- \sum_{t=1}^{T}(y'_0 + tv\cos(H))^2$$

$$+ 2v\cos(H)\sum_{t=1}^{T}t(y'_0 + tv\cos(H))$$

Apply Eq. (6) and expand $\sum_{t=1}^{T}(x^*_t)^2$,

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \frac{1}{T}[(T-1)\sum_{t=1}^{T}(x^*_t)^2$$

$$- 2Tv\sin(H)\sum_{t=1}^{T}tx^*_t - 2\sum_{t=1}^{T-1}\sum_{k=1}^{T-t}x^*_t x^*_{t+k}$$

$$+ T(T+1)v\sin(H)\sum_{t=1}^{T}x^*_t$$

$$+ \frac{4T\sum_{t=1}^{T}t^2 - T^2(T+1)^2}{4}v^2\sin^2(H)$$

$$+ (T-1)\sum_{t=1}^{T}(y^*_t)^2 - 2Tv\cos(H)$$

$$\sum_{t=1}^{T}ty^*_t - 2\sum_{t=1}^{T-1}\sum_{k=1}^{T-t}y^*_i y^*_{t+k}$$

$$+ T(T+1)v\cos(H)\sum_{t=1}^{T}y^*_t$$

$$+ \frac{4T\sum_{t=1}^{T}t^2 - T^2(T+1)^2}{4}v^2\cos^2(H)]$$

$$= \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \frac{1}{T}\sum_{t=1}^{T-1}\sum_{k=1}^{T-t}[(x^*_t - x^*_{t+k} + kv\sin(H))^2$$

$$+ (y^*_t - y^*_{t+k} + kv\cos(H))^2]$$

$$\geq \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2].$$

This proves the theorem. □

Theorem 3. *When the speed and the direction of a target are unknown, given the estimated locations of the target over T time points calculated by some localization algorithm, $(x^*_1, y^*_1), (x^*_2, y^*_2), \ldots, (x^*_T, y^*_T)$, adjusting them by Eq. (11) improves the localization accuracy.*

Proof. Proving this theorem is equivalent to proving that

$$\sum_{t=1}^{T}[(x^*_t - x_t)^2 + (y^*_t - y_t)^2] \geq \sum_{t=1}^{T}[(x'_t - x_t)^2 + (y'_t - y_t)^2]. \tag{19}$$

From Eq. (9), $f(v_x, v_y, x'_0, y'_0) = \sum_{t=1}^{T}[(x'_t - x^*_t)^2 + (y'_t - y^*_t)^2]$.

From $\frac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial v_x} = 0$ and $\frac{\partial f(v_x, v_y, x'_0, y'_0)}{\partial v_y} = 0$,

$$\begin{cases} \sum_{t=1}^{T} x'_t = \sum_{t=1}^{T} x^*_t, \\ \sum_{t=1}^{T} y'_t = \sum_{t=1}^{T} y^*_t. \end{cases} \qquad (20)$$

If a target is moving with a certain speed v and a bearing H, the actual location of the target (x_t, y_t) at time t is

$$\begin{cases} x_t = x_0 + t v_x \\ y_t = y_0 + t v_y. \end{cases} \qquad (21)$$

From Eqs. (8) and (21),

$$\begin{cases} x'_t - x_t = x'_0 - x_0 \\ y'_t - y_t = y'_0 - y_0 \end{cases} \qquad (22)$$

$$\sum_{t=1}^{T} [(x^*_t - x_t)^2 + (y^*_t - y_t)^2]$$

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (x^*_t - x'_t)^2 + 2(x^*_t - x'_t)(x'_t - x_t)$$
$$+ (y'_t - y_t)^2 + (y^*_t - y'_t)^2 + 2(y^*_t - y'_t)(y'_t - y_t)]$$

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T} [(x^*_t)^2 - 2x_t x^*_t - x'_t(x'_t - x_t - x_t)$$
$$+ (y^*_t)^2 - 2y_t y^*_t - y'_t(y'_t - y_t - y_t)]$$

