P4D.6 A GROUPING ALGORITHM FOR ESTIMATING WIND SPEEDS IN DOPPLER SPECTRA

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1. INTRODUCTION

Wind profiling radars have to distinguish atmospheric signals from other signals, or “clutter” (e.g., ground clutter and radio-frequency interference), to achieve accurate wind measurements. Recently, spectral and time-series data have improved wind estimation methods (Clothiaux et al. 1994, Jordan et al. 1997, Cornman et al. 1998, Morse et al. 2002), and have successfully handled various clutter-contaminated data. This paper presents a new method for removing clutter from wind profilers that measure Doppler spectra. In estimating radial velocity, this method maintains established data measurements (for instance, of continuity and proximity of Doppler spectra signals). However, the method does not require that a signal feature distinguish atmospheric signals from Doppler spectra. Moreover, since this method does not aim to remove specific signals, signal analysis is not required. Actual data showing a significant clutter effect on wind measurements demonstrate the algorithm’s improved radial velocity measurements. Converting radial velocity estimated by the algorithm to horizontal wind speed and direction is also verified.

2. METHODS

Perceptual grouping and figure-background segregation model studies have sought to separate atmospheric signals from other signals (Malsburg and Schneider 1986, Sompolinsky et al. 1990, Sporns et al. 1991). A lattice model inspired by the self-organization (Malsburg 1973) and Hopfield (Hopfield 1982) models formed the basis for this study. Using a neural network field approach, this study developed an algorithm that extracts atmospheric signals from Doppler spectra. The following four features characterize the lattice model used. First, a spectral bin corresponding to range and frequency lattice points (i.e., Doppler velocity) on a two-dimensional lattice. Second, a unit cell outputs if its "potential" for depending on inputs from surrounding cells exceeds the output threshold. Third, the unit cell of each lattice point has two kinds of connecting interaction: the excitatory connection (positive value) promotes simultaneous unit cell output, while the inhibitory connection (negative value) inhibits simultaneous unit cell output. Finally, the connecting interaction between unit cells is allowed to change in response to potentials and outputs.

A grouping algorithm can automatically find first moments using a lattice model. Unit cells have an output value of either 0 or 1, according to the sum of the input received. The initial output is also digitized as 0 or 1 by comparing spectral density with its average at each range-gate. The output of each unit is iteratively calculated until the “energy” (given by the Liapunov function) of the network of unit cells converges. Finally, the first moment is computed using the final output value at each range-gate.

3. RESULTS

As an example of how clutter affects moment estimation, Figure 1 shows the lowest five range gates of spectra measured by 1.3-GHz boundary layer radar. Although a notch filter removed the effect of ground clutter, radio frequency clutter likely affected radial velocity estimation. Power supply trouble with the 1.3-GHz boundary layer radar amplifier caused the 210-m gate to show as an exception.

Figure 2 illustrates sequential changes in the network system output. Figure 2a plots initial output patterns calculated using the same spectra as Figure 1. Figures 2b, 2c, and 2d show the output patterns after five, ten, and twenty-nine iterations, respectively. Lattice point outputs from unnecessary signals, such as the clutter seen in Figure 2a, disappear in Figure 2d. Figures 3a, 3b, 3c, and 3d compare two kinds of first moments in four tilted directions. The first moment calculated by the grouping algorithm (solid line) continuously estimated radial velocity, and successfully eliminated unnecessary signal effects, such as the clutter shown by the standard first moment (dashed line).

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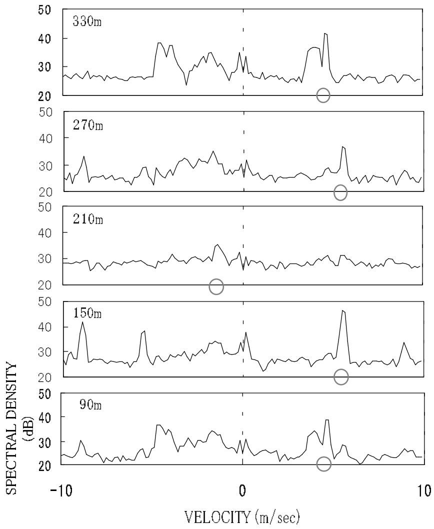

Figure 1: Five stacked spectra (beam: S - W, date and time: 8/17/2001, 20:40, site: Tsukuba). Circles show standard first moments.

