A Probabilistic Model for AGV Mobile Robot Ultrasonic Sensor

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ABSTRACT

An autonomous guided vehicle (AGV) is a multi-sensor mobile robot. The sensors of a multi-sensor robot system are characteristically complex and diverse. They supply observations, which are often difficult to compare or aggregate directly. To make efficient use of the sensory information, the capabilities of each sensor must be modeled to extract information from the environment. For this goal, a probability model of ultrasonic sensor (PMUS) is presented in this paper. The model provides a means of distributing decision making and integrating diverse opinions. Also, the paper illustrates that a series of performance factors affect the probability model as parameters. PMUS could be extended to other sensors as members of the multi-sensor team. Moreover, the sensor probability model explored is suitable for all multi-sensor mobile robots. It should provide a quantitative ability for analysis of sensor performance, and allow the development of robust decision procedures for integrating sensor information. The theoretical sensor model presented is a first step in understanding and expanding the performance of ultrasound systems. The significance of this paper lies in the theoretic integration of sensory information from the probabilistic point of view.

Keywords: AGV, probability model of ultrasonic sensor (PMUS), decision-making, obstacle avoidance, mobile robots.

1. INTRODUCTION

Automated Guided Vehicle (AGV) is an intelligent machine that has ‘intelligence’ to determine its motion status according to the environmental conditions. For an AGV to operate it must sense its environment, be able to plan its operations and then act based on this plan. This type of system must be placed in a known space from which it can determine its orientation via the use of markers (e.g. white lines, walls, obstacles, global positioning systems, etc.). The model of the AGV itself may be easy to establish, however, the environmental model is difficult to obtain. The running environment could be varied, such as the path orientation, road flatness, obstacle position, road surface friction, etc. There are many uncertainties of what conditions will emerge during its operation.

The purpose of this research is to apply a rotating sonar as an effective sensor into a mobile robot design, which is going on in the University of Cincinnati Robotics Center. The mobile robot was constructed during the 1998-1999 academic year, called BEARCAT II. Its design has inherited many features of its predecessor, BEARCAT I, such as vision guidance, sonar detection and digital control. In addition, BEARCAT II achieved many innovative motion activities, such as a rotating sonar, ZTR (Zero Turning Radius), current control loop, multi-level controller design (conventional control and fuzzy logic control). The purpose of this design is to offer a design experience that is at the very cutting edge of engineering education. It is multidisciplinary, team implemented, theory-based, hands-on, outcome assessed, and based on product realization. It encompasses the very latest technologies impacting industrial development and taps subjects of high interest to students.

The sonar system may also be considered as an important element in the intelligent controller, which gets data from the sonar system to make decisions. Thus, a high reliability of sonar readings is a critical factor for the success of the whole system. The challenge of constructing an intelligent controller is to determine its requirements, what information is needed to be satisfied, how to measure it, and how to use the acquired information in a manner that will achieve the desired performance of the machine. The overall objective is to build a robot, which follows a course marked by solid or dashed lines of various colors, avoids obstacles, and adapts variations in terrain and weather. This implied the design of separate subsystems with discrete design objectives integrated in an upper level control logic that enables the robot to function as an integral system meeting all the performance requirements.

Benefits of sonar systems include low cost, ease of implementation, easy maintain, etc. The disadvantages are reflection, slow processing speeds, and wide beam pattern, all of which contribute to potentially large errors [4-5]. Sonar ranging is based upon measuring the time it takes for a burst of continuous wave ultrasound to be returned to the sensor detectors. The reflection strength depends on the size, shape, texture, and orientation of the reflecting surface. Large surfaces reflect more and increase the chance of being detected. Depending on its shape, a reflecting surface may cause dispersion or a focusing of the reflected beam.

In the BEARCAT I design, we have used four static sonar transducers to detect obstacles in four directions, which worked well in the outdoor environment. However, the static sonar system usually can detect obstacles only in fixed directions and will also cost more than a single sonar control unit. On the other hand, the rotating sonar is inexpensive and has the ability of detecting obstacles in any direction. If we define a smaller angle of sweep to obtain readings, we can have more detailed information for the decision of obstacle avoidance.

In this paper a probabilistic model of the ultrasonic sensor (PMUS) is discussed. PMUS provides a quantitative ability to analyze ultrasonic sensor performance, and allow the development of the robust decision procedures for integrating ultrasonic sensor information. Through building PMUS, an integrated multi-sensor model can be logically extended. An overall system design and development is presented in the next section. The hardware for the rotating sonar is discussed in Section 3. In Section 4 the most important probabilistic model and the performance factors for the model are presented. Conclusions and recommendations for further research are presented in Section 5.

