A Beacon System for the Localization of Distributed Robotic Teams

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Abstract

This paper presents the design of a localization system for a team of centimeter-scale robots that collaborate to map and explore unknown environments. The localization system uses ultrasound to measure the distance from each moving robot to three stationary robots that serve as beacons. From these distance measurements the position of the robots is derived using a trilateration algorithm. The robot team can move over large distances by using a leap-frogging approach in which different robots serve as beacons at different times. The localization system is able to obtain position estimates more accurate than can be achieved through dead reckoning, and yet, does not require any landmarks or previously deployed beacons.

Keywords: collaborative positioning, localization, ultrasonic range finder, miniature mobile robotics.

1 Introduction and Related Work

In this article, we present the design of a localization system for a team of centimeter-scale robots that collaborate to map and explore unknown environments. The robots, called *Millibots*, are configured from modular components that include sonar and IR sensors, camera, communication, computation, and mobility modules. Robots with different configurations use their special capabilities collaboratively to accomplish the given task. A typical Millibot is shown in Figure 1.

For distributed robotic applications that require robots to share sensor information (e.g. mapping, surveillance, etc.) it is critical to know the position and orientation of the robots with respect to each other. Without knowing the position and orientation of the sensors, it becomes impossible to interpret the sensor data in a global frame of reference and integrate it with the data coming from other robots. Moreover, the Millibots require position knowledge to move to predetermined locations, avoid known obstacles, or reposition themselves for maximum sensor efficiency.

Conventional localization systems do not offer a viable solution for Millibots. Many robotic systems rely on a Global Positioning System (GPS) and compass for determining their position and orientation in a global frame of reference [7]. However, due to its large size, limited accuracy, and satellite visibility requirements, GPS is not appropriate for the small Millibots that operate mostly indoors. Dead reckoning, another common localization method, generally suffers from accuracy problems due to integration errors and wheel slippage [3]. This is even more pronounced for Millibots that rely on skid steering for which track slippage is inherent to the steering mechanism. Conversely, other localization systems that are based on landmark recognition [1][9] or map-based

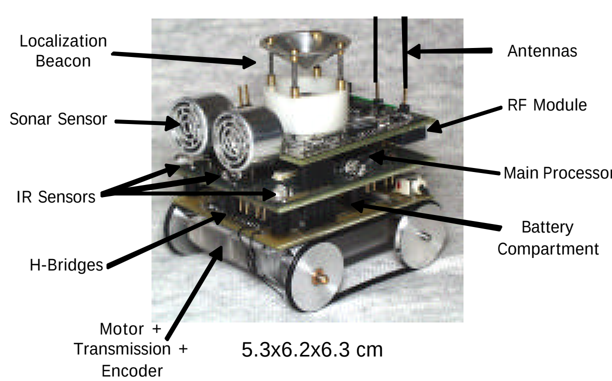


Figure 1: Millibot prototype

positioning [15] require too much computing power and sensing accuracy to be implemented on Millibots.

To overcome the problems encountered in the implementation of existing localization methods for a team of Millibots, we have developed a novel method that combines aspects of GPS, land-mark based localization, and dead reckoning [14]. The method uses synchronized ultrasound pulses to measure the distances between all the robots on a team and then determines the relative positions of the robots through trilateration. Similar systems have been developed [8] and are even commercially available. However, they are both too large and too expensive for operation on Millibots. Moreover, the system described in this article is more flexible because it does not require any fixed beacons with known positions, which is an important relaxation of the requirements when mapping and exploring unknown environments.

2 System Concept

2.1 Trilateration

The Millibot localization system is based on trilateration [3], i.e., determination of the position based on distance measurements to known landmarks or beacons [10] [11]. GPS is an example of a trilateration system; the position of a GPS unit on earth is calculated from distance measurements to satellites in space. Similarly, the Millibot localization system determines the position of each robot based on distance measurements to stationary robots with known positions.

