SPATIAL AND TEMPORAL ANALYSIS OF WEATHER RADAR REFLECTIVITY IMAGES

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ABSTRACT

This paper illustrates the use of a primitive symbolic description of an image to obtain more robust identification of amorphous objects than would be possible with more conventional edge or gradient-based segmentation techniques. An algorithm is described which uses a simple multi-level thresholding operation to form a symbolic representation of weather radar reflectivity images. This representation allows the use of detailed rules for the detection and quantification of the image features. A method is described for using this information to identify significant intensity peaks in an image, and examples of its performance are shown.

INTRODUCTION

This paper discusses the initial results of an effort to develop automated algorithms for the interpretation of time sequences of radar images of thunderstorms. The radar images are acquired at regular intervals in time, as the radar scans through a sequence of elevation angles (Figure 1). The information thus obtained depicts the time evolution of the three-dimensional structure of the storms being observed. An automated interpretation and analysis capability is desired for use in the detection of weather events which may be hazardous to aviation, and in particular, to the identification of storm cells which may give rise to microbursts (small scale downdrafts which hit the Earth's surface and cause a strong divergent outflow of wind).

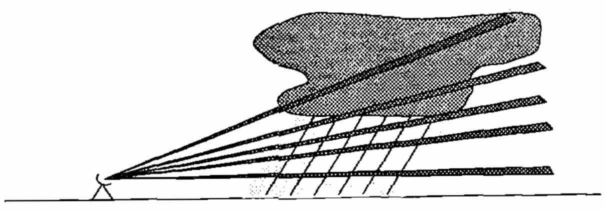

Figure 1: Weather radar data acquisition scenario

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The primary goal of the interpretation process is to locate the storm cells present in the image sequence, and identify those characteristics which are important in determining the storm severity and likelihood of producing a microburst. One such characteristic is the height vs. time profile of the storm reflectivity [1]. This profile is useful in identifying the collapsing stage of the cell life cycle, during which microbursts are formed. An example of the changing vertical structure of a severe thunderstorm is shown in Figure 2. Parameters such as the size and vertical extent of the raincore, and the rate at which it falls to the surface are of interest.

The interpretation task is a difficult one, for two reasons. First, the objects of interest in the images (i.e., storm cells), are not very well defined. They appear in various shapes, sizes, and intensities, and are often clustered together into complex aggregates. Second, the desired analyses require the association of individual radar observations at different altitudes and points in time. Hence, the storm cells not only need to be recognized, but coherently tracked in space and time.

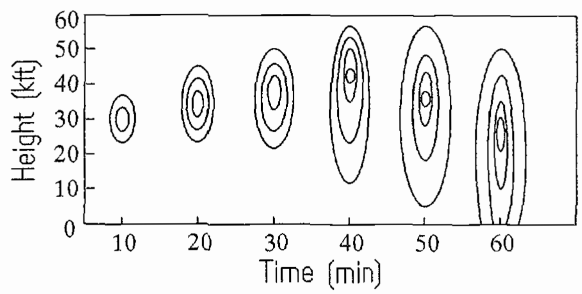

Figure 2: Vertical reflectivity cross sections depicting the time-height profile of a typical severe thunderstorm (adapted from [2])

While automated algorithms for processing weather radar images exist [3], the common techniques detect and characterize storm cells using single (fixed) level thresholding [4] or more adaptive peak-finding [5] methods. While these methods have proven useful for applications such as storm tracking and hail storm detection, they are not always able to resolve and independently track the small-scale storms typical of microbursts, and do not provide all the information about storm structure that would be useful for the discrimination of microburst-producing storms. In particular, the information required

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to derive the time–height storm profile is not conveniently available.

The approach described here is to generate, at an early stage, a symbolic representation of the image to be processed. This symbolic representation then provides a basis for the identification of the primitive features in the image, the association of features between images, and the computation of the important characteristics of the resulting objects. The two main advantages of this approach are: (1) the use of a symbolic representation for the low-level image, thus allowing more complex spatial reasoning rules to be used to perform the feature identification task, and (2) the use of multiple-level threshold information, allowing more complete characterization of the detected storm cells, and more level-adaptive analyses to be performed.

SYMBOLIC IMAGE DESCRIPTION

The first stage of the image analysis process is to generate a basic description of the image in a form which is readily accessed and manipulated symbolically. The description is generated by thresholding the image at each of a number of fixed intensity threshold levels, and for each threshold level identifying the contiguous regions which contain data points having an intensity above the corresponding level. Each of these regions becomes a component of the image description, and a set of basic characteristics are computed for each, including the area, centroid, and bounding box.

