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Comment

Comments on "Wind Gust Detection and Impact Prediction for Wind Turbines"

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Abstract: We refute statements in "Zhou, K., et al. Wind gust detection and impact prediction for wind turbines. *Remote Sens.* **2018**, *10*, 514." about the impracticality of motion estimation methods to derive two-component vector wind fields from single scanning aerosol lidar data. Our assertion is supported by recently published results on the performance of two image-based motion estimation methods: cross-correlation (CC) and wavelet-based optical flow (WOF). The characteristics and performances of CC and WOF are compared with those of a two-dimensional variational (2D-VAR) method that was applied to radial velocity fields from a single scanning Doppler lidar. The algorithmic aspects of WOF and 2D-VAR are reviewed and we conclude that these two approaches are in fact similar and practical.

Keywords: lidar; wind; Doppler; aerosol; motion estimation; optical flow; cross-correlation; wind energy; gust prediction; variational analysis

1. Introduction

Zhou et al. [1] provided an excellent example of the value of remote observations of two-component wind fields in the lower atmospheric boundary layer. They obtained two-component wind fields by applying a 2D variational (2D-VAR) method [2] to single component velocity data from a single Doppler lidar. While their paper mentions cross-correlation (CC) and wavelet-based optical flow (WOF) algorithms as alternative ways to obtain such wind fields, statements about these two methods are inaccurate and do not consider the latest published research on this subject. In this note, we correct statements in [1] based on our recent work [3,4] and put the CC, OF, and 2D-VAR methods into perspective. We contend that the WOF and 2D-VAR algorithms are in fact similar and that motion estimation methods should not be discounted for remote wind sensing applications such as the one they developed.

2. Statements in Zhou et al. [1] About Motion Estimation Methods

Zhou et al. [1] described an algorithm to detect and track wind gusts. Their algorithm operates on two-dimensional (2D) two-component (2C) wind fields which must first be made available. They chose to compute the wind fields by applying a 2D variational analysis method (2D-VAR) to radial component velocities measured by a single Doppler lidar ([1], Section 2.2). Alternative approaches to remotely observe similar 2D-2C wind fields are also mentioned in the introduction of the paper:

> "*Mayor adapted two computer-vision methods for flow motion estimation: the cross-correlation method and the wavelet-based optical flow method [5,6].*"—(Zhou et al. [1], Section 1).

However, after the above sentence, the paper continues with:

> "*[...] the cross-correlation method has limitations for non-uniform velocity fields and the optical flow method requires relatively small (few pixels) movement and is computationally demanding. These requirements make them impractical.*"—(Zhou et al. [1], Section 1).

We thank Zhou et al. [1] for citing these two papers [5,6]. Their statements regarding our research results are however inaccurate and do not include the latest peer-reviewed research in the field. The purpose of this note is: (1) to correct their statements; and (2) to demonstrate that the method they chose and the motion estimation approach that we have been focused on are, in fact, comparable in terms of temporal and spatial discretization, accuracy, and computational load, and thus are similarly practical given the presently available information.

3. The Practicality of Motion Estimation Methods

The quoted statements above ignore the abundance of published evidence of the strong skill of motion estimation algorithms and dismiss the approach for use in meteorological applications [3–5,7–9]. The literature shows that two numerical techniques (cross-correlation (CC) and wavelet-based optical flow (WOF)) are capable of extracting horizontal 2D-2C vector wind fields from near-horizontal aerosol lidar scans. We believe that these flow fields could be used in applications such as gust detection and prediction for wind turbines. In fact, the WOF motion estimation technique is currently in use for other short-term wind prediction applications [10].

First, we begin with the statement: "*[...] the cross-correlation method has limitations for non-uniform velocity fields*". While this statement is correct in that the CC approach has limitations, as does any measurement technique, it fails to acknowledge the vastly more important point that the algorithm works well over a wide range of wind conditions. This includes moderate and strong winds, when non-uniformity in wind direction is small compared to light wind conditions that may occur in boundary layers driven exclusively by convection [4]. Zhou et al. [1] focused on detecting and tracking gusts in the context of wind power production. Given that windy conditions are favorable for generating electricity, our opinion is that the CC method would not be limited by non-uniformity of the wind field within the interrogation window in such applications. Furthermore, Hamada et al. [4] (Section 4.a.1 "Light wind case") showed good results for cross-correlation even when winds are light and variable.

