Spatio-temporal Visual Saliency for Adaptive Weather Sensing

D. Schvartzman[1,2], **T.-Y. Yu**[1,2], **and S. M. Torres**[1,3]

[1]Advanced Radar Research Center, University of Oklahoma, Norman, OK, USA
[2]School of Electrical and Computer Engineering, University of Oklahoma, Norman, OK, USA
[3]Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma and NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma, USA

Abstract— In this paper, the spatio-temporal saliency is applied to weather radar observations with the goal of exploiting information-theory-based methods for adaptive weather sensing with Phased Array Radars (PAR). PARs can dynamically and adaptively change the beam pointing direction and associated acquisition parameters, which can potentially lead to improved warnings and forecasts. Using spatio-temporal saliency, scanning strategies can be tailored to extract maximum information from the atmosphere. In this paper we present the spatio-temporal saliency as a driver for adaptive sensing, its behavior for different types of weather phenomena, and its applications to adaptive weather sensing. We demonstrate the advantages of this algorithm using data collected by Next Generation Weather Radars (NEXRAD).

1. INTRODUCTION

The Next Generation Weather Radar (NEXRAD) network consists of 160 high-resolution S-band Doppler weather radars operated by the National Weather Service (NWS), an agency of the National Oceanic and Atmospheric Administration (NOAA). The Weather Surveillance Radar-1998 Doppler (WSR-88D) surveils the atmosphere by mechanically rotating a parabolic antenna using one of the pre-defined Volume Coverage Patterns (VCP) to scan the atmosphere. These volumetric scans for non-clear air conditions take between 4 to 6 minutes to complete, and therefore the temporal resolution of the NEXRAD network, is of the order of 5 minutes. However, faster updates are desirable for better understanding and forecasting of fast-evolving weather phenomena [1]. Previous reports show that updates on the order of 20 seconds are required to observe tornadogenesis more accurately, which is further supported by the observation of the Supercell Tornado in Moore, Oklahoma on May 20th of 2013 [2].

Researchers have been exploring and assessing possible successor technologies beyond NEXRAD, and PAR technology is showing great potential as a candidate for multi-function and cost-effective system [3]. The National Weather Radar Testbed (NWRT) Phased Array Radar was installed in Norman, Oklahoma to demonstrate this concept. Research efforts have demonstrated that the NWRT is a promising radar to perform efficient, versatile and fast updated observations that lead to a better characterization of severe weather [1]. The beam agility enables PAR to observe weather phenomena of interest in different regions more frequently with possibly independent scanning strategies. This is known as *focused observations* [4].

The present work investigates the Spatio-Temporal Saliency, an information-theory-based method, and its interpretation in the context of weather radars with the ultimate goal of driving an adaptive scanning strategy for weather observations. The saliency method provides a mean to tailor strategies that can extract maximum amount of visual information defined from the entropic measures (in the Shannon entropy sense) in space and time. This information measure can provide a single metric that contemplates complex tradeoffs, among temporal resolution, spatial sampling and data quality, involved in the design of scanning strategies for weather observation.

2. THE SPATIO-TEMPORAL SALIENCY MODEL

Attention is an instinctive biological mechanism that allows living animals or humans to selectively focus on part of incoming stimuli and discard less interesting signals. There is a large amount of information and attention-gazing events around us that it becomes a challenge to select the ones that provide more relevant information. Several computer vision research focuses on modeling how the human vision system selectively attends to certain events while ignoring others. The visual saliency is a mathematical model of selective attention. Consequently, the visual saliency can be used to distribute the finite perceptual and cognitive resources on the most relevant regions of interest.

The application of the model to weather observations has two parts and it is depicted in Figure 1. In the first part, the spatial saliency from a single reflectivity scan at time $t = k$ is computed. It involves a multiscale decomposition (on this work three scales are used), filtering of each feature at every scale, and activation. The features used here are intensities, contrast, and 4 orientations (0°, 45°, 90°, 135°) of the radar reflectivity.

Specifically, the input data of radar reflectivity in polar coordinates is resampled into an 800 by 800 rectangular coordinate system (525 m × 525 m). Then, three spatial scales are created using Gaussian pyramids. These Gaussian pyramid decomposition consists of two stages, a low-pass filtering and a down-sampling by a factor of 2. The decomposition is applied 2 consecutive times to obtain the three scales, yielding images of 800 × 800 (initial), 400 × 400 and 200 × 200 pixels.

