LOCALIZATION IN WIRELESS SENSOR NETWORKS UNDER NON LINE-OF-SIGHT PROPAGATION

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I. ABSTRACT

This paper addresses ranging in indoor quasi-static sensor environments and presents a time-of-arrival (TOA) based ranging algorithm. A statistical model of the multipath channel in the form of the signal return and noise characterization is derived, and utilized to distinguish signal components from noise. The algorithm then uses multiple signal receptions at each base station, to differentiate between line-of-sight (LOS) and non-LOS components, and accurately estimate the LOS position in the received multipath signal. The location is estimated through a mathematical programming problem formulation. Using a synthesized bandwidth (BW) of 2 GHz, a 4-bit analog-to-digital converter (ADC) and with 5-10dB signal-to-noise ratio (SNR), range estimation with sub-meter accuracy is achieved. Furthermore, the associated range estimation error does not increase with increase in the transmitter-receiver range.

II. INTRODUCTION

Wireless sensor networks combine wireless communication components, minimal computation capabilities and some sensing of the physical environment into a network. All these components together in a single device form a sensor node. Sensor networks are used in surveillance type tasks, such as asset tracking, finding people in emergency situations etc. Most sensor nodes measure some physical quantity(s) at a given position and localization of the sensor nodes is essential to these applications.

Several localization techniques have been investigated including exploiting the received signal strength (RSS) indicator [1], time of arrival (TOA) [2][3], time difference of arrival (TDOA) [4], or angle of arrival (AOA) [5]. We will focus on the time-based approaches. Most of the work reported in the literature is based on assumptions that the LOS signal is always present, for e.g. [2], [3]. In [3] it is assumed that the LOS is the earliest arrival and the results showed that the estimation error increases rapidly with the transmitter-receiver range. These approaches, despite using bandwidths in excess of 1 GHz, do not achieve sub-meter (<1m) ranging accuracy that some sensor network applications require.

Many approaches proposed in the literature try to find some distinct properties of NLOS range measurements to distinguish them from LOS measurements, e.g. [6], [7], [8]. These attempts and our own work on NLOS identification point to the difficulty of using pure statistical characteristics to distinguish NLOS measurements from LOS measurements. We solve this problem by using multiple signal receptions in a maximum likelihood (ML) estimation framework. Location algorithms for NLOS propagation have been studied in the literature. In [9] the property that NLOS errors are always positive is used for location estimation by adding some constraints or penalty function.

We present a localization algorithm based on statistical modeling of the multipath channel. Our work is aimed at industrial and residential sensing and control networks. The goal is to develop localization solutions that would provide an accuracy of 0.5-1m. The LOS/NLOS and noise peaks are characterized during an initial calibration phase, which is used to distinguish signal components from noise. Multiple signal receptions at each base station (BS) are used to differentiate between LOS and NLOS components, and estimate the LOS position in the received signal. The mathematical programming approach presented here assumes that all range estimates are LOS and bounds each range estimate. Bounds are determined by the Cramer-Rao lower bound (CRLB) on the estimation error. Infeasibility of the constraints helps to identify NLOS estimates. This method will be shown to give more accurate position estimates than previously reported approaches. Simulations results show that the ranging error does not increase with the range. It will also be shown that no prior information about the channel is needed and the calibration phase is sufficient to gather all the necessary information. Suitable modifications to this algorithm enable it to be used in low BW systems.

III. OVERVIEW OF RANGING APPROACH

Consider a setup in which a number of sensor nodes and base stations communicate with each other for localization of the nodes. The range to a base station is calculated using the Two-Way Time Transfer (TWTT) method. In our

implementation of the TWTT, base station ***A*** sends a message to sensor ***B*** along with the time at which it was sent. After a turnaround time *T*, ***B*** sends a message back to ***A*** along with the time at which it was sent and the arrival time of the message it received from ***A***. Both ***A*** and ***B*** determine the arrival times of the message they receive by determining the time of earliest arrival corresponding to the message. Using the message transmission times and the earliest arrival times of the messages at both ***A*** and ***B***, ***A*** can determine the time of flight between ***A*** and ***B***. This information is fed back to a central location where it is fused with similar information from other BSs to produce a location estimate of ***B***.

In multi-band communication systems, the whole bandwidth is divided into several sub-bands. In each time interval, a signal is transmitted in one of the sub-bands. To determine the earliest arrival time, we assume that the sensors and base stations transmit a short duration Gaussian monopulse with a bandwidth of 528 MHz. Signals from 4 sub-bands are combined to give a virtual large BW (≈ 2GHz) signal using the technique in [10]. The transmit signal is passed through the channel before being input to a matched filter receiver. The matched filter output is subjected to thresholding to detect local peaks. A threshold is chosen based on the desired error performance and the estimated SNR.

