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Reply on RC2

Maria Krutova et al.

Author comment on "Development of an automatic thresholding method for wake meandering studies and its application to the data set from scanning wind lidar" by Maria Krutova et al., Wind Energ. Sci. Discuss., https://doi.org/10.5194/wes-2021-90-AC2, 2021

Thank you for your comment and very detailed review of the methods used. Because of one of the questions we were able to identify an error in the deficit-based threshold. I will answer it in the beginning, since it had most affected the revision.

L329: How is the "free flow" wind speed calculated? Is this automatic or manual?

The free-flow wind speed is taken from the reference wind speed series since the lidar scan is quite noisy to rely on the specific value near a wind turbine. However, as explained in Sec. 3.2, the lidar measures radial velocity, but not the actual wind speed. Thus, the threshold calculated as 0.95Uref would not match well the free-flow radial velocity when the wind direction is too different from the scanned azimuths. This explains better performance of the deficit-based threshold on the bimodal case (wind blows along the scanned azimuths; the radial velocity is rather close to the actual wind speed) compared to aligned and parallel wakes (the direction difference is higher there).

This was not relevant for the ATS method, as it scales all information to the range of [0,1] regardless of the specific wind speed values. On the contrary, the deficit-based method has to work with the wind speed data and wind speed threshold defined in the same frame. Normally, a retrieval procedure should be carried out to reconstruct the wind field. Since we were not interested in the local flow direction, estimating a wind speed would be enough. The radial wind speed is a projection of the actual wind speed vector to the line of sight and can be approximated as:

u = U/cos(ref_WindDir – azimuth)

The estimation is added to the subsection on the deficit-based threshold (adding it to the Data section would make confusion, whether the same procedure is applied during the ATS method). The derivation of the expression will be provided in appendix.

This estimation, although being very crude, improved the performance of the deficit-based threshold for the parallel wakes, but not for the aligned subset – the threshold from the wind speed is still largely underestimated. The correction affected the results for the confusion matrices (Fig. 12-14) and Table 2. The deficit-based threshold cannot be compared to the manual threshold anymore, so we will replace Fig. 15 with a box plot.

The affected plots are provided in the supplement.

Major Comments

This study is not replicable in its current state

The manually segmented wakes are not uploaded to a publicly accessible database. This is problematic, as two scientists would manually segment the scans differently, and as such, the results here are not immediately reproducable.

That is the valid remark. We prepare the manual data set for the upload as well as the manual thresholds. The supplementary video will be re-recorded to include manual wake identification and deficit-based thresholding results.

L364-366: Additionally, parts of the novel algorithm are not presented in the paper.

We will add the crucial parts of the algorithm (thresholding and centerline detection) as pseudocode to the article. The full code is not quite optimized yet and lacks a function to allow centerline detection in the far wake, so it would be available upon request for now.

In its current state, the motivation for the study is somewhat weak

The new methodology seeks to improve the thresholding approach to wake identification. The authors state that "the most common wake detection method is… Gaussian". Is the thresholding approach common and important? When would this approach be used instead of the more popular Gaussian approach? The authors provide only one citation in the paragraph where the this technique is first discussed (L65), so it would appear that this approach is not commonly used.

The thresholding approach was also used as a step in the analysis in Bastine, D.; Witha, B.; Wächter, M.; Peinke, J. Towards a Simplified DynamicWake Model Using POD Analysis. Energies **2015**, 8, 895-920. We did not include that reference, as their method required subtracting LES flow without wind turbine from the wake field, which is impossible to perform for lidar data. We will add this reference to the introduction to show different thresholding approach applications.

We believe that the thresholding approach had limited use due to its low flexibility. The automatic algorithm allows to overcome this disadvantage. Moreover, the algorithm is constructed in a way to require as little supplementary data as possible.

