CRANFIELD UNIVERSITY

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Can satellite synthetic aperture radar be used to detect and classify offshore installations?

School of Energy, Environment and Agrifood

Geographical Information Management

MSc

Academic Year: 2015 - 2016

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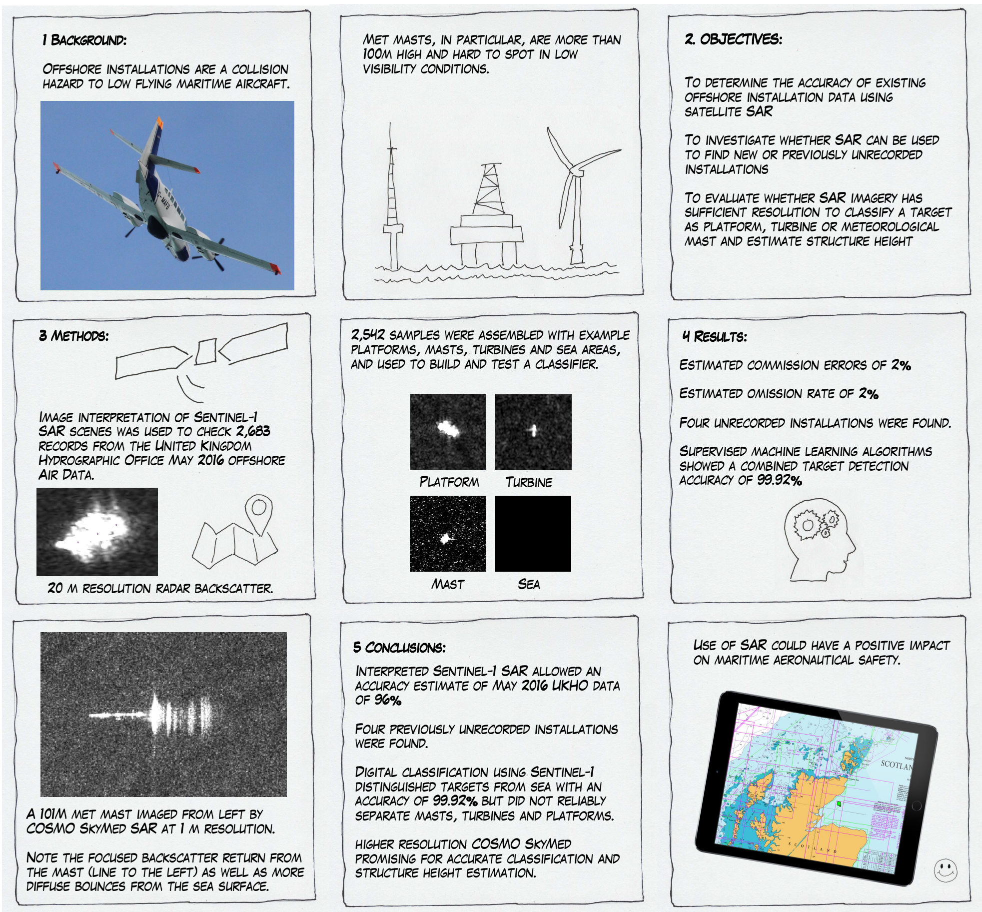
September 2016

GRAPHICAL ABSTRACT



Images courtesy AirTask Group, European Space Agency, COSMO-SkyMed Radar Science and Innovation Research (CORSAIR) and the United Kingdom Hydrographic Office

ABSTRACT

Wind turbines, petrochemical platforms and meteorological masts are a collision hazard to low flying maritime aircraft, especially in low visibility conditions. Offshore installation databases exist and are used for situational awareness, but information can be incorrect or out of date.

The feasibility of using satellite borne Synthetic Aperture Radar (SAR) to improve the detection, classification and charting of offshore installations is assessed.

Sentinel-1 SAR imagery depicting platforms, turbines and masts was compared to COSMO-SkyMed within a defined study area.

Offshore data supplied by the United Kingdom Hydrographic Office (UKHO) in May 2016 was cross referenced with interpreted Sentinel-1 SAR imagery showing commission errors of 2%. Four previously unrecorded installations were found using target detection in a sample Sentinel-1 time series from the North Sea, an omission error rate of 2%.

A supervised machine learning classifier, trained using Sentinel-1 SAR image chips depicting offshore installations, was unable to accurately separate platforms, turbine and masts but showed a combined target detection accuracy of 99.92%. Initial visual interpretation of COSMO-SkyMed spotlight imagery suggests that it could enable more accurate class separation and may be suitable for structure height estimation.

Approximately 7500 words.

Keywords: Remote sensing, Sentinel, COSMO-SkyMed, aeronautical safety, wind turbine, meteorological mast, maritime.

ACKNOWLEDGEMENTS

I would like to thank Mike Collins and Philip Linning from Airtask Group Ltd for introducing me to the problem and for their domain experience and expertise. The Inverness crew diverted on more than one occasion to fly and photograph the study area. The Airtask supplied photographs are copyright © 2016 Airtask Group Ltd.

I am grateful to the UKHO for licensing their data and charts and for their openness. In particular, Austin Capsey, Ray Paice and Catherine Seale from the Bathymetry, Geodesy and Imagery Centre, were generous with their time, expertise and feedback. Products supplied by the UKHO are © Crown Copyright and/or database rights. Reproduced by permission of the Controller of Her Majesty's Stationery Office and the UK Hydrographic Office (www.ukho.gov.uk).

The European Commission is to be commended for providing full, free and open Sentinels data under The Copernicus Programme, without which this project would not have been possible. This paper contains modified Copernicus Sentinel data 2016.

My thanks to Andrea Minchella and the COSMO-SkyMed Radar Science and Innovation Research (CORSAIR) Programme at the UK Satellite Applications Catapult as well as Alex Farman at Telespazio, for providing COSMO-SkyMed imagery. COSMO-SkyMed imagery is © ASI 2016 processed under license from ASI - Agenzia Spaziale Italiana. All rights reserved. Distributed by e-GEOS.

