Automatic Wind Turbine Identification Using Level-II Data

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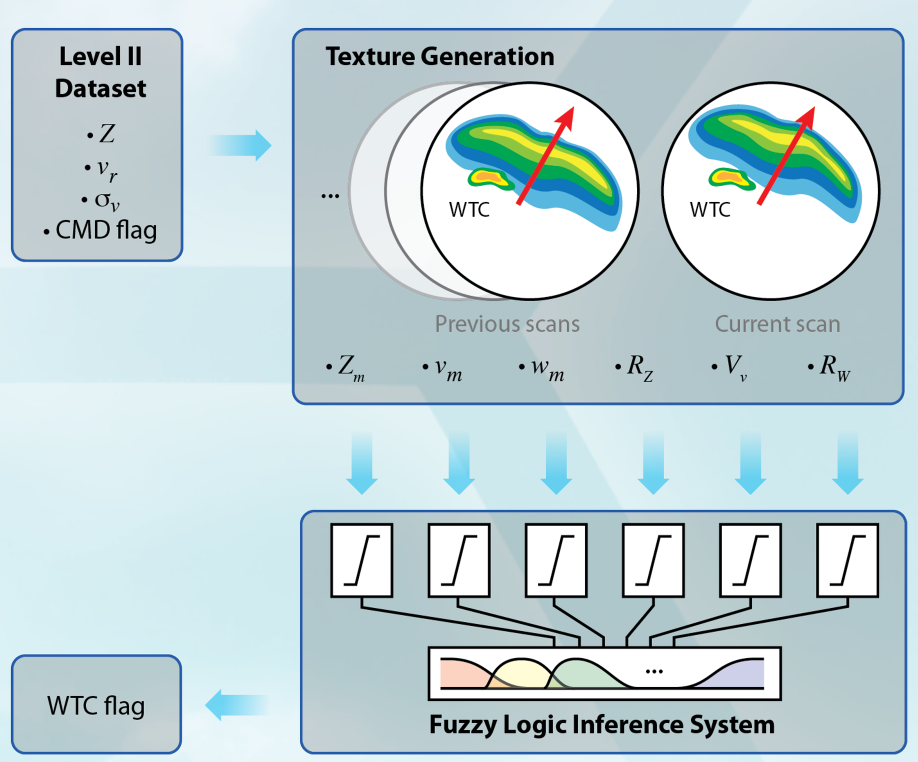
Abstract

In this work, an automatic wind turbine identification scheme was developed, with a restriction that only Level-II data are available. The motivation is to minimize modification to the existing data processing infrastructure of the WSR-88D. The concept is to process several consecutive scans of images and look for features that move. This was accomplished by processing a set of six running-temporal textures, which are derived from the moment data, to find temporal continuity. A fuzzy logic inference system is used to combine information from the six textures to make a final decision of detection. Some results will be presented to demonstrate the potential of this algorithm.

Automatic Wind Turbine Identification

If a wind farm is still present within the radar domain after GMAP filtering, it can be visually identified from Level-II data when one observes several consecutive images and look for visual queues to locate stationary targets versus moving targets. Understanding how human visual systems identify these residual signals of wind turbine clutter, it was believed that by processing several consecutive images at a time, a similar detection could be realized for computer implementation.

In the present implementation, a time window with seven (arbitrary, user changeable) images is considered. Out of these seven images, temporal average, correlations of up to lag five (flexible) and the resulting variance are considered. The six textures are (1) average of reflectivity, (2) average of velocity, (3) average of spectrum width, (4) correlation of reflectivity, (5) variance of velocity, and (6) correlation of spectrum width.



Block diagram of the flow of processing

1) Average of reflectivity: The average of reflectivity can be considered as a "blur" composite of the images. For features that are non-stationary, such as the isolated storm cells, this texture will be smeared. On the other hand, for features that are stationary, such as the wind turbine clutter, they will be summed consistently and thus result in strong reflectivity for those regions. The texture is mathematically described as

$$Z_{\mathrm{m}}(t) = \frac{1}{N}\sum_{n=0}^{N-1} Z(t-n)$$

2) Average of velocity: The average of radial velocity has been found to be near zero when sufficient images are used for averaging, which is exactly opposite of the signatures found in typical weather signals, except in regions along the zero isodop. It should be mentioned here that calculating the average of velocity should be done to mitigate abrupt value change when velocity values are near the aliasing velocity. For example, two values that are close to $\pm v_a$ should have an average of near $\pm v_a$, instead of zero. For simplicity, the mathematical expression of the texture is described as follows

