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Classification of active sonar echoes using a one-class classification technique

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ABSTRACT

A typical approach to data classification based on machine learning algorithms is binary classification. This involves the classifier to be trained using representative data sets provided from two object classes. In reality, data from one of the classes may be not well-defined or readily available and so the one-class classification technique is gaining popularity. In this research we apply this method to the problem of classification using active sonar echoes from different classes of objects. A one-class classification research tool was developed in Matlab® to implement several one-class classification techniques found in literature. The tool was applied to three sets of data: simulated, laboratory and at-sea. The performance of the selected classifiers on different data sets will be discussed in this paper.

1 INTRODUCTION

The exercise of classification often involves assigning object samples as training datasets in order to train classification models, which in turn are then used to discriminate between other object classes. This is typically the norm and has been used for building binary and multi-class classification models. However, in many real-world situations, it is often difficult to have samples from more than one class or in particular, it may not be possible to obtain datasets from both target and non-target classes or, perhaps one may not be properly characterised. In these cases traditional binary-classification methods will not achieve their full potential and effectively the problem reduces to a one-class classification method whereby data from a single class is used to train the classifier.

This method has been used in many cases where the target class is relatively easy to obtain but the outlier class is difficult to characterise such as in pattern and image recognition, fault detection, web-page classification, credit scoring in finance, document classification, disease detection or person identification based on biometric data (Juszczak et al., 2009). In contrast, outlier class samples can be easily obtained in the ocean whereas the target characterisations cannot and in this case, outlier class is often used to train one-class classifiers. Typically undersea outlier data is a combination of clutter, ambient noise, reflections, reverberations or scattering from seamounts, which makes studies challenging as there are many unknown parameters contained in the outlier dataset. This is why one-class classification yet to be widely adopted in sonar processing areas and undersea warfare.

In this paper, a brief review of different one-class classification categories is present in Section 2. Section 3 covers details of three sets of data used in this analysis: simulated, laboratory and at-sea. In section 4 we show multiple one-class classifiers implemented in a tool which allows users to select different features potentially suitable for a particular dataset. The performance of selected classifiers presented in Section 5 shows that these classifiers perform superior to sonar data and finally, conclusion and future work are given in Section 6.

2 THEORY

One-class classification algorithms are based on the premise that the object to be identified belongs to a particular class and all others are rejected as false classifications. The algorithms are developed by either estimating the probability density function or by fitting a model to the dataset. One-class classifiers can be sub-divided into three categories namely: density, reconstruction and boundary.

- **Density based classifiers**: the calculations are based on the estimation of the probability density function (PDF) of the feature values in the complete feature space of the data to the class (Mazhelis, 2006). Since there is no second class present, the assumption of a uniform PDF for the second class is applied.

- **Reconstruction based classifiers**: the calculations are based on the evaluation of a best-fit reconstruction of an observation vector associated with a model which has been estimated during the training phase (Pla et al., 2013). The closer the fit the more likely the best reconstruction vector is achieved.
- **Boundary based classifiers**: the calculations are based on a boundary built around the training data. It takes into account both the distances between the observation vectors in the test dataset and the observation vectors of the training dataset and the distances between the observation vectors in the training set (Mazhelis, 2006).

3 DATASETS

In this analysis, three sets of data were used – simulated, experimental and at-sea. Simulated data was generated using a numerical scattering computer model whilst the experimental data was collected in a laboratory as scaled underwater measurements and finally, at-sea data was collected from trial activities. Input data of the training and test datasets is called “signal” of form MxN matrix in Matlab® format where M represents snippet time series while N represents number of snippets (Trojan, Kouzoubov, 2007)

3.1 Simulated Data

A numerical model was used to produce acoustic scattering data for a concrete cylinder and a metal object of similar size. Echo snippets were obtained from 361 different aspect angles. The duration of each echo was 901 time samples. The time series plots of target and non-target simulated data are given in Figure 1.

