CHAPTER 13

BIRD RADAR STUDY IN THE BELGIAN PART OF THE NORTH SEA: DEVELOPMENTS TO IMPROVE BIRD DETECTION

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ABSTRACT

Dedicated bird radars have been used in ornithological studies for many years. This techniques has the advantage that it provides continuous data on a large scale. However, there are also several restrictions to this technique: the recorded radar data have a low taxonomic resolution and radars also records objects other than birds (e.g. sea surface, ships, rain). All unwanted detections are being referred to as clutter. The goal of this study is to develop a reliable filter, based on the differences in target characteristics as

recorded by the radar, to post-process the vertical radar data which removes as much clutter from the database as possible. This will result in a more accurate bird flux and therefore an improved outcome of the bird collision model.

The model tests showed very high scores for the criteria accuracy, sensitivity and specificity. The model precision is a lower in one of the two tests. This is caused by a relatively high number of false positives in the model results. This will be improved in the future by including variables in the decision tree analysis which are linked to the bird track level, instead of only using the variables recorded by the radar which describe the single targets, as was the case in the current model.

13.1. INTRODUCTION

Complementary to the seabird surveys, also a continuous monitoring of birds to study the impact of wind farms, making use of a bird radar, is performed (Brabant et al., 2012; Vanermen et al., 2013).

The goals of this study are:

(1) to assess to what extent wind farms are a barrier to local and migrating birds;
(2) to measure the flux of birds through the wind farm area and the temporal variation thereof (e.g. seasonal, diurnal);
(3) to estimate the number of birds colliding with the turbines based on the flux data, by using a mathematical bird collision risk model;
(4) to determine the temporal variation of bird intensity and direction of flight in the area to the south of the radar location and how this will change once the Norther wind farm is being built and operational.

These objectives will be achieved making use of a dedicated Merlin bird radar (DeTect-inc., Florida, USA) which is installed on the offshore platform in the C-Power wind farm on the Thorntonbank. The radar system consists of two radar antennas (Kelvin-Hughes Sharpeye solid state S-band antennas), one scanning in the horizontal pane and one in the vertical. The detection range of the radar antennas can be specified in the system's settings. For the horizontal scanning radar (HSR) the range is maximum seven nautical miles, but is usually set at four nautical miles. The range of the vertical scanning radar (VSR) is set to track to a height of two nautical miles. The radar operates continuously year-round and the system is remotely controlled. The system is operated by software called Merlin which is specifically designed to track individual birds.

The flight paths can be determined with the horizontal scanning radar. This radar registers targets 360° around its location. The Merlin software links consecutive registrations of a target, and thus registers the flight path of a moving target. This way it is possible to determine a bird's flight path, flight direction and changes in that direction (DeTect Inc., 2010; Brabant et al., 2012).

The flux of birds (birds/(km*hr)) can be deducted from the VSR-data. By rotating in the vertical pane the VSR is creating a 'radar screen' that registers all the targets moving through that screen. As this 'radar screen' is fairly narrow (opening angle 22°) every registration can be seen as one or a group of birds passing through that area. The flux of birds is expressed as migration traffic rate (MTR), i.e. number of birds that pass through a certain area during a certain time period (Krijgsveld et al., 2011).

The use of radar has several advantages and have been used in similar research for several years abroad, for instance in Denmark (Petersen *et al.*, 2006) and the Netherlands (Krijgsveld *et al.*, 2011). They provide continuous data on a large scale, also during conditions where it is very difficult to gather visual data (e.g. at night, during bad weather conditions, far offshore). However, there are also several restrictions to this technique: the recorded radar data have a low taxonomic resolution and radars also records objects other than birds (e.g. sea surface, ships, rain). These unwanted detections are being referred to as clutter.

The biggest problem offshore is the clutter caused by waves, i.e. seaclutter (figure 2). Waves and to a lesser extent rain result in large amounts of noise in the database. All this clutter needs to be filtered out before being able to study the bird movements in the area (HSR) and to reliably determine the real-time flux of birds in the wind farm area at different altitudes and to calculate a real-time collision risk (VSR).