2. SYSTEM DESIGN AND DEVELOPMENT

An autonomous mobile robot is a sophisticated, computer controlled, intelligent system. The adaptive capabilities of a mobile robot depend on the fundamental analytical and architectural designs of the sensor systems used. The mobile robot provides an excellent test bed for investigations into generic vision guided robot control since it is similar to an automobile and is a multi-input, multi-output system [6-9]. The major components of the robot are: vision guidance system, steering control system, obstacle avoidance system, speed control, safety and braking system, power unit and the supervisor control PC. In the next Section, an overview is given of the specific information on the obstacle avoidance system.

3. OBSTACLE AVOIDANCE SYSTEM

3.1 The Polaroid Ultrasonic Ranging System

The obstacle avoidance system consists of single or multiple ultrasonic transducers. A Polaroid ultrasonic ranging system is used for the purpose of calibrating the ultrasonic transducers. An Intel 80C196 microprocessor and a circuit board with a liquid crystal display are used for processing the distance calculations. The distance value is returned through a RS232 port to the control computer. The system requires an isolated power supply: 10-30 VDC, 0.5 amps. The two major components of an ultrasonic ranging system are the transducer and the drive electronics. In the operation of the system, a pulse of electronically generated sound is transmitted toward the target and the resulting echo is detected. The elapsed time between the start of the transit pulse and the reception of the echo pulse is measured. Knowing the speed of sound in air, the system can convert the elapsed time into a distance measurement [10].

The drive electronics has two major categories - digital and analog. The digital electronics generate the ultrasonic frequency. A drive frequency of 16 pluses at 52 kHz is used in this application. All the digital functions are generated by the Intel microprocessor. The analog functionality is provided by the Polaroid integrated circuit. The operating parameters such as the transmit frequency, pulse width, blanking time and the amplifier gain are controlled by the developers software provided by Polaroid.

3.2 Motor Control

Using a closed loop DC motor arrangement, the transducer is made to sweep an angle depending on the horizon (this is about 64 degrees for a range of 8’ and about 53.13 degrees for a range of 10’ 10” horizon). The loop is closed by an encoder feedback from an Reliance Electric motor with encoder, as illustrated in Figure 2.

The drive hardware comprises two interconnect modules, the Galil ICB930 and the 4-axis ICM1100. The ICM 1100 communicates with the main motion control board, the DMC 1030 through an RS232 interface. The transducer sweep is achieved by programming the Galil [11]. By adjusting the Polaroid system parameters and synchronizing them with the motion of the motor, distance values at known angles with respect to the centroid of the robot are maintained.