3.2 Experimental Data

Acoustic scattering data of an actual concrete cylinder and a metal object were collected from laboratory tank measurements. These physical objects had the same geometry and material properties as their mathematical model counterparts. The 8192x361 dataset obtained consisted of echoes taken at 361 aspect angles each of length 8192 time samples. The time series plots of target and non-target experimental data are shown in Figure 2.

3.3 At-sea Data

The data used here was collected from the Clutter09 at-sea trial which was conducted in the Malta Plateau channel, between Malta and Sicily in 2009. Backscattered echoes from an oil rig, wellhead, two passive acoustic targets and two echo repeaters (labelled here as *Oilrig*, *Wellhead*, *PAT1*, *PAT2*, *Echo1* and *Echo4* respectively) were treated as targets whilst all other echoes were considered as false-alarms or clutter. The transmit signal was a Linear Frequency Modulation (LFM) up-sweep chirp of duration 1.1 seconds from 500 to 3500Hz every two minutes. The beam-formed data was matched filtered and normalised before the detection and extraction processes were performed. Echo snippets were then generated in a Wave Audio File format of duration of 0.5 seconds before and after the respective regions of interest. An in-house Matlab® program was developed to convert echo snippets from wav format to Matlab® format and the dataset further was reduced to 1000 time samples before and after the detection point. The time series plots of the target and non-target data are presented in Figure 3.

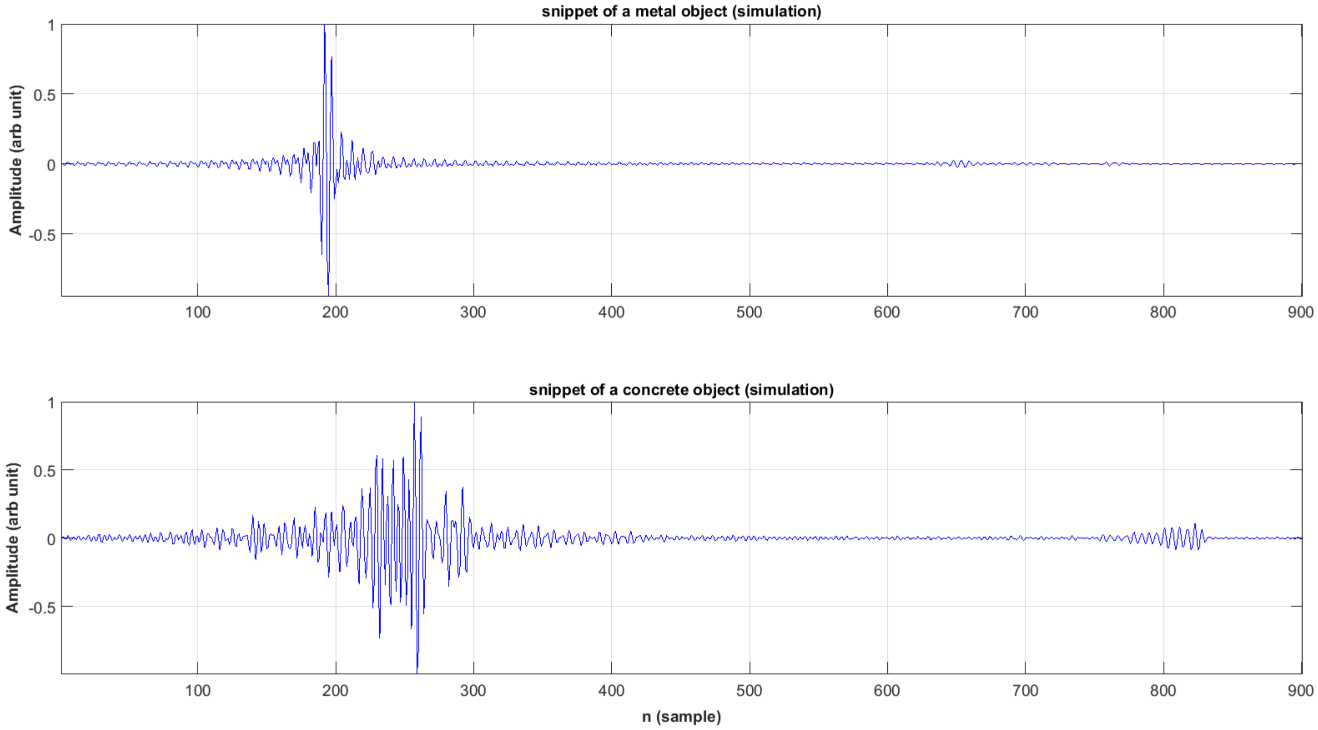

Figure 1: Plots of simulated time-series snippets.