The validation methodology could be stronger

Wakes are manually segmented by hand-selecting a threshold between 0 and 1. I expected that wakes would have been segmented differently. I thought that a bounding countour was going to be manually drawn around every wake. This means that the validation study very specifically tests the question of "can we automatically pick the best threshold between 0 and 1" instead of "is our new idenfitication/characterization algorithm the best algorithm for the task". This is still presumably an important question, but we wish the authors to more clearly

state that the primary goal of the text is to automatically pick the best threshold for wake identification

Yes, the comparison against manual detection describes, whether the automated method can perform better than the fixed threshold and whether the ATS method can be a replacement for the manual thresholding. We chose this approach because it allowed to perform a comparison for the whole data set in a relatively short period. Drawing a bounding contour requires time similar to manual centerline detection, performing it for the data set even without the corrupted scans (~475 valid scans) would be too time-consuming. We will consider to include few examples with manually drawn contour for some complicated cases.

The terminology regarding different wake identification algorithms was ambiguous, which made it difficult to assess what technique was being used at a given time

"Image processing" is a massive field of study, and as such, it is ambiguous to refer to one wake identification algorithm as simply an "impage processing" technique. Please be more specific about this terminology, and if this technique is coming from the image processing field, provide a citation as such.

The wake identification uses thresholding methods – this will be more emphasized in the text whenever the image processing is mentioned. In the centerline detection algorithm, the image processing is used only in a form of the connectivity analysis and contour extraction. After the contour is extracted, the centerline detection mainly relies on the geometrical properties of the curves.

Throughout the manuscript, please make a stronger distinction when "wake identification" is being carried out vs. when "wake characterization" is being carried out, in accordance with the cited Quon et al. (2020). Unless its meaning is exceedingly obvious in the context, please refrain from using "wake detection"

e.g. Sec 4.2: The title of this section says "Wake detection". However, this subsection appears to be describing wake *characterization* moreso than wake *identification* (and "detection" implies "identification").

Since we have only introduced a centerline detection algorithm, but did not perform throughout analysis of the wake behavior, it felt too much to call it wake characterization. Your point is valid, nevertheless; the descriptions are corrected to refer to the thresholding method as 'wake identification' and centerline detection as 'wake characterization'.

The structure of the different sections and subsections was unexpected, and as such, it made the narrative of the document more difficult to follow.

I recommend that wake identification methodology subsections should be placed next to eachother in Section 4, and similarly, wake characterization metholody subsections should be grouped together

This is rather hard to fulfil, because the Gaussian method perform boths actions simultaneously. Splitting the manual detection would produce two short disconnected descriptions. As suggested by RC1, we summarized the methods in a table closing the

Methodology section: name the method is referred to further, input data, basic principles and level of the automatization.

I recommend that Section 2 be made into a subsection of the contents Section 3

Section 3 already includes several different topics, so we do not feel it would benefit from including technical information on the measurement site. We will regard the possibility to move all data description to Section 2 and leave Section 3 with just lidar data quality and prepocessing.

Is this truly an automatic algorithm that avoids the need to manually preprocess and manually segment?

Yes. All the corrections mentioned can be implemented and parametrized to run as a part of the main algorithm. This includes:

- Despiking and outlier removal, both depend on the parameters (see next comment). This procedure is not unique to the method and can be performed with any other tool convenient for user.

- Selection of the wake shape to perform centerline detection: the algorithm either selects a shape that contains a wind turbine or, if the wind turbine happens to lie in the free-flow, the largest wake shape in a prescribed radius (1-2D).

- Adjust the wake shape for the centerline detection: if the wake shape contains more than one turbine, increase the threshold until wind turbines belong to different shapes. This is a common case for the aligned wakes subset and some scans from the bimodal subset. Right now, we ran the thresholding algorithm with the same parameters for all scans. It could be that subset-specific processing and parameters can lead to a higher threshold, thus removing the necessity for the correction.

- Determine wind direction for the wake search to avoid ambiguity during the centerline detection: if available, take the wind direction from measurements, or run the centerline search method with a large step and approximate the wake direction from the found points.

The only non-automated part is the definition of the subset types which was performed after the manual inspection of the data set and entropy characteristics. However, it was only used to structure the results of the wake detection. No subset-specific corrections were yet applied during the preprocessing and wake detection.

