4.6 DEVELOPMENT OF AN EVENTS-ORIENTED VERIFICATION SYSTEM USING DATA MINING AND IMAGE PROCESSING ALGORITHMS

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1. INTRODUCTION

The overall goal for this work is to develop new forecast verification techniques that provide information on forecast quality that is consistent with subjective impressions of the value of a forecast. Here, we use the term *value* as defined by Murphy (1993) as the incremental benefits realized by decision makers through the use of forecasts, while *quality* is defined as the correspondence between forecasts and observations. Traditional objective forecast verification techniques typically provide information on specific aspects of forecast quality, such as bias or accuracy. On the other hand, forecast value is very difficult to quantify. A forecast by itself contains no value, it only obtains value once a decision maker takes some action because of it. Since value depends upon how a decision maker uses forecast information, the estimation of value will vary for different decision makers as well as different forecasting situations. Note that value is defined as the *incremental* benefits of forecast information, or the benefits of a decision made when the forecast was on hand minus the benefits of a decision made without having the forecast. Therefore, estimation of value will also depend on the prior information that the decision maker has available to them. Due to differences in prior information, as described by Murphy (1993), the same set of forecasts can lead to quite different estimates of value, even in the case of two decision makers faced with the same situation. For example, if a decision maker has access to prior information that is the same as a given forecast, that particular forecast is of zero value to the decision maker, no matter how accuract the forecast was. In addition, the relationship between forecast quality and value is quite complex.

Again, the goal of this work is to develop techniques that provide information on forecast quality that is *consistent* with subjective impressions of forecast value, and not try to estimate actual forecast value itself. The subjective impression of forecast value likely comes down to the decision maker's answer to the question: "How well did the forecast help me do my job?" In order to answer this question, we will focus on a particular decision making problem, analyze what the decision maker's job entails, and determine what aspects of the forecast information are significant in the decision making process. By producing verification information on the quality of these critical components of the forecast, we then meet our goal of providing information consistent with subjective impressions of value.

In this work, we choose to focus on a specific set of decision makers, forecasters at the National Weather Service's Storm Prediction Center (SPC). SPC forecasters are charged with producing convective outlooks that predict the occurrence of hazardous convection in the next 0-72 hours, and specifically the probability of certain types of hazardous weather (hail, wind, or tornado). Due to the uncertainty involved in forecasting these kinds of events, the precise location and timing of their occurrence is not as critical as determining the type of event that is likely to occur over a general area in a given time period. Here, the product of the decision making process is a forecast, but rather than verifying the resulting forecast product, we will focus on verifying the forecast information that was used as guidance during the decision making process. The forecast guidance information that is utilized by the SPC forecasters is output from numerical weather prediciton (NWP) models. NWP models are decades away from explicitly resolving the hazardous weather events that SPC forecasters are tasked with forecasting. Therefore, SPC forecasters use the numerical guidance to investigate the dynamic and thermodynamic "ingredients" for hazardous convection in pre-storm and near-storm enivronments and create forecast products based upon their experience and knowledge of current meteorological research as well as model performance. Model predicted precipitation is often used in the determination of location and timing of convective initiation.

An important part of the decision making process is the prediction of the modes of convection, where convective mode is defined as the dominant shape and structure of the convective rainfall pattern over a region. For example, if cellular convection (i.e., supercells) is expected, the forecaster may predict a higher probability

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of tornadoes. If the convective mode is expected to be mainly linear (squall lines), the forecaster may lean towards a higher probability of wind damage. Therefore, an aspect of numerical guidance that could be very helpful in the decision making process for SPC forecasters is guidance related to the spatial structure and shape of the precipitation pattern. In this work, we will focus on verifying the shape and structure of rainfall patterns, and therefore provide verification information that is consistent with subjective impressions of the forecast value of NWP guidance to SPC forecasters.

To this point, the determination of which decision makers to focus on has been made and the aspects of the numerical guidance to be verified have been selected, but the manner in which the quality of these numerical forecasts will be determined has not yet been defined. A question naturally comes to mind: Why not use traditional measures of accuracy to determine the quality of the rainfall pattern forecasts? Objective forecast verification is typically performed by an automated system which compares values of forecast and observed variables valid at the same set of points in both time and space, where a variety of statistics can be computed to measure the accuracy of the forecast. However, as described by Baldwin et al (2001), traditional objective accuracy measures may actually show a forecast system that never predicts realistic looking patterns as more accurate than one that does predict realistic features. This is due to the fact that small forecast errors in phase, displacement, or time lag can produce very large differences between forecast and observed scalar variables at specific locations, for fields containing high-amplitude small-scale features. On the other hand, when a human performs "subjective" verification, by visually comparing the forecast and observed fields, the comparison is much less tightly focussed. A human analyst will naturally take errors in phase or displacement into account. Other attributes of the fields will also be considered, for instance, a forecast field with spatial variation similar to the observed field might subjectively be considered of higher quality than a forecast field with quite different spatial variability. If the spatial variation of the field is important to the decision making process, such as in the case of SPC forecasters, alternatives to traditional verification techniques should be explored that provide information on the quality of the spatial variability of the forecasts.

