MIND: A Nonparametric Decision Fusion Method for Accurate Indoor Localization using Sensors with Monotonically Increasing Error Functions

A nonparametric fusion method for extracting accurate distance measurements from low-quality sensors is proposed. The method applies to sensors with error functions that are monotonically increasing with respect to (w.r.t.) the actual value to be measured (arguments are presented on why a monotonically increasing error function is something to be expected with range-estimating sensors). The proposed method has been developed in order to enhance the performance of localization systems that utilize commercially available sensors for range estimation to achieve localization through triangulation of range estimates. The proposed method is based on evaluating multiple sensor measurements and using the minimum measured distance as a more efficient estimate of the real distance compared with calculating and selecting the distance average. Thus, the proposed method is code-named MIND (from MINimum Distance). It is shown analytically that MIND outperforms, in terms of location estimation accuracy, the sensor with the minimum mean error when used in a multi-sensor configuration. An experimental testbed consisting of four Cricket sensors in a symmetric bundle configuration was used to evaluate the MIND fusion method experimentally. For each Cricket sensor, performance characteristics were established through extensive laboratory analysis and were found to yield highly inaccurate range estimates. However, when these low-quality Cricket sensors were fused in a four-sensor symmetric configuration, it was shown experimentally that the MIND fusion method exhibits near-optimal performance and largely overcomes most of the flaws of the underlying low-quality Cricket sensors, delivering a localization solution of extended accuracy, availability, and robustness.

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I. INTRODUCTION

In this paper we propose a simple yet accurate fusion method in order to enhance the performance of an underlying localization testbed. The proposed nonparametric method is capable of extracting accurate range measurements from low-quality sensors. For a nonparametric estimator, knowledge of the underlying statistics is not required for determining the functional parameters of the estimator, and performance is shown to be efficient in an asymptotic way (e.g. as the number of samples exceeds a certain threshold, or approaches infinity) [1–2]. Provided that the data statistics are perfectly known, an optimal data fusion scheme may be applied to improve the performance of a multi-sensor bundle in terms of location accuracy in accordance with the Optimal Sensor Fusion theory [3–6]. Alternatively, improvement in the accuracy of range estimation and localization can be achieved with the use of Kalman [7–8] or particle [9–10] filters. However, a priori knowledge of the probability distribution functions (pdfs) required for implementing an optimal fusion scheme may not be readily available and/or may be too time consuming to acquire and computationally expensive to process, in particular in real-time applications and low-cost solutions. Instead, a suboptimal heuristic decision fusion scheme, such as the one proposed herein, may provide a data fusion solution that is relatively easy to implement, yet robust and efficient in terms of performance.

The proposed minimum distance (MIND) method is based on evaluating multiple sensor measurements and using the minimum (measured) distance as a more efficient estimate of the actual distance compared with calculating and selecting the distance average. Furthermore, it is analytically proven that MIND yields more accurate results than the sensor with the minimum mean error, while exhibiting nearly optimal empirical performance, albeit being suboptimal. Granted that range sensors commonly exhibit monotonically increasing error characteristic with respect to (w.r.t.) the true distance, the proposed technique may be used in a wide range of applications. To the best of our knowledge, the approach of selecting the minimum distance among the measured distance from multiple sensors has not been proposed in the literature as a decision fusion rule for sensors with monotonically increasing errors.

In the context of developing a real-time localization system, we performed an extensive analysis of a set of low-quality, off-the-shelf, range estimation Cricket sensors [11–12] that are frequently used in commercially available localization systems, and we established a model of the sensor performance characteristics. The Cricket sensors were found to deliver highly inaccurate range measurements, resulting in a localization system of poor efficiency and accuracy. When the proposed MIND method was applied in a multiple-sensor receiving array (Cricket bundle), the range estimation accuracy was drastically improved, overcoming most flaws of a single-sensor system. Furthermore, it is experimentally shown that the proposed method improves both the accuracy and the robustness of the localization system. To the best of our knowledge, this is the first reference to a multi-sensor fusion system with an array of Crickets that has been made in the open literature.

II. MOTIVATION

1) *Monotonically Increasing Distance-Measuring Error with respect to True Distance in a set of Off-the-Shelf Range Estimation Sensors*: The commercially available Cricket localization system consists of a number of wireless nodes (the so-called "crickets"), which are set to act as either beacons or listeners [11–12]. The most common way to use the Cricket system is to attach beacons on a free line-of-sight (LOS) spot, like on a room's ceiling, and use them as static nodes acting as anchored reference points. Beacons will periodically transmit an ultrasonic pulse, together with an RF pulse bearing a beacon identifier, a time stamp, and other useful data. On the other hand, listeners are typically attached to fixed or mobile objects that are to be localized. They capture beacon transmissions and calculate their distance to nearby beacons using the time-of-arrival (TOA) difference between RF and ultrasonic pulses. The distances to nearby beacons may then be used in order to calculate the listener's position coordinates by triangulation [13].

