Abstract

Detecting gust fronts is important because of the strong wind shear, turbulence, and cross-winds, which pose significant safety hazards, including destruction of property and air traffic delays (Hwang, 2013, p. 6, Liggett and Yu, 2015, p. 1). Doppler radar is important in detecting gust fronts, because it allows meteorologists to see characteristics such as wind convergence, debris along the front, and changes in wind speed and direction. Gust fronts produce signatures that are observable by Doppler weather radars (Campbell and Olsen, 1987, p. 5, Klingle and Smith, 1986, p. 905, Wakimoto, 1982, p. 1060). By examining images generated by radars, experienced human observers can reliably detect and track gust fronts.

Since the upgrade of Weather Surveillance Radar 1988 Doppler (WSR-88D) to polarimetric capabilities, artificial intelligence has been utilized as the leading detection method of gust fronts. There are several limitations to artificially detecting gust fronts motivating researchers to improve algorithms for more accurate gust front detection. Visual identifications by professional operational forecasters are critical in providing guidelines to algorithms for improving lead times and detection. Ergo, this study focused on the analysis of how visual detection by operational meteorologists is a valid, reliable method for detecting gust fronts (Delanoy and Troxel, 1993, p. 150).

Gust Front Detection with Doppler Radar

A gust front is defined as a propagating boundary of a parent storm caused by the descending, cold, and dense air from a storm that is pushing surrounding air at the surface. The gust front, or outflow, is produced as the storm downdraft reaches the ground and is deflected horizontally, pushing under the warmer, lighter ambient air. This downdraft is driven by precipitation drag and evaporative cooling of raindrops. Propagation of the gust front can span many miles ahead of the generating thunderstorm (Delanoy and Troxel, 1993, p. 150, Klingle et al., 1987, p. 905, Liggett and Yu, 2015, p. 1, Wakimoto, 1982, p. 1060).

Detecting gust fronts is imperative due to the aviation threat of air traffic delays and excess fuel consumption to and for departing and leading aircrafts, and safety hazard to people from strong wind shear, turbulence, and cross-winds (Hwang, 2013, p. 6, Liggett and Yu, 2015, p.1). The change of wind speed and direction, as well as synoptic fronts, forces a change in active runway configuration and rerouting aircraft in the terminal area associated with gust fronts (Delanoy and Troxel, 1993, p. 150, Hermes, 1993, p. 693, Troxel and Delanoy, 1994, p. 182). With increased lead times in detecting gust fronts, which flow from and can produce strong parent storms, operational meteorologists can improve forecasts of severe weather. The goal of this study, visually detecting gust fronts from WSR-88D, analyzed the gust front characteristics via various Doppler products to help modify future versions of current algorithms.

It is imperative to understand gust front characteristics before detecting the signature. Gust front characteristics include: sharp rise in pressure known as “pressure jump”, decrease in temperature, abrupt changes in wind speed and direction, and rainfall after the passing of the outflow boundary (Charba, 1974, p. 140, Klingle, 1985, p. 2, Hwang, 2013, p. 3). Gust fronts are known for demonstrating strong turbulence and wind convergence (Klingle, 1985, p. 2). Researchers have agreed on numerous gust front characteristics through discoveries during various case studies. (Wakimoto, 1982, p. 1060, Charba, 1974, p. 141, Klingle, 1985, p. 2, Lee, 1996, p. 1).

Doppler radar is important in detecting gust fronts, because it allows meteorologists to see characteristics such as wind convergence, debris along the front of the storm, and changes in wind speed and direction. Gust fronts produce signatures that are observable by Doppler weather radars (Campbell and Olsen, 1987, p. 6, Klingle and Smith, 1986, p. 906, Wakimoto, 1982, p. 1061). By examining images generated by radars, experienced human observers can reliably detect and track gust fronts. For greater than twenty years of use and analysis, researchers have found Doppler variables useful in detecting gust fronts (Delanoy and Troxel, 1993, p. 151). Doppler velocity images depict gust fronts as boundaries between converging velocities. In reflectivity images, gust fronts appear as thin lines of increased intensity in the Doppler wind field. These radar signatures of radial shear, appear as a broadened feature, and Doppler velocity spectra as a result of insects, dust, and debris propagating at the leading edge of the front (Delanoy and Troxel, 1993, p. 151, Klingle, 1985, p. 3, Klingle et al., 1986, p. 906, Zrnic and Lee, 1983, p. 4).

