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Keywords

machine perception, plant recognition, robot navigation, ultrasonic sensing

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Plant Acoustic Density Profile Model of CTFM Ultrasonic Sensing

Phillip McKerrow, *Member, IEEE*, and Neil Harper

***Abstract*—Many applications require the sensing of plants. When an ultrasonic sensor insonifies a plant, the resultant echo is the superposition of the echoes from the leaves. As a result, the echo contains information about the geometric structure of the foliage. In this paper, we present a model of sensing that facilitates the extraction of geometric features from the echo for plant classification, recognition and discrimination. We model the echo from a CTFM ultrasonic sensor with the acoustic density profile model. Then, we identify a set of features that represent plant geometric characteristics and use these to perform an inverse transform from echo features to plant geometry.**

***Index Terms*—Machine perception, plant recognition, robot navigation, ultrasonic sensing.**

I. Introduction

SURFACES with rough texture or complex geometry are common in nature. Plants have complex geometry and are found in many potential applications for mobile robots. If a robot can sense the geometry of a surface then it may be able to recognize, or discriminate between, plants. Machine perception of plants will enable a robot to navigate using the plants as landmarks. The ability to identify a plant as a weed will enable a robot to remove it from among a crop.

Vision research has succeeded in recognizing plants in situations where either the background or the lighting is controlled. Some of the problems encountered with vision systems may be solved with sonar [12]. When a surface is insonified with ultrasonic sound, the resultant echo contains information about the geometric structure of the surface, in particular, depth and area information

There is sufficient information in the echo of a CTFM ultrasonic signal from a plant for a neural network to recognize 1 of 4 plants over a wide range of orientations [3]. However, the echo can vary considerably with rotation. To achieve robust classification [5], we sought to find a set of features that: a) could be easily extracted from the echo, b) were invariant with orientation [7], and c) represent defined geometric characteristics of a plant [6].

In Section VI, we present the acoustic density profile model of CTFM ultrasonic sensing as a basis for perceiving the geometric structure of a plant from its echo. The acoustic density profile is a transformation from the physical structure of the object to information in the echo. It can be thought of as a forward transformation from object structure, to echo, to acoustic density profile. To validate it, we applied it to the recognition and classification of leafy plants [4].

However, an inverse transformation is required to obtain data for reasoning about the physical structure of a plant. In Sections VII–XIV, we seek to establish an inverse transform from acoustic density profile to plant physical shape. With this model, we transform echo signal features into acoustic features and transform some acoustic features into geometric features related to the foliage structure (the size, shape, orientation, and overall positioning of the leaves).

The Wollongong Botanic Gardens supplied 100 plants, in family groups, for these experiments. Plants of the same family are not necessarily similar in terms of the information in their echoes, which depends more on the foliage structure. A database was built for each plant containing echoes from 360° of rotation in 1° steps.

II. Perception of Plants

Billingsley and Schoenfisch [1] developed a system for driving tractors along rows of crops to till between them. It uses vision to detect the rows of young plants against a soil background. Kimoto and Yuta [10] used the standard deviation of ultrasonic range readings to detect a hedge from a moving robot. Macedo *et al.* [11] extend this approach to discriminate between obstacles and long grass using statistical analysis of the variation in range readings made with a laser range finder.

Maeyama *et al.* [13] used a combination of vision and ultrasonic sensing to detect trees along a path. Mandow, *et al.* [14] used pulse-echo ultrasonic sensing to navigate along rows of plants in a green house. Nabout *et al.* [15] found that plants have many different complex forms that cannot be described using simple geometric models. They state that their vision system could recognize 17 different weed species to 82% accuracy.

Guyer *et al.* [2] attempted to identify plants from the shape of their leaves. They placed leaves in isolation against a soil background so that the leaves were all at the same distance from the camera and orthogonal to it. They achieved 68% recognition when trying to separate one leaf from the leaves of seven other plant species. Errors in classification were due to poor images, poor segmentation, and natural scene variation. They state that the major problem for vision systems is biological variability within plant species.

Singh and Montemerlo [16] attempted to classify plant cuttings using vision. They graded three different cultivars of *geraniums* as small, medium, or large to an accuracy of 90%. The

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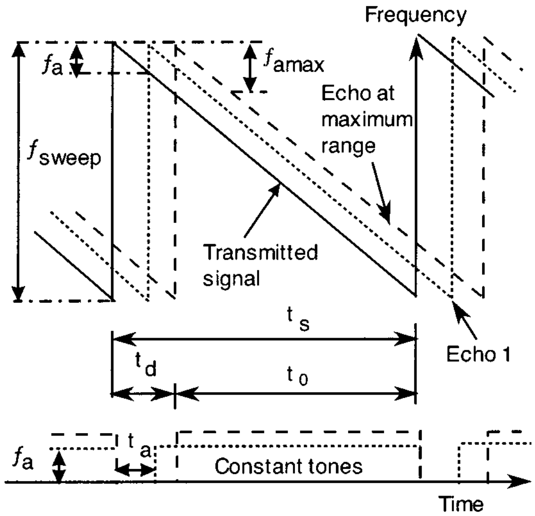

Fig. 1. CTFM signals. $f_{\rm sweep}$ = sweep frequency range, f_a = audio frequency, $f_{a\,\max}$ = maximum audio frequency, t_s = sweep time, t_d = time to echo at maximum range, t_o = time period for FFT sampling, t_a = time to echo.

grade of the cutting was determined from carefully selected features extracted from a single image. They found that the appearance of the cutting is changed significantly by the change in viewing angle of the sample but good feature calculation can reduce the effects of this.

III. CTFM

Echo data was captured with a continuously transmitted frequency modulated (CTFM) ultrasonic system developed by Leslie Kay [8], [9] as a mobility aid for blind people. The system uses oval transducers with a horizontal beam angle of 40° and a vertical beam angle of 20° measured relative to the beam axis. The plants were placed so they were completely inside the beam, and the pots were outside. A CTFM system transmits a sine wave that is repeatedly frequency swept over a one-octave bandwidth ($f_{\rm sweep}$ is 100 to 50 kHz with a sweep period t_s of 102.4 ms). The echo is a delayed and filtered version of the transmitted signal.

The echo is demodulated with the transmitted signal to obtain a set of audio tones (f_a is 0-5 KHz) proportional to range (Fig. 1). 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 time to the arrival of an echo from maximum range (t_d) and the time to capture the samples (t_0) for the fast Fourier transform.

In the time domain, the complexity of the audio signal is proportional to the geometric complexity of the target. It contains a tone for each range where sound is scattered. We can separate these tones by transforming the audio signal into the frequency domain with an FFT.

