Recognising Plants with Ultrasonic Sensing for Mobile Robot Navigation

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Abstract

Mobile robots navigate through many environments that include plants. A sensor that can recognise plants would be useful for navigation in these environments. Two problems make plant sensing difficult: plant similarity and plant asymmetry with rotation. A CTFM ultrasonic sensor produces a signal that contains information about the geometric structure of plants. Correlation of echoes from many orientations show that plants can be recognised with sufficient accuracy for navigation.

1. Introduction

Mobile robots navigate through many environments that include plants. The tasks performed by mobile robots in these environments range from fetch and cary to agricultural applications. Mowing a lawn requires the ability to detect the boundary between the part of the lawn that has been mown and the part that has not. Similarly harvesting grain requires the combine to track the boundary between the harvested and unharvested parts of the field. A sensor that can recognise plants would be useful for navigation in these environments.

Plants have rough or complex geometry. If we can sense the geometry of plants, or some characteristics of the geometry, then we can recognise plants with sufficient accuracy for them to be used as landmarks for navigation. Vision research has succeeded in navigating using plants only in highly constrained situations. Often the environment has been controlled to make plant recognition easier. Some systems require the plant to be placed in front of a known background. Others require artificial lighting.

Some of the problems encountered with vision systems can be solved with ultrasonic sensing. When a plant is insonified with ultrasonic energy the resultant echo contains information about the geometric structure of the plant. This paper discusses the recognition of plants using the geometric information in ultrasonic echoes, in particular the problem of variance with rotation.

In previous research, we demonstrated that there is sufficient information in the echo for a neural network to recognise 1 of 4 plants over a wide range of orientations [3]. To investigate the problems of classifying plants, we obtained 100 young trees and shrubs from the Wollongong Botanic Gardens. They were chosen in accordance with plant taxonomy to give a variety of leaf shapes and foliage structures. A database containing echoes from 360° of rotation in 1° steps was built for each plant.

Two problems were immediately obvious: plant similarity, and asymmetry with rotation. The echo received by the sensor varies depending on the angle from which the plant is insonified as it depends on the structure and orientation of the leaves. However, there is information in the signal which is relatively invariant with orientation and which characterises the structure of the plant. We can capture this information by extracting features from the echo in the frequency domain.

Auto correlation of the echo can be used to find repetitive structures in plants [6]. Cross correlation of both the echo and the features with rotation shows that the features are more invariant with rotation. Also, knowledge of the variance of a plant with rotation can be used to determine the heading of the plant from the robot and thus is useful for localisation.

2. Machine recognition of plants

A commercial system that uses plants for navigation is the Steeroid system [1] developed for driving tractors along rows of young crops to till between them. This system uses vision to detect the rows of young plants against a soil background. Kimoto and Yuta [8] used the standard deviation of ultrasonic range readings to detect a hedge from a moving robot. Maeyama *et al.*, [9] used a combination of vision and ultrasonic sensing to detect trees along the side of a path.

The AURORA robot [10] was developed to spray chemicals on plants in a greenhouse. It detects plants using pulse-echo ultrasonic sensing. It can navigate along

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plant rows, where there is very little room to manoeuvre, using the natural structures. Mandow *et al.,* [10] claim that the high computation costs associated with vision sensing along with inherent illumination requirements rendered vision inappropriate for this task.

An automated fruit picker has to find and pick fruit up to 600mm inside a tree. Sevila [13] identified the problems that have to be overcome when using vision to find fruit on a tree. First, only part of the fruit is visible due to occlusion by the leaves. Second, the fruit are shadowed by the leaves and the light reaching individual fruit varies greatly. Third, from outside a tree, a human can only see 85% of the fruit.

Nabout *et al.,* [11] identified plants so that they could separate weeds from crop in order to apply herbicides. They found that plants have many different complex forms which cannot be described using simple geometric models. They claim that they could recognise 17 different weed species to 82% accuracy.

Ollis and Stentz [12] used vision to guide an automated harvester through fields of alfalfa hay. They developed a crop line tracking system to detect the boundary between cut and uncut crop. Each scan line in the image is processed separately to find a boundary which divides the two roughly homogeneous regions that correspond to cut and uncut crop. This edge is found by computing the best fit pixel discriminant function. An adaptive function was required to address the variability in the image due to changing lighting conditions and soil type. Using this system they have successfully tracked and cut curved rows over a mile long.