$$v_{\mathrm{m}}(t) = \frac{1}{N}\sum_{n=0}^{N-1} v(t-n)$$

3) Average of spectrum width: The average of spectrum width is high for wind turbine targets because it represents the collective spectrum of a widely distributed velocity, which comes from different parts of the blades that exhibit different velocities. Of course, regions with weather may also exhibit wide spectrum width when the air motion is turbulent. If the weather pattern is scattered and has sufficient motion, however, this feature will be blurred similarly to the average of reflectivity. The texture is described mathematically as

$$w_{\mathrm{m}}(t) = \frac{1}{N}\sum_{n=0}^{N-1} w(t-n)$$

4) Correlation of reflectivity: The correlation of reflectivity is expected to be high for stationary targets and low for moving targets. This is the texture that closely mimics our visual system to lock on features that are stationary, which is, in the interest of this project, the wind turbine clutter. Of course, a situation with stratiform precipitation would also result in high correlation values, as the whole map appears stationary. The texture is described as

$$R_Z = \mathrm{MED}\left\{\sum_{n=0}^{N-1}\left[Z(n)-Z_m\right]\left[Z(n-\tau)-Z_m\right]\right\}_{\tau=1}^{L}$$

5) Variance of velocity: The variance of velocity is high as the velocity being measured directly depends on the blade orientation, which appears random from one scan to another. Conversely, for the weather signals, this measurement would typically be low except for regions that are extremely turbulent. The texture is described as

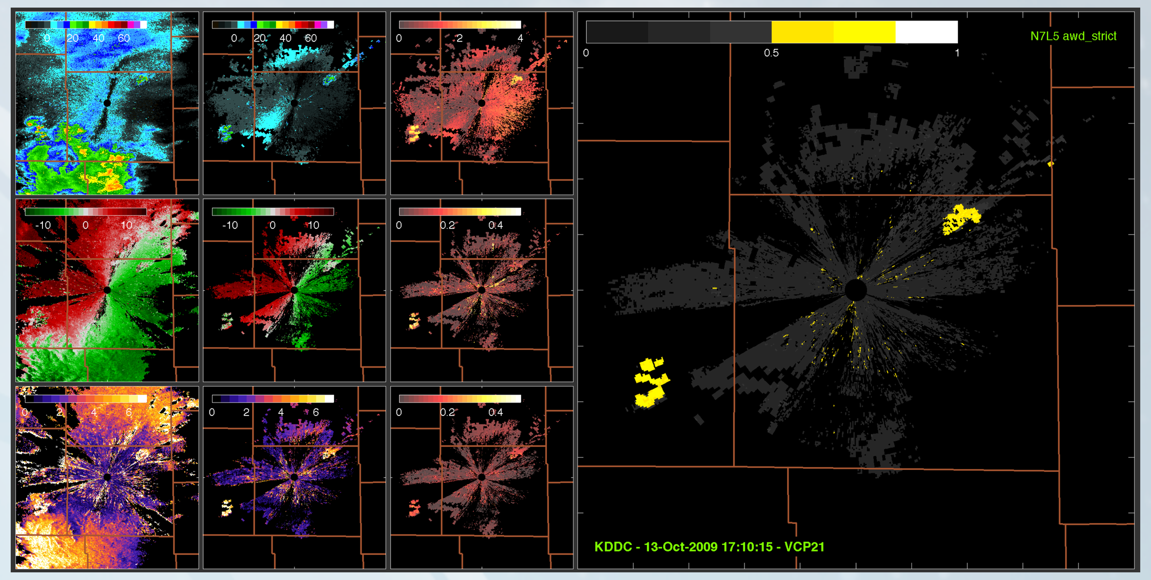
$$R_w = \mathrm{MED}\left[\sum_{n=0}^{N-1} w(n)w(n-\tau)\right]_{\tau=1}^{L}$$

6) Correlation of spectrum width: The pattern of a storm usually changes, i.e., the spatial pattern of the storm translates and deforms across the radar domain. It is no surprise that the pattern of spectrum width also behaves in a similar way much like the translation of reflectivity structure. Distinctively, wind turbine clutter also exhibits high values in this texture but they would stay on the same location, which is advantageous for the success of identification. It is formulated as

