10R.5 TORNADO DETECTION USING A NEURO-FUZZY METHOD

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1. INTRODUCTION

The Weather Surveillance Radar-1988 Doppler (WSR-88D) has been developed and deployed to improve the detection and forecast of tornadoes. The current Tornado Detection Algorithm (TDA) (Mitchell et al. 1998) searches for strong azimuthal shears in the velocity field. However, when a tornado is located at far range or the size of the tornado is small compared to the radar resolution volume, the shear signature will be smoothed and difficult to identify. Figure 1 shows the smoothing effect on shear signature as a function of the ratio of the cross-beam dimension (beam width) to the radius of tornado's maximum wind.

The Doppler spectrum from a tornado vortex is different from typical Gaussian-like spectrum produced by most other weather phenomena. A broad and flattened tornado spectral signature was shown using simulation, and bimodal spectra were observed by pulse Doppler radar (Zrnic and Doviak, 1975). In general, a large spectral width and small fluctuation could be described as tornado's spectral signatures.

However, a similar spectral signature can be produced by a uniform wind field and reflectivity with a shape that is the reciprocal of the antenna beam pattern. Moreover, the spectrum width depends on the size of tornado vortex. Therefore it is difficult to determine a threshold for the spectral width or the strength of the shear to identify a tornado. In this work, a neuro-fuzzy method is developed for the first time based on spectral width, the flatness of a spectrum, and other parameters to improve tornado detection.

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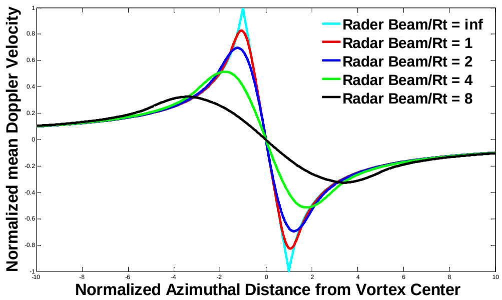

Fig. 1 Smoothing effect on azimuthal shear. The horizontal axis is the azimuth distance from the vortex center normalized by the radius of maximum wind of the tornado (Rt). The vertical axis is the Doppler mean radial velocity normalized by the maximum tangential velocity. Results from different ratio of transverse dimension of the radar beam to Rt are coded in color.

2. FUZZY LOGIC METHOD

A fuzzy logic approach has inherent advantages over other methods such as decision trees and neural networks. For a decision tree, a threshold is necessary. But there exists overlap region between the tornado case and no-tornado case in each parameter set, so it is difficult to accurately determine the threshold. In the case of neural network, a large amount of data sets are needed to train the algorithm. On the other hand, the fuzzy logic method has the ability to describe the system of interest and to deal with the data set inside the overlap region using simple rules (Liu and Chandrasekar 1999).

3.1 **Parameters Used In Fuzzy Logic**

In the neuro-fuzzy method developed in this work, five parameters will be used: spectrum width (σ_v), reflectivity (Z), signal to noise ratio (SNR), azimuthal velocity difference (Δv), and the standard deviation of the Doppler spectrum (STD).

The spectrum width, reflectivity, and signal to noise ratio can be estimated directly using the spectral method, where both Z and SNR are in dB (Doviak and Zrnic, 1993). The velocity difference is defined as the absolute of velocity difference between two adjacent gates in the azimuthal direction.

The standard deviation of a spectrum is introduced to quantify the flatness of a spectrum. After the Doppler spectrum is calculated using the Periodogram method, random fluctuations will occur inside it unavoidably. These random fluctuations normally have relatively low values compared to the spectrum. To avoid this effect, the spectrum is first sorted, and then only the first 70% which have higher values will be used for calculation. This 70% is from testing that suggests it provides the most accurate standard deviation.

3.2 Fuzzy logic in tornado detection

Basically, there are four parts that compose a fuzzy logic system: fuzzification, rule inference, aggregation, and defuzzification (Liu and Chandrasekar 1999). Figure 2 depicts these elements in relationship to our work. In fuzzification, the precise measurements in the real-world domain defined as crisp inputs will be converted to membership degree in the fuzzy domain. The degree of membership is a value between 0 and 1. The function used in this procedure is termed a membership function. In the tornado detection algorithm, two membership functions of tornado and non-tornado cases are defined for each parameter through a statistical analysis and knowledge learned from the data.

