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iTPS: an improved location discovery scheme for sensor networks with long-range beacons

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Abstract

In this paper, we present time-based positioning scheme (iTPS), a purely localized location detection scheme for sensor networks with long-range beacons. iTPS relies on time difference of arrival (TDoA) of radio frequency (RF) signals measured locally at each sensor to detect range differences from the sensor to four base stations. These range differences are combined to estimate the sensor location through trilateration. iTPS is an improvement over TPS (Cheng et al., IEEE INFOCOM, 2004), which produces two ambiguous position estimates when sensors are close to any base station. iTPS substantially reduces the number of ambiguous estimates and can improve accuracy. Features of iTPS include low communication overhead for sensors, no requirements for time synchronization, low computational overhead due to simple algebraic operations, and high scalability. We conduct extensive simulation to test iTPS and compare it with TPS. The obtained results show that iTPS is an efficient and effective scheme for location discovery in sensor networks with long-range beacon stations.

Keywords: Sensor networks; TDoA; TPS; Location discovery; Trilateration

1. Introduction

Sensor location detection has become an active research topic in recent years [17,23,29,32,34], especially when the technologies of sensor, actuator and radio have become more and more mature [1,26]. Sensor networks are anticipated to extend human beings' "tactile" sensation to every corner of the world. They will provide a global view of monitored areas based on local observations measured by each sensor. In this paper, we will propose an algorithm for effective sensor self-positioning when the network contains multiple base stations with long-range beacon signals. This research targets the large class of future unattended distributed networks of sensors interacting with the physical world for monitoring and control. Example applications include habitat monitoring and infrastructure surveillance, which have been well-documented in [6,9,22,39].

Almost all applications of sensor networks require sensors to be aware of their physical positions. For example, the detection of a target or an event in surveillance or monitoring sensor networks is always associated with location information [15,21,31]. Further, knowledge of sensor location can be used to facilitate network functions such as packet routing [8,19] and collaborative signal processing [13]. Sensor position can also serve as ID, as it may be unnecessary or impossible for each sensor to have a unique ID before its deployment [33]. However, sensor self-positioning is difficult for outdoor large-scale micro-sensor networks.

The challenges of location discovery in wireless sensor networks are multi-fold. First, the positioning algorithm must be distributed and localized in order to scale well for large sensor networks. The well-studied techniques for cellular networks or PCS systems [4,5,20] do not work well as they rely on reception of an individual phone's signals

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at base stations for subscriber position estimation. Sensors are required to position themselves. Second, localization protocols must minimize communication and computation overhead for each sensor due to resource constraints (power, CPU, memory, etc.). Third, a sensor network usually consists of hundreds of thousands of low-cost sensors. The positioning functionality should not increase the cost and complexity of sensor construction. Fourth, a location detection scheme should be robust. It should work in various harsh environments, and should not depend on network connectivity. Finally, location information should be provided with high precision and confidence even in noisy environments. These challenges have resulted in considerable research in sensor location discovery. Scientists have proposed different schemes based on application requirements.

In this paper, we present a time-based positioning scheme (iTPS) for efficient location discovery in sensor networks. The design objective of iTPS is to seek an effective method that can solve many of the difficulties of sensor position computation mentioned above. iTPS is an improvement over TPS, a time-based sensor self-positioning scheme presented in [7]. Unlike many time-of-arrival (ToA)/time-difference-of-arrival (TDoA) methods [35], iTPS avoids the requirement that base stations be synchronized in time. This algorithm does not require intensive computations [34], matrix manipulations, ordinary least squares [16], or non-linear least squares [5]. iTPS relies on TDoA measurements of beacon signals from base stations at the sensor.

Another contribution of this paper is the study of the deficiency of TPS, the algorithm presented in [7]. TPS results in two ambiguous position estimates for sensors that are in close vicinity of base stations. iTPS, the modified algorithm presented in this paper, retains all the benefits of TPS, and at the same time, significantly reduces the number of ambiguous estimates and improves accuracy. As in TPS, TDoA measurements in iTPS are combined via trilateration to calculate a sensor position. This algorithm requires no time synchronization. Sensors compute their positions independently of one another. Both TPS and iTPS avoid overhead of additional sensor transmissions by requiring only reception of the beacon signals. The computation overhead is low, as the location detection algorithm involves only simple algebraic operations over scalar values. Both schemes are not adversely affected by increasing network size or density and thus offer scalability. We conduct extensive simulation to test iTPS and compare it with TPS. The obtained results show that iTPS is potentially an effective scheme for location discovery in sensor networks with long-range beacons.

This paper is organized as follows. Section 2 briefly summarizes the related work. Section 3 outlines TPS and presents our simulation study of the deficiency in TPS. iTPS, the improved sensor positioning scheme, is proposed in Section 4. Simulation study is reported in Section 5. We conclude our paper in Section 6.

