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# Feature Extraction for Autonomous Navigation using an Active Sonar Head*

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## Abstract

*A critical problem in sensory interpretation is the derivation of the right mapping between sensor signals and properties of the world. In this regard, the method proposed here uses active sensing to acquire environmental features for reliable navigation in indoor environments. The features utilized are lines, corners, and edges extracted from common indoor room features such as walls, room corners and room edges, respectively. These features are abundant in indoor environments and allow for closed-form location estimates from time-of-flight sonar information. Subsequently, a multiple hypothesis testing procedure is utilized to accurately localize and identify those features. Experiments using a new active sonar system, implemented using a 3 DOF binaural sonar head, shows that the system is able to correctly localize and identify indoor environmental features, and that active sensing strategies based on sensor reconfiguration makes the process of feature extraction more accurate.*

## 1 Introduction

Coping with uncertainty in sensing, modeling, and actuation is an important scientific and technological issue in robotics [12]. This is especially the case in robot navigation, where a mobile robot operates in large, unstructured environments, generating significant uncertainty in the robot's position and consequently in the functional identity of the objects detected by the robot. Priorities in mobile robot research are thus sensory interpretation and reasoning under uncertainty [5, 6].

A critical problem in sensory interpretation is the derivation of the right mapping between sensor signals and the properties of the world. Work in this area addresses the problem of how to detect features, how to combine features and create models, and how to match features to models. The performance of the sensing system is highly dependent on the quality of feature detection, since it is the first information processing step executed. Moreover, the majority of sensors (e.g. sonars, cameras, lasers) currently utilized in robot navigation present a combination of high accuracy measurements and outliers, creating the need of sensor models and systems that better capture the relevant physics of the sensor-environment-task interaction, with the intent of controlling the influence of outliers [11, 1].

This paper shows how environmental features can be identified using an active sonar system. The features utilized are lines, corners, and edges extracted from common indoor room geometries such as vertical planes (walls), corners and convex corners (edges), respectively. These features are not only abundant in indoor environments, but they also allow closed-form location estimates from time-of-flight sonar information. Subsequently, a multiple hypothesis testing procedure is utilized to accurately localize and identify those features [1, 2]. As an analogy, these features can be viewed as anchors; they generate a region where the robot can navigate freely while bounding its positional uncertainty [16]. In addition, feature sets can be acquired in the process of executing a navigation/sensing task by employing active sensing. Over time, this acquired spatial knowledge can be used to improve the navigational skills of the robot [17].

Section 2 discusses related work, followed by an introduction of our active sonar system in Section 3. Section 4 describes the multiple hypothesis testing method used for feature localization and identification. Section 5 presents ideas for improving feature extraction by using active sonar sensing strategies. The experiments are discussed in Section 6, and Section 7 concludes the paper.

## 2 Related Work

Sound-based navigation has been shown to be effective, not only in man-made systems, but primarily in nature. Bats master echolocation[18, 20, 7], suggesting that sonars can extract complex features directly from the environment. Current research in sensing shows the ability of an adaptive sonar system to differentiate heads and tails on a coin by manipulating the sensor's configuration [10].

Methods used to extract information from sonar are highly dependent on sonar configuration. Sonar configu-

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ration encompasses not only the spatial configuration of transducers over the robot, but also how their functionality is distributed – e.g. the geometric relationship between transmitter, world, and receiver is important, and the kind of signal processing utilized is also important (analyses in time, amplitude, frequency, and phase) [20, 9]. Only recently have different sonar configurations been explored to better fulfill task requirements, with the introduction of sonar arrays, virtual sonar sensors, and more recently, adaptive sonar heads motivated by biological systems [3, 14, 8, 4, 10, 20, 2].

## 3 Binaural Sonar System

As previously discussed, the sonar configuration is an important factor in the accuracy of the measurement obtained. Here we present a sonar apparatus that allows the system to improve feature detection and identification by changing its configuration. Figure 1 shows our 3-DOF binaural sonar head[1] and its functional diagram. The pan axis permits the localization of features in any direction, while the vergence axes allow the system to adjust the sonar configuration to feature distance and feature type, thereby producing better quality measurements.