The open source Python libraries, scikit-image, (Walt et al., 2014), scikit-learn, (Pedregosa et al., 2011), and GDAL, (GDAL Development Team, 2016), were used extensively in this project.

Finally, my thanks to Toby Waine, Boris Snapir and Tim Brewer at Cranfield University for their wisdom, encouragement and inspiration.

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Can satellite synthetic aperture radar be used to detect and classify offshore installations?

Robert Blackwell

November 27, 2016

Abstract

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Keywords: Remote sensing, Sentinel, COSMO-SkyMed, aeronautical safety, wind turbine, meteorological mast, maritime.

Introduction

Airtask Group Ltd operates a fleet of maritime survey aircraft including the Facility for Airborne Atmospheric Measurements (FAAM) BAe 146 based at Cranfield University, Bedfordshire. This aircraft is frequently required to fly at low level (50 feet minimum safe altitude) to undertake meteorological and scientific experiments. An operator uses on board radar and electronic charting systems to highlight hazards and advise the pilot, but new installations may not yet be charted. With the growing number of installed and planned offshore wind farms, this has become a key safety concern. Meteorological masts are particularly dangerous, being more than 100 m high, quick to erect and hard to spot in low visibility conditions.

The United Kingdom Hydrographic Office (UKHO) maintains a database of offshore installations, but much of the information is contributed by third parties and can be incorrect or out of date. Historically, the data has primarily been used by shipping rather than aircraft. An accuracy assessment of the UKHO offshore air data extract would be beneficial to aircraft operators.

Satellite borne Synthetic Aperture Radar (SAR) is widely used for ship detection applications, (Crisp, 2004), because of its all-weather remote sensing capability. Images are constructed by measuring the amplitude and phase of backscatter following illumination of a scene by a pulse of radio frequency energy. Backscatter is usually quoted in terms of σ^0, the normalised backscatter coefficient. Ships are strong scatterers and typically appear as bright spots. Sea areas cause diffuse specular reflectance providing a contrasting, dark background in SAR imagery. It seems reasonable to suppose that ship detection techniques could be employed and extended for the detection and verification of offshore installations.

COSMO-SkyMed provides one of the highest resolution SAR services available using X-band radar (9.6 GHz) in spotlight mode with 1 m ground resolution over a 10 km swath, (Fiorentino and Virelli, 2016). Imagery is available on a commercial basis with a nominal 16-day repeat cycle. The satellite requires specific tasking and it would be expensive to image all 2683 points of interest in the UKHO offshore air data.

Sentinel-1A is a C-Band (5.405 GHz) SAR sensor, (Potin, 2013). The Interferometric Wide Swath (IW) imagery has a resolution of $20m \times 22m$ $(range \times azimuth)$ over a 250 km swath. Up-to-date imagery is freely and openly available with a 12-day repeat frequency (6-day in conjunction with the newly available Sentinel-1B). Ramona et al. (2015) report the successful use of Sentinel-1 SAR for ship detection.

This study had three key objectives:

1. To determine the accuracy of existing offshore installation data using satellite SAR.
2. To investigate whether SAR can be used to find new or previously unrecorded installations.
3. To evaluate whether SAR imagery has sufficient resolution to classify a target as a platform, turbine or meteorological mast and estimate structure height.

Materials and methods

The study consisted of four parts:

1. Comparison of Sentinel-1 SAR and COSMO-SkyMed images depicting platforms, turbines and masts.
2. Verification of UKHO offshore air data using interpreted Sentinel-1 SAR imagery to determine errors of commission.
3. Search for previously unrecorded installations in a sample Sentinel-1 SAR time series to estimate errors of omission.
4. Evaluation of the digital classification of platforms, turbines and masts using Sentinel-1 SAR imagery.

Comparison of Sentinel-1 SAR and COSMO-SkyMed images depicting platforms, turbines and masts

Whilst Sentinel-1 SAR imagery was available across a wide area, only a limited number of acquisitions were available using COSMO-SkyMed and these had to be carefully planned and procured. A study area was established in the Moray Firth, off the north east coast of Scotland for imagery comparison purposes. The area covers a representative set of offshore installations including, the Beatrice and Jacky petrochemical platforms, Beatrice wind turbines and a Moray Offshore Renewables Ltd. (MORL) meteorological mast, see figure 1. Plans are being considered for an additional three wind farms in the vicinity.

COSMO-SkyMed spotlight imagery was acquired between 9th July and 7th August 2016 for Beatrice 11/30-A, the Beatrice Wind Farm Demonstrator turbines and the MORL mast.

A visual inspection of the study area was made using Sentinel-1 IW Ground Range Detected (GRD) and COSMO-SkyMed spotlight products as well as photographs from a 35 mm digital SLR camera taken from an Airtask survey aircraft, see figure 2. Further photographic images are included in appendix 1.

Verification of UKHO offshore air data

The UKHO publishes offshore air data under licence to maritime aircraft operators on an approximately quarterly basis. This study used the May 2016 issue covering UK and surrounding waters, see figure 3. Each record was cross-referenced with Sentinel-1 SAR imagery allowing errors of commission to be recorded.

The Sentinels Scientific Data Hub Application Programming Interface was used to select suitable GRD products from May 2016 (see appendix 2), covering points in the UKHO offshore air data. All imagery was orbit corrected, calibrated to σ^0 and ortho-rectified, using the Range Doppler Terrain Correction tool from the Sentinel-1 Toolbox.