Apply Eq. (22),

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T} [(x^*_t)^2 - 2x_t x^*_t - x'_t(x'_0 - x_0 - x_t)$$
$$+ (y^*_t)^2 - 2y_t y^*_t - y'_t(y'_0 - y_0 - y_t)]$$

Apply Eq. (20),

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T} (x^*_t)^2 - 2\sum_{t=1}^{T} x_t x^*_t - (x'_0 - x_0)\sum_{t=1}^{T} x^*_t$$

$$+ \sum_{t=1}^{T} x'_t x_t + \sum_{t=1}^{T} (y^*_t)^2 - 2\sum_{t=1}^{T} y_t y^*_t$$

$$- (y'_0 - y_0)\sum_{t=1}^{T} y^*_t + \sum_{t=1}^{T} y'_t y_t$$

Apply Eqs. (8) and (21),

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \sum_{t=1}^{T} (x^*_t)^2 - 2\sum_{t=1}^{T} x_t x^*_t - x'_0 \sum_{t=1}^{T} x^*_t$$

$$+ 2x_0 \sum_{t=1}^{T} x^*_t + x'_0 v_x \sum_{t=1}^{T} t + v_x^2 \sum_{t=1}^{T} t^2$$

$$+ \sum_{t=1}^{T} (y^*_t)^2 - 2\sum_{t=1}^{T} y_t y^*_t - y'_0 \sum_{t=1}^{T} y^*_t$$

$$+ 2y_0 \sum_{t=1}^{T} y^*_t + y'_0 v_y \sum_{t=1}^{T} i + v_y^2 \sum_{t=1}^{T} t^2$$

Replace x'_0 and y'_0 using Eq. (10),

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \frac{1}{T}\left[(T-1)\sum_{t=1}^{T}(x^*_t)^2 - 2T v_x \sum_{t=1}^{T} t x^*_t \right.$$

$$+ T(T+1)v_x \sum_{t=1}^{T} x^*_t - 2\sum_{t=1}^{T-1}\sum_{k=1}^{T-t} x^*_t x^*_{t+k}$$

$$+ \frac{4T \sum_{t=1}^{T} t^2 - T^2(T+1)^2}{4} v_x^2$$

$$+ (T-1)\sum_{t=1}^{T}(y^*_t)^2 - 2T v_y \sum_{t=1}^{T} t y^*_t$$

$$+ T(T+1)v_y \sum_{t=1}^{T} y^*_t - 2\sum_{t=1}^{T-1}\sum_{k=1}^{T-t} y^*_t y^*_{t+k}$$

$$\left. + \frac{4T \sum_{t=1}^{T} t^2 - T^2(T+1)^2}{4} v_y^2 \right]$$

$$= \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2]$$

$$+ \frac{1}{T}\sum_{t=1}^{T-1}\sum_{k=1}^{T-t}[(x^*_t - x^*_{t+k} + k v_x)^2 + (y^*_t - y^*_{t+k} + k v_y)^2]$$

$$\geq \sum_{t=1}^{T} [(x'_t - x_t)^2 + (y'_t - y_t)^2].$$

This proves the theorem. $\square$

7.2. Relaxing the constraint in LAS

In our algorithm LAS that uses the spatial relationships to improve localization accuracy, we assumed that the group members strictly maintain their relative positions within the group over time. However, this may not be realistic in real-world situations. After we look at LAS and the proof of Theorem 1 closely, we find that this constraint can be relaxed. The inputs to LAS are the estimated locations of targets from the baseline algorithm (from which we can calculate the estimated relative positions to the centroid) and targets' actual relative positions. We can treat targets' actual relative positions as their initial relative positions before they enter the sensor field. Thus, the adjustment in Eq. (3) is based on targets' estimated positions, targets' calculated relative positions to the centroid, and targets' initial relative positions to the centroid. The actual deviation of targets from the group during movement is neither known nor used. Therefore, whether targets move closer towards or farther away from each other, the proof of Theorem 1 is still valid as long as they do not exchange positions in the group so that we can correctly identify them.