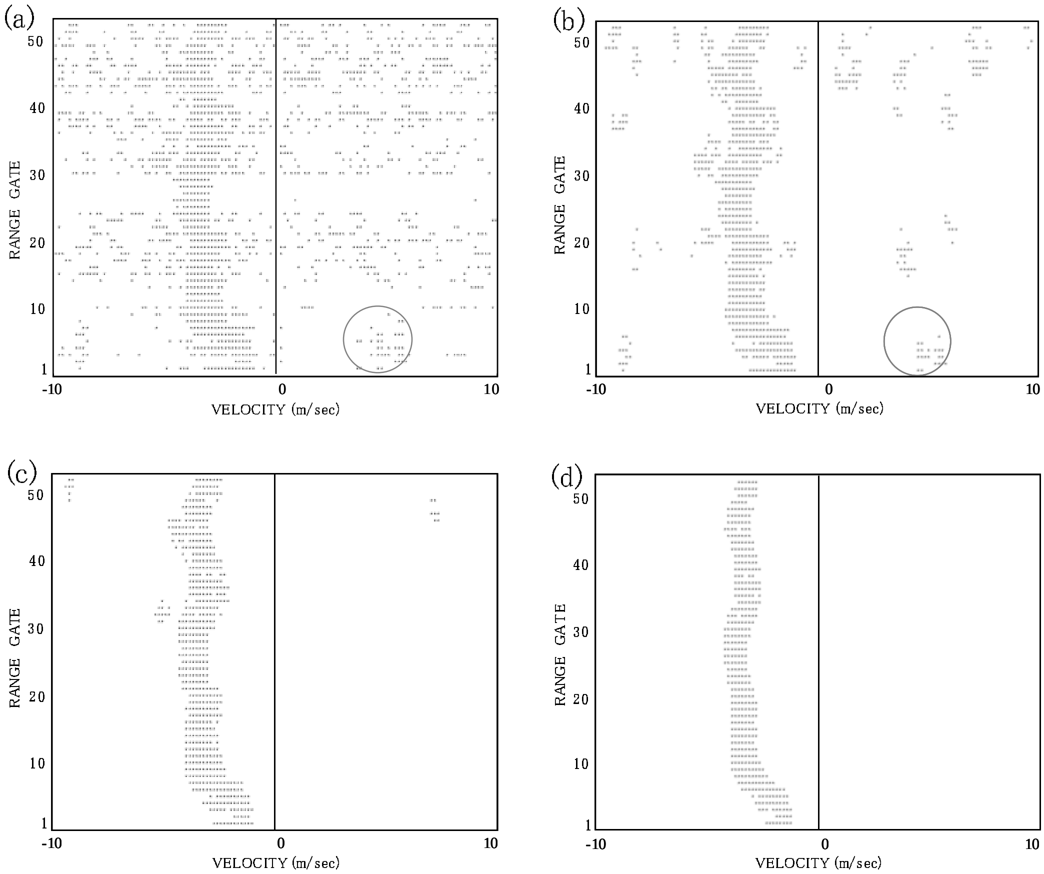

Figure 2: Output patterns of the initial state (2a) and after five (2b), ten (2c), and twenty-nine (2d) iterations (beam: S-W, date and time: 8/17/2001, 20:40, site: Tsukuba). The asterisk and the blank symbol represent 1 and 0, respectively. Circles indicate lattice points corresponding to clutter signals.

