AD-A169 744 SHORT TERM FORECASTING OF CLOUD AND PRECIPITATION ALONG COMMUNICATION PATHS(U) AIR FORCE GEOPHYSICS LAB HANSCOM AFB MA A R BOHNE ET AL. 31 DEC 85 AFGL-TR-85-0343 1/1

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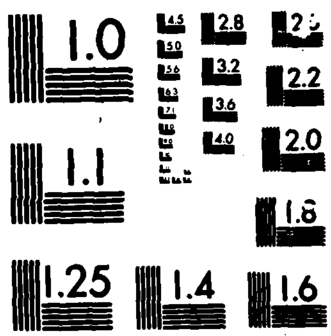
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AFGL-TR-85-0343
ENVIRONMENTAL RESEARCH PAPERS, NO. 941

AD-A169 744

# Short Term Forecasting of Cloud and Precipitation Along Communication Paths



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31 December 1985

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SECURITY CLASSIFICATION OF THIS PAGE

A169744

## REPORT DOCUMENTATION PAGE

| | |
|---|---|
| 1a. REPORT SECURITY CLASSIFICATION: Unclassified | 1b. RESTRICTIVE MARKINGS |
| 2a. SECURITY CLASSIFICATION AUTHORITY | 3. DISTRIBUTION/AVAILABILITY OF REPORT: Approved for public release; distribution unlimited. |
| 2b. DECLASSIFICATION/DOWNGRADING SCHEDULE | |
| 4. PERFORMING ORGANIZATION REPORT NUMBER(S): ERP, No. 941 AFGL-TR-85-0343 | 5. MONITORING ORGANIZATION REPORT NUMBER(S) |
| 6a. NAME OF PERFORMING ORGANIZATION: Air Force Geophysics Laboratory; 6b. OFFICE SYMBOL (If applicable): LYR | 7a. NAME OF MONITORING ORGANIZATION |
| 6c. ADDRESS (City, State and ZIP Code): Hanscom AFB Massachusetts 01731 | 7b. ADDRESS (City, State and ZIP Code) |
| 8a. NAME OF FUNDING/SPONSORING ORGANIZATION; 8b. OFFICE SYMBOL (If applicable) | 9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER |
| 8c. ADDRESS (City, State and ZIP Code) | 10. SOURCE OF FUNDING NOS. |
| 11. TITLE (Include Security Classification): Short Term Forecasting of Cloud (Contd) | |

| PROGRAM ELEMENT NO. | PROJECT NO. | TASK NO. | WORK UNIT NO. |
|---|---|---|---|
| 62101F | 6670 | 19 | 01 |

12. PERSONAL AUTHOR(S): Alan R. Bohne and F. Ian Harris*

| 13a. TYPE OF REPORT | 13b. TIME COVERED | 14. DATE OF REPORT (Yr., Mo., Day) | 15. PAGE COUNT |
|---|---|---|---|
| Scientific. Interim. | FROM 1 Oct 84 TO 30 Sep 85 | 1985 December 31 | 32 |

16. SUPPLEMENTARY NOTATION

*SASC Technologies Inc., Lexington, Massachusetts

| 17. COSATI CODES | | | 18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number) |
|---|---|---|---|
| FIELD | GROUP | SUB. GR. | Forecasting, Satellite, Short term, Storm structure, Radar |

19. ABSTRACT (Continue on reverse if necessary and identify by block number)


Candidate techniques for forecasting precipitation and clouds along arbitrary paths are presented in this report. Mapping the troposphere into a three-layer model representing the lower, middle, and upper regions is suggested. The data to be ~~utilized~~ are radar reflectivity factor and visible and infrared satellite imagery. ~~Taken~~ in combination, they provide for an effective description of the storm environment. Features to be tracked and forecast are discrete contours of these data which would be generated through threshold and field gradient methods. Efficient storage and analysis requires an efficient method for description of these features. ~~The~~ use of field attributes is suggested. Examples of candidate methods for generating the various attribute lists, such as simple icon and positional chain coding up through complex polynomial and vortex fitting are presented. Contour translation and rotation will be determined through use of cross correlation. Methods for detecting changes in individual contours such as in size and shape, are


| 20. DISTRIBUTION/AVAILABILITY OF ABSTRACT | 21. ABSTRACT SECURITY CLASSIFICATION |
|---|---|
| UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT. ☐ DTIC USERS ☐ | Unclassified |

| 22a. NAME OF RESPONSIBLE INDIVIDUAL | 22b. TELEPHONE NUMBER (Include Area Code) | 22c. OFFICE SYMBOL |
|---|---|---|
| Alan R. Bohne | (617) 861-4405 | LYR |

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directly linked to the attribute set chosen, and examples are provided. Due to the rapid data update rate of 5 to 10 min and the large volume of data to be processed, the use of simple and efficient forecast tools is suggested. ~~A variety~~ Various ~~of~~ candidate techniques, such as simple linear exponential filtering, are discussed. Finally, the general philosophy for solution of the problem and a general outline of the entire analysis process is presented.

Keywords: Atmosphere models; Weather forecasting; Storm structure; Atmospheric precipitation.

## Contents

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## 1. INTRODUCTION

Communications between satellite and ground station systems are affected by the intervening meteorological environment. With the trend towards higher communication frequencies, knowledge of the state of the atmosphere along the communication path and the ability to provide short term forecasts of this environment, becomes essential. This requirement demands knowledge of the present and future three-dimensional structure of precipitation and cloud content throughout the region of interest. This report is concerned with a review of data sources for the real-time observation of cloud and precipitation systems, and techniques for combining and extrapolating these data, to prepare the desired forecast. There are two sources of data which provide a reasonable data base for solution of this problem.

First, radar, preferably Doppler Radar, at non-attenuating frequencies (for example, 3 GHz) provides the best mechanism for interrogating the interior precipitation structure of storm regions. The primary radar parameter is the equivalent radar reflectivity factor, which can be interpreted as a measure of precipitation intensity and thus can be related to attenuation of a transmitted signal. Occasionally, however, the radar coverage is not adequate. Depending upon the radar sensitivity, a certain mass of precipitation is required to provide sufficient signal to make reliable measurements. Thus the radar does not identify the total storm

(Received for publication 31 December 1985)

outer boundary. Also, near storm top, due both to sensitivity and radar scan requirements, loss of information may also occur. Finally, at lowest levels where active meteorological events such as gust fronts and newly initiated convection may be present, the radar observations may be deficient. Fortunately, these regions where radar measurements can be lacking may usually be successfully interrogated by satellite. The visible and infrared imagery data are highly attenuated in storm precipitation regions, making the satellite well suited for monitoring storm tops, the outer storm environments, and regions well removed from active precipitation generation. The radar and satellite data are thus highly complementary and may provide sufficient and appropriate information.

Past efforts have usually been interested in providing forecasts of large scale meteorological features. This generally resulted in use of large time (hrs) and spatial (tens of km) scales, or the use of a single parameter to represent the total storm (for example, center of mass) environment. Here, however, forecasts are desired on time scales of 5 to 30 min and spatial scales of a few km. Thus this problem is significantly different. In the ensuing discussions, traditional techniques for storm detection and tracking will be presented. They represent some of the basic methodologies still in use today, and results of such efforts are pertinent to the present study. Then the focus will be directed to a more detailed discussion of the current problem, and proposed methods for its solution. Last, a short graphical demonstration outlining the solution methodology will be given.

