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Wind turbine angular velocity estimation using polarimetry

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***Abstract*—Wind turbines usually cause significant interference in the conventional radar operations which might degrade the detection capabilities. Wind turbines do not only block the radar beam focusing on a specific target, thus creating shadowing effects, but also impose Doppler spectra contamination due to the continuous blade rotation. Therefore in order to identify, detect and possibly mitigate the presence of Wind Turbine Clutter (WTC), fundamental features of the blades rotation need to be estimated, such as rotation (angular) velocity. This information can be directly extracted by initially evaluating the angular displacement of the blades between successive radar measurements. In this paper, a method to estimate this rotation angle is proposed which is based on both radar polarimetry and estimation theory.**

***Index Terms*—wind turbine, angular velocity estimation, radar polarimetry**

I. Introduction

Wind energy is increasingly becoming mainstream and competitive among the conventional sources of energy as its electric capacity has been continuously increased during the past 10 years, especially in North Europe such as the Netherlands [1].

The power output and the efficiency of wind turbine is a function of the size of the blades $(70 - 90 \text{ m})$, the blades rotation speed $(10 - 30 \text{ rpm})$ as well as the turbine heights $(100 - 200 \text{ m})$. An extended installation of such wind turbines (wind farms), each of them characterized by a large Radar Cross Section (RCS), impacts on the operational capabilities of radar systems. Due to their high rotational velocity, the rotating blades of wind turbines generate strong clutter returns with wide continuous Doppler spectra and therefore might mask objects of interest and distort their estimated features [2][3]. Suppression and mitigation of WTC still remains one of the challenging tasks in the radar community [4][5].

A fundamental approach to detect the presence of this type of clutter is to automatically evaluate its rotation speed by estimating the blades displacement angle from at least two sequential measurements. In case of an aspect angle different than zero, this angle can be identified through the use of wind turbine spectrogram. However, when the radar beam axis and the rotation axis coincide, the estimation task becomes an extremely tough and complicated process. Nevertheless, this task can be facilitated by considering the fact that the RCS of a wind turbine varies for different transmitted polarizations. [6]. Therefore, in this paper we attempt to form a simple estimation rule for the angular velocity by exploiting fundamental principles of radar polarimetry. This rule is based on multiple sequential polarimetric time measurements while estimation theory is used in order to extract properly the rotational angle. Consequently, the angular velocity can be easily further calculated by multiplying the extracted angle with the time period between two successive radar coherent processing intervals (CPI).

This paper organized as follows: In Section II the received data model is formulated in terms of polarimetry. In Section III the numerical estimation approach is derived for both the back-scattered signal and the rotation angle. In Section IV, simulated results of the model in Section II are presented for a predetermined angular displacement. Section V provides a summary of this research.

II. Received Data Model

A typical three-blade wind turbine, is characterized by a symmetrical construction as the angular displacement of the blades is 120^o. Due to this, the actual total response remains approximately constant between measurements on each polarimetric channel. According to [7], when a monostatic measurement configuration is used, the polarization scattering matrix (PSM) of any target is characterized by three (unknown) complex scattering coefficients (in this case $S_{HV} = S_{VH}$). Let us assume that for an instant moment of time, say t_1, the PSM obtained from Wind Turbine will be (noiseless case):

$$\boldsymbol{S_{WT}}(t_1) = \begin{bmatrix} S_{HH}^{WT}(t_1) & S_{HV}^{WT}(t_1) \\ S_{HV}^{WT}(t_1) & S_{VV}^{WT}(t_1) \end{bmatrix} \quad (1)$$

where all of the elements in the above matrix are implied to be complex quantities. We now perform a new measurement, say at time moment t_2. Within the time interval $\Delta t = t_2 - t_1$, we consider that the wind turbine has been rotated with angular velocity Ω on a rotation angle $\alpha = \Omega \Delta t$ along the radar line of sight and moreover this angle is less than 120^o (faster rotation will create an ambiguity). The new polarization scattering matrix $\boldsymbol{S_{WT}}(t_2)$ after rotation is related with the initial PSM $\boldsymbol{S_{WT}}(t_1)$, as follows:

$$\boldsymbol{S_{WT}}(t_2) = \boldsymbol{U}(\alpha)^T \boldsymbol{S_{WT}}(t_1) \boldsymbol{U}(\alpha) \quad (2)$$