In several studies in the past, filters were developed to classify radar data and to remove as much clutter as possible (Krijgsveld et al., 2011; Rosa et al., 2015; Vang et al, 2011). As our radar antennas are making use of the solid state technique compared to the more conventional magnetron antennas, and there are site specific circumstances (e.g. radar platform, turbines, bird community), it is necessary to develop these kind of data filters on a case-by-case base.

The first focus of this bird radar research is therefore to develop a clutter filter. The goal of this study is to develop a reliable filter which removes as much clutter from the vertical database as possible. This will result in a more accurate bird flux and therefore an improved outcome of the bird collision model.

13.2. METHOLOGY

To remove clutter from the vertical radar database as effective as possible, DeTect and RBINS developed a filtering model based on the differences in target characteristics as recorded by the radar.. This development consisted of four steps:

1. Develop a reference dataset;
2. Create a classification model based on the reference data;
3. Validate the model with test data;
4. Evaluation of the model.

STEP 1 - REFERENCE DATASET

We used MERLIN Editor, a Merlin software application which allows selecting individual targets and storing them in separate reference databases (e.g. weather, side lobes, birds). We classified targets as birds, rain, turbines and side lobes. This hence resulted in four reference datasets. This process was done through a remote connection with the radar system and not by visual observations at the radar site. To avoid bias in the reference datasets, we selected data from several periods in the year, each with its typical bird activity, i.e. spring migration, autumn migration and local bird movements.

Each target was stored in the database with a unique target identification code and over 40 variables describing the characteristics of the target (e.g. time of recordings, speed, heading, size, reflectivity). The variables in the Merlin vertical radar database most important for classification analysis are summarized by Rosa et al. (2015) (Table 1). The entire database table can be found in DeTect Inc. (2010).

Table 1. The target variables in the Merlin vertical radar database most important for classification analysis (Rosa et al., 2015).

Name	**Description**
Area	Number of pixels that create the target in the radar image
Ellipse Ratio	Ratio of the major axis of the equivalent ellipse to its minor axis
Ellipse Major and Minor	Total length of the major/minor axis of the ellipse that has the same area and same perimeter as the target
Hydro Radius	Ratio of target area to its perimeter
Maximum Segment	Length of longest horizontal line segment in a target
Perimeter	Length of the outer contour of a target in pixels
Target’s height and width	The maximum height/width of a bounding rectangle in pixels
Waddell’s disk	Diameter of a circle with the same area as the target
Average Reflectivity	Average (mean) reflectivity over the entire target area
Range	Distance or range away from the horizontal radar location to the target
Track length	Number of points belonging to the same bird track
Bearing	Orientation between the radar and the target (> 0 – 360 degrees)
Bearing fitness	Constrains the change in heading a track can make from scan to scan and still be correlated with a new plot. Value ranges from 0 to 1

Table 2 shows the number of reference targets which were selected in Merlin editor and which were used to develop the three DT models.

Table 2. Number of targets in the reference datasets used for the three step decision tree model.

Model 1	sidelobes	yes	64065
		no	67720
Model 2	weather	yes	160026
		no	68841
Model 3	birds	yes	67720
		no	78779

STEP 2 – MODEL BUILDING

The reference datasets were used to develop three decision tree (DT) models which uses discriminating variables to classify different target types (e.g. rain, birds). The first model extracts the sidelobe-interference (Figure 1). The second one filters out the clutter caused by weather (e.g. rain) and the third one extracts the birds from the remaining targets. The analysis was done with SQL server 2008 R2.

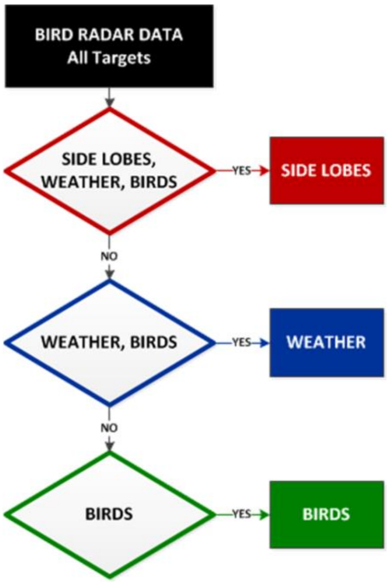


Figure 1. Schematic overview of the three decision tree models which were developed.