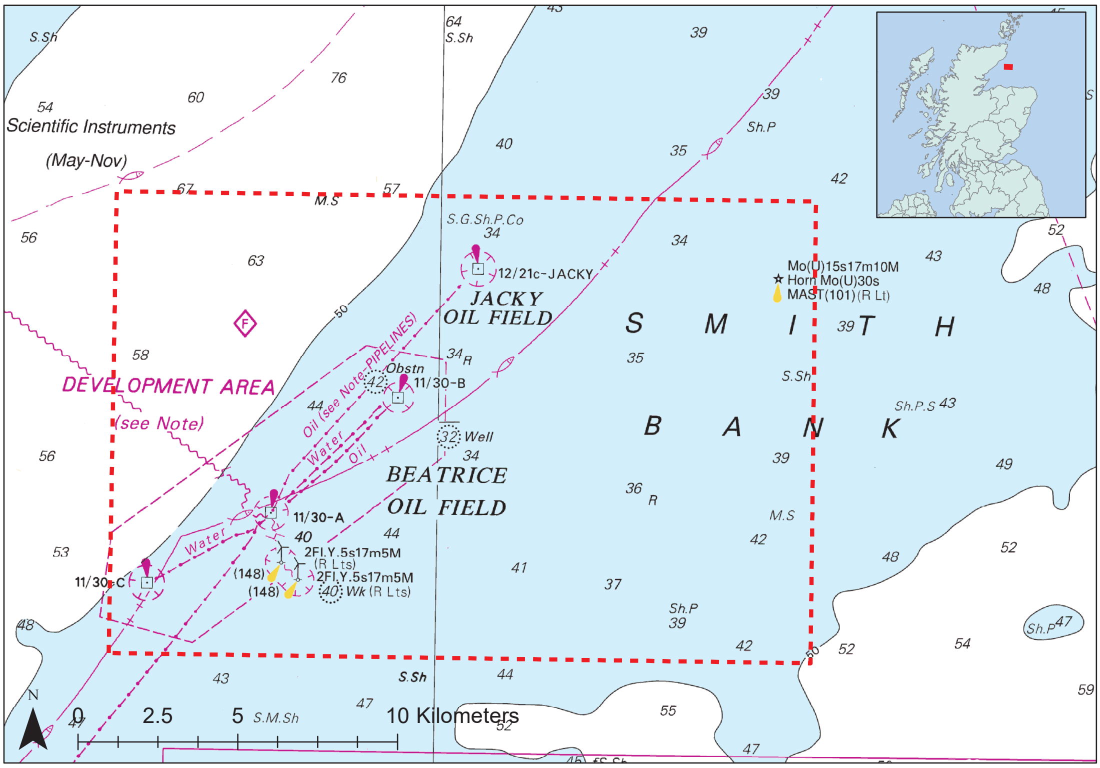


Figure 1: UKHO Admiralty Chart 115 Moray Firth, Edition Date 04/04/2013, showing the study area (red-dashed box), used for comparison of Sentinel-1 SAR and COSMO-SkyMed images depicting platforms, turbines and masts. Not to be used for Navigation.

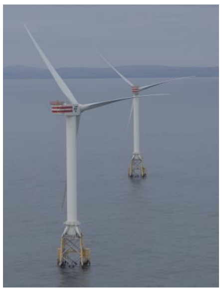
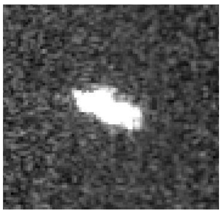
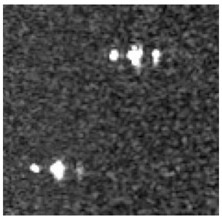
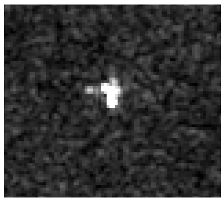
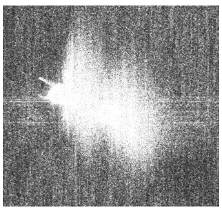
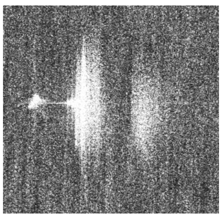
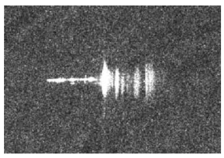
	Platform	Turbine	Mast
Photograph			
Height	86m	148m	101m
Position	3.0890°W, 58.1141°N	3.0823° W, 58.1004° N	2.8204° W, 58.1819° N
Description	Beatrice A 11/30 consists of two bridge linked platforms.	Beatrice Wind Farm Demonstrator comprising two 5MW wind turbines.	MORL Met Mast.
Sentinel-1 SAR, GRD IW VH Ascending			
Sentinel-1 Notes	Covers approx. 30 x 30 pixels.	An individual turbine covers an area of approx. 29 x 29 pixels with a central core approx. 9 x 9 pixels.	Covers approx. 12 x 12 pixels.
COSMO SkyMed Spotlight			
COSMO SkyMed Notes	Covers an area of about 700 x 700 pixels with (presumably) reflections from the sea covering a much wider area.	Image shows upper right turbine only, covering an area of about 450 x 450 pixels with reflections from the sea covering a much wider area.	Covers an area of about 275 x 150 pixels. Clear line to the left approx 117 pixels long.

Figure 2: Comparison of aerial photography, Sentinel-1 SAR and COSMO-SkyMed SAR imagery of a platform, turbine and mast from the Moray Firth study area, April to August 2016.

