Texture Analysis: A Technique for Autonomous Lawnmower Navigation*

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2001 Florida Conference on Recent Advances in Robotics
May 10-11, 2001, Florida A&M / Florida State University

*Partly sponsored by the Department of the Navy, Coastal Systems Station, under Grant No. N61331-01-1-G002. The content of the information does not necessarily reflect the position or the policy of the Government, and no official endorsement should be inferred.

Abstract

Mowing a lawn can be a difficult and tedious chore. The goal of this paper is to introduce the idea of using the visual property of texture to design an autonomous lawnmower robot that mows a lawn similar to how a human would (in some type of pattern.) Previous autonomous lawnmowers that have been designed, the LawnNibbler and LawnShark for example, rely on the principle of randomness to mow in a confined area. While this method will work, it will take an extraordinary amount of time. This paper first presents an overview of texture segmentation and then the wavelet transform is introduced. Texture analysis will be accomplished by use of the wavelet transform. The current state and future research of this project are then presented.

Introduction

The goal of this project is to design an autonomous lawnmower that safely and effectively mows an area typical of a homeowner's yard. The previous versions of autonomous robot lawnmowers that were designed relied on the principle of randomness to mow an area. Thus they had no realization where they had mowed or didn't mow. The premise was as follows: given a long period of time, eventually the vast majority of the mowing area would be cut. Obviously this process would take considerably longer than if a human had mowed the same area, but the point was (and still is) that the human did not have to perform the task.

The main effort of this research is to design a robotic lawnmower that mows similar in fashion to how a human would mow. This could be mowing in a plow type fashion (going back and forth) or starting at the outside of the perimeter of the mowing area and then working towards the center of the mowing area. In order for the mower to determine where the mower has cut and not cut, computer vision with image processing techniques will be used. Instead of attempting to identify specific objects in the mowing area (trees, hedges, sidewalks, etc.) the image will be segmented according to the different textures in the image. A probabilistic model for the texture of grass will then be constructed. This will enable the mower to recognize where the grass is in the mowing area.

Image segmentation will be carried by means of the wavelet transform. Certain properties of the wavelet transform will also be used to allow the mover to mow in a pattern rather than just mowing randomly in the mowing area.

Texture Segmentation

Texture is an important quality to consider when examining the content of an image. Practically every object (natural or man made) contains some texture on the macroscopic level. Thus, the use of texture information would be a practical means of segmenting objects in an image.

It would also be highly infeasible and impractical to recognize every object in the mowing area. These objects could be such things as trees, shrubs, sidewalks, flowers, etc. Being able to correctly identify just one object could possibly take seconds to compute, let alone several objects. Also, it is not important to be able to recognize objects by being able to identify every object distinctly, but so long as the robot is capable of knowing what is grass and what isn't is enough to enable it to accomplish the goal of mowing as a human would.

Thus, the property of texture was chosen to accomplish this task. Figure 1 below shows some examples of different textures. They are all from the Brodatz texture database. Figure 2 shows a sample result of texture segmentation. This is what an "ideal" segmentation would look like.

Once the objects in an image are segmented based on their texture, every pixel in the image can be assigned a label indicating which region it belongs.

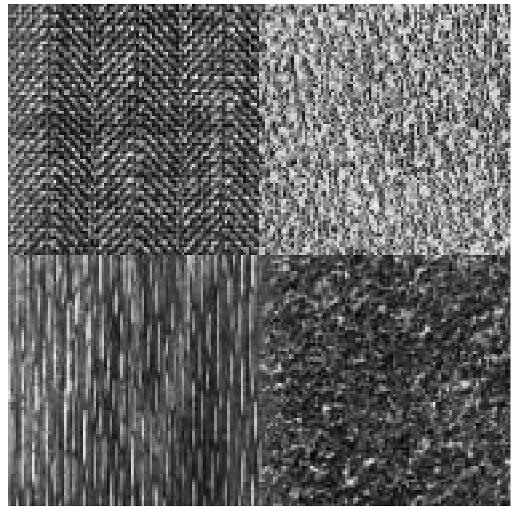

Figure 1: Some sample Brodatz textures. From upper left going clockwise, D17: Herringbone weave, D24: Pressed calf leather, D68: Wood grain, D29: Beach sand.