The localization system uses ultrasound pulses to measure the distances between robots. Periodically, each beacon simultaneously emits a radio frequency (RF) pulse and an ultrasonic pulse. As is illustrated in Figure 2, the RF pulse, traveling at the speed of light (3×10^{8} m/s), arrives at all receivers almost instantaneously. The ultrasonic pulse, on the other hand, traveling only at 343

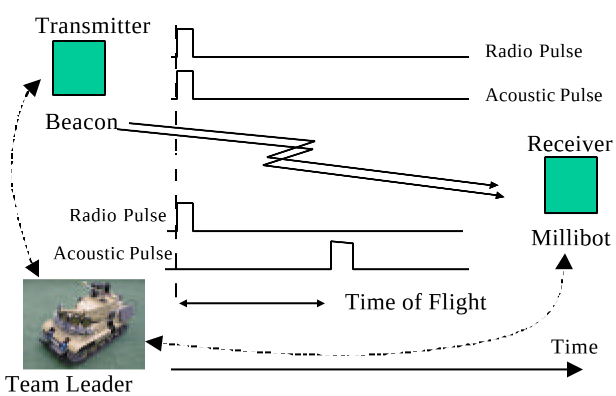


Figure 2: Ultrasonic distance measurement.

m/s (assuming 20°C air temperature) arrives at the receiver with a delay proportional to its distance to the beacon. Each Millibot measures this delay, using the RF pulse for synchronization, and converts it to a distance measurement by multiplying with the speed of sound. A team leader coordinates the pinging sequence to ensure that beacon signals from multiple robots do not interfere with one another.

After all the beacons finish pinging, every Millibot has a set of distance measurements from its current position to each beacon position. This information is sequentially transmitted to the host computer, which determines the actual position of every Millibot. In the future, we plan to calculate the Millibot positions on the local processor of each Millibot. However, currently the processor does not have the necessary computation power to perform these floating-point computations.

2.2 Initial Positions

When a team of Millibots is first deployed, they automatically determine their position with respect to a local frame of reference. To accomplish this, the team leader collects distance measurements between any arbitrary pair of robots by pinging the beacon of each robot possibly multiple times to achieve more accurate distance measurements and collecting the measurements from all the other robots. The team leader then assigns the position (0,0) to an arbitrarily chosen robot. A second robot is assigned a position on the X-axis. This defines a frame of reference in which the position of all other robots is determined through trilateration. However, based on distance measurements alone, there remains an ambiguity about the sign of the Y coordinates of each robot. To resolve this ambiguity, the team leader commands one robot to follow a short L-shaped trajectory, and redetermines its position through trilateration. If the robot turned to the left, but the assigned coordinate system indicates a right turn, the sign of the Y-coordinates of all robots is reversed.

2.3 Leap-Frogging

An important advantage of the Millibot localization system is that it does not rely on fixed beacons. Instead, a minimum of three Millibots (but not necessarily always the same three) serve as beacons at any time. The Millibots that serve as beacons remain stationary. The other robots can move around in the area that is within reach of the beacons. While they sense the environment, they can determine their position with respect to the current beacons. When the team has explored the area covered by the current beacons, other robots will become stationary and start serving as beacons. In this fashion, the team can move over large areas while maintaining

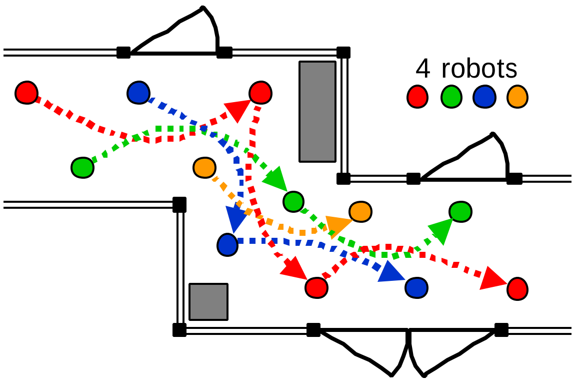
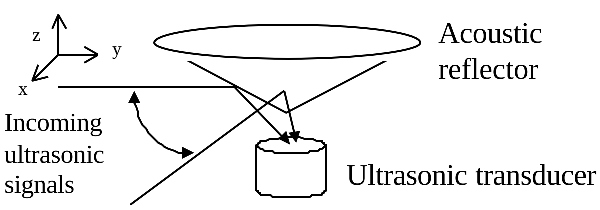


Figure 3: Leap-frogging movement sequence.

good position estimates as illustrated in Figure 3. This leap-frogging approach allows a team to move forward while always maintaining three stationary beacons in known locations.

In order to avoid numerically ill-conditioned configurations (e.g. collinear beacons), careful planning of the movement sequence is required. The localization algorithm is most accurate when the beacons are at the vertices of an equilateral triangle. When a team moves over a large distance, the beacon that is farthest removed from the goal will be replaced by a Millibot in a position closer to the goal and equidistant to the other two beacons.