L139-144: Is the despiking process manual or automatic? If it is manual, that potentially hinders the ability to apply the ATS algorithm on larger datasets.

- It is automatic but uses two parameters: maximum allowed wind speed (here – radial wind speed magnitude) – values above are considered non-physical; and removed and wind speed difference – if the wind speed falls into allowed range but differs from the local mean of the nearby points by the specified value, it is considered a spike.

Sec 4.1: This section has statements like "A similar point in the first derivative graph *can* be used" and "only a second derivative inflection point *can* be used". *Are* they used in your algorithm? Please be precise.

Yes, we use both, since the threshold based only on the second derivative may appear too strict. The paragraph is re-written as follows:

A similar point in the first derivative graph T1 is used as a control value. We select the threshold as an average value between first and second derivative inflection points to smooth the threshold detection outcome. If the points initially laid close to each other, the averaged threshold T=(T1+T2)/2 would not deviate too far from T2. If the difference between T1 and T2 is high, the smoothing prevents the threshold from being too strict -- a strict threshold may leave weak wakes undetected.

L265-266: The use of "preferably" makes me think that this algorithm is not automatic

Knowing the wind direction prior to the centerline detection allows to skip few conditional steps in the centerline search algorithms. Suppose, there is no information on the wind direction. According to the algorithm, we first draw a circle of a radius D centered at the wind turbine position.

(Note: the algorithm was updated and improved to cover more exceptions, so its current description may differ in details compared to the original article)

If there are only two intersections, the algorithm calculates a middle point of the arc. Two intersections split a circle into two arcs, hence, two midpoints: 'upstream' and 'downstream' of the wind turbine. Having only two intersections guarantees, that one point will lie inside the wake shape – the algorithm can take it as a wake point and proceed to the next step by increasing the circle radius.

However, if the very first circle finds more intersections and the wind direction is unknown, the algorithm does not get enough information to select a centerline point. To allow it continue, we first discard all midpoints in the free flow – that leaves only the points inside the wake shape. Then the algorithm draws few more circles with a step of 0.25-0.5D (the step is larger than used for the centerline detection) and searches for new midpoints. At this stage all points are accepted, since the actual wake direction is unknown. The wake direction is estimated by fitting a linear regression to the found points. While the wake direction estimated in a such way may strongly differ from the reference wind direction, it was generally enough to narrow the search for the actual centerline detection.

This complex algorithm is used solely to obtain an approximation of the wake direction to resolve ambiguity in the centerline detection if no other information about wind or wake direction is provided. The information on the wind direction allows to skip to the centerline detection and reduce errors caused by an erroneous estimation.

The centerline detection algorithm restarts from the beginning with a smaller step (~0.1D). Now, if two or more centerline point candidates are found, they are compared against the estimated direction (which midpoint inside a wake shape gives the lowest deviation from the estimated direction?) or local wake direction (which midpoint turns the wake by the lowest angle?). These checks attempt to prevent the centerline point identification upstream or on a side of an irregular wake.

The conclusion does not sufficiently summarize the manuscript

Please summarize the strengths and weaknesses of the novel algorithm, especially relative to the other wake identification/characterization techniques

The conclusion is now re-written to summarize the main features of the ATS method and areas for the improvement. The uncommon preprocessing procedures such as entropy criteria are also detailed.

Minor Comments

L3: What is the difference between a "wake pattern" and a "wake shape"?

The terms were supposed to make a distinction between a data set of dynamically changing wakes and an instantaneous wake. Since we are further referring to 'wake shapes' as cluster of points detected by the thresholding method, the mention in the abstract is changed to 'the wake edges and centerline' to avoid confusion.

L18: It is a drastic oversimplification to state that the velocity deifict at 5D decreases to 20%. Consider citing review articles such as Stevens and Meneveua (2017) and Prote-Agel et al. (2020) in the introduction

L20: Please provide a citation for "The typical turbine spacing in the wind farms is usually 8D", as I believe onshore and offshore spacing differ

L38: Is it correct to say that lidar measurements are in situ? I think of lidars as remote sensing instruments

L63: This sentence implies that thresholding algorithms are always applied 6–8D downwind of a turbine

These suggestions are considered and necessary corrections were implemented.

