Wind Field Reconstruction from Lidar Measurements at High-Frequency using Machine Learning

PO.079

Clym Stock-Williams[1], Paul Mazoyer[2], Jan-Willem Wagenaar[1], Sébastien Combrexelle[2]

[1]ECN part of TNO, The Netherlands; [2]Leosphere, France

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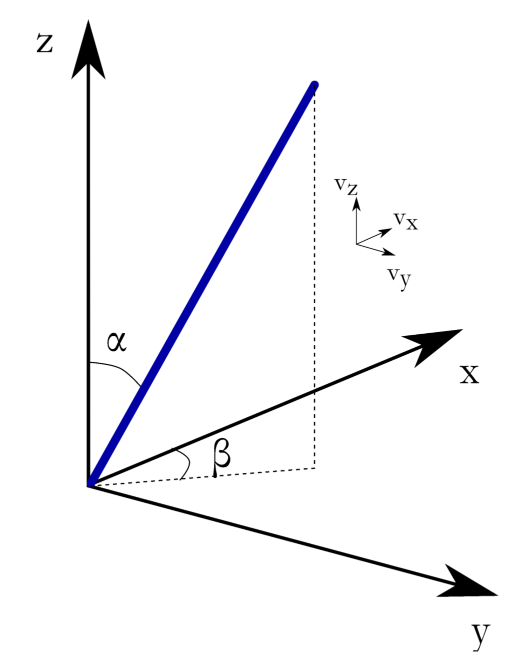
Problem Statement

- Wind speed measured at hub height is insufficient to represent either the power available for extraction by a modern wind turbine, or the loading on it. Light Detection and Ranging ("Lidar") units offer the potential to measure wind velocity across the whole rotor diameter, answering this information gap.
- Lidar units work by pointing a laser beam into the sky and analysing the backscatter signal using the Doppler effect to determine the radial wind speed:

$$v_b = -\left(v_x \sin\alpha \cos\beta + v_y \sin\alpha \sin\beta + v_z \cos\alpha\right)$$



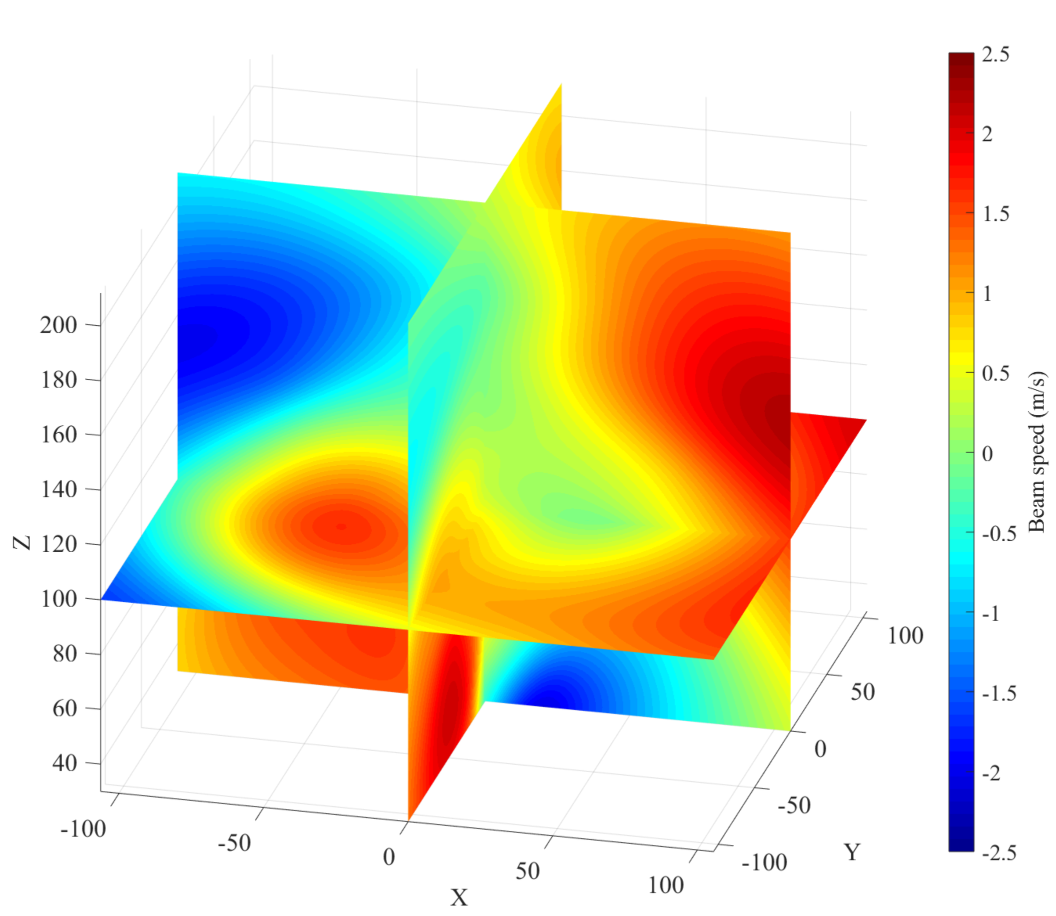
- Pointing the Lidar beam in a different direction obtains a different resolution of the wind velocity, but at a <u>different location</u> and at a <u>different time</u>.
- This "Cyclops Effect" results in sensitivity to spatial inhomogeneity, such as that caused by complex terrain and wind turbine wakes, generating biases which are currently addressed with specific modelling (e.g. Windcube FCR for complex terrain) [1].
- The more powerful machine learning methods offer an alternative solution to this issue, by removing assumptions involved in other reconstruction techniques and making use of information from <u>all</u> the data points in space and time.