Furthermore, each texture in the image can then be compared to a database in order to recognize what type of texture it

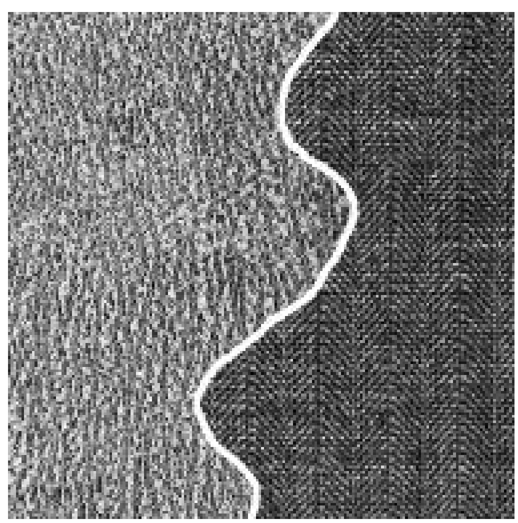

Figure 2: An example of texture segmentation.

is. This can be thought of as "texture classification." As stated earlier, the main texture of interest for this research is that for the grass in the mowing area. This classification could possibly be carried out by means such as a neural network or Bayes classifier.

So far, this section has focused on segmenting an image based on texture information alone. However, how does one represent texture? Texture can be represented by using a statistical approach or using a spatial/frequency approach [1]. For this project, texture will be represented using a spatial/frequency approach by use of the wavelet transform.

Wavelet Transforms

Wavelet transforms can be thought of as a multi-resolution decomposition (multiple scale signal view) of a signal into a set of independent spatially oriented frequency channels [2][3]. The theory behind wavelets is quite complex. However, the wavelet can be simply thought of as a band-pass filter. To begin a wavelet analysis, one starts with a *prototype* wavelet, it is the "mother wavelet" from which all other wavelets are constructed. High frequency (contracted) versions of the prototype wavelet are used for fine temporal analysis while low frequency (dilated) versions are used for fine frequency analysis [2].

For this research, the discrete wavelet transform (DWT) will be used. To compute the (one-dimensional) DWT, a input vector *x* (length 2n) is first convolved with some discrete time low-pass filter (LPF) of some given length, and then it is convolved with some discrete time high-pass filter (HPF) of some given length. Figure 3 below shows the first step in computing the DWT, first low-pass filtering.

As can be seen, the filter is moved in increments of two along the length of the input vector, *x*. This is equivalent to

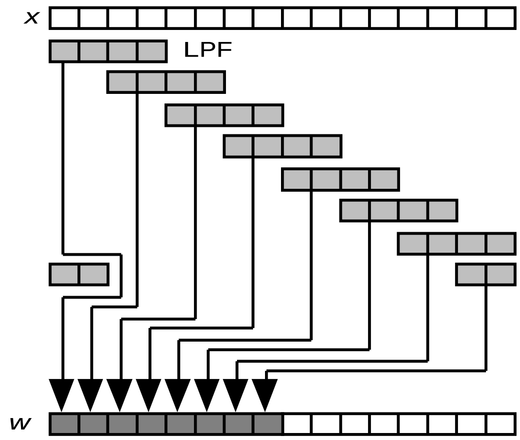

Figure 3: First step in computing the 1-d wavlet transform: low pass filtering (in increments of two) on an input signal x.

downsampling by a factor of two. The resultant vector produced is half as long as the original input signal *x*. Next, as shown in Figure 4, the input vector x is then convolved with a discrete time HPF