The FFT divides the echo up into $n = 512$ frequency bins of width $\delta f = 10$ Hz. When transformed from frequency space to geometric space, the bins represent a set of concentric annuli each $\delta r = 3.4$ mm thick (Fig. 2). The frequency of an FFT line f_m is proportional to the range r_m to the annulus containing the surfaces that produced that component of the echo.

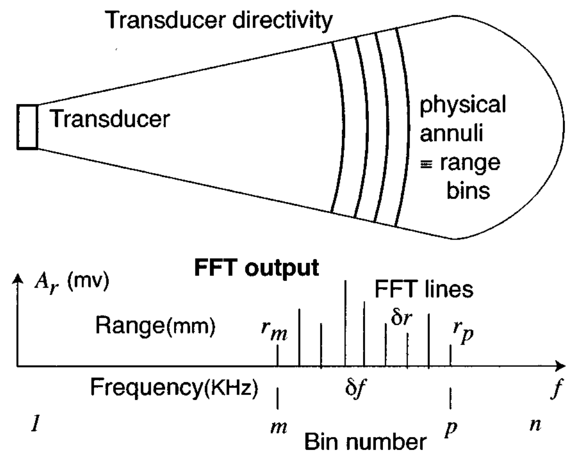

Fig. 2. Amplitude of each spectral lines produced by the FFT is proportional to the density of acoustic reflectors in the annulus at that range.

The amplitude A_r of the FFT line at range r is the absolute value of the complex number output from the FFT. It is proportional to the pressure of the echo and hence to the area of the surfaces normal to the receiver in the annulus. The output of the FFT is an integer value, which is converted to millivolts for display on the acoustic density profile graphs (1 bit = 0.039 mv).

IV. Data Characteristics

Specular surfaces produce a narrow-band echo that transforms into a large amplitude spectral line at a single range. Diffuse scatterers produce a wider band signal with much smaller amplitudes. Objects with multiple surfaces generate echoes from each surface and the resulting echo contains information about all of the surfaces.

The amplitude of a spectral line 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 (Fig. 3). Also, the maximum amplitude (12 mV) is significantly smaller than that from a flat wall (100 mV) or a 10 mm diameter metal rod (20 mV). The echo from a flat surface at 500 mm is used as the maximum calibration point for the sensor system. The minimum calibration point is obtained by pointing the sensor into open space and calculating the mean and standard deviation of the noise.

When a plant is in the field of audition, a CTFM system can detect it independent of the distance to the plant, the height of the plant and the width of the plant. Properties of a plant which modify the echo include: its size, orientation and number of leaves, the spatial positioning and orientation of the leaves within the plant, and the acoustic shadowing of back leaves by front leaves.

Leaves with surfaces angled to the sensor reflect most of the ultrasonic sound away from the receiver. Also, the surface properties of the leaves affect the amount of ultrasonic sound returned. Smooth and flat leaves reflect more in one direction than textured and curved leaves. In general, the more leaves on a plant and the larger the leaves, the greater the percentage of ultrasonic sound reflected to the sensor.

The location of leaves in the plant determines the distribution of acoustic energy throughout the spectra. Peaks in the echo

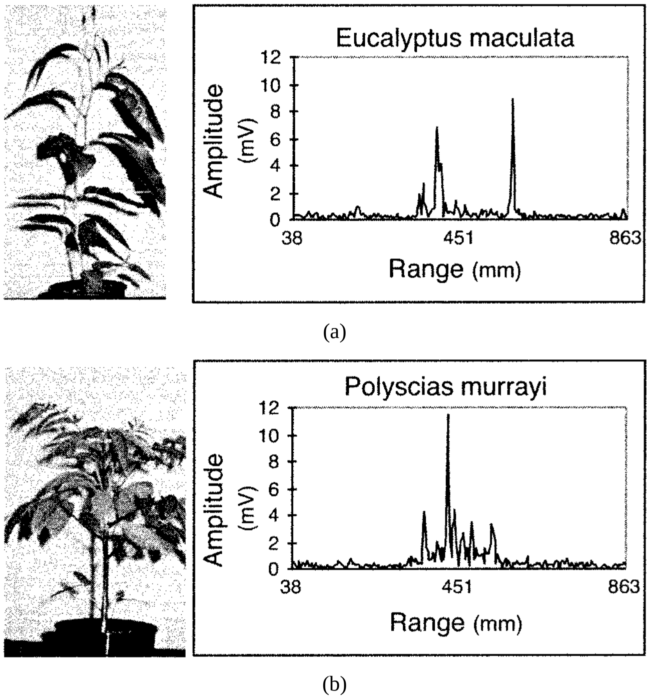

Fig. 3. Echo spectra of (a) Eucalyptus maculata and (b) Polyscias murrayi.

spectrum may indicate groups of leaves. Small changes in the orientation of a plant can result in large changes in the echo spectra [7]. However, as many leaves are not flat, they will return ultrasonic sound from several different orientations.

Acoustic shadowing occurs when one leaf occludes another. Multi-path echoes occur when ultrasonic sound reflects off several leaves before returning to the receiver. Some refraction may occur, but it will result in a very small contribution to the amplitude in the range cell.

Dense plants have more shadowing and less of the echo originates at leaves beyond the front surface of the plant. In general, the echo from dense plants has one region with large amplitude which corresponds to the front of the plant (e.g., *Polyscias murrayi* in Fig. 3). In contrast, the echo from *Eucalyptus maculata* includes echoes from the leaves at the back of the plant. Note, the background in the images was not present when the plant was sensed.

V. Data Preprocessing

Raw data from the FFT is generally in the range of 0 to 100 mV. Before features are extracted, the region of the echo corresponding to the plant is selected with a window and the amplitude is normalized. Windowing discards data that does not belong to the plant and it transforms absolute range data into relative range data.

The raw data is normalized so that it is equivalent to measurements at a range of 400 mm. Normalization removes any variation with range to ensure that when spectra or features from different plants are compared the differences are due to plant geometry.

After the features are calculated, they are normalized again, this time to a common scale. Each feature has its own range of values and its own units: some in millivolts, some are counts and some are percentages. Before they can be used in a reasoning system, they all have to be converted to comparable scales. We choose to scale them so that most feature values lie between 0 and 100. We determined a scale factor for each feature from the mean and standard deviation of the set of values for the feature for all 100 plants.