2. Related work

The majority of existing sensor location detection schemes first measure distances or angles from a sensor to several beacon stations (with a priori location information) based on ToA, TDoA, angle of arrival (AoA), received signal strength indicator (RSSI), etc., then combine the measurements to obtain location estimates through *triangulation*, *trilateration*, or *multilateration*. In outdoor environment, global positioning system (GPS) [25] is the most popular localization system in the transportation industry and military. But installing GPS on every wireless node may not be an attractive option due to form factor, antennae requirements and increased power consumption. GPS-less systems use either long-range beacon nodes [3,7,23], where manually placing several (at least 2, as required by AoA) powerful beacon stations are feasible, or short-range beacon nodes [17,18,24,30–32], where a small percent of sensors with positioning functionality (e.g. sensors have GPS installed) are randomly dropped over the monitored area.

Systems with long-range beacon stations [3,7,23] shift complexity from sensors to beacon nodes, whose transmission ranges are large enough to cover all the sensors under consideration. These systems may also require beacon stations to have special equipment such as directional antenna [23] and special functionality such as time synchronization [23]. iTPS, presented in this paper, and TPS, presented in [7], rely on the transmissions of radio frequency (RF) signals from multiple beacon nodes for sensor location estimation. Both schemes put no special requirements on beacon stations except long transmission ranges.

Short-range beacon location detection is either based on network connectivity [24,30,34], where global flooding is involved for range estimation, or relies on the simultaneous transmissions of both RF and ultrasound signals [11,18,31,32], where acoustic signals suffer a significant dependence on local atmospheric conditions. Connectivity-based schemes do not scale well due to global flooding and are not reliable due to the dynamics of wireless sensor networks. Systems based on both RF and ultrasound make sensor construction more complex and more expensive. Sunlight and other environmental radiation also decrease the precision of ultrasound. iTPS requires no connectivity information. Therefore our scheme scales well to large networks. Sensors in iPTS passively listen to the RF signals transmitted by base stations, which result in zero communication overhead. Since RF signals perform better compared to ultrasound, infrared, etc., in outdoor environments [28], iTPS is more reliable. Both long- and short-range location detection schemes usually require intensive computation [32] for better performance. iTPS only involves simple algebraic operations over scalar values. Therefore its computation overhead is low.

Observed time difference (OTD) [12,38] describes implementation of a time difference system in time division multiple access (TDMA) phone systems to calculate range difference hyperbolas but does not provide a trilateration algorithm. E-OTD [36] is an improvement on OTD but uses a trilateration technique based on solving a system of linear equations [10] that is computationally expensive. iTPS is similar to these systems in that we envision using long-range beacons similar to cellular towers to broadcast signals for TDoA measurements, and then to use time differences to calculate range differences and to trilaterate a position.

Positioning systems for in-door localization [2,14,17,27,29,37] do not work well in outdoor sensor networks since the whole network needs to be pre-planned. iTPS is a pure localized scheme that requires no sensor network pre-configuration.

3. A study on TPS

In this section, we provide a brief overview on TPS [7], the time-based positioning scheme for efficient location discovery for sensor networks with long-range beacons. We also examine an important deficiency of TPS: the calculation of two ambiguous positions when sensors are close to any base station.

3.1. A brief overview on TPS

TPS relies on TDoA of RF signals measured locally at a sensor S to detect range differences from the sensor to three base stations A, B, and C, as shown in Fig. 1. These range differences are averaged over multiple beacon intervals before they are combined to estimate the sensor location through trilateration. Let d_{sa}, d_{sb}, and d_{sc} be the distance from S to A, B, and C, respectively. Let k_1 and k_2 be the averaged range differences from S to B and to C, relative to A. Then we have $d_{sb} = d_{sa} + k_1$ and $d_{sc} = d_{sa} + k_2$. Applying trilateration generates the following three equations: $(x - x_a)^2 + (y - y_a)^2 = d_{sa}^2$, $(x - x_b)^2 + (y - y_b)^2 = (d_{sa} + k_1)^2$, and $(x - x_c)^2 + (y - y_c)^2 = (d_{sa} + k_2)^2$.

In [7] we give an efficient way to solve these trilateration equations when A, B, and C are located at $(0, 0)$, $(x_1, 0)$, and (x_2, y_2), respectively, where $x_1 > 0$, $y_2 > 0$. Since, we can always transform real positions to this coordinate system through rotation and translation, the following solutions from [7] can be treated as a general one:

$$x = \frac{-2k_1 d_{sa} - k_1^2 + x_1^2}{2x_1}, \tag{1}$$

$$y = \frac{(2k_1x_2 - 2k_2x_1)d_{sa}}{2x_1y_2} + \frac{k_1^2x_2 - k_2^2x_1 + x_2^2x_1 + y_2^2x_1 - x_1^2x_2}{2x_1y_2}, \tag{2}$$