As a basis for the development of these alternative verification techniques, the traditional point-to point verification approach is expanded to the verification of events, which are defined as regions containing similar characteristics, properties, or *attributes*. Baldwin et al (2002) outline the general framework to follow in order to perform an events-oriented verification. To summarize briefly, this process involves identifying events within forecast and observed fields and associating a set of attributes to each event, known as an attribute vector. Observed and forecast events must be described by the same set of attributes, for example, the location, shape, scale, amplitude, orientation, continuity, intermittancy, etc., of the event. Once the events have been identified and the attributes associated with them have been determined, the quality of the forecasts can be determined by measuring the similarity between forecast and observed events. There are numerous possible choices of similarity measures, for example, the correlation coefficient or the generalized Euclidean distance.

To this point we have established the motivation for verifying the quality of the spatial shape and structure of rainfall patterns, and defined the general framework for performing this type of verification. The problem now becomes developing a method for objectively identifying events and selecting a proper set of attributes to describe the events in a way that discriminates between different phenomena. Development of an automated system for locating and extracting events has not yet been attempted, and edge detection image processing algorithms will most likely prove to be fruitful. The remainder of this paper will focus on the determination of a set of attributes that are effective at discriminating among different types of spatial rainfall patterns. Here, a small test data set has been collected, populated with numerous cases of interesting rainfall patterns. These events were chosen and classified subjectively. The choices of attributes are validated by comparing the results from an objective classification, using hierarchical cluster analysis, to the subjective classification (performed by a SPC scientist). If there is good agreement between the objective and subjective classifications, we can assume that the set of attributes is a good one. The goal of selecting attributes for use in the events-oriented verifcation will have been accomplished. The next section will describe results of this comparison, and this will be followed by some concluding remarks.

2. RAINFALL CLASSIFICATION: SPATIAL ANALYSIS

The purpose of this particular work is to determine a set of attributes that is most useful in discriminating between three different types of possible events that could be found in a rainfall field: linear, cellular, and stratiform rainfall patterns. A preliminary data set has been collected to test various data mining techniques. This data set consists of 1h accumulated rainfall analyses obtained from the NCEP "Stage IV" analysis system (Baldwin and Mitchell 1998) for the period covering late summer/early fall of 2000. The domain size was chosen to be fixed at 128 x 128 4km grid boxes, which is approximately 500km by 500km. A set of 48 separate precipitation events occuring at different times and locations across the United States was selected for inclusion in the target data set. The selection criteria was based upon the occurrence of "typical" rainfall patterns that are often found across the U.S. during the year. Each case was subjectively classified (by a SPC meteorologist) into a set of three event classes; linear, cellular, and stratiform. This subjective classification was based solely upon the rainfall pattern, no other information, such as meteorological conditions, location, time of year, etc. associated with each event was provided. There are 17 cases (test data set numbers 1-17) subjectively classified as linear events, where the precipitation field is more or less consistent along a line, with a large variation in the direction normal to the line. There are 21 cases (numbers 18-38) subjectively classified as cellular, where the precipitation field consists of nearly circular-shaped features. The remaining 10 cases (numbers 39-48) are subjectively classified as stratiform, where the precipitation field shows little variation in any direction over a large area.

As the first step in this multi-faceted analysis process, we chose to objectively classify events by analyzing the similarity of bulk "global" measures representing the statistical distribution of rainfall, using hierarchical cluster analysis as the classification tool (Baldwin and Lakshmivarahan 2002). The parameters of the gamma distribution (α, β) fit to the observed histogram were used as attributes in this system. To validate this system, results from the test data set were compared to the subjectively classified rainfall patterns. In the initial work, Baldwin and Lakshmivarahan (2002) found that the system successfully separated the stratiform events from the linear/cellular cases (which were grouped into a parent "convective" class) with over 90% accuracy. However, these attributes proved to be less successful in further separating the convective cases into linear and cellular events. This was due to the fact that the attributes were only able to describe the overall distribution of rainfall across the region, and not able to more specifically describe how the rainfall amounts were organized spatially. In order to further refine the classification and separate the linear and cellular cases, attributes related to the shape and structure of the spatial features are required.