Subsequently, the multi-scale pre-attentive features are filtered by a Gabor filter pyramid (i.e., multi-scale). These filters are particularly suited for detecting regions that stand out from their surroundings, since they are similar to simple cells of the visual cortex in the brain [5]. A Gabor filter is the product of a sinusoid and a Gaussian. This implementation uses 4 orientations, at 3 different scales.

The key of this algorithm is the entropy-based normalization or activation function applied to the feature maps. This function is applied to suppress comparable peaks and enhance only unique features in each map for every scale, at both local and global scales. The activation function is based on the information theory concept proposed by Shannon and highlights more informative regions. The Entropy function is defined as follows:

$$H(I_i) = -\log_2 \left(\frac{1}{N|I_j|} \sum_{i=1}^{N} n_i \right) \tag{1}$$

For each feature map, (1) is applied to compute the cross-scale occurrence probability of each pixel [6]. It is computed by normalizing the sum of the co-occurrence probabilities of the pixel at all scales as indicated by 1, where the n_i is the occurrence of the pixel j within the ith scale of the image I_i. This is known as the self-information or information content map, and it is used to represent the attention value for that pixel. This function enhances regions that stand out from their surroundings and attenuates regions that are common across the image.

The next step is to combine the maps across scale and features using a weighted sum to form the final spatial saliency map. These weights were obtained after a training process in which an expert meteorologist selected the regions with more meteorological information, and the weights were adjusted to fit that as best as possible. Figure 1 shows all feature maps for the same tornadic storm.

As we can see from Figure 1, most of the feature maps are activated in the supercell region, at several scales. Particularly, the hook echo region has all of those types of features, mostly at small and medium scales. Since it consists of a small, very well defined strong reflectivity core, it has high intensity and contrast features. Furthermore, since the hook echo has a circular shape (as does

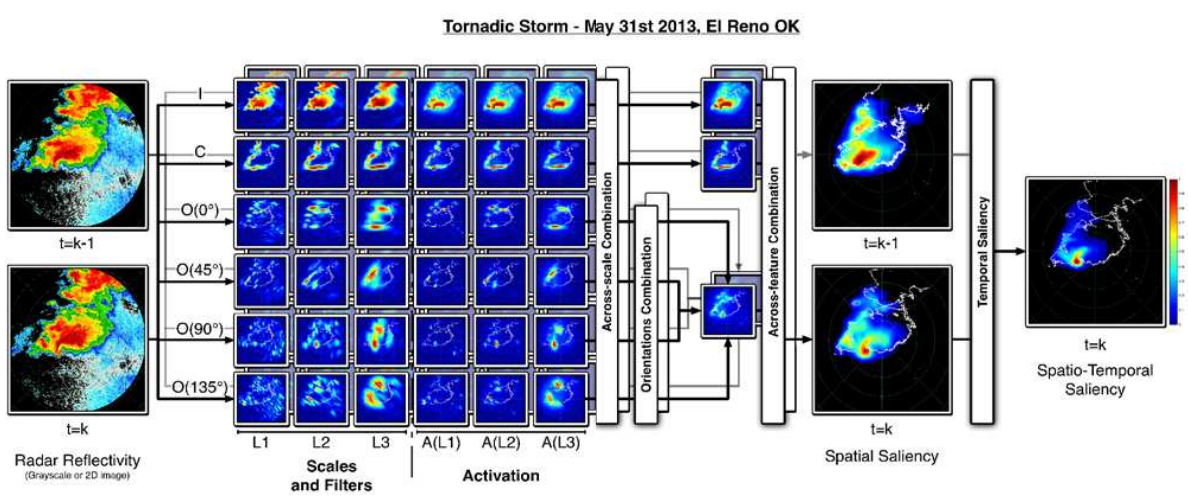

Figure 1: Spatio-temporal saliency feature map computation from tornadic supercell storm.

the tornado itself) it also activates orientation features for all 4 orientations, at small and medium scales. Also, we see a relatively high saliency in the forward flank core region of the supercell, and also to the north-west of the hook echo. The spatial saliency is also computed from the radar reflectivity at time $t = k - 1$.

