Automated Detection of Polarimetric Tornadic Debris Signatures Using a Hydrometeor Classification Algorithm

JEFFREY C. SNYDER AND ALEXANDER V. RYZHKOV

Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, and NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma

(Manuscript received 21 May 2015, in final form 18 June 2015)

ABSTRACT

Although radial velocity data from Doppler radars can partially resolve some tornadoes, particularly large tornadoes near the radar, most tornadoes are not explicitly resolved by radar owing to inadequate spatio-temporal resolution. In addition, it can be difficult to determine which mesocyclones typically observed on radar are associated with tornadoes. Since debris lofted by tornadoes has scattering characteristics that are distinct from those of hydrometeors, the additional information provided by polarimetric weather radars can aid in identifying debris from tornadoes; the polarimetric tornadic debris signature (TDS) provides what is nearly "ground truth" that a tornado is ongoing (or has recently occurred). This paper outlines a modification to the hydrometeor classification algorithm used with the operational Weather Surveillance Radar-1988 Doppler (WSR-88D) network in the United States to include a TDS category. Examples of automated TDS classification are provided for several recent cases that were observed in the United States.

1. Introduction

Doppler weather radar has proven to be an effective tool for the detection of tornadoes (e.g., Zrnić et al. 1977; Zrnić and Istok 1980; Bluestein and Unruh 1989; Bluestein et al. 1993; Wurman and Gill 2000; French et al. 2009; Tanamachi et al. 2012; Houser et al. 2015). Scattering of radar-emitted electromagnetic radiation by debris lofted within tornadoes can produce distinct structures in radar fields that may confirm to operational meteorologists that a tornado is occurring. Radars that transmit and receive at two orthogonal polarizations (most often horizontal and vertical) provide additional information that allows for the classification of the source of scattering within a radar volume owing to the different scattering behaviors of different meteorological (e.g., Zrnić and Ryzhkov 1999) scatterers. In polarimetric radar observations of tornadoes examined in Ryzhkov et al. (2005), Bluestein et al. (2007), Kumjian and Ryzhkov (2008), Snyder et al. (2010, 2013), Palmer et al. (2011), Schultz et al. (2012a,b), Bodine et al. (2013, 2014), Kingfield et al. (2014), Snyder and Bluestein (2014), Van Den Broeke and Jauernic (2014), Bluestein et al. (2015), and Kurdzo et al. (2015), among others, tornado debris sampled by polarimetric radars typically was characterized by a local maximum in radar reflectivity factor at horizontal polarization $Z_H$, low copolar cross-correlation coefficient $\rho_{hv}$, low differential reflectivity $Z_{DR}$, and a vortex signature in radial velocity $V_R$. The combination of these characteristics constitutes the tornadic debris signature (TDS), which can be particularly prominent if a tornado near the radar lofts a substantial amount of debris.

In areas where visual confirmation of a tornado is difficult or where $V_R$ data may not unambiguously indicate the presence of or potential for a tornado, a signature such as a TDS can provide operational meteorologists with extremely valuable information pursuant to the mission to mitigate loss of life. Of the 745 tornadoes examined in Van Den Broeke and Jauernic (2014), $\sim 62\%$ of the tornadoes that were rated 2 on the enhanced Fujita (EF) scale (i.e., EF2) or greater were associated with a TDS and 100% of the tornadoes that were rated EF4 or EF5 were associated with a TDS. Poststorm surveys and studies indicate that a significant amount of the population does not immediately take recommended tornado-safety precautions until or unless a tornado is
confirmed (visually or otherwise) and that many seek personal, specific details of the threat before seeking shelter (e.g., Tiefenbacher et al. 2001; Donner 2007; Chaney and Weaver 2010; Schumacher et al. 2010; NWS 2011a,b; Johnson 2013). Although a TDS can provide strong evidence that a tornado is occurring, the authors are unaware of research about whether the presence of a TDS specifically modifies the response of those in the warned area. The confirmation of a tornado (or lack thereof) can affect warning decisions by National Weather Service (NWS) meteorologists (e.g., NWS 2002). Near-real-time tracks of tornadoes that can be created from observed TDSs may be valuable to emergency responders as well (e.g., Smith 2014).