3. Navigation strategies

Navigation is the science (or art) of directing the course of a mobile robot as it traverses the environment (land, sea, or air). Several strategies that have been identified in both animal and human navigation [12] are: piloting, dead reckoning, celestial navigation, charting, indirect navigation and electronic navigation.

Piloting is a navigation strategy that uses known landmarks. They are used sequentially to find the way to the goal. The navigator must be familiar with the area, and know which landmarks to look for. A landmark is a feature in the environment whose position can be sensed and that is close enough to the desired path that its direction varies significantly with the position of the navigator. A number of strategies are used to achieve piloting: following continuous landmarks, such as crop lines; feature matching, such as detecting trees; and compass piloting.

A sensor that can detect plants is suitable for piloting or landmark navigation. The strategy chosen for navigation will depend on the nature of the environment (static or dynamic), the robot's knowledge of the path (has or doesn't have a map), and the symmetry of the plants. These also impact the sensing strategies. One common navigation strategy is the teach/replay strategy where the robot is taught a path by driving it along the path. As it moves, it senses objects beside the path to select appropriate candidates for landmarks. The location and features of these objects are stored in the map. Autonomous navigation then becomes the replay of this path, with the robot looking for landmarks to confirm that it is following the path. We plan to implement this strategy for landmark navigation using the plant sensing system described in this paper.

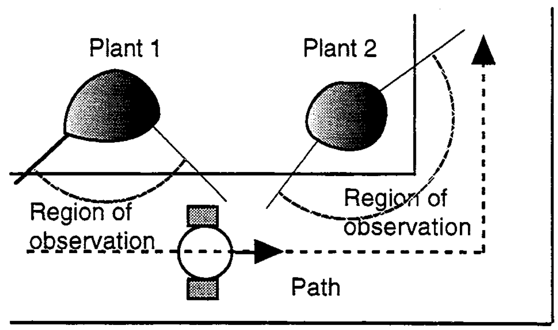

Figure 1. A simple path flanked by 2 plants

Consider the robot moving along the path in Figure 1. This path consists of two straight trajectories, and two plants have been recorded as landmarks. The proposed navigation system will determine the expected bearing to the first plant from the current location and the map. Then the sensor is pointed in the direction of the bearing. As the robot moves, this bearing changes and hence the direction of the sensor axis is changed. When the sensor detects the plant, it will localise the robot to the map from the range and bearing of the plant. Also, the system can count plants to determine when the robot is at the bend in the path. Once at the bend the robot can track the range to the plant as it turns to confirm that it is on the new trajectory without any tracking error.

The above proposal assumes that the plants are symmetrical and, as a result, can be reliably detected with in the regions of observation shown in Figure 1 with a single set of features. While some plants are symmetrical, many are not. This asymmetry can be used to advantage to determine the orientation of the robot to the plant. Even the most asymmetric plants have regions where the features change slowly. So a plant can be divided up into sectors with partial symmetry, as shown in Figure 2, and a set of features recorded for each sector. Then, when a robot tracks around a plant it should be able to use the feature information to determine its orientation relative to the plant. We can use correlation to determine the symmetry of plants (Section 9)

Three problems with this proposed strategy are: plant growth, plant motion with wind, and plant disappearance.

The impact of plant growth can be minimised by updating the feature set every time the robot travels along the path. The effect of wind can be minimised by averaging the features over several readings or by using echo tracking (Section 10). Plant disappearance requires the navigation system to be intelligent enough to realise that a plant is not where it should be and look for other landmarks.

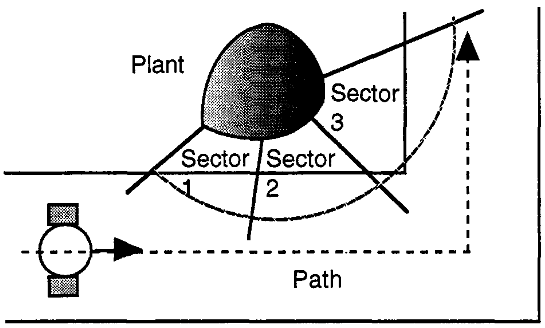

Figure 2. A plant which is acoustically different between sectors but similar within sectors