where

$$d_{sa} = \frac{-\beta - \sqrt{\beta^2 - 4\alpha\gamma}}{2\alpha}, \tag{3}$$

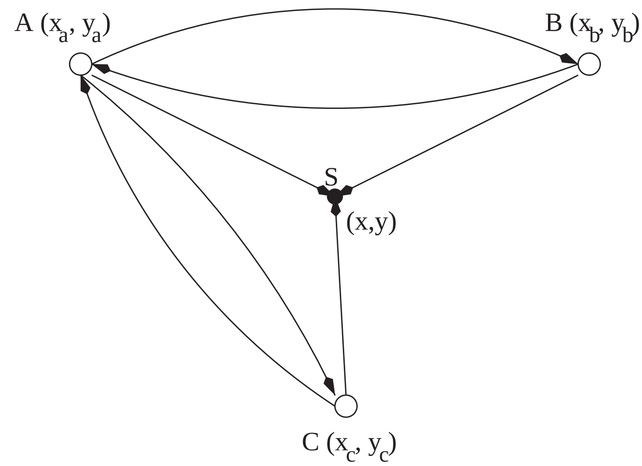


Fig. 1. Algorithm presented in [7]. Sensor S will measure the TDoA of beacon signals from base stations A, B, and C locally. S also will receive the turn-around delay information from B and C. B's transmission will start after it receives A's beacon signal, while C's transmission will start after it receives both A and B's beacon signals. The beacon transmissions are repeated once every T seconds.

$$d_{sa} = \frac{-\beta + \sqrt{\beta^2 - 4\alpha\gamma}}{2\alpha}, \tag{4}$$

$$\alpha = 4[k_1^2y_2^2 + (k_1x_2 - k_2x_1)^2 - x_1^2y_2^2], \tag{5}$$

$$\beta = 4[k_1(k_1^2 - x_1^2)y_2^2 + (k_1x_2 - k_2x_1) \times(k_1^2x_2 - k_2^2x_1 + x_2^2x_1 + y_2^2x_1 - x_1^2x_2)], \tag{6}$$

$$\gamma = (k_1^2 - x_1^2)^2y_2^2 + (k_1^2x_2 - k_2^2x_1 + x_2^2x_1 + y_2^2x_1 - x_1^2x_2)^2. \tag{7}$$

3.2. A deficiency of TPS

In TPS, when a sensor is located near a base station, the algorithm generates two positive values of d_{sa}, which produce two ambiguous position estimates. In this section, we study this deficiency of TPS by simulation. The results are reported in Fig. 2(a) and (b).

Fig. 2(a) shows the sensor locations where two position estimates are calculated by the algorithm. Only one of these estimates corresponds to the actual sensor position, and the figure shows which of the two position estimates is valid for the location. Selecting the incorrect position estimate can result in a large error. Our previous work [7] calculated sensor positions based on only one of these solutions. The two solutions come from the quadratic formula, with Eq. (3) corresponding to positions inside the triangle formed by the base stations. In our previous work we prohibited sensor placements in close proximity to the base stations. This prohibition prevented TDoA measurement errors from *moving* a calculated estimated position into an area where

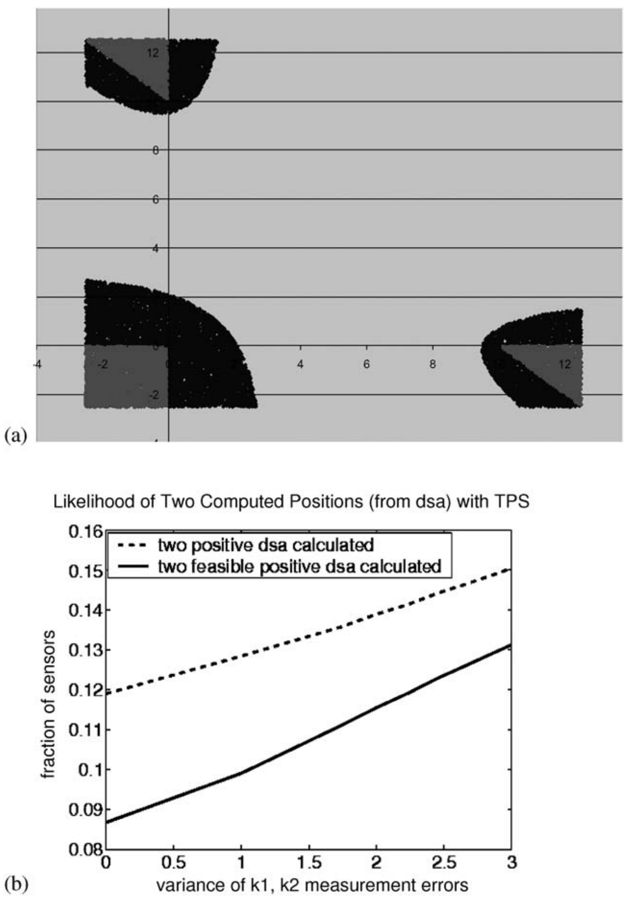


Fig. 2. (a) This graph shows regions where sensors compute two positive d_{sa} from the quadratic formula using the three base station arrangement of [7]. Base stations are located at (0,0), (10,0) and (0,10). In the black regions, the d_{sa} from Eq. (3) is appropriate for use in position computation. In the gray regions (behind the base stations) the d_{sa} from Eq. (4) is appropriate for position computation. (b) This graph shows the likelihood that sensors located interior to three base stations that form an acute triangle may compute two positive d_{sa} using the equations of [3]–[7]. By applying a "feasibility" test (sensors must be placed within a general region) when we obtain two possible positions, we can rule out some of the calculated d_{sa} as unreasonable and reduce the number of cases from the dashed line to the solid line.

