# FEATURE SELECTION AND CLASSIFICATION FOR FALSE ALARM REDUCTION ON ACTIVE DIVER DETECTION SONAR DATA

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***Abstract:*** *A requirement for many modern active sonar applications is to detect a threat fully automatically without a human operator. Regarding this, the major challenge is to achieve a high probability of detection and a low false alarm rate at the same time. In active sonar signal processing, often only the signal-to-noise ratio (SNR) and sometimes also the Doppler of echoes are used for detection. However, echoes have further characteristics that can be used to assess their relevance and hence improve the detection performance.*
*In this paper, a method for false alarm reduction by classification of contacts is presented. Initially an overview about the categories of used features is introduced and their individual suitability to distinguish between target contacts and false alarms is shown. Furthermore, one feature selection method is applied to determine the best subset of features for classification. Finally, two different classification algorithms are investigated regarding their performance and robustness for reducing the number of false alarms.*
*The algorithms are applied to recorded data of diver detection trials that were carried out in cooperation between the WTD71 and ATLAS ELEKTRONIK. The trials were conducted with the "Cerberus" diver detection sonar developed by ATLAS ELEKTRONIK UK.*

***Keywords:*** *Active Sonar, False Alarm Reduction, Feature Selection, Classification*

## 1. INTRODUCTION

In the last years the requirements for active sonar systems changed fundamentally. While in the past the detection was done mainly by a sonar operator, nowadays the systems should work more automatically. Since the performance depends on the attention of the operator who cannot be highly attentive all the time, the automation plays an important role. With suitable algorithms it is possible to support the operator or in the ideal case to detect, track and classify targets fully automatically in real time. Therefore, a high probability of detection and simultaneously a low false alarm rate are essential [1], [2].

In standard high frequency active sonar applications typically broadband frequency modulated (FM) pulses which provide a high range resolution or narrow-band continuous wave (CW) pulses which provide Doppler information are used. In case of linear or hyperbolic frequency modulated pulses (LFM / HFM) usually only the SNR of the contacts is used as a measure of reliability whereas for CW pulses in addition to the SNR also the Doppler information is considered. However, the contacts contain much more information that can be used to improve the detection performance [1], [3]. One major challenge is to extract this information.

In this paper a method for feature extraction and classification based on contacts is presented. The investigated algorithms are applied to recorded data of diver detection trials that were carried out in cooperation between the WTD71 and ATLAS ELEKTRONIK. The trials were conducted with the "Cerberus" diver detection sonar developed by ATLAS ELEKTRONIK UK. It should be noted that all results are based on the transmission of FM-pulses which are processed with an experimental signal processing in MATLAB. The signal processing of the Cerberus itself is not considered.

The paper is organised as follows: The standard active signal processing chain and its extension for subsequent reduction of false alarms is briefly described in Chapter 2. In Chapter 3 the feature extraction and two different methods for analysing the individual suitability of features are introduced. The theory of one feature selection method and two different classification algorithms is presented in Chapter 4. In Chapter 5 two datasets are introduced and a method for the association of the contacts into different classes is given. Chapter 6 shows experimental results for feature analysis, feature selection and classification with respect to the reduction of false alarms. Finally, the conclusions are given in Chapter 7.

## 2. EXTENSION OF ACTIVE SIGNAL PROCESSING CHAIN

A block diagram of the considered active signal processing chain is given in Figure 1. The grey blocks indicate the standard active signal processing chain. In a first step, the azimuthal direction of incidence of the signals is determined by means of a broadband beamformer. In the second step a matched filter which maximises the SNR is applied. For subsequent detection with, e.g. a threshold detector, the data are normalised. The normalisation is divided into two parts: the estimation of the background noise and the normalisation to that. This results in an estimate of the SNR which is used for detection. After applying a threshold detector neighbouring threshold crossings are merged to contacts. Finally, the tracking algorithm associates the contacts from successive pings to tracks. The contacts and tracks are displayed in the detection display.