L69: What is the difference between an "image" and "processed wind speed data"? Is an "image" a raw version of the wind speed data?

The 'image' implies that the data did not originally have information about the wind speed at all. It could be a photo or a figure from the publication. We do not focus on images in the study, but remark few specifics in the Appendix.

The 'processed data' refers to the data after despiking and normalization by scaling to the range of [0,1]. While the value distribution resembles a respective grayscale image (as shown in Fig. A1), the data can be reverted back to the original wind speed as long as the minimum and maximum wind speed values used in scaling are preserved.

L116-117: I am surprised to hear that you only encounter two types of noise. I imagine there are more variables that confound your signal (e.g. solid objects). Perhaps it is more appropriate to say "two primary challenges that obfuscate the wake signal" rather than "noise". Also, please clarify what is meant by "high wind speed due to the measurement error"

Those types of noise were the types we had encountered in the particular data set and considered an obstacle for the accurate wake detection. This will be emphasized stronger to avoid misinterpretation. The measurement errors due to crosswind effects and beam reflection from rotor blades were described further in this subsection. The paragraph is slightly re-written to point out at the description.

L125: Where does the reference wind direction come from? A sonic on the mast? Wake angles?

L150: What does "reference data" refer to?

The reference wind and direction were mentioned in lines 98-99. We agree, that the mention was too brief and had to be more emphasized. Section 2 is now rearranged to describe the reference data prior to the more detailed description of lidar data.

L163: What is "directional entropy"? How does it differ from Shannon entropy?

We chose this term to have a short reference to the Shannon entropy calculated across the beam range or azimuth. Apparently, it matched a pre-existing term, which definition is different from what we had implied. The 'directional entropy' is now replaced by the 'row and column entropy' to avoid confusion.

L174-177: Are all the low entropy scans indicative of strong crosswind effects? The "also" on L175 makes it seem like this is only true sometimes.

Also to clarify, are "cross wind corrupted" scans and "spiked data" scans the same? Also, what is the difference between mostly blue scans (e.g. index 310) vs paritually blue scans (e.g. 405)?

The entropy plot was presented for the data scaled to [0,1] – higher values are closer to zero, lower values are closer to one. The difference between 'mostly blue' and 'partially blue' is caused by the maximum radial velocity in a lidar scan. The corrupted scans tend to have clear non-physical values 100-1000 m/s, while spikes show more realistic values within 15-50 m/s. Scaling a range [0,1000] to [0,1] smooths low velocities stronger than when the same procedure is applied to a range [0,50].

We now consider adding or replacing the existing plot by the entropy calculated for the data before scaling to the range of [0,1]. It renders the same patterns at wind turbine positions, but processes spiked and corrupted data differently from the entropy calculated for the scaled data. The corrupted scans can be still identified from the entropy across the beam range (similar to Fig. 6a), but the spiked scans blend with other non-corrupted scans.

L182: Scans 1-50 and 301-375 show substantial decreases. Why are smaller ranges stated?

The range for Fig. 6 was restricted to preserve the features for the non-corrupted scans. If the figure is plotted for the full range, the non-corrupted scans shift to red tones making the entropy fluctuations less distinguishable. At the same time, no interesting patterns are revealed for the corrupted scans except for the aforementioned gradual decrease of entropy. We decided to limit the color range to preserve more valuable information in the lidar scans suitable for analysis.

The figure with and without colorbar limits is provided in the supplement for the comparison.

Figure 5: Label the AV7 and AV10 wake

Labels were added

L210: Could you please clarify why the "bimodal subset" sees a bimodal distribution of wind speeds but the "parallel wakes" subset does not see a bimodal distribution? I don't understand why the "parallel wakes" subset also wouldn't see one large peak that represents the free flow and a second peak that represents the wakessds. Does this happen because the "bimodal" wakes largely stay within the field of view of the lidar whereas the "parallel" wakes leave?

