Distance Sensing for Mini-robots: RSSI vs. TDOA

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***Abstract*—This paper reports a compact, robust distance-only sensor for networked small robotic platforms. Two methods of sensing distance (neglecting heading) between robots are discussed: Received Signal Strength Indicator (RSSI) and Time Difference of Arrival (TDOA). Both implementations make use of a commercially available wireless sensor network board for communication and processing. Although RSSI requires no additional hardware, TDOA requires several additional components including a sound source and microphone. While experimental results indicate that both methods can provide distance sensing within a local neighborhood, TDOA sensing was found to be more robust and accurate, providing 1 cm distance resolution over a range of 80 cm versus 2.4 cm for RSSI. These sensors have been integrated onto mini-robotic platforms by incorporating a heading estimator and controller.**

I. INTRODUCTION

Great advances have been made towards achieving autonomous mini-robots that are able to coordinate and communicate with one another in a smooth fashion [1]. In order to allow for coordinated movement such as following a leader or moving in simple formations, the robots must know their location relative to the other robots; this is challenging for very small robots operating under severe resource constraints in the absence of specialized environmental sensors. The focus of this paper is robust, compact distance sensing to support decentralized coordination of autonomous mini-robots.

A variety of location systems have been developed for wireless sensor networks [2],[3],[4] or small robotic platforms [5]. In this work we consider two methods for measuring distance between autonomous mini-robots: received signal strength indicator (RSSI) and time difference of arrival (TDOA). In this context, most of the existing systems are poorly matched to the size, range, and desired resolution of distance sensing for the mini-robots, ~1 in, ~1 m, and ~1 mm respectively. For example, RSSI-based distance estimation has only been shown to be feasible in idealized settings [2], and typical variability is on the order of meters which would be completely useless in controlling a swarm of mini-robots. TDOA-based distance estimation is somewhat more accurate, but existing implementations such as [6] include transducer arrays, greatly increasing sensor size. We propose a design for a TDOA distance-only sensor that requires fewer components and is more suitable to miniature robotic platforms, at the cost of losing directional specificity.

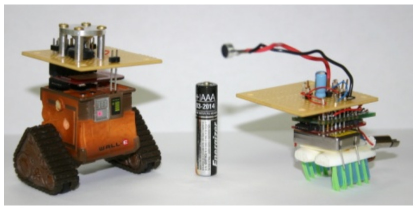

Figure 1. Two mini-bots with full RSSI and omnidirectional TDOA sensing (sound source left, microphone right), AAA battery shown for size.

We report results from implementation of RSSI and TDOA distance sensing on mini-robots, two versions of which are shown in Fig. 1. We used a commercially available wireless sensor network board (Texas Instruments eZ430-RF2500) as the platform for experiments. The eZ430-RF2500 board incorporates a radio chip (CC2500) as well as a 16-bit microcontroller (MSP430). The eZ430-RF2500 has built-in RSSI functionality, and TDOA is implemented using a few external components. Implementations and experimental results for distance sensing are described in Sections II and III. Integration of these methods onto mini-robotic platforms is described in Section IV, and Section V summarizes the work.

II. RECEIVED SIGNAL STRENGTH INDICATOR

RSSI measures the power in a received radio signal. It has been used in a variety of systems for location estimation in wireless sensor networks [4],[8],[9]. Theoretically the received power is inversely proportional to distance^x (where x=2 and 4 in free space and two-ray ground models respectively) [1]. The TI eZ430-RF2500 boards used in this work have built-in RSSI measurements. Given proper settings, the RSSI measurement is appended to the end of the packet received by the radio chip.

To verify that RSSI would function as expected, we set up a simple experiment. We used two test boards, one transmitting an RF signal on two alternating frequencies and the other taking RSSI measurements on those frequencies. We left the receiving board stationary and moved the transmitting board away in 5 cm increments.

In addition to RSSI, we tried to use Link Quality Indicator (LQI), another built-in measurement in the CC2500, but dropped its use due to implementation issues. LQI is a metric for received signal quality, which reflects non-ideal channel effects such as noise, multipath effects, carrier frequency offset, etc.

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A. RSSI Implementation

1) Timing: In order to obtain more reliable measurements, it is possible to transmit multiple packets and then average RSSI values. However, the latency of distance measurement is important as the total time for the network of robots to determine their relative distances will scale quadratically with the number of robots. RSSI memory is not available immediately, so it is necessary to allow for settling time after each transmission before reading the RSSI value. The latency was less than 0.2 sec to receive 100 RSSI measurements and average them.