In order to evaluate the Cricket sensors range estimation performance, a simple testbed was set up as illustrated in Fig. 1. The beacon and listener are placed parallel to each other at preselected distances and misalignment angles. The misalignment angle, denoted by ϕ_j, is defined to be 0° when the beacon and listener face each other directly and varies from 0° to 180°, with a step of 10°. The true distance-to-beacon (DTB), denoted by x_i, varies from 20 cm, to 1 m, to 2 m, to 3 m, and finally to 4 m. For any given (x_i, ϕ_j) the corresponding measurements are denoted by

$$y_{i,j}(t) = f(x_i, \phi_j, t) \qquad (1)$$

where $f(.)$ is a (generally nonlinear) stochastic process with parameters x_i, ϕ_j, and corresponds to the underlying mechanisms of the sensor measurement. The temporal average of these measurements is given by

$$\overline{y_{i,j}} = \frac{1}{T}\sum_{t=1}^{T} y_{i,j}(t) = \frac{1}{T}\sum_{t=1}^{T} f(x_i, \phi_j, t) \qquad (2)$$

where T denotes the observation period (temporal sample size). In our analysis herein we assume that x_i and ϕ_j remain constant throughout the observation period T (static case) so that time averaging is meaningful as a means of smoothing out noise.

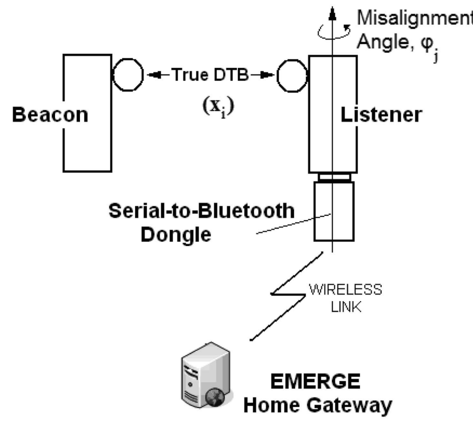

Fig. 1. Cricket sensor performance testbed, using one beacon, one listener, and a serial-to-bluetooth adapter.

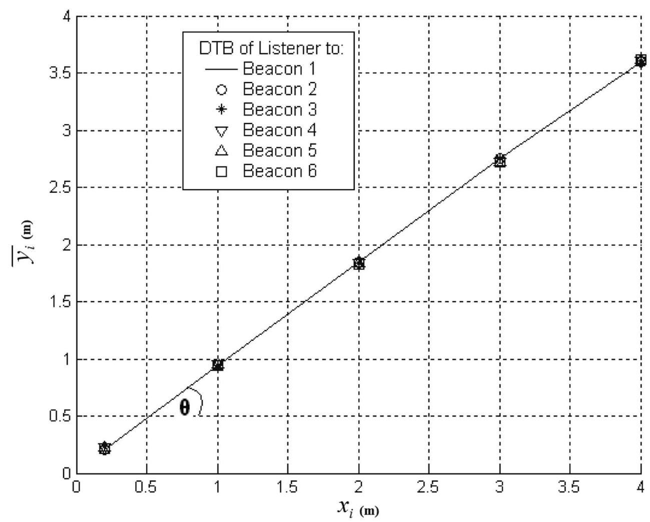

Fig. 2. Average measured versus true beacon-listener distance for a sample size of 80, $\phi = 0°$.

Fig. 2 displays the average $\overline{y_i}$ versus x_i for a sample size equal to 80, with misalignment angle equal to $\phi = 0°$ and various beacon-listener couples (since $\phi = 0°$, $\overline{y_{i,j}}$ reduces to $\overline{y_i}$). Since the measurement $\overline{y_i}$ is a random variable, the sample size theoretically affects the average output of the sensors; however, the pattern of the average $\overline{y_i}$ variation remains unaffected. It is observed that there is a monotonically increasing error between $\overline{y_i}$ and x_i, with the respective plots being almost identical, linear, and retaining a constant slope (equal to $\tan\theta$ as illustrated in Fig. 2) for all different beacon-listener node combinations.

DEFINITION A sensor is called monotonic in the mean if the average estimation error is monotonically increasing w.r.t. true distance (as in Fig. 2 for example). More specifically, in the case of range estimation sensors, a monotonic in the mean sensor will exhibit an average distance estimation error that is monotonically increasing w.r.t. the actual distance that is being measured.