To find such attributes, we turn to the field of geostatistics. Geostatistics is concerned with the study of phenomena that fluctuate in space, of which rainfall is certainly an example. There are several measures of spatial variability and continuity to choose from (Deutsch and Journel 1988), for this work we examined three; 2-D plots of the semivariogram, correlogram, and covariance. All three measure some aspect of the spatial field as a function of a 2-d separation vector **h** (Fig 1). The semivariogram γ(h) is defined as half of the

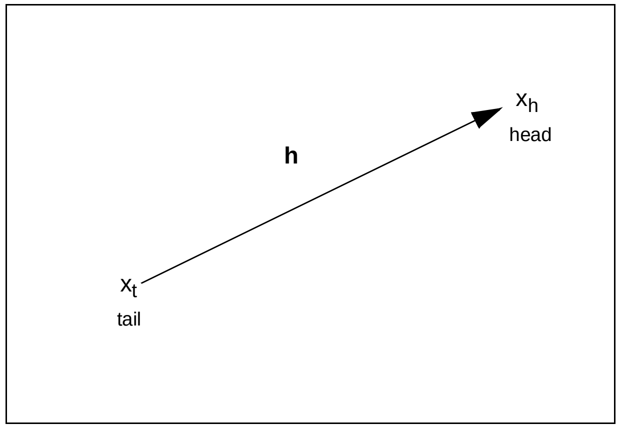

Figure 1: A conceptual example of the separation vector **h**

average squared difference between the pairs of all values separated by **h** (Eq. 1). The covariance C(h) is the traditional covariance (Eq. 2) between all possible pairs of "tail" and "head" values separated by **h**. The correlogram ρ(h) is also known as the auto-correlation, which is the covariance normalized by the respective tail and head standard deviations (Eq. 3).

$$\gamma(h) = \left(\frac{1}{2N(h)}\right)\sum_{N(h)}(x_t - x_h)^2 \qquad (1)$$

$$C(h) = \left(\frac{1}{N(h)}\right)\sum_{N(h)}(x_t x_h - m_t m_h) \qquad (2)$$

$$\rho(h) = \frac{C(h)}{\sigma_t \sigma_h} \qquad (3)$$

Here m_t and m_h are the means of the tail and head values, respectively, and σ_t and σ_h are the standard deviations of the tail and head values, respectively. N(h) is the total number of possible pairs of tail and head values for a given separation vector **h**. These statistics were computed using GSLIB, a freely available library of software packages for geostatistics developed at Stanford University (Deutsch and Journel 1988).

Examples of 2-D semivariogram, covariance, and correlogram plots are found along with the rainfall field for case number 11 in Figures 2-5. The rainfall field (Fig 2) shows heavier precipitation located along a line oriented more or less parallel to the y-axis (approximately

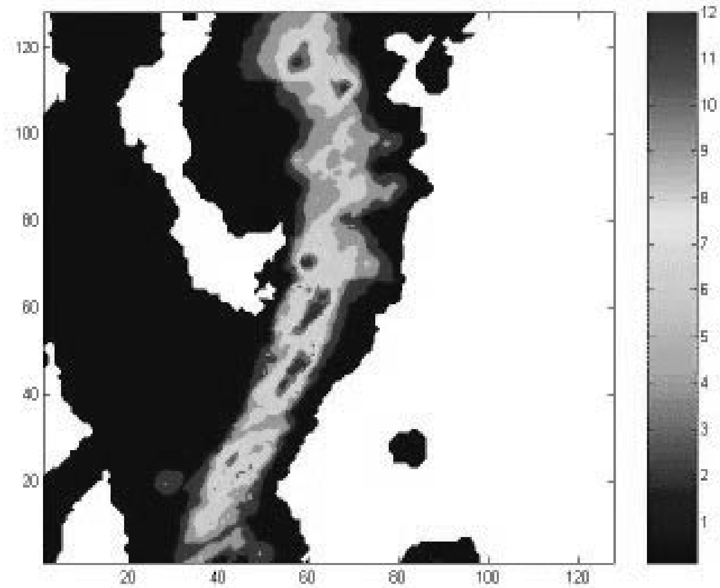

Figure 2: Rainfall analysis for case # 11. 1h accumulated rainfall (mm) valid 0200 UTC 21 Sep 2000.