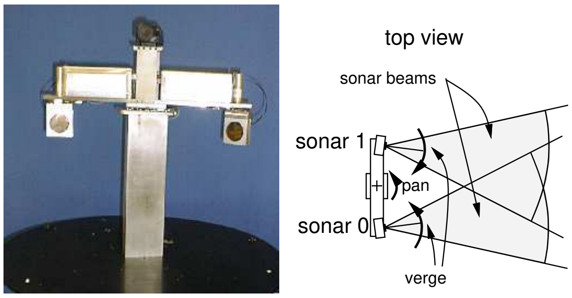


Figure 1. Sonar head (left) and its top view functional diagram (right).

The active sonar hardware is composed of two Polaroid 600 Series instrument grade electrostatic transducers [15], two ranging modules (Polaroid 6500 Series module) modified to accept two modes of operation (transmit-receive, and receive only), and a 10MHz counter board with two 24-bit counters for time-of-flight (TOF) computation of sonar echos [1].

Isaac, our autonomous three-wheeled robot, is depicted in Figure 2. Its chassis is a MRV-3 model from Denning Mobile Robotics, Inc., upgraded at our laboratory to support on-board processing on a VME architecture. The sonar head can be seen on top of Isaac.

[1]Manufactured by Sunderland Manufacturing, Wendell, MA.

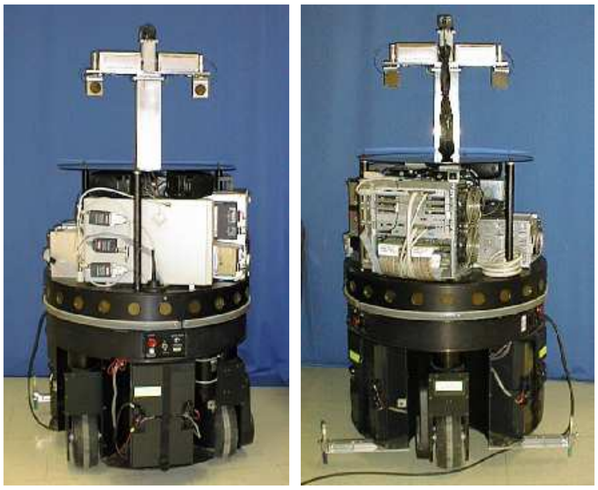

Figure 2. Mobile robot and binaural sonar head; front view (left), view from the back (right).

## 4 Extracting Features from Sonar Range

The goal of extracting features from the environment is to use them as landmarks, or beacons, in navigation tasks. Therefore, the features selected should be easy to detect and abundant enough in the environment to permit their use as navigational feedback. This work uses lines, corners, and edges extracted from common indoor room features. These features are common in indoor environments, and allow closed-form estimates from TOF information [11, 13, 8, 2].

The feature models employed here use only range information from a pair of sonars. The range is easily obtained from TOF, since the velocity of sound in air is approximately constant ($\approx 343m/s$ in indoor environments). One of the sonar pair operates as a transmitter and receiver ($T$), returning the range $r_1$, and the other operates as a receiver only ($R$), producing $r_2$. Our sonar pair operates in two distinct firing modes: ($T$,$R$), where the leftmost sonar sends the signal; or ($R$,$T$), where the rightmost sonar sends the signal. The range pair ($r_1$, $r_2$) is used to compute a position estimate for each feature type, assuming that both readings come from the same feature. A detailed description of the feature extraction method can be found at [1, 2].

### 4.1 Line, Edge, and Corner Features

The line feature model uses the range pair ($r_1$, $r_2$) and the position and orientation estimate of the sonars to create a line observation ($r$, $\theta$). The edge and corner feature models also use the sonar range pair and the current position and orientation of the sonars to create the edge and corner position observations (($x_e$, $y_e$), and ($x_c$, $y_c$), respectively).