VI. Acoustic Density Profile

From a signal processing point of view, the FFT produces the spectrum of the demodulated echo. From an acoustic point of view, the amplitude of each spectral line is proportional to the density of the acoustic reflectors in the annulus at that range. Hence, the name acoustic density profile. From a geometric point of view, the amplitude of each FFT line is a function of the area within the annulus that reflects ultrasonic sound back to the transducer.

The amplitude of a range line is a function of the properties of the leaves in the annulus at that range: their area, texture, orientation, and the amount by which they are occluded. In each annulus, ultrasonic sound is reflected by surfaces and refracted by edges. Thus

$$A_r = f\begin{pmatrix}\text{reflecting area, texture, surface curvature,}\\ \text{refraction, shadowing, multiple reflections}\end{pmatrix} \quad (1)$$

$$A_r = \sum_{1}^{b}(\text{reflected energy}) + \sum_{1}^{c}(\text{refracted energy}) \quad (2)$$

where

b number of reflecting surfaces;

c number of refracting surfaces.

The amplitude can be further abstracted by considering the ultrasonic sound to be scattered from q sections of leaf surfaces (including edges) with elemental area δa_q, and each with its own directivity function d_{lq}. The directivity function takes into account the area, curvature and texture of the surface. The proportion of the transmitted energy A_t falling on a section of a leaf surface is determined by the directivity function of the transmitter in the direction of the surface d_{tq}

$$A_r = \sum_{1}^{q}(A_t * d_{tq} * d_{lq}). \quad (3)$$

VII. Plant Features

In our study of plants, we found 19 features that are useful for discriminating between plants (Table I). These features were selected from an original set of 67 using feature filtering. The ones with the lowest predictive quality were removed. The chosen features can be easily extracted from the echo, have small variation with orientation, have good ability to discriminate between plants, and represent geometric characteristics of a plant. As these features are calculated from the acoustic density profile, they measure certain fundamental properties of the echo.

Consider the plants shown in Fig. 3. The acoustic density profile of the *Polyscias murrayi* has a higher peak than that of *Eucalyptus maculata*. So, a feature which may distinguish these

TABLE I
FEATURES WHICH CHARACTERIZE THE ACOUSTIC DENSITY PROFILES OF PLANTS

Feature	Description
no_above_threshold 1-9	Counts of the number of range cells above a specified threshold
sum_of_density_pro file	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_a rea	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.

plants is the maximum amplitude of the acoustic density profile. If this feature is consistent through rotation, then it may be a good feature for classification.

In Fig. 4, a feature and its standard deviation is plotted for all 100 plants. The values are averaged over 360° of rotation, with samples taken every 1°. The ability of a feature to discriminate between plants is determined by the slope of the line and the standard deviation. The slope is a measure of how easy it is to separate two plants. The standard deviation is a measure of how much the feature changes with rotation.

Whether this feature is considered to be a good feature or not depends on the application. If the task requires discrimination between plants from any angle then this feature will only discriminate between about 10 out of the 100 plants. To discriminate between more plants, it has to be combined with other features. This is typical of most features.

However, many tasks require recognition over a small angle of rotation. For example, in landmark navigation, a mobile robot will typically return to within 5° of the original sample angle. Correlation of the features over this range [7] shows a much smaller variation and hence a greater ability to discriminate.

VIII. GEOMETRIC INTERPRETATION OF FEATURES

The acoustic density profile is the result of a forward transformation from plant structure to echo, and from echo to spectrum. The model provides a way to invert this echo generation process to obtain a physical interpretation of the echo. The inverse transformation attempts to obtain geometric information about the plant. It can be decomposed into two separate transformations: signal features to acoustic features and acoustic features to plant features.

A problem with many inverse transforms is that they do not produce a one to one mapping. However, if we can achieve a transformation from the 19 signal features to plant geometry, at least in concept, then we are well along the way to a scientific basis for plant recognition and classification.

In the following sections, we consider some of the 19 features and determine an inverse transform to geometric features. Often, we will find a $1:1$ mapping from signal feature to acoustic feature. For example, the length of the acoustic density profile is the acoustic depth of the plant.

Unfortunately, most transforms from acoustic feature to geometry are 1 to many or many to 1. One geometric parameter may contribute to several acoustic features or several geometric features to one acoustic parameter. For example, threshold features measure both leaf density and leaf size, but we have not been able to distinguish between them.

IX. AMPLITUDE OF RANGE LINES

The height of a range line in the acoustic density profile is the simplest signal feature. It is proportional to the square root of the energy in the reflected signal. Hence, it is a transformation of the acoustic area of the plant at that range. Thus, the first transform (from signal feature to acoustic feature) is from signal amplitude to acoustic area.

The second transform (from acoustic feature to plant feature) is more complex. The acoustic area is the sum of the areas of the sections of leaves in the annulus at that range which reflect the energy to the receiver. The acoustic area is a function of the geometric area of the leaves of the plant, but not a simple function.

For a section of a leaf to reflect toward the receiver it must be oriented near normal to the axis of the receiver. In air, most leaf surfaces are specular reflectors, diffuse reflectors are rare, and there is virtually no absorption. The surface curvature of the leaf spreads the echo, which makes it weaker at the receiver. The transformation is complicated further by acoustic shadowing, and multiple echo paths.

From (3), we see that the area and directivity of the scattering surfaces in an annulus determine the amplitude of the resultant range line. Consequently, range lines with the same amplitude can represent echoes from a small number of large leaves or a large number of small leaves. We are yet to find features that map to leaf size or shape. While both leaf geometry and foliage structure contribute to the echo, the set of features discussed here only map to foliage structure. Also, we removed the leaves from a plant and found that very little of the echo comes from the branches.

Thus, for this simple feature, we have a one to one transform from signal feature (amplitude) to acoustic feature (acoustic area). Then, we have a complex mapping from acoustic feature to plant feature (near normal area, diffraction, leaf curvature, acoustic shadowing, and multiple echoes).