north-south) with strong variations in amounts normal to the line, consistent with the definition of a linear event. It is therefore not surprising that this event was subjectively classified in the linear class. Plots of the semivariogram, covariance, and correlogram (Figs 3-5) provide fairly consistent information, that rainfall values are similar over a large distance in the direction approximately parallel to the y-axis, and similar to other values only over a short distance in other directions. The semivariogram (Fig 3) provides information on the average squared difference, therefore the value at the origin (**h**=(0,0)) is zero and values increase as **h** moves further from the origin. The covariance (Fig 4) plot works in the opposite sense, indicating how pairs of values simultaneously vary from their means, the value at the origin is the overall variance of the field. The correlogram (Fig 5) operates in a similar fashion to the covariance plot, except the value at the origin is normalized to 1.0. Since these three statistics provide similar information on the spatial variability of the rainfall field for all cases, we decided to focus our analysis on one of the statistics. Since the correlogram is normalized, its values will not depend on the units or overall magnitude of the field. For this reason, the correlogram was selected for more detailed analysis.

As can be seen in Figure 5, the shape of the closed contours in the correlogram appear to be quite elliptical. This was also found to be true in every other correlogram (not shown). This discovery led to the idea that a fairly compact way to model the information found in the correlogram would be to fit ellipses to particular contour levels. The lengths of the semi-major (a) and semi-minor (b) axes could be computed and used to calculate the eccentricity ($=\left(\sqrt{a^2+b^2}\right)/a$) and area ($=\pi$ ab) of each ellipse. Parameters such as these could then be used as attributes in the subsequent objective classification scheme. As a simple approximation to these parameters, ab was used as an area estimate and a/b was used for eccentricity (a circle will have a/b of 1.0 and a/b will increase as the ellipse gets flatter). While it is possible to obtain a set of these parameters representing any number of contour levels on the correlogram, we decided as a first step to fit the 0.6 correlation contour for each case. This decision was made because the 0.6 contour was closed on each correlogram plot and ellipses fit to those contours varied in size and eccentricity across the 48 cases. The ellipses were fit by hand (see Figure 5 for estimates of major and minor axes), therefore ab and a/b values will likely not match those found by objective shape fitting algorithms (for examples of such algorithms, see Davies 1997). However, the purpose of this experiment is to determine whether or not parameters of this type will be useful in an objective classification scheme, and errors in the ab and a/b estimates are likely small compared to differences in those parameters across the 48 cases in the test data set. Table 1 provides the estimated values of the lengths of the semimajor and semi-minor axes, the angle between the major axis and the x-axis, ab, and a/b. These estimates of ab

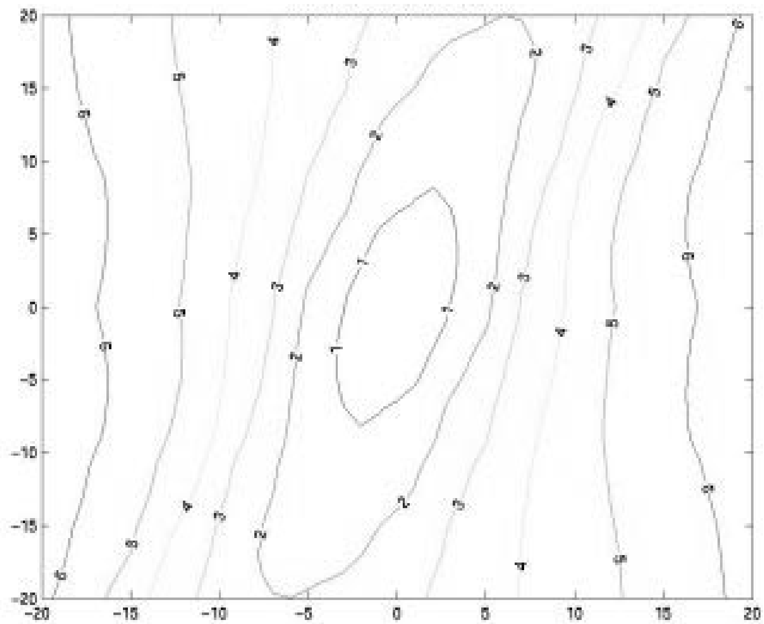

Figure 3: Semivariogram for case # 11. Contour interval = 1.

and a/b are then used in the classification algorithm in order to find clusters of similar rainfall events.