The second part of the model is to use the Mutual Information to account for temporal changes in the scans (between $t = k$ and $t = k - 1$). to further strengthen regions salient in time, and attenuate slow-evolving regions. The result obtained after this step is performed is the rightmost map shown in Figure 1.

3. THE SPATIO-TEMPORAL SALIENCY OF WEATHER RADAR ECHOES

Different weathers can have different types of salient features, which most times also correspond to meaningful meteorological information. We show now spatio-temporal saliency maps of several types of weather to illustrate the flexibility of the model. Figures 2(a) to 2(f) below show different types of storms and Figures 2(g) to 2(l) their corresponding spatio-temporal saliency maps.

Figure 2(a) shows stratiform precipitation consisting of several highly structured and small cells with relatively low reflectivity, and Figure 2(g) shows its ST-saliency map. The intensity and contrast features do not produce salient features in space, because the echoes are weak. Some orientation features are observed mainly at medium scale, but since the system is very disorganized and there is no clear orientation, the normalization function filters out those features. In addition, since the temporal evolution of the storm is slow, the temporal saliency further some regions. The most salient region is the highest reflectivity core to the south-west of the radar, as a consequence of the intensity and contrast maps. A similar analysis can be carried out for Figures 2(b) and 2(h).

In Figure 2(c) a weak convective system embedded in a region with biological scatterers is shown. Figure 2(i) shows its ST-saliency map. Since region with biological scatterers is fairly uniform in intensity and shape, there are no salient features in that region and the weather echoes are clearly identified, despite of the fact that the echoes consist of a very thin line. The orientation feature map for the 45° Gabor filter resonates with the weather echoes at all scales. The temporal saliency identifies three particular cells as evolving faster than the other small, highly reflective cores and peaks are shown in the final spatio-temporal saliency map.

A supercell thunderstorm with a pronounced rear-flank downdraft is presented in Figure 2(d). This supercell was part of a line of thunderstorms developed over central Oklahoma, and it is carefully analyzed in the context of fast scanning by [7]. In particular, the fast evolving rear-flank downdraft has a pronounced spatio-temporal saliency. The forward flank also presents a high saliency core, due to the fine structure (which triggers the intensity and contrast maps at multiple scales) and a the rapid evolution as compared with other parts of the storm. A descending mesocyclone is observed in the radial velocity map, as noted by [7] and is located near the inflow boundary in the forward flank region. Finally, high saliency is obtained in the region of the inflow boundary due to the ubiquitous structure and high reflectivity of those branches that stick out in the front of the storm. The last two examples in Figures 2(e) and 2(f) can be analyzed using

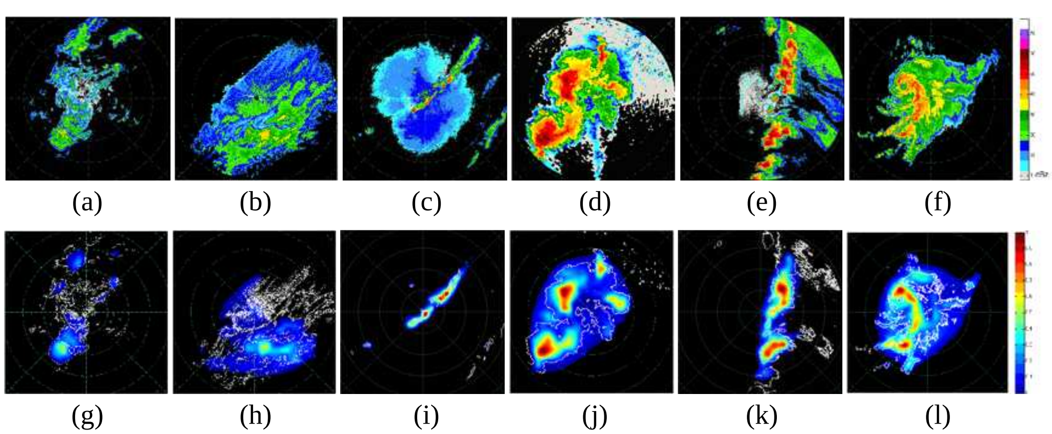

Figure 2: Examples of spatio-temporal saliency for several types of weather echoes, (a) and (g) stratiform precipitation; (b) and (h) snow storm; (c) and (i) weak convection; (d) and (j) supercell thunderstorm; (e) and (k) hail storm; (f) and (l) cyclone.

the same arguments. Regions with low reflectivity echoes, biological scatterers and stratiform (relatively uniform) precipitation are well attenuated.