7.3. Time synchronization issue

In our algorithms LAT1 and LAT2 that use temporal relationships to improve accuracy, we have not discussed whether our

algorithms still work if the sensor clocks are not synchronized. In real-world applications, it is hard to make sensor clocks perfectly synchronized due to the limitation of the materials that are used to make clocks and ambient influence. But our algorithms do not require accurate time stamps. After the T estimated positions corresponding to T time points are obtained from the baseline algorithm, Eqs. (7) and (11) match the first position with time 1, the second position with time 2, etc. Accurate time is not a parameter in our algorithms. In other words, as long as the baseline localization algorithm is good enough to determine the correct order of the T estimated positions in the timeline, which is not a hard task, we can improve the localization accuracy by using LAT1 and LAT2 as proved in Theorems 2 and 3. The order of the positions is required because otherwise we cannot correctly identify the positions (e.g. mistake position 1 for position 2).

8. Simulations

Since our approach is the first of its kind, which serves as an extra step after obtaining the location estimates from existing algorithms, there is no work in the literature to compare it with. Besides the theoretical proofs, we also conducted simulations to see if our algorithms can further improve the localization accuracy using a simulator built in the Matlab language. We can start with location estimates from some localization algorithm in the literature that needs improvement. Here, we chose two most investigated localization techniques in WSNs, tracking by signal strength and tracking by time of arrival, as our baseline algorithms. Signal-strength localization has errors due to ambient noise and to errors in matching signals between sensors, and time-of-arrival localization has errors due to path nonlinearity by refraction and to the measurement of short times, so estimates from both can often be improved in real-world applications. Location estimation based on signal strength is usually less accurate than location estimation based on time of arrival, so our simulations provided an opportunity to see how our methods handled different degrees of initial accuracy. Our previous work [22] implemented these two baseline localization algorithms, so we build our simulation using these.

8.1. Simulation for tracking by signal strength

We call the baseline algorithm using signal strength in our previous work [22] our original method (ORG). We compared it with LAS, LAT1, LAT2, LAST, and LATS.

We built on the code for the simulation in [22]. It uses a grid of 100×100 sensors (the green dots in Fig. 4). The size of a green dot shows the signal strength received by this sensor. The larger the size, the stronger the signal. Random targets (the blue diamonds in Fig. 4) are created in the sensor space, and signals from these targets are received by the sensors in the field to make estimates of locations (the red stars in Fig. 4). Following discussions of acoustic, seismic, and magnetic signals in the literature [15], we assumed that the inverse-square law is a good model to calculate the signal strength for this simulation, where each signal strength is

$$s_i = c + \frac{a}{(m+d)^2}, \quad 1 \le i \le N.$$

Here, s_i is the sensed signal strength in the ith sensor, c is a random factor, a is the intensity of the target, d is the distance from the target to the sensor, m is the minimum-distance factor from the target which is a feature of each sensor, and N is the total number of sensors in the network. Parameter c was set to 0 in these experiments to model the situation of no background noise. To avoid unstable behavior with very-near targets, m was set to 5 based on experiments in [22]. The total signal strength received

by each sensor is assumed to be additive from all these targets. For instance, if the signal is sound, the intensity from each target would be added at each sensor.

The method reported in [22] estimates the locations of targets in two steps. First, we assign crude estimates of target locations as the sensor locations that receive the maximum signal strength in their neighborhood (local maxima). In this simulation, the neighborhood of a sensor included all the sensors that are one grid space away from the current one. Second, we adjust locations based on the observed ratio of signal strengths, a variation on the approach of [15]. If initially the observed signal strength is assumed to be only due to each sensor's nearest target, then, for any two sensors 1 and 2, the following holds true due to the assumed inverse-square law:

$$s_1[(x - x_{1s})^2 + (y - y_{1s})^2 + m^2] = s_2[(x - x_{2s})^2 + (y - y_{2s})^2 + m^2].$$