The bimodal case has two wakes corresponding to the larger percentage of data points than in other cases. This happens because wakes form in the lidar near range. While the near range occupies rather small area in m², it has the same amount of data points as the far range, which in turn was not subjected to the wakes in our data set. When the scan data are presented as a histogram, the far wake and free flow points are encountered nearly equally often in the bimodal subset – those are the points forming two clearly separated peaks or merging into a flat one. Since the two wakes do not form on a regular basis, it limits the application of the thresholding methods that are working with a distinctive bimodal histogram.

Appendix touches this property of the bimodal subset and shows how the far wake peak disappears when the histogram is plotted for the image of a lidar scan sector and not the original polar coordinates matrix. The reference to the appendix is now added to the bimodal subset description.

Figure 2 is replaced with an example from the bimodal subset to show the difference between the lidar scan presented as a polar coordinate matrix and as a scanned sector plotted in the Cartesian coordinates.

Considering the other subsets: A hint on a double peak can be seen in some aligned subset scans, mostly because of a good contrast between wakes and free flow, and large wake area in general. Parallel wakes subset has shorter wakes visible. AV7 wake leaves the scanning area before transition to the far wake. AV10 far wake is scanned at the heigher height than AV7 (158 m vs. 97m, see Fig. 1c), so it is weaker and easier merges with the noise.

Sec 3.4: What is the wind speed forcing of the LES?

The description of LES input parameters is expanded.

L232: You deal with at least two types of velocity distributions: unimodal (Fig 8a) and bimodal (Fig 8c). I am confused why you say you tend to only see one peak. As a reader at this point, I am wondering how the ATS algorithm performs on unimodal vs. bimodal data.

The bimodal cases have either two peaks of a different height, or a flat single peak. This results in strong fluctuations for the second derivative of the intensity distribution. The first derivative still shows one distinctive peak.

Section 5.6 deals with the specifics of the bimodal histogram and thresholding. The reference to the results from this section is also added to the methodology section.

L248-257: You say "We detect the threshold at the point where… the curvature approaches zero". But when you also say that "the curvature graph tail may fluctuate and complicate the detection of zero curvature". I am confused - do

you use curvature, the second derivative, or the first derivative to select your threshold. Are you doing this on polynomial-fit curves or on the raw curves? Please clarify. This is one of the most important sections of the paper, but it is difficult to understand your algorithm.

We use first and second derivative curves, fit the polynomial to them to find the concave point and estimate two thresholds. The final value as their average.We do not use curvature plot because it can provide only one value for the threshold, which could be erroneous. The reasoning behind this is directly connected to the bimodal subset.

Usually, the second derivative in the bimodal subset has monotonically decreasing local minimums. If the ATS algorithm choses the local minimum and fitting range incorrectly, the threshold would be overestimated and could cut down most of the far wake. Calculating a supplementary threshold from the first derivative allows to compensate overestimation and preserve larger part of the far wake.

L264: What does "shape" mean?

The term is now clarified at the end of the ATS method description as follows:

Because of the wake irregularity, especially in the lidar scan, the method usually detects several clusters of the high intensity points. Any cluster may be a part of the wake as well as falsely detected noise. We do not yet make a distinction between wake and noise, and refer to the detected points as 'wake shapes'.

The mentions of ‘wake shape’ as a general shape of the wake are now removed to avoid confusion.

L269: Please demonstrate centerline detection on an instantaneous wake so we could get a sense of how this behaves on observational data

The figures related to LES wake detection were reworked. Figure 9 now demonstrates wake identification on the instantaneous LES data. Figure 10 shows the grayscale plot, thresholded image and color-coded wake shapes. Figure 11 shows the wake characterization via Gaussian method and centerline detection from the ATS method results. The contours and centerlines are plotted in a way to keep uniform legend. An additional figure shows a complex case of centerline detection for the irregular wake from a lidar scan to support the explanation of the centerline detection algorithm.

