WALL/CORNER CLASSIFICATION. A NEW ULTRASONIC AMPLITUDE-BASED APPROACH

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Abstract: In this work, a simple model of the amplitude response of the ultrasonic echoes is used to assess about the nature of the detected objects, enabling its classification between walls and corners. The ultrasonic signal comes from a unique pair of rotating emitter/receiver transducers. The amplitude of the echoes together with their time of flight are used in a simple data fusion process that exploits the geometric features of the two main types of reflectors -walls and corners- to identify the detected objects in a scene, locating them into the map with reasonably good precision. To apply the amplitude-based model, only one parameter of the environment is needed: the reflection coefficient of each surface. The data fusion process can be carried out using different algorithms. Each of these algorithms has its pros and cons, yielding different success percentages and different computational costs.

In this paper, a comparative study on two classification algorithms is also presented. The first one is based directly on the amplitude model, and the other is based on the k-neighbours algorithm, widely used in pattern recognition. Finally, a comparative table shows the results obtained in the classification of targets with distances from sensor ranging between 0.5 to 4 metres, and with incidence angles ranging between 20° to 70°.

Keywords: Map building, Ultrasonic transducers, Data Fusion, Classification algorithms.

1. INTRODUCTION

Sonar sensing is one of the most useful and cost-effective modes of sensing in autonomous robots. Ultrasonic transducers are light, robust, and inexpensive devices. These characteristics explain their widespread use in applications such as navigation in autonomous robots, map building, or obstacle avoidance. Although these sensors provide accurate distance information on locating targets based only on the time of flight information of the echo, they may not provide directly information about the nature of the detected objects. In this paper, additional characteristics of the received echoes are used to obtain more information on detected targets by means of simple data fusion techniques. The primary aim of data fusion is to combine data from multiple sensors to perform inferences that are not possible using a single sensor. In our case, the different measurements used in the data fusion process are obtained from the same ultrasonic sensor, but they correspond to different points of view of the same received signal.

Since the standard electronics for the widely used Polaroid sensor do not provide the echo amplitude directly, most sonar systems employ time-of-flight (ToF) measurements to extract information in order to classify the targets (Barshan and Ayrulu, 1998). In (Kuc and Bozma, 1991) a single Polaroid sensor is used to differentiate between edges, planes and right corners. Edges are differentiated from planes and corners using only one measurement. The planes are differentiated from corners by taking two measurements from two separate locations. A Triaural sensor arrangement which consists of one transmitter and three receivers is proposed in (Peremans, et al., 1993) to differentiate edges/right corners/planes using ToF. A similar sensing schema is proposed in (Barshan, 1999) to estimate the radius of curvature in cylinders. All these techniques have in common the extreme precision required in ToF estimation. Also, at least two measurements from different locations, or a particular geometric array combination which enable the multiple-firing of the transducers, are indispensable requirements in these approaches to reach satisfactory results in the targets classification.

The need of taking multiple readings from different locations or emitters is mainly due to the poor angular resolution of the ultrasonic transducers (Kuc and Barshan, 1990), which show typically beam angles of ±15 degrees (Polaroid), or ±22 degrees (piezo-ceramic).

Several authors have used the amplitude of the received echoes to enhance their classification results. In (Kuc and Barshan, 1990) and in (Ayrulu and Barshan, 1998) one array of Polaroid
transducers is used, measuring the ToF and the amplitude of received echoes. Also, in (Barat and Oufroukh, 2001), only one Polaroid transducer is used to classify between four types of reflectors using ToF, amplitude and frequency of the received echoes. However, amplitude is a parameter very sensitive to environmental conditions and to the surface characteristics of each reflector, making difficult the management of this information without having a consistent model.

The purpose of this paper is to present a method of classification between walls and right corners using only one rotating ultrasonic sensor, composed of two piezo-ceramic transducers (a transmitter/receiver pair) and the simple amplitude model described in (Martinez et. al., 2003). After an entire circular scan has been performed, the peak amplitude values of echoes are obtained. These peak values together with their corresponding ToF and angular position are used to locate the detected obstacles. After, different classification algorithms can be used to classify these obstacles as planes (walls) or corners, obtaining a high-quality map, which can be subsequently refined in successive ultrasonic scans.