Here, s_1 and s_2 represent the signal strength received by the two sensors, m represents the minimum-distance factor as mentioned above, (x, y) is the position of the tracked target, and (x_{1s}, y_{1s}) and (x_{2s}, y_{2s}) are the coordinates of the two sensors. Rearranging this gives an equation of a circle for the locus of points on which the target could lie. The center and radius of this circle are

$$x_c = \frac{s_1 x_1 - s_2 x_2}{s_1 - s_2}, \qquad y_c = \frac{s_1 y_1 - s_2 y_2}{s_1 - s_2}$$

$$r = \sqrt{\frac{s_1 s_2[(x_{1s} - x_{2s})^2 + (y_{1s} - y_{2s})^2]}{(s_1 - s_2)^2} - m^2}.$$

Next, we use the idea of trilateration [8] to locate the targets. If we can get three sensors measuring the signal strength of the same target, we can intersect their circles to reduce the locus of the target to two points. If there are more than three sensors measuring the same target, a *consensus center* can be obtained by finding the set of all intersection points and repeatedly removing the point furthest from the centroid of the set until there are only two points remaining. The centroid of these two points is the inferred target location.

For our simulation, we generated a group of N targets randomly in a 100×100 grid. It traveled in some direction with some speed across the grid. As it traveled, the signal strengths received by the sensors were calculated at evenly spaced times. The time starts from 1 and the interval between time points is one second. We infer the target locations from the signal strength patterns using the ORG algorithm. Then, by considering the spatial–temporal relationships of targets, we apply LAS, LAT1, LAT2, LAST, and LATS to adjust the locations of the targets. For example, Fig. 4(a)–(f) show the snapshots of the tracking simulator with a group of four targets at time point 5.

We tested groups with 2, 3, ..., and 10 targets and with signal variances 1 and 3. Signal variance is the error in the signal strength perceived by the sensor. For each experiment, we did 100 runs. The tracking error is averaged over these runs to assess the estimation performance. Fig. 5(a) and (b) confirmed the performance of our methods. The proposed algorithms improve the localization accuracy of the ORG algorithm. With the increase of target number, the increase of the tracking error of our proposed algorithms slows down, especially the combined ones. The figures show that LAT1 performs better than LAT2. This is because, if more parameters are known, the results can be more accurate. Similarly, the combination of the spatial and temporal relationships is better than each one alone. However, there was not much difference between LAST and LATS. This means that whether the locations are adjusted first by the spatial relationships or by the temporal relationships does not matter much. Also, the signal variance has little effect on the tracking error.
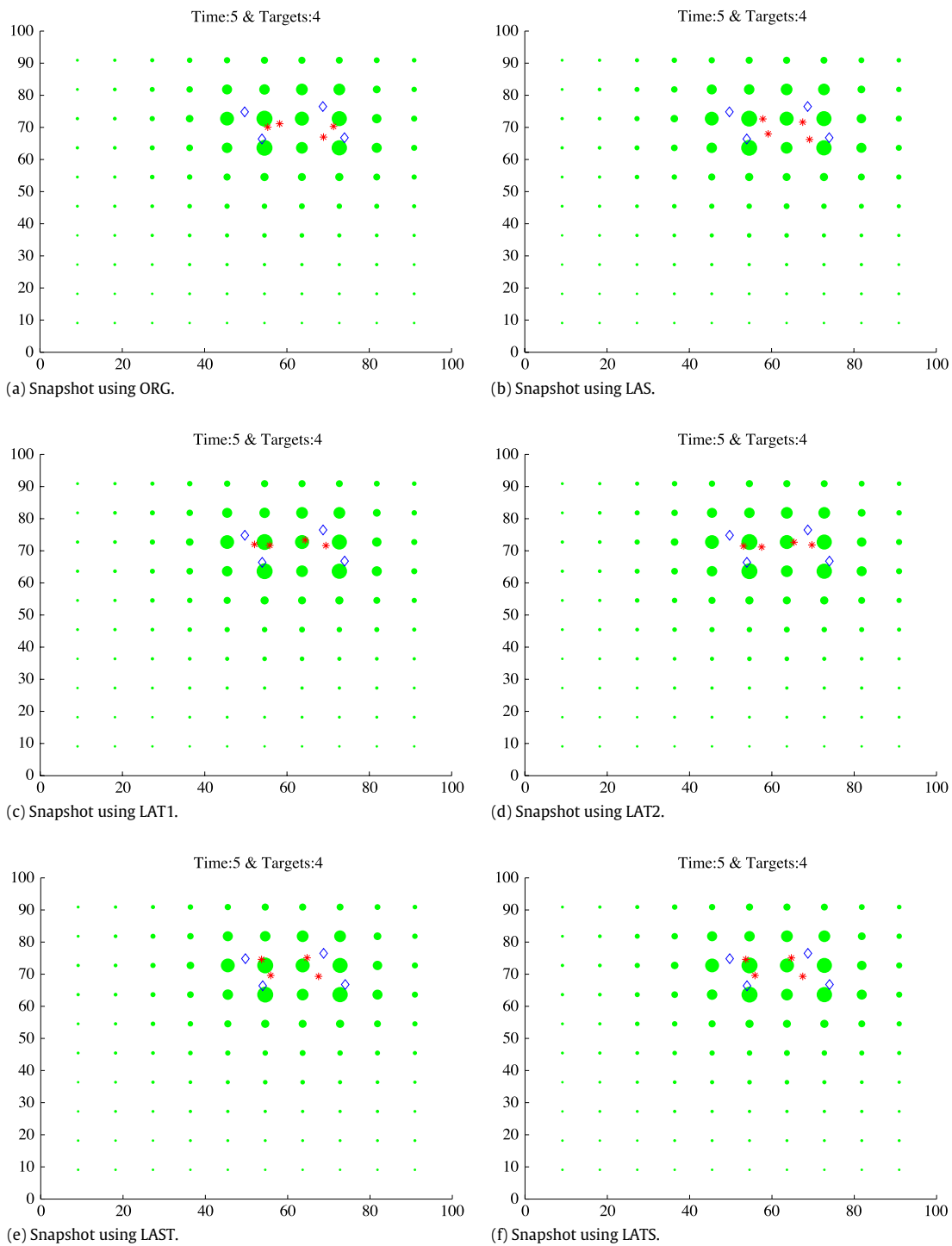
(a) Snapshot using ORG.