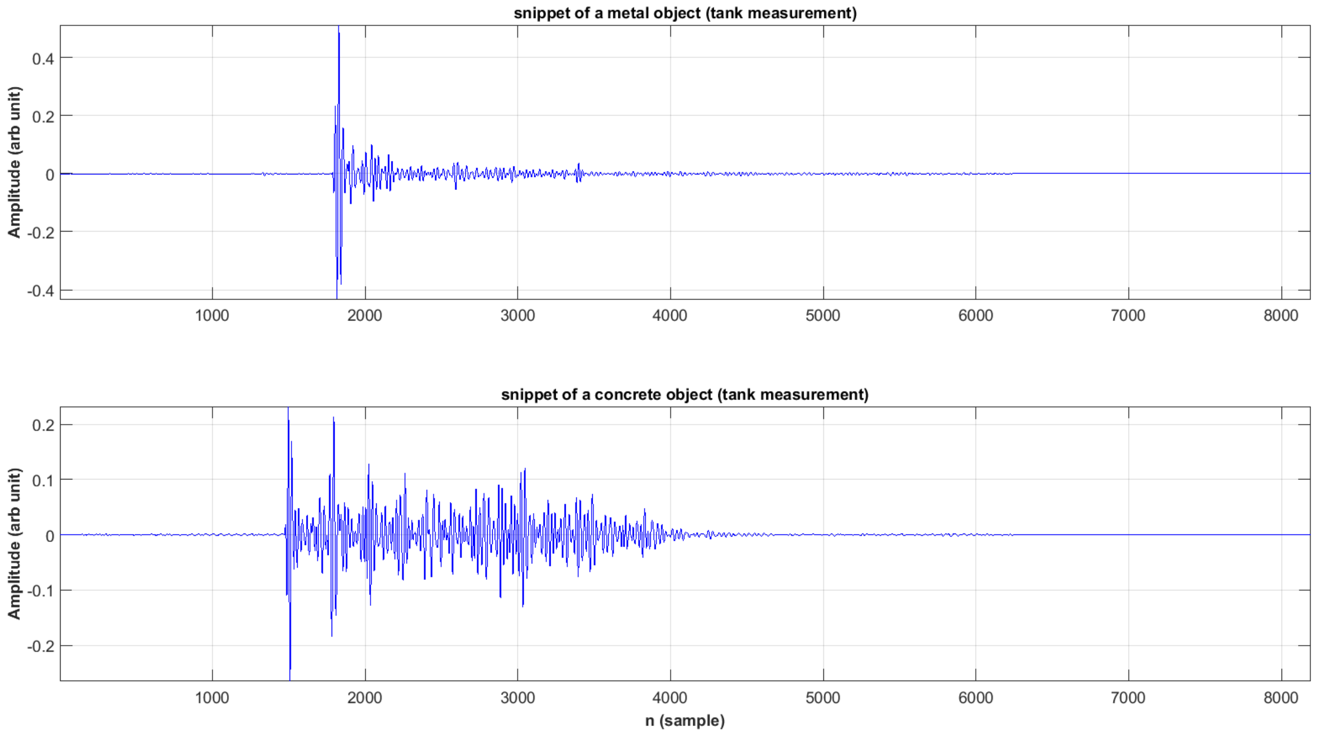

Figure 2: Plots of experimental time-series snippets.