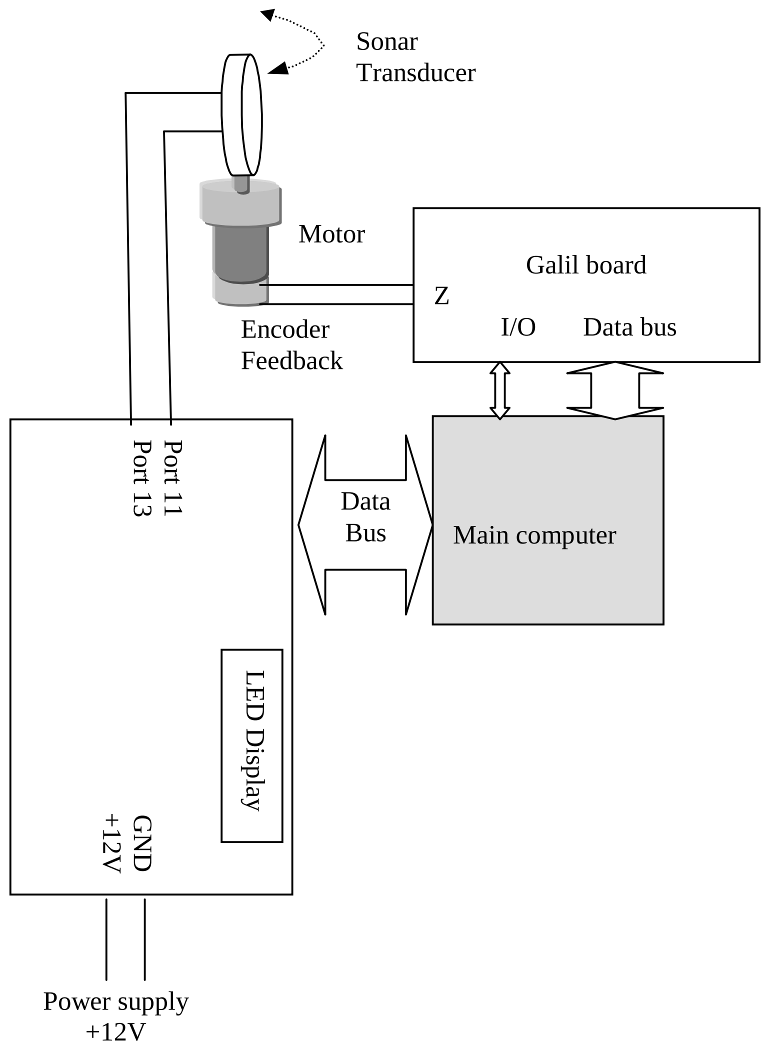

Figure 1 the functional diagram of the rotating sonar system

4. THE PROBABILISTIC MODEL OF ULTRASONIC SENSOR (PMUS)

4.1 Multi-Sensor Integration System

According to the previous work [15], a lot of research on the basic mathematical and geometrical relationships between the robot and obstacles has been done. Before the robot system makes any decision, we would like to know the distance, width, and the shape of the obstacle. Then, the robot will make a decision to turn left, or right, or go straight. We call this range detection. However, we still have no idea on the performance accuracy of the robot motion because of the environmental factors. Now a robot state model will be built to confirm the system decision, which was made by the geometrical model. By combining information from many different sources, it should be possible to reduce the uncertainty and ambiguity inherent in making decisions based on only a single information source.

We maintain that the key to efficient integration of sensory information is to provide a purposeful description of the environment and to develop effective models of sensor's ability to extract this information. This model can provide a quantitative ability to analyze sensor performance, and allow the development of robust decision procedures for integrating sensor information. We can divide a sensor model into three parts: an observation model, a dependency model, and a state model. An observation model is essentially a static description of sensor performance, it describes the dependence of observations on the environment. A dependency model presents the relation between the observations or actions of different sensors. A state model describes the dependence of sensor observations on the location or the physical state of a sensing device [17]. In this paper, we focus on building a model for the ultrasonic sensor as well as a probabilistic model of sensor capability built in terms of an information structure. According to the information from the model, the robot system will reconsider its decision-making process.

4.2 Building PMUS

The feature observations derived from a sensor are in general some complex function of the actual physically measured variables. In the case of an ultrasonic sensor, it must be recognized that the performance of the ultrasonic ranging systems is significantly affected by target characteristics (i.e., absorption, reflectivity, directivity) and environmental phenomena, as will be discussed below. According to Durrant-whyte [16], we will consider a mobile robot multi-sensor system as a team of decision-makers. The sensors are members of the team. Each individual sensor can make local decisions based on its own observations, but must cooperate with the other team members to achieve a common objective. The observations $\boldsymbol{z}$ made by a sensor are described by an information structure η. Each sensor can make a decision δ, based on these observations, resulting in an action $\boldsymbol{a}$, usually an estimate of a feature description, describing the opinion of the sensor. According to the relationship of all these variables, a general decision tree could be achieved, illustrated as figure 2. All geometric features in the environment are modeled by the functions $\boldsymbol{g(x, p)=0}$, $\boldsymbol{x}$: Each function defines a family of features, parameterized by the vector $\boldsymbol{P}$. Our world model characterizes each feature by a probability density function $\mathbf{f_g (P)}$ on this parameter vector. Consider a sensor taking observations of a geometric feature, we can model this observation as a conditional probability distribution $\mathbf{f_g (z \mid P)}$ that describes the likelihood of feature observation given all prior information about $\boldsymbol{P}$. This distribution is our observation model: $\mathbf{f_g (z \mid P)= f_p (\eta^P)}$.

The exact form $\mathbf{f(\,.\mid P)}$ will depend on many physical factors. It is unlikely that we can obtain an exact description of the probabilistic character of observations in all but the simplest of cases. In the absence of an exact observation description, we propose to use an approximate model, coupled with a decision procedure robust to model inaccuracies. There are two different ways to approach this approximation problem; we can model the observation noise as a class of possible distributions, or as some nominal distribution together with an additional unknown likelihood of errors and mistakes.