## 2. TRADITIONAL TRACKING TECHNIQUES

### 2.1 Radar Data Fields

The use of radar data for storm identification and tracking has been a subject of interest for some time. The feature generally monitored has been the radar reflectivity factor. The general manner in which it has been used may be demonstrated with a few examples.

Austin and Bellon[1] developed the Short-Term Automated Radar Prediction (SHARP) method which utilizes simple cross-correlation analysis of the entire data field to determine the average translation of the precipitation field with time. This method generally performs well in non-evolutionary environments, where initiation and dissipation effects are slight, where the environmental winds do not vary greatly with height, and where the precipitation environments are shallow. This method

1. Bellon, D. E., and Austin, G. L. (1976) SHARP (Short-Term Automated Radar Prediction) A Real Time Test, 17th Conference on Radar Meteorology, Amer. Meteorol. Soc., Boston, pp 522-525.

is most useful when no well defined storm structure such as localized cells, or when data extends beyond the viewing region of analysis, occurs. This method has been used successfully to make 2-hr forecasts of large scale precipitation motions.

Elvander[2] compared a number of tracking and forecasting techniques. These included the SHARP method, a linear least squares (LLS) tracking of individual centers of area or mass, and a more robust technique developed by the Stanford Research Institute (SRI) (Wolf et al[3]) which employs a global track of the entire field but also includes adjustments for individual storms for deviations from the field average value. The methods were employed with both radar reflectivity factor and vertically integrated liquid (VIL) data as input. Whereas the SHARP method results in one translation and forecast vector for the entire data field, the LLS and SRI methods return track and forecast vectors for the individual storms of interest. For reflectivity tracking only the 0 degree elevation data were used. In most situations, including large and small distributions of storm cells, and frontal and squall line situations, the simple cross-correlation (SHARP) method performed best in forecasting motions of individual storms. The linear least squares method was least successful. In tracking VIL the LLS method was preferred. Some additional observations common to most tracking and forecasting methods were found. Tracking and forecasting with VIL was found more accurate than with use of reflectivity factor data at any single height level. The trackability of storm cells generally increased with increasing precipitation intensity (reflectivity). Forecast errors increased with forecast lead time (here a linear trend was observed. It is informative to interpret these results for some apply generally to all tracking methodologies.

The relative behavior of the methods when using VIL vs reflectivity factor data suggests that a vertically averaged feature is easier to track than features at a single height level. This is understandable when one considers that at a single height level the radar contours change in response to two basic effects, evolution and movement of precipitation features through this level from adjacent levels. This latter effect is particularly noticeable when a coarse horizontal grid (here 7 × 7 km) is used. As the precipitate moves up and down within the storm it may remain at the same horizontal grid location for numerous height levels, but jumps in and out of these same levels individually as the precipitate travels vertically. Thus VIL, when used with a coarse grid is relatively insensitive to the effects of vertical

2. Elvander, R.C. (1976) An Evaluation of the Relative Performance of Three Weather Radar Echo Forecasting Techniques, 17th Conference on Radar Meteorology, Amer. Meteorol. Soc., Boston, pp 526-532.

3. Wolf, D.E., Hall, D.J., and Endlich, R.M. (1977) Experiments in automatic cloud tracking using SMS-GOES data, J. Appl. Meteorol., 16:1219-1230.

displacement of the precipitate, and behaves as a conservative quantity. The structure at a single height level, however, may vary significantly. In tracking VIL the LLS method was preferred over whole field cross-correlation presumably because the individual storm cells had varying propagation velocities, different from the average field value. When tracking reflectivity at a single level the LLS method was less accurate than the SHARP method because the apparent varying motions induced upon the center of mass due to the precipitate vertical motions and vertical wind shear were greater than the displacement differences between the whole storm motions and the field average value.

The SRI method determined both the global and individual storm motions. This method pre-processed the input data to describe the data field in terms of clusters, where clusters consisted of neighboring regions of similar structure. Cross-correlation was performed on the clusters to determine their displacements. As a result of the clustering process, this method was most successful in monitoring the dissipation, splitting, and merging of storm cells. However, the SRI method was computationally intensive and offered no increase in accuracy in actual tracking ability.

A slightly modified version of the centroid tracking method was employed by Collier[4] where comparisons were performed between whole field cross-correlation and a modified storm center of mass tracking technique. Here a very coarse grid of 20 $\times$ 20 km was used. The data were pre-processed using a low threshold to classify areas as containing rain or no rain. Adjacent grids of rain were combined into clusters. The centers of mass of the clusters were determined without regard to actual precipitation intensity, thus areal centers of mass were determined. These centers were then individually tracked. Analysis indicated that for situations where little evolution is ongoing and the echoes are moving rather uniformly, whole field cross-correlation techniques were the simplest to implement and quite reliable. In non-stationary environments, however, tracking the individual clusters through use of the center of mass method was preferred. Skilled subjective analysis resulted in very little increase in accuracy of the forecasts over the cluster-centroid technique. Here the large grid filtered out evolutionary and vertical transport effects noted in the previous study. This allowed for individual storm tracking to be superior over applying the whole average field motion to the individual storms comprising the field. Thus the usefulness of these various tracking algorithms is seen to be dependent not only upon the meteorology, but also upon such parameters as grid scale size in the horizontal and vertical directions.

4. Collier, C.G. (1981) Objective Rainfall Forecasting Using Data from the United Kingdom Weather Radar Network, Proc. AAMAP Symposium, Hamburg, Germany, pp 25-28.

Further assessment of short term forecasting of precipitation using radar data was considered by Ciccione and Pircher.[5] Once again cross-correlation and centroid methods were studied, but with a horizontal grid scale resolution which could be reduced to 2 km. Both methods determined the whole field translation with no concern for the deviating motions of the individual storms comprising the field. They noted large scale phenomena were better tracked and forecast when a large grid resolution was used. Accuracy decreased with increasing forecasting period and the standard error of displacement increased from zero at zero lag to an asymptotic value near 20 percent at 2 hrs time lag. Success also increased with increasing proportion of rain containing area and with increasing verification area. On the other hand, during periods where the rain was distributed in small areas, cell lifetimes were small, and grid resolution small, success increased with decreasing lag times and small resolution. This last effect simply indicates that as the pace for evolving features increases, finer spatial and temporal resolution is required. Cross-correlation was clearly the superior method. The results here suggest that the overall motion of the sum of the cells was fairly well aligned with the field motion, but that a fair amount of deviation of individual storms from the field average value resulted in a somewhat more erratic track for the field center of mass, resulting in less accuracy when field center of mass was employed. This result once again underscores the difficulty in applying whole field translation to individual storms.

A significant ongoing tracking and forecast effort is that being employed with the Next Generation Weather Program (NEXRAD).[6] Here a mass weighted centroid method is being employed for prediction of future individual storm locations, as determined by the storm center of mass. This parameter is obtained by correlating the various layer centers of mass as determined from data acquired from a sequence of elevated radar scans through the storm of interest. Assuming the storm centroid a conservative quantity between radar scan sequence intervals, the displacement of the storm center of mass is measured through use of a nearest neighbor algorithm. A linear least squares method is applied to the history of centroid locations to develop forecasts of future positions. Although a useful storm tracking and forecasting technique, it offers no insight into the evolving nature of internal storm structure.

