초음파의 반사 신호를 이용한 실내환경의 재질 인식

Material Classification Using Reflected Signal of Ultrasonic Sensor

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Abstract : Material information for environment may be useful to accomplish mobile robot localization. A procedure to classify a set of indoor materials (glass, steel, wood, aluminum and concrete) with the reflected signal of ultrasonic sensor is proposed in this paper. The main idea is to use material-specific reflection characteristics for the recognition of material type. To achieve the classification task, we modeled reflected signal as a maximum amplitude with respect to distance. In this way, we can generate echo signal models for the given materials and these models are used to compare with the current sensor reading. The experimental results show that the proposed method may give material information during map building task of mobile robot.

Keywords : ultrasonic sensor, echo signal model, curve fitting, localization, classification

I. Introduction

Ultrasonic sensors are widely used in material sciences to develop a new material [1] and in robotics to avoid collisions and to build map of environment. Ultrasonic sensors are widely used in robot systems to avoid collisions with obstacles and for map building because they are simple and give distance information directly. They are low-cost, easy to implement, low bandwidth for data processing, and light independent characteristics. However, there are disadvantages for ultrasonic sensors. Environmental ambient temperature affects sensor characteristics. Wide beam bearing gives uncertain angular measurement for object position[2].

The most common usage of ultrasonic sensor is to measure the time of flight which is the elapsed time between transmission and reception of a sonic pulse [4]. Environmental features have been obtained from the received ultrasonic echoes. The duration of the echo signal and the energy are analyzed for heterogeneous environment [5]. A combination of echo amplitude and time of flight has been used to recognize the detected surface such as distinguishing between walls and corners [3,9]. If time of flight is only measured, two transmitters and two receivers are necessary and sufficient for discriminating planes, corners, and edges in two dimensional space [6]. A method to extract multiple acoustic landmark for the indoor navigation of a mobile robot using specular effect was proposed [7]. Classification of targets such as a plane, corner, edge, and cylinder in indoor environment was studied by the multiple reflection patterns obtained with polygonal reflector [8]. Many other publications referred in the above focused on the recognition of object shape using ultrasonic sensors. A technique for computing the distance to an unknown planar surface and, at the same time, estimating the material of the surface using infrared sensor was proposed [10].

This paper applied the method of echo signal amplitude and time of flight measurement to distinguish five types of materials such as wood, steel, concrete, aluminum, and glass for indoor environment[11]. In the next section, we study ultrasonic sensor model to establish echo signal characteristics. and algorithm to differentiate as set of materials will be explained. Experimental results are shown in section III. Conclusion for the proposed method are commented in section IV.

II. Material Classification Algorithm

Ultrasonic wave from transducer propagates through air and reflects from the surface of object. The echo signal amplitude obtained will decrease as the distance increases. This decay in the amplitude of ultrasonic signal has been modeled using different models. Cracknell modeled ultrasonic attenuation in air by two terms: one is exponential decay due to air absorption, and the other is hyperbolic decay due to beam spreading [12]. If considering the object's surface orientation relative to the normal incident angle, the amplitude model can be expressed as

$$y(d,\theta) = A_0 C_r \frac{e^{-2\alpha d}}{2d} e^{-4\theta^2/\theta_0^2} \tag{1}$$

where y is amplitude of echo signal, A_0 is a constant, α the attenuation coefficient of the air, d the distance between transducer and object (Note that $2d$ is the total path length

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traveled by the wave)[12]. A reflection coefficient C_r is to model the total intensity reduction of the ultrasonic beam reflected on a surface. We modeled a constant reflection coefficient value C_r, as expressed

$$C_r = \frac{y_{reflected}}{y_{incident}} \in [0, 1]. \tag{2}$$

θ_0 is the dispersion angle of wave and θ is the beam incident angle at which the object is viewed by the transducer. It is difficult to accurately measure the attenuation coefficient α, since it depends on air density, air temperature, and the square of the signal frequency. By the exhaustive experimental work, we have to approximate α for the given environment. The reflection coefficient C_r is a factor to model the total intensity reduction of the ultrasonic beam reflected on a surface. This value may be used as a key to differentiate the type of material in this work.