Polarimetric radar data can be used to classify scatterers with a hydrometeor classification algorithm (HCA) such as that used in the Weather Surveillance Radar-1988 Doppler (WSR-88D) network (Park et al. 2009). This HCA uses fuzzy logic to classify the dominant scatterer type that is associated with a radar echo at each range gate. As currently implemented, the HCA does not have a TDS class; it tends to classify TDS events as either rain mixed with hail (RH) or unknown (UK). This short paper describes a modification to the existing HCA to allow for the classification of echoes as tornado debris and presents several examples of TDS identification using the new HCA. Like many other output classes used in the HCA, it is very difficult to assess exactly how well the algorithm performs since a comprehensive geospatial verification dataset does not yet exist (i.e., just as we do not know the exact spatial distribution of HCA-provided output classes such as hail or wet snow, we do not know the exact spatial distribution of debris). About the best one can do at this time is to look at the data carefully and make some subjective assessment as to whether (or where) a TDS is present [as in Kingfield et al. (2014)]. As with the existing HCA, the membership functions, weights, and “rules” are based on qualitative examinations of the data, theoretical expectations that follow from the scattering characteristics of debris (Bodine 2014), and observations that have been reported in previously published work. Modifications to the algorithm are expected, however, as algorithm evaluation and validation continue.

2. Methods, data, and challenges

The HCA that is used with WSR-88D (Park et al. 2009) was modified to add a TDS output class. The input data used by the HCA are preprocessed in a manner similar to that used in the WSR-88D product generator (Istok et al. 2009). This preprocessor estimates attenuation and differential attenuation and filters $Z_H$, $Z_{DR}$, and $\rho_{HV}$ by means of a running average over windows of three, five, and five range gates, respectively. Unlike the existing HCA classes, however, the identification of a TDS requires some estimate of vertical vorticity, which is accomplished by adding azimuthal wind shear (AS; Smith and Elmore 2004) as an input variable. Because debris from tornadoes can be advected away from the maximal AS typically found near the center of the tornado, the AS field is “dilated” by determining the 95th-percentile value of valid AS in a neighborhood of four radials by eight range gates around each gate. This algorithm is not designed to classify regions of debris fallout that can occur well away from the tornado in the forward-flank region of a supercell (e.g., Magsig and Snow 1998; Knox et al. 2013)—the primary intention of the TDS classification is to identify TDSs that are associated with the debris field near tornadoes.

In total, the HCA requires seven input variables, although some output classes do not use all of the input variables. For TDS classification, the HCA uses the following five inputs: 1) dilated AS, 2) a texture parameter for differential phase $\Phi_{DP}$ ("SD($\Phi_{DP}$)") defined as the standard deviation of measured $\Phi_{DP}$ over a window of nine range gates, 3) filtered $Z_H$, 4) filtered $Z_{DR}$, and 5) filtered $\rho_{HV}$. Although SD($\Phi_{DP}$) naturally increases as $\rho_{HV}$ decreases (e.g., Bringi and Chandrasekar 2001), observed high variability of $\Phi_{DP}$ in TDSs (e.g., Bodine et al. 2013) exceeds that expected on the basis of a reduction in $\rho_{HV}$ alone; the complex scattering that occurs in the presence of debris of variable size, composition, and orientation can result in enhanced SD($\Phi_{DP}$). To despeckle HCA output, the results are filtered through a neighborhood mode filter of five range gates by three radials that is centered on each range gate. Note that mode filtering reduces some of the detail in the HCA output, but because, unlike many of the other HCA classes, TDSs are typically singular features (e.g., the spatial distribution of heavy rain may be complex, whereas TDSs tend to be quasi circular owing to the nature of the underlying feature that produces the TDS), mode filtering can reduce false detections that are associated with noisiness in the observations.