Reducing the false alarm rate using a machine learning algorithm requires extraction of features that contain suitable information to distinguish between target contacts and false alarms. The extension of the standard signal processing is visualised by the green block. In a first step features of all contacts are extracted and in a second step a supervised machine learning algorithm is trained with them. The classifier is supposed to provide a likelihood value for class affiliation which could directly be used for reducing the number of contacts. Alternatively, the classification result can be used within the following tracking algorithm. However, in both cases the classifier simplifies the contact association in the tracking.

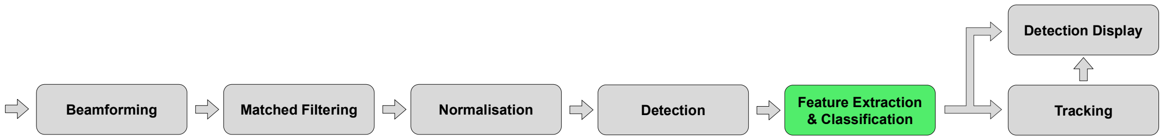


*Figure 1: Standard active signal processing chain (grey) and its extension (green) for subsequent false alarm reduction.*

Figure 2 shows an example of an echo of a diver after the four signal processing stages beamforming, matched filtering, normalisation and detection. In this example the diver was equipped with a closed breathing system. For improved visualisation a section of 7 m and 28 beams is displayed. In the upper image the data after beamforming and matched filtering is shown. Due to high background noise and reverberation the identification of the diver echo is clearly not possible. In the normalised data the presence of the diver results in an increased SNR at a range of 114 m to 115 m. It is visible that the SNR of the diver echo fluctuates strongly over range and is increased in more than one beam signal. Finally, the lower image shows the binary detector output where single threshold crossings were combined to a contact. All contacts are forwarded to the tracking stage, which is not considered in this work.

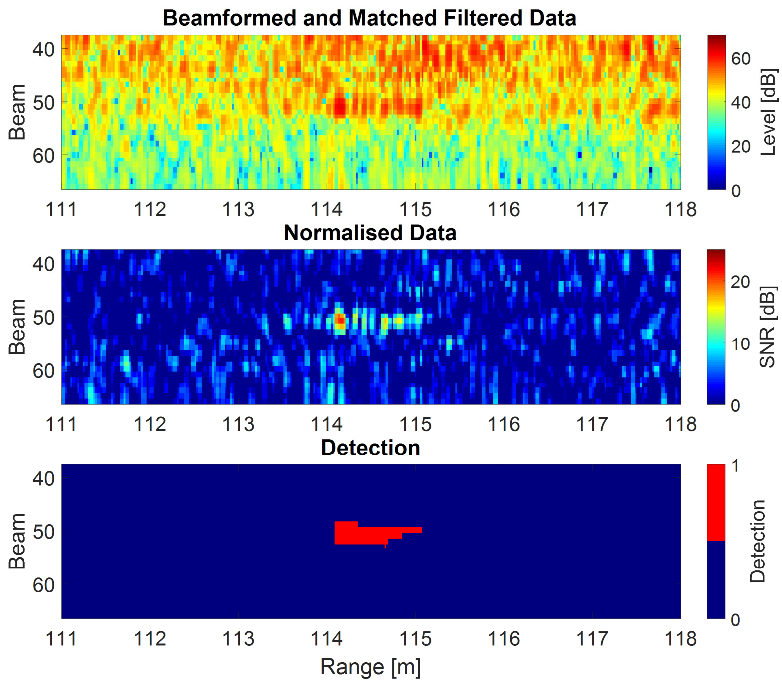


*Figure 2: Example for a diver echo after different signal processing stages.*

## 3. FEATURE EXTRACTION AND ANALYSIS

As introduced in Chapter 2 the feature extraction is applied to the contacts that are formed in the detection process. Features can be extracted from the data of the different processing stages. To achieve the best results with respect to false alarm reduction as many independent features as possible have to be extracted and combined by a supervised machine learning algorithm. The categories of the extracted features, the number of features in each category and examples for each category are listed in Table 1.