The echo signal amplitude shows maximum value when the incident angle is normal to the object's surface. To simplify echo signal model, we assumed that the incident angle is zero ($\theta = 0$). This assumption can be realized in real application by rotating mechanism of sensor module. At a given distance to an object, we receive maximum amplitude of echoes at $\theta = 0$. At some position, a robot is able to know an initial relative angle between the current sensor orientation and the one in which the sensor is perpendicular to the surface and maximum echo amplitude is received, by rotating sensor module. For this assumption, *a priori* map may be used. This fact has been used by some authors for map building and for target localization [7]. The following simplified model can be used as

$$y(d, 0) = B\frac{e^{-2\alpha d}}{d} \tag{3}$$

where $B = \frac{A_0 C_r}{2}$ is a constant for the given object. Equation (3) specifies the characteristics of echo signal reflected from a given material. Since attenuation coefficient α is independent of the type of material, parameter B represents the characteristic feature of material.

Given data of echo signal amplitude for each material, (d_{ij}, y_{ij}), $i = 1, 2, \cdots, 5$, $j = 1, 2, \cdots, N$, where i is the index of material and j is the index of data, we need to determine attenuation coefficient α. We apply data linearization method for exponential curve fitting to fit

$$y = B_i\frac{e^{-2\alpha_i d}}{d} \tag{4}$$

to each set of data points $(d_{i1}, y_{i1}), (d_{i2}, y_{i2}), \cdots (d_{iN}, y_{iN})$ and obtain B_i and α_i. To perform this procedure, we take logarithm of both sides and obtain

$$ln(y \cdot d) = \alpha_i(-2d) + ln(B_i) \tag{5}$$

$$z = m_i x + n_i \tag{6}$$

Use the change of variables $x_{ij} = -2d_{ij}$ and $z_{ij} = ln(y_{ij} \cdot d_{ij})$ on all data points and obtain (x_{ij}, y_{ij}), $i = 1, 2, \cdots, 5$, $j = 1, 2, \cdots, N$. After fitting the new points with a least squares line of (6), we obtain

$$B_i = e^{n_i} \tag{7}$$

and

$$\alpha_i = m_i. \tag{8}$$

Ideally, attenuation coefficient α_i are same, however, the curve fitting results does not give same values due to experimental limitation and noise. To correct this mismatch, we use mean value of $\alpha_i i = 1, 2, \cdots, 5$ for five different surfaces. By using

$$\alpha = \frac{1}{5}\sum_{i=1}^{5}\alpha_i, \tag{9}$$

we apply curve fitting to the data with $z = mx + p_i$ where $m = \alpha$, and obtain $B_i' = e^{p_i}$ as a characteristic feature of material i.

III. Experiments

1. Material Classification

We used Polaroid ultrasonic sensor acting as both a transmitter and a receiver to recognize material of object[13]. The time-variable-gain amplifier of the Polaroid sensor was disabled to obtain attenuated echo signal accurately. The received echo signal was processed through envelope detector and then, peak value was obtained by a peak detector. We used five types of materials such as wood, steel, concrete, aluminum, and glass. Processed data was recorded at six different distances, every 0.05m from 0.65m to 0.9m. At each distance, five experiments were performed for each material. The obtained data was divided into two sets, training data set and test data set: the training data at distances 0.7m, 0.8m and 0.9m was used to generate each signal models and the test data at distances 0.65m, 0.75m, and 0.85m was for testing the obtained models.