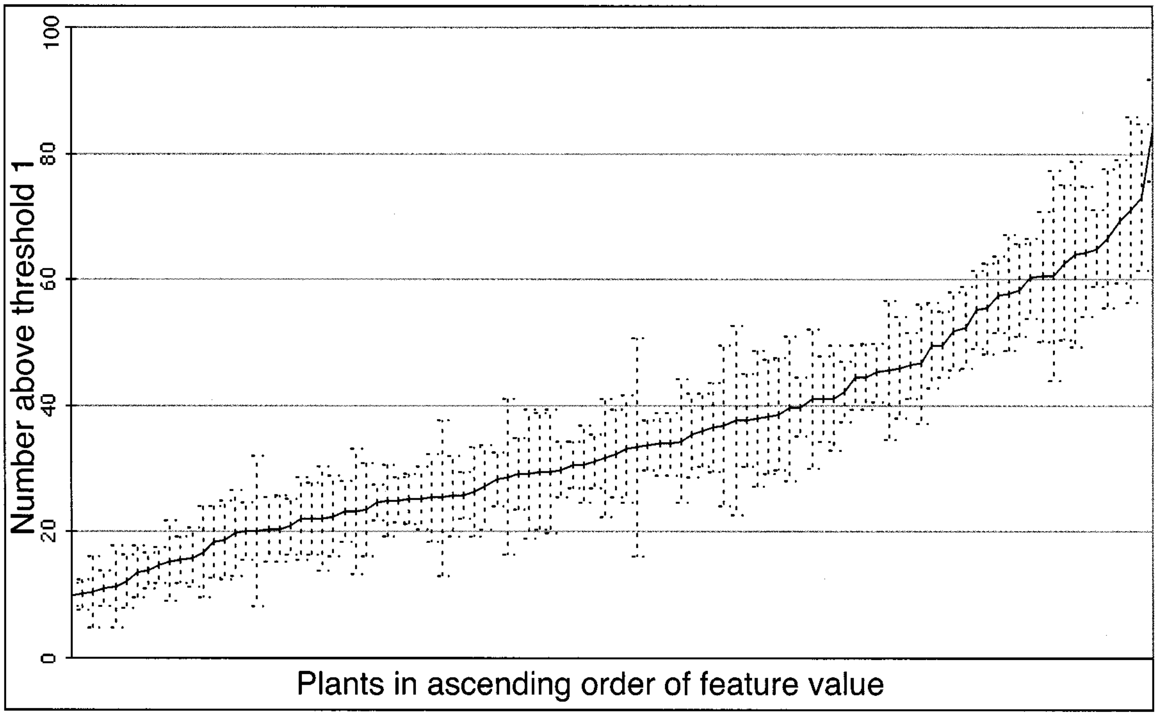

Fig. 4. Distributions of values for the threshold 1 feature for all 100 plants—Average and standard deviation for 360 samples separated by 1° of rotation.

X. Length of Acoustic Density Profile

The length of the acoustic density profile is calculated as the distance between the first and the last range line in the echo reflected from a plant. It is the acoustic depth of the plant. When surfaces at both extremities of the plant reflect ultrasonic sound to the transducer, then it is also the physical depth of the plant. However, in practice, it is the distance between the first and last detectable surface of the plant.

The relationship between these features is given in the following equations.

$$\text{signal depth} = (p - m)\delta f \tag{4}$$

$$\text{acoustic depth} = (p - m)\delta r \tag{5}$$

$$\text{physical depth} >\approx (p - m)\delta r \tag{6}$$

where $m =$ range to nearest part of the plant causing a reflection, $p =$ range to most distant part of the plant causing a reflection, δf is the width of one FFT range bin, and δr is the equivalent range (Fig. 2).

When a plant has dense foliage, the signal may not penetrate to the far side and the acoustic depth is less than the physical depth. Such plants are characterized by a single prominent peak near the left hand end of the acoustic density profile, for example, Polyscias murrayi, in Fig. 3.

In contrast, when a plant has sparse foliage, the transmitted signal reaches the far side and the acoustic depth equals the physical depth. Such plants are characterized by large peaks at the ends of the acoustic density profile, for example Eucalyptus maculata in Fig. 3. Occasionally, a multipath echo will result in an acoustic depth that is greater than the physical depth.

The average and standard deviation of the acoustic depth of the 100 plants used in our experiments is plotted in Fig. 5. The acoustic depth varies from 42 mm to 351 mm with most of the plants being evenly spread between the two extremes. Consequently, acoustic depth can be used as a discriminatory feature. The variation of acoustic depth with 360° rotation is shown by the standard deviation.

Symmetric plants have evenly spread foliage and their acoustic depth has a low standard deviation. The acoustic depth of asymmetric plants and plants with sparse foliage has a high standard deviation. Many plants have regions of local symmetry where the acoustic depth is constant over a few degrees. Such asymmetry can be useful in determining the direction from a robot to a landmark [7].

XI. Sum of Range Lines

$$A_{tot} = \sum_{r=m}^{p} A_r. \tag{7}$$

The sum of the range lines in the window is the area under the acoustic density profile. It is the square root of the total acoustic energy reflected toward the transducer by the plant. It is proportional to the density of the foliage on the plant, with variation due to the surface size, surface orientation, and reflectivity (texture and curvature).

The amplitude of the acoustic density profile at each range is proportional to the acoustic area at that range. Thus, the sum of the amplitudes of the range lines in the acoustic density profile of a plant is proportional to the total acoustic area of the plant. The 100 plants used in this research have different values for this feature (Fig. 6).

A plant that has many large curved leaves, or many randomly oriented small leaves, will reflect a lot of energy to the transducer