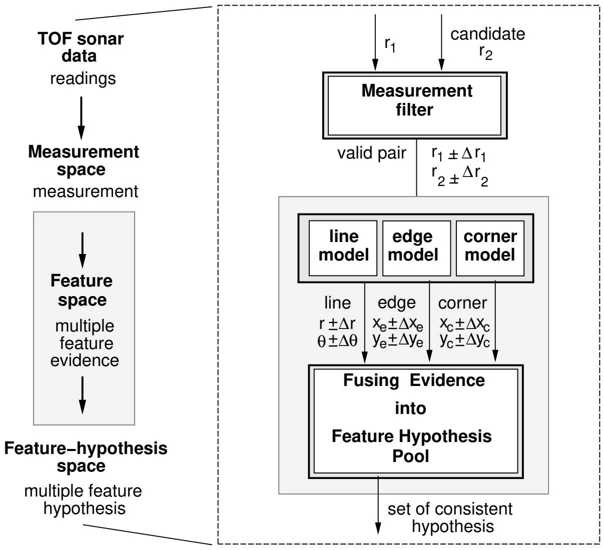


Figure 3. Feature localization procedure.

## 4.2 Feature Localization Procedure

Figure 3 depicts the process of extracting feature localization hypotheses from raw sonar data. The raw sonar information is pre-filtered to discard measurements with readings from different features, avoiding inconsistent sonar measurement pairs. Each consistent sonar measurement $(r_1, r_2)$ is then transformed into feature observations using the feature models. Information is ultimately expressed in the form of multiple feature observations, each composed of a line ($r \pm \Delta r$, $\theta \pm \Delta\theta$), edge ($x_e \pm \Delta x_e$, $y_e \pm \Delta y_e$), and corner localization ($x_c \pm \Delta x_c$, $y_c \pm \Delta y_c$). The uncertainty in each feature parameter is obtained by calculating the maximum possible error generated by the transformations from measurement to feature space, and it is a function of the uncertainty in the sonar measurements $r_1$ and $r_2$, given by $\Delta r_1$ and $\Delta r_2$ respectively, the non-linear transformation from measurement space to feature space, and the transducers' spatial configuration together with sonar beam angles. The multiple feature observations are then fused into the feature hypothesis pool, where each hypothesis keeps a Kalman filter running for each feature type.

In updating the feature hypothesis pool, the problem of verifying whether a new observation belongs to an existing feature-hypothesis in the pool has to be addressed. The metric used computes the probability that a sample could belong to both Gaussian distributions (current observation and any pool hypothesis). A new hypothesis is created when the highest value obtained with the metric is less that a threshold ($thr = 0.3$). A detailed description of the feature localization method can be found at [1, 2].

## 4.3 Feature Identification Procedure

The last step is to identify the feature type which best accounts for the data in each *stable* hypothesis at the feature hypothesis pool. When the belief in a feature hypothesis is sufficiently high, the hypothesis is considered stable ($\sigma^2 < 0.001$). The degree of belief in a feature hypothesis is determined by the diagonal terms of the covariance matrix of the corresponding Kalman filters ($\sigma^2$).

The approach used calculates a confidence measurement for each feature in a stable hypothesis, and selects the feature with the highest relative confidence value, as follows:

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*Feature confidence measurement:*

1. *On the last $n$ measurements ($n \leq 20$) fused into an stable hypothesis, use their corresponding sonar configurations to:*
   (a) *Compute which sonar measurements the current filter estimate generates;*
   (b) *Compare the above measurements with the original measurements fused, by using the same metric used to select in which hypothesis to fuse a new observation;*
2. *Compute each feature confidence by taking the average of all the metric values over the $n$ measurements;*
3. *Select the feature with the best confidence value, higher (0.2) than the second best on this hypothesis.*

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The feature identification process is computational expensive; it requires information from multiple sonar configurations and sometimes even different robot poses to correctly distinguish the three possible features [1, 2]. We propose that information acquisition must be done actively, based on previous knowledge of how and where relevant information can be obtained.