the other solution of the quadratic formula was required. Fig. 2(b) shows that as TDoA measurement errors increase (represented by the variance of k_1 and k_2, whose errors are normally distributed with mean 0 in the simulation), the frequency of both quadratic formula solutions being feasible increases. The TDoA measurement errors are *moving* position estimates into areas with two solutions. If base stations are arranged in an obtuse triangle, sensor placement in a greater position of the field will result in two calculated positions. Our work in [7] avoids this situation by arranging base stations in acute triangles. iTPS proposed in Section 4 allows greater freedom for positioning sensors and base stations. iTPS improves robustness against range errors resulting from using the incorrect quadratic formula solution and improves positioning accuracy.

4. iTPS: the time-based positioning scheme using four base stations

In this section, we will present a four base station algorithm, iTPS, that shows a considerable reduction in ambiguous solutions and improves accuracy over the algorithm, TPS, presented in [7]. Given the locations (x_a, y_a), (x_b, y_b), (x_c, y_c), and (x_d, y_d) of base stations A, B, C, and D, we are going to determine the location (x, y) for sensor S, as shown in Fig. 3. Let d_{ab}, d_{ac}, and d_{ad} be the distance from base station A to B, to C, and to D, respectively. Then $d_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$, $d_{ac} = \sqrt{(x_a - x_c)^2 + (y_a - y_c)^2}$, and $d_{ad} = \sqrt{(x_a - x_d)^2 + (y_a - y_d)^2}$. Let d_{sa}, d_{sb}, d_{sc}, and d_{sd} be the unknown distances from S to A, B, C, D, respectively. This time-based location detection scheme consists of two steps.

Step 1: *Range detection*: A will be the master base station and will initiate a beacon signal every T seconds. Consider any beacon interval i, at times t_1^i, t_b^i, t_c^i, t_d^i, sensor S, base stations B, C, and D will receive A's beacon signal, respectively. At time $t_b^{i\prime}$, which is $\geqslant t_b^i$, B will reply A with a beacon signal conveying information $t_b^{i\prime} - t_b^i = \Delta t_b^i$. This signal will reach S at time t_2^i. After receiving beacon signals from both A and B, at time $t_c^{i\prime}$, C will reply A with a beacon signal conveying information $t_c^{i\prime} - t_c^i = \Delta t_c^i$. This signal will reach S at time t_3^i. After receiving beacon signals from A, B, and C, at time $t_d^{i\prime}$, D will reply A with a beacon signal conveying information $t_d^{i\prime} - t_d^i = \Delta t_d^i$. This signal will reach S at time t_4^i. From triangle inequality, $t_1^i < t_2^i < t_3^i < t_4^i$. Let $\Delta t_1^i = t_2^i - t_1^i$, $\Delta t_2^i = t_3^i - t_1^i$, and $\Delta t_3^i = t_4^i - t_1^i$. Let v be the speed of RF beacon signals from A, B, C, and D. Then we have $d_{ab} + d_{sb} - d_{sa} + v \cdot \Delta t_b^i = v \cdot \Delta t_1^i$, $d_{ac} + d_{sc} - d_{sa} + v \cdot \Delta t_c^i = v \cdot \Delta t_2^i$, and $d_{ad} + d_{sd} - d_{sa} + v \cdot \Delta t_d^i = v \cdot \Delta t_3^i$, which gives

$$d_{sb} = d_{sa} + v \cdot \Delta t_1^i - d_{ab} - v \cdot \Delta t_b^i = d_{sa} + k_1^i, \tag{8}$$

$$d_{sc} = d_{sa} + v \cdot \Delta t_2^i - d_{ac} - v \cdot \Delta t_c^i = d_{sa} + k_2^i, \tag{9}$$

$$d_{sd} = d_{sa} + v \cdot \Delta t_3^i - d_{ad} - v \cdot \Delta t_d^i = d_{sa} + k_3^i, \tag{10}$$

where d_{sa}, d_{sb}, d_{sc} and d_{sd} are non-negative reals and $k_1^i = v \cdot \Delta t_1^i - v \cdot \Delta t_b^i - d_{ab}$, $k_2^i = v \cdot \Delta t_2^i - v \cdot \Delta t_c^i - d_{ac}$, and $k_3^i = v \cdot \Delta t_3^i - v \cdot \Delta t_d^i - d_{ad}$. Averaging k_1^i, k_2^i, and k_3^i over I intervals gives

$$k_1 = \frac{v}{I}\left[\sum_{i=1}^{I} (\Delta t_1^i - \Delta t_b^i)\right] - d_{ab}, \tag{11}$$

$$k_2 = \frac{v}{I}\left[\sum_{i=1}^{I} (\Delta t_2^i - \Delta t_c^i)\right] - d_{ac}, \tag{12}$$

$$k_3 = \frac{v}{I}\left[\sum_{i=1}^{I} (\Delta t_3^i - \Delta t_d^i)\right] - d_{ad}. \tag{13}$$