The corrected figures are provided in the supplement.

L276: Remove the word "presumably"

done

Fig 10c: "helper lines" and "intersections" have the same legend elements

This was caused by an error in the plotting script; the ‘intersection’ labels should refer to the black dots. ‘Helper lines’ are labelled correctly and refer to the concentric circles described in the centerline detection algorithm.

L283-284: Why is the wake direction ambiguous under these conditions? I would

think that the wake direction is especially obvious in the "aligned" scenario

The ATS algorithm often identifies AV7 and AV10 wake as a single shape in the sligned subset. While it is obvious to a human eye, the algorithm running on the identified shape would detect a centerline point upstream and downstream for AV7 – both points looking equally valid for the algorithm because they lie inside a merged wake. If the wind or wake direction is known, the algorithm can search for the centerline points only along that direction. If no particular search direction is prescribed, the algorithm cannot choose a centerline point of two (or more) unless special routines are run to approximate the wake direction before the thresholding.

L285: I asked this earlier, but where does the reference wind direction come from?

See earlier comment on the reference wind direction.

L287-288: This seems like a major limitation. In the conclusion, please note that your algorithm does not work on weak wakes.

In this particular case, we did not regard AV11, because it is was scanned at the far lidar range near the scan border. The AV11 wake is not seen in the 'parallel' subset due to the flow direction leading it outside the scan and is often obstructed by the low speed formations (Fig. 14a). However, it becomes more clear in the aligned and bimodal case (can bee seen in Fig. 12e and 13e). Still, the part of the wake captured is rather small compared to the wakes presented in the same scan. Overall, the weakness of the wake was not a big problem for the identification, but very little information could be used from it compared to other wakes.

The point on weak wakes is rather vali for the parallel subset, we will see if we can include it some where in the description.

L295: "This feature" implies that the important feature is the transition from a single Gaussian to a double Gaussian. I believe you would like to say that the Gaussian distribution of wake deficit speeds is the important feature

The line changed to

The wake deficit distribution is similar to the Gaussian distribution in the far wake (Ainslie, 1988) and often shows a doubleGaussian peak in the near wake (Magnusson, 1999). The similarity to the Gaussian distribution makes a base for a widely used method to detect wake boundaries and centerline (Vollmer et al., 2016; Krishnamurthy et al., 2017).

L297: Can you roughly quantify "small plane inclination"?

About the same where we can use approximation sin A ~ A. If a wind turbine is scanned at the hub height, the plane elevation of 0.1 rad (5.7 degrees) would capture the wake until 5D. Considering the wake expansion, the wake could be also captured at further downstream distances of ~10D.

L319: Do reference wind directions and actual wake directions often significantly differ? If so, could you quantify a large discrepancy from either literature or this analysis?

We will cite Gaumond et al. (2014) in this section, but leave the details for the discussion

in Section 5.5., where this problem is covered. Gaumond et al. (2014) observed a normal distribution of cup anemometer measurements taken within 10 minutes with a standard deviation of 2.67 degree. We got roughly five degree offset for the wake direction, which was enough to divert the automatic extraction of the wake profiles for the Gaussian method.

L343: Is the centerline assumed to be a straight line (as is assumed with the Gaussian calculations) or it is allowed to turn?

Both Gaussian and manual centerlines can turn. Probably, some wording in the Gaussian section implied that we regard a straight line, while this is not the case. The Gaussian method returns one center point per wake profile. However, we need to extract the wake profile to get the data for fitting. This was done by extracting data along the line perpendicular to the wind direction. The Gaussian distribution peak may shift from the middle of the extracted profile depending on the wake movement.

The manual centerline does not require intermediate lines, so we can draw it as a curve immediatelly.

L356: Do additional errors occur or do they not occur?

The wording is changed to avoid confusion:

Overall, the Gaussian method performs well in the range of $2<x/D<10$. Further downstream ($x/D>10$) the wake recovers to the free flow and the wake deficit function becomes too weak to fit accurately; the fitting result may contain errors.