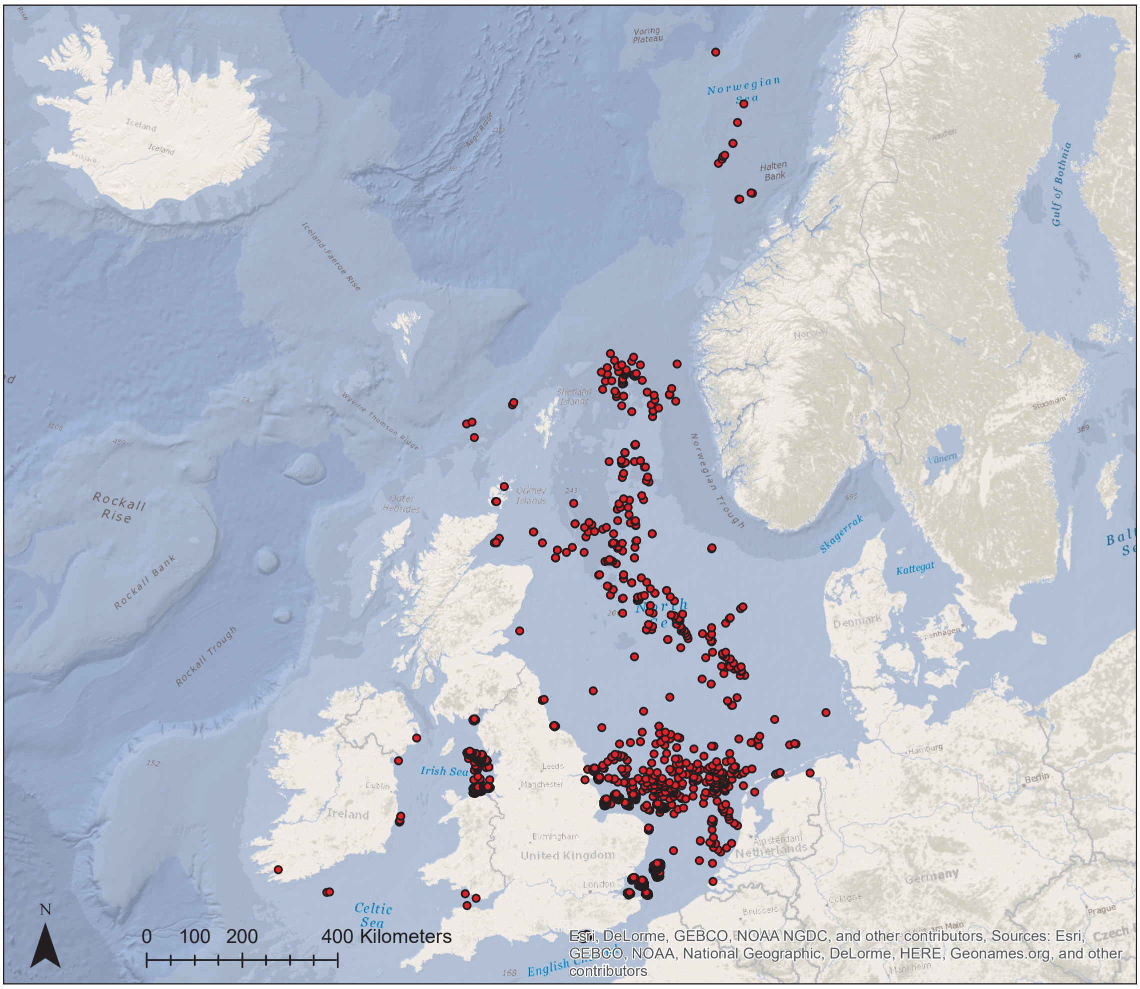


Figure 3: Extent of the May 2016 UKHO offshore air data with all offshore installations marked as red dots. Note that all points are located in sea areas, avoiding the need for land-sea masking.