The organization of the paper is as follows: In the next section the ultrasonic amplitude model is described. Also, the main knowledge that can be extracted from a single circular scan is detailed, exploiting the geometric properties of planes and corners in the reflection of ultrasonic waves. In section 3, a classification algorithm directly based on this amplitude model- is described and applied. In section 4 the application of conventional pattern recognition techniques to our classification problem is detailed. K-neighbours algorithm is used in this paper for its simplicity and ease of application. Finally, in section 5 experimental results of the described classification algorithms are discussed using a set of ultrasonic scans performed in numerous office environments in our faculty. These results can serve to evaluate and compare the described algorithms.

2. EXTRACTING THE KNOWLEDGE FROM THE ECHOES. THE ULTRASONIC AMPLITUDE MODEL.

The robot YAIR\(^1\) has a rotating ultrasonic sensor on its top. The sensor has two transducers: one transmitter and one receiver, enabling the two transducers to have the same rotating axis. This two-transducer array rotates driven by a stepper motor with 1.8 degrees per step, giving up to 200 angular samples in each scan. In each angular position, the emitter sends a train of 16 ultrasonic pulses at the resonant frequency of transducers (40 kHz).

The signal obtained in the receiver is amplified with programmable gain, and demodulated using the same frequency of emission. Thus, the base band signal is obtained after removing the frequencies above 4 kHz from this demodulated signal. The resulting signal is then sampled at a rate of 10 ksamples/sec and digitized using a 12 bits A/D converter. Typically, up to 256 samples of this signal are recorded before the stepper motor advances to the next position, repeating the process. Thus, in each angular position a vector of 256 samples is stored and processed, and the complete scan will produce an array of 200 angular echoes.

In a previous paper (Martínez et. al., 2003) a theoretical model for the amplitude of received ultrasonic echoes has been presented. This model can be used to predict the expected amplitude of echoes from simple reflectors, like planes or corners. Also, this model can be used to classify the received echoes between these two types of reflectors depending on the amplitude of their received echoes, following a statistical approach.

Below, the main characteristics of this model are summed up and their use in knowledge extraction for classification purposes is detailed. The main idea of the basic classification algorithm is that the echoes coming from surfaces with a single reflection (walls) are always bigger than the ones received from surfaces with two reflections (corners), assuming the same distance from sensor.

The general equation that models the peak amplitude \(A_m\) of a received echo is:

\[
A_m(x, \theta) = A_0 \cdot Cr^N \cdot e^{-\frac{\mathbb{E}m}{2}} \cdot e^{\left(-\frac{\mathbb{E}m}{2}\sin^2 \theta\right)}
\]

(1)

where:

\(A_0\) is the peak amplitude of the echo obtained in the ultrasonic receiver, measured in Volts.

\(Cr\) is the reflection coefficient of the reflector’s surface. It is a number between 0 and 1, and represents the ratio between the intensity returned back to the transducer and the incident intensity of the acoustic beam. This single parameter includes both the absorption and the additional dispersion effects. This is an evident simplification of the complex phenomena occurred in the reflection of the ultrasonic beam. Nevertheless, this simplification will provide good results and agrees well with the experimental data obtained.

\(N\) can take two values, depending on the reflector’s shape: a value of 1 in the case of a wall, and a value of 2 in the case of a right corner. This means the number of reflections suffered by the ultrasonic beam on the target’s surface before reaching the receiver. In acute corners, \(N\) can take values higher than 2, but in this paper, these type of targets are not considered.

\(^1\) YAIR stands for Yet Another Intelligent Robot, and is currently being developed under Spanish government CICYT grant DPI2002-04434-C04-03.
\( \alpha \) is the attenuation coefficient of the air, 
\( (\alpha = 0.275 \text{ dB m}^{-1}) \).

