P2.2 Segmenting Radar Reflectivity Data using Texture

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Abstract

A novel method of performing multiscale segmentation of radar reflectivity data using statistical properties within the radar data itself is introduced. The method utilizes a K-Means clustering of texture vectors computed within the reflectivity scan.

Splitting an image into several components, by assigning one of these components to each pixel in the image, is termed image segmentation. The traditional way to segment radar reflectivity images is to term contiguous areas within a reflectivity band, for example all adjoining gates with reflectivity values between 40 and 45 dBZ a "cell" or a region (Johnson et al., 1998). There are numerous problems with such hard thresholds. These have typically been resolved heuristically, using runs with tolerances (Johnson et al., 1998) or using fuzzy logic (Lakshmanan and Witt, 1997).

In this paper, we present a more sophisticated approach that uses, besides the actual reflectivity value within a gate, the distribution of reflectivity values around that gate. This distribution is used to cluster similar pixels together (Lakshmanan et al., 2000).

1. Introduction

Many image processing algorithms and techniques lend themselves to a concept of scale – that the results of the analysis would be different if one were concerned with a different level of detail. Radar data algorithms (e.g: Wolfson et al. (1999); Johnson et al. (1998)) have typically focused on a single scale in isolation. Here, we introduce a method of extracting all the scales from an image at once in such a manner that there is an explicit, hierarchical relationship between the segmented results at different scales.

This is, however, not the way multiscale segmentation is commonly approached. Multiscale segmentation usually refers to segmentation performed on images that have been blurred to different degrees. Traditionally, multiscale segmentation is done in one of two ways. Image pyramids where wavelets or filter banks are employed to obtain the image at different scales (with the original image as the most fine resolution available). Each of these images is then segmented. The second way utilizes quadtree decomposition where the entire image is assumed to be a single region, then split into smaller regions, on each of which the process is repeated. Similar regions are merged at each stage.

Typically, the relationship between the segmented regions at the different scales are of no interest. If they are, then components at different scales have to be associated in some, often heuristic, manner. In this paper, we present a multiscale segmentation method that yields a hierarchically arranged tree such that the relationships between regions at different levels of the segmentation is explicit.

2. K-Means Clustering

Images are segmented using an iterative hierarchical segmentation method. A vector of textural measurements are associated with each pixel. As in Lakshmanan et al. (2000), we used a common set of neighborhood statistics (mean, variance, coefficient of variation, skewness, kurtosis, contrast and homogeneity).

The images were then requantized to a fixed number of levels using K-Means clustering. It should be empha-

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sized that this fixed number of levels ("K" in the K-means clustering) is not the number of regions in the resulting segmentation. The number, K, is the number of levels into which the image is requantized. The requantization is an iterative process that makes use of K-Means clustering to partition the image values into the K bins.

The measurement space (the radar reflectivity values of the gates) was divided up into K equal intervals and each pixel was initially assigned to the interval in which its reflectivity value lay. A Markov assumption, that a pixel belongs to the same interval as its neighbors, was imposed. In each iteration, the best label for each pixel in the image was chosen based on a cost factor that incorporated two measures. The first measure is the Euclidean distance, $d_m(k)$, between the texture vector at that pixel and the cluster mean of the candidate k, given by:

$$d_m(k) = \parallel \mu_k^n - T_{xy} \parallel \tag{1}$$

where μ_k^n is the cluster mean of the k^{th} cluster at the n^{th} iteration and T_{xy} the texture vector at the pixel (x, y). The second measure is a contiguity measure, $d_c(k)$, that measures the number of neighbors whose labels differed from the candidate label k, and is given by:

$$d_c(k) = \sum_{ij \epsilon N_{xy}} (1 - \delta(S_{ij}^n - k)) \tag{2}$$

where S_{ij}^n is the label of the pixel (i, j) at the n^{th} iteration and N_{xy} is the set of 8-neighbors of the pixel (x, y). Then the choice of the label for the pixel (x, y) in the $(n + 1)^{th}$ iteration, S_{xy}^{n+1}, is given by the label $k \epsilon S_{N_{xy}}^n$ for which the energy, $E(k)$, given by:

$$E(k) = \lambda d_m(k) + (1 - \lambda) d_c(k) \tag{3}$$

is minimum. We used $\lambda = 0.6$ for all the images. The candidates that were considered were the labels at the n^{th} iteration of the pixels within the 8-neighborhood of (x, y). At the end of each iteration, the cluster attributes (the μ_k's) were updated based on all the pixels that were labeled as belonging to the cluster at that time.

The requantization, then, consists of these steps: (a) Initialize the K means somehow – we simply divided up the measurement space into equal intervals. (b) Assign the closest mean to each pixel. (c) Start iterating on the clustering scheme by reassigning pixels based on the Markov assumption. (d) Iterate until stable.