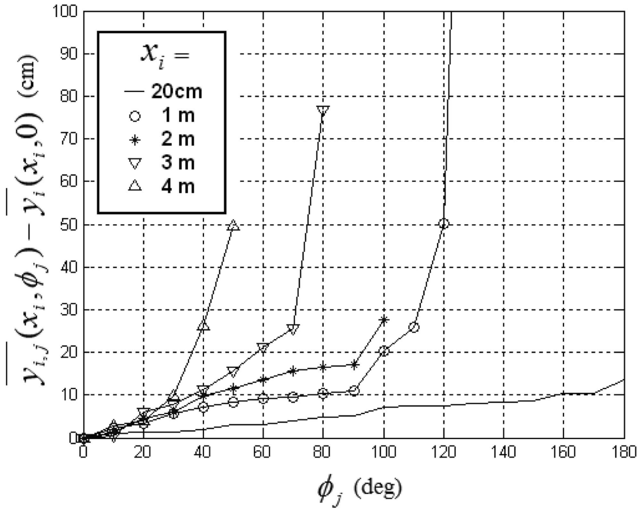

Fig. 3. Average measured DTB error versus true distance x_i and misalignment angle ϕ_j.

In Fig. 3, $\overline{y_{i,j}} = \overline{y_{i,j}}(x_i,\phi_j) - \overline{y_i}(x_i,0)$ versus the misalignment angle ϕ_j is plotted for the Cricket sensors for various x_is. It is pointed out that the x_i estimation error increases with transmitter-receiver distance and misalignment angle. Furthermore, it is observed that for some beacon-listener distances the ultrasonic pulse received signal strength (RSS) drops under the receiver sensitivity for misalignment angles larger than a specific value, e.g. for $x_i = 2$ m no measurements could be obtained for $\phi_j > 100°$. Also, an indirect conclusion drawn by Fig. 3 is that the estimation error increases monotonically w.r.t. distance even for sensors at different altitudes, since a different altitude essentially corresponds to a different beacon-listener misalignment angle.

Finally, Fig. 4(a) illustrates the empirical pdf of a sample of 100 range measurements from a Cricket sensor for a real beacon-listener distance equal to

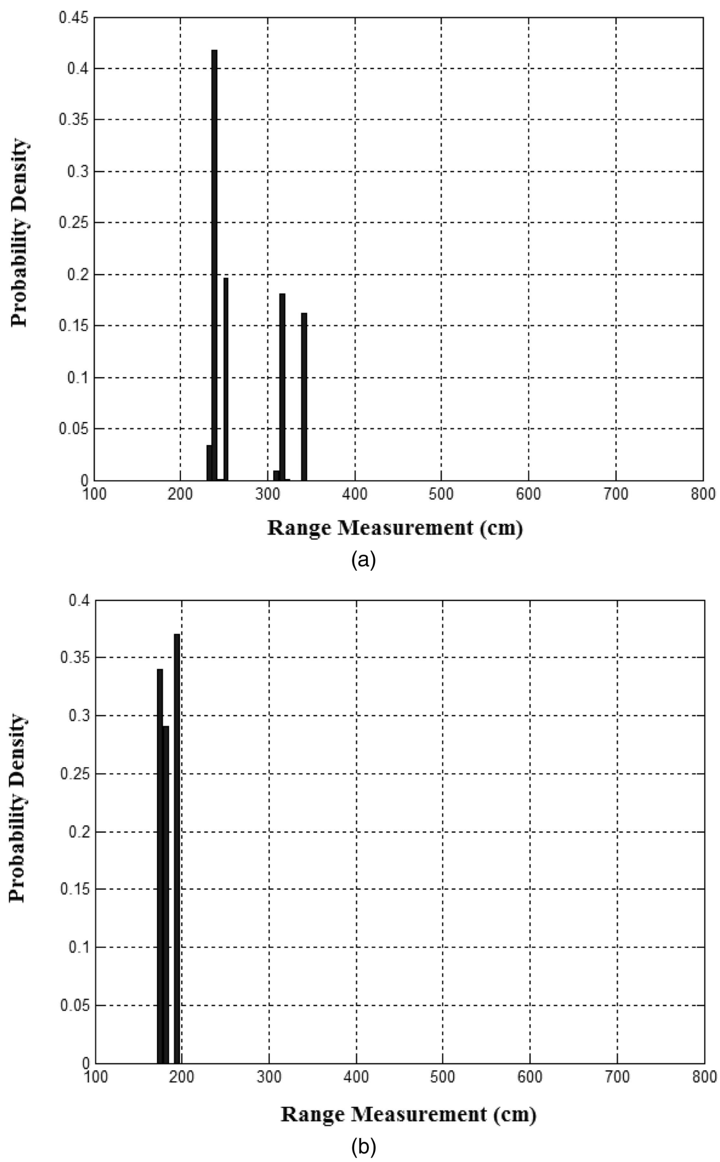

Fig. 4. PDF of range measurements for actual beacon-listener distance equal to (a) $x_i = 240$ cm, (b) $x_i = 180$ cm, respectively.