Since classification is the desired data mining task in this work, hierarchical cluster analysis (Anderberg 1973) has been selected as the primary classification tool for this work. Here, objects will be clustered where objects are defined as rainfall events over regions of fixed size, and attributes are some combination of parameters of the gamma distribution (α,β) fitted to the observed rainfall distribution and estimates of 0.6 correlation ellipse area and eccentricity (ab, a/b). Specifically, the gamma distribution parameters were taken from the results of the generalized method of moments estimation procedure using three moments and q=1 lag correlation, which produced the best objective classification performance in previous work (Baldwin and Lakshmivarahan 2002). The hierarchical cluster analysis method that is chosen for this work is Ward's method, which is based upon the fact that the total variance of all of the objects is constant and can be partitioned into the sum of between-cluster and within-cluster components. The criteria for adding an object to a cluster is minimizing the squared error, which is the same as minimizing the within-cluster variance, and therefore maximizing the between-cluster variance. This forces the objects found within a cluster to be similar while keeping the clusters as separate as possible. Ward's method has provided good results in analyzing meteorological data in previous research (Alhamed et al. 2002).

Now that the set of attributes and the cluster analysis method have been selected, the question now becomes whether or not the attributes require normalization and what combination of these four attributes produces the best objective classification. In order to determine if these four attributes provided unique information, principal component analysis was performed on the correlation matrix representing all four attributes. The smallest eigenvalue of the correlation matrix was approximately 20% as large as the largest eigenvalue. All four components were required in order to explain 95% of the total variance contained in the data set. Therefore, it is reasonable to expect that using all four attributes will result in the best possible objective classification. This will be confirmed by experiment. In order to determine which combination of attributes produced the best objective classification, the results from the cluster analysis algorithm were analyzed in the following manner. First, a "cut level" was located on each dendrogram tree that resulting in separating the 48 cases into four main clusters and a small number of outliers (no more than 5 cases could be considered outliers for any objective classification experiment). For each of the four main clusters, the dominant class was defined as the class (linear, cellular, or stratiform) that contained the highest percent of cases detected for that particular cluster. For all four clusters, the number of cases in the dominant class was summed to produce a total number of "correct" cases, and all cases not in the dominant class were considered "incorrect" cases. The

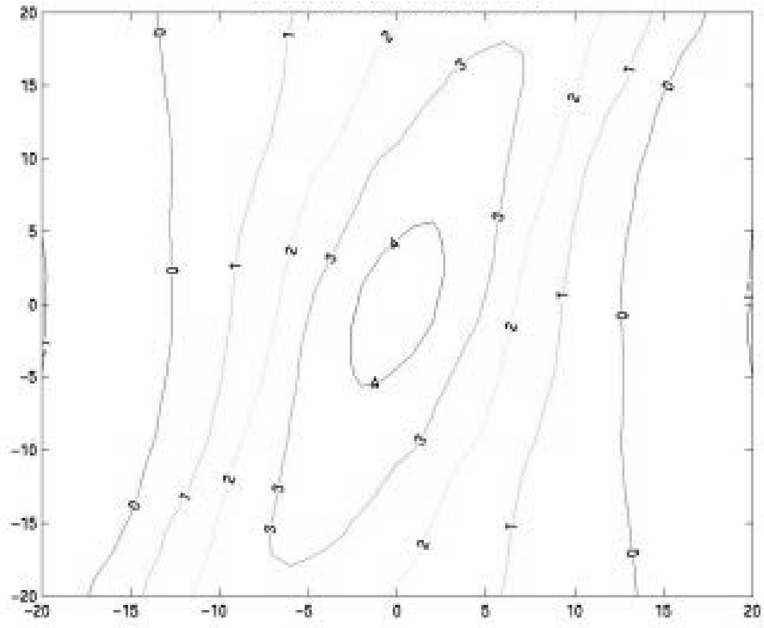

Figure 4: Covariance plot for case # 11. Contour interval = 1.

overall percent correct was computed, this was equal to the total number of "correct" cases divided by the total number of cases (=48) minus the number of outlier cases. For example, figure 6 shows the dendrogram tree produced by the Ward's cluster analysis method using all four attributes after being normalized so each attribute produced zero mean and unit variance ("Z-score normalization"). The "cut level" for this example was made at a value of 3 on the y-axis, resulting in four main clusters and two outlier clusters both containing a total of 5 cases. The dominant class for cluster #1 was stratiform, detecting 8 of 10 cases (80%) belonging to that class, and one case belonging to the cellular (1 of 21 or 4.7%) class. For cluster #2, the cluster detected 47.6% of the cellular cases (10 of 21), 41.2% of the linear cases (7 of 17), and none of the stratiform cases, therefore this cluster was considered to be cellular, with 10 correct cases. Cluster #3 was also considered cellular dominant, with 42.9% (9 of 21) of all cellular cases detected, 11.8% (2 of 17) of all linear cases, and 0% (0 of 10) of the stratiform cases detected, therefore resulting in 9 correct cases. Cluster #4 was considered linear, with all of its 6 cases belonging to that class. The total number of correct cases in this experiment was 33, dividing this by the total number of non-outlier cases (=43) results in a percent correct of 77%. Note that most of the incorrectly classified cases were found in cluster #2, analysis of these cases will likely be the most fruitful path to further improvements in the objective classification. This validation was also repeated to create a two class (combining linear and cellular into a parent "convective" class, as in Baldwin and Lakshmivarahan 2002) percent correct, so that these results can be compared with previous work.