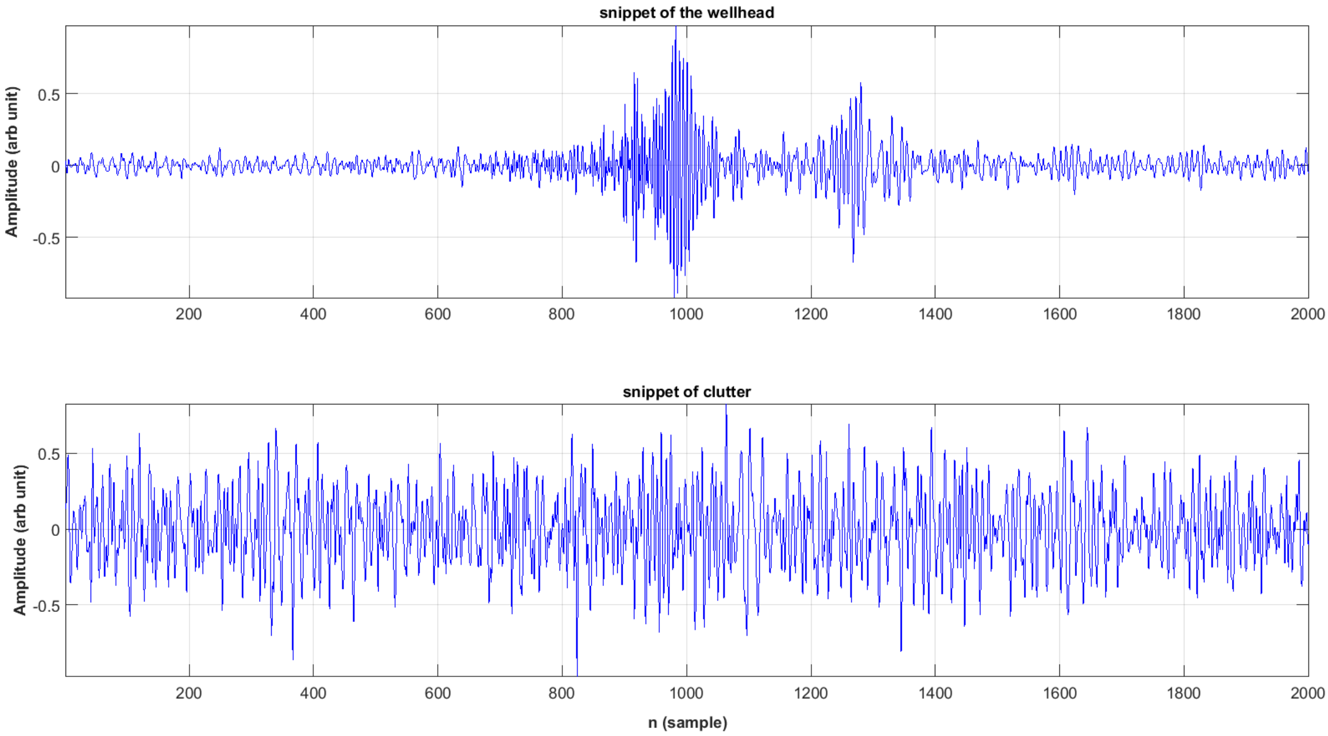

Figure 3: Plots of sea trial time-series snippets.

4 CLASSIFICATION TOOLS

The One-Class Classification Research Tool (OCCRT), which allows the user to enter parameters or to select pre-defined features, was used to visualise the results. OCCRT is a research tool for testing the performance of feature and one-class classification algorithms of time series echoes. This tool is a modified version of the Binary Classification Research Tool (BCRT), which has been developed in Matlab® and includes a Graphical User Interface for user-friendly selection of features and classification algorithms (Kouzoubov, Nguyen, 2011). OCCRT allows the user to specify the training dataset (either target or outlier). After loading the files, OCCRT combines the target and outlier echoes together to form the test dataset. Selection of features, parameters and classification algorithms within OCCRT are the same as BCRT.