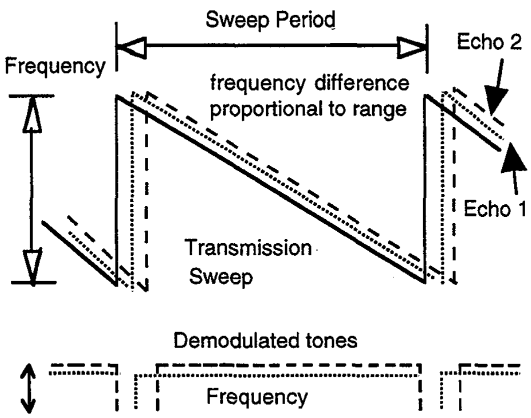

Figure 3. CTFM Signals

4. CTFM

When a plant is insonified the resultant echo contains information about the geometry of the plant, in particular the structure of the foliage. The echo data was produced with a Continuously Transmitted Frequency Modulated (CTFM) ultrasonic system developed by Leslie Kay [11]. A CTFM system transmits a sine wave signal that is repeatedly frequency swept over a one-octave range (typically 100 to 50 kHz with a sweep period of 102.4 ms). The echo is a filtered version of the transmitted signal, offset in time.

The echo is demodulated with the transmitted signal to obtain a set of audio tones (0..5KHz) proportional to range (Figure 3). The audio tone for a target is continuous from the time at which the echo arrives until the end of the sweep. Thus, the sweep consists of two time periods: the first is the time to the arrival of an echo from maximum range and the second is the time to capture the samples for the Fast Fourier Transform (FFT).

In the time domain, the complexity of audio signal is proportional to the geometric complexity of the target. In the frequency domain, each spectral line occurs for each range where energy is reflected. A 1024 point FFT produces positive amplitude values for 512 * 9.77 Hz frequency bands. The amplitude of the spectral line is proportional to the intensity of the echo and hence to the area of the reflecting surface normal to the receiver.

5. Acoustic density profile

The audio tones are range measurements to every near normal surface in the region of insonification. A small amount of the signal results from multiple reflections and interference, and some signal is lost due to shadowing. The frequency spectra includes information about the range, size and orientation of surfaces within the field of audition and can be modelled as an acoustic density profile. In this model, the sensor measures the acoustic area at each range. The acoustic density profile for a specimen of *Leptospermum laevigatum* is shown in Figure 4. The sum of the values in the range cells is a measure of the acoustic area of the plant.

The acoustic density profile is a measure of the acoustic density in each range cell. Each range cell is 3.4 mm deep. Figure 4 shows a significant acoustic density between the ranges of 200 mm and 540 mm and this corresponds to the position of the plant in space. The amplitudes of the individual range lines are a function of the properties of the surfaces at that range (Figure 5):

the area of the leaves in the range cell;
the orientation of the leaves;
the texture of the leaves; and
the amount of occlusion that affects the leaves.

These properties are illustrated in Figure 5, where the boundary of the plant is represented with a circle and leaves with filled ellipses. Waves reflect from the surfaces of the leaves to be detected by the receiver R_x.

With the acoustic density profile model, we can interpret the information in the echo from the plant. We can extract features from the frequency spectra of the received echo, and use them for classification of plants [4]. Also, we can match these features to geometric properties of the plant [5].

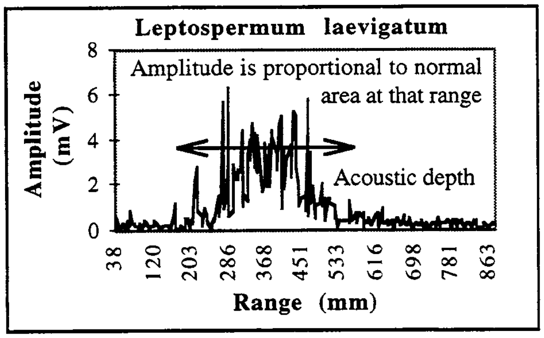

Figure 4. The acoustic density profile model of the demodulated CTFM echo.

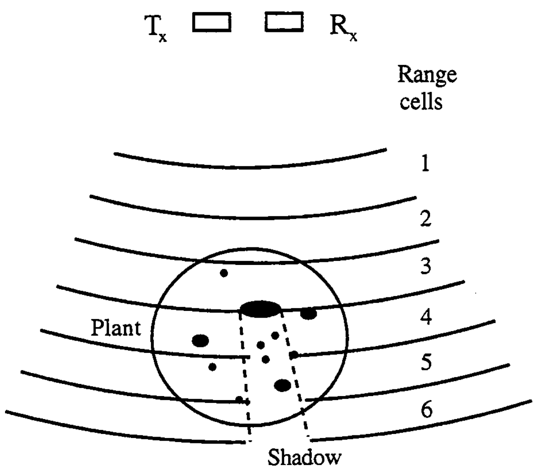

Figure 5. Distribution of reflectors through range cells.