2) Path effects: RSSI measurements are sensitive to the relative orientations of the transmitting and receiving antennas as well to the local environment (i.e., the measurements differed when boards were placed on different surfaces such as the floor and a table top).

B. Experimental Results

The experimental environment was on a platform indoors. Two test boards were connected to different laptops at a height of 2 cm above the platform. The antennas are located at one end of the eZ430-RF2500 board, and the boards were placed with the antenna ends face to face on approximately the same plane. Since channel conditions vary at different frequencies, the measurements were carried out at two carrier frequencies, f1: 2433.2MHz and f2: 2481MHz.

The RSSI measurements at two frequencies are shown in Fig. 2 (errorbars are one standard deviation), where each value is an average of one hundred measurements. RSSI at f2 was not available beyond 79 cm, presumably due to weak signal. Although the measurements are stable and have fairly low standard deviations, we can see that RSSI increases monotonically with distance in band f2, but does *not* increase monotonically in band f1 when the distance exceeds 13 inches. Other methods such as frequency hopping spread spectrum and artificial neural networks have been reported to improve the quality of RSSI distance measurement but have not been used in this investigation of sensing quality [4]; such approaches might also improve TDOA distance estimation.

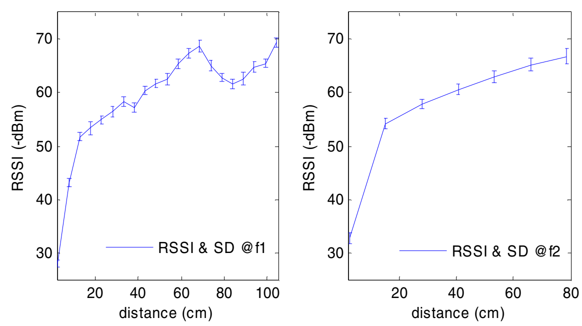

Figure 2. RSSI measurement and its standard deviation vs. distance

III. Time Difference of Arrival

TDOA is another common method of distance sensing in robots. Our approach utilizes the fact that light and sound travel at different speeds. Similar to how people calculate their distance from lightning in a thunderstorm, the receiver is able to calculate distance by measuring the difference in arrival times of an RF packet and an audio signal, both emitted from one transmitting source.

A. TDOA Hardware

We used an omnidirectional microphone (CMC-2742PBJ-A, CUI Inc.), a piezo buzzer (PS1240P02CT3, TDK), and the eZ430-RF2500 board to implement a sensor for TDOA measurement. The piezo buzzer is connected directly to pins of the eZ430 board and tones are generated via an on-board pulse width modulator. The amplification and biasing circuit for the microphone is shown in Fig. 3. Two cascaded non-inverting embedded op-amps in the MSP430 amplify the audio signal. Incorporating a sound-reflecting cone above the buzzer (as seen at the left in Fig. 1) projects the audio pulse omnidirectionally about the robot's workspace.

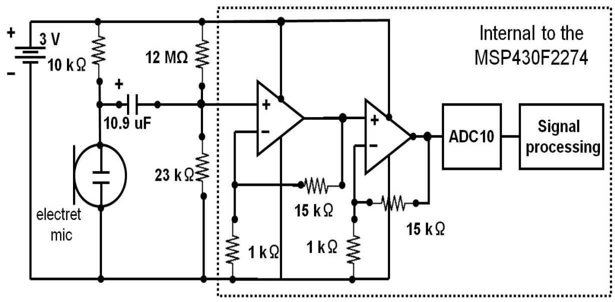

Figure 3: Circuit used to power the microphone and amplify the input signal.

B. Signal Processing

After amplifying the audio signal, the next step is to digitize and process the signal so that we may detect when it arrives in relation to the RF packet. The MSP430 has an internal 10-bit analog-to-digital converter (ADC10), and can transfer at most 255 continuous samples directly into memory without CPU intervention or interrupts. Since we are interested in a range of ~1 m, we programmed the ADC10 with a sampling rate of ~80 ksamples/sec, which provides a range of 1.09 m (~80 cm with 50 sample window) according to (1):

$$D = \frac{1}{n} \cdot N \cdot s \tag{1}$$

where n is the sampling rate, N is the number of samples taken, D is the maximum measurable distance, and s is the speed of sound. We could slow the clock rate in order to increase the distance range, at the cost of distance resolution, or we could delay the onset of sample acquisition in order to shift the sampled range away from the microphone.