A confusion matrix is a table that is often used as the quantitative metric to measure the performance of a classification method. It visualises the percentages of false positives, false negatives, true positives and true negatives of a particular classifier. Another method is to determine the Area Under the ROC Curve (AUC) coefficient. This value is ranging from 0 to 1. Therefore, a 100% of either true negatives or true positives or an AUC of 1 is considered as a perfect classification. To set a performance benchmark here, any classification that achieves an AUC value greater than 0.80 or a true negatives or true positives percentage value greater than 80% is considered to have good performance.

A total of 60 characterisation features are available for selection within OCCRT which are divided into three sets:

Set 1: time-domain matched filter series and frequency- domain power spectra;
Set 2: Short-Time-Fourier Transform (STFT) of the matched filtered time series features calculated using the STFT approach on each snippet for a number of STFT frames; and
Set 3: STFT based on the Gamma-Tone filtered time-series (Ellis, 2009).

A list of the 60 features can be found in Table 1. To avoid adversely affecting the training phase, it is essential to select the features that are relevant to the test dataset being analysed. This process can be performed by using either ranking or subset selection techniques to remove any irrelevant features (Jeong et al., 2012). In this particular case, the ranking technique was chosen.

From the results shown in Table *2* one can see that three sets of features performed outstandingly well with the results very close to each other. Feature sets 1 and 2 have been selected due to set 3 features requiring more computational time.

Nine classifiers, as used by Tax (Tax, 2013) in the open literature, were implemented during the benchmarking process. Each classifier had a set of required parameters such as number of clusters, number of iterations, number of attempts or number of prototypes. All classification algorithms used here required a rejection threshold factor and by default, was set to 0.10. A snapshot of the results is shown in Figure 6 highlighting the performance of the nine classifiers in both confusion matrix and AUC measures.

Table 1: List of features.

Set 1 features	Set 2 features	Set 3 features
time shape mean	peak signal to noise ratio	energy centroid
time shape variance	average signal to noise ratio	energy roughness
time shape skewness	time of peak signal to noise ratio	duration
time shape kurtosis	frequency of peak signal to noise ratio	maximum sub-band attack
time amplitude mean	mean frequency	frequency of maximum sub-band attack
time amplitude variance	rms bandwidth	mean sub-band attack
time amplitude skewness	frequency skewness	minimum sub-band attack
time amplitude kurtosis	frequency kurtosis	frequency of minimum sub-band attack
frequency shape mean	mean time	maximum sub-band decay
frequency shape variance	rms time	frequency of maximum sub-band decay
frequency shape skewness	temporal skewness	mean sub-band decay
frequency shape kurtosis	temporal kurtosis	minimum sub-band decay
frequency amplitude mean	power standard deviation	frequency of minimum sub-band decay
frequency amplitude variance	power standard deviation in time	maximum sub-band synchronicity
frequency amplitude skewness	power standard deviation in frequency	frequency of maximum sub-band synchronicity
frequency amplitude kurtosis	power skewness	mean sub-band synchronicity
temporal centroid	power skewness in time	minimum sub-band synchronicity
	power skewness in frequency	frequency of min sub-band synchronicity
	power kurtosis	
	power kurtosis in time	
	power kurtosis in frequency	
	attack rate	
	decay rate	
	spectral flux	
	temporal flux	

5 RESULTS

To test the performance of the nine one-class classifiers, two types of test datasets were used - balanced and imbalanced. For the balanced test dataset, the number of target snippets equalled the number of outliers whilst the imbalanced dataset had the number of outlier snippets was much greater than the number of targets.

Table 3 and Table 4 show the classification results for these cases using OCCRT as applied to three datasets with differing sources - most of the classifiers gave AUC values greater than 0.90 and many of them achieved the value of 1.0 indicating a perfect classification. Table 5 and Table 6 show the overall performance of the classifiers using the confusion matrix approach which again gives a level of confidence in the technique and in particular, the density classification algorithms earn excellent classification accuracy as the confusion matrix values are above 90%. Here, a few of the classifiers achieved a perfect score. Contrary to this, the Local Outlier Fraction classifier did not perform well particularly, in the case of imbalanced classes using experimental target snippets as training. This is due to some similarities in density and size of both target and outlier data as this method is an outlier detection therefore using outlier data as training is the best option.

