Multiscale Storm Identification and Forecast

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Abstract

We have recently developed a hierarchical K-Means clustering method for weather images. Using this technique, it is possible to identify storms at different scales. In this paper, we will describe an error-minimization technique to identify movement between successive frames of a sequence and show that we can use the K-Means clusters as the minimization kernel. Using this technique in combination with the K-Means clusters, we can identify storm motion at different scales and choose different scales to forecast based on the time scale of interest.

We will show examples of this storm identification and forecast in action on weather radar images.

1. Method

What follows is a short description of an agglomerative texture segmentation technique where the outputs at each stage of the agglomeration is one layer of a dendrogram or hierarchical tree. For more details on the technique, the interested reader is referred to Lakshmanan (2001). Images are segmented using an iterative K-Means segmentation method that yields a hierarchical representation of the regions at different scales. We follow the K-means clustering stage with a region growing step where connected pixels belonging to the same cluster are labeled the same. This ensures that we need not know the number of textures before hand, since K is only an intermediate step to finding the number of regions in the image. A final step uses the Euclidean distance between the mean texture vectors of statistically unsound regions and their statistically sound neighbors to yield a robust segmentation at the finest level of detail. Having obtained the most detailed segmentation, we use the

available inter-cluster distance measurements between every pair of adjoining regions in a dyadic manner to successively merge regions.

2. Weather Radar Images

We wish to segment the reflectivity moment of radar elevation scans. The data have been mapped from polar coordinates into a Cartesian grid tangential to the earth's surface 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.

We segment the reflectivity moment of radar elevation scans obtained from Doppler Weather Service Radar (WSR-88D). The weather surveillance radars used by the National Weather Service scan through thunderstorms starting at a low elevation angle, 0.5° for Volume Coverage Pattern (VCP) 21, and after completing a full 360° azimuthal sweep, progressively increase the elevation angle until an upper limit is reached (19.5° in VCP 21). See Figure ?? Crum and Alberty (1993); Smith (1995).

Depending on the VCP, a new radar volume is collected every 5-12 minutes. The volumes of data in this study were collected every 5-6 minutes. In future work, we will extend the clustering technique discussed in this paper to three dimensions to better segment the data. In a real-time test, several weather algorithms, including our segmentation and tracking algorithm, are run on a single workstation. We found that with some optimization of the processing, it is possible to run the segmentation and tracking algorithm in real-time. The algorithm takes

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 method of this paper, tweaked to process the reflectivity range of interest. The most detailed scale is shown. (c) The next higher scale of segmentation using the method of this paper.

about 30 seconds to process an elevation scan of data.

The data were remapped to a Cartesian plane and were then segmented using the K-Means clustering technique described in Lakshmanan et al. (2001) and in Section 1..

3. Satellite Infrared Images

We demonstrate results of segmenting the infrared window channel (11μ) of GOES satellite imager data. The images are 200×300 with each pixel representing a $4km \times 4km$. The images are projected onto a plane tangential to the surface of the earth. The satellite data were collected over the continental United States using GOES-10 on March 29, 1998. The pixel values were also mapped from radiance values to temperature in degrees Kelvin before the segmentation. Images of the sequence are available at eight minute intervals.

The sequence of satellite images captures a day of significant thunderstorm activity. Several thunderstorms grow and decay during the day and the temperatures of the cloud tops in the images show corresponding changes both in storm geographical extent and in storm severity. Segmentation of this sequence should be able to consistently identify the thunderstorms in the images. Ideally, when storms split or merge, the corresponding segmented regions should do the same. A very important requirement is that small changes in the storm struc-

Figure 2: Using multi-channel satellite data for segmentation. (a) 3.9 micron infrared (b) 6.7 micron water vapor. Due to space constraints, the (c) 11 micron window and (d) 12 micron dirty window channels of data are not shown. (e) Most detailed segmentation using only the 11 micron image (f) Most detailed segmentation using all four channels. The segmentation is more detailed than the segmentation that was achieved in (e), but whether these extra details are useful is yet to be determined.

ture should be reflected as small changes in the segmented region corresponding to the storm.

Studies Browning (1979); Bellon and Zawadzki (1994) have shown that a single storm cell grows and decays in under an hour. Therefore, a storm cell can be expected to stay for no more than seven frames of the satellite sequence. However, a line of thunderstorms within which these cells crop up can be expected Browning (1979) to persist for up to six hours. Therefore, the segmentation should lend itself to segmenting regions corresponding to larger scale features while identifying small scale features that are contained within the large scale feature.

Identification and tracking algorithms for satellite weather imagery have been implemented for mesoscale convective systems Morel et al. (1997) – where the features of interest (storm anvils colder than 240K) are on the scale of about $10,000 \text{ km}^2$. Our goal, however, is to identify storm scale features, features on the scale of about 10 km^2 .

The poor spatial resolution of the satellite image affects our algorithm also, in the scale of features that we can detect. Although we can detect features as small as 10 pixels in the image, this translates to about 40 km^2 , a mid-size storm cell (although significantly more detailed than what could be obtained using earlier approaches). The pruning threshold of 10 pixels was set in the algorithm so that any statistics collected are somewhat reliable. One possible way to relax this threshold is by creating a pseudo-high resolution form of the original image, thus getting less square kilometers in the 10-pixel threshold. Unfortunately, on satellite weather images, even a pseudo-high resolution technique Yao (1999) introduces unacceptable smoothing Lakshmanan (2001), resulting in worse performance. A second possibility, one that we have not yet looked into because of the prohibitive cost for a continuously running system, is to obtain weather satellite data that has higher spatial resolution. A third possibility is to use the multi-channel nature of satellite weather information to form the pixel representation (instead of using a texture vector based on neighborhood statistics).

Instead of using only texture measurements from only the infrared channel, we used texture measurements (mean and variance) computed on four channels corresponding to 3.9, 6.7, 11 and 12 microns (near infrared, water vapor, window and “dirty window” respectively).

Since every pixel of the segmented output actually corresponds to four independent measurements (rather than just one), the minimum pruning size in the algorithm can be reduced from about 10 pixels to about 3. The result of using multi-channel information and a lower size threshold is shown in Figure 2 where it is compared to the segmented result if only the 11 micron image had been used.

Notice that the result of segmenting using all four channels (Figure 2f) has smaller regions than the result that uses only the infrared window channel. It is not clear, however, how significant these smaller features are in the context of thunderstorms.

4. Motion Estimation and Forecast

5. Conclusions

It is possible to use statistics computed in the neighborhood of the pixels of weather images, both radar and satellite, as texture measurements for the purposes of segmentation. A hierarchical texture segmentation technique, where regions identified in successive stages are agglomerated together (see Lakshmanan (2001) for a detailed discussion of the technique), provides a tree representation of the storm structures in the images. The method described here is an improvement over existing segmentation algorithms for weather data in the following ways. It allows reliable tracking of features from frame to frame. On satellite images, it allows for the identification of features in the storm scale, as small as 40 km^2 . On radar images, features as small as 10 km^2 can be identified. It is possible to identify smaller features in satellite images, features of about 10 km^2 , if one uses several channels of satellite imagery, but more study is required to ascertain the significance of these smaller features.

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