By definition, each region at a given threshold level N must lie completely within another region at the next lowest threshold level N-1 (except at the lowest threshold level). This 'nesting' relationship between the regions at different levels is captured by maintaining, for each region R, the name of the region which supports it (i.e., the unique region at the next lower level within which R lies) and a list of those regions at the next highest level which are supported by region R. This supports/supported-by relationship between regions is used as the basis for a structural description of the radar image. This description may be viewed as a set (forest) of directed trees, where each node corresponds to a region, and each edge represents a 'supports' relationship. Figure 3 illustrates the structural representation corresponding to a simple set of regions.

PEAK LOCATION

The 'objects' of primary interest in the radar images are storm cells, which are usually manifest as compact regions of strong reflectivity. The basic approach to recognizing these cells is therefore to locate significant intensity peaks in the image. Since the storms may occur over a large range of amplitudes and spatial scales, this peak finding method must be relatively independent of absolute amplitude and region shape and size. The reliable detection of major peaks in an image, independent of amplitude, size, and shape, is a problem of general interest. The method described here is a rather general approach which could be applied in other contexts as well.

The fundamental observation behind the peak location method is that major peaks will be segmented into 'stacks' of nearly concentric regions, as shown by regions A,B,C, and D in Figure 3. This observation assumes, of course, that the number and spacing of the threshold levels in the segmentation process are adequate to resolve the peaks of interest.

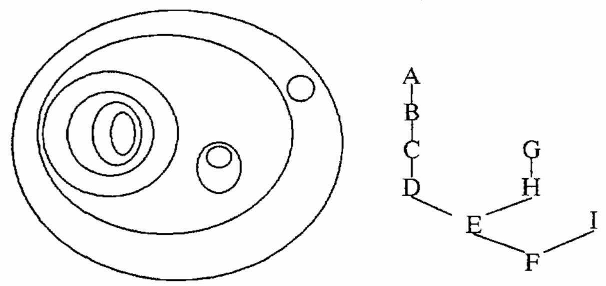

Figure 3: Nested set of contours representing regions at various threshold levels (a), and corresponding structural representation based on 'supports' relationships between regions (b).

Based on this observation, the peak location process attempts to locate collections of regions which exhibit a structural relationship where each region supports just a single region at the next highest threshold level. Since peaks may be embedded in regions of non-zero intensity, this single-support condition need only be met for some set of regions which form the 'top' of a tree.

A basic algorithm for locating such peaks is to scan all the regions in the image, from the highest threshold level down, and flag a region as part of a peak if it supports exactly one region at the next highest level, and that region is either itself flagged as being in a peak, or is at the 'top' of the peak (i.e., it supports no regions). This approach will identify peaks of any amplitude (but at least spanning two threshold levels) and any shape or size. It does require, however, that the peak be completely well-formed. As discussed in the following section, a somewhat more liberal definition of a peak is desirable.

Artifacts from thresholding quantization

The process of thresholding the image, and using the resulting regions as a description, amounts to quantizing the image intensity values. The quantization process induces several artifacts which must be accounted for in the interpretation process. Basically, the quantization effect can induce large jumps (a quantization step size) in the image as a result of very small fluctuations in the original image intensity level, when the intensity is in the vicinity of a threshold level. A desirable characteristic of the interpretation process is that it be relatively immune to these artificial jumps in the quantized image, and that the same image result in the same interpretation despite small changes in the specific threshold levels used.

The small 'spurious' regions generated by the quantization process when the image intensity level fluctuates near a threshold level can hinder the peak location operation. Since the simple peak-finding algorithm requires each region to support exactly one other region at the next level, these noise regions could cause major peaks to be missed. An improvement to the algorithm is desired to allow such minor deviations from the ideal model of a peak.

The search process handles the presence of these extraneous regions by introducing the concept of a 'primary' region. A region R is a primary region if it has an area which is a large fraction of the total area of those regions supported by the same region which supports region R, and is also much larger than the next largest of those neighboring regions. The peak search process is then modified to find stacks of these primary regions, allowing other (less significant) regions to exist as well.

A second common quantization artifact is the 'splitting' of the top region of a peak. If the intensity level at the top of a peak is near a threshold level, then the fluctuations in the intensity may cause the top to be split into several separate regions. In some cases, this splitting of the top level will be handled by the 'primary region' concept, but if the splitting is such that no single region dominates, then the peak will be missed. Since the top threshold level of a major peak is most sensitive to this splitting problem, an additional rule is useful for reliable peak detection. This rule is implemented so as to allow a tightly-grouped cluster of comparably-sized regions to form the top level of an otherwise well-formed peak.