6 CONCLUSIONS AND FUTURE WORK

This paper examined nine classifiers using a one-class classification approach and presented the results of the performance tests of the classifiers. The performance of the classifiers was analysed using simulated, experimental and at-sea data. Most of the classifiers achieved an AUC of over 0.90 and a corresponding confusion matrix value of above 90.0% with an exception of the Local Outlier Fraction classifier. This is a promising finding as potentially these classification algorithms lend themselves to practical applications because they are based on the fact that non-target related training data is readily available, removing the need to collect often difficult to obtain target training data. In conclusion, the performance of the nine one-class classification algorithms depends on the type of training and test datasets, feature selection and the degree of imbalance between the datasets. The performance metric results show promise for potential active sonar applications.

7 ACKNOWLEDGEMENTS

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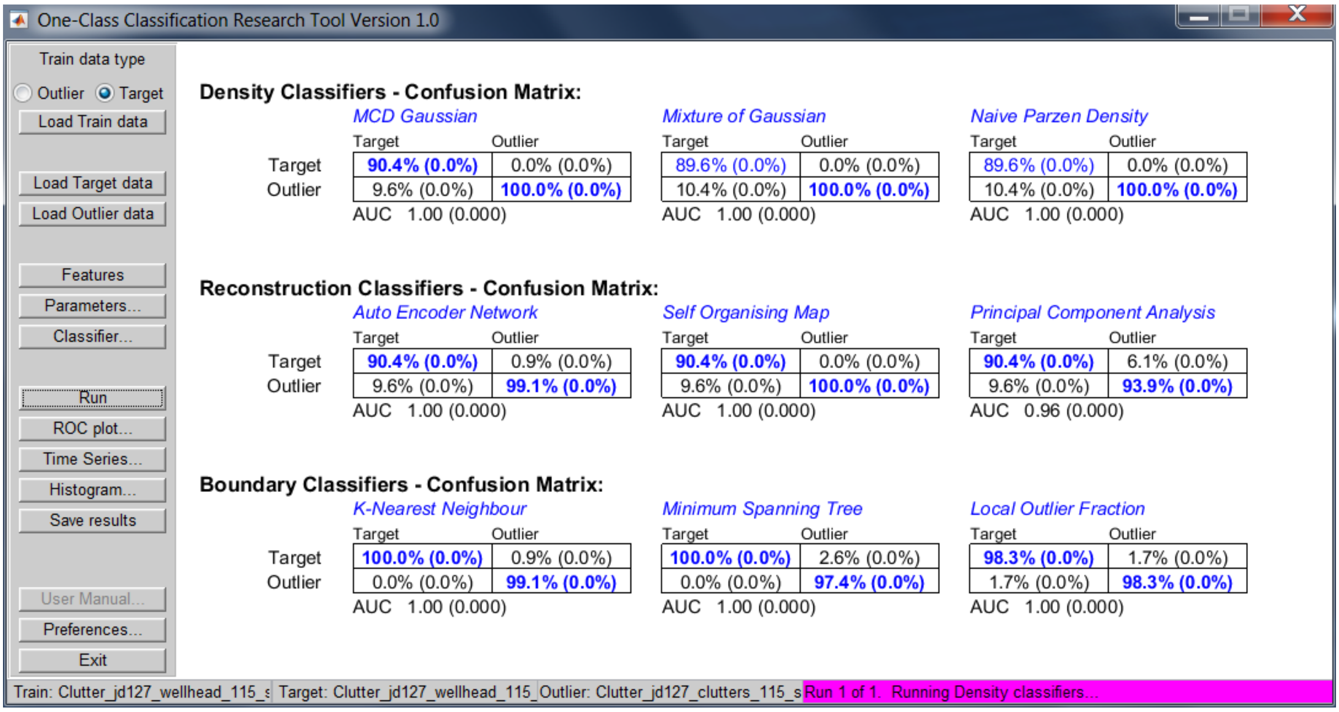

Figure 4: Snapshot of the results of the nine classifiers

Table 2: Ranking features using Sea trial data.