At this point, the image has been requantized, but the quantization has taken the spatial arrangement of pixel values into account. A region growing algorithm is employed to build a set of connected regions, where each region consists of 8-connected pixels that belong to the same K-Means cluster. If a connected region is too small, then its cluster mean (the mean of the texture vectors at each pixel in the region) is compared to the cluster means of the adjoining regions and the small region is merged with the closest mean. This process is repeated until the regions are such that all cluster means have reliable statistics. In practice, we considered a region too small if it had less that 15 contributing textural measurements.

The result of the K-Means segmentation, region growing and region merge steps is the most detailed segmentation of the image. From this point onwards, we work exclusively in the domain of the segmented regions. The inter-cluster distances of all adjacent clusters (or regions) in the image are computed. A threshold is set such that half the pairs fall below this threshold. An iterative region merging is carried out whereby if a pair of clusters differ by less than this threshold, they are merged. More or less than half the clusters in the image may get merged because the cluster means are updated at the end of each merge, resulting in a different number of pairs which are closer than the threshold. The region merges are stopped when none of the resulting pairs of adjoining regions are closer than the threshold. The segmentation result at this point is the next coarser segmentation.

Because the results of segmentation at the second stage are formed by region merges only, every region in the coarse segmentation completely contains one or more regions in the detailed segmentation. Thus, there is a hierarchy of containment between the segmented results at these two scales. The inter-cluster distance threshold is relaxed steadily, set at each iteration to be of a value such that half the cluster pairs are closer to each other than the threshold. This process is repeated until the segmented results are stable. The result of the segmentation at each stage gives one level of the hierarchical tree.

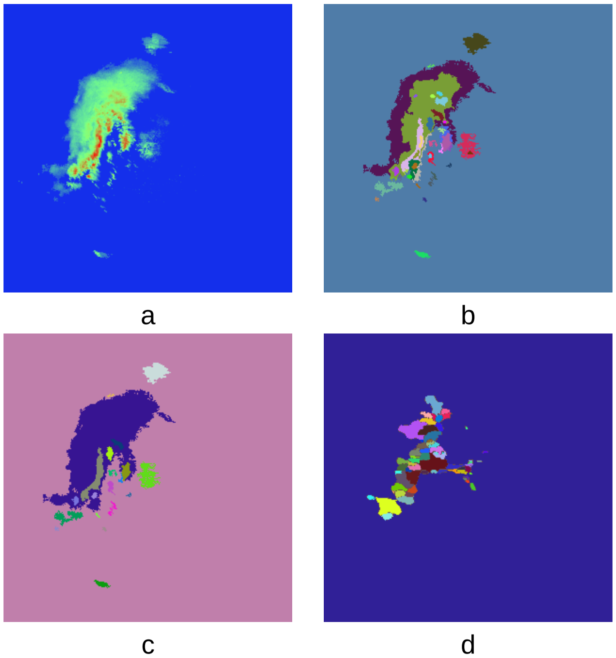

Figure 1: Segmenting a radar reflectivity image. (a) A radar reflectivity image, from Fort Worth May 5, 1995. (b) The result of segmenting the image using the merging K-Means clustering method of this paper. The most detailed scale is shown. (c) The next higher scale of segmentation using the method of this paper. (d) Using a segmentation approach that doesn't use texture, in this case, the watershed segmentation approach of Najman and Schmitt (1996).

3. Results and Discussion

We wish to segment the reflectivity moment of radar elevation scans. The data have been mapped from polar coördinates into a Cartesian grid tangential to the earth's surface at the radar location and where each pixel is a square area of one kilometer on each side. The pixel values, in dBZ, range from about $-7dBZ$ to about $64dBZ$, with the reflectivity values for some pixels missing. Missing values and all reflectivity values less than $0dBZ$ were thresholded to be $0dBZ$ before the segmentation process.

A single 0.5-degree elevation scan of radar reflectivity data collected by the Weather Service Doppler Radar (WSR-88D) at Fort Worth, TX on May 5, 1995 was used to compare the segmentation results of the various techniques. The results are shown in Figure 1.

The major advantage of working within the space of the segmented regions when doing a multiscale segmentation is that the resulting segmented results automatically form a hierarchical tree. This is extremely useful in such applications as tracking – tracking of large regions can be done robustly and the movement of more detailed regions can be constrained to lie within the large regions (adjusted for inter-frame movement) that contain them.

Current work is focused on utilizing the results of this segmentation approach in robustly tracking storms in radar reflectivity images, as well as in satellite weather images. This method is also being extended to three dimensions, to deal with the 3D volume nature of radar reflectivity data.

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