

ON ADAPTIVE UNSCENTED KALMAN FILTERING FOR FLOATING DOPPLER WIND-LIDAR MOTION CORRECTION: EFFECT OF THE NUMBER OF LIDAR MEASUREMENT HEIGHTS

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ABSTRACT

This work studies the influence of the number of lidar measurement heights on the performance of the floating Doppler wind lidar motion-correction algorithm, recently published by the authors. The work is in the context of offshore wind energy and continuous-wave focusable ZephirTM300 lidar. A down-sampling technique applied over the lidar-measured wind speed time-series is used to simulate different height-sounding configurations. The operation of the filter under one, three, and five measurement heights of the lidar is studied by using data from El Pont del Petroli measurement campaign. The filter is proved to remove apparent turbulence addition in all three cases, showing a deterioration of statistical indicators as the number of sounding heights increase.

Index Terms— DWL, floating, wind profile, Kalman filter, motion correction

1. INTRODUCTION

Doppler Wind Lidars (DWLs) sited on offshore floating platforms or buoys are being accepted in the wind energy (WE) industry as an alternative to costlier meteorological masts (metmasts) [1]. As offshore wind farms are deployed further off-coast and to higher depths, metmasts are not a feasible solution for wind resource assessment [2]. Floating Doppler Wind lidars

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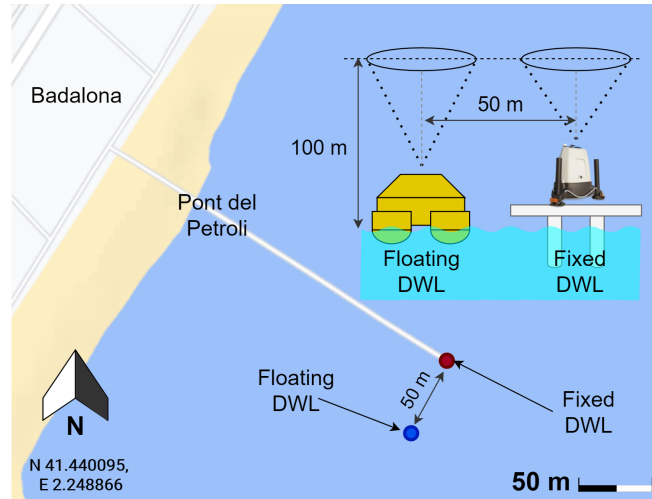


Fig. 1. El Pont del Petroli campaign location and scheme of the instrumental set-up. Adapted from [5].

18 (FDWLs) are able to reliably measure the mean horizontal wind speed (HWS) and wind direction (WD) at a ten-minute level
 19 in a more flexible and cost-effective manner [3]. However, the wave-motion effect over the FDWL buoy induces an error on
 20 the lidar-measured wind vector and turbulence intensity (TI). TI is defined as the ratio between the standard deviation of the
 21 HWS (σ_{HWS}) to the mean HWS. In comparison to the anemometers sited on metmasts, which measure “true” point-wise TI,
 22 DWLs measure an apparent TI as a consequence of the lidar probe length (spatial average) and temporal average inherent to
 23 the DWL measurement algorithm. Moreover, the wave-induced buoy motion causes an apparent turbulence addition to the TI
 24 measurements by FDWLs in comparison to fixed DWLs. [4].

25 Correct assessment of the TI is of main importance for the industry because overestimation of the TI may lead to wind
 26 turbine over-design and extra costs. Therefore, compensation of the FDWL motion-induced error in wind-vector measure-
 27 ments is an active topic of research in the state of the art. So far, different methodologies have been presented towards this
 28 purpose, which either require access to the lidar internal line-of-sight (LoS) measurements [2] or to carry out the compensation
 29 statistically at a post-processing level [6]. Recently, an on-the-run FDWL motion-correction method which does not require
 30 accessing the lidar internal LoS measurements has been presented by the authors [5]. The method is based on an adaptive
 31 Unscented Kalman Filter (UKF) that takes into account the FDWL dynamics as well as the lidar wind-retrieval algorithm to
 32 estimate the motion-corrected wind vector. The filter was validated using experimental data from El Pont del Petroli (PdP)
 33 campaign, in which two identical lidars, one floating and one fixed, the latter used as reference, were configured to measure
 34 the wind at a single height of 100 m above sea level. However, in practice, continuous-wave, focusing DWLs are usually set
 35 up to measure the wind profile by sequentially sounding the wind at multiple heights. In this paper we present a methodology
 36 to simulate the measurement height configuration by down-sampling the lidar-measured wind-vector time-series and we assess
 37 the performance of the FDWL motion-correction UKF in relation to the number of measurement heights chosen.