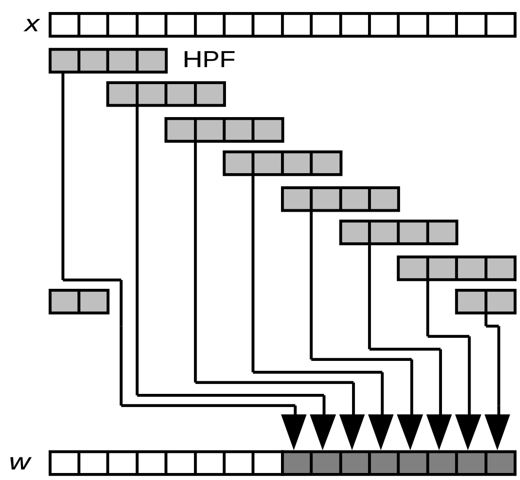

Figure 4: Second step in computing the 1-d wavelet transform: high pass filtering (in increments of two) on an input signal x.

in the same manner as the LPF. However, the result of these convolutions are placed in the second half of the *w* vector. This is considered as a first level wavelet decomposition. This process can be continued again and again, each time working with the previous generated vector as the input to the next level. This process is illustrated in Figure 5 shown below. Because each level decreases the length of the workable vector by a factor of two, this process cannot be continued forever.

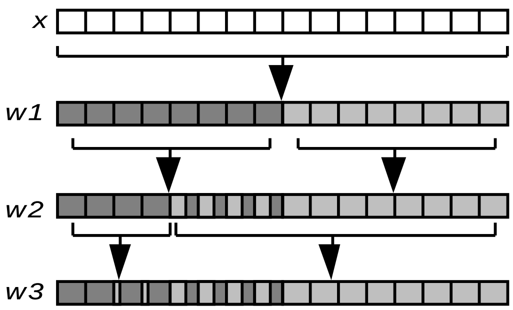

Figure 5: Three level wavelet transform

Another way to convolve the input vector with the discrete time filters is to not subsample the output at every level. This is known as an overcomplete wavelet decomposition [4]. This has tremendous advantages when wavelet transforms are used for texture analysis. When performing texture analysis, an algorithm that is invariant due to translations in the input image would be highly desirable. Shifting of the input signal (as is done with the method stated earlier) will result in a modification of the wavelet transform [4]. By performing an overcomplete wavelet transform, this should eliminate this problem [1].

Up till now, there has been no mention of what types of filters would be good to use in a wavelet analysis for the low and high pass filters. One type of filters that are commonly used is the Daubechies. For the purposes of this research, Lemarie-Battle wavelets are currently being investigated. These wavelets (filters) exhibit the property of being Quadrature Mirror Filters (QMF). Such types of filters are preferred due to the fact that the filters generated from the prototype will not exhibit a multi-lobe property [1]. Also, Lemarie-Battle wavelets are symmetrical providing better accuracy in texture boundary detection [1].

Once an appropriate prototype filter has been chosen, other filters must be generated from the prototype. Typically, the high pass filter is generated from the low pass one by shifting it in the frequency domain. For example:

$G_0(\omega) = H_0(\omega + \pi)$ or alternatively,
$g_0(n) = (-1)^n h_0(n)$.

where H/h represents the low-pass filter and G/g represents the high-pass filter.

Now that the type of filters have been specified, the input signal can then be decomposed into wavelet packets. One type of decomposition is shown in Figure 7 below. This type of decomposition is referred to as a balanced tree wavelet decomposition [5]. The “basis” functions that result from such a decomposition are referred to as wavelet packets. The filters for levels 1, 2 ,….. can be constructed by inserting the appropriate number of zeros between the filter coefficients for the prototype filters.