Since the upgrade of Weather Surveillance Radar 1988 Doppler (WSR-88D) to polarimetric capabilities, the Machine Intelligence Gust-Front detection Algorithm (MIGFA) was developed as the leading algorithm for gust front detection. Still today, it uses knowledge-based image processing and data fusion techniques to recognize the three principal gust front signatures observed in the radar data: velocity convergence, thin lines, and motion (Troxel and Pughe, 2002, p. 112). Most recently, the Neuro-Fuzzy Gust-front Detection Algorithm (NFGDA) was developed in 2013 at the Advanced Radar Research Center (ARRC), University of Oklahoma. This algorithm differs from MIGFA as it was designed to utilize polarimetric variables which provide both a horizontal and vertical power return for discriminating between meteorological and non-meteorological scatters (Park et al., 2009, p. 734).

Data

In this study, a compilation of severe weather events were obtained from the National Oceanic & Atmospheric Administration (NOAA) Storm Prediction Center (SPC) Archives. This was used to identify severe thunderstorm events with strong gust front signatures. Subsequently, level-II base data from specific radars were downloaded from the National Center for Environmental Information (NCEI) Next-Generation Radar (NEXRAD) inventory.

Methods

Data from each of the eight cases were observed in GR2 Analyst via the Doppler radar products base reflectivity, base radial velocity, storm relative velocity, and spectrum width. An organized gust front signature showcased thin line, low reflectivity values (10-20 dBZ, light blue and green on radar). The radial velocity had a change in wind speed over a given distance (also defined as shear) and traveled away from the radar (red on radar), the storm relative velocity removed storm motion which enhanced the gust front signature. Finally, spectrum width showed variance in the wind field and the gust front signature was variable showing noisy signals. In radar, the gust front was seen from the debris it carries and has positive values (gray on radar).

Additionally, this project qualitatively modeled successful identification methods from previous works to classified outflow boundaries as organized gust front signatures (e.g. Klingle, 1985, p. 4, Wakimoto, 1982, Zrnic and Lee, 1983, p. 6).

Results

Cases were qualitatively classified as followed: normal, complicated, and abnormal. Four of eight cases (radar identification names: KABR, KILX, KLBB, KSJT) showcased normal gust front signatures via Doppler radar following all criteria from the methods section. Complicated cases (radar identification names: KJAX, KVAX, KLSX) either had a sea breeze structure or had multiple gust fronts propagating in the image. Finally, the sole abnormal case (radar identification name: KDMX) lacked only the reflectivity signature in Doppler radar when more thoroughly examined.

Discussion

Though artificial intelligence is the leading detection method of gust fronts, visual identifications are critical in providing guidelines to algorithms for improving lead times and improved detection. Limitations of the detection algorithms were identified through this study. Although human aspects are difficult to implement through machine intelligence, researchers need to improve algorithms for more accurate gust front detection. The identified gust front characteristics were consistent with past literature and studies. Seven of the eight identified cases displayed structured gust front signatures. Effects of the environment yielded a lack of a thin line, low reflectivity (10-20 dBZ) signature in the KDMX case.

Conclusion

In conclusion, there is still a need for gust front signatures to be further evaluated visually by operational forecasters. The results of this study show that utilizing the expertise of professional visual detection will improve algorithm guidelines and therefore lead times and detection. Immediate next steps would be to take these findings and implement pre-cautions, including unique blocks of code within the current detection algorithms specifically to detect complicated and abnormal cases.

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