| Feature category | Nr. of features | Example |
|---|---|---|
| Level | 13 | Contact SNR |
| Extent | 4 | Extent in Range |
| Statistical | 16 | Centralised moments |
| Spectral | 7 | Centre of gravity of spectrum |
| Sub-band | 14 | Sub-band correlation |

*Table 1: Overview of different feature categories for feature extraction.*

Two different methods will be introduced to evaluate the suitability of the features for class separation. One method is the determination of the probability density function (pdf) for different contact classes. The idea is to estimate the pdf for both false alarms and target contacts. A comparison of the pdfs gives an impression about the suitability for class separation of an individual feature. The higher the diversity of both pdfs the more suitable is the corresponding feature. In the ideal case the pdfs are completely separable.

A second method for assessing the performance of an individual feature is the consideration of receiver operating characteristic (ROC) curves. For generating these curves different thresholds are defined in the range of the minimum and maximum feature values and then compared with each feature value. If a feature value exceeds the threshold (or falls below, depending on the considered feature) the contact is classified as target contact. In the reverse case, i.e. the feature value falls below (or exceeds) the threshold the contact is classified as false alarm. For the target contacts this results in the true positive rate which indicates the relative number of correctly classified target contacts and for the false alarms it results in the false positive rate which indicates the relative number of false alarms classified as target contact. Ideally, the true positive rate reaches a value of one and a false positive rate of zero simultaneously.

## 4. FEATURE SELECTION AND CLASSIFICATION

For classification two different machine learning algorithms are investigated, on the one hand the AdaBoost algorithm according to [4] and on the other hand the "$k$ nearest neighbour" ($k$ −NN) classifier. Both are "supervised learning classifiers" which require a training dataset.

Within the training process the AdaBoost classifier iteratively extracts the most suitable features. In each iteration, that feature which leads to the smallest possible false positive rate and holds simultaneously a demanded minimal true positive rate is selected and represents a binary "weak" classifier. A cascaded sequence of the "weak" classifiers ends up in one "strong" classifier. In this way the most relevant features of the training dataset are selected automatically.

The $k$ −NN classifier is a simple parametric classification algorithm which does not require classical training. The feature space of a training dataset is stored and used as reference for class estimation of new data samples. For each new sample the distance to the $k$ nearest neighbours of the "training feature space" can be calculated by different metrics. In this work the statistical mahalanobis metric is used. In the standard realisation of the $k$ −NN classifier the class of new samples is estimated by a majority decision regarding the classes of the $k$ nearest neighbours. Due to unbalanced datasets a score which indicates the relative number of the class of the nearest neighbours is used for decision making. In contrast to the AdaBoost algorithm the $k$ −NN classifier does not select any features. However, using the whole feature space will lead to high computational costs. Moreover, an oversized feature space could lead to bad classification results. This effect is known as "Curse of Dimensionality" [5], [6]. For these reasons a selection of the most relevant features has to be conducted before applying the classifier. This is done by the wrapper-method sequential forward feature selection (SFFS), introduced in [7]. As a first step the classifier is trained with each feature itself and then the feature which performs best is added to the empty feature subspace. In the following iterations the remaining features are combined with the features in the feature subspace and that feature which leads to the best performance is added to the feature subspace and so on. For each combination of features the area under the ROC curve (AUC) is used as measure for its performance. When the AUC does not increase anymore the optimal feature subspace is found.

## 5. DATASETS

In this work two similar datasets from a diver detection trial are considered. In both datasets the target was a diver equipped with a closed circuit breathing system. The diver moves away from the sonar, turns and approaches the sonar. The tracking results for the second part of one run in which the diver approaches the sonar is shown in Figure 3. The position of the sonar is marked with the green star. It can be seen that a track on the diver is available for the whole considered section. Moreover, there are some tracks which do not belong to any target.