Fig. 1 shows the matched filter output in the presence of Gaussian noise. The waveform has significant multipath components and the signal peak does not occur at the leading edge of the waveform. We record the received signal peaks due to the multiple pulses and estimate the LOS as the earliest peak across all returns (the underlying assumption). A calibration phase, explained next, aids in differentiating noise from LOS/NLOS peaks and multiple measurements are used to distinguish LOS from NLOS measurements.

IV. CALIBRATION AND STATISTICAL MODELING

In the calibration phase, two sets of training runs are carried out. The first set is carried out in an ideal noise free condition. Here we report results based on IEEE 802.15.3a channel model 3 (CM3). In the absence of noise the local peaks detected will either be due to the LOS or the NLOS components. It is reasonable to assume that under noise-free conditions and over a set of simulations, the first detected peak would be due to the direct path or the LOS and all other peaks are due to NLOS components. The measured peak strengths are normalized by the strength of the global peak in the output of the matched filter due to the corresponding received signal. Histograms are estimated for the strengths of the LOS and NLOS peaks using these measurements.

The second set of training runs are carried out in the presence of Gaussian noise but in the absence of a transmit signal, i.e., under noise-only conditions. The procedure outlined above is followed to estimate a histogram for the relative strength of the noise peaks. The histograms obtained from simulations using 250 different channel realizations are shown in Fig. 2. It is seen that the relative strength of LOS/NLOS peaks follows an exponential distribution, whereas that of the noise peaks follows a lognormal distribution. The histograms for the time difference between the location of the local peaks and the global peak in the matched filter output are also estimated (not shown here). These results agree with the IEEE 802.15.3a channel model and illustrate an alternative approach for estimating these characteristics in the absence of a channel model. This characterization of LOS/NLOS and noise peaks is used in the ranging algorithm described next.

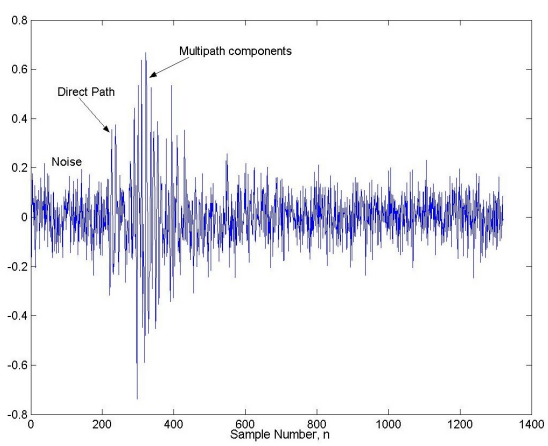

Fig. 1 Matched-filter output in the presence of Gaussian noise

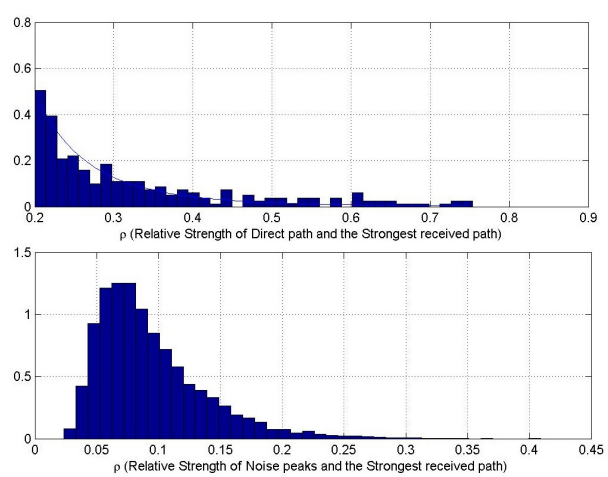

Fig. 2 Relative strength distribution for the LOS/NLOS peaks and the noise peaks

V. RANGE ESTIMATION ALGORITHM

Since the sensors are static, multiple signal returns are collected and used for range estimation. Using multiple returns helps to average over noise and increases the effective signal power and SNR, resulting in improved ranging accuracy.