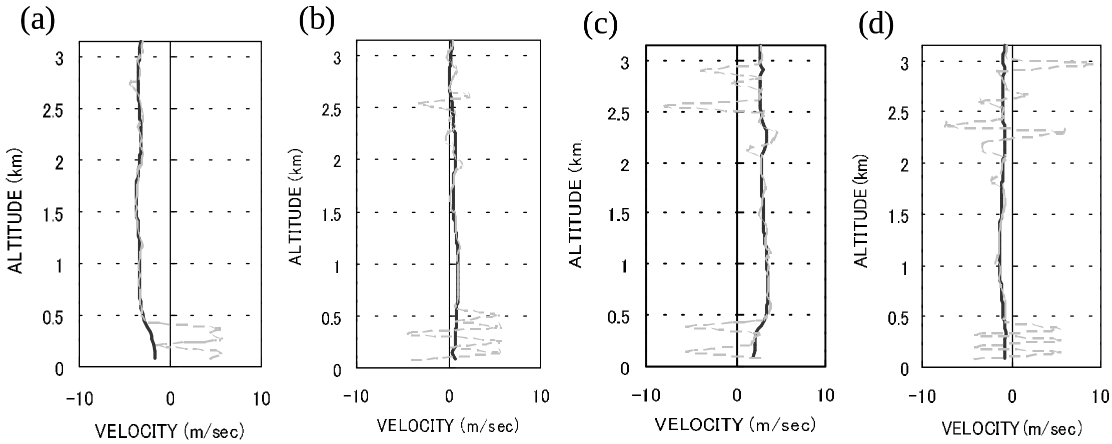

Figure 3: Profiles of S-W (3a), N-W (3b), N-E (3c), and S-E (3d) oblique beam radial profiles (data and time: 8/17/2001, 20:40-20:42, site: Tsukuba). Solid and dashed lines represent grouping algorithm and standard moment method results, respectively.

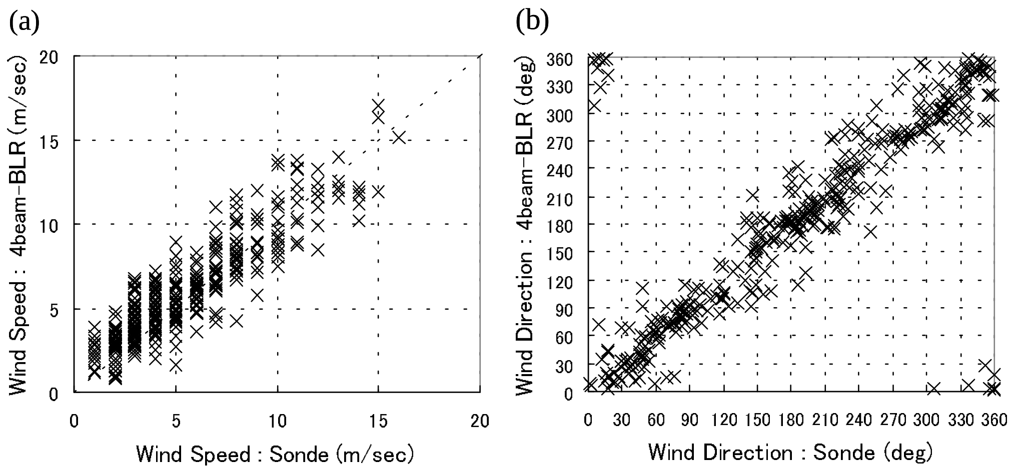

Figure 4: Comparison of 1.3-GHz boundary layer radar winds determined by a grouping algorithm and 65 sonde ascents. 4a and 4 b show horizontal wind speed and direction, respectively (time period: 8/01-8/31/2001, site: Tsukuba).

Furthermore, two-minute observations using four oblique 1.3-GHz boundary layer radar beams were converted into horizontal wind using the grouping algorithm; the results were compared to observations from 65 sonde ascents. Figures 4a and 4b compare wind speed and direction, respectively in 370 plots. The boundary layer radar and sonde data had average wind speed and direction differences of 0.4 m/sec and 1.9 deg, and standard deviations of 1.4 m/sec and 23 deg, respectively. The results showed good agreement, though the comparisons were limited to boundary layer data from about three km or less.

4. CONCLUSIONS

Using a grouping algorithm for moment estimation eliminates the need for data smoothing, training data, picking a peak for each signal, and determining signal features based on the appearance of Doppler spectra. The horizontal wind speeds obtained using the grouping algorithm agreed well with sonde wind data. The results suggest that a grouping algorithm can improve wind velocity estimation accuracy in wind profilers.

5. ACKNOWLEDGMENTS

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