This validation technique was performed on a series of objective classification experiments. The question of normalizing the attributes prior to the cluster analysis was investigated by analyzing the raw attributes, normalizing each attribute by the maximum value for the 48 cases, and normalizing each attribute vector to produce zero mean and unit variance. For each of these types of normalization, different combinations of subsets of the four attributes (α, β, ab, a/b) were used, the six possible combinations of two of the four, plus the four possible combinations of three of the four, and all four attributes, resulting in 11 different experiments for each type of normalization. The percent correct was considered for the three classes (linear, cellular, stratiform), as well as for the two classes (combining the linear and cellular classes into a parent "convective" class). Results from the unit variance normalization proved to be better on average than the results from the raw attributes and the "max normalized" attributes, therefore those results will be the only ones shown here.

Figure 7 shows the percent correct results for all of the different combinations of attributes in the two class case. The best combination of two of the four attributes were ab and β, producing 98% correct, although several

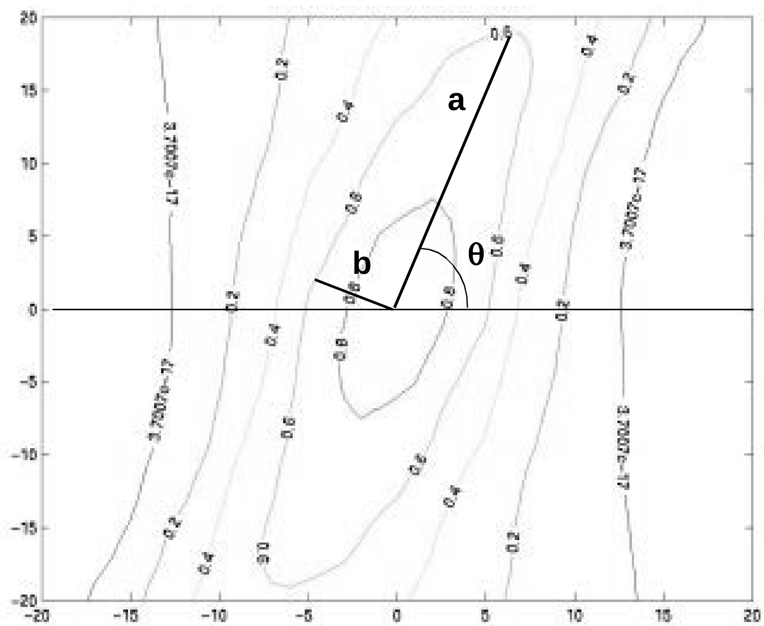

Figure 5: Correlogram plot for case # 11. Contour interval = 0.2.

other combinations of two attributes produced similar results. The best combinations of three of the four attributes were the two experiments that included both α and β, both of which produced 98% correct. The experiment using all four attributes produced 98% correct, practically tied with the best two of four attributes experiment. Most of the experiments produced greater than 90% correct, which is consistent with results found in previous work (Baldwin and Lakshmivaran 2002). In the two class case, there does not seem to be any significant advantage in using more than two attributes, but there is no disadvantage either.

Figure 8 shows the percent correct results for all of the different combinations of unit variance normalized attributes in the three class case. The best combination of two of the four attributes were a/b and β, producing 77% correct, and this experiment was clearly superior to the other combinations of two attributes. In particular, the α, β experiment, which relied only on information from the gamma distributions and without information from the correlogram only produced 46% correct, the worst of all of the various combinations of attributes. The best combination of three of the four attributes was α, β, and a/b, which produced 78% correct. The experiment using all four attributes produced 77% correct, again practically tied with the best two of four and three of four attribute experiments. It appears that the addition of information on the elliptical nature of the 0.6 contour in the correlogram, in particular the eccentricity, provides a useful tool for discriminating between linear and cellular cases.