2. MATERIALS AND METHODS

2.1. Materials

The PdP experimental campaign took place in June 2013. In the campaign, the NEPTUNE proof-of-concept FDWL buoy was tested against a reference fixed lidar sited 50 m away at El Pont del Petroli pier (Badalona, Spain, see Figure 1). Both the fixed DWL and the FDWL were identical ZephyrTM300 models, calibrated on-shore and user-configured to measure the wind vector at 100 m. The ZephyrTM300 is a continuous-wave focusable DWL measuring at a rate of 1 scan/s (50 LoS/scan) at any given height and with 10 user-configurable measurement heights. The FDWL buoy hosted two inertial measurement units (IMUs) to measure the buoy and lidar attitudes, i.e., 6-Degrees of Freedom (DoF) motion.

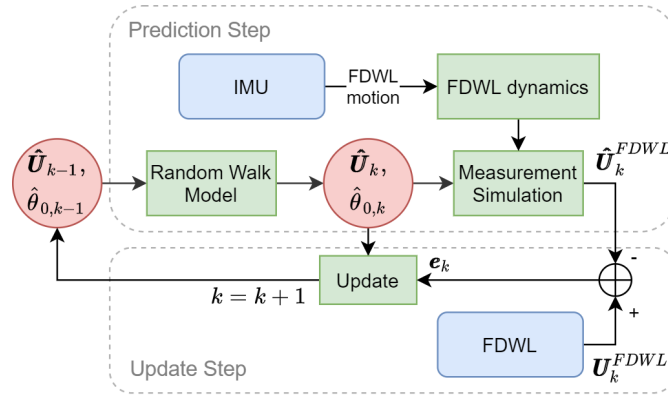


Fig. 2. Block diagram depicting the motion-correction UKF recursive algorithm.

2.2. Methods

2.2.1. Review of the FDWL motion-correction filter

The UKF takes advantage of the knowledge of FDWL dynamics as formulated by Kelberlau et al. [2] as well as the lidar internal wind-retrieval algorithm to recursively estimate the “clean” (i.e., motion-free) wind vector $\hat{\mathbf{U}}_k$ and lidar initial scan phase $\hat{\theta}_{0,k}$ at each discrete time k . The filter uses the FDWL-measured wind vector \mathbf{U}_k^{FDWL} and the FDWL 6-DoF motion measurements by the IMUs on the buoy to carry out the estimation. Figure 2 depicts the FDWL motion-correction UKF block diagram. Each recursive loop of the filter consists of the following prediction and update steps (refer to [5] for further insight in the filter):

53 Prediction step:

- 54 1. “A priori” predict present-time $\hat{\mathbf{U}}_k$ and $\hat{\theta}_{0,k}$ from previous $\hat{\mathbf{U}}_{k-1}$ and $\theta_{0,k-1}$ by assuming a random-walk model.
- 55 2. Predict present-time FDWL-measured wind vector $\hat{\mathbf{U}}_k^{FDWL}$ given $\hat{\mathbf{U}}_{k-1}$ and $\hat{\theta}_{0,k-1}$ by considering the lidar wind-
- 56 retrieval algorithm and buoy-motion attitude (IMU measured).

57 Update step:

- 58 1. Compute the measurement estimation error \mathbf{e}_k as the difference between the estimated $\hat{\mathbf{U}}_k^{FDWL}$ and actual FDWL mea-
 59 surement \mathbf{U}_k^{FDWL} .
- 60 2. “A posteriori” update the predicted $\hat{\mathbf{U}}_k$ and $\hat{\theta}_{0,k}$ as a function of \mathbf{e}_k .