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5. Ciccone, M., and Pircher, V. (1984) Preliminary Assessment of Very Short Term Forecasting of Rain from Single Radar Data, Proc. Second International Symposium on Nowcasting, Norrkoping, Sweden, pp 241-246.

6. Bjerkaas, C.J., and Forsyth, D.E. (1980) An Automated Real-Time Storm Analysis and Storm Tracking Program (WEATRK), AFGL-TR-80-0316, AD A100253.

This short summary attempts to demonstrate that primary efforts in precipitation forecasting have been focused on storm scale through large scale phenomena. Large scale efforts generally track only gross features at one altitude, while storm scale efforts have been reduced to a study of storm centroid motions. These methods, successful in their own applications, do not address the current problem. For forecasting cloud and precipitation structure along a communication path, it is the internal three-dimensional storm structure which must be observed, understood, and forecast. Thus this effort requires a different approach.

### 2.2 Satellite Data Fields

Analysis of satellite data has essentially followed along the same route as that taken for radar, with cross-correlation and centroid methods predominating. Some potential problems associated with use of radar data were briefly noted. Use of satellite visible and infrared imagery also present some difficulties. The satellite frequencies of the standard GOES type satellite are generally attenuated by intervening cloud and precipitation. As a result of this only the outer cloud boundary that faces the viewing direction of the satellite is observed. Difficulty in differentiating between storm side and top may result. Use of complementary infrared data may remove some of this ambiguity, however this may be difficult owing to the considerablv larger footprint of the infrared image as compared to the visible. Further complications arise from variation in observed cloud brightness between observations. This is partly due to the varying orientation of the storm feature relative to the satellite and the sun, both of which mav change differently with time. This effect may again result in false identification of storm features. The resulting outcome of these concerns is an ambiguity in the vertical and horizontal locations of exterior storm features relative to a coordinate svstem fixed to the earth's surface. Obviously such uncertainty can introduce significant error in the placement of tracked features, and ultimately significant error in their forecast locations. A further difficulty lies in the initial registration of the entire satellite data field itself. Thus with use of satellite data, much effort is taken in first determining the actual location of features of interest, both in height and horizontal direction, prior to its use as input into a forecasting technique.

As an example of a verv robust method the SRI (Wolf et al[3]) technique discussed earlier will be presented in some greater detail as it has been used with satellite data. The first task is landmarking. This is accomplished bv correlation techniques. First, clouds are thresholded out bv eliminating brightness values above a certain threshold. A landmark template is then passed over the imagery field in a coarse fashion to determine rough displacement of the current observation from the previous. Next, a fine template is emploved with the best match defining the

the proper field location in geographical sense. Accounting for the variation in cloud brightness between observations is done statistically, by forcing the brightness frequency distributions for the different observational periods to match as well as possible. The alternative approach would be to rely upon the sinusoidal variation of sun height alone. Once properly registered, a more complete discrimination between cloud and ground features is performed by use of a series of thresholding applications. After elimination of ground targets the data are smoothed and thresholded again to retain only the brighter features.

Clusters are now formed by estimating the brightness deviations between neighboring grid points. Locations where sharp deviations are detected are removed. This has the effect of locating and removing the outer edge of the actual cloud boundaries, while still retaining the shape of the cloud boundary. Touching groups are now formed from touching regions exhibiting similar brightness values. Further smoothing and elimination of small isolated features to be considered as noise is continued, resulting in a field of cloud areas which form the tracers. Tracer translation is done either by pattern recognition or correlation. The pattern recognition method compares attributes of the individual tracers (clusters) to determine the translation. Such attributes are size, location of center, average brightness, average IR temperature, and the rms dispersion of the tracer region along the x and y axes. The relative translation of two features which have similar attribute values and which lies within predetermined bounds, such as mean field translation plus a deviation, is a measure of the displacement. Cross-correlation of successive observations of individual clouds may also be performed to determine the different translation velocities. In any case, tests are performed over individual tracers resulting in a field of varying tracer motions. Through the clustering process this method provides additional information concerning storm dissipation, splitting, and merging. As stated earlier, however, it does not necessarily provide better tracking and forecast capability over the simpler correlation and center of mass techniques for the storm and field scales. Also, as currently employed, it still does not determine the evolution of distinct structures such as contour boundaries.

The methods discussed may, varying with meteorological situation, return a reasonable estimate of cloud or precipitation feature motion with time if this feature is not evolving on a time scale comparable to a few observation periods. The problem being addressed here demands more attention to the evolutionary nature of the observed systems as well as the general translation of the features. This can be accomplished only by monitoring the motion, shape, size, and intensity of cloud and precipitation structures with time. Of the few techniques discussed here, the SRI method is most closely aligned to the problem as it is seen here. It offers the potential to provide a measure of the change in shape and size required to accurately forecast the trend in the tracked feature. However, the SRI model removes significant amounts of actual data and is a heavy computational burden. A number of other methods exist for monitoring the spatial distribution of the cloud and precipitation data. Spectral techniques may be employed to analyze the distribution. However, the spectral information does not easily lend itself to determining the shape and size at any single location. On the other hand, shape fitting methods and boundary tracking techniques appear to be useful alternative methods for monitoring the changes of shape and size of the tracers. The remainder of the discussion will focus on their application to the present problem.

## 3. THE FORECAST PROBLEM

The goal of this effort is to provide short term forecasts, for 5- to 10-min intervals for a maximum length of 30 min, with a spatial resolution of a few km. This can be accomplished only by monitoring the motion, shape, size, and intensity of cloud and precipitation structures with time. A compromise must be struck between the spatial scales and the grid scale employed to accommodate the expected 5- to 10-min update interval of radar data and potential storm feature evolution. To forecast for a given location we must have some knowledge of the precipitation content within a region which could influence that location by simple advection or other means over the maximum predictive time interval. Thus we need to know the translation speed and direction for the data in an appropriate corridor. If this location is to be truly arbitrary, then we need to be able to project the vector displacement for the entire field of data. Simple field translation may be sufficient for very short forecast periods, over which the field is nearly stationary (5 to 10 min) in structure. However, for longer forecasting intervals (20 to 30 min), the structure probably will not be effectively stationary. Evolution at a given height level, whether a result of real precipitate distribution growth at that level, or a response of passage through this level from an adjacent level, should be expected.

Proper solution of this problem requires knowledge of the behavior of the precipitation structures at various height levels in the environment. It was noted that tracking vertical integrated liquid resulted in smaller errors than when tracking features at a single height level. Thus some form of vertical averaging is desired. However, for projection of cloud and precipitation amount along an arbitrary communication path, some knowledge of the vertical structure is required. This is easily seen in storm regions, such as with the anvil or high reflectivity factor aloft, where the precipitation content there should not be attributed to all height levels as may occur with a vertically averaged quantity. Another reason to retain some vertical structure is that knowledge of vertical motion of a precipitation volume provides some forewarning for new development at adjacent height levels. Thus new development at a lower (or higher) level need not always be unexpected, and a feedback mechanism is available. Thus for a proper identification of cloud and precipitation along some arbitrary path, some facility for retention of vertical structure is desired.