As is described in Section 5, the accuracy of the position estimates gradually deteriorates as the number of leaps increases. We expect several parameters to affect the accuracy, including the number of leaps, the shape of the leap-frogging pattern and the size of each leap. Careful characterization of these dependencies is the subject of ongoing work.



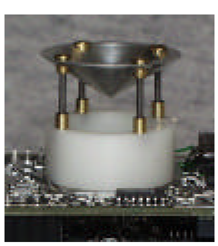


Figure 4: The localization sensor with acoustic reflector.

3 Hardware description

We designed a single localization module that can serve either as a beacon or as a localization sensor. To produce and detect beacon signals, each Millibot is equipped with a modified, low-cost ultrasonic transducer. This transducer can function either as a receiver or as an emitter. For localization to be effective, it is important that the sensor can detect signals coming from any direction around the Millibot. As is illustrated in Figure 4, an ultrasonic transducer is positioned to face straight up, pointing towards an aluminum cone that reflects all incoming and outgoing sound waves. The result is a transducer with 360-degree coverage in the horizontal plane. The ultrasonic transducer with reflector is approximately 2.5cm tall. It can reliably measure distances up to 3m with a resolution of 4mm while consuming only 25mW. The design and construction of this detector was paramount in achieving a beaconing system at this scale.

Despite the fact that electrostatic transducers are usually the family of choice for ultrasonic ranging applications, we decided to use piezoelectric transducers in our design. Electrostatic transducers couple to the air more efficiently than piezoelectric transducers, and have a higher dynamic range. However, they usually operate at very high voltages (150-200 VDC), and are too large for the Millibots. On the other hand, piezoelectric transducers are inexpensive, work at low voltages and fit easily within the power and size budget of the Millibots [5]. And although the piezoelectric transducers have some latency in their response due to mechanical inertia, we were able to obtain reliable and accurate ultrasound detection up to 3m.

4 Position Estimation Algorithms

Several algorithms can be used for solving the mobile robot localization problem. Our first implementation combines two separate, independent algorithms: one for tracking the position of robots moving across the field, and the other for determining the position of the robots that serve as fixed beacons.

As described in [14], we use an Extended Kalman Filter (EKF) to keep track of the position of the moving robots. Kalman filter-based techniques have proven to be robust and accurate for keeping track of the robot's position [10] [11]. To provide noise rejection and develop a model dependent estimation of position and orientation, an EKF is applied to the distance data collected by each Millibot. The EKF is an optimal estimator that recursively combines noisy sensor data with a model of the system dynamics [2]. Inputs to the EKF include distance measurements between the robot and the beacons as well as the velocities of both tracks. The dynamics in this application are the kinematic relationships that express the change in position of the robot as a function of the track speeds. The EKF fuses this dead reckoning data with the beacon measurements. The two inputs complement each other to produce an optimal estimate of the robot's local position and orientation.

Before a robot switches into beacon mode, its position is estimated more accurately to avoid building up large position errors with respect to the global reference frame. Position estimation for beacon robots is different from that for moving robots in several respects. Since the beacon robots remain in the same position until they become moving robots again, we do not have to consider their dynamics as in the EKF. Furthermore, the orientation of the beacon robots is not important; the sonar pulses are transmitted in a circular fashion.

As a result, we only need to compute the position of the future beacon and can use a trilateration algorithm that is more accurate than the EKF. Our algorithm determines the most likely position of the robot given the measured distances to the current beacons. As has been verified in our experiments, the distance measurements can be assumed to be normally distributed. Based on that assumption, the likelihood of being located at position (x,y), given the distance measurements R_{1m}, R_{2m}, and R_{3m} is given by the probability density function:

$$P(x,y\,|\,R_{1m},R_{2m},R_{3m}) = \prod_{i=1}^{3} N(R_i - R_{im}, \sigma_i)$$

where $N(x,s)$ is a normal distribution with zero mean and a standard deviation of s evaluated at x, and R_i is the distance from (x,y) to beacon i. As the position estimate for the robot, we select the position (x,y) for which the probability density function $P(x,y\,|\,R_1,R_2,R_3)$ is maximum. To compute this maximum, we first determine an initial estimate based on the closed form trilateration expression derived in [12]. The BFGS non-linear optimization algorithm [6] is then used to iteratively improve this initial estimate. Because of the proximity of the starting point, only a few iterations are necessary to reach the optimum.