\( x \) is the distance between the transducers pair and the target (in metres).

\( \theta \) is the angle of sight under which the target is viewed by the transducer (incidence angle).

\( \theta_0 \) is the angle of sight that will produce a value of amplitude approximately equal to 0.02 times the one obtained when the incidence is normal to the surface (when \( \theta \) is zero). This is the angular aperture of the transducer, and in our case \( \theta_0 = 55 \) degrees.

In this paper, only two types of targets are assumed as representatives of the main part of the scene: walls and corners. In fact, the target points detected in scanned scenes are mainly coming from targets with a single reflection (flat surfaces) or targets with two reflections (right corners). The flat surface amount needed to produce an echo is small enough to represent almost any form of room outline as if it were formed by small flat pieces. Acute corners produce more than 3 reflections, and thus, the final intensity received is considerably reduced. Also, edges are targets that produce much reduced amplitude echoes. In our approach, only echoes with amplitude enough to be considered as walls or corners are taken into account, disregarding echoes with more reduced amplitude, which are considered as noise for map building purposes.

The eq. (1) models the theoretical behaviour of the peak amplitude of the received echoes from the targets in the scene. So, it can be used to predict the readings to be obtained from a given scene or, the more important, to identify the type of the target which produces a given echo.

In the first case, it is necessary to know the parameters of each target: its distance \( x \), its reflection coefficient \( Cr \), the exponent \( N \) (1 for walls, 2 for corners), and the angle \( \theta \) under which the target point is being observed by the transducer. From these parameters, the predicted value of the peak amplitude of an echo from the target can be obtained.

In the second case - the classification problem after a reading \( A_m \) has been taken - only one of the above-mentioned parameters is needed: the reflection coefficient \( Cr \). In fact, the distance \( x \) is a datum obtained from the ToF of the echo, and the angle \( \theta \) is not needed anymore if the reading \( A_m \) corresponds with a sight angle of \( \theta = 0 \) degrees. (This later is possible if a complete scan has been taken, given that the peaks of the scanned ‘mountains’ will always correspond with a zero sight angle with the target point). Under these conditions, the value of \( N \) can be derived from eq. (1), as shows the next equation:

\[
N = \frac{\ln \left( \frac{2 \cdot A \cdot x}{A_m} \right) - 2 \cdot \alpha \cdot x}{\ln C_r}
\]  

(2)

The value of \( N \) obtained from this equation can be used for target classification purposes, as will be later explained in section 3.

Moreover, there are other geometric characteristics in the echoes obtained from a corner that differentiate them from the ones obtained from a plane surface (wall). In the Fig.1, an experimental ultrasonic scan taken into an environment composed by two walls and their corresponding corner has been plotted. Solid arcs indicate zones where a detectable peak is found. The marks (circles for walls and triangle for corner) are placed where the maximum of each arc is located. Note that these ‘mountain’ peaks correspond with the points where the incidence angle is zero in the case of walls, and with the corner point in the corners. Thus, each detected object produces an arc of approx. 110º=2\( \theta_0 \) in the ultrasonic scan, taking the appearance of ‘mountains’ in a 3D representation.

Fig.1. Ultrasonic scan plot obtained from a scene with two walls that form a corner. Solid arcs indicate zones where a detectable peak is found. The marks (circles for walls and triangle for corner) are placed where the maximum of each arc is located.

Taking a look into the particular echoes obtained from the normal incidence point of a wall and the one corresponding with the corner point, it is easy to discover interesting differences between these echoes. In the Fig.2, individual plots of the echoes corresponding with the wall 1 and with the corner of the Fig 1 have been plotted. Abscissas values represent the distance \( x \), derived from the time-of-flight as follows: \( x = c \cdot \text{ToF}/2 \), being \( c \) the sound speed.