# 5 Active Sonar Sensing Strategies

Methods to extract information from sonar are highly dependent on sonar configuration – the geometric relationship between transmitters, reflective features, and receivers. The objective is to evaluate the performance of our feature localization and identification method as sonar configuration varies, and to create active sonar sensing strategies that facilitates the identification of feature sets which actively resolve robot localization errors.

There are several parameters in the system that influence the accuracy of the feature detected. The error associated with the sonar measurements $r_1$ and $r_2$ is directly proportional to the measurements' values

$$\Delta r_1 = p r_1 \ , \quad \Delta r_2 = p r_2 \ , \quad p \leq 0.01.$$

Therefore, to obtain a precise measurement, it is desired to have the sensor closer to the object being measured. However, this alternative is normally expensive since it produces extra robot displacements that may go against the current path objectives, while at the same time causing an increase in the robot's localization error.

Another alternative comes from the observation that in feature space the sensor distance to a feature, the configuration of the sensors, and the feature type play an important role on feature error minimization and on feature identification. Some techniques used in radar systems exploit the configuration of the antennas to improve measurement quality, and can also be applied here [19].

Figures 4, 5, and 6 show a reduction in feature error caused by employing an active sonar procedure. Figure 4 depicts how changing the vergence angle of the sonar transducers can produce a smaller overlap area of the sonar cones and thus improve the localization of an edge feature. Moreover, since the signal coming from an edge is weaker, it should be observed only in a small vergence region.

In Figure 5, the same strategy employed in the edge case affords the precise localization of the line feature. The error is reduced with the decrease of the overlapping area of the sonar cones from the transducers. In addition, the line feature should be detected over a larger vergence region than for the edge feature. As shown, a more precise measurement is obtained when the overlap between the receiver and transmitter cones is minimized by rotating the transducers, or by increasing their distance ($d$). This is also true for the corner feature (Figure 6), with the exception that the receiver and transmitter cones do not necessarily need to overlap, because the error region in the corner case is produced by the reflection boundary, and not by the receiver cone boundary. This fact also contributes to the fast identification of features, since it is a way of differentiating them. All these facts can be used on the design of active sonar sensor controllers.

## 6 Experiments

The experiments were designed with two objectives. The first was to test the new active sonar hardware and validate the feature extraction method, previously tested in simulation [2]. The second was to analyze the performance over different sonar configurations, specifically, over different sonar vergence angles.

In the first experiment, different configurations were tested for all the 3 features. The configuration is defined as the two sonars vergence angles, $(\gamma_0, \gamma_1)$ in degrees, as described in Figure 7. The features were constructed using long sheets of foam cardboard positioned at approximately the same distance to the sonar head, and centered.