	Features set 1				Features set 2				Features set 3 (Gamma-tone Filters)			
	non-target as training class		target as training class		non-target as training class		target as training class		non-target as training class		target as training class	
	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier
Classifiers	%	%	%	%	%	%	%	%	%	%	%	%
Density												
MCD Gaussian	100	90.4	90.4	100	100	90.4	90.4	100	100	90.4	90.4	100
Mixed Gaussian	100	89.6	89.6	100	100	89.6	89.6	100	100	89.6	89.6	100
Naïve-Parzen	100	89.6	89.6	100	100	89.6	89.6	100	100	89.6	89.6	100
Reconstruction												
Auto Encoder	100	90.4	90.4	99.1	100	90.4	90.4	100	100	90.4	90.4	99.1
Self-Organising Map	100	90.4	90.4	100	95.7	90.4	90.4	100	99.1	90.4	90.4	100
PCA	100	90.4	90.4	100	99.1	90.4	90.4	99.1	100	90.4	90.4	93.9
Boundary												
K-NN	100	100	100	100	94.8	100	100	99.1	88.7	100	100	99.1
Min. Spanning tree	97.4	100	100	98.3	93.9	100	100	98.3	88.7	100	100	97.4
Local Outlier Fraction	93.9	94.8	97.4	90.4	87.8	95.7	97.4	99.1	68.7	98.3	98.3	98.3

Table 3: Area Under the ROC Curve results – balanced classes.

	Simulated data		Experimental data		Sea trial data	
	non-target as training class	target as training class	non-target as training class	target as training class	non-target as training class	target as training class
	Features set 1		Features set 1		Features set 1	
	AUC	AUC	AUC	AUC	AUC	AUC
Classifiers						
Density						
MCD Gaussian	0.96	0.94	0.98	0.97	0.99	1.00
Mixed Gaussian	1.00	1.00	1.00	1.00	1.00	1.00
Naïve-Parzen	0.96	0.99	0.97	0.99	1.00	1.00
Reconstruction						
Auto Encoder	0.94	0.98	1.00	0.93	1.00	1.00
Self-Organising Map	0.97	0.99	0.99	0.97	1.00	1.00
PCA	0.93	0.99	0.99	0.98	1.00	1.00
Boundary						
K-NN	1.00	1.00	1.00	1.00	1.00	1.00
Min. Spanning tree	1.00	1.00	1.00	1.00	1.00	1.00
Local Outlier Fraction	0.98	0.99	1.00	0.99	0.98	1.00

Table 4: Area Under the ROC Curve results – imbalanced classes.

	Simulated data		Experimental data		Sea trial data	
	non-target as training class	target as training class	non-target as training class	target as training class	non-target as training class	target as training class
	Features set 1		Features set 1		Features set 1	
	AUC	AUC	AUC	AUC	AUC	AUC
Classifiers						
Density						
MCD Gaussian	0.98	0.99	0.99	0.97	0.99	1.00
Mixed Gaussian	1.00	1.00	1.00	1.00	1.00	1.00
Naïve-Parzen	0.96	0.99	0.97	1.00	1.00	1.00
Reconstruction						
Auto Encoder	0.95	0.98	1.00	0.95	0.99	1.00
Self-Organising Map	0.99	1.00	1.00	0.92	1.00	1.00
PCA	0.97	0.99	1.00	0.99	1.00	1.00
Boundary						
K-NN	1.00	1.00	1.00	1.00	1.00	1.00
Min. Spanning tree	1.00	1.00	1.00	1.00	1.00	1.00
Local Outlier Fraction	0.95	0.91	0.99	0.53	0.96	1.00

Table 5: Confusion matrix results – balanced classes.