In using fuzzy logic, the aggregation values $A$ for each output class $i$ are calculated as

$$A(i) = \frac{\sum_{j=1}^{7} W_j(i) Q_j P_j(i)}{\sum_{j=1}^{7} W_j Q_j},$$

where $W_j(i)$ is the weight of input variable $j$ for output class $i$, $Q_j$ is the quality value for input variable $j$, and $P_j(i)$ is the membership function value of variable $j$ for output
class \(i\). The quality vector \(Q\) accounts for observations that may be detrimentally affected by, for example, low signal-to-noise ratio or nonuniform beamfilling (Park et al. 2009). The weight for each input variable was determined empirically on the basis of testing and past literature results; for the TDS output class (Fig. 1), dilated AS and \(\rho_{hv}\) are weighted most heavily, followed by \(Z_{DR}\), \(ZH\), and \(SD(\Phi_{DP})\). Testing has shown that the latter can sometimes be useful to reduce false TDS classifications near strong gust fronts owing to the very high \(SD(\Phi_{DP})\) that can sometimes be found there (e.g., Hwang and Yu 2013).

Membership functions used for TDS classification (Fig. 1) were developed by using TDS characteristics reported in the literature with some modification from internal testing of the algorithm. For example, Schultz et al. (2012a) defined a TDS as having \(\rho_{hv} < 0.70\), and Ryzhkov et al. (2005) and guidance from the NWS Warning Decision Training Division (see Topic 7: Convective Storm Structure and Evolution at http://www.wdth.noaa.gov/courses/dloc/outline.php, accessed in 2015) note that \(\rho_{hv}\) should be less than 0.80 to identify a TDS. Data examined for this algorithm support observations made by others (e.g., Bodine et al. 2013), however, that \(\rho_{hv}\) within some TDSs may not be as low if precipitation mixes in with the debris. In examining the radar characteristics of a large dataset of TDSs associated with 1169 tornado paths, Kingfield et al. (2014) found that the vast majority of TDSs had \(\rho_{hv} < 0.96\); they also observed a positive correlation between \(Z_{DR}\) and \(\rho_{hv}\) within some TDSs, indicating that a two-dimensional membership function for \(\rho_{hv}\) and \(Z_{DR}\) may be appropriate in a future version of the algorithm. In the testing carried out during the course of the development of this algorithm, we found that setting the upper bound of \(\rho_{hv}\) at or below 0.8 resulted in missed TDS detections and yielded many misclassifications of RH or UK along the periphery of TDSs, where it appeared that rain may have been mixing with the debris. As such, the \(\rho_{hv}\) membership function used in the modified HCA has full membership up to 0.85, tapering to no membership at 0.92.

In developing the membership functions and weights, we strived to minimize false TDS classifications while still properly classifying all range gates composing a TDS. For example, although there are observed cases of TDSs associated with low \(Z_H\) (e.g., less than 20 dBZ), expanding the lower bound of the membership function for \(Z_H\) down to 20 dBZ increases the false classification of TDS in tests carried out during the development of the algorithm. As noted in Schultz et al. (2012b), a higher threshold for \(Z_H\) reduces false positives at the

![TDS Membership Functions](image-url)