STEP 3 – MODEL VALIDATION

The SQL Data Mining models developed in Step 2 were tested with vertical bird radar data which were not used to build the model (i.e. validation dataset). These datasets were visually analysed and then analysed by the DT models, in the order shown in figure 1. The visual analysis was done by a radar expert and he classified the data in side lobes, weather, birds and unknown targets. We validated the model with two test datasets 13 and 17 April 2014. The test data of 17 April 2014 (test 2) contains a lot of rain. On the 13th there was no precipitation.

STEP 4 – MODEL EVALUATION

The results of both analyses (visual and classification models) were then compared to assess the performance and effectiveness of the model on non-reference data. The model performance was assessed based on four parameters: accuracy, sensitivity, specificity and precision (Table 2). These were calculated with a confusion matrix, using the Caret package in R.

Table 3. Model performance assessment parameter equations. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives.

Accuracy	TP + TN / (TP+TN+FP+FN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Precision	TP/(TP+FP)

13.3. RESULTS

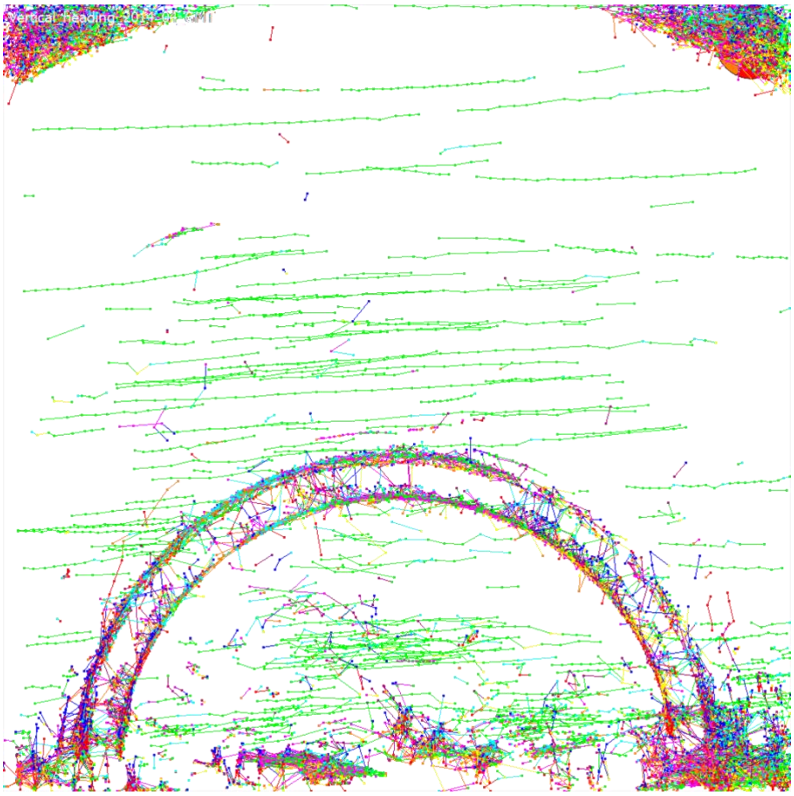
The number of false positives (i.e. targets which are considered as birds by the model, but which are not) is considerably high (Table 4): 35.6% of the number of true positives in test 1 and 12.9% in test 2. However, the assessment criteria accuracy, sensitivity and specificity are all very high (between 89.4% and 99.2%), both for test 1 and 2 (Table 5). This means that the model effectively filters clutter from the vertical bird radar data, without losing significant numbers of bird targets. This is also shown in visualizations of the data of both tests, before and after application of the model (figure 2 & 3). Figure 3 clearly demonstrates that the model is very effective in removing rain from the data, revealing underlying bird tracks.

Table 4. Model validation test results: birds versus clutter. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives.

	Test 1	Test 2
TP	1609	9294
TN	33831	151648
FP	573	1200
FN	182	133

Table 5. Model performance assessment parameter values.