➢ Identifying Candidate LOS Component

To estimate the position of the LOS component, the time axis is divided into small time bins. For each bin two hypotheses are proposed: (i) the bin contains returns due to noise or (ii) the returns are due to LOS or NLOS component. The likelihood of the peaks coming from the LOS/NLOS distribution is calculated looking across all of the collected returns and using the histograms for the relative strengths of the LOS/NLOS components. Similarly, for each bin the likelihood of the returns being due to noise is calculated using the histogram for the relative strength of the noise peaks. The earliest bin that has a higher likelihood of containing a LOS or NLOS component is chosen as the estimate of the direct path signal. The likelihood function under each hypothesis is evaluated as a product of the probabilities of the returns in a bin, across all the collected returns, being either due to LOS/NLOS or due to noise. The likelihood evaluation procedure is illustrated in Figs. 3 and 4.

Consider the case where we use three returns for ranging at each node. We record all the peaks detected in the three returns in a given time bin. For each detected peak, the relative strength is calculated (say ρ_1). The probability of the peak being due to noise, $P(\rho_1)$, is found by locating ρ_1 on the relative strength distribution (x-axis) for the noise peaks and reading the corresponding value on y-axis. The product of these probabilities for all peaks in a given bin, gives the likelihood of the bin containing a noise peak. If a time bin does not contain any return, the probability of the return being less than the threshold, P_0, is used to evaluate the likelihood function.

$$P_{noise}(t_i) = \prod_{j=1}^{N} P(\textit{return in time bin i in signal j is due to noise}), \text{ where } N = \text{number of signal returns collected at each BS.} \quad (1)$$

Similar computation is done to obtain the likelihood associated with the bin containing a signal return (LOS or NLOS peak). The earliest time bin t_i with $P_{signal}(t_i) \geq P_{noise}(t_i)$ is chosen as the LOS position estimate. Note that the peak chosen as the LOS estimate may actually correspond to a NLOS component. The location algorithm described next takes this possibility into account while estimating the location.

➢ Location Estimation Algorithm

In this algorithm range estimates to a given node (say ***A***) from a number of other nodes are used. Each range estimate provides a circle centered on the corresponding node, on which node ***A*** lies. In the absence of measurement error, the

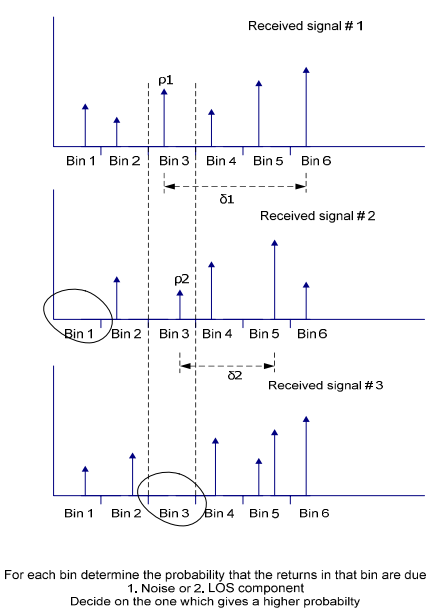

Fig. 3 Illustration of likelihood evaluation

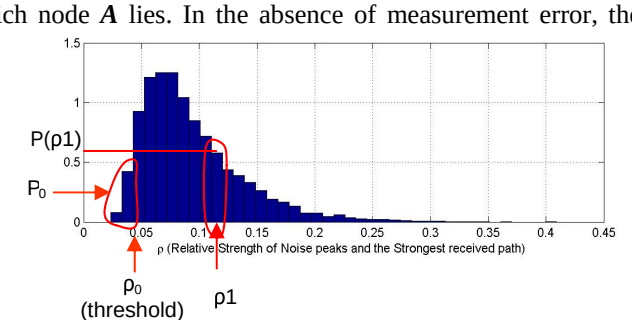

Fig. 4 Illustration of likelihood function evaluation

Location Estimation Algorithm

(x, y): source position; (x_i, y_i): i^{th} BS position;
r_i: range estimate from the ith BS to the source.
δ: range estimation error; a multiple of CRLB on the range estimation variance [10].

$$(r_i - \delta)^2 \leq (x_i - x)^2 + (y_i - y)^2 \leq (r_i + \delta)^2 \quad (2)$$

Let $K_i = x_i^2 + y_i^2$ and $R = x^2 + y^2$.

$$(r_i - \delta)^2 - K_i \leq -2x_i x - 2y_i y + R \leq (r_i + \delta)^2 - K_i.$$

In matrix form [9], $h_1 \leq GZ \leq h_2$, where $Z = [x \quad y \quad R]^T$ (3)

Constrained minimization to find ML location estimate:

$$\min\{(h_2 - GZ)^T \Psi^{-1} (h_2 - GZ)\}, \text{ subject to (3)}$$

where $\Psi = 4c^2 BQB$, $B = diag\{r_1, \ldots, r_M\}$, and Q is the noise covariance matrix.

position of ***A*** is given by the intersection of the circles derived from the range estimates. Due to measurement error, the estimates correspond to circular rings whose width depends on the estimation error.