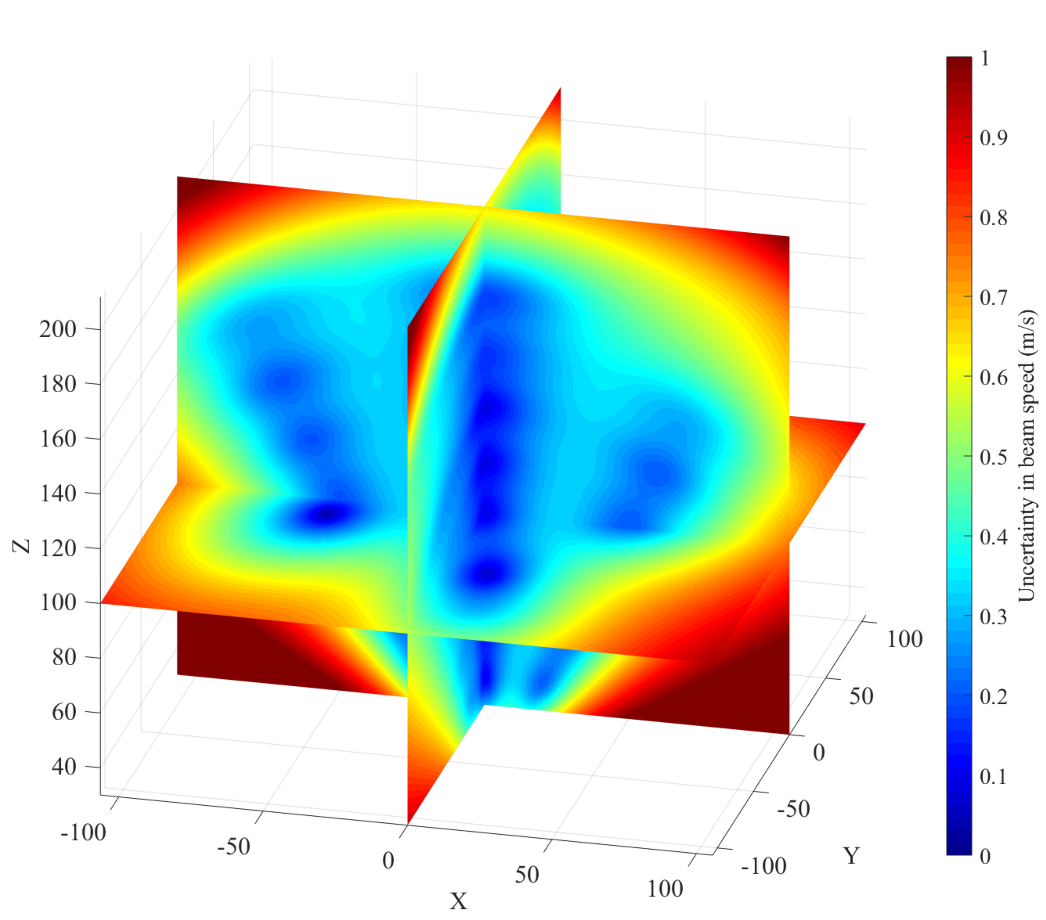
Method

Gaussian Processes [2] are a Bayesian non-parametric machine learning method. They express a probability distribution over functions, which is then combined with data to make predictions at any other point in the input space.

Gaussian Process regression on the measured radial beam speed data creates a "Virtual Lidar", providing **mean (⬆, upper image)** and **uncertainty (⬇, lower image)** estimates.

The standard deviation estimates combine uncertainty inherent to the Lidar measurements with uncertainty caused by the distance in space and time between measurement and prediction.





The Virtual Lidar maps:

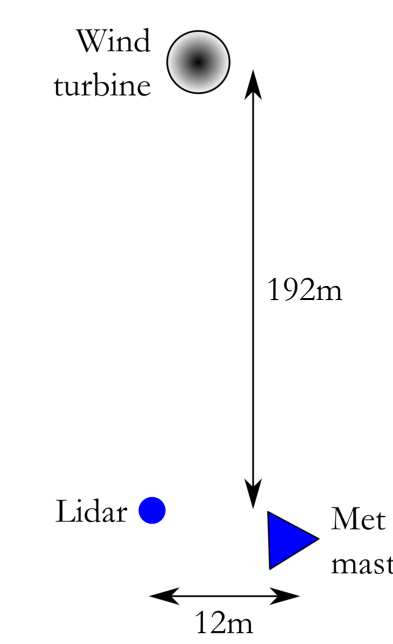
$$[\alpha_1, \alpha_2, r, t] \rightarrow v_b$$

where we used the well-behaved co-ordinate system $\alpha_1 = \alpha\cos\beta$, $\alpha_2 = \alpha\sin\beta$; r is the distance from the Lidar unit and t is time.

- Perform this regression independently for data collected within 60 second periods, to capture changes in turbulence length scales.
- Fit another Gaussian Process to the hyperparameters of these Virtual Lidar models in time, to ensure reliable long-range inference.
- Combine output predictions using a Mixture of Experts.
- Resolve the Cyclops Effect using either of the following approaches (or using physical turbulence modelling):