All of the material on wavelet transforms up to this point has been for the one dimensional case. However, when dealing with images (or higher dimensions) a tensor product extension can be used [4]. A tensor product extension can be thought of as a

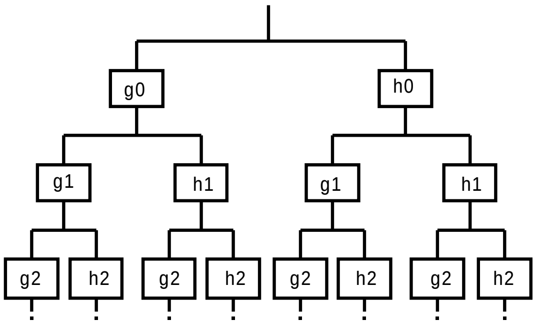

Figure 6: "Balanced" tree for wavelet decomposition.

crossproduct. Thus, four distinct types of 2D filters (basis functions) result from the crossproducts of the high and low pass filters: LL, LH, HL, HH (where LL = low-pass low-pass, LH = low-pass high-pass, etc.). For images, the decomposition can be carried out be means of successive one-dimensional processing along the rows and columns of the image. For example, if one wanted to compute the LH basis function, one would process the rows of the image with the low-pass filter and then process the columns of the result with the high-pass filter.

Current Research

Currently, software has been written to allow the 2-dimensional (overcomplete) wavelet transform to be performed on an input image. The level and type of wavelet transform basis function can be specified. The data that is produced is then written back in a .ppm (portable pixel map) image format after the data has been scaled.

As discussed earlier, the input image is decomposed as shown in the wavelet decomposition tree shown in Figure 6. However, not all sub bands need to be computed. Only those that show a level of "high activity" need to be computed and retained when performing texture analysis on an image. Thus, some method of determining the level of the activity in a particular basis function needs to be implemented. Also, after the selected basis functions have been selected, some form of discriminate function needs to be employed to separate out the different regions of texture. Finally, the separated textures must be classified.

To mow as a human would, the robot must know more than just where the grass is in the mowing area. Typically, humans key off of the boundary between the cut and uncut lawn as a guide on where to make the next pass. An additional property that wavelets bring to the table is that the 2D basis functions (LL, LH, HL, HH) exhibit orientation selectivity [6][7]. The LH filter tends to preserve horizontal features while the HL filter tends to preserve vertical ones. This additional property could be exploited to enable the mover to "see" the boundary between the cut and uncut lawn by looking for vertical features in the lawn area.

As an illustrative example of this, Figure 7 below shows a sample "cross" image. The next two figures show the cross mage after filtering the image with the LH and HL 2D filters respectively.

As can be seen in Figure 8, there are lines where the vertical features in the image are, namely the vertical boundaries of the cross.

Figure 9 shows the result of filtering the cross image with the 2D LH filter. In this figure, one can see the horizontal lines representing the horizontal sections of the cross.

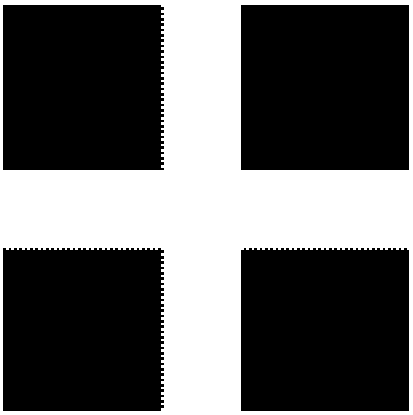

Figure 7: Sample “cross” test image.

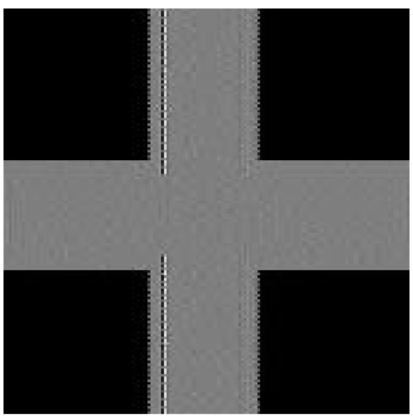

Figure 8: Cross image after processing the “cross” image with the 2D HL filter.