6. Data characteristics

Specular surfaces have a narrow-band signal which often consists of a very large magnitude at a single range. Diffuse scatterers result in much smaller magnitudes. Objects with multiple surfaces generate echoes from each surface and the resulting echo contains information about all of the surfaces (Figure 6). It includes the absolute range to the object and the geometric structure of the object.

Each spectral line has two parameters: frequency and amplitude. The frequency represents the absolute range to the surface and the amplitude is a function of the size, specularity and orientation of the surface. Since there are many reflective surfaces in a plant, the return signal is complex. Also, the maximum amplitude (12 mV) is significantly smaller than that for a flat wall (100 mV) or a 10 mm metal rod (20 mV).

When a plant is in the field of audition, a CTFM system can sense it independent of the distance to, the height of and width of the plant. The plant properties that modify the echo include the size, orientation and number of leaves; their spatial positioning and orientation within the plant; and acoustic shadowing of back leaves by front leaves (Figure 5).

Leaves with surfaces at an angle to the sensor reflect most of the acoustic energy away from the receiver. The surface of the leaf also has an effect on the amount of acoustic energy returned - smooth flat surfaces reflect more back to the receiver than textured surfaces. In general, the more leaves on a plant and the larger the leaves, the greater the percentage of acoustic energy reflected to the sensor.

The location of leaves within the plant determine the distribution of reflections throughout the echo. Peaks in the echo spectra may indicate groups of leaves. Small changes in the orientation of a plant can result in large changes in the echo spectrum, due to the specular nature of leaves. Many leaves are not flat and will return energy from several different orientations.

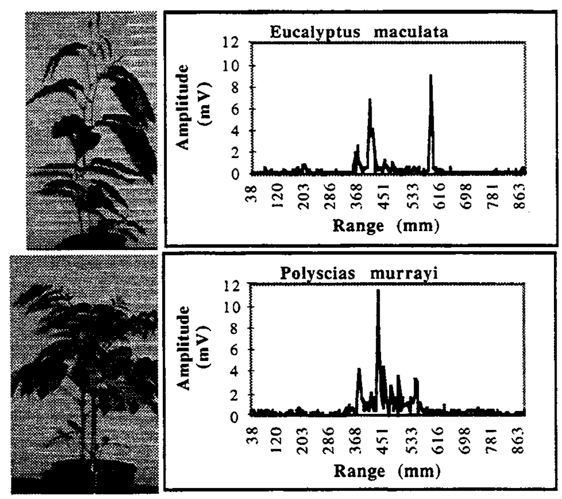

Figure 6. Acoustic density profiles of two plants.

Acoustic shadowing occurs when one leaf occludes another. Figure 5 shows some acoustic shadowing on the bottom right hand corner. The large leaf prevents the bulk of the acoustic energy from penetrating into the range cells behind it. Some refraction may occur in this situation. Refraction allows a small amount of the acoustic energy to penetrate but this will result in a very small contribution to the amplitude in the range cell.

Dense plants have more shadowing and less of the echo comes from leaves beyond the front surface of the plant. In general, the echo from dense plants have one region with large amplitude which corresponds to the front of the plant (e.g. *Polyscias murrayi* in Figure 6).

In contrast, the echo of *Eucalyptus maculata* includes echoes from the leaves at the back of the plant. The amplitude of the spectral lines of sparse plants is lower. Note, the background in the images is not present when the acoustic density profile is measured.

7. Plant database

The Wollongong Botanic Gardens supplied 100 plants for these experiments, in family groups. Plants of the same family are not necessarily similar in terms of their acoustic density profile, which depends more on the size, shape, orientation and overall positioning of the leaves.