**FIG. 1.** The \(Z_H\), \(Z_{DR}\), \(\rho_{hv}\), AS, and \(SD(\Phi_{DP})\) membership functions for the TDS class. Numbers in parentheses following the name of each input variable represent the weight of the variable. The four numbers listed along the abscissa represent the four points of each trapezoidal membership function, except for the AS membership function, which has no upper bound, and the \(\rho_{hv}\) membership function, which has no lower bound.
expense of missing some of the more subtle TDSs. Using a higher threshold such as $Z_H > 45$ dB as in Ryzhkov et al. (2005) results in too many missed TDS classifications, particularly along the periphery of the TDS. In the data examined in Kingfield et al. (2014), nearly all TDSs were associated with $Z_H > 30$ dBZ, the same $Z_H$ threshold that is currently used as one of the criteria for a TDS according to the Warning Decision Training Division (see Topic 7: Convective Storm Structure and Evolution at http://www.wdtb.noaa.gov/courses/dloc/outline.php, accessed in 2015). As a consequence, the modified HCA uses 30 dBZ as the lower bound for complete membership in the $Z_H$ membership function. Note that, owing to the nature of the fuzzy-logic method, a TDS classification can still be made even if some inputs are outside the nonzero part of their respective membership functions.

The HCA selects the output class with the highest aggregation value subject to the rules that are detailed in Park et al. (2009), provided that the aggregation value for the selected output class is at least 0.4. If the aggregation values for all available classes are less than 0.4, the HCA classifies the range gate as UK. For the HCA to classify a range gate as TDS, the following criteria must be met:

1) $\rho_{hv} \leq 0.92$,
2) $Z_H \geq 25$ dBZ,
3) $\text{AS} \geq 0.005$ s$^{-1}$,
4) the center of the radar beam must be below the melting layer, and
5) TDS aggregation value $\geq 0.80$.

The melting layer is found with the melting-layer detection algorithm (Giangrande et al. 2008); in-house training has found that false TDS classifications are often found in the melting layer. As a consequence, the TDS class is restricted to areas in which the center of the radar beam is below the melting layer. The higher aggregation value required for TDS classification (i.e., 0.8 instead of 0.4) reduces TDS misclassification by requiring the observations to fit the membership functions more closely. If the aggregation value for the TDS class is less than 0.80, the output class with the next highest aggregation value is chosen. The rules, although somewhat arbitrary, have been chosen on the basis of internal testing and are used to reduce false TDS classifications. Modifications to these hard rules are likely as the algorithm undergoes further testing.

The modified HCA provides the aggregation value of the selected classification. In the examples provided in section 3, we will show the TDS class colored (typically from orange to white) depending upon the aggregation value; the aggregation value can be seen as a “goodness of fit” estimate for the TDS class. In a quasi-operational environment, the addition of the aggregation value to the output of the HCA allows a meteorologist to assess how well the observations fit the TDS membership functions.

There are several sources of false TDS classification that appear in preliminary testing of the algorithm, the most common of which include contamination caused by nonuniform beamfilling (NBF; Ryzhkov 2007), the melting layer, ground clutter, and gust fronts. All four of these features tend to be associated with or cause a reduction in $\rho_{hv}$. Given the nature of NBF and the melting-layer signature, areas affected by these features tend to be located farther from the radar than are areas affected by ground clutter. Gust fronts associated with convective storms may be associated with significant horizontal wind shear and low $\rho_{hv}$ (since the source of scattering is often nonmeteorological in nature). Methods for reducing the influence of these features are currently being investigated.

### 3. Examples of automated TDS detection

A series of supercells produced tornadoes across central and eastern Oklahoma on the afternoon and evening of 10 May 2010. Several of these tornadoes occurred within 40 km of a primarily research-focused polarimetric WSR-88D (with identifier KOUN) that is located in central Oklahoma. In fact, around 2250 UTC, four tornadoes were ongoing simultaneously to the east and northeast of the radar (labeled A–D in Fig. 2). A hook echo is associated with the southern supercell that produced tornadoes B and C. There is another area of enhanced $Z_H$ that is associated with tornado A, which was nearing the end of its life. With each of these three tornadoes (A–C), $Z_{DR}$ is between −1 and 1 dB (Fig. 2b), $\rho_{hv}$ is generally less than 0.6 (Fig. 2c), and $V_R$ reveals strong cyclonic rotation (Fig. 2d). A fourth tornado, labeled D in Fig. 2a, is beginning at this time—the primary indication of this tornado is reduced $\rho_{hv}$ and strong cyclonic rotation. The AS is highest for tornadoes B, C, and D (Fig. 2e); AS near tornado A is lower owing to the smaller size and magnitude of the associated cyclonic couplet. Each tornado appears to be associated with a TDS, although the close proximity of tornadoes B and C makes it hard to tell that two different tornadoes are ongoing.