L371: Does "wake deficit" refer to the Gaussian method?

No, this is a method that uses 5% wake deficit or 95% of the free flow wind speed as a threshold.

L387: What does "it" refer to?

The manual threshold criteria. The line is changed to:

The aligned wakes subset utilizes the same manual threshold criteria for the wake splitting as bimodal subset (Fig. 13), although the condition may be harder to fulfill.

Figure 15: Why is the Corrupted data included here but excluded in Table 2?

The original intention was to show data for the scans that allowed manual identification despite strong crosswind effects. The figure became obsolete after we had to correct the implementation of the deficit-based method.

L430: Could you please remind me - does the ATS centerline detection only work for the closest wake shape? Is that why the algorithm doesn't detect the centerlines in the far wake?

Yes, we detect the centerline only for the first continuous shape near the wind turbine as of the current moment. Searching for the centerline in the far wake requires to determine which of the disconnected shapes downstream are identified correctly as a wake and the order in which they should be connected. We tested an algorithm for the LES case, which used the scheme: search for the next large shape in the downstream wake direction – extract he centerline – recalculate the wake direction – repeat until the end of the domain is reached. This algorithm is not applicable well to the lidar data due to the higher amount of false positives and a different way to store data. The LES data are simulated so that the wake is aligned with one of the Cartesian axes which gradually simplifies the centerline search. The lidar data are stored in the matrix defined by the polar coordinate system, i.e., the geometrical approach requires coordinate transformation back and forth. Right now, we are looking for the alternative solution for the centerline algorithm and see it as a good topic for a follow-up study.

L450: The previous section also compared Gauss and the ATS. Please be more specific with this header.

The subsection titles are now changed to

Comparison of the ATS wake identification against the manual identification and deficit-based thresholding

Comparison of the wake characterization using Gaussian and ATS methods

L465-466: I am surprised that the estimated wake direction deviates so strongly from the reference wind direction. You cite a few studies in the following paragraphs. How large are the deviations in those studies?

The deviations are not always mentioned explicitly. Gaumond et al. (2014) provides 2.67 degree standard deviation for the measurements. From the plots provided in publications on LES simulations and lidar measurements, we see that the Coriolis effects become noticeable at ~6D. That could a partial explanation for the difference between wind and wake direction, because the distance between met mast and closest wind turbine is ~8D. However, that explanation might not be enough. We had observed an offset of an order of 5°. If the same effect was observed for the wake, it would imply a deviation of the wake center $8D*\tan(5^{o}) = 0.7D$. The cited articles show weaker effects for about the same distance. Besides, we could expect a normal distribution of the deviations from a number of effects (measurement error, yaw deflection, atmospheric conditions), yet we see a nearly constant offset.

Apart from the Coriolis effect, we are leaning towards the imperfection of the lidar orientation as the main cause for the deviation between wind and wake. We have performed a quick comparison to SCADA data for the same period and noticed a similar offset for the wind direction measured at the mast by the anemometer and at the wind turbine by SCADA system – this supports the assumption, that the wind-wake deviation is present and is not caused by the limitations of the centerline search algorithm or yaw deflection. Since the SCADA data deals with its own uncertainties and was not a focus of the original study, we are yet unsure whether to include it into the revised article, although it could make a good reference data set for the next study.

L490: See my comment about L210. Also, does your quantification of "near wake" agree with standard definitions of "near wake"? Also, please state why someone would want to distinguish between "near wake" and "far wake" within a lidar scan.

This section mainly served to show the capability of the ATS method for the particular

condition, Based on your comment about ATS method performance for unimodal vs. bimodal histogram we will correct this part to focus more on the bimodal case specifics.

L505-506: As written, a reader would not understand that you developed a new preprocessing methodology. Please make that clearer.

The main novelty includes only entropy criteria. The despiking part is not specific to the method and can be performed in any other way convenient for the user. This will be emphasized more clearly.

Please also note the supplement to this comment:
https://wes.copernicus.org/preprints/wes-2021-90/wes-2021-90-AC2-supplement.zip