Fig. 1 shows the result of generating echo signal model by curve fitting explained in Section II and the models for each material are listed in Table 1. Using the obtained echo signal model, the results are fairly satisfactory in most cases, providing about 94% true recognition as shown in Fig. 2 and in Table 2. In general, the recognition rate of the short distance is greater than or equal to that of the long distance. However, for the material, Glass of Table 2, the recognition rate of the distance 0.85m is greater than that of the distance 0.75. This case appears due to the small

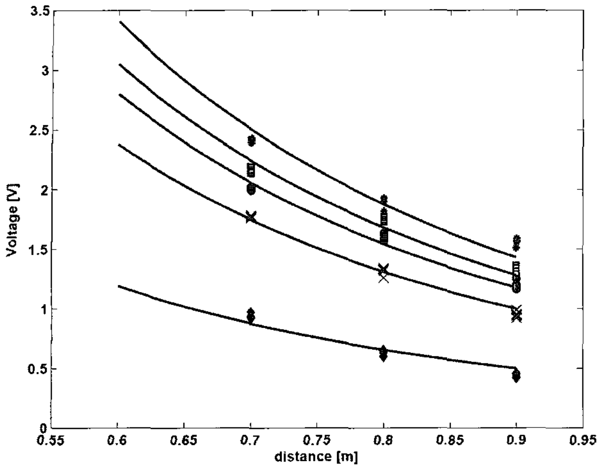

그림 1. 반사 신호 모델 학습을 위한 곡선 맞춤(● 나무, x: 알루미늄, *: 유리, □: 철, ◆: 콘크리트).

Fig. 1. Curve fitting to generate reflected signal models on training data set (● Wood, x: Aluminum, *: Glass, □: Steel, and ◆: Concrete).

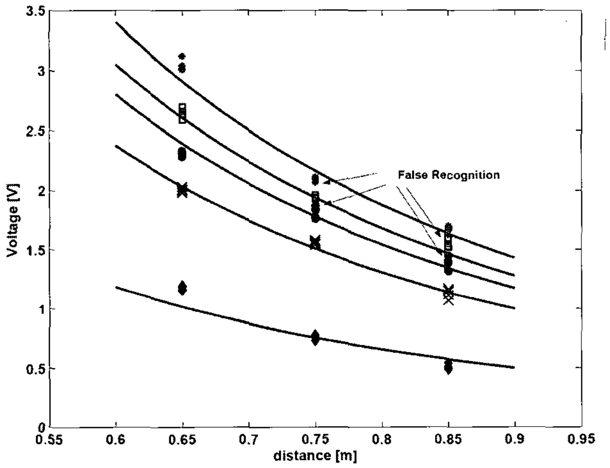

그림 2. 생성된 반사 신호 모델을 사용한 재질 인식 결과(● 나무, x: 알루미늄, *: 유리, □: 철, ◆: 콘크리트).

Fig. 2. Classification results to check the validity of the generated reflected signal models on test data set (● Wood, x: Aluminum, *: Glass, □: Steel, and ◆: Concrete).

set of data for curve fitting. If we use samples of more finely divided distances for curve fitting, general tendency of recognition rate will be common for all materials.

As it can be observed, some of data may be classified as different material. The proposed echo signal model can be used to build a map for mobile robot navigation. The information on material can be used as a landmark for fast localization of a robot. It seems more suitable for autonomy of a mobile robot to utilize the material information which is inherent in the environment.

The application of the proposed echo signal model requires distance between transducer and object. The

표 1. 다섯 개의 재질에 대한 초음파 센서 반사 신호 모델: 감쇠 계수 $\alpha = 0.77$.

Table 1. Ultrasonic sensor reflected signal models for five materials: Attenuation coefficient $\alpha = 0.77$.

Material	Model Parameter(B) $y = B\frac{e^{-2\alpha d}}{d}$	RMS error for curve fitting
Glass	5.1494	0.1148
Steel	4.6131	0.0210
Wood	4.2352	0.0473
Aluminum	3.5948	0.0675
Concrete	1.8004	0.0351

표 2. 재질 인식 결과.

Table 2. The classification results of true recognition for the test data set.