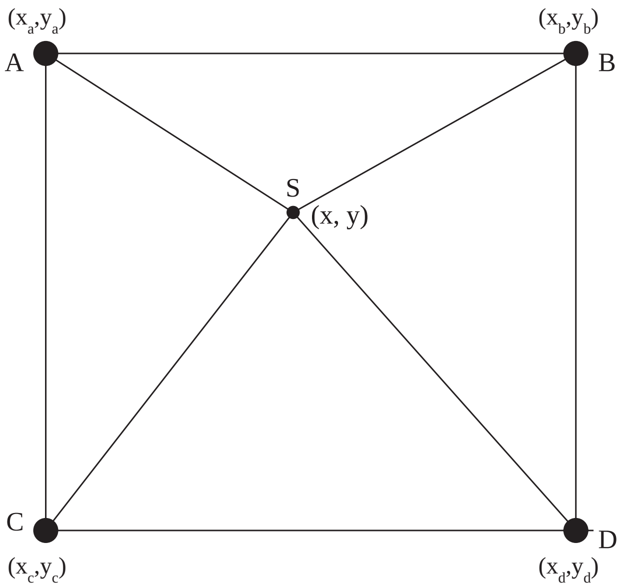


Fig. 3. Sensor S will measure the TDoA of beacon signals from base stations A, B, C, and D locally. S will receive turn-around delay information from D in addition to B and C. B's transmission will start after it receives A's beacon signal, while C's transmission will start after it receives both A and B's beacon signals. D's transmission will start after it receives the beacon signals from A, B, and C. The TDoA information will be used to compute the distance from S to A, and subsequently to trilaterate S's position. This measurement can be repeated over several beacon intervals.

We are going to combine k_1, k_2, k_3 to compute coordinates (x, y) for sensor S in next step.

Remark. (i) All arrival times are measured locally. In other words, t_1^i, t_2^i, t_3^i, t_4^i are measured based on sensor S's local timer; t_b^i and $t_\text{b}^{i\prime}$ are based on B's local timer; t_c^i and $t_\text{c}^{i\prime}$ are based on C's local timer; t_d^i and $t_\text{d}^{i\prime}$ are based on D's local timer. There is no global time synchronization. (ii) We require A to periodically initiate the beacon signal transmission for two reasons: First, averaging k_1^i, k_2^i and k_3^i over multiple beacon intervals can help decrease measurement errors. Second, sensors may miss beacon signals while sleeping; or sensors may be deployed at different times; or sensors may be relocated during their lifetime. Periodic beacon signals from A and reply signals from B, C and D facilitate location detection in these cases.

Step 2: *Location computation*: From Eqs. (8)–(13), we have $d_\text{sb} = d_\text{sa} + k_1$, $d_\text{sc} = d_\text{sa} + k_2$, and $d_\text{sd} = d_\text{sa} + k_3$. Geometrically, position (x, y) must satisfy the following equations:

$$(x - x_\text{a})^2 + (y - y_\text{a})^2 = d_\text{sa}^2, \tag{14}$$
$$(x - x_\text{b})^2 + (y - y_\text{b})^2 = (d_\text{sa} + k_1)^2, \tag{15}$$
$$(x - x_\text{c})^2 + (y - y_\text{c})^2 = (d_\text{sa} + k_2)^2, \tag{16}$$
$$(x - x_\text{d})^2 + (y - y_\text{d})^2 = (d_\text{sa} + k_3)^2, \tag{17}$$

where $d_\text{sa} > 0$ and it is unknown.

To compute (x, y), we need to compute d_sa first. Let us divide Eqs. (14)–(17) into two overlapping groups. Group I contains Eqs. (14)–(16), while group II contains Eqs. (14), (15), and (17). Note that by applying TPS [7] to base stations A, B, C, we obtain the set of equations in group I. Similarly, by applying TPS to base stations A, B, D, we obtain the set of equations in group II. As shown in [7], solving the equations in either group I or II results in at most two solutions to d_sa, among which one and only one is correct for our location estimate. Based on this observation, we can compute d_sa from the set of equations in one group, and rely on the second group of equations for ambiguity resolution. In iTPS, we adopt the same method as shown in [7] for solving the equations in each group. We refer the readers to the complete procedure and error analysis in [7].