For each plant, a portfolio was established which contains data about the plant and a photograph. The portfolio contains the information in Table 1, the conditions under which the plant was processed ie. date, time, temperature and humidity; and a sample acoustic density profile for the plant. In addition, a database was built for each plant containing echoes from 360° of rotation in 1° steps

Table 1. Characteristics of plants [2]

The scientific name of the plant species.
The assigned common name.
The family of plant to which this species belongs.
Total height of the specimen from the soil to the top
The total with of the plant at its widest point
The average leaf length from the base to the tip.
The average width of the leaves at their widest point.
Count of the total number of leaves on this specimen
Estimate of plant density – scale: high, medium, low
Leaf shape of plant.
Arrangement of the leaves in relation to each other.
Leaves composed of several parts are compound.
The shape of the leaf at its apex
The shape of the leaf at its base
Pattern of the leaf around its outer edge.
Manner in which the veins of leaves are arranged.
The hairy or scaly surface of the leaf
Notes about the physical characteristics of the plants

8. Feature extraction

There is sufficient information in the echo for a neural network to recognise 1 of 4 plants over a wide range of orientations [3]. However, the echo can vary considerably with rotation. To achieve more robust classification we sought to find a set of features that: a) could be easily extracted from the echo, b) were invariant with orientation, and c) represent defined geometric characteristics of a plant.

Consider the plants shown in Figure 6. The acoustic density profile of the *Polyscias murrayi* has a higher peak than the *Eucalyptus maculata*. So a feature which may distinguish these plants is the maximum amplitude of the acoustic density profile. If this feature is consistent through rotation then it is a good feature for classification.

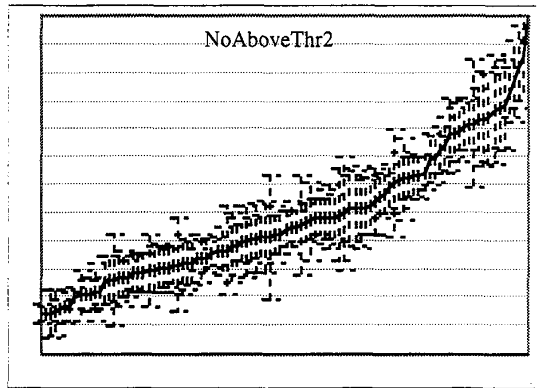

Figure 7. Distribution of one feature for 100 plants. The x axis is the plant's in ascending order of feature value (y axis). The standard deviation is shown by the dashed lines.

Table 2. The features in the plant acoustic density profiles

Feature	Description
`no_above_threshold 1-9`	Counts of the number of range cells at a specified threshold
`sum_of_density_profile`	Sum of all of the range cells
`variance_range, stdev_range, mean_abs_dev_range coeff_of_var_range`	The variation of the detected reflections from the central point of the acoustic density profile.
`front_to_peak_dist`	Distance from the first detectable surface to the surface with the highest amplitude.
`length_of_density_profile`	The range over which reflections are detected.
`freq_75_acoustic_area`	The range from the first detected reflecting surface to the cell where 75% of the sum is accumulated.
`no_of_major_peaks1, no_of_major_peaks2`	Count of range cells which have reflections significantly stronger than those around it.

To establish candidate features, we studied the acoustic density profile of different objects and defined measures to characterise the shape of the patterns. We developed a set of 67 features. Then we reduced this set down to a manageable set of 19 features (Table 2) using the visualisation of the distributions.

In Figure 7, a feature and its standard deviation is plotted for all 100 plants. Features were selected based on the slope of the line and the standard deviation. The standard deviation is a measure of how much the feature changes with rotation. The slope of the line is a measure of how easy it is to separate two plants. This is a good feature for plant recognition. However, the standard deviation shows that all plants vary with rotation.

9. Plant variation with rotation

The acoustic density profile changes from one orientation of a plant to its adjacent orientation due to changes in the relative positions of the leaves. We can compare adjacent acoustic density profiles with local correlation (pairwise cross correlation). As a mobile robot moves around a plant it may use local correlation to confirm that it is still sensing the same plant. Generally, the variation between two echoes increases with the angle of separation between them.

Also, local correlation provides information about the characteristics of the plants being analysed. For example, plants with a thick outer layer of foliage have acoustic density profiles which are more consistent through rotation, as all of the reflections come from a concentrated area at the outside of the plant. Those with a wide spread of leaves vary substantially between adjacent orientations but can often produce similar acoustic density profiles from opposite sides of the plant.

Normally, a person has difficulty seeing the differences between two adjacent acoustic density profiles. As a result, local correlation usually results in very high correlation values. The local correlation between the 360 adjacent records of Crinum pedunculatum (Figure 8) is an average of 0.87, with a standard deviation of 0.08. In conrast, the local correlation of Pittosporum crassifolium is an average of of 0.79 and a standard deviation of .07 (Table 3).