For generating the feature space it is necessary to figure out which contacts are caused by the diver. Therefore, the target track is considered to be the ground truth. Each contact which appears in the surrounded area of the track position of the diver is assumed to be a diver contact. All other contacts are assumed to be false alarms. For the first dataset (in the following named as “Run01”) 252 diver contacts and 28660 false alarms are extracted. In the second dataset (in the following named as “Run02”) the speed of the diver was slightly lower resulting in more transmissions and hence in more contacts. In total 320 diver contacts and 49910 false alarms are extracted.

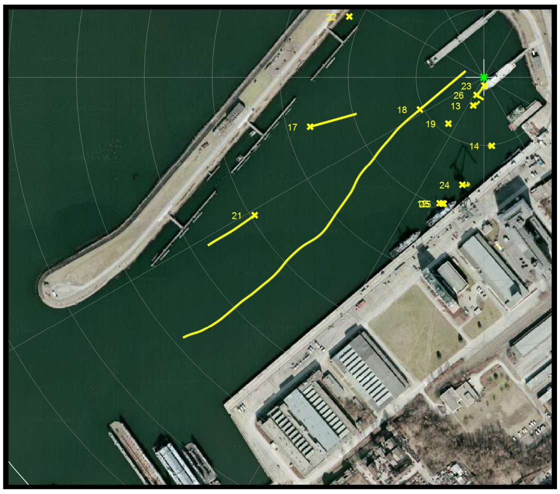


*Figure 3: Tracking results for a section of one observed dataset.*

## 6. EXPERIMENTAL RESULTS

In this chapter the results of the individual feature analyses and the contact classification are presented. In this work in total 54 features of the contacts are extracted (see Table 1). In the standard signal processing the probability of detection and the false alarm rate depend only on the detection threshold. An increased threshold leads to a lower false alarm rate but also to a lower probability of detection and vice versa. Therefore, the “Contact SNR” can be regarded as reference feature which represents the standard signal processing.

## A. INDIVIDUAL FEATURE ANALYSIS

As described in Chapter 3 the performance of the individual features is analysed by their pdfs and ROC curves. For dataset “Run01” two examples for the results of the individual analyses are given in Figure 4. On the left-hand side the pdf for the feature “Contact SNR” is illustrated for the classes “diver contacts” and “false alarms”. This evaluation shows that a complete separation of false alarms and diver contacts cannot be achieved. However, it can be seen that it is more reliable that a contact with a small SNR is a false alarm and contacts with an increased SNR are more often diver contacts. This indicates that the feature contains relevant information for class separation.

On the right-hand side of Figure 4 the ROC curves for the features “Contact SNR” and “Extent in Range” are displayed. Again, it is visible that the “Contact SNR” is useful for class separation. The ROC curve represents the performance for different detection thresholds. By increasing the detection threshold the false positive rate can be reduced by e.g. 80% while the true positive rate decreases only by 20%. A similar performance is given for the “Extent in Range”. Both ROC curves illustrate that the individual features are very useful for classification.