In this effort, description of the field of precipitation or cloud intensity will be accomplished by use of radar reflectivity factor for radar data and brightness level for satellite visible imagery. These parameters are most easily transformed into measures of attenuation. The data field structure at any single height level will consist of a series of intensity levels and will appear in the field image as a series of contour boundaries, some closed, some open. These contours will be termed the "features" of the meteorological field. These features may be described in a number of ways through use of descriptive parameters which will be termed "attributes". Thus in the final analysis, tracking and forecasting of a field of data will ultimately result in tracking or forecasting a set of attributes. A demonstration of the use of attribute parameters in the forecasting problem is presented in Section 7.

## 4. FEATURE DEFINITION AND EXTRACTION

### 4.1 Field Analysis vs Comparison

The basic methods for feature extraction are generally derived from (a) field comparison or (b) field analysis. Field comparison implies taking successive field patterns, or subsets of field patterns at different times, and iteratively adjusting the location of one field relative to the other until a measure of maximum comparison, usually a maximum cross-correlation, is obtained. Here the feature of interest would be an intensity contour boundary. Quite often one assumes the structure of the meteorological field is stationary and evolution is of no concern. In this case one generally employs a simple form of field comparison to determine the simple field translation.

Field analysis requires some analysis of the data and its subsequent description in terms of a limited number of descriptive attributes. When the new field is described, then a comparison is made between the two sets of attributes. Description of the fields may include such parameters as centroid locations, where each location may represent a simple areal average, or an intensity weighted value for each intensity class. Alternately, the descriptors may be derived from some form of pattern analysis. In any case the primary difference is that field analysis attempts to determine the underlying patterns of the data field whereas comparison develops no understanding of these basic underlying structures.

Pattern analysis may be used to provide a description of the contour of a given intensity class. The methods may include fitting the contour in small segments using straight lines or arcs. Alternatively the actual shape of the entire contour may be fit by polynomial or polygonal means, or by combinations of basic shapes such as ellipsoids as utilized in vortex analysis. Such methods offer different degrees of complexity for generation of the attributes, and in their use in determining the contour changes. In the forecasting effort here, detection of field changes and their forecast effects are required. Thus here we emphasize field analysis. The attributes describing these features may vary from codes defining line segments to the constants forming the polynomial fit to the contour boundary.

Description of the field changes may be accomplished in a number of ways once the general translation between two successive intervals is determined. In field analysis, one may forecast by noting the changes in the field attributes. A forecast may be derived by determining the evolution of the attributes and forecasting their future values. Alternatively, one may forecast the change in the attributes and adds these to the initial attribute states. In vortex analysis, as demonstrated by Williamson,[7] a contour is fit by the resulting boundary of overlapping ellipsoids of varying sizes and orientation. Thus this method may include forecasting of basic ellipsoid parameters such as amplitude and center. Shape fitting requires a wholly contained boundary. Contour fitting may be accomplished on a partial boundary. Thus the applicability of pattern analysis may vary with field structure.

The current effort requires detection of field changes and development of their time histories for forecast purposes. Particular methods for feature extraction will be discussed. One of the major constraints of this effort is the rapid data and forecast update rate of 5 to 10 min. This places severe limitations on the types of analysis that may be performed, and the definition of attributes by which the features of the field will be tracked. Noting that the basic image size involved in this analysis is 512 by 512 pixels, and that within each image there will likely be a number of features to be monitored it seems highly unlikely that analyses can be performed pixel by pixel on a routine basis. In addition a number of images may be required to be retained, thus making storage of field data a problem. Focus will now be directed towards developing appropriate and efficient methods for the description of field attributes.

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7. Williamson, D. L. (1981) Storm track representation and verification, Tellus, 33:513-530.

### 4.2 Feature Detection and Definition

Feature detection will be a result of some form of picture segmentation, where this is broadly defined as "picking out the objects of interest from the background". The two general approaches for obtaining the features are structural and statistical. Structural methods are to be employed when the data field contains features that have obvious coherency, or patterns discernible by eye. This is the expected state of affairs in typical radar data as shown in Figure 1, where a complex set of quantized reflectivity factor contours are evident.

There are a number of ways of detecting these boundary contours. The procedure may be considered three-fold, namely: (a) silhouette, where the data field is thresholded with all pixel locations having a value above the threshold given a prescribed value (for example, one), and all pixels with values below the threshold a value of zero); (b) search, where the first boundary point of the contour of interest is located; and (c) follow, where the contour is followed and described in some manner. Assuming structural methods are in use, a number of boundary detection methods are available. The simplest is the gradient operator, that estimates the data gradient from the pixel locations about the pixel of interest. Because the data field has been described in binary fashion, all possible gradient values are known in advance, and boundary crossings are easily determined. More complex transformations exist for determining boundaries, but a simple gradient operator is both quick and simple and should be adequate.

When the data field presents a noisy appearance, containing no easily describable features, statistical methods may first be employed to locate those regions that have similar structure in the statistical sense. Here the field of data is described in non-descriptive terms, such as the form of the intensity distribution, its mean and variance, either for the entire field, or more likely for subset regions of the large scale field. After thresholding, the data field is first segmented if there are filled and closed areas. Each area is now investigated to determine its intensity distribution and associated parameters. When areas are determined to have differing parameters, a new feature area has been located. Here then a contour represents a boundary between two regions having differing distribution parameters. This edge may then be traced to define its boundary as described in the pure structural methodology.

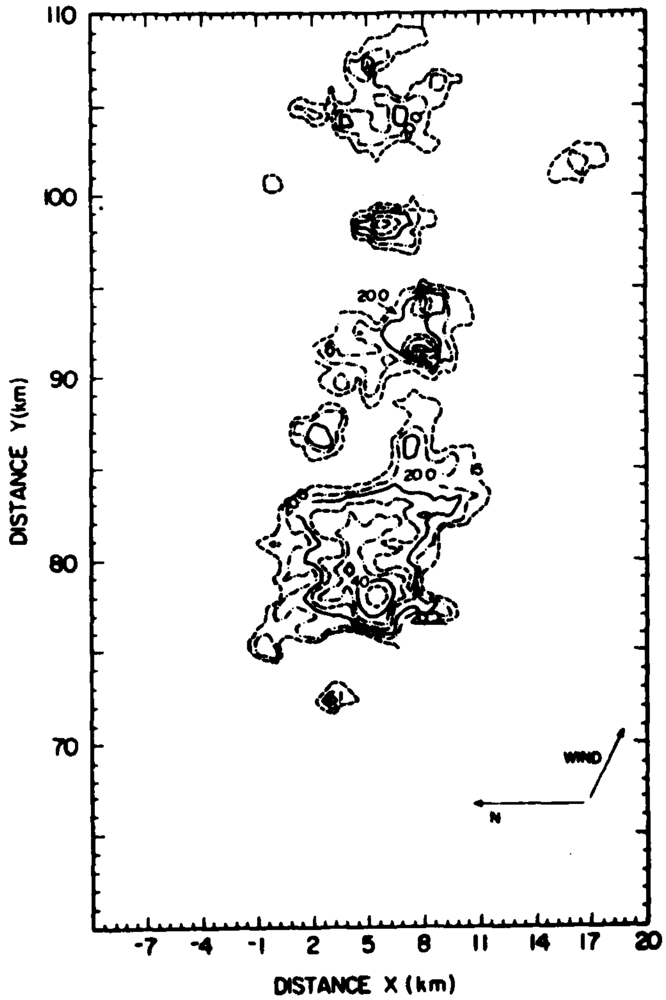
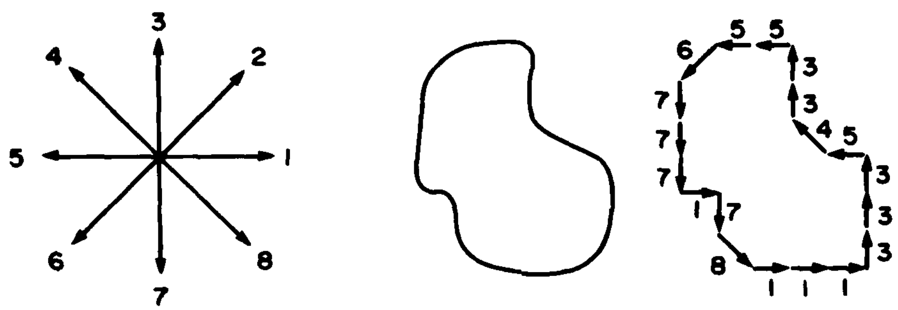