61 2.2.2. Emulation of the DWL height-measuring configuration

62 Continuous-wave focusing DWLs measure the wind at multiple heights sequentially and, therefore, this means that *they sound a*
 63 *particular height every n scans* ($\simeq 1$ scan/s), with n the number of measurement heights. When a lidar is configured to measure
 64 at multiple heights, this is equivalent to down-sampling (DS) the wind-vector time-series by a factor n ,

$$\mathbf{U}^{DS:n}[k] = \mathbf{U}[n \cdot k], \quad (1)$$

65 where $\mathbf{U}[k]$ is the wind-vector time-series and $\mathbf{U}^{DS:n}[k]$ is the down-sampled version by a factor n . Figure 3a shows an example
 66 of the HWS time-series measured by the FDWL and the fixed DWL. The fixed-DWL time-series is shown along with its factor-3
 67 and factor-5 down-sampled versions, which emulates 3- and 5-height sounding configurations, respectively.

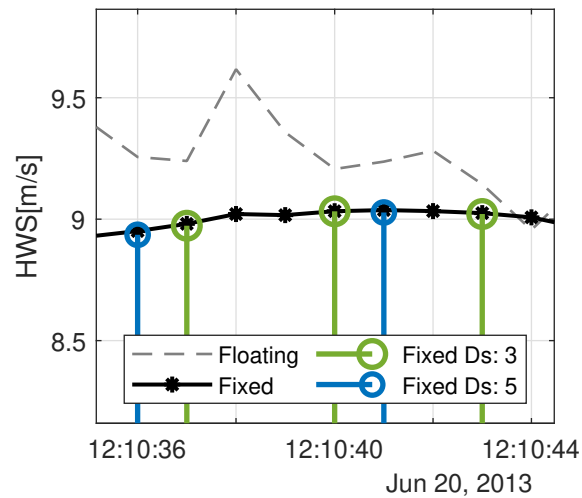


Fig. 3. Example of the HWS time-series measured by the FDWL (dashed gray trace) and the fixed DWL (black trace) at the 100 m in height (single measuring height). The fixed-DWL time-series is shown along with its down-sampled versions by a factor of 3 (green samples) and 5 (blue samples).

68 **3. RESULTS AND DISCUSSION**

69 As it can be observed in Figure 3, the instantaneous HWS measurements by the fixed DWL and FDWL are not identical since
 70 the instruments were 50 m apart. In order to study the UKF motion-correction performance, the TIs measured by the FDWL
 71 ($TI_{Float.}$) at the *single measuring height* of 100 m, with and without correction, were compared (at 10-minute resolution)

72 against the TIs measured by the reference fixed DWL (TI_{Fixed}) considering three measurement-height configurations: (i)
 73 single-height sounding, and (ii) 3, and (iii) 5 sounding heights. Cases (ii) and (iii) were emulated by inputting to the filter
 74 factor-3 and -5 downsampled time-series, respectively).

75 Figure 4 shows three scatter plots comparing the TI measured by the FDWL (with and without motion correction) and the
 76 fixed DWL as a function of the number of lidar measurement heights (panels a-c). Numerical analysis yielded three statistical
 77 indicators for each measurement height: coefficient of determination (R^2), Root-Mean-Squared Error (RMSE) and Linear
 78 Regression line (LR).

79 The RMSE is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (TI_{Float,i} - TI_{Fixed,i})^2}{N}}, \quad (2)$$

80 where N is the number of 10-min samples of the 24 hour period under study.

81 On one hand, Figure 4 shows at a glance that without motion correction and irrespective of the number of measurement
 82 heights chosen, the huge majority of TI measurements by the FDWL, TI_{Float} , fall above the ideal 1:1 line. This bias evidences
 83 the additive TI due to buoy motion. After correction, the scatter points shifted down to virtually lay along the ideal 1:1
 84 line, showing noticeable bias reduction between the TI measured by the fixed and the FDWL. This is evidenced by red LR
 85 lines, virtually overlapping the ideal 1:1 line in all three panels, which demonstrates effective motion correction by the UKF.
 86 Quantitatively, LR offset values, which are indicative of the average additive turbulence caused by wave motion, greatly reduced
 87 from $\simeq 2\%$ (uncorrected) to -0.14% (corrected) when measuring at 1 height (panel a), and to -0.4% when measuring at 3 and 5
 88 heights (panels b), and c), respectively).