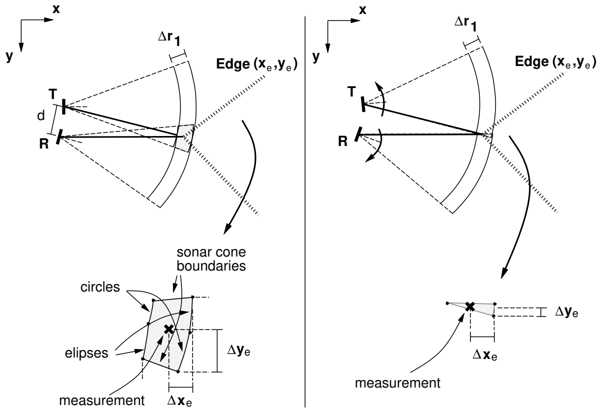


Figure 4. Edge error after minimization procedure

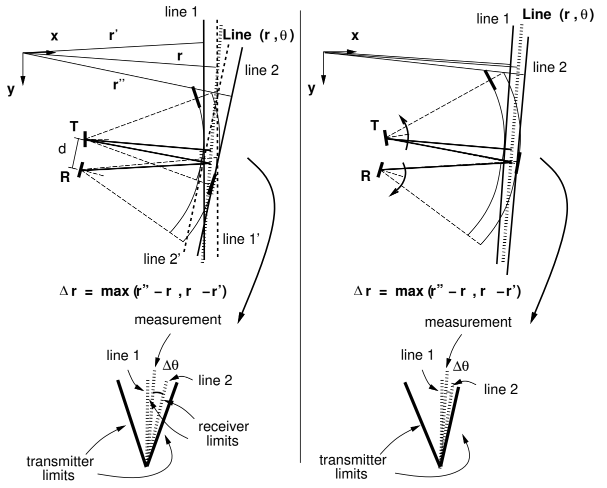


Figure 5. Line error after minimization procedure

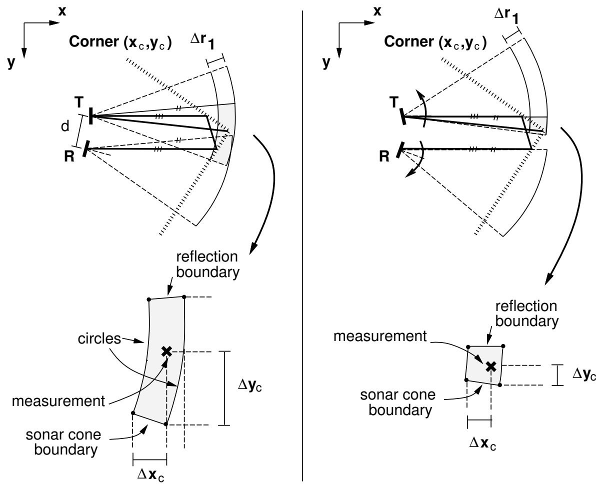


Figure 6. Corner error after minimization procedure

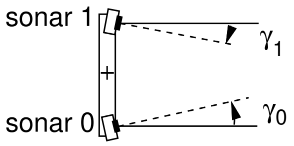


Figure 7. Description of the sonar head verge angles.

The line feature was approximately positioned at $(r = 0.98, \theta = 0)$, the edge feature at $(x = 0.98, y = 1.5)$, and the corner at $(x = 0.98, y = 1.5)$. After 30 sonar firings interleaving (T, R) and (R, T) firing modes, the location of the most probable feature type was reported, together with information regarding whether this feature was only localized (L) or localized and identified (I). The results of this experiment are presented in Table 1, where the dash symbol represents no feature detected, and the cross symbol denotes configurations not tested.

| Feature Extraction | | | |
|---|---|---|---|
| Config. | Actual Feature Type - $r, x, y$ in $m$, $\theta$ in $deg$ | | |
| $(\gamma_0, \gamma_1)$ in $deg$ | Line $(r, \theta)$ at $(0.98, 0)$ | Edge $(x, y)$ at $(0.98, 1.5)$ | Corner $(x, y)$ at $(0.98, 1.5)$ |
| $(0, 0)$ | $(0.980, 0.0)$ | $(0.954, 1.559)$ | $(0.979, 1.502)$ |
| L/I | L (line) | I (edge) | I (corner) |
| $(-2.5, -2.5)$ | $(0.987, 0.3)$ | – | $(0.978, 1.495)$ |
| L/I | L (line) | – | I (corner) |
| $(-5, -5)$ | $(0.988, 0.3)$ | – | $(0.979, 1.513)$ |
| L/I | L (line) | – | I (corner) |
| $(-7.5, -7.5)$ | – | – | $(0.979, 1.504)$ |
| L/I | – | – | I (corner) |
| $(2.5, 2.5)$ | xx | $(0.959, 1.541)$ | $(0.979, 1.507)$ |
| L/I | xx | I (edge) | I (corner) |
| $(5, 5)$ | xx | $(0.963, 1.542)$ | $(0.978, 1.500)$ |
| L/I | xx | L (edge) | L (corner) |
| $(6.7, 6.7)$ | $(0.967, -0.3)$ | $(0.962, 1.534)$ | $(0.980, 1.517)$ |
| L/I | L (line) | L (edge) | L (corner) |
| $(0, -5)$ | $(1.000, 0.9)$ | – | $(0.978, 1.501)$ |
| L/I | L (line) | – | I (corner) |
| $(-5, 0)$ | $(0.991, 0.5)$ | – | $(0.978, 1.489)$ |
| L/I | L (line) | – | I (corner) |

Table 1. Experiment 1: Feature Extraction after 30 sonar firings at different configurations $(\gamma_0, \gamma_1)$.