x_i = 240 cm. The specific case is presented in order to demonstrate the random nature of the Cricket range measurements; however, for most real distances the variance of measurements is not so large, as can be deduced from Fig. 4(b) which illustrates the empirical pdf of 100 range measurements for a real beacon-listener distance equal to x_i = 180 cm.

Based on the above measurements, it is considered that the Cricket range estimation sensors produce a monotonically increasing error w.r.t. the actual distance as well as with the misalignment angle. Based on this observation, we develop next a method for extracting accurate measurements from low-quality sensors which is suitable for the entire class of monotonic error sensors, i.e., sensors that are monotonic in the mean w.r.t. real distance and misalignment angle. In the following paragraph, it is justified that this type of error is expected in range estimation sensors; therefore, the proposed method is in general suitable for range estimation applications.

2) *Justification of the Monotonicity of the Error in Range Estimation Sensors*: The increasing error between $\overline{y_i}$ and x_i is expected, since an increasing x_i causes a decreasing RSS, which in turn causes higher detection circuits' response time [11], resulting in an increasing positive error. The error between $\overline{y_i}$ and x_i may be due to other factors as well, e.g. environmental factors, such as air humidity, pressure, and temperature; hardware factors, such as timing and arithmetic quantization; or errors in detecting ultrasonic signals and variable RF-triggered interrupt service routine delays, all of which cause increasing errors with decreasing RSS. On the other hand, non-line-of-sight (NLOS) and multipath propagation are well known to be major error sources in range estimation and wireless location systems [14], while both multipath and NLOS propagation are becoming more severe for increasing distances [15]. Indeed, increased distance or angle of misalignment involve stronger multipath effects due, among others, to the degeneration of LOS (Ricean model) channels to NLOS ones (Rayleigh model) [15], which in turn cause increasing errors in range measurements.

Insofar as the Cricket sensors are concerned, the sensors' ultrasonic radiation patterns are directional and consist of one main beam lobe at $\phi = 0°$, with a 3 dB-beamwidth of about 90° and relative sidelobe level remaining under 20 dB [16]. Therefore, the RSS as well as transmitter and receiver sensitivity drop along directions different than $\phi = 0°$, resulting in monotonically increasing errors with misalignment. Hence, regardless of x_i, the most reliable DTB measurements are the ones corresponding to $\phi = 0°$. This impact is in general expected in sensors with directional beam patterns.

III. MIND FUNCTIONALITY AND PERFORMANCE

Since a low-quality sensor could yield large errors on y_i measurements, a bundle of colocated range estimation sensors may be used to extract more accurate measurements and thus location estimates. Each one of the N homogeneous and error-monotonic sensors delivers a DTB measurement, namely $y_{k,i}$, $k = 1,2,\ldots,N$, while the mean $y_{k,i}$ over time is denoted by $\overline{y_{k,i}}$. Correspondingly, the instantaneous measurement error is denoted by $e_{k,i} = |y_{k,i} - x_i|$, while the mean measurement error is denoted by $\overline{e_{k,i}} = \overline{|y_{k,i} - x_i|}$.

With the proposed MIND approach, all sensors measure their distance w.r.t. the beacon, and the smallest among all measurements is selected as the DTB estimate. The MIND scheme is found to offer a range estimate that is better, or at least as good as, the one achieved by selecting the "best" sensor.

DEFINITION The best sensor is defined herein to be the sensor which corresponds to the smallest mean error among all sensors of the bundle.

Indeed, it is easy to show that, in the case of monotonically increasing errors, the proposed MIND method yields an error which is smaller than, or equal to, the error delivered by any sensor, and, thereupon, also by the best sensor. More specifically, it holds that

$$\overline{e_p} \leq \overline{e_{k,i}}, \qquad k = 1,2,\ldots,N \tag{3}$$

where $\overline{e_p} = \overline{|y_p - x_i|}$ is the mean error that the MIND method yields. Inequality (3) implies that given a set of N homogeneous, monotonic in the mean sensors, the selection of the minimum measurement yields the smallest in the mean distance estimation error. Thereupon, the proposed method offers a performance which is, at least, "better" than the best sensor.

Furthermore, it is straightforward that the minimum mean error sensor (best sensor) provides an upper bound in the mean estimation error of the MIND method. In addition, the MIND estimator is unbiased and converges to the true distance with probability one.