89 On the other hand, increasing the number of sounding heights caused the TI points to scatter more widely. Specifically,
 90 when measuring at a single height (Figure 4 a)), a one-to-one point correspondence was found for most of the points lying not
 91 further than 1% bias from the 1:1 line whereas when measuring at 5 heights (Figure 4 c)), many points lay further than 2%
 92 bias from the 1:1 line. Consequently, the determination coefficient, R^2 , reduced from an almost ideal value, $R^2 = 0.94$, when
 93 measuring at a single height, to $R^2 = 0.88$ and $R^2 = 0.81$ when measuring at 3 and 5 heights, respectively. Regarding the
 94 RMSE, it increased from 0.74%, when the lidar measured at a single height, to 1.03% and 1.34% when the lidar measured at 3
 95 and 5 heights, respectively. The poorer one-to-one-point correspondence attained for increasing measurement height numbers
 96 (equivalently, lower sampling rates in the simulation) stated that less wind information was retained in the 10-min time-series.
 97 This is to say that the number of samples in a 10-min segment reduces by a factor equal to the number of measurement heights.
 98 Under these circumstances, the filter may face an observability problem in which the measurements no longer provide enough
 99 information for the filter to properly estimate the state variables [7]. Besides, as fewer and fewer samples become available in
 100 the 10-min time-series, the filter convergence time increases.

101 In turn, when comparing DWL measuring at a single height to point-like measurements such as those coming up from
 102 anemometers, DWLs inherently smooth out small turbulence scales (i.e., high-frequency time-series variations) on account of

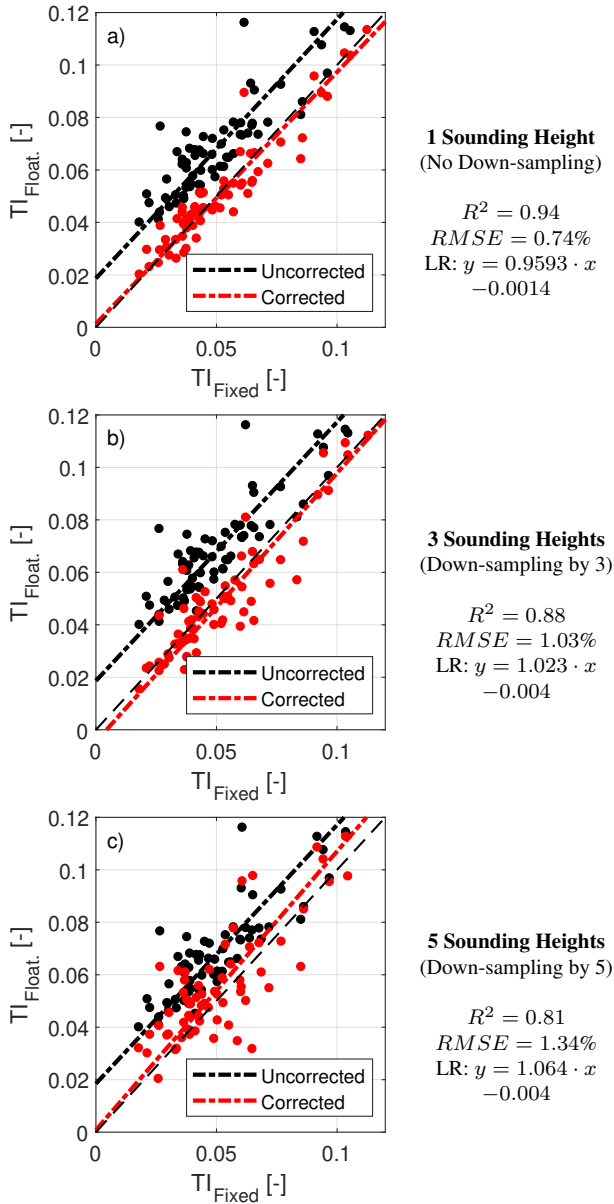


Fig. 4. Scatter plots comparing the TI measured by the FDWL with/without motion correction (red/black dots) and the reference fixed lidar as a function of sounding heights number (panels a-c), 20 June 2013. Color-coded dot-dashed lines represent the linear regressions (LR) of the measurement sample. (Dashed black lines) Ideal 1:1 line. TI_{Fixed} and TI_{Float} denote the fixed-DWL- and FDWL-measured turbulence intensity.