(b) Snapshot using LAS.

(c) Snapshot using LAT1.

(d) Snapshot using LAT2.

(e) Snapshot using LAST.

(f) Snapshot using LATS.

Fig. 4. Snapshots of comparing algorithms: the blue diamonds show the actual locations of the targets, the green dots represent the sensors, and the red stars are the estimated locations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

8.2. Simulation for tracking by time of arrival

In the second simulation, we localized using the time of arrival [22], a method which we named ORG-T. All other methods follow the same naming scheme. Analogously to before, we created five more methods: LAS-T, LAT1-T, LAT2-T, LAST-T, and LATS-T.

The principle of time-of-arrival tracking is that the speed of transmission of nearly all signals is relatively constant over space, so the differences in times at which a signal is received are near to proportional to the differences in distances from the source of

the sound. Thus, in a two-dimensional plane, the locus of points of a target based on the differences in time of arrival of the same signal transmitted from that target to two sensors is a hyperbola. Three sensor readings from targets reduce the locus to (generally) two points, and four readings reduce it to one point. However, it is best to obtain as many readings as possible to compensate for inaccuracies, and then use a fitting method such as least squares to minimize the overall error.

Again suppose that we have a set of N sensors at locations (x_i, y_i) for $i = 1$ to N. Assume that the corresponding peaks arrive
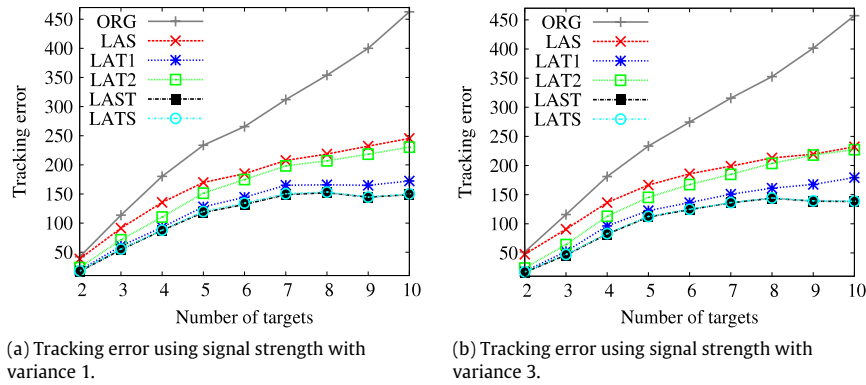
(a) Tracking error using signal strength with variance 1.