Figure 1. Contours of Radar Reflectivity Factor at 3.35 km Altitude for Storm Complex Observed Near Wallops Island, Virginia. Contours are in recycling dot, dash, solid pattern. Minimum and maximum contour plots shown are 15 and 40 dBz, respectively. Positions are relative to radar location

### 4.3 Boundary Description

The description of the boundary is now pursued. It is assumed that the boundary has been determined. A number of methods for description are available, from very simple pattern methods to complex curve fitting. The most primitive methods employ icons or position chain codes. Icons may be fixed length vectors in the eight possible directions of movement from the current image location (Freeman chain code), or combinations of straight lines or arcs. An example of the simplest, albeit a very attractive technique, is the Freeman chain code icon representation shown in Figure 2. The boundary is described by a series of code characters (for example, here values 1 through 8). Alternatively, a position chain code could be a series of successive *(x, y)* pixel locations. The next level of complexity would be fitting boundary segments of varying length by straight lines, arcs, or simple polynomials. Polygonal or polynomial approximation, or vortex fitting, to the full boundary would represent about the most complex form of boundary description method.




(a) (b) (c)

CHAIN CODE 6 7 7 7 1 7 8 1 1 1 3 3 3 5 4 3 3 5 5

(d)

Figure 2. Description of Contour Boundary Using Chain Coding With (a) the Eight Freeman Chain Code Elements, (b) the Contour to be Described, (c) Following the Contour With Chain Code Elements, and (d) the Resultant Chain Code Stored in Memory

There are inherent tradeoffs with each level of complexity. The primitive techniques are very fast computationally. For example, the Freeman chain code, if used judiciously, and employing a memory of the previous value, results in less than four searches, on the average, to find the next chain component. Their usefulness is determined by the difficulty with which they may be transformed into a form suitable for higher level analysis. For example, how difficult is it to transform the code back into a spatial representation to determine differential boundary change? Advancing to higher level methods the computational intensity increases nonlinearly with increasing complexity of the technique employed. Thus polynomial curve fitting is quite computationally intensive when compared to the more primitive methods. However, it may be more easily transformed into the spatial form and more readily useable for subsequent analysis. There exists a concern in the use of high level boundary description, however. For accurate forecasting on small spatial scales, as much information about the contour boundary structure as possible must be retained. Thus notches, cusps, particular features of the boundary which make it unique from other contours in the data field must be retained. Shape fitting, through use of high level routines, invariably produces a highly smoothed contour shape. The boundary features that are lost are precisely those which may be very important to be retained. The primitive methods, however, offer potential for memorizing all features in the boundary. For example, the Freeman chain code logs the contour pixel to next pixel, thus allowing for no information loss. These concerns make the primitive techniques the more attractive, although later more extensive analysis may be more involved.

Finally, in all methods some facility must be present to allow for data field smoothing and data rejection. A casual observation of a typical radar reflectivity factor image (Figure 1) makes the most casual observer aware of the generally very complex intensity structure. Smoothing operations will be generally performed prior to the feature extraction process to reduce the noisy appearance, which is a result of true meteorological complexity, measurement methods and errors. If a primitive boundary description method is used, it is much more difficult to remove noise from the code sequence than first smooth and then code the contour. If a high level method such as polynomial fitting is employed, the noise may introduce significant errors into the fit relation. Rejection of data may be done by the requirement for a minimum areal extent enclosed by a boundary contour. This assumes that noise is random and adjacent pixel values will not uniformly rise above the predetermined threshold for a contiguous set of pixels. The requirement for vertical structure, however, does force interrogation of adjacent levels to determine whether a region is part of a precipitation or cloud volume extending to other levels, in which case areas which fall below the areal threshold may be retained.

## 5. FEATURE MOTION AND EVOLUTION

### 5.1 Feature Translation and Rotation

Once the feature boundaries are determined, overall motion of these features must be determined. This may be performed by cross-correlation, or by image processing methods, of the contour boundaries. In cross-correlation the contours for two successive observations are translated and rotated until the minimum mean square error is obtained. Here error is determined by measuring the difference in contour boundary locations for a single image row, and then summing up the squared errors for all rows. Iteratively moving one image around the general location of the other until this value is a minimum yields the optimum contour translation and rotation components and minimizes the overlap difference between the two contours. An alternative approach to find the condition of maximum overlap is to perform video subtraction of the two images after each iteration until the minimum area results. The results of these two different processes are the same. Image video subtraction and area sum can be performed very efficiently in the image processor, and is the preferred route. Determining feature motion by measuring the displacement of the center of mass is not considered appropriate since it does not allow for the effects of rotation of the boundary.

### 5.2 Feature Evolution

Once the general overall motion of a contour has been obtained the change in contour structure must be determined. With a history of the translation, rotation, and change, the future feature structure may be forecast. There are numerous methods for detecting these changes. However only three, which demonstrate three different levels of complexity, will be discussed.

First, assume a very primitive contour descriptor has been employed. The Freeman chain code will serve as our example. Our information consists of the starting pixel location for the contour, and a series of code characters. Other information such as overall translation and rotation are also assumed available. One may compare the two successive chain codes to locate positions along the chain where the codes differ. This allows one to immediately focus upon those areas where measurable change in boundary structure is occurring. Chain segments where the codes have remained the same are assumed to have no detectable change during this time interval. The chain code sequences of interest are transformed into spatial terms for interpretation. Alternatively a chain code grammar has been developed to eliminate the spatial transformation step and provide for immediate interpretation. In any case, with the changes interpreted in a spatial context, time histories are developed, understood, and forecasts of future change determined.