Local correlation for these plants is quite good as it exceeds the generally accepted threshold of positive correlation of 0.7. When all 100 plants are orderd by local correlation, Crinum pedunculatum is in 4^{th} position and Pittosporum crassifolium is in the 73^{rd} position. However, we will see that the flat physical shape of Crinum pedunculatum results in much more variation with rotation than occurs with Pittosporum crassifolium.

The average local correlation for all 100 plants is 0.80, with a maximum average of 0.9 and a minimum average of 0.74. The local correlation with respect to rotation for the plants in Figure 8 is graphed in Figure 9. The graphs show how much the raw acoustic density profile changes with respect to the previous orientation as the plant is rotated. A low value for the correlation indicates a significant change between one orientation and the next.

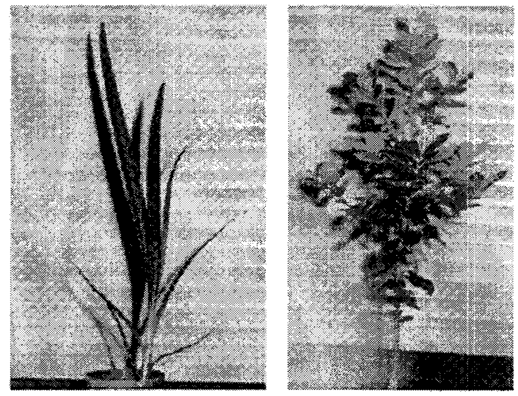

Figure 8 Images of a. Crinum pedunculatum and b. Pittosporum crassifolium

The plants with the highest local correlations are those with very few leaves. These plants have either small leaves (and don't have narrow band component in their echo) or only 1 or 2 large leaves (e.g. palms) (and their echo has a narrow band component).

The plants with the lowest local correlations are those wih a large number of leaves, which cause many specular reflections. Their echo changes significantly between orientations because the set of leaves that produce the echo change. Also, the positions of the specular reflectors change slightly in the acoustic density profile as their absolute range changes through rotation which results in a lower correlation.

A sequence of low correlations indicates that the acoustic density profile is continuing to change substantially with subsequent orientations. One plant was observed to have a branch protruding toward the sensor. The branch was sticking out of the field of audition of the sensor and as the plant is rotated, echoes from less and less of it were received. In a practical system, this branch information may be used to our advantage because particular plants may be characterised by the fact that they have protruding branches.

In summary, most of the plants are well correlated in terms of local correlation. There are groups of adjacent orientations however, where the acoustic density profile changes significantly from one orientation to the next as a sudden change in foliage structure is present. However, this is in contrast to the rest of the orientations where there are only small changes from one orientation to the next. The results show that plants with small, sparse foliage are more correlated through rotation.

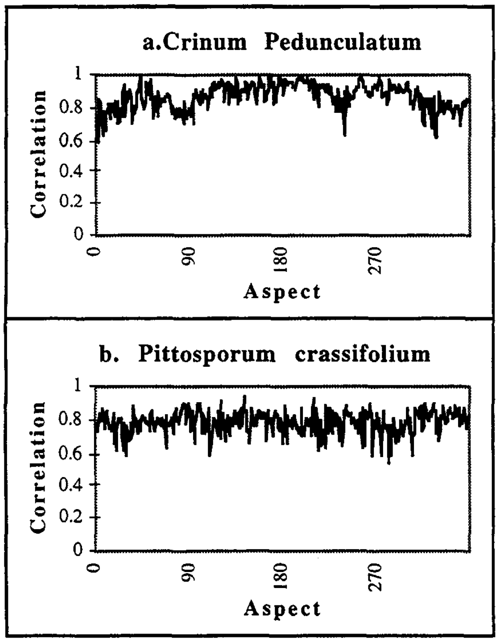

Figure 9. Local correlation by angle of the plants in Figure 8

10. Global Correlation

When a mobile robot is sensing irregularly or is moving at high speed in a static, known environment, there may be large angular separation between successive samples of a plant. We can compare any acoustic density profile from a plant with a reference acoustic density profile with global correlation. The reference profile can be selected at a random orientation or can be the average of the acoustic density profiles from all 360 orientations.

Global correlation of the raw acoustic density profile is generally weak. Plants with a high number of reflective surfaces are worse than those with a smaller number of reflective surfaces. Several of the records on each side of the reference point are highly correlated to it, but drop off significantly with small angular rotation. This high correlation is due to the fact that the acoustic density profile changes gradually as the plant orientation is changed.