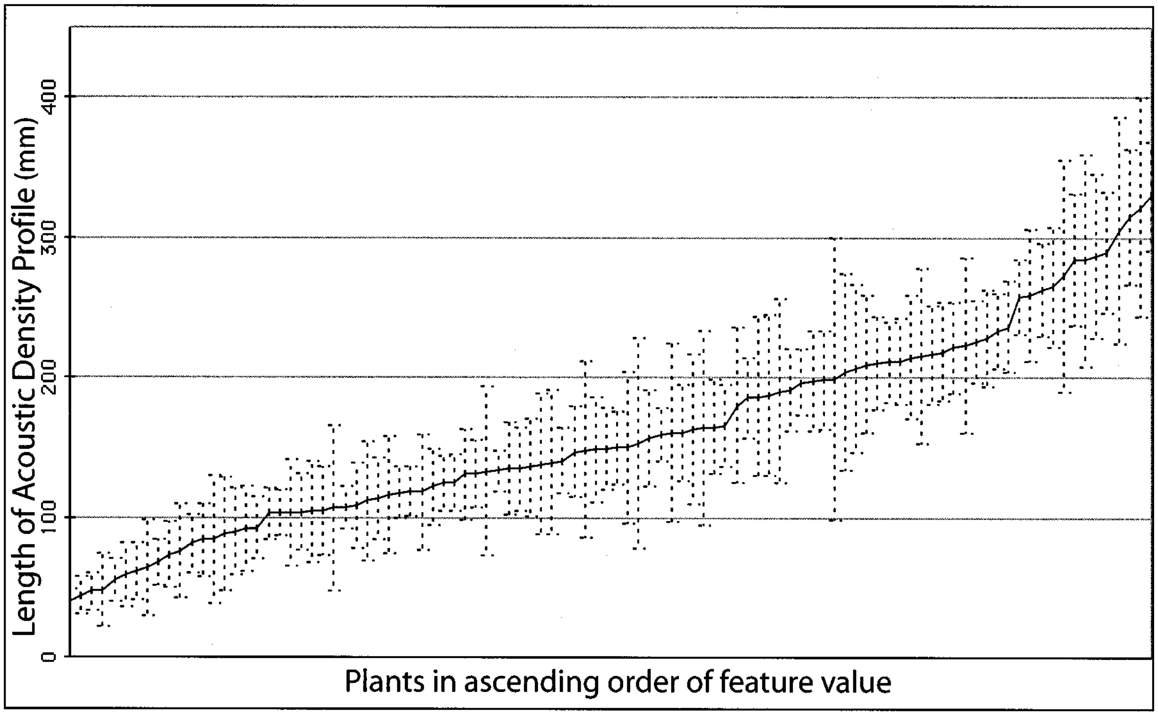

Fig. 5. Average and standard deviation for the acoustic depth of 100 plants, averaged over 360°.

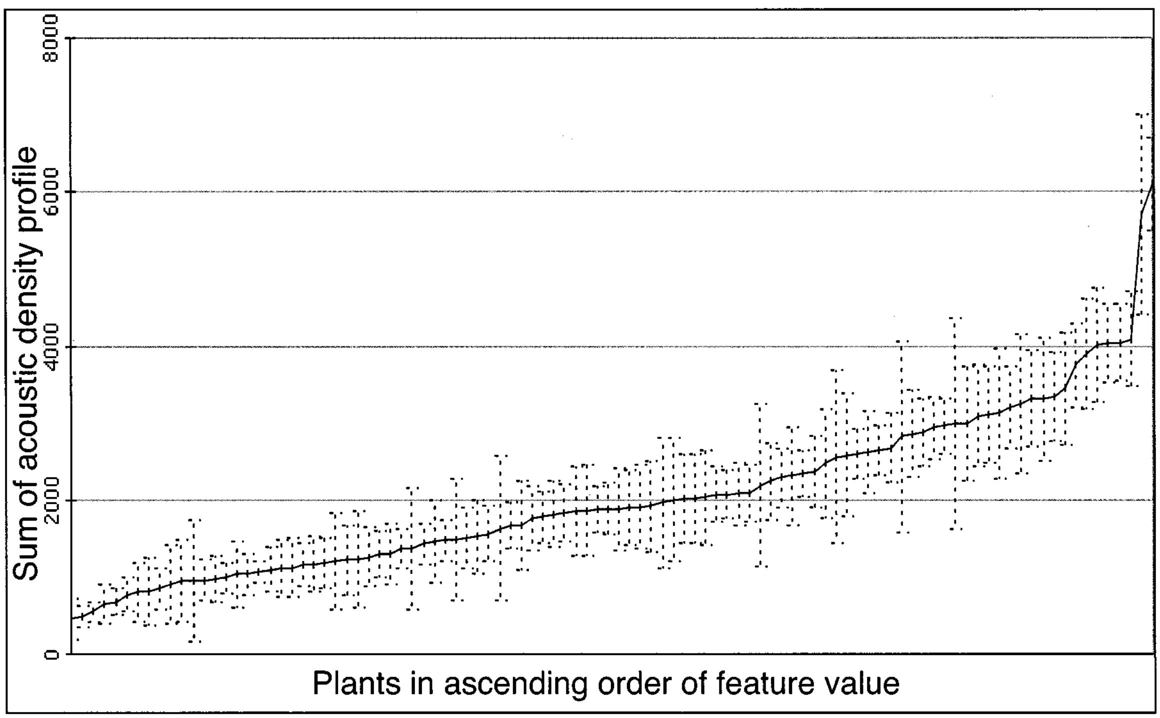

Fig. 6. Average and standard deviation for the sum of range lines for all 100 plants averaged over 360°.

resulting in a high value for this feature. A less dense plant will reflect less energy resulting in a smaller value. For example, *Microcitrus australis* (Fig. 8) is a spindly plant which reflects very little energy. In contrast, *Leptospermum laevigatum* (Fig. 9) is a bushy plant that reflects a lot of energy toward the transducer.

The effect of leaf size is more difficult to quantify. A plant with a few large flat leaves may have a high value for this feature, but it will normally have a high standard deviation. A plant with a few small leaves will have a low value and a low standard deviation.

Thus, the first transform is from the sum of the individual range lines of the acoustic density profile to the acoustic area of the plant. The second transform is from the acoustic area to the physical area of the foliage of the plant.

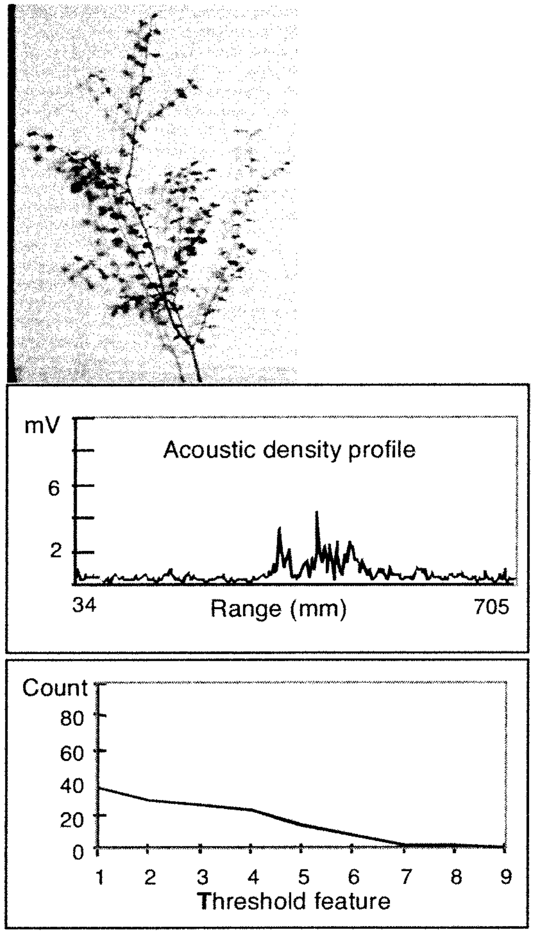

Fig. 7. Image, acoustic density profile at one orientation, and threshold curve averaged over 360° for a class a) plant: *Pittosporum James Sterling*.