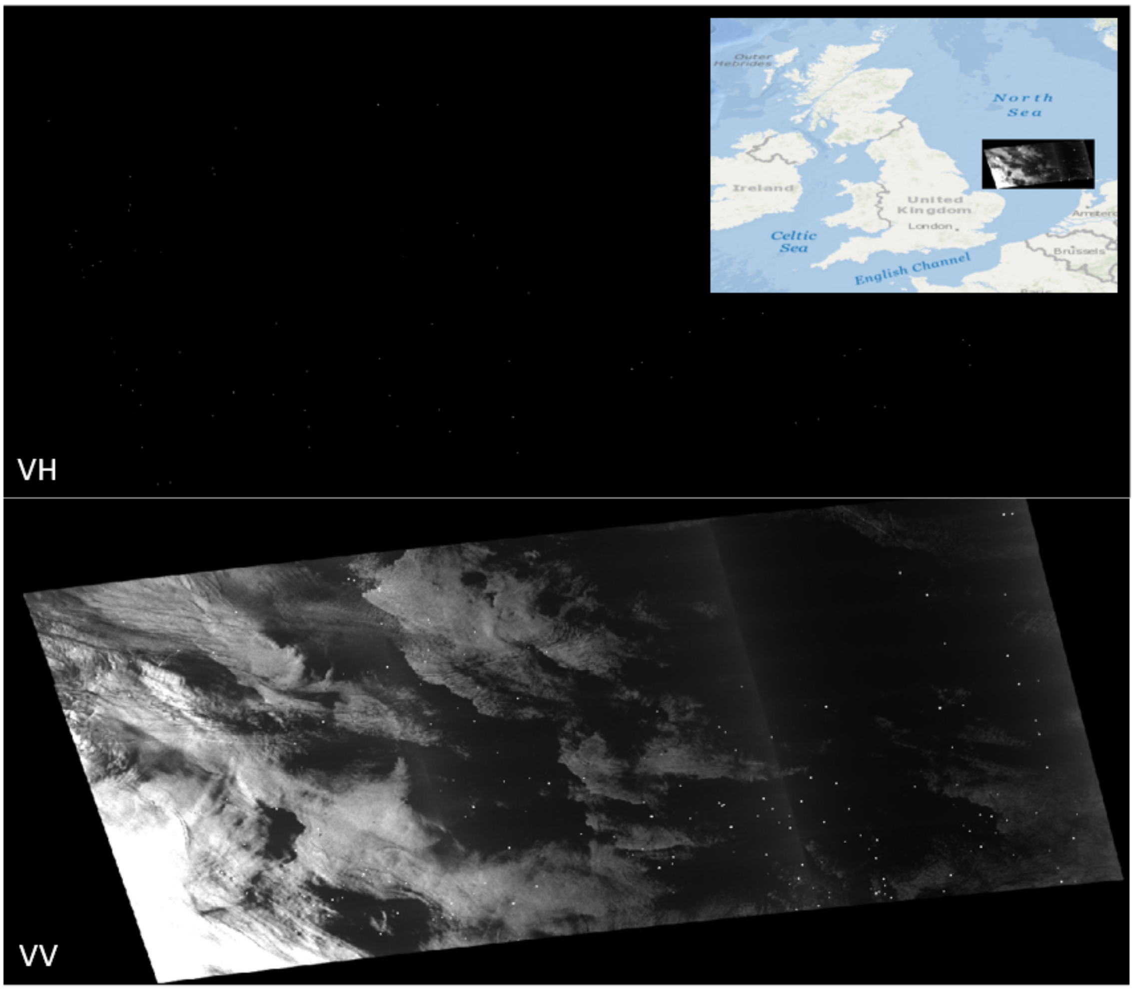


Figure 4: Comparison of VH (top) and VV (bottom) polarised imagery acquired on 26th May 2016 across a 250km swath south of Dogger Bank in the North Sea. Both images are calibrated to Sigma nought. Targets appear as white dots on a uniform dark background in the manually colour stretched VH image. Targets are obscured by white streaks of radar clutter in the histogram equalised VV image. This is thought to be caused by short wavelength capillary waves (surface ripples) as distinct from longer wavelength ocean swell. The images were acquired around low tide so the possibility of effects caused by shallow water or exposed sand banks cannot be discounted.

Ramona et al. (2015) report that Sentinel-1 Vertical-Horizontal (VH) polarised imagery is more suitable for detecting small maritime targets. In order to investigate this further, VV and VH polarised imagery was visually compared and radar clutter which would obscure targets, was observed in some VV imagery. Figure 4, shows clutter in a Sentinel-1 image acquired on 26th May 2016. Consequently, this study selected VH polarised Sentinel-1 SAR imagery.

Crisp (2004) describes ship detection algorithms in terms of pre-processing, land sea masking, pre-screening and discrimination steps. A semi-automated tool-chain was established based on this approach:

Pre-processing: For each point of interest in the UKHO offshore air data, a 256×256 pixel image chip was produced by subsetting calibrated Sentinel-1 SAR imagery.

Land sea masking: The distribution of points of interest was visually validated as being contained only within the sea area (figure 3).

Pre-screening: A web application was created with one page for each record in the UKHO offshore air data, displaying the corresponding image chip with appropriate histogram stretches applied.

Discrimination: The web pages were augmented with buttons to allow classifications to be recorded by a human interpreter. All 2683 points were classified according to the schema shown in table 1.

Table 1: Schema used to classify records from UKHO offshore air data cross-referenced with Sentinel-1 SAR imagery.

Class	Description
Platform	The text describes a platform and the Sentinel-1 backscatter response is consistent with figure 2.
Turbine	The text describes a turbine and the Sentinel-1 backscatter response is consistent with figure 2.
Mast	The text describes a mast and the Sentinel-1 backscatter response is consistent with figure 2.
Removed	The text describes a removed structure and there is no strong scatterer in the centre of the Sentinel-1 image frame.
Other	The text describes another kind of installation such as a buoy, substation or floating storage, and there is a corresponding Sentinel-1 backscatter response.
Unconfirmed	Either a) The text suggests that an installation is present, but there is no strong Sentinel-1 backscatter from the target location or b) The text suggests that a structure has been removed, but the Sentinel-1 imagery shows the presence of a strong scatterer in the vicinity.
NoData	The Sentinel-1 image is unusable. (The Sentinels

Class	Description
	Scientific Data Hub can sometimes return missing, noisy or otherwise unusable data).
Planned	The text indicates that the structure is either planned or under construction.

Search for previously unrecorded installations

Having found commission errors, estimating errors of omission entailed searching for installations in SAR imagery and cross referencing detected targets with existing UKHO data records to discover previously unrecorded installations.

Crisp (2004) discusses a number of strategies for ship detection in SAR images based on ships being "radar bright" targets. One approach is to use a simple Gaussian "blob" detector. Peng, Wang and Li (2011) highlight the need to use multi-temporal images to remove ships; a blob must be present in consecutive time series scenes to be regarded as a permanent installation.

Undertaking blob detection over a wide area would have required a large quantity of Sentinel-1 SAR imagery and been computationally expensive, so a sample was selected instead. Two VH images, dated 14th and 26th May 2016 respectively, formed a time series with a 12-day interval covering the same footprint depicted in figure 4.

The scikit-image toolkit, (Walt et al., 2014), includes a Laplacian of the Gaussian blob detector and this was used to extract the coordinates of target points in both scenes. Only targets present in both scenes were then considered. The results were compared with May 2016 UKHO offshore air data to identify previously unrecorded targets. By measuring omissions within the sample area, an omission rate was estimated for the whole data set.

Evaluation of the digital classification of platforms, turbines and masts using Sentinel-1 SAR imagery

The Sentinel-1 image chips classified as either *Platform*, *Turbine* or *Mast* were used to build a machine-learning training and evaluation data set. A random selection of 500 sea areas was sampled from all the assembled Sentinel-1 SAR imagery (see appendix 2), visually validated as containing no strong radar scatterers, labelled as *Sea* and added to the set.

Ten features were extracted from each of the images:

Histogram parameters: Crisp (2004) suggests that Constant False Alarm Rate (CFAR) algorithms that compare the image histogram at the centre of a target scene with the histogram of the surrounding area, are effective target detectors. The minimum, maximum, mean and standard deviation of σ^0 were therefore extracted as features based on the 8×8 pixel centroid as well as the full 256×256 pixels of each image chip.

Bright spot statistics: Structures vary in size, and turbines are often installed in groups. The Laplacian of the Gaussian blob detector from scikit-image, (Walt et al., 2014) was used to count the number of bright spots and measure the size of the central bright spot in each 256×256 pixel image.

Half the data from each category was used to train a decision tree classifier, random forest classifier and linear discriminant analysis classifier, these being a selection of popular machine learning algorithms implemented in scikit-learn, (Pedregosa et al., 2011). The remaining data were used to evaluate classifier performance using accuracy assessment techniques described by Congalton (1991).

Unfortunately, there were insufficient images to repeat the classification method using COSMO-SkyMed.