The MIND approach offers a new and simple method for location estimation, since it may be used with any type of sensors that yield monotonically increasing errors, and also with range estimation sensors that are expected to deliver this type of error as discussed in the previous section. In the following paragraph, this method is applied to the Cricket sensors, and empirical results are obtained by comparing the performance of MIND against that of a (nonrealizable, ideal) genie-assisted optimal sensor selection.

In order to provide a lower bound for the performance of the proposed method, the concept of a "genie" [17] is introduced. At every experiment the genie reveals the sensor with the true minimum DTB from the target. In that sense, it is a nonrealizable

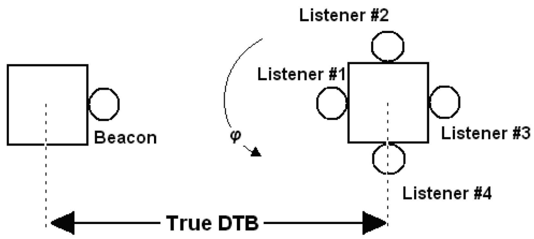

Fig. 5. A Cricket beacon and a multi-sensor bundle of Cricket listeners.

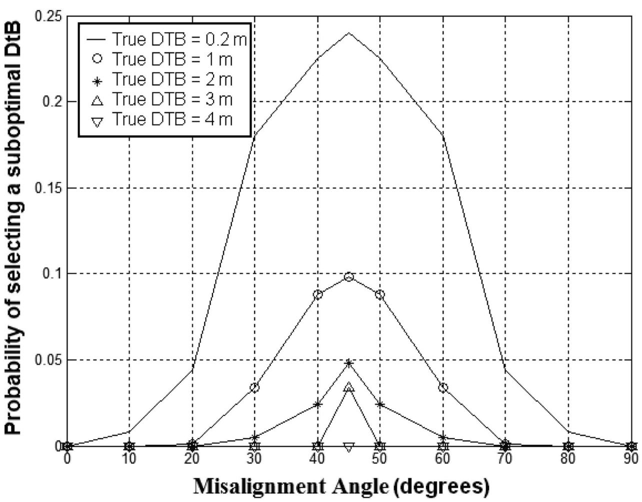

Fig. 6. Probability of selecting suboptimal DTB using proposed fusion method.

fusion scheme, but constitutes a useful conceptual framework for providing a lower bound in the mean estimation error of the proposed MIND method. In this context, the performance of the MIND method may be evaluated by its mean differential error w.r.t. the genie-based fusion method.

A fusion system with Cricket sensors is used in order to evaluate MIND's performance experimentally with real data from real operational conditions. Since the 3 dB-beamwidth of each Cricket node is 90° [16], a bundle consisting of four listeners symmetrically attached to each other is proposed, as illustrated in Fig. 5, since this configuration will cover the horizontal plane with four symmetrical ultrasonic radiation patterns; thus, the needs for minimum correlation among radiation patterns as well as complete horizontal plane coverage are simultaneously satisfied. It is noted that in Fig. 5 all listeners have the same DTB.

Using the testbed illustrated in Fig. 5, the probability that the MIND method does not deliver the same measurement as the assumed underlying genie is empirically calculated and displayed in Fig. 6, for real distances x_i equal to 0.2 m, 1 m, 2 m, 3 m, and 4 m, and for a misalignment angle ϕ_j spanning between (0°, 90°) with a step of 10°. Larger misalignment angles are not evaluated due to cylindrical symmetry. According to Fig. 6, the proposed fusion method delivers optimal estimates in more than the 90% of cases for $x_i \geq 1$ m, while this number increases as x_i increases. Since the Cricket beacons are usually attached to the ceiling, which is the typical case for an indoor localization scenario, the beacon-listener distance is usually larger than 1 m. Therefore, the proposed method is expected to yield optimal x_i estimates more than 90% of the time in typical indoor localization scenarios. Furthermore, the difference in range estimation error between the MIND and the genie $|e_p| - |e_{\text{opt}}|$, was found to be always lower than 5 cm even for $x_i = 4$ m, which implies that the proposed method, albeit theoretically suboptimal, offers an efficient means of achieving range estimates.

IV. LOCALIZATION USING MIND AND MEASUREMENTS RESULTS

1) *Triangulation and Summary of Algorithm*: The proposed method may be combined with Cricket sensors in order to develop a real-time localization system. Besides the MIND considerations, Cricket sensors need to be calibrated in order to obtain more accurate single-sensor measurements. According to Fig. 2, the plots of y_i versus x_i are almost identical, meaning that in the case of a serial production of bundles their calibration could be based on one single plot of any sensor. The plotted line in Fig. 2 is approximated by

$$y = a \cdot x + b. \tag{4}$$

From Fig. 2 and the corresponding measurements, it follows that $\tan\theta = a = 0.893$ and $b = 0.052$ m.