	Test 1	Test 2
Accuracy	97.91%	99.18%
Sensitivity	89.84%	98.59%
Specificity	98.33%	99.21%
Precision	73.74%	88.56%



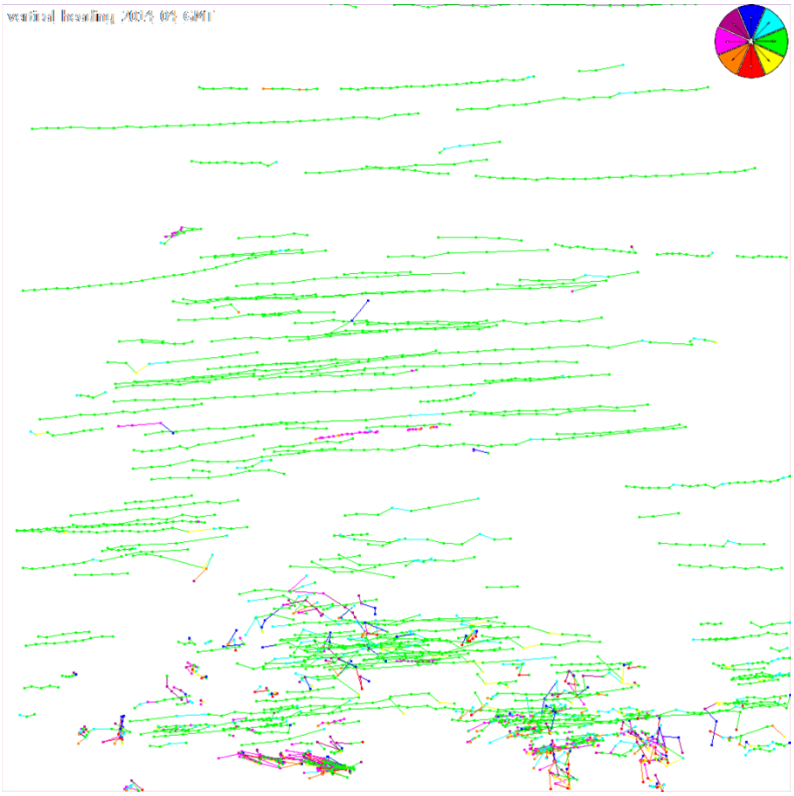


Figure 2. Visualisation of the vertical radar data of April 13th 2014, before and after the implementation of the decision tree models. Top image shows all tracks registered by the vertical radar, the image below shows the tracks which are classified by the model as birds.