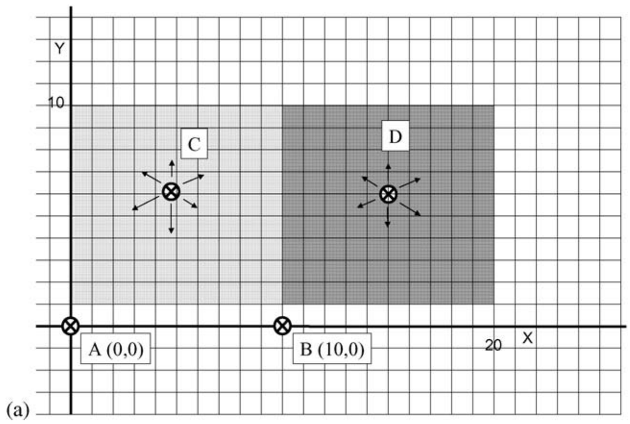
5. Simulation

We decided not to simulate our algorithm in a specific medium (RF, sound, underwater acoustics) or to specify a type of keying (direct sequence spread spectrum, phase measurements, narrowband pulses) as it would be difficult to objectively evaluate algorithm performance without encountering implementation-dependent issues. TDoA timer drift, signal arrival time correlation error and reception delays in the sensor will contribute to position error. Reception and transmission delays, time-stamping inaccuracies, and turn-around delay measurement errors in the base stations contribute as well. Communication channel noise and signal velocity will vary with temperature and atmospheric conditions. We model these sources by introducing gaussian error with increasing variance to the final k_1 , k_2 and k_3 values. Note that it is reasonable to assume that the distributions of the errors of k_1, k_2, and k_3 are the same. We did not attempt to model multi-path/non-line of sight (NLOS) propagation. NLOS propagation is obviously an area of concern as it is the primary error contribution in many TDoA systems and is present in a large number of environments [35,11]. This is an area for future work.

Given the granularity of timing required for RF TDoA measurement, acoustics may be the most realistic transmission media to implement iTPS in a sensor. A wide-band acoustic ToA measurement system is implemented in [11]. In this paper, the precise ToA measurements are not needed by the sensors, which require TDoA measurements, but at specialized beacon nodes. An implementation of our algorithm with acoustics could utilize the [11]'s correlation function, outlier rejection and multi-modal detection and clustering mechanisms.

5.1. Simulation setup

MATLAB was used to perform all simulations. Base station A was arbitrarily fixed at (0,0). Coordinate translation and rotation can be applied to any real world system to align with required coordinates. Base station B was fixed at (10,0). Random positioning of the third and fourth base stations fa-



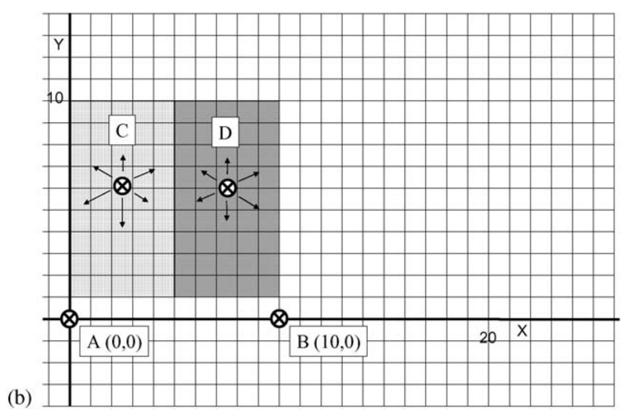


Fig. 4. Simulation base station setup. In (a) base station C is randomly placed in area bounded by (0,1) and (10,10). Base station D is randomly placed in area bounded by (10,1) and (20,10). In (b) base station C is randomly placed in area bounded by (0,1) and (5,10) while base station D is randomly placed in area bounded by (5,1) and (10,10).

cilitate simulation of most three and four base station geometries. Obtuse triangle geometries were tested with base station D in (a) of Fig. 4 while acute triangle geometries were tested with base station D in (b). In both (a) and (b) of Fig. 4 base stations A, B, and C generally form acute triangles (Some C positions do create obtuse triangles.) Geometry (a) allows comparison of four base station system (A,B,C,D) with that of obtuse triangle and acute triangle three base station systems. Geometry (b) allows testing with four base stations in the more optimal acute triangle arrangements. For both (a) and (b), 1000 random C and D base station placements were simulated to encompass as many geometries as possible. Our previous work [7] provided a detailed error analysis of base station geometry and found that acute triangle base station arrangements provided best performance.

In order to test our algorithm's ability to accurately calculate sensor positions on the periphery of the sensor field, we needed to include sensor locations outside the polygon formed by base stations A,B,C,D and triangles by base stations A,B,C and A,B,D. We chose to create a bounding box which exceeded the maximum and minimum base station x and y-coordinates by 2 units, see Fig. 5. 1000 sensors were then randomly placed inside the bounding box. Unlike our previous work [7], we did not limit sensor proximity to base stations.