The Cricket bundle position coordinates (x, y, z) may be estimated via triangulation. In the case where there are four beacons with coordinates denoted by (x_i, y_i, z_i), $i = 1,2,3,4$, while r_i, $i = 1,2,3,4$ denote the respective DTB estimates, it follows that

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = r_i^2. \tag{5}$$

By applying some simple algebraic calculations, it can be pointed out that

$$a_i \cdot x + b_i \cdot y + c_i \cdot z = d_i \tag{6}$$

where $i = 1,2,3$, while $a_i = 2 \cdot (x_{i+1} - x_i)$, $b_i = 2 \cdot (y_{i+1} - y_i)$, $c_i = 2 \cdot (z_{i+1} - z_i)$, and $d_i = (r_{i+1}^2 - r_i^2) - (x_{i+1}^2 - x_i^2) - (y_{i+1}^2 - y_i^2) - (z_{i+1}^2 - z_i^2)$. Then, (6) may be easily solved in order to calculate the (x, y, z) coordinates.

Furthermore, since smaller DTB measurements correspond to smaller range estimation errors, the beacons corresponding to smaller DTB estimates are preferable. Thereupon, in the case where the multi-sensor bundle collects DTB values from more beacons than the number required for triangulation, the beacons corresponding to the smallest measured DTB estimates are used.

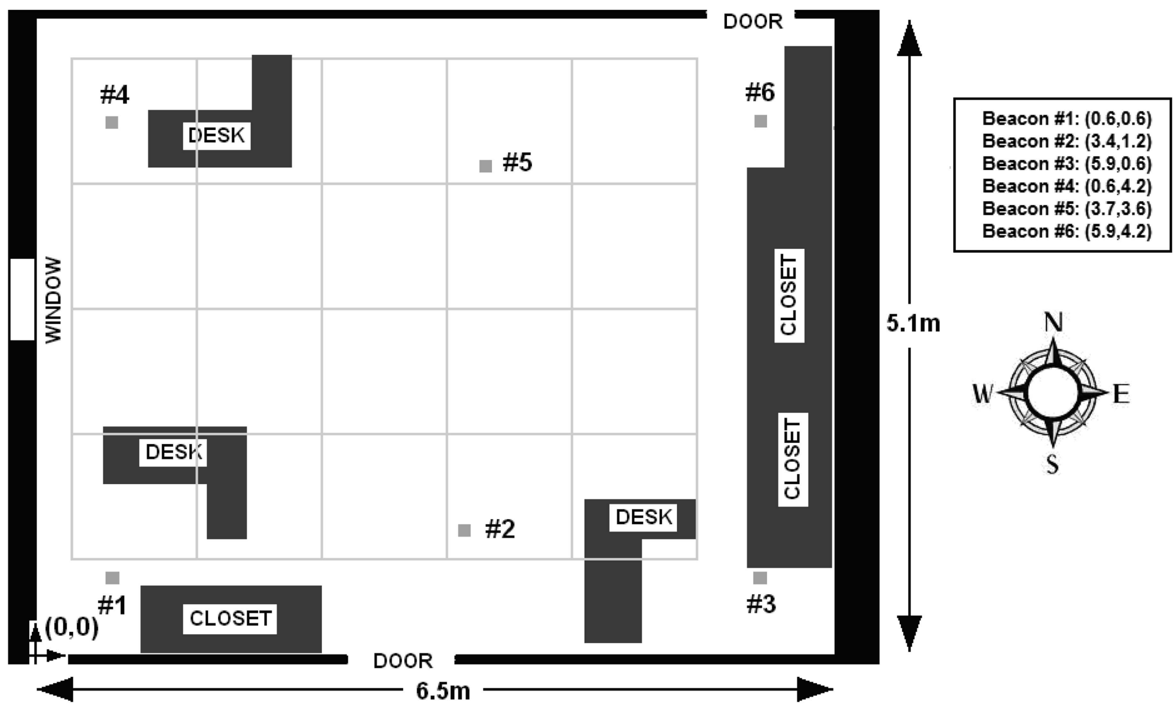

Fig. 7. Layout of measurements area.

The steps of the localization algorithms using triangulation and MIND with Cricket sensors are summarized as follows.

1) Measure the DTB to all available beacons from all listening sensors.
2) For each beacon, select the smallest measured DTB.
3) Select a number of different beacons in order to perform triangulation, under the restriction that beacons corresponding to smaller DTB measurement values are preferred.
4) Calibrate the selected DTB measurements.
5) Perform triangulation using the calibrated DTB measurements.