5 System Performance

Reliable distance measurements between robots are essential for the localization system. Therefore, the design of a good 1-D range finder is fundamental. For performance tests two localization modules were attached to a rail equipped with a distance scale. In order to determine the range accuracy and precision of the unit we took 200 measurements and computed the mean value and standard deviation at regular distance intervals. In Figure

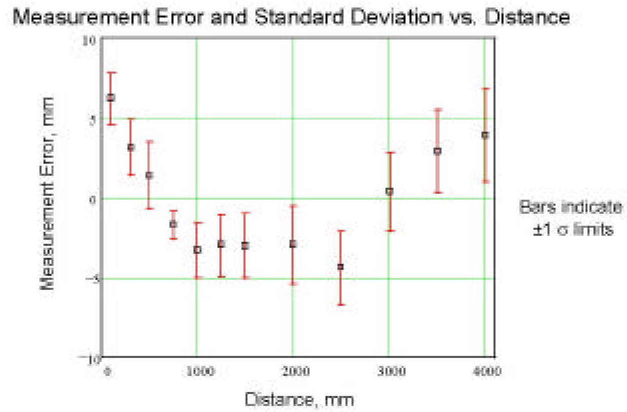


Figure 5: 1-D range measurement performance.

5, the measurements are compared to the expected distance, assuming a linear relationship between the distance and time measurement.

The performance of the ultrasonic range finder is affected by several factors. Some of these factors are a result of the hardware design, while others depend on environmental factors.

Our system uses a threshold detector to measure the time of arrival of ultrasonic signals. This time instant is determined by the moment at which the incoming ultrasonic signal exceeds for the first time a certain reference level. The amplitude of the ultrasonic signal changes with the traveled distance due to beam spreading and attenuation. This results in small measurement errors at low signal-to-noise ratios. We compensate for the above errors by using an experimentally determined calibration equation. While there are many different techniques for getting accurate time of flight measurements [4][13], we decided to use this method in order to keep our hardware within the constraints of the Millibots.

The measurement process also introduces quantization noise. Our circuit can measure the time of flight with a resolution of 10μs. Assuming a 20°C air temperature, the quantization interval is equivalent to a distance of 3.43mm.

In addition to the noise introduced by the measurement system, several environmental factors influence the accuracy of the measurements. Room temperature drift and temperature gradients influence the distance measurement process because the speed of sound is a function of temperature. One can compensate for changes in room temperature using a temperature probe, but temperature *gradients* cannot easily be measured. Similarly, one cannot easily account for air turbulence and wind [16]. These effects are more pronounced when the sound travels over longer distances because it has a larger probability of crossing zones that affect its propagation speed and consequently its time of flight.

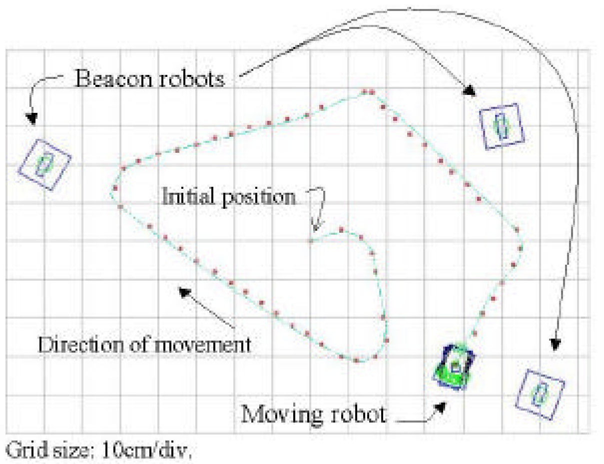


Figure 6: GUI snapshot of localization system.

We are in the process of determining the importance of each of these effects on the overall system performance. However, preliminary tests show very promising results. We have tested both modes of position determination. Figure 6 depicts a test run for the EKF algorithm. It shows a snapshot from the GUI that controls the Millibot fleet [14]. Three Millibots serve as stationary beacons while a fourth Millibot moves across the workspace under joystick control. The position of the robot is recorded and plotted on the screen. The maximum position error registered in this particular run was 2.5cm. Previous tests for localization based solely on dead reckoning produced very inaccurate results in similar tests, due mainly to wheel slippage.