As is evident from the Fig 2, the echo from a wall has a principal peak placed at the distance \( dw_1 \), and no other previous peak appears in the plot of the Fig.2 a). On the other side, in the Fig.2 b) the plot shows also a principal peak placed at the distance \( dc \) from the corner, but there are two previous ghost peaks with minor amplitudes, placed at the distances \( dw_1 \) and \( dw_2 \). This constitutes an interesting fact that will be exploited in the wall/corner classification problem addressed in this paper.
This phenomenon is due to the angular response of ultrasonic transducers. As already indicated, any detected object extends its influence during an arc of $2\theta_0$ degrees in the ultrasonic scan, with a maximum on its centre, as predicted for the eq. (1).

![Graph](image)

The existence of the ghost peaks in the echo of a corner will depend on the geometric position of the sensor into the corner scene. In the Fig.1, the complementary angles $\beta_1$ and $\beta_2$ can be calculated as follows:

$$\beta_1 = \arccos\left(\frac{dw_1}{dc}\right);$$
$$\beta_2 = \arccos\left(\frac{dw_2}{dc}\right)$$

Thus, the condition that must be accomplished for the existence of the two ghost peaks is:

$$(\beta_1 < \theta_0) \text{ and } (\beta_2 < \theta_0)$$

When the angles $\beta_1$ or $\beta_2$ become greater than $\theta_0$ (55° in our case), the corresponding wall fails to produce their respective ghost peak. A particular case with only one peak is when $\beta_1 = \beta_2 = 45^\circ$. In this case both ghost peaks coincide in the same position, appearing as only one previous peak in the corner’s echo. Other particular cases with only one previous peak occur when the length of one wall is smaller than the distance to the other wall. This is often the case of the protruded pillars in corridors or other similar geometries.

The ghost peaks previous to the corner’s main peak must also accomplish the following relationships:

$$dc = \sqrt{dw_1^2 + dw_2^2}$$
$$\beta_1 + \beta_2 = 90^\circ$$

The amplitude of the ghost peaks can be also predicted using the amplitude model. Let us name as $d_i$ and $A_i$ the distance and peak amplitude of $i^{th}$ peak ($i \in \{1,2\}$), respectively. Then, it must be accomplished that

$$A_i = A_{\text{ul}}(d_i, \beta_i)$$

In some cases, experimental data show us that it is also possible the existence of additional ghost peaks previous to the main peaks in corners, and even in walls. This is possible when other objects exist in the neighbourhood. These cases can be easily detected, as they will not accomplish the equations (3 to 7).

3. CLASSIFICATION PROCEDURE BASED ON AMPLITUDE MODEL

The first approach for classify between walls and corners is very straightforward by using the eq. (2). In this paper, this simple algorithm is called ACA (Amplitude Classification Algorithm). As indicated in (Martinez et al, 2003) the parameter $N$ obtained from this formula has a quasi-normal distribution around the value of 1 in the case of walls, and around 2 in the case of corners. The standard deviation of these distributions will depend on the surface characteristics of the environment. Using the normal distribution hypothesis, the density of probability for each class $w_i$ (walls or corners) can be obtained from the calculated $N$:

$$P(N)_{w_i} = f_{\text{dist}}(N, n_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{1}{2\sigma_i^2}(N-n_i)^2}$$

where:

- $n_i$ is the mean value of the parameter $N$ for the class $w_i$;
- $\sigma_i$ is the standard deviation of the $N$ for the class $w_i$.

In (Martinez et al, 2003) the values obtained from experimental data are $n_{\text{wall}}=1$ and $n_{\text{corner}}=2$, $\sigma_{\text{wall}}=0.3$ and $\sigma_{\text{corner}}=0.31$. Also, the membership probability $P_i$ for each class is calculated using the following equations:

$$P_i(w_i) = \frac{f_{\text{dist}}(N,1,\sigma_{\text{wall}})}{f_{\text{dist}}(N,1,\sigma_{\text{wall}}) + f_{\text{dist}}(N,2,\sigma_{\text{corner}})}$$

$$P_i(\text{corner}) = \frac{f_{\text{dist}}(N,2,\sigma_{\text{corner}})}{f_{\text{dist}}(N,1,\sigma_{\text{wall}}) + f_{\text{dist}}(N,2,\sigma_{\text{corner}})}$$
3.1 Application of the Amplitude Classification Algorithm (ACA):