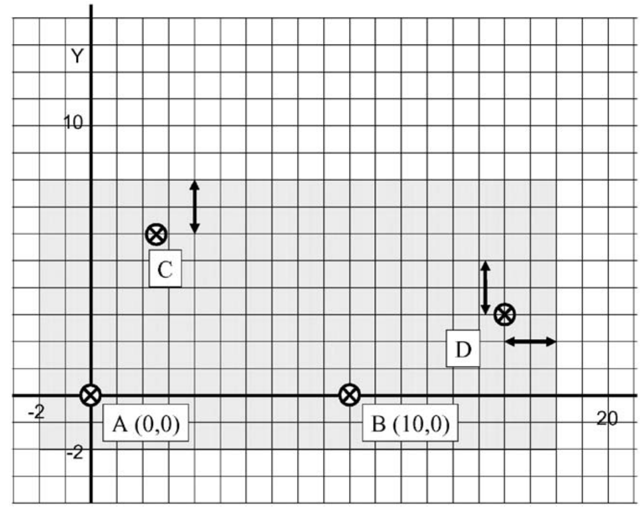
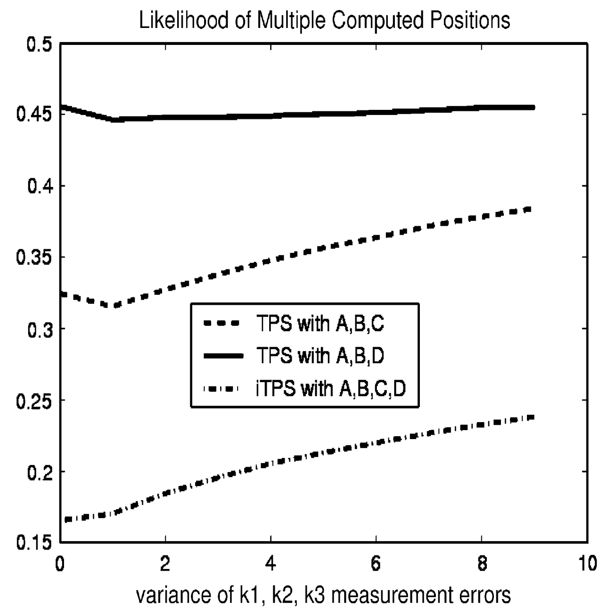


Fig. 5. Each base station setup was tested with 1000 different sensor placements. Each sensor was placed randomly in area bounded on the x-axis by -2 and two units greater than D's x-coordinate; and bounded on the y-axis by -2 and two units greater than the larger of the C or D's y-coordinate.

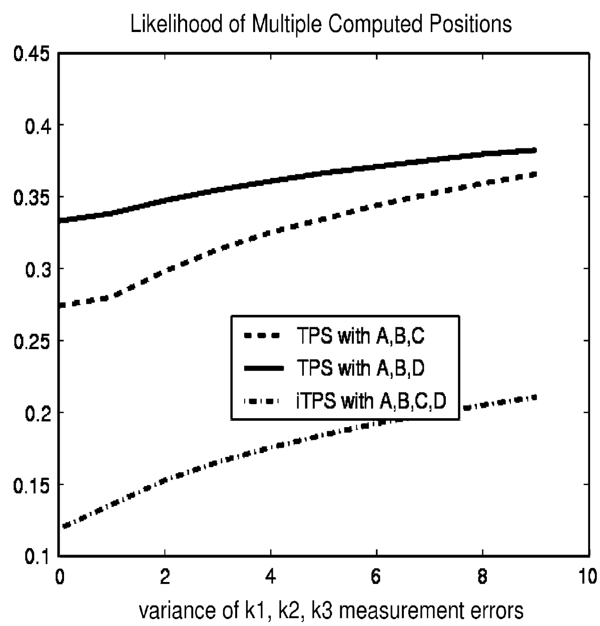
We established an arbitrary calculated d_{sa} range limit of 25. This limit was based on the maximum possible d_{sa} of a sensor located at (22,12) being 25. If one of a sensor's d_{sa} calculations was negative or exceeded this arbitrary limit, it was discarded and no subsequent position calculation was attempted. By ruling one of a sensor's two d_{sa} as being unfeasible, the percentage of ambiguous results was significantly reduced. Fig. 6(a) shows where d_{sa} were discarded only if negative and Fig. 6(b) shows where d_{sa} were also compared with range limit. If a significant TDoA measurement error occurs, a very large d_{sa} can result, and if not discarded can result in extremely large position error. Unfortunately, with large TDoA measurement errors, significant numbers of sensors may be unable to compute their position because both their d_{sa} have been discarded. As Fig. 6 shows, the addition of the fourth base station greatly reduces the number of sensors with multiple computed positions.

5.2. iTPS

In iTPS, four d_{sa} are calculated. One of the two d_{sa} from the A,B,C base station equations should correspond with one of the two d_{sa} from the A,B,D base station equations. We test two approaches to computing position with iTPS. In the first approach, we average the final positions computed by the two sets of equations for three base stations. We will refer to this as *averaging final positions*. In the second approach, we find the d_{sa} pairs with the closest value of the four possibilities and then use that pair to compute an average d_{sa}

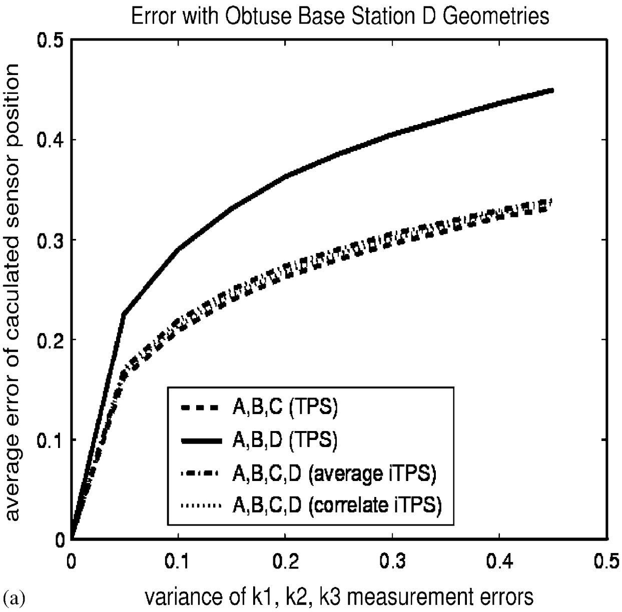


(a)