$$\boldsymbol{F}(a)=\begin{bmatrix}\cos^2\alpha & \sin\alpha\cos\alpha & \sin\alpha\cos\alpha & \sin^2\alpha\\ -\sin\alpha\cos\alpha & \cos^2\alpha & -\sin^2\alpha & \sin\alpha\cos\alpha\\ -\sin\alpha\cos\alpha & \cos^2\alpha & -\sin^2\alpha & \sin\alpha\cos\alpha\\ \sin^2\alpha & -\sin\alpha\cos\alpha & -\sin\alpha\cos\alpha & \cos^2\alpha\end{bmatrix}$$

where

$$\boldsymbol{U}(\alpha)=\begin{bmatrix}\cos\alpha & -\sin\alpha\\ \sin\alpha & \cos\alpha\end{bmatrix}$$

Hereafter we omit the notation 'WT' for reading purposes. After performing some typical mathematical calculations on the above matrix expression, we can directly obtain the vectorized form of (1):

$$\boldsymbol{L}(t_2)=\boldsymbol{F}(\alpha)\,\boldsymbol{L}(t_1) \tag{3}$$

where:

$$\boldsymbol{L}(t_i)=\begin{bmatrix}S_{HH}(t_i)\\ S_{HV}(t_i)\\ S_{HV}(t_i)\\ S_{VV}(t_i)\end{bmatrix},\quad i=1,2,$$

while $\boldsymbol{F}(\alpha)$ is shown at the top of this page.

Since we have three measured and unknown complex polarimetric coefficients, these 4×1 vectors that include these elements can be reformulated as 3×1 vectors through the following expression:

$$\boldsymbol{x}(t_2)=\boldsymbol{W}(\alpha)\,\boldsymbol{x}(t_1), \tag{4}$$

where:

$$\boldsymbol{x}(t_i)=\begin{bmatrix}S_{HH}(t_i)\\ S_{HV}(t_i)\\ S_{VV}(t_i)\end{bmatrix},\quad i=1,2,$$

and

$$\boldsymbol{W}(\alpha)=\frac{1}{2}\begin{bmatrix}1+\cos2\alpha & \sqrt{2}\sin2\alpha & 1-\cos2\alpha\\ -\sqrt{2}\sin2\alpha & 2\cos2\alpha & \sqrt{2}\sin2\alpha\\ 1-\cos2\alpha & -\sqrt{2}\sin2\alpha & 1+\cos2\alpha\end{bmatrix}$$

Consequently it turns out that a simple polarimetric received data model in case of a monostatic radar system, when multiple successive measurements (N) of rotated with a constant angular velocity target are obtained, can be formulated as follows:

$$\begin{aligned} t_0:\quad \boldsymbol{z_0} &= \boldsymbol{x}+\boldsymbol{c_0}+\boldsymbol{n_0}\\ t_1:\quad \boldsymbol{z_1} &= \boldsymbol{W}(\alpha)\,\boldsymbol{x}+\boldsymbol{c_1}+\boldsymbol{n_1}\\ t_2:\quad \boldsymbol{z_2} &= \boldsymbol{W}(2\alpha)\,\boldsymbol{x}+\boldsymbol{c_2}+\boldsymbol{n_2}\\ &\;\;.\\ t_{N-1}:\quad \boldsymbol{z_{N-1}} &= \boldsymbol{W}((N-1)\,\alpha)\,\boldsymbol{x}+\boldsymbol{c_{N-1}}+\boldsymbol{n_{N-1}} \end{aligned} \tag{5}$$

where it has been used the equality $\boldsymbol{W}(\alpha)\cdot\boldsymbol{W}(\alpha)=\boldsymbol{W}(2\alpha)$. In this system of equations $\boldsymbol{z_i}$, $i=0,1,...N-1$ denotes the received data on each measurement $(3\times1 \text{ vector})$, $\boldsymbol{n_i}$, $i=0,1,...N-1$ is a complex zero mean White Gaussian noise with covariance matrix $\boldsymbol{C}_n=\sigma_n^2\boldsymbol{I}$, $\boldsymbol{c_i}$, $i=0,1,...N-1$ is environmental clutter with known polarimetric covariance matrix $\boldsymbol{\Sigma}_c$ [8], $\boldsymbol{x}=[S_{HH},S_{HV},S_{VV}]^T$ is the actual complex polarimetric back-scattered signal of wind turbine and $\boldsymbol{W}(\alpha)$ is the rotation matrix, as defined before, for a specific rotation angle α. The time interval between sequential measurements $\Delta t=t_2-t_1$ in this study assumed to be constant and depends on the polarimetric radar architecture. It can be equal to the coherent processing interval (CPI) for a radar that estimates the targets PSM after Doppler processing, or to pulse repetition interval (PRI) for a radar that directly estimates the PSM from every received pulse. Gathering all of these N measurements, we can easily rewrite the above system in a more systematic matrix form:

$$\begin{bmatrix}z_0\\ z_1\\ z_2\\ .\\ z_{N-1}\end{bmatrix}=\begin{bmatrix}I\\ W(\alpha)\\ W(2\alpha)\\ .\\ .\\ .\\ W((N-1)\,\alpha)\end{bmatrix}\boldsymbol{x}+\begin{bmatrix}c_0\\ c_1\\ c_2\\ .\\ .\\ .\\ c_{N-1}\end{bmatrix}+\begin{bmatrix}n_0\\ n_1\\ n_2\\ .\\ .\\ .\\ n_{N-1}\end{bmatrix} \tag{6}$$

or, alternatively:

$$\boldsymbol{z}=\boldsymbol{F}(\alpha)\,\boldsymbol{x}+\boldsymbol{c}+\boldsymbol{n}, \tag{7}$$

where now $\boldsymbol{z}$, $\boldsymbol{c}$ and $\boldsymbol{n}$ are $3N\times1$ complex vectors while $\boldsymbol{F}(\alpha)$ is a $3N\times3$ real matrix.

III. Maximum Likelihood Estimation of the Rotation Angle

As we experience a complex white Gaussian noise with zero mean and covariance $\boldsymbol{C_n}$ the data will also follow a complex Gaussian distribution with mean $\boldsymbol{F}(\alpha)\,\boldsymbol{x}$ and total covariance matrix $\boldsymbol{Q}=\boldsymbol{\Sigma}_c+\boldsymbol{C}_n$ or alternatively $\boldsymbol{z}\sim CN(\boldsymbol{F}(\alpha)\,\boldsymbol{x},\,\boldsymbol{Q})$. The probability density function (PDF) of the data can then be explicitly formulated as [9]:

$$p(\boldsymbol{z};\boldsymbol{x},\alpha)=\frac{1}{\det(\pi\boldsymbol{Q})}\times \exp\left[-\left(\boldsymbol{z}-\boldsymbol{F}(\alpha)\,\boldsymbol{x}\right)^H\boldsymbol{Q}^{-1}\left(\boldsymbol{z}-\boldsymbol{F}(\alpha)\,\boldsymbol{x}\right)\right] \tag{8}$$

where H denotes complex conjugate transpose or Hermitian. We initially consider that the rotation angle is known and so will be the matrix $\boldsymbol{F}(\alpha)$. This means that the previous PDF is converted into a likelihood function $p(\boldsymbol{z};\boldsymbol{x})$ over the unknown complex vector $\boldsymbol{x}$. Taking the natural logarithm of this likelihood function we have:

$$\ln p(\boldsymbol{z};\boldsymbol{x})=-\left(\boldsymbol{z}-\boldsymbol{F}(\alpha)\,\boldsymbol{x}\right)^H\boldsymbol{Q}^{-1}\left(\boldsymbol{z}-\boldsymbol{F}(\alpha)\,\boldsymbol{x}\right) -\ln\left(\det(\pi\boldsymbol{Q})\right)$$

By taking now the derivative with respect to $\boldsymbol{x}^H$ of the above expression and equating it to zero we obtain the Maximum Likelihood Estimation (MLE) of the complex vector:

$$\hat{\boldsymbol{x}}_{MLE} = \left(\boldsymbol{F}(\alpha)^T \boldsymbol{Q}^{-1} \boldsymbol{F}(\alpha)\right)^{-1} \boldsymbol{F}(\alpha)^T \boldsymbol{Q}^{-1} \boldsymbol{z},$$

where $\boldsymbol{Q} = \sigma_n^2 \boldsymbol{I} + \boldsymbol{\Sigma}_c$.