There are three steps to follow for classifying an obstacle as wall or corner:

a) For each obstacle, obtain its feature vector \( v = (\text{distance}, \text{amplitude}, N) \).
   \{distance and amplitude\} are directly measured from echo, and \( N \) from eq. 2

b) After, obtain \( P_{\text{d}}(\text{wall}) \) and \( P_{\text{d}}(\text{corner}) \) using eqs. (10, 11).

c) Classification’s rule:
   If \( P_{\text{d}}(\text{wall}) > P_{\text{d}}(\text{corner}) \) Then Wall Else Corner

4. CLASSIFICATION ALGORITHM USING PATTERN RECOGNITION TECHNIQUES.

A rule partitions the decision space into regions \( w_i, i \in \{1...c\} \), this rule is called the decision rule. Each one of these regions corresponds to a different target class. An unknown target is assigned to class \( w_i \) if its feature vector \( x = (x_1, x_2...x_d) \) falls into the region \( w_i \).

See (Duda and Hart, 1973). Let \( P(w_i) \) be the a priori probability of a target belonging to a class \( w_i \), and \( P(w_i|x) \) the posterior probability of the feature vector \( x \). The Bayes minimum error’s rule is applied to classify a target with feature vector \( x \) as follows:

\[
P(w_i|x) > P(w_k|x) \quad \forall i \neq k
\]

A more convenient formulation of this rule is the Bayes’ theorem:

\[
P(w_i|x) = \frac{P(x|w_i) \times P(w_i)}{P(x)}
\]

In other words, the vector \( x \) will be classified as \( w_i \) if its \( P(w_i|x) \) is maximum. The \( P(w_i|x) \) are the class-conditional probability density functions, which are unknown and need to be estimated using training sets. The training sets are several feature vectors belonging to each class. A total of \( m = m_1+m_2+...+m_c \) feature vectors are used.


Among the \( m \) vectors selected for the training set, the \( k \) nearest neighbours (those with smaller distance) to the feature vector of the target to be classified must be found, by computing their Euclidean distance. This set of \( k \) vectors will be used as a classifier’s rule. Let us suppose that \( k_j \) of these \( k \) vectors come from class \( w_j \). Then a k-nn estimator for class \( w_j \) can be defined as \( P'(w_j|x) = k_j/k \), and \( P'(x|w_j) \) can be obtained from \( P(x|w_j) \times P(w_j) \). The vector \( x \) is classified as \( w_j \) if \( k_j = \max(k_j) \). In other words, the \( k \) nearest vectors come from the same class as the majority of its \( k \) nearest neighbours.

As a rule, to obtain good results, numerous and representative feature vectors must be elected for the training set. This implies high computational costs in the execution of the algorithm, as the Euclidean distance from each of these vectors must be computed for all detected objects.

4.2. Application of the k-nn algorithm.

Next, some details are given on the application of the k-nn algorithm using the knowledge extracted from the amplitude model, as previously described.

a) First, the following feature vector has been elected and must be obtained for each obstacle as follows:

\[
v = \left( \frac{90 - \beta_1 - \beta_2}{\beta_1 - \beta_2}, \frac{a_1 - a_2}{A_1 - A_2}, a \right)
\]

In the above equation \( N \) is obtained from eq.(2), \( a_1 \) and \( a_2 \) are the measured amplitude of the ghost peaks, and \( A_1 \) and \( A_2 \) are their respective theoretical values obtained from eq.(7).

b) Next, the Euclidean distance to each training set vector must be computed and the results ordered to find its \( k \)-nearest neighbours.

c) Classification’s rule:
   The obstacle will be classified into the class with more occurrences into the \( k \)-nn set previously found.

5. RESULTS

Four data sets have been used for the experiments with the two classification algorithms described in this paper.