(b) Tracking error using signal strength with variance 3.

Fig. 5. Tracking error with different group sizes and variances using signal strength.

(a) Tracking error using time of arrival with variance 1.

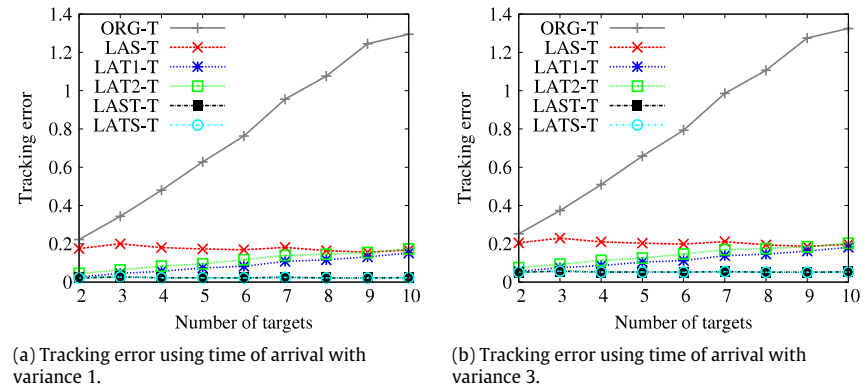(b) Tracking error using time of arrival with variance 3.

Fig. 6. Tracking error with different group sizes and variances using time of arrival.

at each sensor at time t_i. We want to minimize

$$G_D = \sum_{i=1}^{N} \sum_{j=i+1}^{N} |E_D(i,j)|,$$

where

$$E_D(i,j) = \sqrt{(x - x_i)^2 + (y - y_i)^2} - \sqrt{(x - x_j)^2 + (y - y_j)^2} + c(t_j - t_i).$$

Here, c is the average speed of the signal and (x, y) is the position of the tracked target as before. The derivatives of G are (where "sgn" is the sign of its argument)

$$\frac{\partial G_D}{\partial x} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} 2 * sgn(E_D) * \left[\frac{x - x_i}{\sqrt{(x - x_i)^2 + (y - y_i)^2}} - \frac{x - x_j}{\sqrt{(x - x_j)^2 + (y - y_j)^2}} \right]$$

$$\frac{\partial G_D}{\partial y} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} 2 * sgn(E_D) * \left[\frac{y - y_i}{\sqrt{(x - x_i)^2 + (y - y_i)^2}} - \frac{y - y_j}{\sqrt{(x - x_j)^2 + (y - y_j)^2}} \right].$$

The two ratios are equivalent to the cosine (for x) and sine (for y) of the bearing angles from the estimated target location to the sensor. Thus we can optimize the location of the tracked target by moving its position by a weighted sum of the vectors towards or away from each of the sensors.

Fig. 6(a) and (b) show the results based on time-of-arrival localization. We observe that the localization accuracy of tracking by time of arrival is much better than that of tracking by signal

strength. Similar to the results from using signal strength, the tracking error of ORG is much higher than that of the locations adjusted by our proposed algorithms. Also, with an increase of number of targets, the increase of the tracking error of our algorithms slows down or stops. Other observations for the signal-strength experiments also hold in time-of-arrival experiments.

9. Conclusion

In this paper, we have presented that using two additional constraints can improve the localization accuracy of positions of targets estimated from sensors alone. The additional constraints were an assumption of consistency of relative locations within a group of targets and an assumption of consistency in the velocity vector. We have shown relatively simple mathematics by which they can be applied to sensor-based estimates, and proved that these methods never decreased the quality of the estimates. Furthermore, we relaxed the condition that targets should strictly keep their relative positions in the group and explained that perfect time synchronization is not required. We have also displayed results of simulation on an idealized sensor grid with random targets, confirming that the methods did indeed improve the tracking accuracy considerably. In the future, we will consider fault tolerance, connectivity, and security issues in the localization algorithms.