The next level of effort employs what may be termed a raster vector approach, potentially most useful for closed contour regions. With the contour data residing in the image processor one may consider defining it by listing the starting and end points for each successive horizontal raster line. Thus the contour will be a chain code, with the elements of the code being the element line number, and starting and ending points (n, x1, x2), as many sets as required to describe the contour positions along that single raster line. In the initial description, all raster vectors will be horizontally oriented. A succession of observations of the contour of interest will result in a series of measurements of its translation, rotation, and chain code sequences. One may choose to follow each raster vector element in time. For this case the chain code elements must be described on a grid which is allowed to translate and rotate, thus applying the translation and rotation to each raster vector. In this manner one is able to measure the evolution of a particular set of contour relative locations, either as pair or individually, to develop their histories, and forecast their future change. Alternatively, one may define raster vectors as always being horizontally oriented, even though the contour may be rotating in time. In this case a time history of a raster vector element, a given raster vector number (n), may eventually represent different locations along the contour. In this method, which will be termed the "simple" raster vector method, the rotation is actually accounted for by the raster vector end point variations. Both methods will be tested to determine their applicability to this problem.

As a final example, it is assumed that a shape fitting technique has been employed to describe a closed contour. The vortex fitting routine will serve as our example. A contour has been described by a series of overlapping ellipsoids of varying amplitudes, centers, eccentricities, and other attributes. With successive observations a sequence of ellipsoid attributes is developed. With a time history of attributes for each individual ellipsoid, future ellipsoid shapes, sizes, orientations, and locations may be forecast. This composite set of forecast ellipsoids then represents the forecast contour in location, shape, and size. In this approach actual measurement of feature translation and rotation is not necessary, since it is essentially being accounted for by variation in the attributes of the ellipsoids describing the contour. Feature translation and rotation may be determined aposteriori if desired.

It has been shown how the variables describing a contour of interest may be tracked and their time histories developed for use in making forecasts. Alternatively, instead of tracking the time varying attributes, the change in the attributes may be tracked, and forecasts built upon adding to an initial reference attribute value a forecast of the change of the attribute from this reference. For example, in the vortex fitting scheme, instead of tracking ellipsoid amplitude, we make the initial amplitude the reference value and track the change in the amplitude from the reference value. This method has the advantage of allowing one to use the second time derivative of the quantity of interest in the forecast process, since the quantity being tracked is the change in the attribute rather than the attribute itself. Whether this is truly beneficial depends somewhat upon the meteorology of the situation, the rate of feature evolution, the noise in the data, and the method used for feature description. Another factor which must be considered is that tracking change in a variable rather than the variable itself results in less information. Two successive locations yield two attribute values but only one attribute change value. It is quite possible that the lifetimes of the features may be so short as to demand use of as much data as possible to remove the effects of noise to discern the true trend and thus make a reasonable forecast. This would preclude use of the change method. In the final analysis both methods will be tested to determine which allows for the most accurate forecasts.

## 6. FORECAST TOOLS

The method by which a forecast is made is somewhat dependent upon the feature description approach employed. If a relatively primitive descr ption tool such as chain coding is used, then boundary description processing is very quick. Here, however, a large number of elements may be required to develop the full contour code, and to forecast values for each item in the data set a large number of computations may be involved. Thus a simple forecasting method, requiring very few computations and little computer memory allocation is desired for the primitive methods. Conversely, a high level contour description method such as vortex fitting requires only a small number of parameters to be retained and tracked. The potential for use of a complex forecasting technique is now present. It must be noted, however, that this is not necessarily a clear cut possibility, for the time involved in developing the contour description in the high level method may preclude use of any but the simplest forecasting tools. Only experience with real data analysis will provide a guideline. In this effort, forecasting techniques exhibiting a broad range of complexity will be tested. However, because of the hard time limit available for data and forecast updates, it is expected that the main focus will initially remain with the simpler methods.

For the moment, concern will focus only on simple techniques, and little consideration will be paid to whether the variables, or their changes, are being tracked. Potential applications will be discussed later. The simplest forecast model of any practical use is the simple smoothing filter. This filter inherently assumes the data to be stationary since it does not include a trend factor. A useful form is the simple exponential filter, as demonstrated by Makridakis and Wheelright,[8] which may be written as

8. Makridakis, S., and Wheelwright, S.C. (1978) Forecasting Methods and Applications, John Wiley and Sons, New York.

$$F_{t+1} = KX_t + (1-K)F_t \ . \tag{1}$$

where K is a weight in the range of 0 to 1. This relation may also be written as

$$F_{t+1} = KX_t + K(1-K)X_{t-1} \dots K(1-K)^{N-1}X_{t-N+1} \tag{2}$$

$$= F_{t+1} = F_t + KE_t \tag{3}$$

where

$$E_t = X_t - F_t \ . \tag{4}$$

In these relations $X_t$ is the measured variable at the current observation, $F_t$ is the previous forecast for the current time, $E_t$ is the measured error of the forecast for the current observational time, and $F_{t+1}$ is the forecast for one time interval into the future. Depending upon the form of the relation one may interpret this filter [Eq. (3)] as forming a new forecast by adding to the current observation the error of the forecast for this current observation. Equation (2) indicates that this filter naturally gives greater weight to current observations than to previous ones.

Another version of a smoothing filter is the moving average filter, which is written as

$$F_{t+1} = (X_t + X_{t-1} \dots X_{t-N+1})/N \tag{5}$$

$$= X_t/N - X_{t-N+1}/N + F_t \tag{6}$$

where all observations are given the same weight. As noted these two filters may be useful relations if the parameter is basically stationary and variations in the parameter reflect noise input. In essence these filters attempt to determine the true mean value by smoothing out the noise.

At first glance these simple routines may seem of little use, however, if we are tracking the change in a parameter such as position, then we are essentially estimating an average velocity of translation, which is now a very useful parameter in forecasting quantities such as motion of large scale, or stratiform environments. The exponential filter employs the concept of negative feedback [Eq. (3)], where the new forecast is adjusted for the error oncurred in the previous forecast. Also, the exponential filter allows the option for varying the relative weight given to recent vs past observations. This is particularly relevant for meteorological systems where feature evolution may demand that the history of the parameter focus primarily on recent observations. In addition the exponential filter requires very little storage memory, with only the present observation and the previous forecast of the parameter required to make a new forecast. The moving average filter, on the other hand, requires retention of N observations and is more computationally intensive. Thus the simple exponential filter may be useful when used with the primitive feature description methods where many parameters are updated.

As stated above, however, these simple smoothing filters inherently assume the variable to be stationary. For the exponential form one also must decide upon a value for a weighting factor. This last concern may be removed by use of the adaptive simple exponential filter which automatically adjusts the weight value dependent upon the error detected in the last forecast. With these simple filters forecasting for more than one time interval ahead requires the assumption that

$$X_{t+2} = F_{t+2} \tag{7}$$

$$X_{t+3} = F_{t+3} \tag{8}$$

and so on. Thus one sees that forecast values tend to a constant value, since all forecasts are assumed to have zero error. Again, whether or not this is a serious drawback may be dependent upon the variable being forecast.

The next obvious step is to consider a parameter as exhibiting a linear trend. The standard linear regression technique uses a formulism of

$$F_{t+m} = A + BX_{t+m} \tag{9}$$

where $X_{t+m}$ is the independent variable (generally time) at the future time m intervals ahead, and $F_{t+m}$ is the forecast. The parameters A and B are determined through the relations

$$A = \Sigma F/N - B\Sigma X/N \tag{10}$$

$$B = (N\Sigma FX - \Sigma F\Sigma X)/(N\Sigma X^2 - (\Sigma X)^2) . \tag{11}$$

It is noted that again N values of both F and X are retained in memory for each new computation, and computational complexity has increased significantly over the simpler filters previously discussed.