While results of ~75% correct may not have reached the level of 98% performance of the two class case, we have come closer to our goal of finding useful attributes to describe the rainfall pattern. A brief look at the cases that were incorrectly classified (note cluster #2 in figure 6) showed that these cases had quite similar qualitites and might be on the fuzzy border between linear and cellular type events. For example, a group of convective cells organized along a line could be subjectively classified as linear or cellular, depending on the opinion of the analyst. Global information, either from bulk properties of the overall distribution of rainfall amounts or from a overall analysis of the spatial statistics, might not provide enough discriminating power to distinguish these events. Therefore, future work entails further analysis of the incorrectly classified cases. Perhaps more local information, such as moving window variances, local graidents, or analysis of feature edges from image processing routines, will prove to be useful in classifying these "fuzzy" types of rainfall patterns.

Acknowledgements: Ying Lin of NCEP/EMC provided archived Stage IV rainfall data. Ahmed Alhamed provided cluster analysis software. The GSLIB software library was used to compute the geostatistics.

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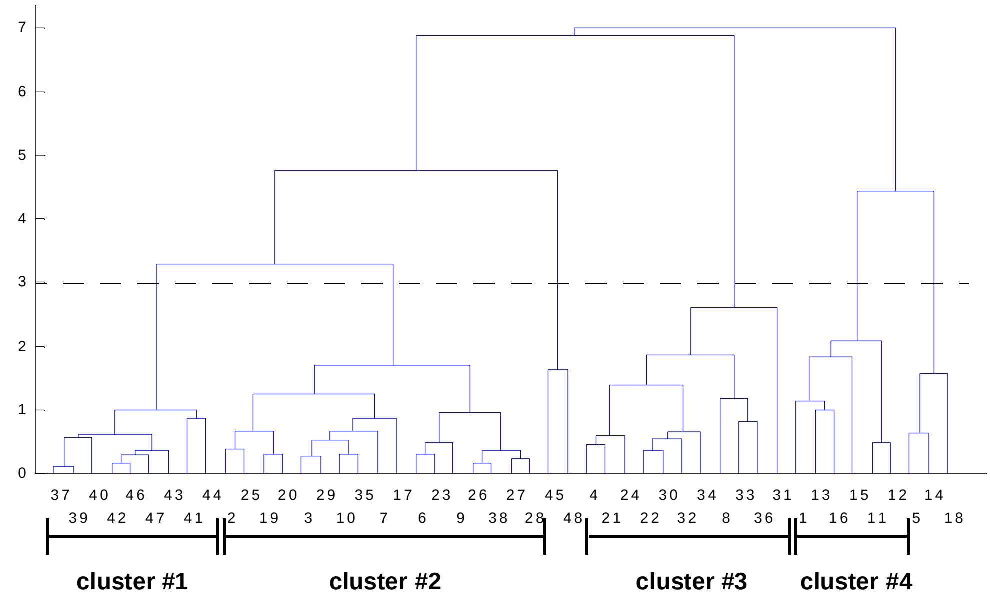

Figure 6: Dendrogram resulting from Ward's method for the four attributes normalized to have zero mean and unit variance.

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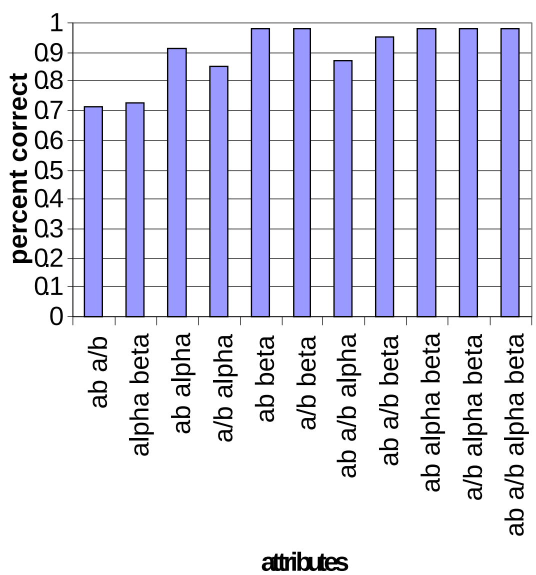

Figure 7: Percent correct for the two class experiments.

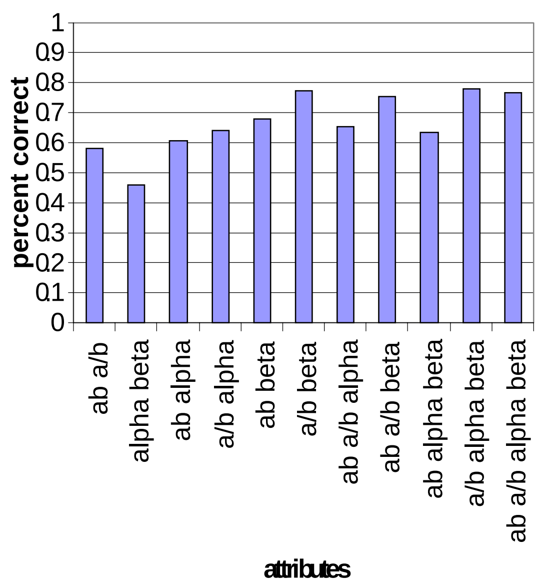

Figure 8: Percent correct for the three class experiments.