In the rule interference step, the relationship between a fuzzy input and output will be established in the form of IF-THEN. In the IF side, several antecedents will be given and in the THEN side one consequent will be obtained. For example, when a tornado exists, all of these five parameters must satisfy certain conditions at the same time. In regions close to the tornado center, the spectrum width and the azimuthal velocity difference should reach a large value, the standard deviation should be small, and the reflectivity and the signal to noise ratio should be reasonable high. So the correlation product is used as the rule inference to combine all of these parameters together. There are two groups of membership functions. One is for the TRUE case in which a tornado vortex is detected. The other one is for the FALSE case where no tornado is detected. The membership function MBF1-C till MBF5-C are used for the TRUE case and MBF1-D to MBF5-D are used for the FALSE case. The final confirmation degree Dc and Dd is the multiplication of five membership degrees for the case of TRUE and FALSE, respectively.

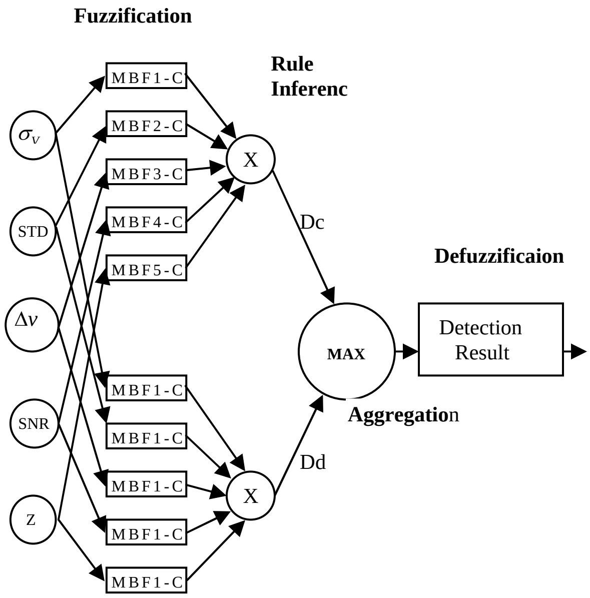

Fig. 2 the flow chart of the fuzzy logic method of tornado detection

The two final degrees will be inputs of another node termed aggregation. In this node, a MAX operation will be performed to make the final decision, which means if Dc is larger than Dd, a tornado is detected and otherwise, no tornado is detected.

In the defuzzification part, the fuzzy output of rule inference can be converted back to a crisp output which can be understood and implemented by users. In the tornado detection algorithm, when the output of the aggregation is TRUE, the crisp output will be the coordinate of the tornado in the form of azimuth angle and range according to the radar. If the output is FALSE, crisp out put will be non-tornado information.

3.3 **Membership Functions**

In the fuzzy logic method, the key component is the membership function. There are many ways to decide the membership functions: intuitions, inferences, rank orderings, neural networks, genetic algorithms and inductive reasoning (Timothy 2004). In this algorithm, the inference is used to determine the membership function which is deduced based on statistical analysis and knowledge learned from the data.

For the crisp input of spectrum width, the S-shape and Z-shape functions are used for the TRUE and FALSE cases, respectively. In other words, a large spectrum is favorable (has a large value of membership degree) to the TRUE case (Zrnic and Doviak, 1975). The combination of S-shape and Z-shape function are also used for velocity difference and the standard deviation. The plots in Figure 3 are these two membership functions for velocity difference. For reflectivity and SNR, two S-shape functions were selected with properly designed breaking points because that high reflectivity and SNR are not necessarily associated with the existence of a tornado. For example, ground clutters or heavy precipitation can produce strong reflectivity. The plots in Figure 4 are these two membership functions.

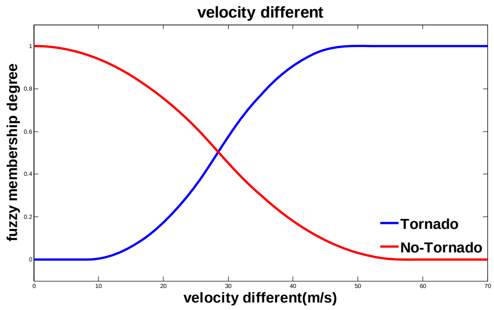

Fig. 3 the S and Z shape membership function of velocity difference.

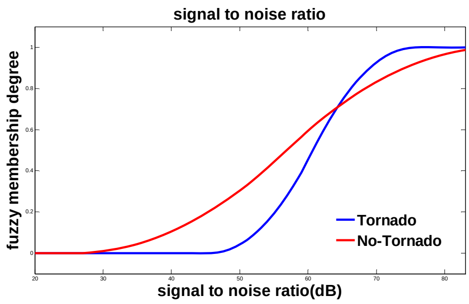

Fig. 4 the S shape membership function of signal to noise ratio

4. NEURAL NETWORK

The S- and Z-shape membership functions are mathematically defined by two breaking points x_1 and x_2 in the following form. The S-shape membership function is showed in equation 1.