An easier way to incorporate trend in the forecast process is by use of a modified form of the exponential or moving average filter. The Holt two-parameter linear exponential filter is of the form

$$F_{t+m} = S_t + B_t m \tag{12}$$

where

$$B_t = A(S_t - S_{t-1}) + (1 - A) B_{t-1} \tag{13}$$

$$S_t = CX_t + (1 - C)(S_{t-1} + B_{t-1}) . \tag{14}$$

In this formulation Eq. (14) corrects $S_t$ for the error in the last estimate by adding in the previous trend estimation, while Eq. (13) effectively updates the trend. Thus both smoothing of the data and linear trending is accounted for in this method. A potential drawback is the use of the two weighting constants A and C. These terms should generally be determined through some form of error analysis (for example, mean square error minimization). This requirement could seriously degrade its real time applicability. If a useful set of weights applicable to many meteorological situations can be determined through analysis of case studies, then this method is preferred over the standard linear regression formulism for the following reasons. The method does allow for preferential weighting and therefore responds to recent changes in trend more rapidly than the standard formulism. This may be a significant factor in attempting to trend a meteorological phenomenon where the attribute trend changes from one value to another. However, if the weighting values are found to have no preferred narrow range then it may be necessary to resort to standard regression methods.

Extension to a quadratic fit may also be done. The standard quadratic relation is

$$F_{t+m} = A + BX_{t+m} + CX^2_{t+m} \tag{15}$$

where this is usually rewritten as a linear relation in terms of two independent variables $X1(=X)$ and $X2(=X^2)$ as

$$F_{t+m} = B_0 + B_1 X1_{t+m} + B_2 X2_{t+m} . \tag{16}$$

or

$$F = XB . \tag{17}$$

F is now an N*1 vector matrix of observations, B is a 3*1 vector matrix of constants, and X is a N*3 matrix of independent inputs. The solution is most easily obtained through matrix operations and the desired constants are given by

$$B = (X'X)^{-1} X'Y . \tag{18}$$

Again the data are generally smoothed before serving as input to these relations. Once again, an alternative approach which invokes the use of weighting constants and preferential weighting may be considered. The Brown quadratic smoothing exponential filter may be written as

$$F_{t+m} = A_t + B_t m + 0.5 C_t m^2 \tag{19}$$

where

$$A_t = 3S'_t - 3S''_t + S'''_t \tag{20}$$

$$B_t = \frac{\alpha}{2(1-\alpha)^2} [(6-5\alpha)S'_t - (10-8\alpha)S''_t + (4-3\alpha)S'''_t] \tag{21}$$

$$C_t = \frac{\alpha^2}{(1-\alpha)^2} (S'_t - 2S''_t + S'''_t) \tag{22}$$

$$S'_t = \alpha X_t + (1-\alpha)S'_{t-1} \tag{23}$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1} \tag{24}$$

$$S'''_t = \alpha S''_t + (1-\alpha)S'''_{t-1} \tag{25}$$

which as in the standard regression method must be re-evaluated after each new data input. However this formulism requires far less computer memory storage and computations. Again it is necessary to find an acceptable range of weights useful to the variety of meteorological environments expected. However, the potential difficulty in this task is offset by the realization that the features being tracked and forecast will generally not be evolving in a simple linear or quadratic fashion. For a very short period of time, such variation may appear reasonable. However, the effects of using a finite vertical and horizontal grid size, coupled with evolution and vertical transport effects, and limited lifetime of the features being tracked suggest that no simple trend will exist. The effect of forcing a standard linear or quadratic fit to the data may result in greater forecast error than that found to occur with these simpler filters which adapt to changes more rapidly and which may possibly run with a generic set of weights.

One may consider use of higher level forecasting models such as higher order polynomial fits, autoregressive moving average models (ARMA), or Kalman filters. However, their proper use requires an extensive historical data set for the feature being tracked, much greater than is expected to be available here. Even if the data requirements could be satisfied, these methods may quickly become extremely computationally burdensome. Their proper use may also require knowledge, or interpretation, concerning the state of the features which cannot be reasonably satisfied with the data at hand. For example, the ARMA model requires use of the autocorrelation function to identify characteristics of the data time series. The interpretation of this autocorrelation function allows one to choose the proper smoothing filter and model. Application of the Kalman filter requires substitution of the past variance of the forecast variable in place of the desired current value. With the limited data sets expected to be available here, and the changing nature of the features being tracked, it is believed that these requests cannot be adequately satisfied. Thus, although high level forecasting techniques such as the Kalman filter may be tested, it is strongly felt that most effort will be directed towards use of the simpler, more efficient, and realistically useful methods of the type outlined earlier.

## 7. EXAMPLES OF METHODS

To bring this discussion into focus and provide a better understanding of the proposed solution of the problem, a demonstration, in graphical sense will be presented. A simple evolving data field will be studied using three approaches discussed earlier. The generalized flow chart representing the steps involved in solution of the problem is shown in Figure 3. Figure 4 shows the three successive observations of the generalized intensity field, which is portrayed as containing an advancing line type feature from the west, and two closed features in the eastern portion of the viewing area. For the purposes of discussion the line feature is described by simple icon chain coding, the large closed contour by vortex fitting, and the small closed feature by use of the simple raster vector.