Second, we have shown that "*small (few pixels) movement*" is not a problem for WOF applied to non-Doppler scanning elastic lidars [3]. It is true that the application of optical flow algorithms are often limited to image sequences in which features move with small displacements from frame to frame. However, the WOF algorithm is designed to handle large displacements, first by taking advantage of the multiscale nature of the wavelet framework [11], and second by incorporating the algorithm into a more classical pyramidal approach ([3], (Appendix B)). Velocities as high as 15 $m \cdot s^{-1}$ have been successfully measured [3] (Section 5.a.3, "Strong wind case"). With a typical scan time of 17 s and a 8 $m \cdot pixel^{-1}$ grid spacing, this amounts to displacements above 30 pixel which cannot be deemed "small".

Third, all of the calculations for CC and WOF are performed in real-time during the time between scans (10 s to 20 s) using general purpose graphical processing units (GPGPUs). In fact, the appendix of the paper by Mayor et al. [5] describes the methodology used to accelerate the process using common computer architectures. Further, two conference presentations detail the steps to achieve this performance [12,13]. GPGPUs are available for almost any computer and the models with the required performance cost about 1000 USD.

4. Comparing CC, WOF, and 2D-VAR Methods

We now put the three CC, WOF, and 2D-VAR methods into perspective. Let us first clarify that the objective here is not to state whether any method is better or worse than another.

We first consider the spatial and temporal discretization of the 2D-2C wind fields produced by the three approaches: parameters used in Hamada et al. [4], Dérian et al. [3], and Zhou et al. [1] are listed in Table 1. The time steps are comparable (17 s for CC and WOF, and 30 s for 2D-VAR). (By *time steps*, we mean the elapsed time between scans, which is dependent upon the angular width of the sector scanned and the performance of the lidar used.). The biggest differences lie in the spatial domain: the 2D-VAR method covers a much larger domain than CC and WOF (24 km^2 for 2D-VAR versus 4.6–13 km^2 for the other two). (The area observed is dependent mostly upon the angular width of the sector scan and the maximum range of the useful data. These, in turn, are strongly dependent upon aerosol signal-to-noise ratio for aerosol lidars or the coherent signal-to-noise ratio for Doppler lidars, both of which vary with geographic location and weather conditions.) However, the vector spacing is much finer for WOF than for 2D-VAR: 8 m versus 80 m. WOF provides 10–50 times more vectors than 2D-VAR while operating in a shorter time window. Therefore, it can be safely assumed that WOF could deliver wind fields comparable to those given by 2D-VAR in terms of domain size, spatial, and temporal discretizations.

Table 1. Characteristics of 2D-2C wind field retrieval algorithms.

Method	Hamada et al. [4] (Cross-Correlations)	Dérian et al. [3] (Wavelet-Based Optical Flow)	Zhou et al. [1] (2D-VAR)
Domain shape	60° sector, 0.5 km to 3–5 km range	60° sector, 0.5 km to 3–5 km range	6 km × 4 km
Domain area	4.6 km^2 to 13 km^2	4.6 km^2 to 13 km^2	24 km^2
Vector spacing	sparse	dense, 8 m	dense, 80 m
Number of vectors	variable	$\approx 5 \times 10^4$ to 2×10^5	$\approx 4 \times 10^3$
Time step	≈17 s	≈17 s	30 s
Real-time computations	yes	yes	"possible"

We now examine the accuracy of the estimated wind vectors. Zhou et al. [1] did not comment on the accuracy of the wind fields retrieved with the 2D-VAR algorithm. They cited Cherukuru et al. [2] for details, so we turn to it instead. Cherukuru et al. [2] validated their approach based on 10-min averages, the standard averaging period for the wind energy industry, and compared the 2D-VAR results with measures from a cup and vane anemometer. Hamada et al. [4] and Dérian et al. [3] also considered 10-min averages to validate the CC and WOF algorithms, respectively, by comparing measurements from a Doppler lidar operating in vertical profiling mode. Statistics for the CC, WOF, and 2D-VAR methods are gathered in Table 2. The methods are not directly comparable as Hamada et al. [4] and Dérian et al. [3] gave per-component values, whereas Cherukuru et al. [2] reported on wind speed and direction. Nevertheless, they appear to be similarly accurate.