And Z shape membership function is in the similar form, and when $x < x_1$, $f(x) = 1$; $x > x_2$, $f(x) = 0$.

$$f(x) = \begin{cases} 0; & when\, x < x_1 \\ 1; & when\, x > x_2 \\ 2\times\left(\dfrac{x - x_1}{x_2 - x}\right)^2; & when\, x_1 < x < \dfrac{x_1 + x_2}{2} \\ 1 - 2\times\left(\dfrac{x_2 - x}{x_2 - x_1}\right)^2; & when\, \dfrac{x_1 + x_2}{2} < x < x_2 \end{cases} \qquad (1)$$

A neural network algorithm is designed to subjectively find the breaking points based on the existing data. To obtain the optimal breaking points, some initial values are initially set. Then a set of data which describe typical tornado or no-tornado cases is applied and a detection result can be subsequently used in our fuzzy logic system. By comparing the current system output with the input state, the error can be found easily as $\varepsilon = C_t - C$. If ε is not equal to 0, the modification of the breaking points is necessary.

When initiating the fuzzificaiton procedure, the parameters whose membership functions need to be determined as the first step. For example, if one set of data consisting of five parameters which describe a tornado are plugged in, 5 membership degrees will obtain from MBF-Cs, and another 5 from MBF-Ds. The one from MBF-Cs which has the lowest membership degree and the one from MBF-Ds has the highest membership degree will be chosen to modify their breaking points. Then the gradient descent learning method is used to adjust them.

$$\sigma_{x_1} = -\mu \frac{\partial f_j(x)}{x_1} \prod_{i=1, i\neq j} f_i(x) \qquad (2)$$

$$x_1^{n+1} = x_1^n + \sigma_{x_1} \qquad (3)$$

Where μ is the step length, $f(x)$ is the output of the membership function, and $f_j(x)$ is the one need to be modified.

5. PERFORMANCE EVALUATION

The neuro-fuzzy TDA is tested using the KOUN Level I time series data collected from May 8th 2003 Del City OK tornado and May 10th 2003 Edmond OK tornado. The breaking points for each membership function are obtained by training the neuro-network using the data from the May 8th 2003 tornado and part of the May 10th 2003's tornado. Finally, the neuro-fuzzy TDA is implemented on the data from the May 10th case. The results are compared with those from the NSSL TDA on KOUN Level II data, the NWS TDA on KTLX data, and the tornado damage path from ground survey.

The radial velocity and reflectivity from the lowest elevation angle of 0.5° at 03:43 UTC May 10th, 2003 are shown in Figure 5 and 6, respectively. A tornado is detected in the azimuth of 8.5^{o} and range of 39.625 km from the KOUN radar and is denoted by a blue star. The tornado damage path is superimposed and is denoted by a black line. It is evident that the detected region is consistent with the damage path and is associated with strong azimuthal shear in the velocity field and a well-defined hook signature in the reflectivity field. Additionally, the spectrum width from the detected region is significantly larger than those from other non-tornadic regions.

Figure 7 is the spatial distribution of Doppler spectra from the tornado. The spectrum from detected region is denoted by red line, which is located at 39.625 km in range and 8.5^{o} in azimuth. It is clear that the neuro-fuzzy algorithm detects the region with distinct spectral signature.

A comparison of three different detection results is shown in Figure 8. Results from the conventional TDA on KOUN and KTLX Level II data are denoted by blue triangles and black inverse triangles, respectively, which are termed TDA-KOUN and TDA-KTLX. Results from the neuro-fuzzy on KOUN data with 0.5^{o} angular sampling is denoted by red solid circles. In addition, the time for TDA-KOUN and neuro-fuzzy is denoted by red text and the time for TDA-KTLX is denoted by black text.

At 03:31, 03:43, 03:49, and 03:55 UTC, the tornado locations detected by the TDA-KOUN are within the damage path. However, at 03:37 a tornado was detected approximately 2 km north of the damage path. In addition, two locations at approximately 6 km north and south of the damage path were identified as tornado at 04:01 UTC. After 04:01 UTC no tornado was detected, although the tornado damage path suggested the tornado existed beyond that time.

The detection results from the neuro-fuzzy method and TDA-KOUN are similar from 03:31 UTC to 03:55 UTC. The distance between the tornado and KOUN varies approximately from 35.625 km to 42.625 km during this period. Later time (04:07, 04:13 and 04:19 UTC) when the tornado moved further away from the KOUN, the neuro-fuzzy TDA could still detect the tornado while the TDA-KOUN did not identify the tornado. In comparison, it is also evident that the detection results from our neuro-fuzzy method agree with the damage path more favorably than the results from the TDA-KOUN. These results suggest that the neuro-fuzzy method is less sensitive to the smoothening than the conventional TDA and has the potential to extend the range of tornado detection.