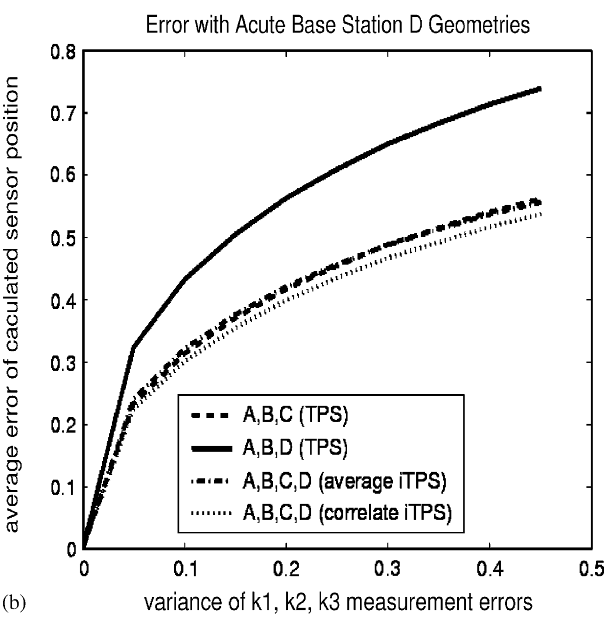


(b)

Fig. 6. Using the fourth base station decreases the number of ambiguous solutions. (a) Only negative d_{sa} calculations were discarded. (b) Both negative and non-feasible d_{sa} (exceeds range limit) calculations were discarded.



(a)



(b)

Fig. 7. (a) Base stations A,B,C are in acute triangle arrangement while A,B,D are in obtuse triangle arrangement. Averaging final positions does not improve performance since the solution from A,B,D *corrupts* the more accurate data obtained from A,B,C. Correlating d_{sa} pairs provides slightly better improvement. (b) Both base stations A,B,C and A,B,D are in acute triangle arrangements. Averaging final positions slightly improves the performance. Correlating d_{sa} pairs provides better improvement.

for use in Eqs. (1) and (2) to calculate an x, y position. We refer to this approach as *correlating*. With four base stations we are able to estimate position at more sensor locations, since if no solution was available from A,B,C equations, a solution might be available from A,B,D base station equations and vice versa. The following simulation only considered the case where solutions were available from both sets of base stations.

The simulation results from geometry (a) of Fig. 4 are presented in (a) of Fig. 7. The A,B,D base stations are in an obtuse triangle arrangement which provides poor algorithm performance, while A,B,C base stations are in acute triangle arrangement which provides very good algorithm performance. Averaging of final positions provides much better accuracy than the A,B,D base stations alone, but actually worse performance than A,B,C base stations since averaging operation *corrupts* the more accurate A,B,C data. Correlating d_{sa} pairs provides slightly better performance than just averaging final positions, but still performs poorer than just A,B,C data. Based on this simulation data, if a sensor detects an obtuse geometry with a set of base stations, it may want to reject measurements from this obtuse set, as averaging them with good geometry measurements will not improve positioning accuracy.

The simulation results from geometry (b) of Fig. 4 are presented in (b) of Fig. 7. The A,B,D base stations are in an acute triangle arrangement which provides good algorithm performance, while A,B,C remain in an acute triangle. Simple averaging of the final positions from three base station solutions provides only slightly better performance at high error rates than calculations from A,B,C. Correlating d_{sa} pairs provides generally better accuracy than either three base station TPS solution.

If only one set of equations provides an estimate with four base stations, we utilize this estimate. Note that this single position estimate is identical to that calculated by a three base station system, so the four base station system can perform no worse than the three station system in this case.

6. Conclusion and discussion

In this paper, we presented iTPS, a time-based positioning scheme for sensor networks with long-range beacon stations. This scheme is an improvement over TPS, a sensor self-positioning algorithm presented in [7]. iTPS not only retains all nice features of TPS, but also can improve accuracy and significantly reduces the number of ambiguous position estimates existing in TPS. To evaluate the performance of iTPS and compare it with TPS, we conducted extensive simulation, which shows that iTPS is simple and effective.

Note that the trilateration Eqs. (14)–(17) in Section 4 can form 4 groups, each containing three of them. However, in our simulation study, we only consider 2 groups, with each containing Eqs. (14) and (15). This can greatly simplify the computation within sensors, thus saving sensor power resource. However, with the introduction of more groups, sensor position accuracy definitely can be improved. This is a tradeoff between position accuracy and computation overhead.

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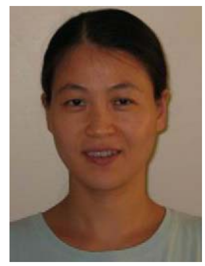

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