Results and discussion

Comparison of Sentinel-1 SAR and COSMO-SkyMed images depicting platforms, turbines and masts

As expected, platforms, turbines and masts all presented as strong scatterers in both Sentinel-1 and COSMO-SkyMed SAR imagery. Platforms such as Beatrice A 11/30 cover an area of several hundred square metres and register a Sentinel-1 radar signature covering several hundred pixels, (figure 2). Some smaller platforms were difficult to distinguish from masts based on size and shape alone.

Figure 2 also shows the additional detail present in the higher resolution COSMO-SkyMed SAR images. The bottom right image shows a meteorological mast imaged from left by COSMO-SkyMed at 1 m resolution. There is a focused backscatter return from the mast (line to the left) as well as more diffuse bounces from the sea surface. The line itself is about 117 pixels in length, and at 1 m resolution is arguably consistent with the structure height of 101 m. This detail is not discernible in the corresponding Sentinel-1 SAR image. Interestingly, this mast was not present in the May 2016 UKHO offshore air data.

Wind farms often consist of regularly spaced turbines and substations that form strong geometric patterns, aiding their visual identification. Turbines can sometimes present a distinctive shape, presumably caused by rotating blades, (figure 2).

Verification of UKHO offshore air data

The results obtained from verification of the May 2016 UKHO offshore air data are summarised in table 2.

Table 2: Frequency chart of May 2016 UKHO offshore air data verified by cross-referencing interpreted Sentinel-1 SAR imagery acquired May 16th - 29th, 2016.

Classification	Count
Turbine	1470
Platform	551
Planned or under construction	468
Removed	63
Other	52
Unconfirmed	46
Mast	21
Nodata	12
Total	**2683**

The data set is dominated by turbines (1470) and platforms (551), with only 21 masts recorded.

Corbetta (2015) forecasts an additional 66 GW of offshore wind production in Europe by 2030. 468 points were noted as planned or under construction.

The fall in global oil prices combined with platforms reaching end-of-life is leading to significant decommissioning work in the North Sea, (Legate, 2016). 63 points recorded as removed in the UKHO offshore air data were corroborated by the Sentinel-1 SAR imagery and could now be deleted.

46 points were marked as unconfirmed and have been passed to UKHO for further analysis. Whilst some of these points can be reasonably explained (for example a buoy that may be too small to register any backscatter), in an aeronautical context, the number can be used to give an approximate commission error estimate for the May 2016 UKHO offshore air data of $46 \div (2683 - 468 - 12) \approx 2\%$.

12 points were classified as no data; unfortunately, the Sentinels Scientific Data Hub sometimes returns results that do not include the specified search point or where the resulting image suffers from edge effects near the search point and is unusable.

Search for previously unrecorded installations

450 bright spots were found across the sample Sentinel-1 time series. Of these, 392 points, when considered as clusters, corresponded with 168 verified, completed installations in the May 2016 UKHO offshore air data.

58 new target points were found. 47 of these corresponded to planned or under construction data. The remaining 11 points formed 4 clusters highlighting 4 omissions that were reported to UKHO and have subsequently been accepted as corrections, see table 3. This allowed an omission error estimate of $4 \div 168 \approx 2\%$.

Table 3: Four confirmed omissions from the May 2016 UKHO offshore air data found in Sentinel-1 SAR imagery of a southern North Sea sample area acquired May 14th and 26th 2016.

Longitude	Latitude	Notes
2.1947°E	54.6000°N	Cygnus BWH, present on UKHO chart.
3.6161°E	53.7429°N	Production well near the Western Mudhole marked on the Netherlands chart.
4.8191°E	53.7099°N	End of a gas pipeline near Terschellinger Bank depicted on the Netherlands chart.
2.8459°E	53.3520°N	Feature to the east of the Indefatigable field marked Racon(T) on the Netherlands chart.

Evaluation of the digital classification of platforms, turbines and masts using Sentinel-1 SAR imagery

A decision tree classifier provided the most accurate results, and an accuracy assessment is shown in table 4.

Table 4: Accuracy assessment of a decision tree classifier of masts, platforms and turbines, trained on Sentinel-1 SAR imagery acquired May 16th - 29th, 2016.

Predicted	Mast	Platform	Sea	Turbine	Total	Producer-accuracy
Actual						
Mast	5	5	0	1	11	45.45%
Platform	5	265	0	6	276	96.01%
Sea	0	0	250	0	250	100.00%
Turbine	2	5	1	727	735	98.91%
Total	12	275	251	734	1272	
User-accuracy	41.67%	96.36%	99.60%	99.05%		**98.03%**

The major diagonal shows images that were classified correctly according to the test data. Off-diagonals were classified incorrectly. The overall accuracy of 98.03% is the ratio of correct classifications to the total number of images. The user-accuracy row summarises errors of commission (inclusion); the classifier made 12 predictions of masts, but only 5 were correct. The producer-accuracy column summarises errors of omission (exclusion); only 5 out of 11 masts were classified correctly.

The classifier tends to confuse masts, turbines and platforms. Machine learning algorithms can be biased towards dominant classes, (Segaran, 2007). The training data comprises 70 times more turbines than masts, and 26 times more platforms, see table 2. This may account for the error distribution.

When the installation classes were combined, as in table 5, an overall offshore installation detection rate of 99.92% was achieved.

Table 5: Accuracy assessment of a decision tree classifier of combined offshore installations, trained on Sentinel-1 SAR imagery acquired May 16th - 29th, 2016.

Predicted	Installation	Sea	Total	Producer-accuracy
Actual				
Installation	1021	1	1022	99.90%
Sea	0	250	250	100.00%
Total	1021	251	1272	
User-accuracy	100.00%	99.60%		**99.92%**

The random forest classifier is an ensemble machine learning method that creates multiple, random decision trees and combines the results. Table 6 shows an accuracy assessment of a random forest classifier trained on the same Sentinel-1 SAR images as above. Overall accuracy is the same as that of the decision tree classifier (98.03%), but class separation accuracy for platforms, turbines and masts is reduced.

Table 6: Accuracy assessment of a random forest classifier of masts, platforms and turbines, trained on Sentinel-1 SAR imagery acquired May 16th - 29th, 2016.