Peak location recursion rule

The complete peak search process may now be stated in the following recursion rule (again, applied to each region from the top level down):

If the given region:

i) supports just one primary region at the next highest threshold level, and

ii) that region is the bottom of an existing peak (or it is at the top level, having no supported regions), and

iii) there are no other supported peaks,

OR

iv) there are multiple supported regions, but no primary one, and

v) all the supported regions are at a top level (having no supported regions), and

vi) the current region has a sufficiently small area (small enough to preclude multiple major peaks),

then add the new region onto the bottom of the peak.

RESULTS

Figures 4 and 5 provide examples of the performance of the peak location algorithm on radar reflectivity images of storms. In each figure, the regions belonging to detected peaks are drawn. Each peak cell region is plotted as a circle centered on the region centroid, having an area equal to the area of the region [intersecting contours are generated because of the circular approximation to the actual region shapes].

The case in Figure 4 shows a relatively simple collection of isolated intensity regions, which are well identified by the algorithm. This example illustrates the ability of the peak-finding procedure to locate regions which are visually perceived as the major intensity peaks in the image.

It is important to note that, while the identification of these peak regions is a very significant part of the task of locating storm cells, not all peaks are necessarily cells, nor are all cells detected as peaks. It is often the case that the information provided by a single image (i.e., a two-dimensional snapshot of a time-evolving three-dimensional complex) is not sufficient for distinguishing individual cells. The peak regions form a useful component of a more complicated spatial and temporal association operation, which is necessary to resolve the ambiguities in the individual images.

Figure 5 illustrates a more complicated scenario, where numerous storms cells are present. The algorithm has again located a reasonable set of intensity peaks, but has failed to adequately capture the full set of storm cells present in the image. Careful comparison between the radar image and the identified cells will show that the two intense precipitation regions (indicated by the arrows in Figure 5) are not identified as peaks. These regions are not identified because they do not fit the model for a peak (the highest level regions are only one level above the region which joins the two, and neither region can be considered 'primary'). This example shows that the 'peak' construct alone is not adequate to fully describe the full range of possible intensity structures characteristics of storm cells.

A sequence of images of the same case illustrated in Figure 4, covering roughly 30 minutes time, generated the storm track shown in Figure 6. Each connected set of points in this figure represents the peak cell detected for the storm (at an altitude of about 3 km) at a different time, as indicated. Each point on the line represents the location of the centroid of the peak region at a different threshold level. The fact that the centroid locations do not coincide at each level indicates that the regions comprising the peak cell are not concentric. This arrangement of contours is typical of storm cells, whose shapes are affected by ambient winds and storm growth and decay processes. The example illustrates that time-coherent observations of the storm cell are possible with the peak location algorithm. The consistency shown here, in both track direction and velocity, for the different threshold levels is of great importance in associating the observations between images at different times. Previous storm identification techniques have suffered from an inability to reliably isolate the individual storm cells present in the image, which is necessary for producing coherent tracks [6]. By using more powerful spatial information and decision rules, the methods described here are able to more reliably identify the major peaks, and hence offer the potential for improved temporal and spatial association.

FUTURE WORK

The peak location algorithm is only a partial solution to the problem of identifying significant features in the radar image. Storm cells will not always be detected as peaks, and there are more complicated formations which need to be recognized. Additional structural models for the more complicated features, as well as methods for using temporal and vertical continuity to resolve ambiguities must be developed.