For these examples, the spatio-temporal saliency seems to highlight meteorologically meaningful regions for several types of echoes. Generally, high reflectivity (strong cores) are well captured, particularly when their highly structured and have fine details. In addition, as can be seen in Figures 2(g), 2(h) and 2(i), weaker non-structured echoes coming from biological scatterers and other non-meteorological echoes are being attenuated and ignored by the saliency model.

4. APPLICATIONS OF ST-SALIENCY TO ADAPTIVE WEATHER SENSING

As an application to the Adaptive Weather Sensing (AWS) framework [8], Spatio-Temporal Saliency can be used to define highly informative regions and their respective update-times. The regions are sectors which are defined by computing the azimuthal distribution of spatio-temporal saliency. The update times computed are proportional to the integrated information content inside the sector and result in a full-load scenario [8]. We call this the FOCUS (Focused Observations by Configuration of Updates-times using Saliency) algorithm.

The following example shows a line of storm cells with a particularly fast evolving supercell to the south-west of the radar. This particular cell was identified as a potentially severe storm and carefully studied in [7]. The time between the images is of about 25 minutes although a 5-minute temporal resolution (NEXRAD Data) was used to run the framework.

The sectors are updated and redefined automatically using the saliency maps, and they are updated (i.e., re-scanned) at different rates, adapted to the evolution of the phenomena being observed. The blue bounding boxes in the reflectivity scans in Figure 3 represent the sectors defined by FOCUS. Update times assigned are not shown in this plot.

For this application, the mean of the reflectivity field for each sector was computed, for both the full time resolution data and the adaptively collected data. The FOCUS algorithm is adjusting the update times of each sector to observe a smooth evolution of the weather in it without wasting time, and therefore we expect to see similar mean reflectivity for each pair of sectors, confirming that no meaningful change in reflectivity was lost. Comparing the plots shown in Figure 4 we can see that there was no abrupt change in the full-time resolution data (left panel) that was not captured by

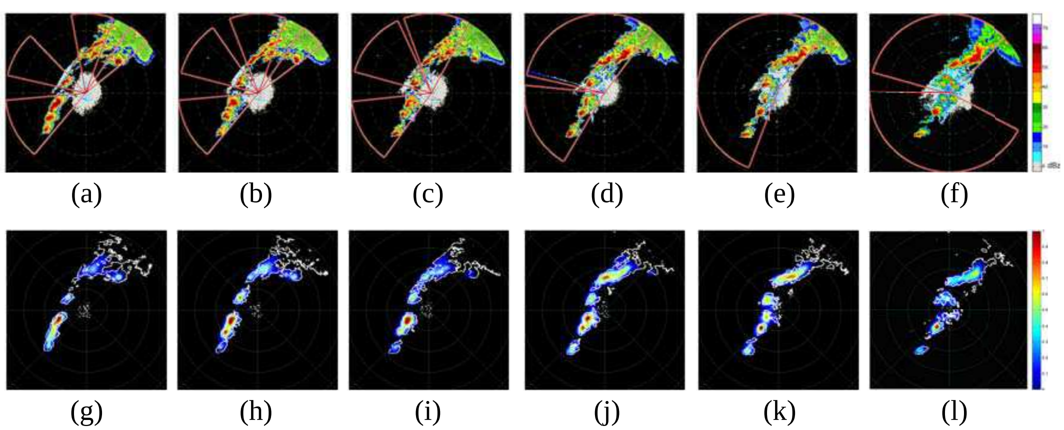

Figure 3: Spatio-Temporal Saliency of the evolution of a line of convective storm cells across Oklahoma.