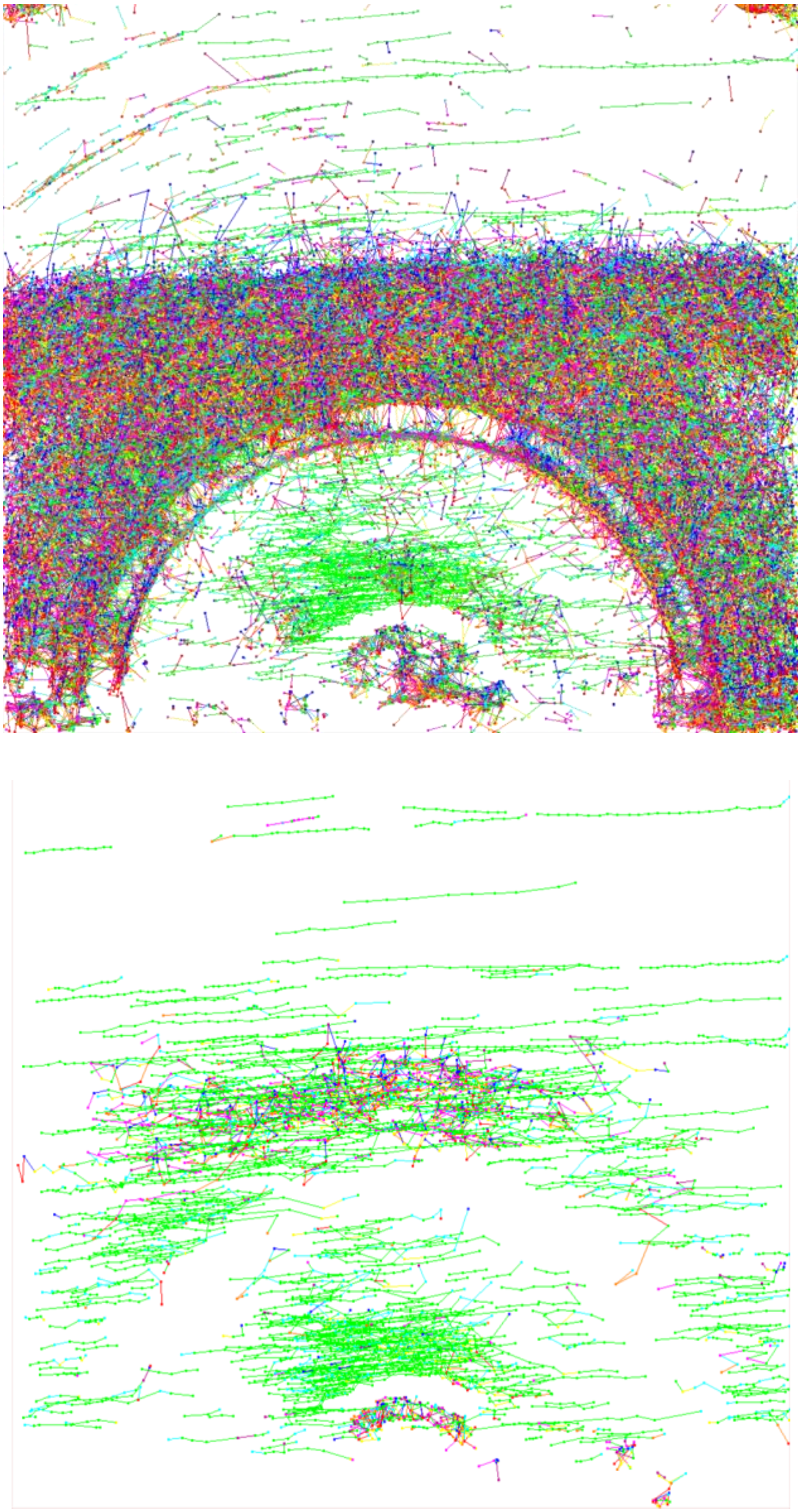


Figure 3. Visualisation of the vertical radar data of April 17th 2014, before and after the implementation of the decision tree models. Top image shows all tracks registered by the vertical radar, the image below shows the tracks which are classified by the model as birds.

13.4. DISCUSSION

Rosa et al. (2015) compared the vlassification success of bird radar data of six machine learning algorithms. The assessment criteria accuracy, sensitivity and specificity they found for the decision tree algoritm are comparable to the rates of this study. However, it is also interesting to assess the model precision as this is a measure for the number of true positives compared to the number of false positives (i.e. targets which are considered as birds by the model, but which are not). Compared to the other model assessment criteria, the precision rate is lower, especially in the first test (Table 5). This means that the model, at its current state is overestimating the number of birds with 35.6% and 12.9% in test 1 and test 2 respectively. As these bird data are used to measure the flux of birds in the wind farm and, in a next step, are then used to estimate the number of collisions of birds with wind turbines, it is important that the model is as precise as possible.

Therefore the model will be improved so the number of false positives is reduced to a minimum and thus the model precision will increase. Before the model, This will be done by including variables in the decision tree analysis which are linked to the track level, instead of only using the variables which describe the single targets, as was the case in the current model. As the heading and the speed of bird tracks is far more consistent compared to the erratic tracks of clutter, the standard deviation of speed and heading of the different targets within a track will be less. Therefore these variables at track level should help to further discriminate birds from clutter.

Once the model is final it will be applied to all historical data and in (near) real-time to the new data. This will result in an improved registration of the bird flux in the wind farm and therefore an improved assessment of the collision risk for birds, based on the bird flux at rotor swept height.

This current model is only applicable on VSR data. It is our aim to also develop a filter for the HSR data, based on a similar approach. The biggest challenge in this process will be to cope with seaclutter.

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