	Simulated data				Experimental data				Sea trial data			
	non-target as training class		target as training class		non-target as training class		target as training class		non-target as training class		target as training class	
	Features set 1 & 2				Features set 1 & 2				Features set 1 & 2			
	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier
Classifiers	%	%	%	%	%	%	%	%	%	%	%	%
Density												
MCD Gaussian	**91.4**	**90.0**	**90.0**	**92.0**	**96.4**	**90.0**	**90.0**	**98.6**	**100**	**90.4**	**89.6**	**100**
Mixed Gaussian	**99.7**	**90.0**	**90.0**	**99.7**	**100**	**90.0**	**90.0**	**100**	**100**	**89.6**	**89.6**	**100**
Naïve-Parzen	**89.2**	**90.0**	**90.0**	**97.0**	**93.4**	**90.0**	**90.0**	**99.2**	**100**	**89.6**	**89.6**	**100**
Reconstruction												
Auto Encoder	**86.7**	**90.0**	**90.0**	**94.7**	**98.1**	**90.0**	**90.0**	**79.8**	**100**	**90.4**	**91.3**	**100**
Self Organising Map	**92.5**	**90.0**	**90.0**	**98.1**	**97.0**	**90.0**	**90.0**	**93.1**	**100**	**90.4**	**90.4**	**100**
PCA	**88.1**	**90.0**	**90.0**	**95.6**	**97.8**	**90.0**	**90.0**	**97.2**	**100**	**90.4**	**91.3**	**100**
Boundary												
K-NN	**95.6**	**100**	**100**	**99.4**	**96.7**	**100**	**100**	**86.1**	**96.5**	**100**	**100**	**100**
Min. Spanning tree	**92.2**	**100**	**100**	**93.6**	**96.7**	**100**	**100**	**83.9**	**96.5**	**100**	**100**	**99.1**
Local Outlier Fraction	**91.1**	**97.0**	**97.0**	**93.6**	**99.7**	**96.7**	**97.2**	**93.9**	**87.0**	**96.5**	**97.4**	**98.3**

Legend:

Excellent	Good	Acceptable	Poor
k>=90%	90%>k>=80%	80%> k > 70%	K<= 70%

Table 6: Confusion matrix results – imbalanced classes.

	Simulated data				Experimental data				Sea trial data			
	non-target as training class		target as training class		non-target as training class		target as training class		non-target as training class		target as training class	
	Features set 1				Features set 1				Features set 1			
	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier	Target	Outlier
Classifiers	%	%	%	%	%	%	%	%	%	%	%	%
Density												
MCD Gaussian	**98.3**	**90.0**	**90.0**	**93.6**	**97.0**	**90.0**	**90.0**	**100**	**100**	**90.0**	**90.0**	**100**
Mixed Gaussian	**100**	**90.0**	**90.0**	**100**	**100**	**90.0**	**90.0**	**100**	**100**	**90.0**	**90.0**	**100**
Naïve-Parzen	**90.0**	**90.0**	**90.0**	**94.7**	**93.6**	**90.0**	**90.0**	**100**	**100**	**90.0**	**90.0**	**100**
Reconstruction												
Auto Encoder	**86.1**	**90.0**	**90.0**	**93.6**	**98.6**	**90.0**	**90.0**	**68.7**	**100**	**90.0**	**90.0**	**100**
Self Organising Map	**98.1**	**90.0**	**90.0**	**99.2**	**98.1**	**90.0**	**90.0**	**77.6**	**100**	**90.0**	**90.0**	**100**
PCA	**90.9**	**90.0**	**90.0**	**98.1**	**100**	**90.0**	**90.0**	**98.6**	**100**	**90.0**	**90.0**	**100**
Boundary												
K-NN	**84.2**	**100**	**100**	**84.8**	**95.8**	**100**	**100**	**42.4**	**93.9**	**100**	**100**	**99.1**
Min. Spanning tree	**80.9**	**100**	**100**	**82.0**	**95.3**	**100**	**100**	**36.0**	**93.9**	**100**	**100**	**99.1**
Local Outlier Fraction	**84.2**	**96.7**	**98.3**	**71.2**	**97.5**	**95.0**	**95.0**	**32.1**	**71.3**	**93.3**	**98.3**	**99.1**

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