103 the spatial and temporal average imposed by the conical scanning pattern at a given height and focusing length [8].

104

4. CONCLUSIONS

105 A study on the FDWL motion-correction performance when using the UKF method [5] and in relation to the number of lidar
 106 measurement heights (ZephirTM300) was presented. It was shown that, at a given height, the effect of sequentially measuring
 107 at N different heights is equivalent to down-sampling the wind vector at that height by the same factor. The TI measured by the

108 FDWL, with and without motion-correction, was compared against the TI measured by the fixed DWL for three configurations
109 (1, 3, and 5 measurement heights).

110 The experimental results successfully showed that the filter was able to take the sea motion out of the wind speed measure-
111 ments, hence to virtually remove the apparent turbulence induced by wave motion for all three height measurement configu-
112 rations. Numerical analysis also showed that statistical indicators deteriorated as the number of sounding heights increased.
113 Thus, the coefficient of determination reduced from $R^2 = 0.94$ (1 height) to 0.81 (5 heights), and the RMSE increased from
114 0.74% (1 height) to 1.34% (5 heights).

115 Future work plans to validate the quantitative statistical indicators retrieved by the UKF simulator with reference to experi-
116 mental wind-speed data measured under real conditions.

117 5. REFERENCES

- 118 [1] Carbon Trust, “Carbon Trust Offshore Wind Accelerator Roadmap for the commercial acceptance of floating LiDAR
119 technology,” Tech. Rep., Carbon Trust, Oct. 2018.
- 120 [2] Felix Kelberlau, Vegar Neshaug, Lasse Lønseth, Tania Bracchi, and Jakob Mann, “Taking the motion out of floating lidar:
121 Turbulence intensity estimates with a continuous-wave wind lidar,” *Remote Sens.*, vol. 12, no. 5, 2020.
- 122 [3] Y. L. Pichugina, R. M. Banta, W. A. Brewer, S. P. Sandberg, and R. M. Hardesty, “Doppler lidar-based wind-profile
123 measurement system for offshore wind-energy and other marine boundary layer applications,” *J. Appl. Meteorol. Climatol.*,
124 vol. 51, pp. 327–349, Feb. 2011.
- 125 [4] A. Salcedo-Bosch, M. A. Gutierrez-Antunano, J. Tiana-Alsina, and F. Rocadenbosch, “Floating Doppler wind lidar mea-
126 surement of wind turbulence: a cluster analysis.,” in *2020 IEEE Int. Geosci. Remote Se. (IGARSS-2020)*, Virtual Event,
127 2020, IEEE.
- 128 [5] Andreu Salcedo-Bosch, Francesc Rocadenbosch, and Joaquim Sospedra, “A robust adaptive unscented kalman filter for
129 floating doppler wind-lidar motion correction,” *Remote Sens.*, vol. 13, no. 20, 2021.
- 130 [6] Miguel Gutiérrez-Antuñano, Jordi Tiana-Alsina, Andreu Salcedo, and Francesc Rocadenbosch, “Estimation of the Motion-
131 Induced Horizontal-Wind-Speed Standard Deviation in an Offshore Doppler Lidar,” *Remote Sens.*, vol. 10, no. 12, pp.
132 2037, dec 2018.
- 133 [7] Robert Robert Grover and Patrick Y.C. Hwang, *Introduction to Random Signals and Kalman Filtering: with MATLAB*
134 *exercises*, Wiley, 4 edition, 2012.
- 135 [8] Ameya Sathe, *Estimating Turbulence Statistics and Parameters from Lidar Measurements. Remote Sensing Summer School*,
136 Number 0085 in DTU Wind Energy E. DTU Wind Energy, Denmark, 2015.