References

[1] A. Arora, P. Dutta, S. Bapat, V. Kulathumani, H. Zhang, V. Naik, V. Mittal, H. Cao, M. Gouda, Y. Choi, T. Herman, S. Kulkarni, U. Arumugam, M. Nesterenko, A. Vora, M. Miyashita, A line in the sand: a wireless sensor network for target detection, classification, and tracking, in: Computer Networks, vol. 46, Elsevier, 2004, pp. 605–634.

[2] P. Bahl, V.N. Padmanabhan, RADAR: an in-building RF-based user location and tracking system, in: Proceedings of the IEEE INFOCOM'00, Mar. 2000, pp. 775–784.

[3] N. Bulusu, et al., GPS-less low cost outdoor localization for very small devices, IEEE Personal Communications Magazine 7 (5) (2000).

[4] X. Chen, N.C. Rowe, G. Singh, Improving localization accuracy using spatial–temporal information of objects, in: Proceedings of the IEEE International Conference on Communications, May2010, pp. 1–5.

[5] C.R. Comsa, J.H. Luo, A. Haimovich, S. Schwartz, Wireless localization using time difference of arrival in narrow-band multipath systems, in: Proceedings of International Symposium on Signals, Circuits and Systems, Vol2, July 2007, pp. 1–4.

[6] S.K. Das, J. Wang, R.K. Ghosh, R. Rupert, Algorithmic aspects of sensor localization, in: Theoretical Aspects of Distributed Computing in Sensor Networks, Springer, Berlin, 2011, pp. 257–291 (Chapter 9).

[7] L. Doherty, L.E. Ghaoui, K.S.J. Pister, Convex position estimation in wireless sensor networks, in: Proceedings of the IEEE INFOCOM2001, April 2001.

[8] J. Figueiras, H.P. Schwefel, I. Kovacs, Accuracy and timing aspects of location information based on signal-strength measurements in Bluetooth, in: Proc. of the 16th IEEE International Symposium on Personal, Indoor, and Mobile Radio Communications, Sept. 2005, pp. 2685–2690.

[9] L.W. Fong, W.T. Chen, C.-F. Tu, Nonlinear estimation fusion in distributed passive sensor networks, in: Proc. IEEE Intl. Conference on Networking, Sensing, and Control, Okayama, Japan, March 2009, pp. 37–42.

[10] T. He, C. Huang, B.M. Blum, J.A. Stankovic, T.F. Abdelzaher, Range-free localization schemes in large scale sensor networks, in: Proceedings of the ACM MobiCom'03, 2003, pp. 81–95.

[11] W. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy-efficient communication protocol for wireless microsensor networks, in: Proc. of the 33rd Hawaii International Conference on System Sciences, HICSS '00, January 2000.

[12] J. Hightower, G. Boriello, R. Want, SpotON: an indoor 3D location sensing technology based on RF signal strength, Technical Report 2000-02-02, University of Washington, February 2000.

[13] X. Hu, Q. Yan, Multi-algorithm hybrid location model based on data fusion, in: Proceedings of the International Conference on Communications and Mobile Computing, April 2010, pp. 408–412.

[14] W. Koch, R. Saul, A Bayesian approach to extended object tracking and tracking of loosely structured target groups, in: Proc. of 7th International Conference on Information Fusion, 2005, pp. 827–834.

[15] J. Lee, K. Cho, S. Lee, T. Kwon, Y. Choi, Distributed and energy-efficient target localization and tracking in wireless sensor networks, Computer Communications 29 (2006) 2494–2505.

[16] S. Lindsey, C. Raghavendra, PEGASIS: power-efficient gathering in sensor information systems, in: IEEE Aerospace Conference Proceedings, Vol. 3 (9–16), 2002 pp. 1125–1130.

