CELL IDENTIFICATION AND VERIFICATION OF QPF ENSEMBLES USING SHAPE ANALYSIS TECHNIQUES

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Abstract

This poster reports on an examination of a Procrustes shape analysis using an example consisting of different members of a WDSS-II K-means pseudo-radar nowcast ensemble. The Procrustes method allows for the decomposition of forecast error into components such as displacement, size, shape, orientation, and intensity. The decomposition of the different errors allows for the diagnosis of error sources and the potential for model adjustment. This verification scheme has the potential for real-time application for different spatial forecasts for ensemble-type forecasts with many members or, simply, a comparison between different models or nowcasters.

Methodology

A number of WDSS-II K-means nowcasts (Lakshmanan, 2003) were run for a significant severe weather outbreak over Missouri on 12 March 2006. The nowcasts were run by changing the reflectivity thresholds over which storm motion is calculated. For a couple of the runs, RUC20 modeled storm motion vectors were used to initialized the WDSS-II K-means product. For this experiment, only three randomly selected ensemble members were chosen to be verified using the new Procrustes verification scheme. The verification scheme first identifies cells using a minimum reflectivity tolerance of 30 dBZ (however this can be user specified). Cells must meet a minimum spatial criteria which also can be adjusted by the user. Once the cell is identified, the dimensionality of the verification problem is reduced by selecting summary statistics from both the truth cells and the forecast cells. The cells are then compared with the nearest neighbor and a penalty is assessed. Analysis of maximum, average, and minimum intensity errors are calculated as well as those errors based on the Procrustes fit which includes location, dilation, and rotation. These statistics can be viewed individually or as a total sum of squares or a total residual sum of squares. A more mathematical representation of the methodology can be found in Micheas *et al.* (2006). A comparison with standard skill scores including probability of detection (POD), false alarm rate (FAR), and critical success index (CSI) was also accomplished.

Number of Cells in Ensemble Members valid: 12 Mar 06 0300Z				
Lead Time (min)	20-40 Cells	40-60 Cells	RUC20-60 Cells	Truth Cells
10	11	8	9	18
20	4	3	3	18
30	3	3	3	18
40	5	4	5	18
50	5	6	5	18
60	8	6	8	18

Table 1: The number of cells identified by the spatial verification scheme valid 12 Mar 2006 at 0300Z at different lead times for different ensemble members (20-40 dBZ motion, 40-60 dBZ motion, and RUC 20-60 dBZ motion) and the truth. This was done using a reflectivity tolerance set at 30 dBZ, an identifiable cell must have a size of at least 4 adjacent pixels. The number of cells in the ensemble members do not have to match the truth for verification purposes, thus there is some implicit penalty if the number of cells in the forecast do not match the number of truth cells.

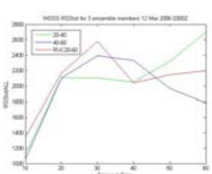

Figure 1: The residual sum of squares (RSStot) for each ensemble member over different lead times all valid for 0300Z on 12 Mar 06. RSStot gives a measure of the accuracy for the Procrustes fit. In this case, the truth and the ensemble nowcasts were defined using 20 angles.