In general, the KTLX radar is located at approximately 20 Km north-east of the KOUN. For the May 10th case, the maximum distance between the tornado and KTLX is approximately 30 km at 04:14 UTC compared to 55 km for KOUN at same time. In general, results from TDA-KTLX shows better agreement with the damage path compared to the results from TDA-KOUN. Compared to the neuro-fuzzy method, spurious detections by TDA-KTLX occurred beyond the damage path at 03:49, 03:54, 03:59 and 04:01 UTC. At 04:01 UTC, the TDA-KTLX identified one tornado that the neuro-fuzzy method missed. It is likely that the tornado was relatively weak and below the capability of the neuro-fuzzy method. Otherwise, it is clear that the neuro-fuzzy method can obtain result similar to the TDA_KTLX which was closer to the tornado.

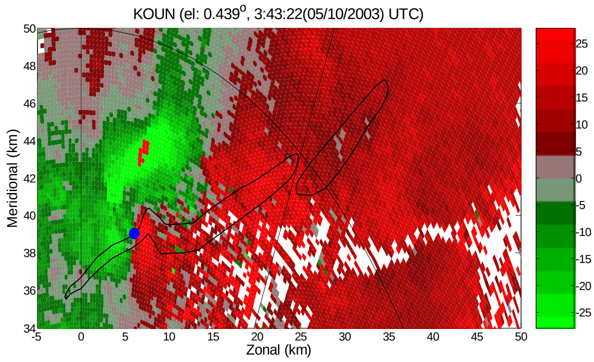

Fig. 5 the PPI of velocity in May 10th 2003 Edmond Tornado

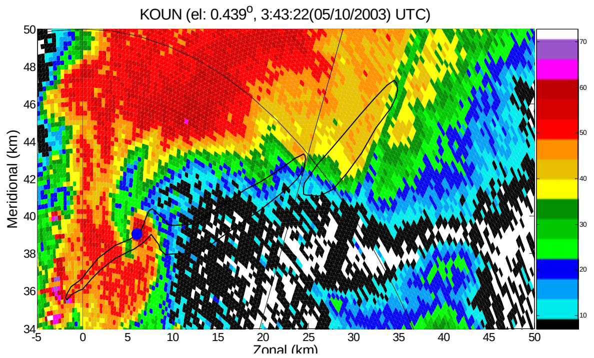

Fig. 6 the PPI of reflectivity in May 10th 2003 Edmond Tornado

6. SUMMARY

The proposed neuro-Fuzzy algorithm is based on a distinct signature in Doppler spectrum in combination with other velocity and reflectivity features to detect tornadoes. In this small case study, it demonstrated improved detection over conventional TDA when the tornado is far away from the radar. Future work will focus on strengthening the ability of the method to detect tornadoes at far ranges.

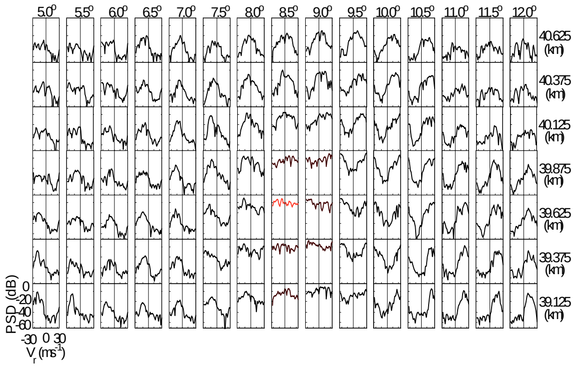

Fig. 7 the Doppler spectrum in May 10th 2003 Edmond Tornado

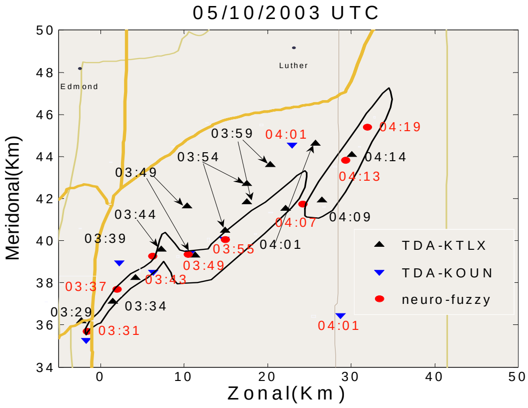

Fig. 8 the comparison of detection results from NWS TDA and this Neuro-Fuzzy method from different on May 10th 2003. The red triangles are from TDA, and blue stars are from this Neuro-Fuzzy method.

7. ACKNOWLEDGMENTS

This work is supported by NOAA CSTAR program through the funding NA17RJ1227. The authors thank NSSL's support for collecting the time series data on KOUN; E. Forren and M. Jain at NSSL for providing KOUN TDA results. And also thank Jennifer Palucki from School of Meteorology University of Oklahoma providing damage path.

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