Table 1: Characteristics of ellipses fit to the 0.6 contour of correlograms and parameters of the gamma distribution fit to the observed histograms for each case of the test data set. The lengths of the semimajor (a) and semiminor (b) axes are in units of grid boxes, the angle between the semimajor axis and the x-axis (θ) is in degrees. α and β result from using the generalized method of moments using three moments, and an assumed lag correlation of q=1 (Baldwin and Lakshmivarahan 2002).

case	a	b	ab	a/b	θ (deg)	α	β
1	14.87	4.47	66.5	3.32	19.7	0.48	6.34
2	11.18	6.36	71.2	1.76	63.4	0.43	3.53
3	11.41	5.39	61.5	2.12	28.8	0.62	2.07
4	7.16	3.91	28.0	1.83	65.2	0.42	4.52
5	20.52	6.26	128.5	3.28	-47.0	0.47	1.27
6	9.19	4.72	43.4	1.95	67.6	0.39	3.07
7	13.12	5.15	67.6	2.55	72.3	0.42	2.65
8	11.66	4.92	57.4	2.37	31.0	0.16	7.92
9	7.83	4.24	33.2	1.84	63.4	0.52	2.17
10	10.44	4.72	49.2	2.21	73.3	0.49	1.88
11	20.08	5.15	103.4	3.90	71.1	0.29	3.06
12	18.68	4.47	83.5	4.18	74.5	0.24	2.88
13	11.54	3.20	37.0	3.61	72.3	0.42	3.47
14	23.05	6.40	147.6	3.60	49.4	0.62	1.44
15	15.40	2.69	41.5	5.72	76.9	0.23	6.53
16	15.34	3.20	49.1	4.79	71.0	0.52	5.07
17	10.30	3.91	40.2	2.64	60.9	0.67	3.12
18	15.79	10.12	159.8	1.56	79.0	0.53	2.26
19	10.11	7.16	72.4	1.41	98.5	0.56	1.96
20	11.41	6.80	77.6	1.68	28.8	0.52	2.58
21	7.78	4.72	36.7	1.65	45.0	0.30	5.08
22	2.55	2.06	5.3	1.24	11.3	0.18	4.31
23	7.50	4.03	30.2	1.86	36.9	0.40	2.70
24	7.28	3.04	22.1	2.39	15.9	0.32	4.28
25	9.92	5.83	57.9	1.70	49.1	0.52	3.35
26	7.76	6.08	47.2	1.28	14.9	0.45	3.44
27	6.52	6.02	39.3	1.08	4.4	0.51	2.93
28	7.81	5.83	45.5	1.34	39.8	0.51	2.57
29	12.66	5.22	66.1	2.43	80.9	0.59	2.43
30	2.55	2.51	6.4	1.02	11.3	0.17	5.40
31	1.41	1.12	1.6	1.26	45.0	0.14	11.79
32	4.16	2.83	11.8	1.47	57.3	0.31	4.93
33	5.83	4.47	26.1	1.30	31.0	0.36	7.35
34	2.83	1.80	5.1	1.57	45.0	0.22	6.48
35	10.59	5.15	54.5	2.06	70.7	0.54	2.62
36	6.73	2.69	18.1	2.50	42.0	0.37	7.48
37	5.00	5.00	25.0	1.00	0.0	0.51	1.14
38	8.14	6.32	51.5	1.29	79.4	0.49	3.18
39	5.32	4.72	25.1	1.13	48.8	0.52	0.91
40	8.02	5.10	40.9	1.57	86.4	0.51	0.62
41	7.07	6.71	47.4	1.05	45.0	0.77	0.46
42	5.66	4.72	26.7	1.20	45.0	0.59	0.59
43	5.83	3.91	22.8	1.49	59.0	0.62	0.60
44	2.50	2.50	6.3	1.00	90.0	0.76	0.68
45	10.00	7.50	75.0	1.33	90.0	1.64	0.69
46	5.83	5.39	31.4	1.08	31.0	0.61	0.91
47	6.02	5.52	33.3	1.09	-4.8	0.68	0.60
48	7.28	7.07	51.5	1.03	15.9	1.11	0.92