The TDOA sensor must be able to isolate the audio pulse from background noise and detect the pulse time of arrival. Similar to the discrete Fourier transform, the Goertzel algorithm acts as a finite impulse response bandpass filter which computes a single Fourier coefficient representing the power present in the signal at a specified frequency [10],[11]. Within each audio sample, a subset of the entire sample set is analyzed using a Hamming window. Both the Hamming window and Goertzel coefficients are pre-computed and stored in memory, reducing computational requirements.

The bandwidth of the response is determined by the sampling rate, the size of the sample window, and the total number of samples. Because our system uses 4 frequencies: 9 kHz, 12 kHz, 15 kHz, and 18 kHz, we chose a 50 sample window size which yields roughly a 3 kHz bandwidth, sufficient to distinguish the frequencies of interest. In order to process the entire data set, the Goertzel algorithm operates on samples 0 – 49, then on samples 1 – 50, and so on. The algorithm then searches for a hit which corresponds to the arrival time of the acoustic signal, by detecting the first sign change in the derivative of the signal envelope (the first peak of peaks) as seen in Fig. 4. When a hit occurs, the first sample index in that window is directly proportional to the TDOA of the audio pulse. The algorithm completes execution as soon as the hit is detected in order to reduce the computational load of the algorithm. Despite the lack of a hardware multiplier, we have estimated the worst case execution time on the MSP430 to be ~90 msecs per measurement calculation (21,000 hardware multiplications).

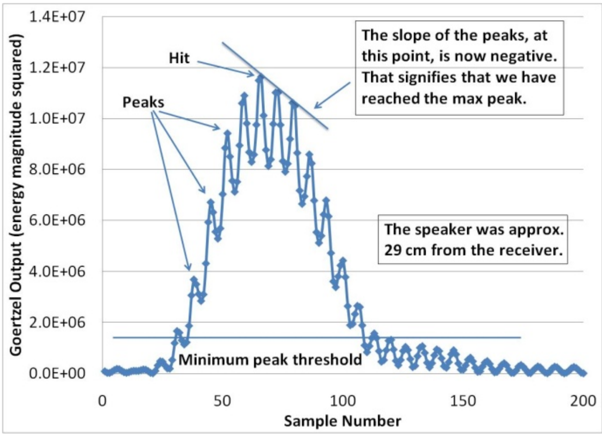

Figure 4: Experimental data showing the output of the Goertzel algorithm and the procedure for identifying the hit.

C. Experiments

1) Distance Calibration and Analysis: The above TDOA system was implemented on two eZ430-RF2500 TI boards; one board with a microphone was set to listen for the TDOA broadcast and another with a buzzer was set to broadcast the TDOA signals. The transmitting board was moved incrementally further away from the receiving board at 50 mm intervals. Ten consecutive measurements were taken at each interval, each corresponding to the time sample with the highest Goertzel output as shown in Fig. 4. Fig. 5 shows results that have been calibrated with respect to the true distance. Measurement resolution was taken to be the distance equivalent to one standard deviation of measurement error. It was computed by inferring errors back to true distance, using the calibrated dataset represented in Fig. 5.

Using leave-one-out cross-validation techniques, absolute and percentage distance errors were computed for each measurement. Mean measurement errors with respect to buzzer/microphone distance are shown in Fig. 6, with error bars equivalent to one standard deviation. Table I summarizes the absolute error, percent error, and resolution for the TDOA data represented in Figs. 5 and 6.

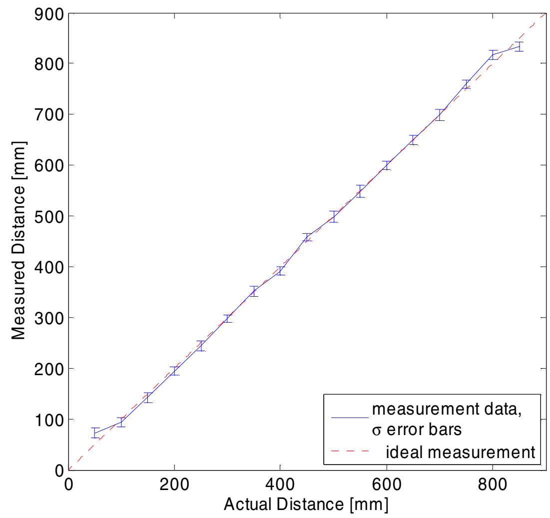

Figure 5: Calculated vs. actual distance for TDOA measurement.