If we replace this estimated vector of parameters, in the PDF in (8) we obtain the following likelihood function with respect to the rotation angle α:

$$p(\boldsymbol{z};\alpha) = \frac{1}{\det(\pi \boldsymbol{Q})} \times \exp\left[-\left(\boldsymbol{z} - \boldsymbol{F}(\alpha)\hat{\boldsymbol{x}}_{MLE}\right)^H \boldsymbol{Q}^{-1}\left(\boldsymbol{z} - \boldsymbol{F}(\alpha)\hat{\boldsymbol{x}}_{MLE}\right)\right]$$

Our goal now is to find the angle α that maximizes the above likelihood function or alternatively that minimizes the *cost function* $\boldsymbol{G}(\alpha)$:

$$\hat{\alpha}_{MLE} = \min_{\alpha} \boldsymbol{G}(\alpha), \quad (9)$$

where:

$$\boldsymbol{G}(\alpha) = \left(\boldsymbol{z} - \boldsymbol{F}(\alpha)\hat{\boldsymbol{x}}_{MLE}\right)^H \boldsymbol{Q}^{-1}\left(\boldsymbol{z} - \boldsymbol{F}(\alpha)\hat{\boldsymbol{x}}_{MLE}\right)$$

or:

$$\boldsymbol{G}(\alpha) = \boldsymbol{z}^H \boldsymbol{Q}^{-1} \boldsymbol{F}(\alpha)\left(\boldsymbol{F}(\alpha)^H \boldsymbol{Q}^{-1} \boldsymbol{F}(\alpha)\right) \boldsymbol{F}(\alpha) \boldsymbol{Q}^{-1} \boldsymbol{z}$$

Since it is almost impossible to find an analytical expression for the estimated parameter $\hat{\alpha}_{MLE}$, we solve this problem numerically. This process includes the choice of an interval of many possible rotation angles and search for the one that minimizes the cost function. Consequently, the accuracy of the estimation will hardly depends on the accuracy of the different angles chosen.

IV. Simulations

We will now provide the results of the simulations regarding with the estimation process analyzed previously. We will also present how this cost function behaves for different number of measurements

1) Rotation Angle Estimation: For our simulations we assume that the surrounding clutter included in our received data is grass with known or independently estimated polarimetric covariance matrix [10]. We also consider that the statistics of the clutter do not vary from measurement to measurement as well as within each reception time.

In summary, all the parameters for our simulation are provided in Table I. We assume that the highest SNR stems from the vertical oriented blade, which explains the chosen values for the received power on each channel.

Figure 1 depicts the behavior of the cost function $\boldsymbol{G}(a)$ for this chosen angle range. We notice that the minimum of this function lies very close to the expected rotation angle which is 5.43 degrees.

Therefore the estimated angular velocity in this case turns out to be $\hat{\Omega} = \hat{\alpha}/CPI$.

Table I
Values of simulated parameters for rotation angle estimation

Parameters	Values of Parameters
α	$5.43°$
$n_{0,1,\ldots,N-1}$	$\sim CN(0, 100I)$
$\lvert S_{HH}\rvert\,(dB)$	20 dB
$\lvert S_{HV}\rvert\,(dB)$	13 dB
$\lvert S_{VV}\rvert\,(dB)$	23 dB
N	100 measurements
angle range	$[-90° : 0.1° : 90°]$

2) Estimation Error vs Number of Measurements: In principle one should expect an improvement on our estimation accuracy as long as more measurements are processed. This consideration is strongly confirmed by the next figure. In this plot, the behaviour and the variation of the cost function is shown for different number of coherently processed measurements. The estimation of this parameter, as it was expected, approaches very well the actual value after several processed measurements while the SNR remains the same. This example reveals the importance of the number of measurements for our estimator in order to be required as low SNR level as possible.

As we notice, the sharpness of the cost function around the actual value of the rotation angle increases as more measurements are added. Consequently for a very high number of measurements, this cost function tends to be a straight line positioned on the actual value of this parameter.

Figure 3 presents the variation of the angle estimation error with respect to different number of coherently processed measurements, for the same expected rotation angle. The same simulation parameters are used as before. We visually recognize that at least 30 measurements are required in order to achieve small errors in our estimation.