As shown in Table 1, the system is able to identify the corner feature in multiple configurations. The edge feature is identified also in some configurations, but 30 firings seem not to be sufficient for the system to identify the line feature. Also, the edge feature can only be localized in few configurations, always with positive vergence angles. Notice that errors in feature localization when the feature was identified were in the order of millimeters for the corner and line, with angular errors smaller than 1 degree. The edge feature presented errors on the order of centimeters, suggesting a possible error in the positioning of the feature; more tests are needed to clarify this problem.

The second experiment was designed to verify if the feature identification could be accelerated by employing an active sensing strategy manipulating the sonar configurations of the first experiment. In this example, the same strategy was used for all the features. At most 6 firings were executed in each configuration, and the system stopped when a feature was identified; the firing scheme was the same used in the first experiment. The sequence of configurations are described in Table 2, being the top one the first configuration.

| Active Sensing Strategy | | | |
|---|---|---|---|
| Config. | Actual Feature Type - $r, x, y$ in $m$, $\theta$ in $deg$ | | |
| $(\gamma_0, \gamma_1)$ in $deg$ | Line $(r, \theta)$ at $(0.98, 0)$ | Edge $(x, y)$ at $(0.98, 1.5)$ | Corner $(x, y)$ at $(0.98, 1.5)$ |
| $(-5, -5)$ | $(0.996, 0.8)$ | – | $(0.978, 1.487)$ |
| L/I | L (line) | – | L (corner) |
| # firings | 6 | 6 | 6 |
| $(0, 0)$ | $(0.973, -0.3)$ | $(0.952, 1.566)$ | $(0.978, 1.491)$ |
| L/I | L (line) | L (edge) | I (corner) |
| # firings | 6 | 6 | 4 |
| $(-5, -5)$ | $(0.974, 0.2)$ | xx | |
| L/I | I (line) | xx | |
| # firings | 2 | xx | |
| $(0, 0)$ | | $(0.953, 1.566)$ | |
| L/I | | L (edge) | |
| # firings | | 6 | |
| $(0, 0)$ | | $(0.953, 1.564)$ | |
| L/I | | I (edge) | |
| # firings | | 2 | |

Table 2. Experiment 2: Active sensing strategy using a sequence of 5 sonar vergence configurations.

Notice that all features were identified with at most 20 firings, and that the line feature was identified after 14 firings. The policy for identifying the edge had a small modification, since nothing is detected in configurations with negative vergence angles; the second $(-5, -5)$ configuration was skipped. The small modification does not affect our active sensing policy because the absence of evidence at the configuration $(-5, -5)$ already indicates the possibility of an edge feature. In comparison with the first experiment (Table 1), the results presented in Table 2 shows the potential of an active sensing strategy in the feature identification process, specially in the case of line feature.

More experiments are necessary to fully validate our new sonar system; better feature identification strategies could be obtained by employing sonar head pan rotations and displacing the robot. Nevertheless, the results from the above experiments indicates that this system has the potential for environmental feature extraction, and that active sensing strategies can accelerate the identification process.

## 7 Conclusions and Future Work

This paper presents a new active sonar system, implemented using a 3-DOF binaural sonar head developed at our lab. The sensing procedure is based on multiple hypothesis testing for localizing and identifying indoor features using sonar data. It demonstrates that accurate feature information can be acquired with the use of an adequate sonar model and configurations. Experiments presented here show that the system is able to correctly localize and identify lines, edges, and corners extracted from common indoor room features. Moreover, it shows the potential of active sensing in this paradigm.

The next step in our research is to development robust active sonar strategies for environmental feature extraction, using optimization methods. Our final goal is to use our system to facilitate autonomous navigation, by providing a reliable way for a robot to acquire spatial information, and to use this information to keep/recover its pose.

## References


[1] E. G. Araujo and R. A. Grupen. Feature extraction for autonomous navigation. Technical Report 97-55, Department of Computer Science, University of Massachusetts, Amherst, October 1997.