  1. Average four widely-spaced points together at each height to obtain the wind velocity (**➲, left**);
  2. Extract local velocity estimates from multiple points in close proximity, using maximum likelihood (**➲, right**).

Results

Data covering 44.6 continuous days from a site with simple terrain (**see diagram ➲**), were used to validate the new method on a Windcube Lidar unit. Only 10-minute data were available from the met mast for validation.



The homogeneous assumption was used to resolve the Cyclops Effect at each height. The average wind speed bias was $-0.01 m/s$ and scatter was $0.11 m/s$, see table below for full details. This meets the threshold for commercial use.

	40m	60m	80m	100m	116m
Wind Speed Bias (m/s)	[−0.03, −0.02]	[−0.01, −0.00]	[−0.02, −0.01]	[−0.01, −0.01]	[−0.02, −0.01]
Wind Speed Scatter (m/s)	[0.12,0.12]	[0.11,0.12]	[0.11,0.11]	[0.11,0.12]	[0.10,0.10]
Wind Turbulence Bias (m/s)	[−0.16, −0.16]	[−0.13, −0.12]	[−0.07, −0.06]	[−0.03, −0.02]	[−0.01, −0.01]
Wind Turbulence Scatter (m/s)	[0.12,0.12]	[0.11,0.11]	[0.09,0.10]	[0.09,0.09]	[0.09,0.09]
Wind Direction Bias (°)	[−5.9, −5.9]	[−5.7, −5.7]	[−4.8, −4.7]	[−5.5, −5.4]	[−5.4, −5.3]
Wind Direction Scatter (°)	[0.84,0.88]	[0.52,0.55]	[0.65,0.69]	[0.59,0.52]	[0.60,0.63]