In addition to the EKF algorithm, we have tested the leap-frogging concept using a Monte Carlo simulation. Figure 7 shows the result of a simulation of 75 leaps in a square pattern. The mean and standard deviation of the position error are depicted in Figure 8. To obtain these simulation results, we made the assumption that the distance measurement errors are uncorrelated with respect to each other and with respect to the beacon positions. Based on the analysis our 1D range measurements we further assumed that the distance measurements have a standard deviation of 4mm. Because the error accumulation depends strongly on the distance measurement error, the robots perform each measurement 8 times, effectively reducing the variance.

The results show that the uncertainty ellipsoid associated with each estimated position increases with the number of leaps, as expected. The position error variances after the final leap are

$$s^2_{\Delta x} = 0.0138\,m^2,\; s^2_{\Delta y} = 0.0139\,m^2,\; s^2_{\Delta x,\Delta y} = -0.008\,m^2.$$

corresponding to an uncertainty ellipsoid with principal axes at 45degrees and maximum and minimum standard deviations of 0.148m and 0.076m, respectively. The angular error has a standard deviation of only 1.07degrees after 75 leaps.

Compared to dead reckoning, the Millibot team maintains position estimates that are at least an order of magnitude more accurate than for most other robot systems. Especially the fact that the localization algorithm is not affected by changes in orientation is a significant benefit

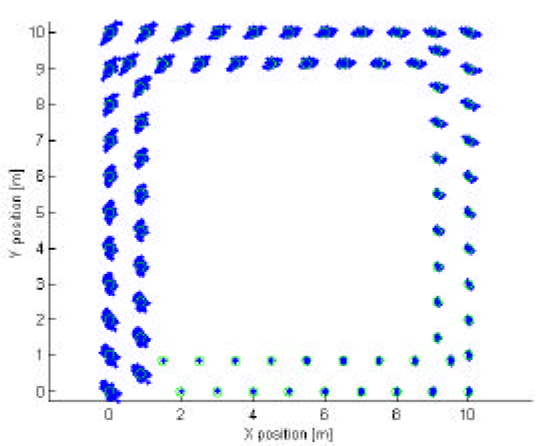


Figure 7: Position estimates for a square pattern of 75 leaps.

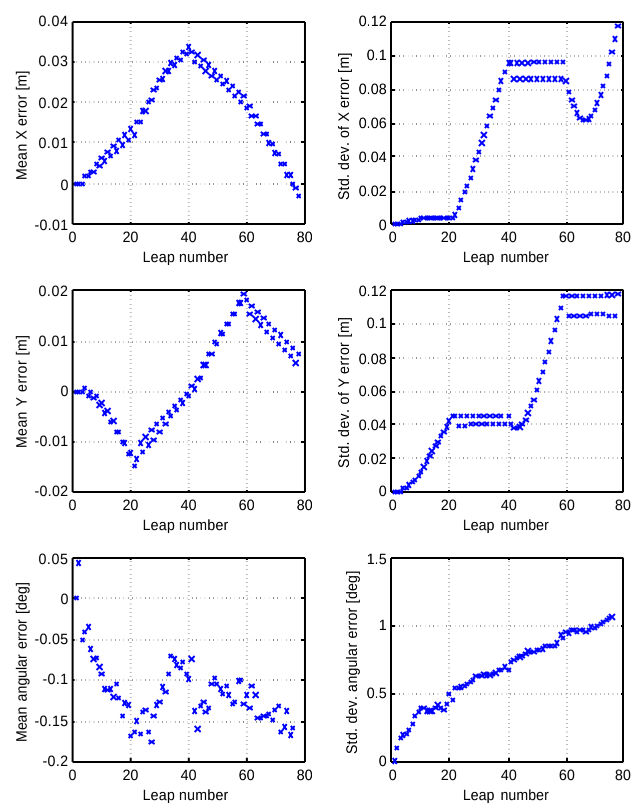


Figure 8: Mean and standard deviation of position error as a function of leap number.

over dead reckoning, where most of the error is caused by rotation in place.

It is interesting to note how the uncertainty ellipsoid evolves along the course of the trajectory. The uncertainty grows more quickly in the direction perpendicular to the direction of movement; when the robots move along the X-axis, the uncertainty ellipsoid is elongated in the Y-direction. This can be explained by the fact that all three distance measurements have a component in the forward direction, resulting in a very accurate measurement in that direction.