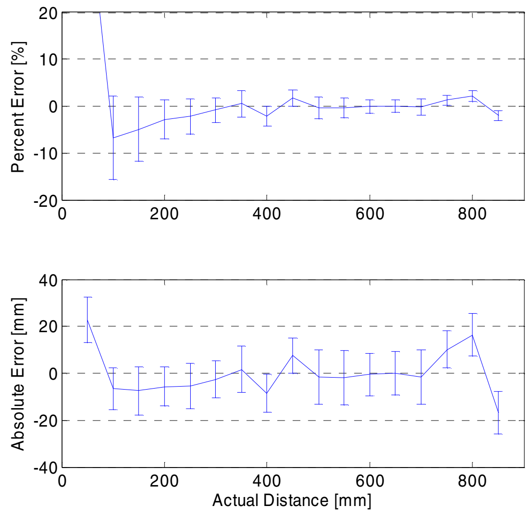

Figure 6: Absolute and percent error for TDOA measurements vs. distance.

TABLE I. SUMMARY OF ACCURACY METRICS FOR TDOA

	absolute error	percent error	σ resolution
Mean	1.0 cm	5.3%	1.1 cm
Median	0.9 cm	2.0%	0.9 cm
Max[a]	4.0 cm	79%	2.6 cm

[a]maximum errors occurred when d = 5cm

2) Directional Sensitivity Analysis: Since the distance-only sensor requires directional invariance, we also tested the directional sensitivity of the TDOA implementation under three conditions: rotating microphone, rotating buzzer with sound-reflecting cone, and rotating buzzer facing outward without the cone. At an approach angle of zero degrees, the microphone and buzzer (no cone) face each other directly.

The distance between buzzer and microphone was fixed at 40 cm. Figure 7 shows the raw TDOA data in units of samples for the three conditions. The buzzer without the cone suffers dropout in two symmetric angular regions behind its "face". The microphone and the speaker with the cone exhibit excellent uniformity in response.

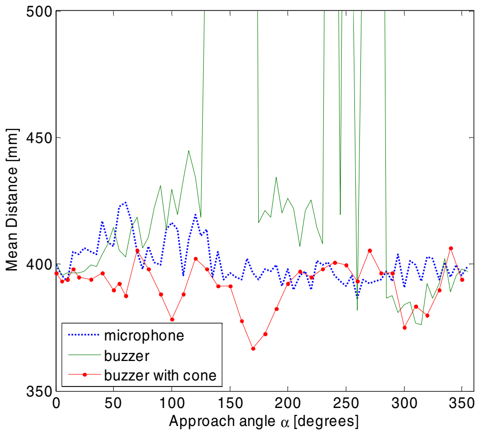

Figure 7: Distance measurements vs. orientation angle.

IV. Navigation System Implementation on Microbotic Platforms Using Distance-Only Sensors

While distance-only sensors implementing TDOA or RSSI offer small sensor packages, their inability to determine heading requires a heading "estimator" or clever control techniques. We propose a navigation system that will enable properly equipped mini-robots to rendezvous with another robot. In order to accomplish this, the robot must move about the environment to empirically determine heading by facing towards the target. One strategy is to drive the heading error to zero by finding the minimum distance directional derivative, which is the steepest descent toward the source of a distance field *d*. Considering a distance sensor that samples in discrete time, the derivative can also be rewritten in discrete time:

$$\frac{d}{dt}d(t) \doteq d(k) - d(k-1) \qquad (2)$$

To gather sufficient data to minimize heading error, the robot will move with a constant turning rate and forward velocity, until the robot turns through the minimum of (2). A second order difference zero crossing test (3) can determine if the minimum has been passed.

$$d(k) - 2d(k-1) + d(k-2) > 0 \qquad (3)$$

$$d(k) - d(k-1) < 0 \qquad (4)$$

(3) and (4) will be true exactly one time index after the minimum of (2) is passed. Since the robot passed the minimum of (2) to determine it, it will correct its heading and then proceed straight towards the target.

In practice, the robot will not always find the correct angle due to discretization and measurement noise, and when traveling great distances robots may pass their target completely. The algorithm can restart if (2) becomes greater than zero and if the absolute distance is above some threshold distance δ. Otherwise, the robot should rendezvous within a local neighborhood δ of its desired target.

TABLE II. Comparisons of Distance metrics

	Range of monotonicity	Resolution
RSSI, f1	33 cm	2.4 cm
TDOA	80 cm +	1.1 cm

V. Conclusions

Two methods of distance-only sensing for small robotic platforms have been explored and contrasted. Sensor range and resolution characteristics summarized in Table II suggest that TDOA is a better candidate than RSSI for distance sensing (i.e., 1.1 vs 2.4 cm resolution). This is at the cost of integrating additional hardware with commercially-available micro-embedded systems. We also outlined computationally frugal control strategies for robotic swarms tailored for such sensor data.

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