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Automatic Target Detection in Swath-Sonar Images, Using Texture Based Unsupervised Classification and Blind Source Deconvolution

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Abstract: In the present paper a methodological scheme bringing together common Acoustic Classification Systems (ACS) and a promising data decomposition approach, called Independent Component Analysis (ICA), is demonstrated regarding its suitability for detecting small targets in Side Scan Sonar imageries. Traditional ACS extract numerous texture descriptors leading to a large feature vector, the dimensionality of which is reduced by means of data decomposition techniques, usually Principal Component Analysis (PCA), prior to unsupervised classification. However, in the target detection issue, data decomposition should point towards finding components that represent sub-ordinary image anomalies (i.e. small targets) rather than dominant information. ICA has long been proved to be suitable for separating targets from background and this study represents a fair exhibition of its applicability on SSS images. The present study attempts to build a fully automated target detection approach that combines feature extraction, ICA and unsupervised classification. The suitability of the proposed approach has been validated by comparing its performance to the equivalent of common ACS approaches, using a large data-set of ground-truthed targets in real SSS imagery. The method exhibited unquestionable superiority indicating that ICA may worth further attention by ATD system researchers and developers.

Keywords: side-scan sonar; target detection; image texture independent component analysis

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1. Introduction

Although in the field of Underwater Acoustic Imaging a large number Automatic Target Detection (ATD) systems have long been developed and their bibliography has been classified [1,2], the present study aims to test the potentiality of using common and widely used feature based image classification approaches against small targets detection in SideScan Sonar (SSS) images by combining them with powerful data mining techniques. Conventional Acoustic Classification Systems (ACS) start by extracting numerous texture descriptors from distinct image neighbourhoods throughout the image and forming large Feature Vectors (FVs). In view of the FVs' high dimensionality, prior to unsupervised classification, a component analysis technique, usually Principal Component Analysis (PCA), is performed to decompose them into a few un-correlated features that explain the majority of the image's variance. However, small targets belong to subordinary image information and do not contribute significantly to the total information variance of the SSS image. Furthermore targets tend to be independent image characteristics rather than un-correlated ones. In this study, a newly available technique, called Independent Component Analysis (ICA), that decomposes the FVs into independent sources, is tested against its ability to separate SSS images into targets and background and lead to accurate target classification.

The proposed methodological scheme consists of the following stages: 1) windowed feature extraction, 2) ICA decomposition, 3) selection of certain components that enhance potential targets through a maximum curtosis criterion, 4) decision of the number of classes that the selected components need to be clustered into so that they are optimally separated in the Euclidean space through validation indices utilization, 5) unsupervised classification and 6) selection of the class or classes that most possibly correspond to areas containing potential targets via a minimum area definition. The above stages are included in the SonarClassMatlab ACS [3]. The classification precision of the proposed system was assessed using a SSS dataset from Igoumenitsa Harbour, Greece, including more than 85 ground truthed man made targets. The classification accuracy of the proposed system was estimated as Pc=tp/(tp+fp), where tp is the number of true positive (expected) and fp the number of false positive (unexpected) predictions, and was compared to the accuracy of following conventional ACS procedures. The method exhibited unquestionable superiority indicating that ICA may worth further attention by ATD system researchers and developers.

2. Feature Extraction

SonarClass utilizes three feature extraction algorithms, namely first order grey-level statistics, Grey Level Co-occurrence Matrices (GLCMs) and 2D power spectrum specifications, leading to a total number of 11 texture descriptives (FVs). The first order statistics provide information about the variability of grey-levels inside each image window and the following 4 features are considered: 1) Grey Mean, 2) Standard Deviation and 3) Kurtosis which are elementary statistics that describe the reflectivity intenseness, contrast and the difference between the targets grey levels distribution from the normal (Gaussian) one respectively and 4) the 3rd order Invariant Moment which is a measure based on central moments that is invariant to translation, rotation and scale changes of the image [11].