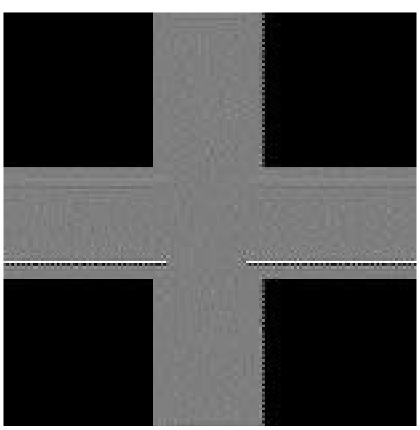

Figure 9: Cross image after processing the “cross” image with the 2D LH filter.

All of this aside, before any image processing can occur, one needs to obtain data from a camera. Typically this requires computer hardware know as a frame grabber. They can tend to be quite expensive and very proprietary. To overcome these problems, a custom NTSC video digitizer was constructed.

This video digitizer was designed as part of a research grant for Coastal Systems Station (Naval Surface Warfare Center) in Panama City, FL. This digitizer interfaces via the PC’s parallel port utilizing the EPP mode. It accepts any NTSC standard video signal. Figure 9 is an image of the video digitizer (taken with the digitizer itself using a Sony Handycam camcorder). Figure 10 is an image of the author of this paper, again digitized using the video digitizer.

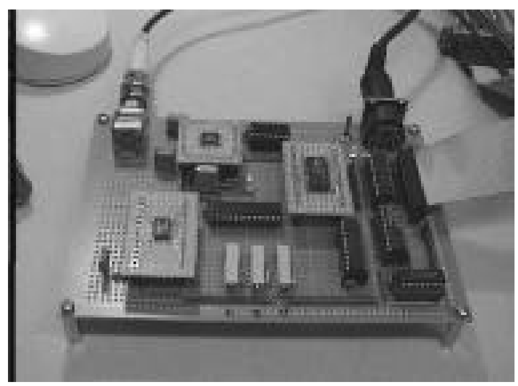

Figure 10: picture of the custom video digitizer board (prototype) taken with the board itself

The control software was written in the LINUX operating system. Currently it digitizes in B&W, but that should be sufficient for identifying textural information. A color version may be designed in the future. The additional color information could be used to augment the reliability of the textural image segmentation.

Figure 11: Picture of the author of this paper taken with the custom video digitizer.

Future Work

After the software has reached the stage whereby an image (typical of a mowing environment) can be segmented according to its texture, a robot platform will be constructed. This platform will house all of the hardware (camera, digitizer, embedded PC, etc.) to allow the mower to mow as a human would. Other sensors such as InfraRed (IR) detectors and sonar will be used to allow the mower to detect obstacles if it should encounter one. The hope is that by having the robot key off the texture of grass, the robot won't have to rely on such things as electric pet fences or other devices to keep it contained within a defined perimeter. Also, this should enable the robot to avoid obstacles such as trees, bushes, etc.

References

[1] A. Laine, J. Fan. "An Adaptive Approach for Texture Segmentation by Multi-channel Wavelet Frames", University of Florida, Center for Computer Vision and Visualization, Aug. 1993.

[2] M. Vetterli. "Wavelets and Filter Banks: Theory and Design" IEEE Trans. on Signal Processing, Vol. 40, No. 9, Sept. 1992, 2207-2232.

[3] K.W. Abyoto, S.J. Wirdjosoedirdjo, T. Wantanabe. "Unsupervised Texture Segmentation Using Multiresolution Analysis for Feature Extraction 東京情報大学研究論集 Vol. 2, No. 1, 1998, 49-61.

[4] M. Unser. "Texture Classification and Segmentation Using Wavelet Frames" IEEE Trans. On Image Processing, Vol. 4, No. 11, Nov. 1995, 1549-1560.

[5] R.M. Rao, A.S. Bopardikar. "Wavelet Transforms: Introduction to Theory and Applications" Addison Wesley, 1998.

[6] A. Laine, J. Fan. "Frame Representation for Texture Seperation" Center for Vision and Visualization, University of Florida.

[7] M. Necybya. "Brief Introduction to Wavelets" Class notes, EEL6668, Fall 2000, University of Florida.