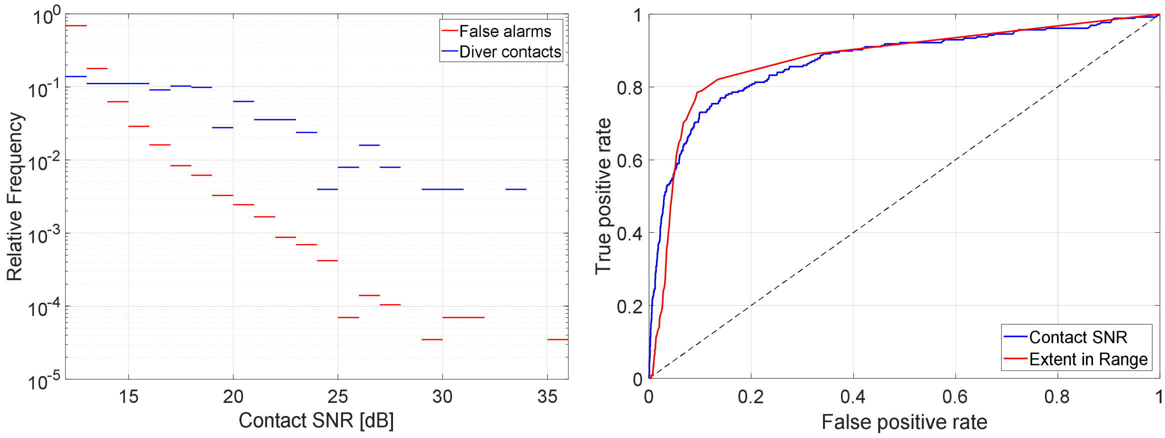


*Figure 4: Two examples for the results of the individual feature analyses (left: pdf for the “Contact SNR”, right: ROC curves for the “Contact SNR” and “Extent in Range”).*

## B. FEATURE SELECTION AND CLASSIFICATION

The results of the SFFS with the $k$ −NN classifier applied to dataset “Run01” are shown in the upper plot of Figure 5. The number of neighbours was experimentally verified and chosen to $k = 200$. It is visible that the AUC is nearly constant after 16 iterations (combination of 16 features) and starts decreasing after 28 iterations due to the “Curse of Dimensionality”. This means, that many features contain redundant information and therefore the feature space for the $k$ −NN classifier is reduced to a combination of these 16 features. All categories listed in Table 1 are represented in this set of features.

The AdaBoost classifier selected 21 of the 54 features. Nine of these features are also selected by the SFFS for the $k$ −NN classifier. This means, the feature space that is used by both classifiers is not the same.

Both classifiers are trained with dataset “Run01” and applied to dataset “Run02” in order to investigate their performance. The classification results for both classifiers are illustrated by the ROC curves in the bottom plot of Figure 5. It can be seen that both classifiers lead to similar performances. In comparison to the standard signal processing (ROC curve for the “Contact SNR”) the false positive rate can be reduced by ~87% (from 0.6 to 0.08) for a constant true positive rate of 0.95.

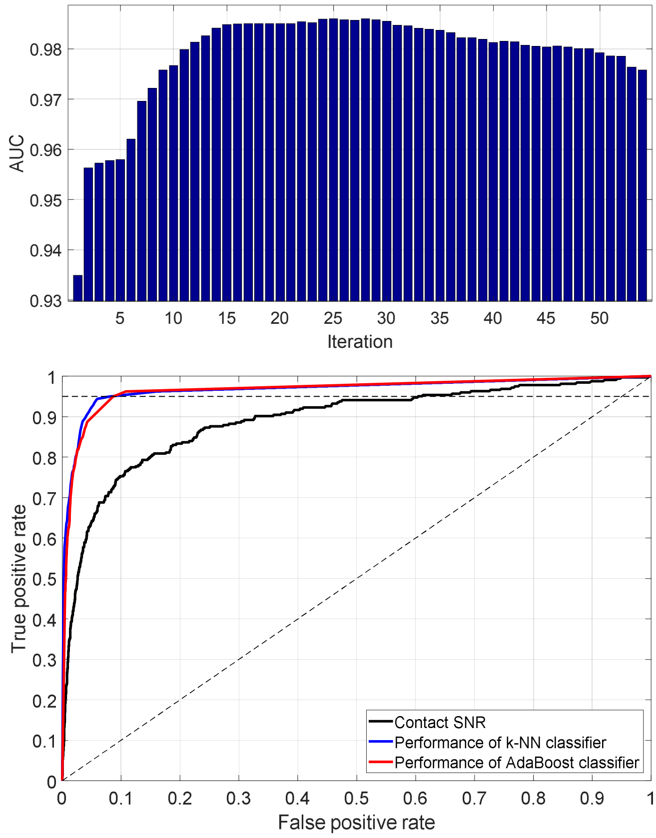


*Figure 5: Results of the SFFS (above) and classification with the k-NN and AdaBoost classifier in comparison to the performance of the "Contact SNR" (below).*