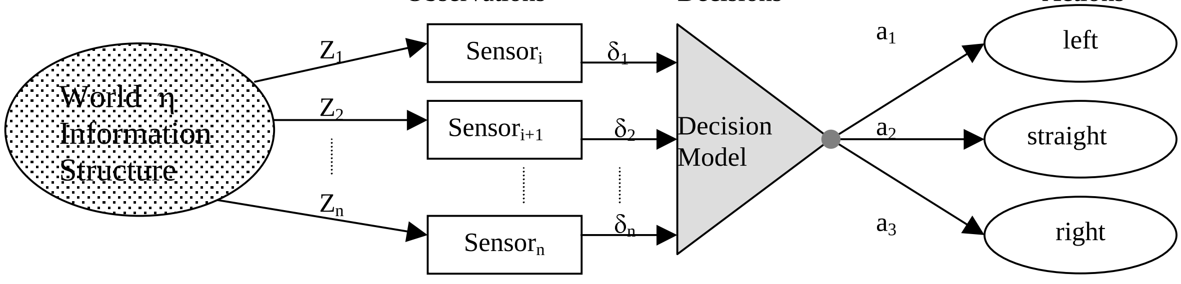

Figure 2. Robot actions decision model

4.3 Performance Factors To Affect Ultrasonic Sensor Model

Information supplied by an ultrasonic sensor is noisy, partial and often spurious. We have previously described a model of the environment, which represents uncertain locations and features as probability density functions on their associated parameter vectors. To develop decision procedures, which are sympathetic to satisfy the actual state of affairs encountered in the operation of the robot sensor system, it is important to analyze the effects of the observation model and prior information on the resulting estimate of the state of nature. During the study of Bearcat II mobile robot, we integrated the performance factors such as target characteristics and environmental phenomena [17 as will be discussed in the ensuing discussion.

1. Atmospheric Attenuation

As an acoustical wave travels away from its source, the signal power decreases according to the inverse square law:
I = intensity (power per unit area) at distance R
I_o = maximum (initial) intensity

$$I = \frac{I_o}{4\pi R^2} \qquad (1)$$

R = range.

There is also an exponential loss associated with molecular absorption of sound energy by the medium itself:
α = attenuation coefficient for medium

$$I = I_o e^{-2\alpha R} \qquad (2)$$

The maximum detection range for an ultrasonic sensor is dependent on both the emitted power and frequency of operation: the lower the frequency, the longer the range. The maximum theoretical attenuation for ultrasonic energy can be approximated by:

$$a_{\max} = \frac{f}{100} \qquad (3)$$

Where:
a_{max} = maximum attenuation in dB/foot
f= operating frequency in KHz.

For a 20-KHz transmission, a typical absorption factor in air is approximately 0.02dB/foot, while at 40-KHz losses run between 0.06 and 0.09dB/foot.

Combining the above spherical-divergence and molecular-absorption attenuation factors results in the following governing equation for intensity as a function of distance R from the source:

$$I = \frac{I_0 e^{-2\alpha R}}{4\pi R^2} \qquad (4)$$

Note that in this expression, which does not yet take into consideration any interaction with the target surface, intensity falls off with the square of the distance.

2. Target Reflectivity

The totality of all energy incident upon a target object is either reflected or absorbed. The directivity of the target surface determines how much of the reflected energy id directed back towards the transducer. Since most objects scatter the signal in an isotropic fashion, the returning echo again dissipates in accordance with the inverse square law, introducing an additional $4\pi R^2$ term in the denominator of the previous equation for intensity. In addition, a new factor *Kr* must be introduced in the numerator to account for the *reflectivity* of the target:

$$I = \frac{K_r I_0 e^{-2\alpha R}}{16\pi^2 R^4} \qquad (5)$$

Where:
K_r = coefficient of reflection.
This coefficient for a planar wave arriving normal to a planar object surface is given by:

$$K_r = \frac{I_r}{I_i} = \left[\frac{Z_a - Z_0}{Z_a + Z_0}\right]^2 \qquad (6)$$

Where:
I_r = reflected intensity
I_i = incident intensity
Z_a = acoustic impedance for air
Z_0 = acoustic impedance for the target object.

The bigger the impedance mismatch between the two media, the more energy will be reflected back to the source. In industrial phenomenon, one allows tank level measurement to be accomplished using an ultrasonic transducer in air looking down on the liquid surface, or alternatively an immersed transducer looking upward at the fluid/air interface.