Distance / Material	0.65m	0.75m	0.85m	Average
Glass	100%	80%	100%	93.3%
Steel	100%	100%	80%	93.3%
Wood	100%	80%	80%	86.6%
Aluminum	100%	100%	100%	100.0%
Concrete	100%	100%	100%	100.0%
Average	100%	92%	92%	94.6%

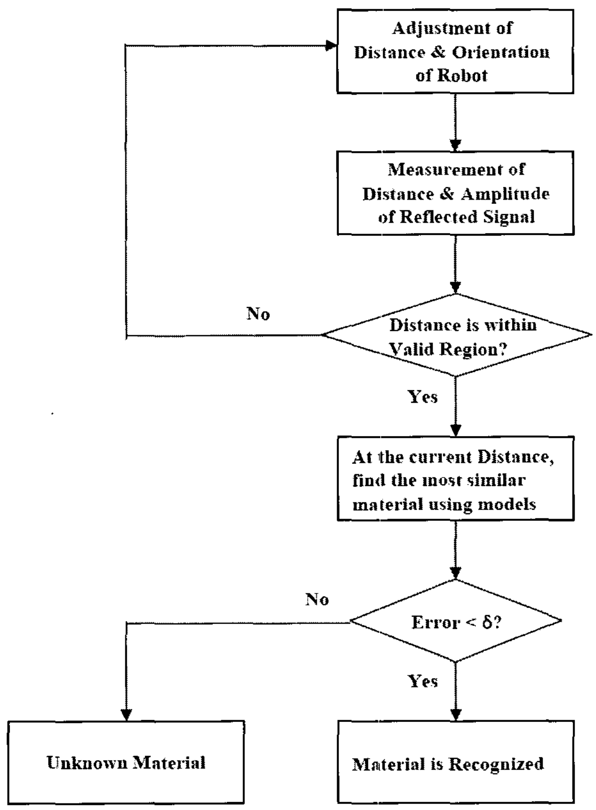

그림 3. 재질 인식 알고리즘의 적용 절차.

Fig. 3. The procedure to apply the material classification algorithm using *a priori* models.

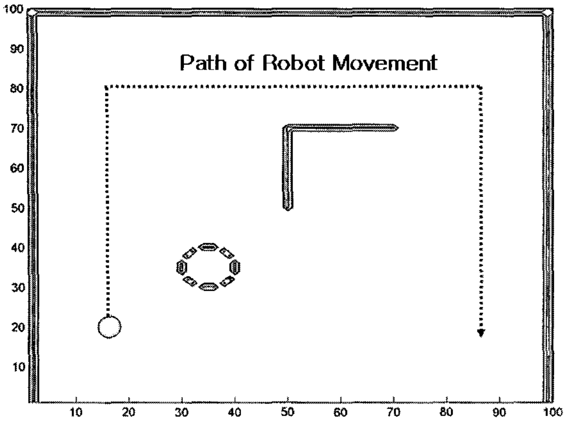

그림 4. 벽, 실리더 형태의 물체, 모서리로 구성된 지도 작성을 위한 가상 환경.

Fig. 4. Artificial environment for map building: flat walls, cylindrical object, and corner-edge object.

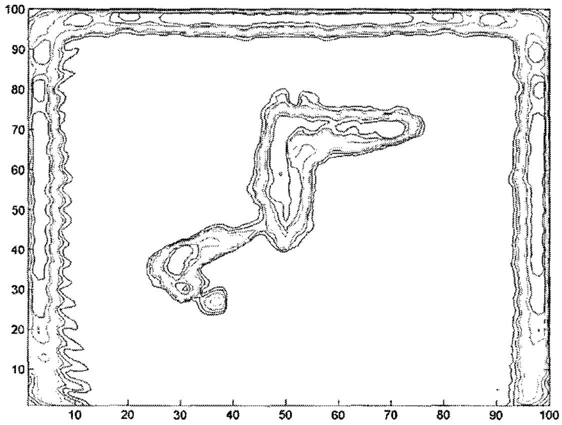

그림 5. 초음파 센서 데이터로부터 추정한 환경에 대한 확률 지도.