Predicted	Mast	Platform	Sea	Turbine	Total	Producer-accuracy
Actual						
Mast	2	6	1	2	11	18.18%
Platform	3	268	0	5	276	97.10%
Sea	0	0	250	0	250	100.00%
Turbine	0	7	1	727	735	98.91%
Total	5	281	252	734	1272	
User-accuracy	40.00%	95.37%	99.21%	99.05%		**98.03%**

Linear discriminant analysis (LDA) finds a linear combination of features that characterises or separates classes using Fisher's linear discriminant methods. Table 7 shows an accuracy assessment of a Linear Discriminant Analysis classifier trained on Sentinel-1 SAR images. Overall accuracy is less (88.76%) and no masts were correctly predicted.

Table 7: Accuracy assessment of a linear discriminant analysis classifier of masts, platforms and turbines, trained on Sentinel-1 SAR imagery acquired May 16th - 29th, 2016.

Predicted	Mast	Platform	Sea	Turbine	Total	Producer-accuracy
Actual						
Mast	0	0	0	11	11	0.00%
Platform	0	174	3	99	276	63.04%
Sea	2	0	228	20	250	91.20%
Turbine	0	4	4	727	735	98.91%
Total	2	178	235	857	1272	
User-accuracy	0.00%	97.75%	97.02%	84.83%		**88.76%**

Conclusions

Visual interpretation of Sentinel-1 SAR imagery acquired during May 2016 was used to estimate commission errors of 2% and omission errors of 2% for the May 2016 UKHO offshore air data.

Four installations, all unrecorded in the May 2016 UKHO offshore air data, were detected in a sample Sentinel-1 SAR time series from May 2016 and have been accepted as corrections by UKHO.

A supervised machine learning classifier, trained using Sentinel-1 SAR image chips depicting offshore installations, was unable to accurately separate platforms, turbine and masts but showed a combined target detection accuracy of 99.92%. Initial visual interpretation of COSMO-SkyMed spotlight imagery suggests that it could enable more accurate class separation and may be suitable for structure height estimation.

Further use of SAR for the maintenance of offshore installation data could have a positive impact on maritime aeronautical safety.

Recommendations

Investigate alternative sources of offshore installation data. The Aeronautical Information Documents Unit (AIDU), a part of the UK Royal Air Force, also distributes low flying charts and information. Much of this data is reportedly derived from UKHO offshore air data but is augmented with data from Ministry of Defence sources. Offshore installations are marked on Electronic Navigational Charts (ENCs) produced by national hydrographic offices.

Further investigate the use of COSMO-SkyMed SAR spotlight imagery for classification and structure height estimation. Sentinel-1 SAR could be used for target detection and pre-screening, with COSMO-SkyMed subsequently providing additional information for confirmation and analysis.

Investigate how sea state and tide conditions affect SAR imagery and digital classification performance. The height of features above the sea surface is generally quoted with reference to Mean High Water Springs (MHWS) but varies according to the tide by several metres. The Centre for Environment, Fisheries and Aquaculture Science (Cefas) WaveNet project maintains a network of wave buoys around the United Kingdom which could provide additional information about sea state and tide at the time of acquisition of SAR imagery.

Equip analysts with the materials, tools and skills required to use SAR imagery for offshore installation detection, verification and database maintenance.

Acknowledgements

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The European Commission is to be commended for providing full, free and open Sentinels data under The Copernicus Programme, without which this project would not have been possible. This paper contains modified Copernicus Sentinel data 2016.

My thanks to Andrea Minchella and the COSMO-SkyMed Radar Science and Innovation Research (CORSAIR) Programme at the UK Satellite Applications Catapult as well as Alex Farman at Telespazio, for providing COSMO-SkyMed imagery. COSMO-SkyMed imagery is © ASI 2016 processed under license from ASI - Agenzia Spaziale Italiana. All rights reserved. Distributed by e-GEOS.

The open source Python libraries, scikit-image, (Walt et al., 2014), scikit-learn, (Pedregosa et al., 2011), and GDAL, (GDAL Development Team, 2016), were used extensively in this project.

Finally, my thanks to Toby Waine, Boris Snapir and Tim Brewer at Cranfield University for their wisdom, encouragement and inspiration.

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Appendix 1 - Aerial photography

The following photographs were taken in the Moray Firth study area using a 35 mm DSLR camera from an Airtask survey aircraft.

Figure 5: Aerial photograph of Beatrice 11/30-A consisting of two bridge-linked platforms. Height 86m. Acquired 14th April 2016.

Figure 6: Aerial photograph of Beatrice 11/30-B platform. Height 82m. Acquired 14th April 2016.

Figure 7: Aerial photograph of Beatrice 11/30-C platform. Height 46m. Acquired 14th April 2016.

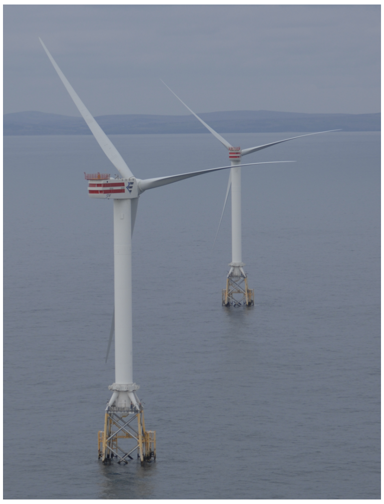

Figure 8: Aerial photograph of Beatrice demonstration wind farm consisting of two 148m 5MW turbines, WT-A 11/30a and WT-B 11/30a. Acquired 14th April 2016.

Figure 9: Aerial photograph of Jacky 12/21c platform. Height 34m. Acquired 14th April 2016.

Figure 10: Aerial photograph of MORL 101m meteorological mast, ST-A01. Acquired 18th July 2016.