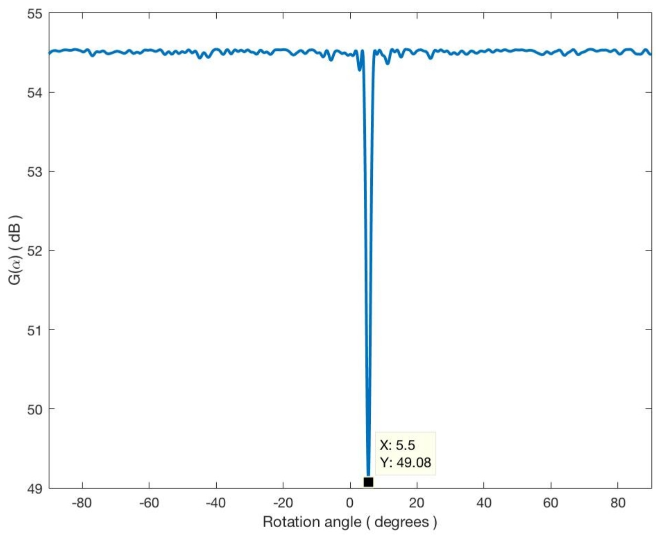

Figure 1. Cost function as a function of the rotation angle estimation.

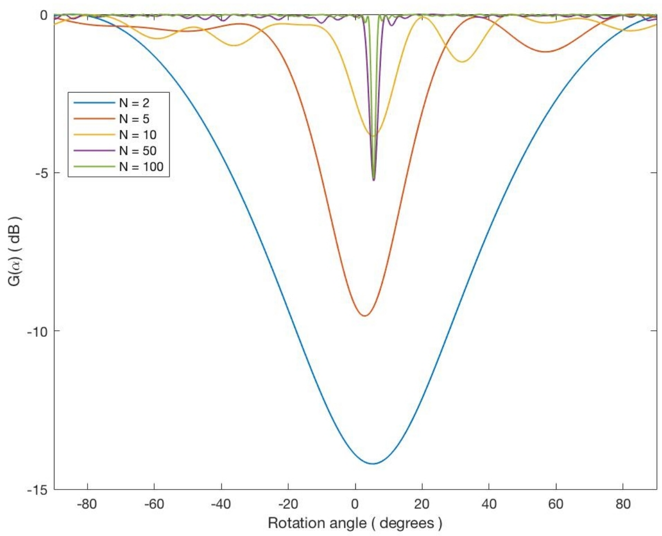

Figure 2. Cost function as a function of the rotation angle estimation for different number of measurements.

V. Conclusions

In this paper we have investigated the novel idea to estimate the instant rotation angle of wind turbine from polarimetric radar data. This has been performed by combining radar polarimetric modeling and estimation theory. We proposed a model-based maximum likelihood estimation approach which allows the incorporation of multiple received measurements. As it was expected the accuracy of the estimation is improved as more measurements are coherently processed. The increase of the measurements generates multiple sub-optimum estimated values, which might make difficult the application of an iterative estimation algorithm. However, the ambiguity with respect to the true optimum value decreases. Although we treated a simplified model for the received data, thanks to the the proposed model-based solution, becomes straightforward to extend the model formulation by introducing the wind turbine mast contribution. The main purpose for the estimation of the angular velocity is that it can be directly applied in a detection rule which would be based on this unique feature. The detection of the presence of a rotating object (a wind turbine in our case) will then facilitate the mitigation of WTC from the received data.

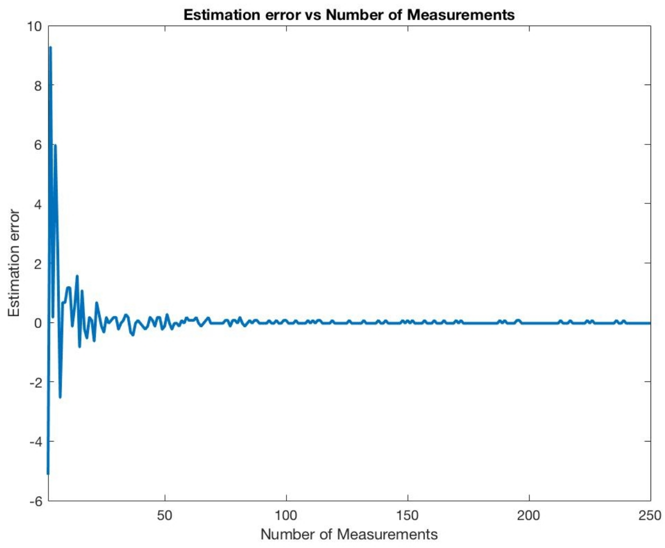

Figure 3. Estimation error (degrees) as a function of the number of measurements.

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