Fig. 5. Probabilistic map of occupied region obtained from ultrasonic sensor data.

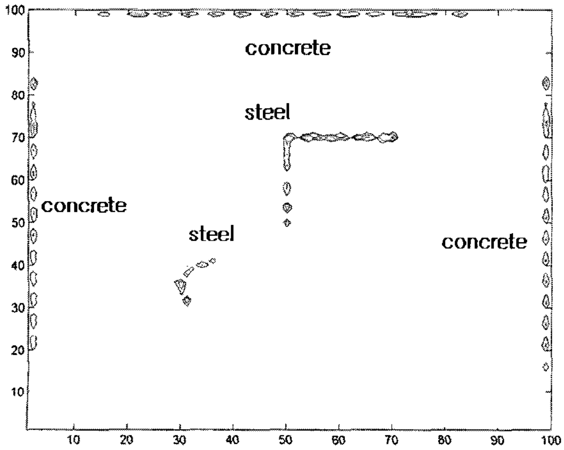

그림 6. 가상 환경에 대해 작성된 최종 지도.

Fig. 6. Final map of the artificial environment.

distance can be obtained easily by the well-known time of flight calculation. The procedure of applying proposed algorithm is shown in Fig. 3. Firstly, robot adjust the orientation of ultrasonic sensor at which maximum amplitude can be received. Processing of distance by time of flight and peak amplitude is done. The obtained data is compared with the echo signal models which are known *a priori* by experiment and we have the most similar material by selecting whose error is minimum. The reliability of recognition result can be adjusted by a design parameter δ. If the difference between current echo amplitude and model amplitude is larger than δ, the result is indefinite. The value of δ may be a function of distance and material type. The smaller is δ, the more cases of indefinite generated. In the experiment, we have used large value (δ =0.5) to check recognition rate with hard discrimination. Typical value of δ for specific material would be $0.3\times d_{min}$ where d_{min} is the minimum difference between adjacent model. These indefinite cases can be compensated by using evidential approach with the Dempster-Shafer inference rule in map building [14].

2. Simulation for Map Building

The proposed material classification algorithm will improve the map information for robot localization. Fig. 4 shows the artificial environment with flat walls(left, right and upper side), cylindrical object, and corner-edge object for simulation. Using Dempster-Shafer inference rule, we get a probabilistic map of occupied region as shown in Fig. 5 [14].

Fig. 5 shows the probability of occupation in the environment. In addition to that, if material information on the environment had been added, the map can be easily used to the localization task. In the simulation, walls are assumed to be made of concrete and other objects are assumed to be made of steel. The environment is assumed to be divided into equal size of grid and each grid has information that if the grid itself is occupied and what the material is for the case of being occupied. Fig. 6 shows the result of map building. This result was obtained by two-stage operation. Firstly, robot moves along the path and we acquire a probabilistic map of occupation like Fig. 5. Secondly, using the obtained map of occupation, robot gathers material information using the proposed algorithm.

IV. Conclusions

We have proposed a method to differentiate a set of materials with ultrasonic sensor measurement for mobile robot navigation. The proposed method is relatively simple and based on the ratio between the magnitude of the reflected signal and the magnitude of the emitted signal.

This ratio depends on the distance to the material, the incident angle of the wave on the planar reflecting surface and the attenuation coefficient of the air. The distance to the obstacle is measured using the time of flight. The incident angle is assumed to be normal to the surface. The attenuation coefficient has been identified, the relation between distance and magnitude of the reflected signal only depends on the material. Experimental results show that different materials have discriminating reflection ratio and therefore can easily be recognized. The further work will be relaxing the hypothesis of the wave being orthogonal to the surface and coupling ultrasonic sensor with a laser scanner.

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