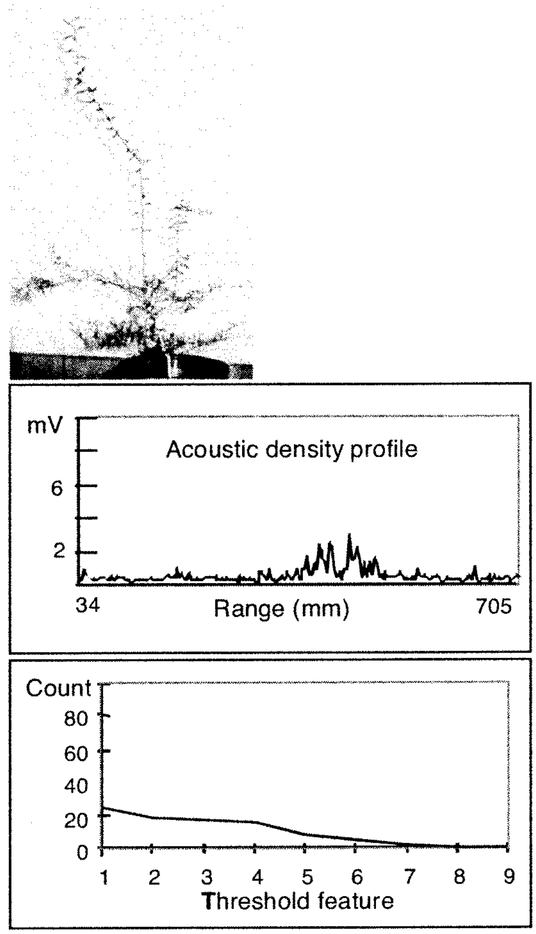

Fig. 8. Image, acoustic density profile, and threshold curve averaged over 360° for a class b) plant: *Microcitrus australis*.

XII. Threshold Features

Nine of the 19 features are counts of the number of range lines where the acoustic density is greater than a given threshold. The threshold count is the number of annuli where the density of acoustic reflectors is sufficient to return more than the threshold level of energy. Threshold features measure the foliage structure: the number, size, texture, density, orientation, and spread of reflective surfaces through the acoustic depth of the plant.

As stated in Section IV, the minimum calibration point of the sensor is the mean value of the noise when measuring empty air. Threshold 1 was set at the mean plus twice the standard deviation of the noise (0.585 mv), so that it is sensitive to very small echoes. The other thresholds are multiples of threshold 1 : 1.333* for threshold 2, 1.667*, 2.0*, 2.667*, 3.333*, 5.0*, 6.667*, 8.333*, and 10.0* for threshold 10. At 5.85 mv, threshold 10 is half the maximum amplitude of the acoustic density profile graphs plotted in this paper. In Figs. 7–11, only a small number of lines in the acoustic density profiles exceed this value. In fact, threshold 10 is not included in the final 19 features.

Threshold 9 is the highest energy level and its count is always very small. Threshold 1 is the lowest energy level and its count is always larger that that for threshold 9. As a consequence, a plot of the 9 threshold features for any plant is always a curve that slopes down and to the right (Fig. 7).

The shape of this threshold curve can be used to separate plants based on the clustering of their foliage. A plant with small leaves spread evenly through out it will have high counts for low thresholds and zero counts for high thresholds. In contrast, a plant with leaves clustered into a few range cells will have high counts for all thresholds.

The values of the threshold features are an indication of the number of leaves. A plant with a few large leaves will only have a small number of range lines and many of these will exceed high thresholds. In contrast, a plant with many small leaves will probably have high values for low threshold features and low values for high threshold features.

To determine the foliage structure of plants using threshold curves, we developed a general model of the relationship between plant foliage and curve shape. The model divides plants into general cases, with 5 cases shown in Figs. 7–11.

The curve shape is determined from the values of thresholds 1 and 9. First, we normalized these two features by dividing them by the acoustic depth of the plant. Deeper plants have more reflective surfaces resulting in higher values for all threshold features. Reducing the dependence of the data on plant depth makes the system more general.

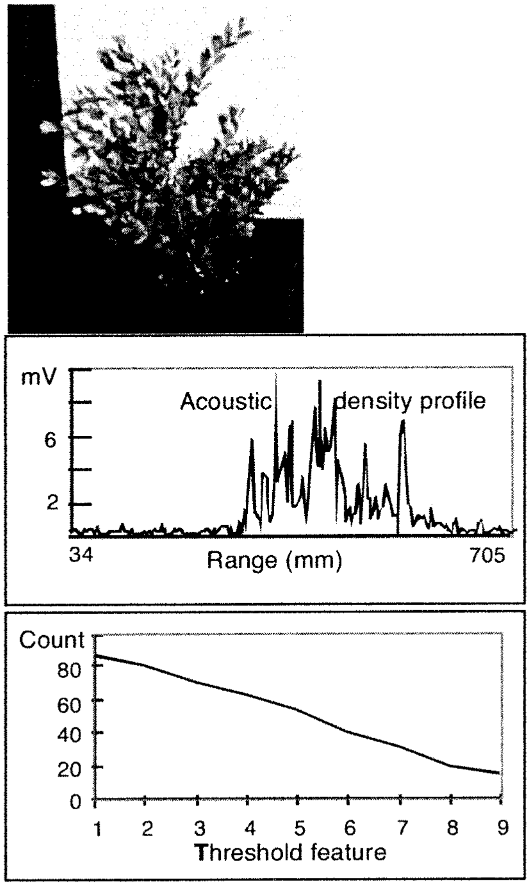

Fig. 9. Image, acoustic density profile, and threshold curve averaged over 360° for a class c) plant: *Leptospermum laevigatum*.

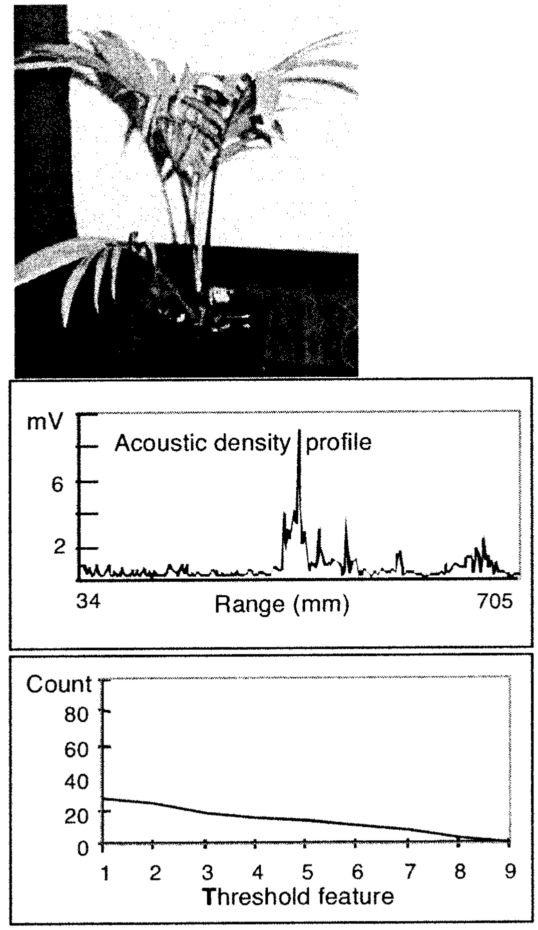

Fig. 10. Image, acoustic density profile, and threshold curve averaged over 360° for a class d) plant: *Rhopalostylis baneri*.