Figure 6 shows the contacts before and after contact classification in the detection display to get an impression of the impact of the false alarm reduction. False alarms are displayed by yellow and diver contacts by red dots. The left-hand side of Figure 6 shows all contacts of a section of 35 pings of "Run02" before classification. In total there are 35 diver contacts and 5905 false alarms. On the right-hand side the contacts after classification with the AdaBoost classifier (at a true positive rate of 0.95 and a false positive rate of 0.08) are shown. After classification 34 diver contacts (97%) and only 396 false alarms (7%) are remaining. Due to this significantly reduced false alarm rate it is much easier for the sonar operator and the tracking algorithm to identify real targets.

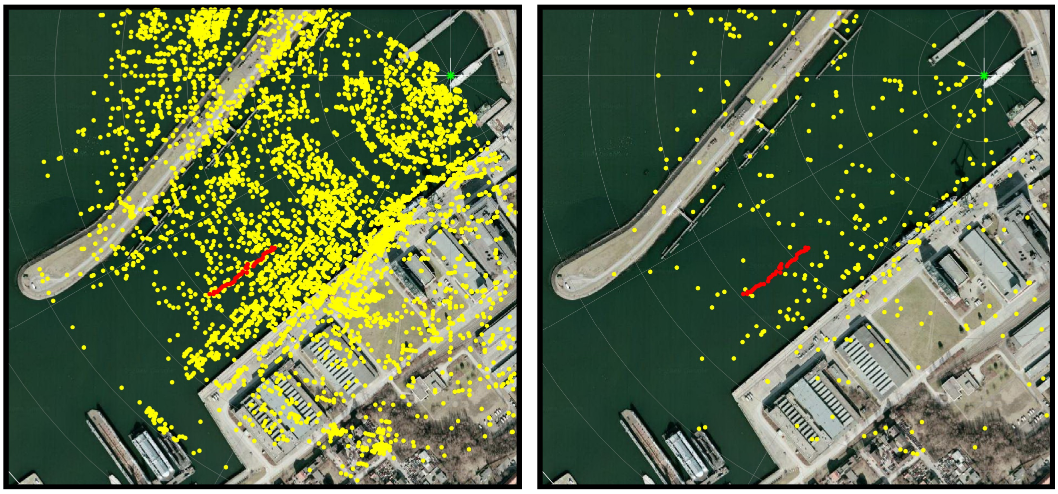

*Figure 6: Detection display for 35 pings of "Run02" before (left) and after classification (right). The red dots show the diver contacts and the yellow dots the false alarms.*

## 7. CONCLUSIONS

This work proposes a method for false alarm reduction in active sonar applications. In a first step several features of the contacts are extracted. Furthermore, two methods for analysing the suitability of individual features for class separation are introduced. By means of these methods it is shown for two features, the “Contact SNR” and the “Extent in Range”, that they are suitable for separating diver contacts and false alarms. Since the features contain redundant information it is necessary to select the best subset of features for classification. For the $k$ −NN classifier this is done by means of the sequential forward feature selection (SFFS) whereas the AdaBoost classifier automatically selects the best subset while training. It turned out that the classification performance is similar for both classifiers. The number of false alarms can be significantly reduced which results in a much clearer detection display. Furthermore, the low false alarm rate leads to an improved tracking performance.

In future work it will be investigated if the classification performance can be further increased by the use of additional features from the tracking such as the estimated speed or trajectory. Moreover, further feature selection methods as well as classification algorithms will be analysed and compared with the methods described in this work.

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