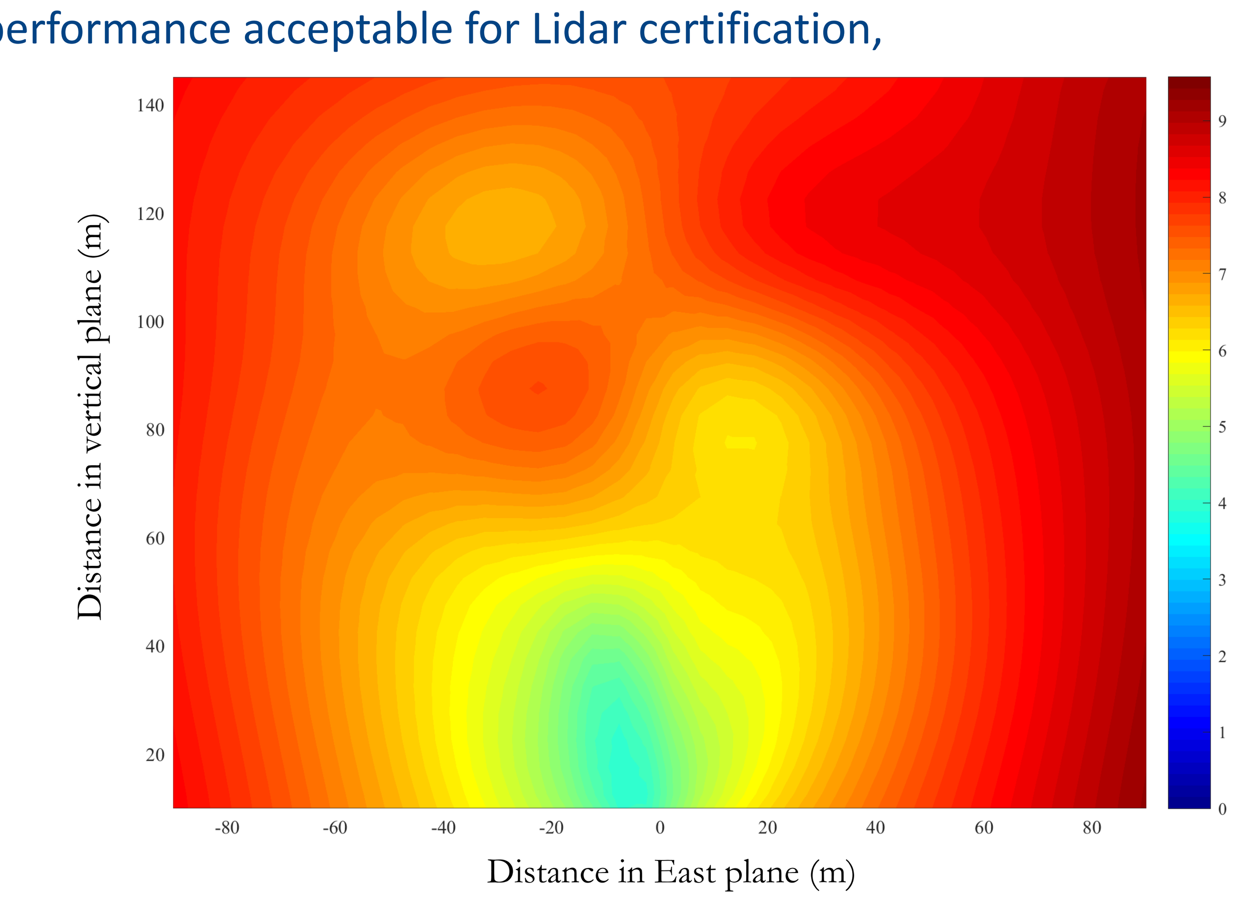
Validation results [90% confidence intervals] ⬆Original method ⬇Gaussian Process