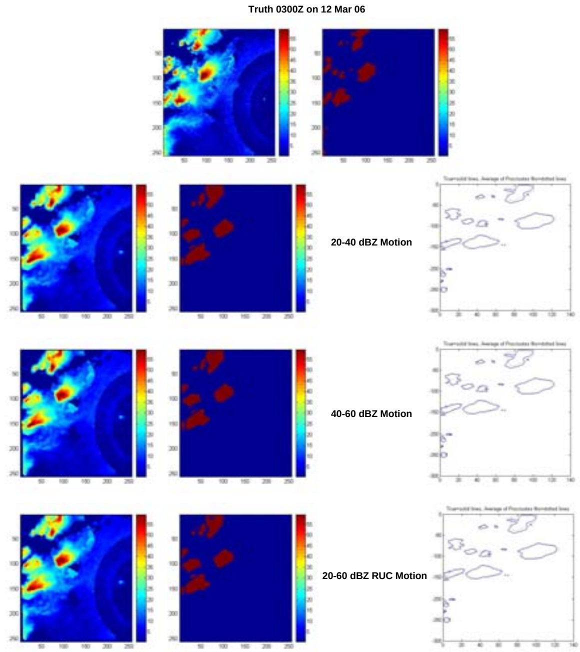

Figure 2: The actual reflectivity images and corresponding cell identification image for the truth (top), and in order from top to bottom 20-40 dBZ threshold WDSS, 40-60 dBZ threshold WDSS, and RUC WDSS nowcasts (left). The Procrustes fit for each member (right) show the truth in solid and the average Procrustes fit as a dotted line. These images are the 10-min lead time nowcast valid at 0300Z on 12 Mar 06.

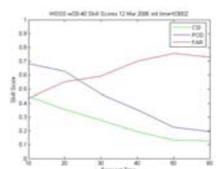

Figure 3: Skill scores for the 20-40 dBZ threshold WDSS K-means nowcast for different lead times all valid at 0300Z on 12 Mar 06. CSI is green, POD is blue, and FAR is red.

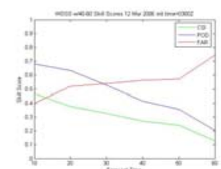

Figure 4: Skill scores for the 40-60 dBZ threshold WDSS K-means nowcast for different lead times all valid at 0300Z on 12 Mar 06. CSI is green, POD is blue, and FAR is red.

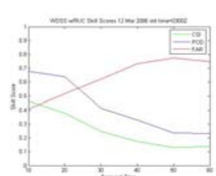

Figure 5: Skill scores for the 20-60 dBZ threshold with RUC storm motion WDSS K-means nowcast for different lead times all valid at 0300Z on 12 Mar 06. CSI is green, POD is blue, and FAR is red.

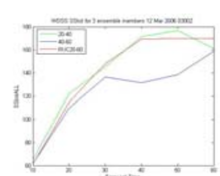

Figure 6: The total sum of squares (SStot) penalty for different lead times all valid at 0300Z on 12 Mar 06 for each of the given ensemble members. 20-40 dBZ in green, 40-60 dBZ in blue, 20-60 dBZ with RUC in red.

Conclusions

It can be shown that although the CSI for all cases is about the same, the randomly selected ensemble WDSS-II K-means nowcasts can have considerable differences by looking at the statistics from a spatial verification technique. By separating the error statistics into individual components, a forecaster can focus on one aspect of the nowcast model or ensemble member, such as the translation error or the intensity error, both of which have a use in hydrological applications. The ability to spatially verify a nowcast or forecast ensemble in real-time by reducing the dimensionality of the problem can yield insight into model error characteristics that may in turn be corrected in real-time.

WDSS 60-min Component Comparison valid: 12 Mar 06 0300Z					
Member	SSmin	SSavg	SSmax	SSscale	SSloc
20-40	0.0002	0.0836	0.6225	0.0003	2.7326
40-60	0.0001	0.0413	0.3602	0.0012	4.1403
RUC	0.0019	0.0152	0.2472	0.0009	5.1624

Table 2: The individual error components for 60-min lead time for 12 Mar 06 valid at 0300 Z. SSmin refers to the sum of squares error based on minimum intensity, SSavg: average intensity error, SSmax: maximum intensity error, SSscale: scale (dilation) error, and SSloc: location (translation) error. SSrot is not given as the rotation component was negligible in this case. All values should be multiplied by 10^5.

Future Work

Development and comparison with a Full Bayesian Procrustes Fit without dimensionality reduction to examine the effects of reducing dimensionality for application in real-time.

Testing the verification on a 200 member ensemble available from the Hierarchical Bayesian Model (HBM) that is being developed at the University of Missouri-Columbia.

Writing a user friendly interface for ease of use and robustness with regards to the cell identification methodology within the verification scheme, including the application of a variable weighting scheme for the components of SStot.

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