2) *Testbed Setup*: The proposed sensor fusion and localization algorithm has been experimentally evaluated within the premises of the Institute of Informatics and Telecommunications (IIT) of the National Center for Scientific Research (NCSR) "Demokritos," Athens, Greece [18]. A total of 6 Cricket beacons were attached on the ceiling of a typical office room, at coordinates as shown in Fig. 7 and facing towards the floor. The room dimensions are equal to 6.5 m $\times$ 5.1 m $\times$ 2.7 m (length/width/height).

A number of DTB measurements were collected over a grid of points with dimensions 1 m $\times$ 1 m, as illustrated in Fig. 7. At each grid point, measurements were collected for four different listener orientations (North, South, East, and West as in Fig. 7) at a height of 1 m above floor level, using four listeners being kept vertical w.r.t. the floor surface. In addition, since in a single-sensor Cricket system listeners are typically located horizontally w.r.t. the floor surface and facing towards the ceiling, further measurements were also collected by placing a single listener horizontally w.r.t. the floor surface and at a height of 1 m. At each grid point, the proposed multi-sensor and single-sensor DTB measurements were collected and then localization performance statistics were calculated. Furthermore, localization performance statistics were also calculated using the genie-based optimal sensor selection method.

Finally, it is noted that position estimation was performed using (6), with the listener's height being kept fixed and equal to z = 1 m, thus turning the 3D-localization problem to a 2D one thereupon only three beacons are needed for localization instead of four.

3) *Measurement Results*: Measurements results indicate that, in the case where a single sensor is used, there are numerous grid points for which no position estimate can be calculated because no ultrasonic pulses from at least three different beacons are detected. On the other hand, in the case where the proposed multi-sensor Cricket bundle and the MIND technique are used, the number of points for which no position estimate can be calculated is drastically reduced, as tabulated in the second column of Table I. Regarding the grid points for which position estimation are feasible, Table I demonstrates the respective mean accuracy and the 95th accuracy percentile.

With the single-sensor approach, position estimation is feasible for less than 45% of points,

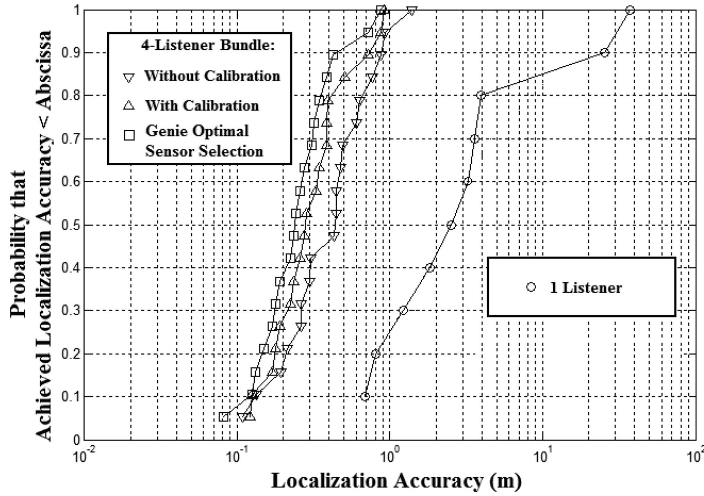

Fig. 8. Empirical cdfs of achieved accuracy.

TABLE I
Summary Measurements Results for the Layout of Fig. 7

	Number of Points Where Localization was (not) Feasible	Mean Accuracy	95th Accuracy Percentile
Single Sensor, 1-Listener (with Calibration)	16 (14)	8.01 m	25.17 m
Proposed Method, 4-Listeners without Calibration	28 (2)	0.49 m	0.93 m
Proposed Method, 4-Listeners with Calibration	28 (2)	0.36 m	0.87 m
4-Listeners, Genie Optimal Sensor Selection (with Calibration)	28 (2)	0.29 m	0.72 m

while the mean accuracy and 95th percentile for these points is 8.01 m and 25.17 m, respectively. These uncommonly large values appear due to the large number of outlier DTB measurements when using a single listener. These outliers are efficiently detected and rejected by the proposed method, without the need of employing computationally intensive and harder to implement techniques such as Kalman filtering for outlier detection [19]. Indeed, in the case where the proposed approach is used, position estimation is feasible for over 93% of points while the corresponding mean accuracy and 95th accuracy percentile are 0.49 m and 0.93 m, respectively. Furthermore, if calibration-based corrections are applied on top of the proposed method, the mean accuracy and 95th accuracy percentile become 0.36 m and 0.87 m, respectively. These data lead to the conclusion that sensor calibration aids in achieving better results, but the main improvement is accomplished by the proposed fusion technique.