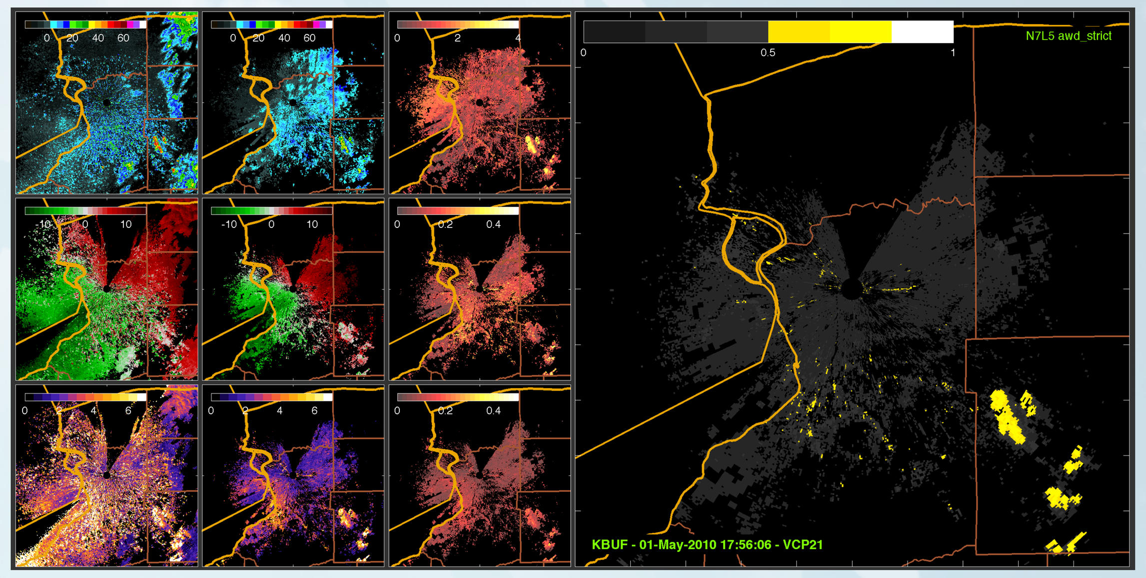
$$V_v = \sum_{n=0}^{N-1}\left[v(n)-v_{\mathrm{m}}\right]^2$$

Experimental Results

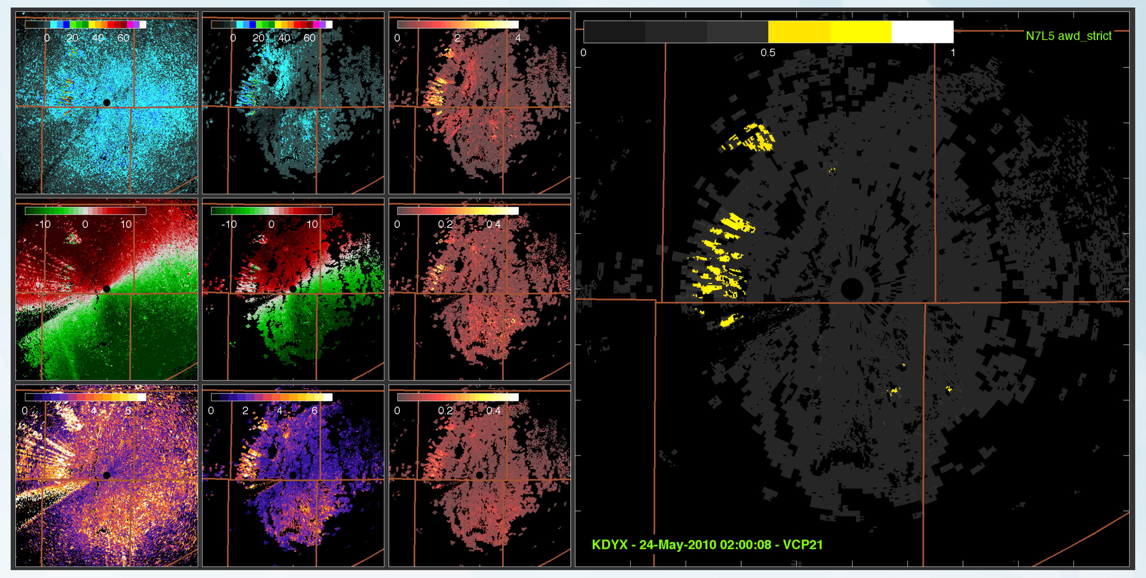
Datasets from the WSR-88D radar in Dodge City, Kansas (KDDC) on 13 Oct 2009 12:00—23:59 UTC was used for the algorithm development and initial tests. In addition, another dataset from Buffalo, New York (KBUF) on 1 May 2010 13:00—23:59 UTC where scattered precipitation moved across the radar domain from the west and another dataset from Dyess AFB, Texas (KDYX) on 20 May 2010 00:00—04:00 UTC where non-precipitation radar returns were found within the radar domain were used in the analysis. One snapshot from each dataset would be shown in the following.