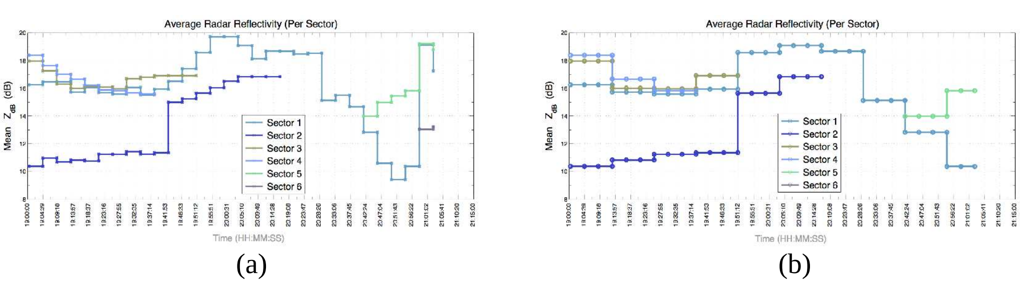

Figure 4: Average radar reflectivity (dBZ) per sector for both full-temporal and adaptively updated data. (a) Full temporal resolution; (b) FOCUS collected data.

the FOCUS defined sectors (which are updated at different rates). This gives an indication that the algorithm is adjusting the update times for the sectors at a rate suited for the temporal evolution of the weather echoes inside of that sector.

5. CONCLUSIONS

Although saliency models have been used in other fields like computer vision and monitoring applications, to our knowledge, this is the fist time it has been used to analyze weather radar data. In this paper, we described the general framework for a spatio-temporal saliency model, presented some study cases using real weather radar data and suggested an application of the algorithm in the AWS field using a PAR. The examples described and the results obtained show that these techniques have a great potential for defining regions that have particularly conspicuous information. Some limitations have to be considered: high reflectivity regions produced by ground clutter or anomalous propagation can deceive the spatial saliency and impact on the final map. Since those artifacts are not changing in time, the temporal saliency partially reduces their saliency. If there is no particularly salient feature, the spatio-temporal saliency can behave in an unpredictable way.

The performance obtained from models like this one critically depends on the features explicitly discernible in at least one feature map can lead to a peak, a rapid detection independent of the number of other distracting echoes [5]. Other aspects of radars have to be studied in the context of saliency, for instance, the impact caused on the saliency maps due to asynchronously collected data, using other spectral moments or polarimetric variables to include more information on the saliency computation, or the fact that only plan-position indicator (PPI) maps are being used in these examples, although radars produce full volume scans. These and other issues will be further studied in future research.

ACKNOWLEDGMENT

We thank the Advanced Radar Research Center from the University of Oklahoma for supporting research in Radar Meteorology and Phased Array Radars. This work was supported by NOAA/NSSL under Cooperative Agreement NA17RJ1227.

REFERENCES

1. Heinselman, P. L. and S. Torres, "High-temporal-resolution capabilities of the national weather radar testbed phased-array radar," *J. Appl. Meteor. and Climatology*, Vol. 50, 579–593, 2011.
2. Kurdzo, J. M., D. J. Bodine, B. L. Cheong, and R. D. Palmer, "High temporal resolution polarimetric radar observations of the 20 May 2013 Newcastle-Moore, Oklahoma EF-5 Tornado using the PX-1000," *27th Conference on Severe Local Storms*, 2015.
3. Weber, M. E., J. Y. N. Cho, J. S. Herd, J. M. Flavin, W. E. Benner, and G. S. Torok, "The next-generation multimission US surveillance radar network," *Bull. Amer. Meteor. Soc.*, Vol. 88, 1739–1751, 2007.
4. Torres, S., R. Adams, C. Curtis, E. Forren, I. Ivić, D. Priegnitz, J. Thompson, and D. Warde, "New weather-surveillance capabilities for NSSL's phased-array radar," *The Seventh European Conference on Radar in Meteorology And Hydrology*, 2013.
5. Itti, L., C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 11, 1254–1259, 1998.
6. Riche, N., M. Mancas, B. Gosselin, and T. Dutoit, "Rare: A new bottom-up saliency model," *2012 19th IEEE International Conference on Image Processing (ICIP)*, 641–644, IEEE, 2012.
7. Heinselman, P. L., D. L. Priegnitz, K. L. Manross, T. M. Smith, and R. W. Adams, "Rapid sampling of severe storms by the national weather radar testbed phased-array radar," *Wea. Forecasting*, Vol. 23, 808–824, 2008.
8. Reinoso-Rondinel, R., T.-Y. Yu, and S. Torres, "Multifunction phased-array radar: Time balance scheduler for adaptive weather sensing," *Atmos. Oceanic Technol.*, Vol. 27, 1854–1867, 2010.