The existing, operational HCA (Fig. 2f) classifies tornadoes A and D mostly as RH (rain–hail mixture), whereas range gates composing the TDS associated with tornadoes B and C are generally classified as UK. The modified HCA (Fig. 2g) classifies each of the tornadoes as TDS, with aggregation values of 1.0 (colored white in
near tornadoes A, B, and C, indicating that the data fit the TDS membership functions exactly. The aggregation values for range gates near tornado D are lower (\(0.8–0.9\); colored orange in Fig. 2g) as a result of slightly higher \(\rho_{hv}\) (0.85–0.90) and \(Z_{DR}\). Mode-filtered results from the modified HCA clearly highlight the TDSs associated with each of the tornadoes (Fig. 2h).

Three other examples of TDS identification and echo classification are shown in Fig. 3. Violent tornadoes in central Oklahoma on 20 May 2013 (left column of Fig. 3) and in central Arkansas on the evening of 27 April 2014 (center column of Fig. 3) each were associated with very prominent TDSs with quasi-circular areas of locally maximized \(Z_H\); strong cyclonic shear evident in \(V_R\); and \(\rho_{hv}\) of less than 0.5. The modified HCA correctly classifies those gates as being a TDS; aggregation values of 1.0 near the center of each TDS generally decrease to \(0.8–0.85\) near the periphery of each TDS, where debris may be sparser and may be mixing with meteorological scatterers. On 16 June 2014, several intense tornadoes occurred in eastern Nebraska; at 2119 UTC (right column of Fig. 3), two tornadoes were ongoing, each associated with a TDS. The new HCA properly classifies both TDSs.

The modified HCA introduced herein can be used to create “TDS tracks” to get information on the paths of tornadoes in near–real time. Six cases featuring TDSs are presented in Fig. 4, which shows all gates for which a TDS classification was selected by the algorithm over some time period (in this specific case, it includes the duration of each event). The \(\sim 300\)-s update interval on commonly used volume coverage patterns in the WSR-88D network yields tracks that “skip” and are discontinuous, although more continuous/complete tracks can be expected as new scanning techniques allow for more frequent low-elevation-angle scans. All of the violent tornadoes (i.e., those rated EF4 or EF5) were associated with TDSs with a high aggregation value (\(\sim 1.0\)). Most of the strong tornadoes (i.e., those rated EF2 and EF3) were also associated with TDSs, whereas comparatively few weak tornadoes (i.e., those rated EF0 or EF1) produced TDSs. These results, while representing a very small sample, agree well with those in Van Den Broeke and Jauernic (2014). It is important to note that the EF-scale rating provided is the maximum observed over the entire path of the tornado, and therefore the lack of a TDS at a particular time or location along the track may be the result of the tornado being weaker at that location/time.

Swaths of high AS can be used to identify the paths of mesocyclones that are associated with supercells (e.g., “rotation tracks”; Miller et al. 2013), but, owing largely to sampling inadequacies (beam height, radar resolution-volume size relative to tornado size, etc.), most tornado...
supercells sampled by WSR-88Ds are not sampled with sufficient resolution to discriminate the tornado from the larger mesocyclone. Figure 5 compares TDS tracks with rotation tracks obtained through the National Severe Storms Laboratory (NSSL) “OnDemand” Internet site (http://ondemand.nssl.noaa.gov/) for tornado outbreaks that occurred on 17 November 2013 and 28–29 April 2014. Not all tornadoes (marked by red curves in Figs. 5a,c) produced a TDS, but essentially all of the TDS tracks were associated with tornadoes. Most of the observed tornadoes were associated with swaths of high AS in the rotation tracks as well (where the tornado paths are marked in green in Figs. 5b,d); there is considerable agreement between the TDS tracks and the rotation tracks, although there are several intense rotation tracks that are not associated with a reported tornado.