However global correlation is improved considerably by correlating features. Global correlation provides a measure of global symmetry, partial symmetry and the rate of change of symmetry. In Figure 11, global correlation with the acoustic density profile is compared to global correlation with features. The latter achieves much better correlation. The reference orientation is arbitrarily chosen as 256°. Global correlation provides more information about the way that plants change through rotation than local correlation does.

These global correlation results are consistent with the physical properties of the plants. *Crinum pedunculatum* has smooth leaves that are very long and thin with the tips oriented vertically (Figure 8). The cross section of the leaf is rounded evenly which means that the leaves will reflect at multiple orientations. In general, the leaves do not protrude horizontally from the central stem so they allow little opportunity for the acoustic energy to penetrate and reflect from other surfaces within the plant except at certain orientations.

The acoustic density profile changes through rotation due to the changing orientations of leaves and leaf edges which cause different amounts of acoustic energy to be reflected. There are three primary leaves, two of which are opposite each other with the third leaf being orthogonal. This means that for any particular signal return, there is a good chance that there will be two other signal returns from different orientation which are very similar as they will be insonifying similar foliage. This is shown by echoes at several orientations, with large angular separation, around the plant being highly correlated to the reference. For example orientations 180 and 256 are highly correlated even though they are 76° apart.

Pittosporum crassifolium is a plant with very dense foliage (Figure 8) so acoustic energy will be returned primarily from the front and the sides of the plant. The foliage is relatively consistent as the plant is rotated, which is shown by the correlation graphs. Beside the notable peak at the point where the reference is correlated with itself, the graphs are relatively consistent for the entire revolution. The other point of note is the large dip in correlations at orientation 144. This is a result of an area of inconsistency in the foliage. Note that correlation using features does not show this dip.

11. Conclusion

The suitability of plants as landmarks for navigation depends on how much they vary with the orientation of the sensor. Correlation of both acoustic density profiles and features can be used to characterise the symmetry of a particular plant. This symmetry information can be used to choose both a sensing strategy and a navigation strategy for the path segment where the plant is growing.

Local correlation gives us an indication of how the acoustic density profile changes with small changes in orientation and whether a plant is locally acoustically symmetric but it does not tell us whether the plant is globally acoustically symmetric. A plant which displays high local symmetry is a very good landmark as the sensor may be a few degrees from the expected orientation and still get good correlation and hence recognition. Partial symmetry is acceptable for mobile robot navigation since the robot will only sense a sector of the plant (usually less than 180°).

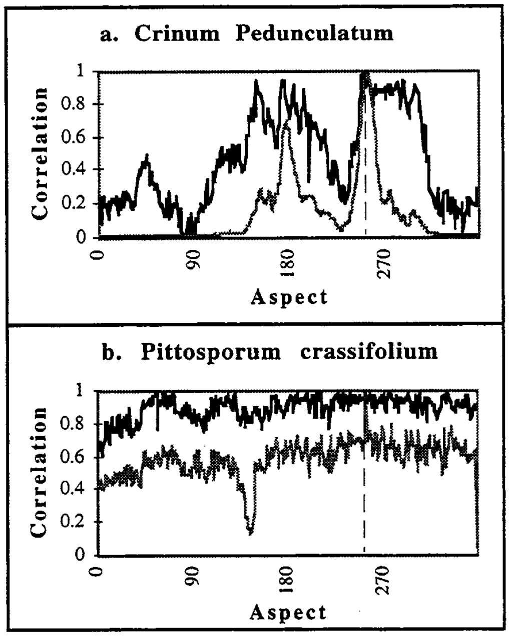

Figure 11. Global correlation. Black - using features, Grey - using acoustic density profile, both correlated with the data at 256°.

Local correlation provides information about the local consistency of the signal but provides no information about how well the acoustic density profile correlates with other orientations which may not be adjacent such as 90° around the plant or even the view from the other side of the plant. Global correlation provides a measure of the change of echo throughout an entire revolution of the plant.

Most plants produce poor cross correlation results when acoustic density profiles all orientations are correlated against a selected orientation. This is because a small change in range places the echoes in different range cells so the acoustic density profiles' will be poorly correlated once an angle more than several degrees from the reference is used. However, the information in the acoustic density profile can be more reliably correlated by considering the features which represent the geometric pattern of the foliage.

12. Acknowledgment

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