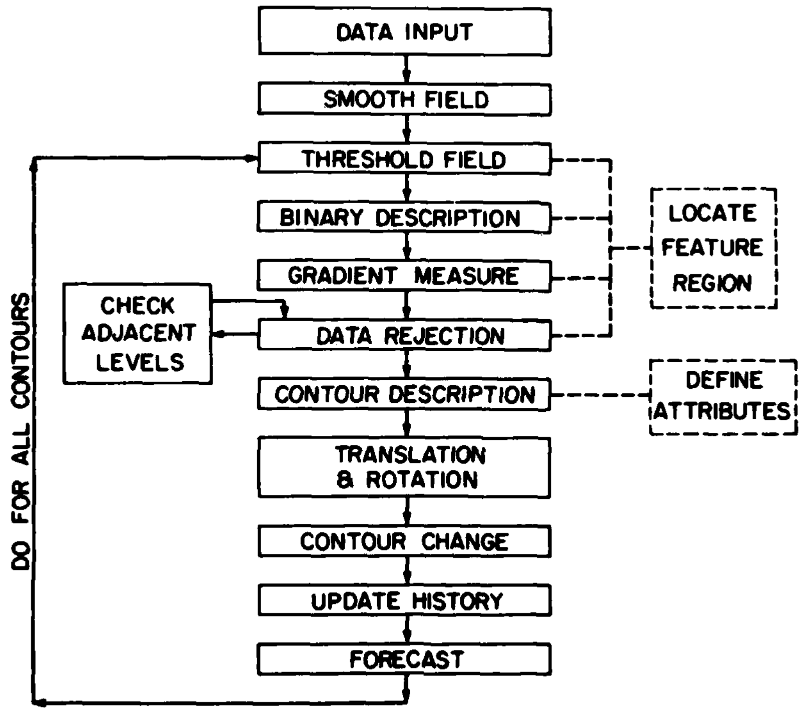



Figure 3. Flow Chart Representation of Forecast Process

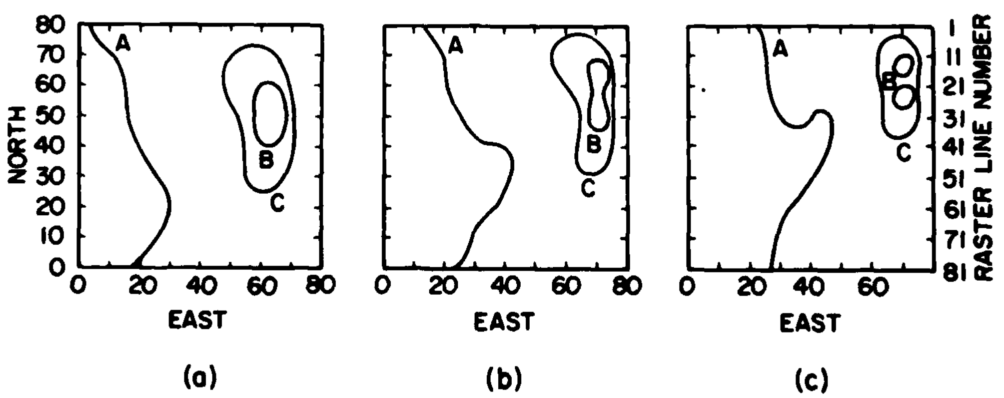



Figure 4. Model Intensity Fields to Be Described by Three Methods: (a) Freeman Chain Code, (b) Simple Raster Vector, and (c) Vortex Fitting

The three successive chain codes are shown in Figure 5. As the line feature advances eastward note that the chain code also evolves. Comparison of the three codes quickly discloses three important facts. First, the main body of the code remains intact, suggesting that this feature is basically stationary in shape. Secondly, the feature is moving northward since there is loss of code at the start (reference position taken as most northern point), and additional new code at the end. Note that this is determined only because the feature is believed to be evolving slowly in comparison to our observational sampling period. Last, rapid structural change is localized and easily detected. The elements of the chain code, representing particular locations along the intensity contour may be tracked, their changes detected and quantified, and a forecast made. The dotted lines indicate successive values of chain code for single elements. The code along these dotted lines represent the time history of the individual code elements. Interpretation of this history allows a forecast to be made through use of the forecasting methods discussed earlier.

The simple raster vector approach is portrayed in Figure 5. Again a sequence of chain codes, with each code element representing the vertical raster line number and starting and ending points of the contour of interest on that horizontal line, is generated. In this example the small closed contour is rotating slowly as it advects eastward, and splits between the last two observations. In this simple raster format the raster vectors are always horizontally oriented, thus each raster vector may eventually be representing different contour elements during the observational period. The alternative would have been to have the raster vector coordinate system rotate with the feature, thus allowing the raster vector to represent the same contour elements for longer time periods. In this example the elements tracked are the start and end points for individual horizontal raster lines. The dotted lines show the track sequence history for individual tracked parameters. It is easily seen how the raster vector end points form a time history which may be modeled to provide a forecast. The progression and growth of the contour along the vertical direction is easily detected by noting the changing beginning and ending raster line numbers while the total separation distance is essentially maintained. Last, the splitting of the contour into two separate contours is noted by the missing raster line numbers (18 to 20) which were included in the original chain code sequence. It is easily noted that the primary difference between this and the simpler icon chain code is its more rapid interpretation in spatial terms.

Finally, the vortex fitting approach is presented in Figure 5. Note that it is assumed that two ellipsoids are used to fit the boundary contour. As time passes the two ellipsoids are automatically modified to yield the best fit to the meteorological boundary. The attributes tracked here are the ellipsoid descriptors, namely the amplitude, size, center, eccentricity, and orientation. The history of each attribute is modeled and forecast. The forecast values determine the future ellipsoid locations, sizes, and shapes, and thus ultimately the forecast intensity contour.

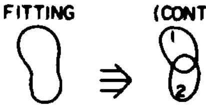
CHAIN CODE (CONTOUR A)

a. 8 8 1 8 7 7 7 7 7 8 8 1 8 7 6 6 6 6 5
b. 1 8 7 7 7 7 7 8 1 1 2 1 8 7 6 6 5 6 6
c. 7 7 7 7 8 1 2 3 2 1 8 7 6 6 5 6 6 7 6

SIMPLE RASTER VECTOR (CONTOUR B)

a. (8,55,60) (9,52,63) • • • • • • • • • (53,59,60)
b. (4,63,64) • (8,57,71) (9,55,73) • • • • • • (46,68,71)
c. (3,67,68) • • • (8,62,72) (9,60,73)-(17,68,69)-(21,69,70)-(28,68,70)

VORTEX FITTING (CONTOUR C)




| | CENTER | AMPLITUDE | SIZE | ECCENTRICITY | ORIENTATION | |
|---|---|---|---|---|---|---|
| a. | 60,25 | 5.0 | 10 | 0.7 | 97 | |
| b. | 62,23 | 4.7 | 9 | 0.6 | 93 | ELLIPSOID #1 |
| c. | 63,27 | 4.5 | 9 | 0.6 | 87 | |
| a. | 62,46 | 4.1 | 7 | 0.5 | 91 | |
| b. | 63,45 | 3.9 | 6 | 0.4 | 89 | ELLIPSOID #2 |
| c. | 64,41 | 3.8 | 6 | 0.4 | 88 | |

Figure 5. Description of Contour Fields of Figure 4 Showing the Three Different Attribute Fields and the Development of Time Histories (dashed lines) for Specific Attribute Elements in (a) Freeman Chain Coding, (b) Simple Raster Vector, and (c) Vortex Fitting Methods

## 8. CONCLUSIONS

This report has focused on candidate techniques for forecasting precipitation and cloud structure at arbitrary locations. A graphical demonstration was provided to show the steps and applicability of some proposed methods. It was determined that a multilevel approach was necessary. Due to the severe time constraint of acquiring new data and providing forecast updates every 5 to 10 min, coupled with the reduced error in tracking and forecasting vertically averaged precipitation quantities while still requiring some knowledge of vertical structure, a simple three layer model, representing the lower, middle, and upper troposphere, is initially suggested. The parameters of interest are the radar reflectivity factor and satellite cloud brightness. These parameters require no additional transformation from their raw data input state, and are readily transformed into measures of signal attenuation. The features to be tracked and forecast are the contours of these intensity values, contoured in discrete values. Description of the contours will follow the process of isolation by means of binary thresholding, contour location by field gradient operation, and description by a variety of attribute description methods. It is proposed that a wide range of descriptive methods, including simple icon and positional chain coding, up through complex methods using polynomials and vortex fitting be tested. Simple translation and rotation of the whole contour will be performed by cross-correlation. Measurement of contour structure change was shown to be implicitly linked to the method of attribute description through use of examples. A range of forecasting methods were proposed. Although complex methods, such as Kalman filtering, will be tested, focus will be directed towards use of simpler, more efficient methods such as linear exponential filtering.

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