False TDS identifications can be seen in parts of Figs. 4 and 5, although it should be remembered that these represent multiple hours of data and thus multiple...
hours of false classifications are accumulated. As noted previously, false TDS classifications often are associated with ground clutter when a supercell with strong low-level rotation passes close to a radar, as seen prominently near the radar on 31 May 2013 in Fig. 4. Although traditional ground-clutter filters reduce the impact of clutter on $V_R$, $\rho_{\text{hv}}$ tends to remain depressed in the presence of ground clutter observed by WSR-88Ds. Implementation of improved clutter filtering (e.g., Torres and Warde 2014) may significantly mitigate the effects of ground clutter on the polarimetric variables. Another area associated with false TDS classification can be seen in the lower-left part of Fig. 5c and is caused by anomalous propagation that was observed several hours after the convective storms passed. These false TDS classifications have relatively low aggregation values, however, which means that further restricting the minimum aggregation value required for TDS
classification can be used to further limit incorrect classifications.

4. Summary

A TDS provides evidence of an ongoing tornado, which may be particularly important when there are limited visual observations available (such as is often the case in rural areas at night). In this paper, we have described a modification to the existing HCA that is implemented within the WSR-88D network to allow for the proper classification of echoes composing a TDS. Whereas the existing HCA typically classifies TDS events as either RH or UK, a qualitative assessment of a limited number of datasets that were examined during the course of this study indicates that the modified HCA can properly detect TDSs, and this tool may speed the creation of a TDS “climatology.”

FIG. 5. (Left) TDS tracks with aggregation values and (right) rotation tracks for tornadic supercells that occurred on (a),(b) 17 Nov 2013 in the lower Great Lakes region and (c),(d) 28–29 Apr 2014 in the southeastern United States. County borders are marked in gray. Yellow stars outlined in red denote the locations of radars that contributed data to the plots. Rotation-track data were retrieved from the NSSL OnDemand Internet site. Tornado paths are plotted in red in (a) and (c) and in green in (b) and (d). Only data from the 0.5°-elevation-angle scans are shown.
The algorithm will continue to be refined to reduce false detections and to improve the detection of TDSs that are marginal or are located far from the radar (where resolution may be poor). For example, additional input variables such as a texture parameter for $Z_{DR}$ may be considered, although it may be difficult to determine how much of the presumed increase in the variance of $Z_{DR}$ is attributable to reduced $p_{DR}$ (e.g., Bringi and Chandrasekar 2001) versus to intrinsic variability in the composition of the scatterers.

An assessment of algorithm performance for marginal TDSs and null cases will be an important aspect of continued algorithm development, although verification of debris within a radar resolution volume is often very difficult and complicates performance evaluation. Aside from the arduous task of examining photographs and video of a tornado to estimate debris coverage (e.g., Wakimoto et al. 2015), if any even exist, there may not be any nonradar data available that can be used to verify the presence or absence of debris independently. Although it can sometimes be easy to identify where the HCA should not classify an echo as debris, there are marginal cases (e.g., tornadoes that loft limited debris or tornadoes far from the radar) for which it is very difficult to determine whether a radar volume contains tornado debris. This algorithm will be optimized and validated in the future using many more cases to evaluate the algorithm in a quantitative and systematic manner.

Acknowledgments. This research was performed while the first author held a National Research Council Research Associateship Award at the National Severe Storms Laboratory. Funding was provided by the NOAA/Office of Oceanic and Atmospheric Research under NOAA—University of Oklahoma Cooperative Agreement NA11OAR4320072, U.S. Department of Commerce. John Krause provided programming and algorithm development expertise. The authors appreciate an early review of this manuscript by Patrick Skinner as well as those provided by two anonymous reviewers.

REFERENCES