Second, we divided the normalized values for these two thresholds into 4 ranges: low, below medium, above medium and high. Using these linguistic divisions, we can divide plants up into 16 categories, suitable for use in a fuzzy inference system. Here, we discuss 5 common classes a)–e) that we observed in the features of the 100 plants that we studied.

a) The expected threshold values are below medium for threshold 1 and low for threshold 9. The acoustic density profile contains many low amplitude lines spread through the acoustic depth. A typical type a) plant is shown in Fig. 7. It has many small leaves spread evenly through it. To enable comparison between plants, they were sorted by normalized value for both threshold 1 and 9. The higher the rating, the higher the threshold value. The Pittosporum in Fig. 7 had a position of 33/100 for threshold 1 and 8/100 for threshold 9.

b) The expected threshold values are low for threshold 1 and low for threshold 9. The acoustic density profile has a few low amplitude lines. A typical type b) plant is shown in Fig. 8. It has sparsely spread small leaves. The Microcitrus in Fig. 8 had a position of 22/100 for threshold 1 and 12/100 for threshold 9.

c) The expected threshold values are high for both thresholds. The acoustic density profile contains many high amplitude lines spread through the acoustic depth. A typical type c) plant is shown in Fig. 9. It has a large number of small leaves, which produce large reflecting areas in each range annulus.

d) The expected threshold values are below medium for threshold 1 and below medium for threshold 9. The acoustic density profile has a few high amplitude lines. A typical type d) plant is shown in Fig. 10. It has large leaves with large open spaces between them.

e) The expected threshold values are above medium for both threshold 1 and threshold 9. The acoustic density profile is more complex than those above and contains many low and high amplitude lines spread through the acoustic depth. A typical type e) plant is shown in Fig. 11. It has a large number of medium sized leaves, which form a mixture of small and large reflective surfaces spread evenly within the plant.

This model is an attempt to develop a general description of plants based on foliage structure. In practice, the threshold values do not fall into four distinct groups, but there is a continuous range of amplitudes. As a result, some plants are on the border between two classes. For example, threshold 1 for *Microcitrus australis* (Fig. 8) is near the border between low and below medium. An analysis of real plants showed that plants with similar geometric characteristics have similar acoustic density profiles and hence similar threshold curves.

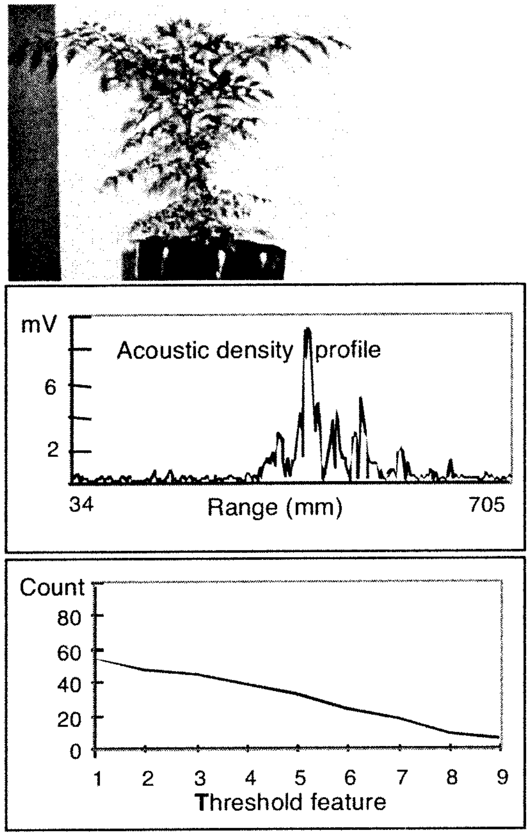

Fig. 11. Image, acoustic density profile, and threshold curve averaged over 360° for a class e) plant: *Radermacheria fenecis*.

Using the above, we may be able to build a rule based discriminator to classify plants into broad classes based on their foliage structure, and achieve a transform from signal feature to plant geometry. It may be possible to refine this system using other information in the threshold curves.

For example, many threshold curves have a knee at threshold 4 where the gentle slope from threshold 2 to 4 increases from threshold 4 to 7 (Figs. 7 and 8). This knee is most obvious for plants with a small number of small leaves.

XIII. Front to Peak Distance

The threshold features throw away the range relationship between the lines, and, hence, have no relationship to the envelope of the acoustic density profile. The ratios of two features in Table I (the front to peak distance, and the distance from the front to the range cell where the sum of the acoustic density profile reaches 75% of the total) to the length of the acoustic density profile are measures of the slope of the front of the envelope.

This slope is the rate of change of the area of the acoustic reflectors in successive annuli. This rate of change is a function of the density of the foliage and the curvature of the front surface of the plant. A large flat surface produces an echo with the highest rate of change. The front surface of a plant is a tessellation of many small surface elements. The rate of change of the acoustic area of a plant decreases as the surface curvature increases and as the density of the leaves decreases.

XIV. Number of Major Peaks in the Acoustic Density Profile

A major peak is a range line in the acoustic density profile that a) exceeds a threshold and b) is greater than n range lines on either side of it. The two features that count major peaks (Table I) have thresholds at the same level as thresholds 5 and 6 of the threshold feature set. The width of the sides of the peaks is $n = 5$, resulting in a minimum distance of 17.2 mm between major peaks. The major peaks occur at places in the plant where leaves are clustered. Thus, these features are a measure of the layering of the foliage. Often, deeper plants will have a higher number of major peaks because they have space for more layers.

Plants with a dense outer layer, such as Polyscias murrayi in Fig. 3, will only have a single major peak. Less dense plants, such as Eucalyptus maculata in Fig. 3, will have a major peak at both extremities. Plants with distinct layering in their foliage will have a peak for each layer that the ultrasonic sound penetrates.