Appendix 2 - Sentinel-1 products

The following Sentinel-1 products, acquired May 16th - 29th 2016, have a combined footprint covering the May 2016 UKHO offshore air data:

```
S1A_IW_GRDH_1SDV_20160516T060536_20160516T060601_011280_01115E_9376
S1A_IW_GRDH_1SDV_20160516T171655_20160516T171720_011287_011198_F002
S1A_IW_GRDH_1SDV_20160517T064722_20160517T064747_011295_0111D7_8341
S1A_IW_GRDH_1SDV_20160517T175810_20160517T175835_011302_011217_3385
S1A_IW_GRDH_1SDV_20160517T175925_20160517T175950_011302_011217_5283
S1A_IW_GRDH_1SDV_20160518T054819_20160518T054848_011309_011256_197F
S1A_IW_GRDH_1SDV_20160518T170326_20160518T170351_011316_01128A_9D07
S1A_IW_GRDH_1SDV_20160518T170351_20160518T170416_011316_01128A_A255
S1A_IW_GRDH_1SDV_20160519T062901_20160519T062926_011324_0112D1_E41B
S1A_IW_GRDH_1SDV_20160519T063106_20160519T063131_011324_0112D1_FF5E
S1A_IW_GRDH_1SDV_20160519T174120_20160519T174145_011331_01130E_B798
S1A_IW_GRDH_1SDV_20160521T061226_20160521T061251_011353_0113C6_4DBB
S1A_IW_GRDH_1SDV_20160521T172442_20160521T172507_011360_011401_9363
S1A_IW_GRDH_1SDV_20160521T172507_20160521T172532_011360_011401_C3E2
S1A_IW_GRDH_1SDV_20160521T172532_20160521T172557_011360_011401_4BCE
S1A_IW_GRDH_1SDV_20160521T172557_20160521T172623_011360_011401_C1CA
S1A_IW_GRDH_1SDV_20160521T172714_20160521T172739_011360_011402_4F36
S1A_IW_GRDH_1SDV_20160523T055655_20160523T055724_011382_0114B6_2515
S1A_IW_GRDH_1SDV_20160523T055749_20160523T055814_011382_0114B6_428D
S1A_IW_GRDH_1SDV_20160524T063648_20160524T063713_011397_011537_7D84
S1A_IW_GRDH_1SDV_20160524T063853_20160524T063918_011397_011537_5CD0
S1A_IW_GRDH_1SDV_20160524T063918_20160524T063943_011397_011537_4F16
S1A_IW_GRDH_1SDV_20160524T174946_20160524T175011_011404_011570_C62E
S1A_IW_GRDH_1SDV_20160524T175011_20160524T175036_011404_011570_57D2
S1A_IW_GRDH_1SDV_20160524T175036_20160524T175101_011404_011570_E79C
S1A_IW_GRDH_1SDV_20160524T175101_20160524T175126_011404_011570_918D
S1A_IW_GRDH_1SDV_20160526T061957_20160526T062026_011426_011629_7BA9
S1A_IW_GRDH_1SDV_20160526T062051_20160526T062116_011426_011629_0390
S1A_IW_GRDH_1SDV_20160526T062116_20160526T062141_011426_011629_F4A7
S1A_IW_GRDH_1SDV_20160526T062206_20160526T062231_011426_011629_AFA6
S1A_IW_GRDH_1SDV_20160526T173236_20160526T173301_011433_011660_1A1F
S1A_IW_GRDH_1SDV_20160526T173301_20160526T173326_011433_011660_42E4
S1A_IW_GRDH_1SDV_20160526T173326_20160526T173351_011433_011660_C080
S1A_IW_GRDH_1SDV_20160526T173435_20160526T173504_011433_011661_1654
S1A_IW_GRDH_1SDV_20160526T173504_20160526T173529_011433_011661_6C55
S1A_IW_GRDH_1SDV_20160527T181429_20160527T181454_011448_0116E3_D66A
S1A_IW_GRDH_1SDV_20160528T060203_20160528T060232_011455_011723_F192
S1A_IW_GRDH_1SDV_20160528T060232_20160528T060257_011455_011723_335F
S1A_IW_GRDH_1SDV_20160528T060437_20160528T060502_011455_011723_8B57
S1A_IW_GRDH_1SDV_20160528T060502_20160528T060527_011455_011723_4A7C
S1A_IW_GRDH_1SDV_20160528T060527_20160528T060552_011455_011723_1EE7
```

S1A_IW_GRDH_1SDV_20160528T060552_20160528T060617_011455_011723_F4BF
S1A_IW_GRDH_1SDV_20160528T060617_20160528T060642_011455_011723_5CB4
S1A_IW_GRDH_1SDV_20160528T060642_20160528T060707_011455_011723_6CCF
S1A_IW_GRDH_1SDV_20160528T171653_20160528T171718_011462_011752_7511
S1A_IW_GRDH_1SDV_20160528T171718_20160528T171743_011462_011752_7EBD
S1A_IW_GRDH_1SDV_20160528T171743_20160528T171808_011462_011752_6D09
S1A_IW_GRDH_1SDV_20160528T171858_20160528T171923_011462_011752_A7D0
S1A_IW_GRDH_1SDV_20160529T175714_20160529T175739_011477_0117CB_B501
S1A_IW_GRDH_1SDV_20160529T175804_20160529T175829_011477_0117CB_EFAD

The following product exhibits radar clutter in the VV polarisation as depicted in figure 4:

S1A_IW_GRDH_1SDV_20160526T173326_20160526T173351_011433_011660_C080

The following products form a time series over the southern North Sea and were used to search for previously unrecorded installations:

S1A_IW_GRDH_1SDV_20160514T173326_20160514T173351_011258_0110A2_F9DC
S1A_IW_GRDH_1SDV_20160526T173326_20160526T173351_011433_011660_C080

Appendix 3 - COSMO-SkyMed products

The following COSMO-SkyMed acquisitions (9th July to 7th August 2016) cover installations within the Moray Firth study area:

EL20160709_6171_252382.6.2_7615103
EL20160718_6179_254534.6.2_7635103
EL20160725_6191_256654.6.2_7657103
EL20160802_6196_258797.6.2_7669103
EL20160803_6213_259073.6.2_7709103
EL20160807_6214_260115.6.2_7711103