	40m	60m	80m	100m	116m
Wind Speed Bias (m/s)	[0.10,0.10]	[0.15,0.15]	[0.11,0.12]	[0.11,0.12]	[0.11,0.11]
Wind Speed Scatter (m/s)	[0.10,0.11]	[0.09,0.10]	[0.08,0.08]	[0.08,0.09]	[0.09,0.09]
Wind Turbulence Bias (m/s)	[−0.09, −0.09]	[−0.04, −0.04]	[−0.00, −0.00]	[0.03,0.04]	[0.04,0.04]
Wind Turbulence Scatter (m/s)	[0.09,0.10]	[0.09,0.09]	[0.08,0.08]	[0.08,0.08]	[0.09,0.09]
Wind Direction Bias (°)	[−5.9, −5.8]	[−5.7, −5.7]	[−4.7, −4.7]	[−5.4, −5.4]	[−5.3, −5.3]
Wind Direction Scatter (°)	[0.75,0.79]	[0.47,0.49]	[0.56,0.59]	[0.54,0.57]	[0.58,0.60]

Conclusions and Further Work

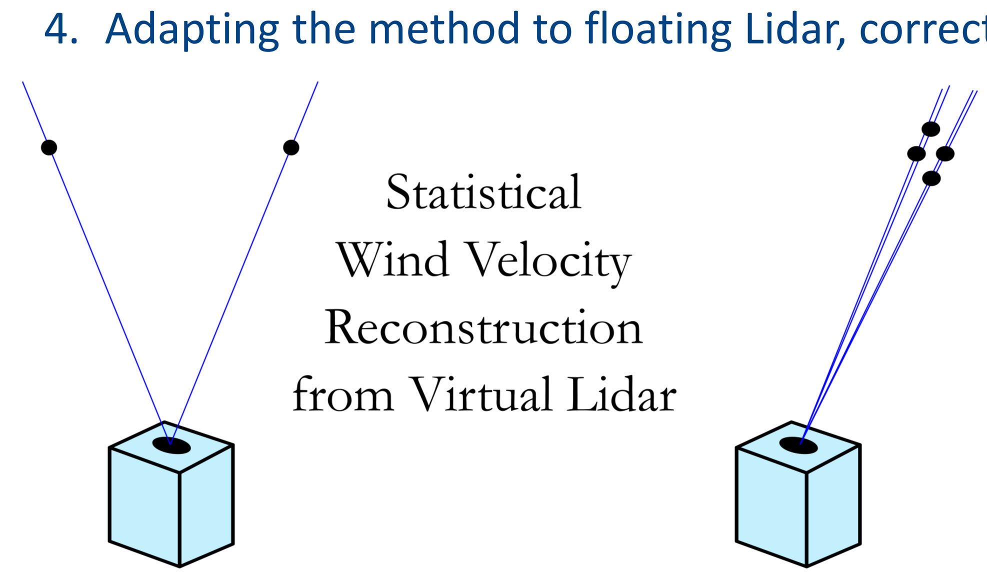
A novel machine learning method, using Gaussian Process regression, has demonstrated the following advantages over current wind field reconstruction algorithms:

- <u>It is naturally robust to overfitting</u>,
- It predicts wind speed <u>uncertainty</u> derived from data density and machine error,
- It is, in theory, applicable to <u>any site</u> and <u>any scanning geometry without tuning</u>, although validation is currently limited to the Windcube in simple terrain.
- Initial validation shows performance acceptable for Lidar certification,
- It infers data during measurement gaps,
- Using the second Cyclops Effect removal method allows <u>instantaneous 3D wake measurements</u> from the upwind turbine (**➲**).



Further work is already planned:

1. Improvement of robustness and power for all aspects of the method;
2. Validation against 1-second sonic anemometer measurements in complex conditions;
3. Application to a scanning Lidar to determine the best scanning patterns for reducing uncertainty based on different measurement campaign objectives;
4. Adapting the method to floating Lidar, correcting for rotation and displacement.



References

1. P. Mazoyer, "Turbulence intensity impact on Windcube accuracy", *Workshop on Vector Averaging Versus Scalar Averaging, Vilnius*, May 2018
2. C. E. Rasmussen and C. K. Williams, "Gaussian Processes for Machine Learning", *The MIT Press*, 2006

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