In comparison, the localization mean and 95th percentile accuracy in the case where a genie selects the optimal sensors for triangulation are equal to 0.29 m and 0.72 m, respectively. This result corroborates that the (suboptimal) MIND method empirically achieves a performance that is directly comparable to that of a genie-assisted sensor selection and thus near-optimal.

The cumulative distribution functions (cdfs) of the localization accuracy for the single- and multi-sensor configurations are illustrated in Fig. 8 in a logarithmic horizontal scale. Clearly, the proposed technique exhibits far superior performance compared with a typical single-sensor system, while it performs almost as well as the optimal genie-based localization.

It should also be noted that there were some points for which the achieved accuracy is better than 5 cm(!). Compared with the literature, the proposed method provides more accurate results with a lower number of beacon sensors. Indeed, the achieved best accuracy in [11] is reported to be 10 cm and for a much denser beacon grid, i.e., more beacons per square meter used. The significance of using less beacons may be pointed out by the fact that a lower number of beacons is easier to deploy, less expensive to maintain, and less energy consuming. On the other hand, there is an increased hardware complexity due to the multiple listeners used (namely four listeners), but the increased accuracy is considered to justify this approach.

In [20], early results about the Cricket platform are presented. Location algorithm error rates on the order of up to 45%–30%, down to 18% or 6% are reported, depending on the localization algorithm and the sample size. Furthermore, in [21], a Cricket-based localization system of 24 beacons has been deployed in an indoor environment of dimensions 5 m $\times$ 10.5 m; the underlying localization technique involves localization w.r.t. mobile nodes, as well as filtering and rejection of outliers. In comparison, we used 6 beacons in a 5 m $\times$ 6.5 m environment. The results in [20] indicate an error of about 7% for the 95th percentile, which is compared with an error of $0.87^2/6.5 \cdot 5.1 = 2.3\%$ for the 95th percentile (i.e., the ratio of an area of a square with an edge equal to the 95th percentile to the area of the room). These results are comparable, but the proposed method achieves its performance with fewer beacons and without filtering or rejecting outliers. With respect to computational cost, the proposed method is more efficient, since it involves only the selection of the minimum distance and simple triangulation, while the method in [21] includes an extensive preparation step during which the connectivity graph is calculated in order to achieve mobile-assisted localization.

In addition, in [22], a compass is used on top of a Cricket-based system, in order to compensate for errors due to the misalignment angle, together with a differential distance estimation algorithm. The proposed system delivers a maximum error of 2.6%, which is comparable to that of the proposed MIND method, but it requires additional hardware. With respect to computational cost, the method in [22] is less efficient, since it requires more time in order to calculate the differential distance.

Finally, in [23], a Cricket localization system together with outlier rejection, Kalman filtering, and a least-squares estimator are used in order to track mobile devices. The relative testbed includes a computer controlled Lego train, moving on a predefined trajectory within a large room. A number of 6 Cricket beacons were placed above the train track, whose dimensions were equal to about 3 m $\times$ 1.3 m; hence, the density of beacons was significantly larger than the one in our testbed. Depending on the different algorithms used, the achieved accuracy error varied between about 7 cm up to about 55 cm for the 95th percentile. These results are comparable to the ones achieved by the proposed method, but the latter does not use outlier rejection, Kalman filtering, or a least-squares estimator. Finally, w.r.t. computational cost, the proposed method is significantly more efficient, since the method in [23] is using three different steps (Kalman filtering, outlier rejection, and least-squares estimation), which are computationally expensive.

V. CONCLUSIONS

A simple, nonparametric fusion method that requires no prior knowledge of any underlying data statistics to implement it has been introduced herein. The proposed MIND method is based in collecting measurements from multiple sensors and selecting the minimum among them as the closest to the true distance estimate. The method is applicable in cases where the underlying sensors are monotonic in the mean, i.e., exhibit monotonically increasing error functions, such as in the general case of range-estimating sensors. The method is shown to obtain accurate distance estimates from low-quality sensors and yields estimates that are at least as good as the ones obtained by the best in the mean error sensor. Empirical evaluation of MIND has shown that the proposed method exhibits near-optimal performance. Furthermore, when applied to a bundle of low-end, commercially-available location sensors, the proposed method delivered far more robust, reliable, and accurate position estimates than the corresponding single-sensor solution. In conclusion, it has been demonstrated through both theoretical analysis and experimental results that multi-sensor data fusion can improve both reliability and accuracy of unreliable and fairly inaccurate sensors to yield near-optimal performance, thus corroborating the theoretical results in [4].

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