[2] E. G. Araujo and R. A. Grupen. Feature detection and identification using a sonar-array. In *Proceedings of the IEEE International Conference on Robotics and Automation*, volume 2, pages 1584–1589, Leuven, Belgium, May 1998. IEEE Computer Society Press.

[3] B. Barshan and R. Kuc. Differentiating sonar reflections from corners and planes by employing an intelligent sensor. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(6):560–569, June 1990.

[4] K. S. Chong and L. Kleeman. Indoor exploration using a sonar sensor array: A dual representation strategy. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 2, pages 676–682, Grenoble, France, September 1997. IEEE.

[5] I. J. Cox and G. T. Wilfong, editors. *Autonomous Robot Vehicles*. Springer-Verlag, New York, 1990.

[6] L. Dorst, M. van Lambalgen, and F. Voorbraak, editors. *Reasoning with Uncertainty in Robotics: International Workshop; Proceedings / RUR'95*. Springer, Amsterdam, The Netherlands, December 1996. (Lecture notes in Computer Science; Vol. 1093).

[7] H. C. Hughes. *Sensory Exotica: a world beyond human experience*. MIT Press, Cambridge, MA, 1999.

[8] L. Kleeman and R. Kuc. Mobile robot sonar for target localization and classification. *International Journal of Robotics Research*, 14(4):295–318, August 1995.

[9] R. Kuc. Biologically motivated adaptive sonar system. *Journal of the Acoustical Society of America*, 100(3):1849–1854, September 1996.

[10] R. Kuc. Biomimetic sonar recognizes objects using binaural information. *Journal of the Acoustical Society of America*, 102(2):689–696, August 1997.

[11] R. Kuc and M. W. Siegel. Physically based simulation model for acoustic sensor robot navigation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-9(6):766–778, November 1987.

[12] T. Lozano-Pérez. Book's foreword. In I. J. Cox and G. T. Wilfong, editors, *Autonomous Robot Vehicles*. Springer-Verlag, New York, 1990.

[13] J. Manyika and H. F. Durrant-Whyte. *Data Fusion and Sensor Management: A Decentralized Information-Theoretic Approach*. Ellis Horwood Series in Electrical and Electronic Engineering. Ellis Horwood Limited, West Sussex, U.K., 1994.

[14] H. Peremans and J. Van Campenhout. Tri-aural perception on a mobile robot. In *Proceedings of the IEEE International Conference on Robotics and Automation*, volume 1, pages 265–270, Atlanta, GA, May 1993. IEEE Computer Society Press.

[15] Polaroid Corporation, OEM Components Group, Cambridge, MA. *Ultrasonic Components*, October 1994.

[16] N. Roy, W. Burgard, D. Fox, and S. Thrun. Coastal navigation - mobile robot navigation with uncertainty in dynamic environments. In *Proceedings of the IEEE International Conference on Robotics and Automation*, volume 1, pages 35–40, Detroit, MI, May 1999. IEEE Computer Society Press.

[17] N. Roy and S. Thrun. Online self-calibration for mobile robots. In *Proceedings of the IEEE International Conference on Robotics and Automation*, volume 3, pages 2292–2297, Detroit, MI, May 1999. IEEE Computer Society Press.

[18] J. A. Simmons and A. D. Grinnell. The performance of echolocation: Acoustic images perceived by echolocating bats. In P. E. Nachtigall and P. W. B. Moore, editors, *Animal Sonar: processes and Performance*, volume 156 of *NATO ASI Series. Series A. Life Sciences*, pages 353–385. Plenum Press, 1988. Proceedings of a NATO ASI on Animal Sonar Systems, held September 10-19, 1986, in Helsingor, Denmark.

[19] M. I. Skolnik. *Introduction to radar systems*. McGraw-Hill, New York, 1962.

[20] V. A. Walker. *One Tone, Two Ears, Three Dimensions: An investigation of qualitative echolocation strategies in synthetic bats and real robots*. PhD thesis, University of Edinburgh, Edinburgh, UK, 1997.