The original Polaroid ranging module transmitted a 1-millisecond chirp consisting of four discrete frequencies: 8 cycles at 60 KHz, 8 cycles at 56 KHz, 16 cycles at 52.5 KHz, and 24 cycles at 49.41 KHz. This technique was employed to increase the probability of signal reflection from the target, since certain surface characteristics could theoretically absorb a single-frequency waveform, preventing detection.

3. Temperature

Consider the expression for wave propagation speed(s) in a gas, as a function of density, ρ , and bulk modulus of elasticity, Km:

$$s = \sqrt{\frac{K_m}{\rho}} \qquad (7)$$

Since both these parameters change with temperature, the speed of sound in air is also temperature dependent, and in fact directly proportional to the square root of temperature in degrees Rankine:

$$s = \sqrt{gkRT} \qquad (8)$$

Where:
s= speed of sound
g= gravitational constant

k= ratio of specific heats
R= gas constant
T= temperature in degrees Rankine (F+460).

For temperature variations typically encountered in indoor robotic ranging applications, this dependence results in a significant effect even considering the short distances involved. A temperature change over the not unrealistic span of 60^o to 90^o F can produce a range error as large as 12 inches at a distance of 35 feet. Fortunately, this situation can be remedied through the use of a correction factor based upon the actual ambient temperature, available from an external sensor mounted on the robot. The formula is simply:

$$R_a = R_m \sqrt{\frac{T_a}{T_c}} \quad (9)$$

Where:

R_a = actual range
R_m = measured range
T_a = actual temperature in degrees Rankine (F+460)
T_c = calibration temperature in degrees Rankine.

For example, known calibration temperature $T_c = 70^o$ F, but actual temperature $T_a = 90^o$ F, if the measured range R_m is 10feet, then we can calculate the actual range R_a is 10.187 feet.

The possibility does still exist, however, for temperature gradients between the sensor and the target to introduce range errors, since the correction factor is based on the actual temperature in the immediate vicinity of the sensor only.

4. Noise

Generally speaking, three kinds of noise will affect the ultrasonic sensor performance: environmental noise, crosswalk noise, and self-generated noise.

5. Other Factors

Still another factor to consider is the beam width of the selected transducer. A number of factors must be considered when choosing the optimal beamwidth for a particular application. Additionally, a final source of error to be considered stems from case-specific peculiarities associated with the actual hardware employed.

As presented above, the decision-making accuracy of the rotating sonar system is effected by the environmental performance factors. According to the related parameters, a series of trial-and-error methods can be utilized to build probability density functions $\mathbf{f_g(z|P)}$----the probabilistic model of ultrasonic sensor ***(PMUS)***.

4.4 Advantages of The Probabilistic Model

Probabilistic models of sensor capabilities have a number of advantages:

(1) Probabilistic models are well suited to describing the inherent uncertainty characteristic of making observations in the real world.
(2) Well-tested methodologies exist for analyzing observations described as probability distributions.
(3) The description of different cues in a common probabilistic framework allows diverse observations to be compared and integrated in a consistent manner.
(4) If a common modeling policy is used, it becomes very easy to extend the system by adding other new sensors.

5. CONCLUSIONS AND RECOMMENDATIONS

To make efficient use of the sensory information in multi-sensor auto-navigated mobile robot, the capabilities of each sensor must be modeled to extract information from the environment. For this purpose, a probabilistic model of ultrasonic sensor (PMUS) is presented in this paper. The model provides a means of distributing decision making and integrating diverse opinions. PMUS could be extended to other sensors as members of the multi-sensor team. However, a stable test platform should be designed, constructed and tested to build a practical model. Also, more sophisticated algorithms for the multi-sensor integration need to be developed.

ACKNOWLEDGEMENTS

This work has been a continual learning experience and could not have been completed without the devoted work and contributions of the previous team members especially: Tayib Samu, KalyanChakravarthi Kolli, Krishnamohan Kola and Wen-chuan Chiang. The authors would like to thank the following staff personnel for their technical assistance: Karthikeyan Kumaraguru, Sameer Parasnis, Nathan Mundhenk, Sampath Kanakaraju, Satish Shanmugasundaram, Thyagarajan Ramesh and Yan Mu. The authors would like to thank the following staff personnel for their technical assistance; Bo Westheider (electronics), Dave Breheim (machinist), Perry Morgan (computer) and Larry Schartman (computer) The vehicle has been sponsored in part by several generous contributions and we thank our current and past sponsors: GE, Futaba, SME Chapter 21, American Showa, Planet Products Corp., SO&A of UC, R.O.V. Technologies, and others.

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