Finally, we briefly mention algorithmic aspects for WOF and 2D-VAR. They are more comparable as they both deliver dense fields, whereas CC is intrinsically a sparse, local approach. Moreover, optical flow is actually a form of 2D variational analysis. For both algorithms, the wind field is obtained by minimizing a cost function defined as an integral over the spatial domain, and the minimization is achieved by a quasi-Newton method. The differences lie in the choice of the data model—which connects the partial observations (aerosol backscatter for WOF and radial velocity component for 2D-VAR) to the unknown (the 2D-2C horizontal wind field)—and the regularizer (which closes the problem and facilitates a successful minimization). In WOF, the data model is based on the advection of a passive scalar field ([3], Equation (4)): the aerosol backscatter, itself similar to a concentration of particles [14]. In 2D-VAR, the data-model involves the advection of an active scalar field and the radial velocity component ([2], Section 3, Equations (5)–(8)). The regularizer used in WOF is a first-order smoothing term that penalizes strong gradients in the estimated velocity fields ([3], Equation (5)). Authors of the 2D-VAR used the departure of the estimated wind field from a prior solution obtained using another method ([2], the "background constraint" in Section 3). We note that the latter requires solving another wind reconstruction problem before running 2D-VAR, which adds to the computational load. To summarize, both approaches solve inverse problems that are different in terms of models but comparable in terms of structure.

Table 2. Accuracy of wind field retrieval algorithms measured on 10-min averages. Values for Hamada et al. [4] are from Tables 4 and 5. Values for Dérian et al. [3] are from Tables 2 and 3 and Section 5.a.4. Zhou et al. [1] did not report on the accuracy of wind retrieval; values listed here for the 2D-VAR are obtained from Cherukuru et al. [2] (Figure 2 and Table 1). "n.r." stands for "not reported". Note that horizontal wind vectors derived from the Streamline Doppler lidar resulted from a Doppler beam swinging technique that placed off-zenith sample volumes for radial velocities approximately 210 m apart, whereas the cup and vane anemometer is sampled at essentially one point in the atmosphere.

Method	**Hamada et al. [4] (Cross-Correlations)**	**Dérian et al. [3] (Wavelet-Based Optical Flow)**	**Cherukuru et al. [2] (2D-Var)**
Reference measure	Streamline Doppler lidar	Streamline Doppler lidar	cup and vane anemometer
Number of points (duration)	891 (≈150 h)	892 (≈150 h)	120 (20 h)
Wind speed RMS error	n.r.	n.r.	$0.383\ \mathrm{m{\cdot}s^{-1}}$
Wind speed correl. coeff.	n.r.	$\sqrt{0.991} \approx 0.995$	0.96
Wind direction error	n.r.	1.1°	−1.4°
Wind direction correl. coeff.	n.r.	$\sqrt{0.944} \approx 0.976$	0.98
West–east component u RMS error	$0.36\ \mathrm{m{\cdot}s^{-1}}$	$0.29\ \mathrm{m{\cdot}s^{-1}}$	n.r.
West–east component u correl. coeff.	$\sqrt{0.993} \approx 0.996$	$\sqrt{0.995} \approx 0.997$	n.r.
South–north component v RMS error	$0.37\ \mathrm{m{\cdot}s^{-1}}$	$0.29\ \mathrm{m{\cdot}s^{-1}}$	n.r.
South–north component v correl. coeff.	$\sqrt{0.995} \approx 0.997$	$\sqrt{0.997} \approx 0.998$	n.r.

In our opinion, the largest weaknesses of the motion estimation approaches (CC and WOF) to wind field measurement using current aerosol lidars are: (1) the failure of the technique during periods when small-scale aerosol inhomogeneities are not present; and (2) the rarity and expense of commercially available scanning aerosol lidars with the required high-performance. Stable stratification can suppress the production of turbulent eddies and the formation of aerosol inhomogeneities that are required. Based on only two field experiments that we have conducted over land in the Central Valley of California, this condition often occurs at night. We also note that at least one compact and portable aerosol lidar with the required performance is now commercially available and that wind fields derived from it are shown in [7]. As laser, detector, and optical technologies mature, we expect to see improvements in the performance and accessibility to this approach of wind field measurement.

5. Conclusions

Motion estimation approaches for computing 2D-2C wind fields are not impractical for the reasons stated in [1]. Two recent peer-reviewed publications document the performance of CC and WOF techniques which are comparable to those published for their 2D-VAR. We have also taken this opportunity to provide a comparison of the WOC and 2D-VAR techniques to show that the two methods actually have much in common and that both are practical.

Author Contributions: S.D.M. and P.D. shared all aspects of producing this note.

Conflicts of Interest: The authors declare no conflict of interest.

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