Figure 7 also shows that the leap frogging algorithm introduces a bias. This is due to the non-linearity in the equations. However, the bias is small compared to the variance and cancels out when moving in opposite directions.

6 Summary

A small, low-power, and accurate localization module has been developed for the Millibot fleet. The module combines sonar-based distance measurements with a trilateration algorithm to determine robot positions within the team. A leap-frogging algorithm allows the team to move over large distances while maintaining accurate position estimates with respect to the initial reference frame. Simulation results indicate that this localization system has the potential to be an order of magnitude more accurate than traditional dead reckoning systems.

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References

[1] Atiya, S. and Hager, G. 1993. Real-time Vision-based Robot Localization. *IEEE Transactions on Robotics and Automation*, Vol. 9, No. 6, pp. 785-800.

[2] Bar-Shalom, Y., and Fortmann, T.E., 1988. *Tracking and Data Association*. Academic Press.

[3] Borenstein, J., Everett, H. R., and Feng, L., 1996. *Navigating Mobile* Robots*: Sensors and Techniques*, Wellesley, MA: A. K. Peters, Ltd.

[4] Cai, C., and Regtien, P.L.1993. Accurate Digital time-of-flight Measurements using Self-Interference. *IEEE Transactions on Instrumentation and Measurement*. Vol. 42, No. 6. December 1993. pp.990-994.

[5] Everett, H.R. 1995. Understanding Ultrasonic Ranging Sensors. *The Robotics Practitioner*. Fall, 1995. pp. 27-38.

[6] Fletcher, R. 1987.*Practical methods of optimization (second edition).* New York, NJ: J. Wiley & Sons, Ltd.

[7] Getting, I. A. 1993. The Global Positioning System. *IEEE Spectrum*, December, pp. 36-47

[8] ISR - IS Robotics, Inc., 1994. “RR-1/BS-1 System for Communications and Positioning - Preliminary Data Sheet.” IS Robotics, Twin City Office Center, Suite 6, 22 McGrath Highway, Somerville, MA 02143, 617-629-0055.

[9] Jenkin, M., Milios, E., Jasiobedzki, P., Bains, N., and Tran, K. 1993. Global Navigation for ARK. *Proceedings of the 1993 IEEE/RSJ International Conference on Intelligent Robotics and Systems*. [1] Yokohama, Japan, July 26-30, pp. 2165-2171.

[10] Kleeman, L. 1992. (May, Nice, France) Optimal estimation of Position and Heading for Mobile Robots Using Ultrasonic Beacons and Dead-reckoning. *Proceedings of the 1992 IEEE International Conference on Robotics and Automation*. pp. 2582-2587.

[11] Leonard, J. F. and Durrant-Whyte, H. F., 1991. Mobile Robot Localization by Tracking Geometric Beacons. *IEEE Transactions on Robotics and Automation*. Vol. 7. No. 3. pp. 376-382.

[12] Manolakis, D.E. 1996. Efficient Solution and Performance Analysis of 3-D position Estimation by Trilateration. *IEEE Transactions on Aerospace and Electronic Systems*. Vol. 32, No. 4. October 1996. pp.1239-1248.

[13] Marioli, D., Narduzzi, C., Offelli, C., Petri, D., Sardini, E., and Taroni, A. 1992. Digital Time-of-flight Measurement for Ultrasonic Sensors. *IEEE Transactions on Instrumentation and Measurement*. Vol. 41, No. 1. February 1992. pp.93-97.

[14] Navarro-Serment, L.E, Grabowski, R., Paredis, C.J.J., and Khosla, P.K. 1999. “Heterogeneous Teams of Modular Robots for Mapping and Exploration,” Technical Report ICES-04-07-99, The Institute for Complex Engineered Systems, Carnegie Mellon University, Pittsburgh, PA 15213.

[15] Stuck, E. R., Manz, A., Green, D. A., and Elgazzar, S., 1994. Map Updating and Path Planning for Real-Time Mobile Robot Navigation. *1994 International Conference on Intelligent Robots and Systems (IROS '94)*. Munich, Germany, Sept. 12-16, pp. 753-760.

[16] Wehn, H. W., and Belanger, P.R. 1997. Ultrasound-Based Robot Position Estimation. . *IEEE Transactions on Robotics and Automation*. Vol. 13, No. 5. October 1997. pp.682-692.