Two wind farms, one located 40 km southwest while the other lies 25 km northeast of the KDDC radar site were successfully identified. Note the similar values in reflectivity, velocity and spectrum width for the precipitation at the southwestern region that would be nearly impossible to identify without a temporal history of data.



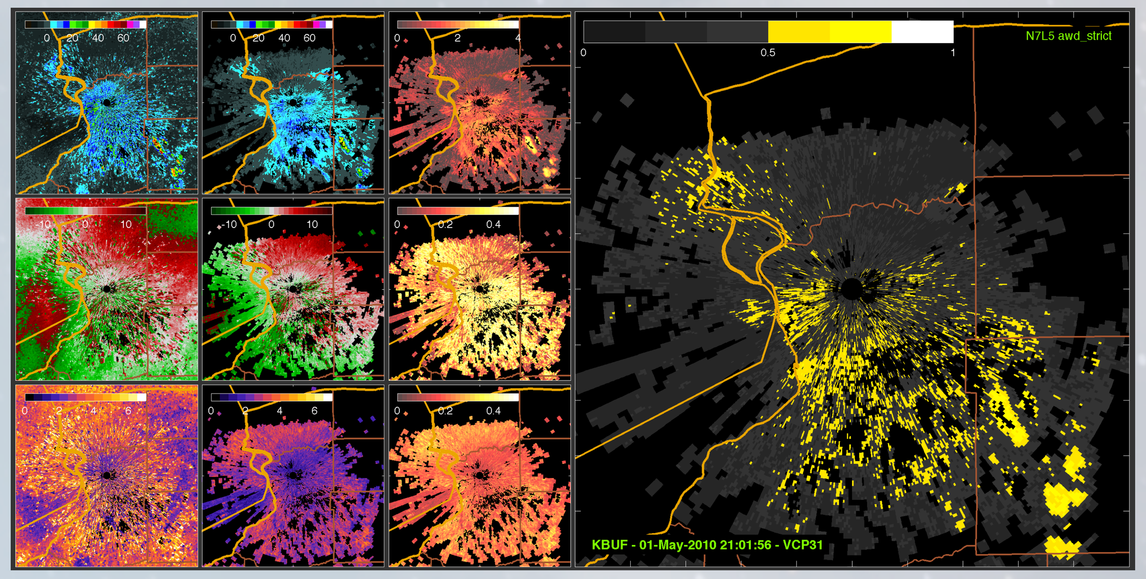
Several wind farms southeast of the radar have been detected using the automated wind turbine identification algorithm.



The wind farm just west of the KDYX radar was detected. Streak-like echoes are due to multipath propagation but the texture signatures of the wind turbine clutter do not change, which make the detection viable.

Limitations

One of the limitations is when majority of the textures are misrepresented. An example is shown in the following figure where large amount of false detections were caused by 4 misrepresented textures.



Low PRF that causes velocity measurements to alias and induces positive bias on the spectrum width estimate could consequently cause large amount of false detections. In addition, lower PRF's are usually accompanied with lower number of pulses per radial, which introduces a positive bias on W_w and, thus, R_w. This would cause four out of six textures to be misrepresented and result in false detections.

Since the core of the algorithm is temporal processing, handling several images at a time also means a long period of observation, which might not be optimum for rapid evolving atmospheric conditions, particularly detections due to anomalous propagation (AP). In theory, the texture signatures of wind turbine clutter are preserved through AP and multipath (MP). The atmospheric conditions that cause the AP and/or MP, however, might not last for that long especially when several consecutive scans are needed for detection. On the other hand, if the number of scans is too low, the quality of textures may not be sound and the spatial pattern of the weather may not have sufficient motion for the algorithm to sample the low temporal correlation of weather features.

Future Plans

Through the initial evaluation, we found that false alarm rate was relatively poor using the initial fuzzy logic setup and testing against complex weather conditions, e.g., anomalous propagation, gust fronts, squall lines and strong circulations. We believe that the fuzzy logic setup can be adjusted to improve the performance for some situations and this work is currently underway. The future work includes

- Using the same test cases, reapply different fuzzy logic settings
- Configure different settings for the fuzzy logic
  - Aggressive setup to reduce false alarm rate
  - Trade off between false alarm rate & probability of detection
- Assess if fuzzy logic setup is site dependent
- Assess if fuzzy logic setup is weather dependent

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This work is partially funded by the U.S. Department of Commerce, National Oceanic and Atmospheric Atmospheric, grant NA08OAR4320904. The authors would also like to thank the Application Branch of the NOAA Radar Operations Center for their support.