- **Data set 1**: Corresponds with ultrasonic data scans collected during one year term. The angles \( \beta_1 \) and \( \beta_2 \) vary between 20° and 70°. The rooms were composed with different materials, mainly with concrete (Cr=0.59) and Pladur® (Cr=0.62). Doors are covered with Railite® (0.64) with wooden frames (Cr=0.5), some metallic water pipes and windows with glass (Cr=0.71).

- **Data set 2**: Similar to the data set 1.

- **Data set 3**: Ultrasonic data scans taken in different days into the same scene, composed with different materials, mainly with concrete (Cr=0.59). The angles \( \beta_1 \) and \( \beta_2 \) vary between 20° and 70°.

- **Data set 4**: Measurements taken along one day, into the same room. Three of its walls were of concrete, and the other was covered by Railite®.

These data sets cover a wide range of situations: the distances vary between 0.5m to 4m, different materials and non-homogeneous corners have been measured, and different orientations can be found. The total number of training feature vectors was 800. The total number of scans taken from different positions was in excess of 1200. From these scans, the total of detected and classified objects was 5018 (3384 walls and 1634 corners).

The basic algorithm ACA has shown very good results for distances under 1.5m, as can be seen in the Table 1, but for longer distances, the other algorithm is better, as can be seen in Table 2. The k-nn algorithm offers the better results, yielding 84% of
success in the worst case (corners, data set 4). The value used for \( k \) was of 10. This value demonstrated to be a good compromise.

Table 1. Results for ACA algorithm (\( C_{\text{MEAN}} = 0.6 \)), distances under 1.5m, all orientations. Percentages of success in each class

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Walls success</th>
<th>Corners success</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>88%</td>
<td>85%</td>
</tr>
<tr>
<td>2.</td>
<td>79%</td>
<td>83%</td>
</tr>
<tr>
<td>3.</td>
<td>92%</td>
<td>87%</td>
</tr>
<tr>
<td>4.</td>
<td>61%</td>
<td>19%</td>
</tr>
</tbody>
</table>

Table 2. Percentages of success in classifications of walls and corners. Distances under 4 m.

<table>
<thead>
<tr>
<th>WALLS</th>
<th>Data Set</th>
<th>Algorithm</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACA</td>
<td></td>
<td>88%</td>
<td>82%</td>
<td>90%</td>
<td>67%</td>
<td></td>
</tr>
<tr>
<td>k-nn ( k=10 )</td>
<td></td>
<td>90%</td>
<td>89%</td>
<td>90%</td>
<td>93%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CORNERS</th>
<th>Data Set</th>
<th>Algorithm</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACA</td>
<td></td>
<td>68%</td>
<td>46%</td>
<td>67%</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>k-nn ( k=10 )</td>
<td></td>
<td>91%</td>
<td>91%</td>
<td>90%</td>
<td>84%</td>
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</tr>
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</table>

6. CONCLUSIONS.

In this work, a simple model of the amplitude response of the ultrasonic echoes has been used to assess about classification of detected objects between walls and corners. The ultrasonic signal comes from a unique pair of rotating emitter/receiver transducers.

The amplitude of the echoes together with their time of flight can be used in a simple data fusion process that exploits the geometric features of the two main types of reflectors -walls and corners- to identify the objects detected in a scene. To apply the amplitude-based model, only one parameter of the environment is needed: the reflection coefficient of each surface. The data fusion process can be carried out using different algorithms. Each of these algorithms has its pros and cons, yielding different success percentages and different computational costs.

The showed results yield very satisfactory success percentages, given the different scenarios and materials involved, as well as the distances up to 4m considered, and taking into account that the measurements used in each case were exclusively data taken from only one scan and from only one position.

Finally, the \( k \)-nn algorithm yields the best results in all the situations, but its higher computational cost must also be considered when real time response is required.

9. REFERENCES


Kuc R., and B. Barshan, (1990) Differentiating sonar reflections from corners and planes by employing an intelligent sensor. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(6), pages 560-569