Refer to the text box below Fig.4 for the problem formulation. Infeasibility of the minimization constraints implies that one or more of the range estimates are NLOS and need to be dropped. It is seen that if at most N estimates are NLOS, then at least N+1 (>3) LOS estimates are needed to obtain an unambiguous location estimate. Figs. 5 and 6 illustrate the case with $N = 1$; four estimates give more than one location estimate, hence 5 range estimates are needed to resolve this ambiguity.

VI. SIMULATION RESULTS

Extensive simulations were carried out using 250 different channel realizations based on the IEEE 802.15.3a channel model. Noise is assumed to be independent for each signal return. Looking at multiple signal returns helps to eliminate large estimation errors by reducing the noise variance. The SNR shown includes quantization noise effects due to a 4-bit ADC used in the receiver.

It is seen that the range estimation error does not increase significantly with the TX-RX range. The approach in [3] looks for the LOS in a small window of the received signal. Estimating the window size becomes extremely difficult at long ranges due to the complex LOS blockage and this results in large estimation errors. In our approach, we are able to average out noise and achieve a higher effective SNR by looking at multiple returns. This approach thus works well even for larger TX-RX distances. TX-RX distances for the simulations ranged from 0-10m. In Table 1, the ranges estimation error resulting from using a single return is compared with the approach using multiple signal returns. The comparison is shown for different values of SNR. For 10-15 dB SNR, the average and RMS estimation errors are smaller than 0.2 m using the multiple return approach.

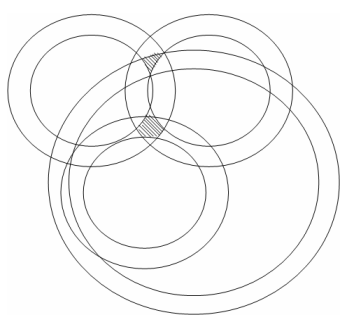

Fig. 5 Location estimation with 1 NLOS and 3 LOS range estimates, illustrating location ambiguity

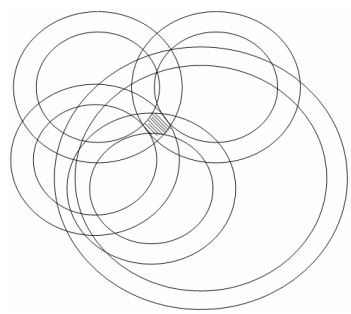

Fig. 6 Location estimation with 1 NLOS and 4 LOS range estimates, location ambiguity resolved

TABLE 1. RANGE ESTIMATION ERRORS (IN METERS)

	Single-return approach		Multiple return approach	
SNR	RMS Error	Average Error	RMS Error	Average Error
4dB	0.755	0.350	0.736	0.369
9dB	0.361	0.155	18.7	0.025
14dB	0.310	0.131	0.066	0.016

The source position estimation using 5 range estimates:

```
Estimated ranges = {4.8900, 0.2850, 1.9200, 0.1950, 3.5400} m
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Actual ranges = {3.4350, 0.2700, 1.9050, 0.2400, 3.5050} m
Position Estimate = (-0.0174,-0.0100) m
Actual Location = (0.0,0.0) m
```

The algorithm found the constraints to be infeasible and proceeded to try solving with 4 constraints. Eliminating the constraint due to the first range estimate, results in a feasible solution set. Thus, even if the ranging algorithm reports some NLOS estimates, the localization algorithm would identify and eliminate them while estimating source location. The sub-meter accuracy achieved here is significantly better than the approaches reported in the literature.

VII. CONCLUSION

A ranging algorithm for NLOS propagation conditions has been presented which uses multiple signal returns. This approach gives sub-meter ranging accuracy even for large TX-RX ranges. The accuracy achievable is limited only by the bin size chosen and the signal-to-noise ratio. The bin size is related to the time resolution achievable with the ranging signal being used, which in turn depends on its bandwidth. We are currently conducting a measurement campaign at the University of Minnesota, using the MICAz mote kit, which is a 2.4 GHz, IEEE 802.15.4 compliant mote module. This is aimed at refining our range estimation approach for low bandwidth and multiband systems.

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