The average and standard deviation for the feature number-of-major-peaks-1 is graphed for all 100 plants in Fig. 12. Plants on the left of the graph have a small number of peaks because they are either very narrow or are deep with only a few leaves. For example, *Melaleuca erubescens* is 60 mm in depth, but *Cordyline australis* is 600 mm in depth, yet both have only have one major peak. Plants with a high value for this feature are not necessarily the deepest, for example, *Leptospermum petersonii* which is 200 mm deep.

XV. Conclusion

When an ultrasonic chirp impinges on an object, it is scattered. The directions in which the ultrasonic sound is scattered are determined by the orientations of the surfaces of the object. The quantity of energy scattered in a direction is determined by the areas of the reflecting surfaces oriented near normal to that direction and the sharpness of the refracting edges.

The time relationship between components of the scattered ultrasonic waves is defined by the relative ranges between the scattering surfaces. The echo impinging on a receiving transducer is the superposition of the ultrasonic waves scattered in the direction of the receiver. As a result, the echo is a measurement of the geometry of the object.

When the echo from a frequency modulated chirp is demodulated, the resultant signal is a superposition of tones. The frequency of a tone is proportional to the range at which the ultrasonic sound was scattered and the amplitude is proportional to the square root of the amount of energy scattered toward the transducer. This time domain signal is decomposed into its frequency components with an FFT.

The resultant spectrum is windowed and normalized to obtain a range independent acoustic density profile for the object. The acoustic density profile is a measure of the density of acoustic scatterers in each range annulus formed by the FFT bins. From the acoustic density profile, we can extract a number of features that are useful for classifying a set of objects. In the research reported here, the objects are plants growing in pots.

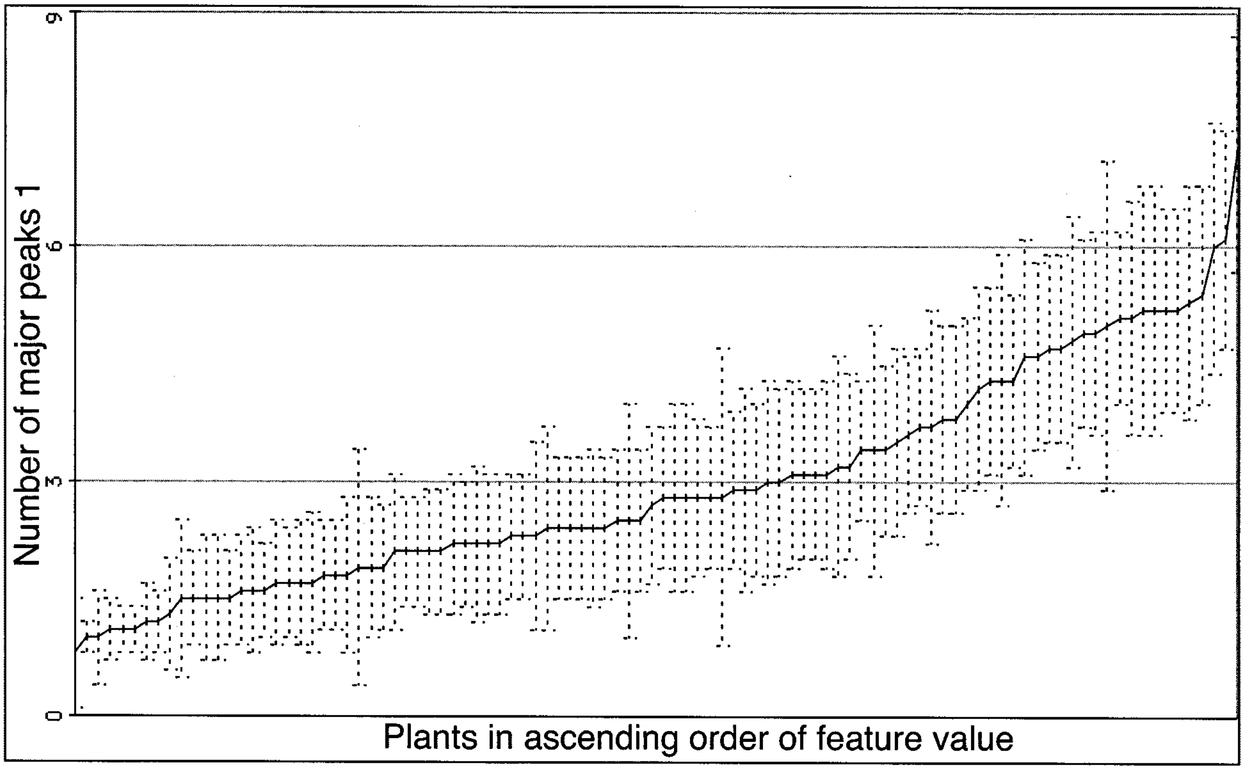

Fig. 12. Average and standard deviation of the feature number of major peaks 1 for all 100 plants averaged over 360°.

The measurement process is a forward transform from geometry to acoustic density profile. The extraction of features is an inverse transform from echo signal to acoustic features to object geometry. In the case of plants, we have been able to transform some of the signal features into geometric features representing plant foliage structure. These transformations include

a) the length of the acoustic density profile is the acoustic depth of the plant;
b) the standard deviation of the acoustic depth is a measure of plant symmetry;
c) the count of range lines with amplitudes above thresholds 1 and 9 measure the density and spread of the foliage through the plant,;
d) the slope of the front of the envelope is a measure of the density of the foliage;
e) the number of major peaks measures the layering of the foliage;
f) the sum of the lines in the acoustic density profile measures the acoustic area of the plant.

In combination, these features measure the geometric structure of the plant: depth, layering of foliage, density of foliage, amount of foliage, and leaf area. The quality of these features for recognizing plants, classifying plants or discriminating between plants depends on the constraints of the application. These constraints include the number of plants, the similarity of the plants, and the orientation over which the plants are to be sensed. Usually, several features are needed to get good results with a statistical or neural network classifier [5].

We have not found a transform to discriminate between large and small leaves. The inverse transform from acoustic density profile to geometry shows that information about the geometry of a plant can be obtained from its echo.

In further research, we are looking at the issues of applying the results of this research to landmark navigation and to discriminating between weeds and plants in a market garden. Moving from isolated plants, used to develop the model in the laboratory, to plants in real environments raises the issues of background clutter, plant overlap and plant changes with growth.

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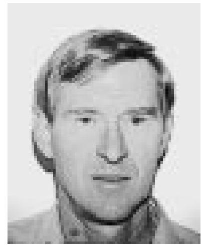

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