[17] D. Moore, J. Leonard, D. Rus, Robust distributed network localization with noisy range measurements, in: Proc. ACM SenSys 2004, Nov. 2004.

[18] A. Nasipuri, K. Li, A directionality based location discovery scheme for wireless sensor networks, in: Proceedings of the ACM WSNA'02, Sept. 2002.

[19] D. Niculescu, B. Nath, Ad hoc positioning system (APS) using AoA, in: Proceedings of the IEEE INFOCOM'03, 2003, pp. 1734–1743.

[20] D. Niculescu, B. Nath, Ad hoc positioning systems (APS), in: Proceedings of the IEEE GLOBECOM'01, Nov. 2001.

[21] N. Patwari, A.O. Hero, M. Perkins, N.S. Correal, R.J. ODea, Relatvie location estimation in wireless sensor networks, IEEE Transactions on Signal Processing 51 (8) (2003).

[22] N. Rowe, M. O'Hara, G. Singh, Wireless sensor networks for detection of IED emplacement, in: Proc. of Intl. Command and Control Research and Technology Symposium, Washington, DC, June 2009.

[23] D.J. Salmond, N.J. Gordon, Group and extended object tracking, IEEE Colloqium on Target Tracking: Algorithms and Applications (1999) 16/1–16/4.

[24] C. Settgast, M. Klepal, Object correlation evaluation for location data fusion, Proceedings of the Ubiquitous Positioning, Indoor Navigation, and Location Based Service (October) (2010) 1–5.

[25] Y. Shang, et al. Localization from mere connectivity, in: Proceedings of the ACM MOBIHOC 2003, June 2003.

[26] X. Sheng, Y. Hu, Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks, IEEE Transactions on Signal Processing 53 (1) (2005).

[27] C.D. Wann, M.H. Lin, Data fusion methods for accuracy improvement in wireless location systems, in: Proceedings of the Wireless Communications and Networking Conference, March 2004, pp. 471–476.

[28] B.H. Wellenhoff, H. Lichtenegger, J. Collins, Global Positions System: Theory and Practice, fourth ed., Springer Verlage, 1997.

[29] C.Y. Yang, B.S. Chen, F.K. Liao, Mobile location estimation using fuzzy-based IMM and data fusion, IEEE Transactions on Mobile Computing 9 (10) (2010) 1424–1436.

Xiao Chen is an associate professor of Computer Science at Texas State University, San Marcos. She received her Ph.D. Degree in Computer Engineering from Florida Atlantic University, and her Master Degree and Bachelor Degree in Computer Science from Shanghai University of Science and Technology. Her research interests are in the areas of delay-tolerant networks, sensor networks, and ad hoc wireless networks. She has served as an associate editor, program committee member, session chair, and reviewer of numerous international journals and conferences.

Neil C. Rowe is Professor of Computer Science at the U.S. Naval Postgraduate School, where he has been since 1983. He has a Ph.D. in Computer Science from Stanford University (1983). His main research interests are the modeling of deception, information security, surveillance systems, image processing, and data mining.

Jie Wu is a distinguished professor and chair in the Department of Computer and Information Sciences at Temple University, and was a program director at US National Science Foundation. He has published over 450 papers in various journals and conference proceedings. His research interests are in the areas of wireless networks and mobile computing, routing protocols, fault-tolerant computing, and interconnection networks. He served as the chair of the IEEE TCDP committee. He has also served as an editor, program chair, and co-chair of numerous international committees, conferences, and journals. He is the author of the text Distributed System Design published by the CRC press. He is an IEEE fellow.

Kaiqi Xiong received his Ph.D. Degree in Computer Science from the Department of Computer Science and his M.S. Degree in Computer Engineering from the Department of Electrical and Computer Engineering, both at North Carolina State University. He has also received Ph.D. and M.S. Degrees in Mathematics from Claremont Graduate School. He is currently an assistant professor in the College of Computing and Information Sciences at Rochester Institute University. His research interests are in the areas of cloud computing, security, performance evaluation, and SLA-based resource provisioning. He has published more than four dozen referred papers in leading journals and conference proceedings. He is a senior member of the IEEE.