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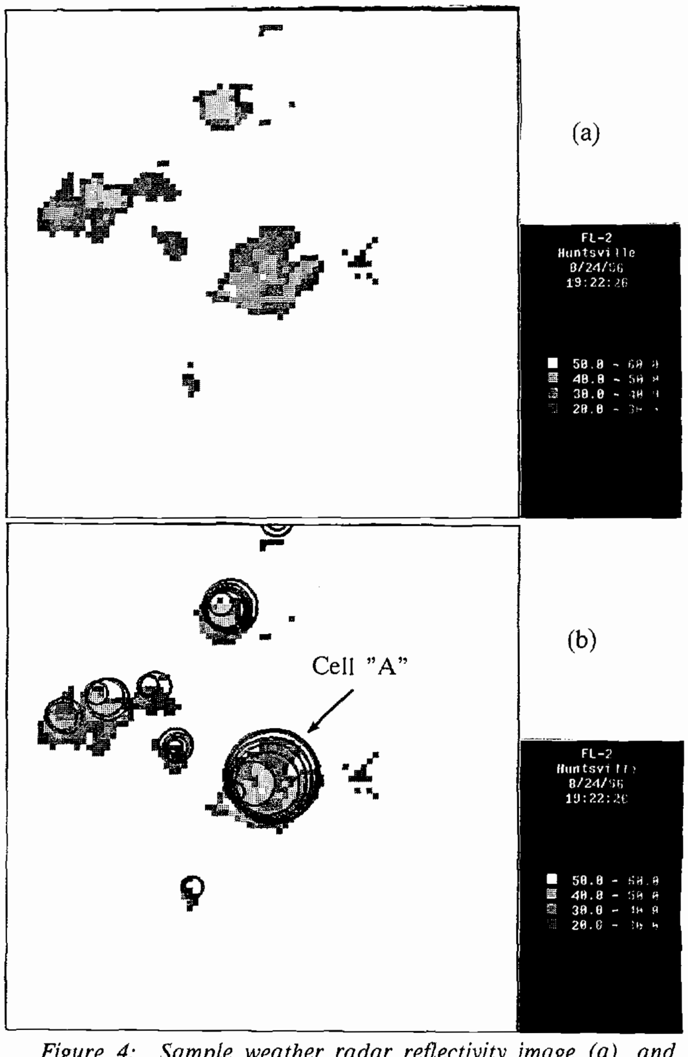

Figure 4: Sample weather radar reflectivity image (a), and corresponding peak cell regions (b). Images are 40 kilometers on each side, and intensity is in units of dBZ. 20 dBZ corresponds to very light rain, while 50 dBZ is extremely heavy rain.

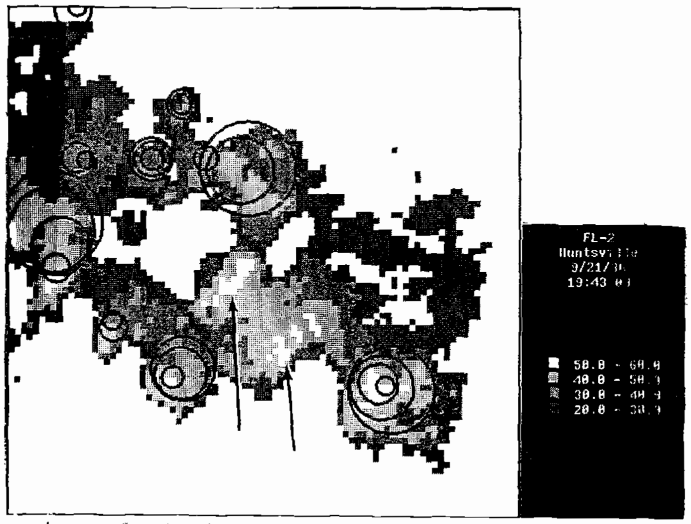

Figure 5: Another sample radar reflectivity image and peak region contours.

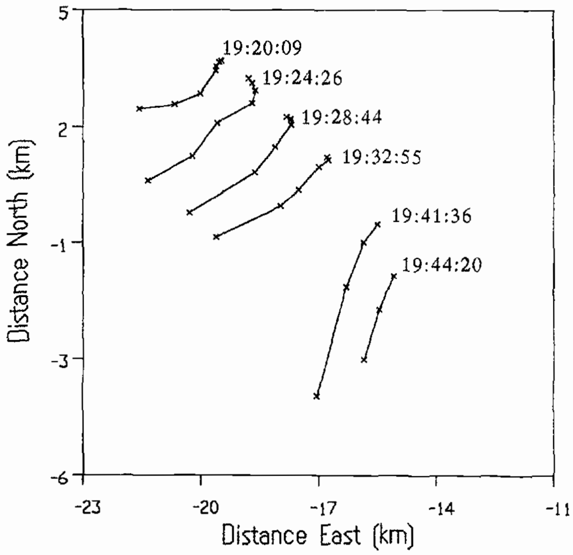

Figure 6: Locus of peak cell region centroids for storm "A" over time period from 19:20:09 to 19:44:20. The points on each curve represent the centroid of a peak cell region at a different threshold level. Displacement between curves indicates cell motion, and change in angle between curves indicates re-alignment of regions at different levels. Note storm was not detected as a peak cell at roughly 19:37.