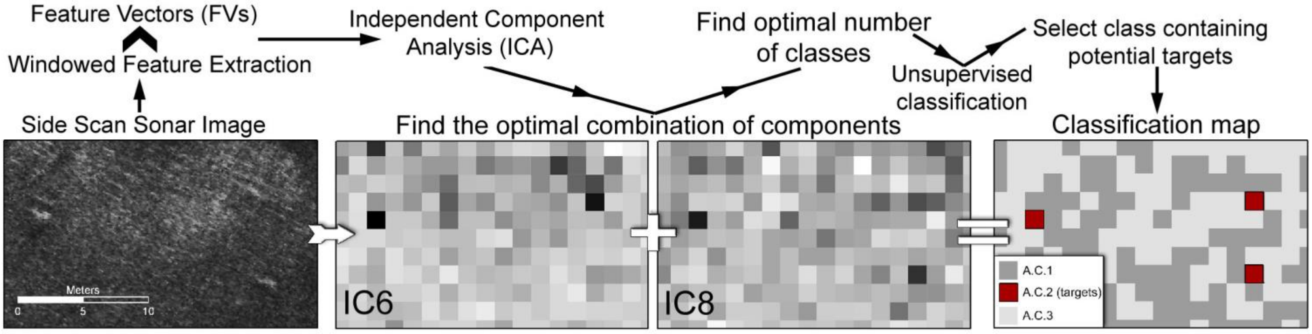
Due to the highly textured appearance of sonar images, texture analysis techniques become natural choices for sidescan sonar image analysis. GLCMs are among the methodologies that have mostly been used for textural analysis and image classification. Statistics over GLCMs are very powerful texture descriptors and are used in many software applications for swath sonar image classification such as the TexAn [2] and the QTC SIDEVIEW TM [12]. SonarClass software calculates 5 GLCM properties out of the 11 that Haralick [9] first described namely: 1) Contrast, 2) Correlation, 3) Energy, 4) Entropy and 5) Homogeneity.

The 2D Fourier spectrum descriptives are 1) Directionality and 2) texture spacing. They are based on [1] approach according to which the power spectrum of a square image is expressed in a polar coordinate system [$S(r,\theta)$] of radius r versus angle θ and decompressed into two independent one-dimensional functions of r [$Sr(\theta)$] and θ [$S\theta(r)$]. Peaks in the $Sr(\theta)$ mean directional texture while peaks in the $S\theta(r)$ mean periodical texture. Analyzing $Sr(\theta)$ and $S\theta(r)$ for a fixed value of r and θ yields the behaviour of the spectrum along a circle centred on its origin or a cross section passing through its origin. Fakiris and Papatheodorou [5] suggested a simplified computational approach for Bajcsy and Lieberman descriptors for the needs of the SonarClass.

In the case of the proposed methodological scheme where the detection of potential targets in SSS images is considered, the image windows the features are extracted from must have dimensions that equal the maximum expected ones of the targets to be detected. They should also be sliding, with an offset half the size of the image window, to ensure that the biggest portion of any target will be included in just a single image window.

Important key features of SonarClass are that: (i) the combination of parameters that provide the highest between-classes discrimination power is automatically identified through an iterative optimization procedure that makes use of cluster validation indexes and a set of training samples and (ii) the offset (d) and theta (θ) parameters, that greatly control the GLCM efficiency, are automatically calibrated through the same optimization procedure [5]. For the needs of the proposed approach the calibration stage is optional and might be used to find the optimal d and θ GLCM parameters, in the case that a training set of ground-truthed SSS image targets exist.

Figure 1. Overview of the proposed methodological scheme for automatic target detection in SSS imageries using feature based acoustic classification and ICA. IC6 and IC8 correspond to the 6th and 8th Independent Components of the FVs.



3. Independent Component Analysis

The purpose of using a component analysis technique is to transform the high-dimensional FVs into low-dimensional components so that the difference between the targets and the background becomes maximized. PCA is an ordinary feature reduction method in ACS [12]. It decorrelates the FVs so that all the features' information can be projected into a few (usually 3) components and reduce data quantity. However, small targets might not show up from the surrounding background of the highest variance after conventional PCA processing, as they belong to subordinary information. A probable solution would be to find which principal component or combination of components (out of the 11 available ones in our case) correspond to the contribution of the targets to the FVs' variance. Normally these principal components will be the ones contributing in the smallest amount to the total variance of the feature space.

A more sophisticated multivariate data analysis method (also referred as project pursuit or blind source separation technique), is the ICA. ICA assumes that the observed multivariate data, typically given as a large database of samples, are linear or non-linear mixtures of some unknown non-gaussian and mutually independent latent variables, called independent components, that are attempted to be determined. ICA can be seen as an extension of PCA and Factor Analysis (FA) but it is a much richer technique, capable of finding the sources of data variability when these classical methods fail completely. ICA has been successfully used in a variety of studies for target detection in hyperspectral imagery [3,15]. Its potentiality lies in the fact that small targets in a natural background can be seen as independent anomalies in the image scene and so they are included in one or a couple of independent components in the ICA model.

However there is still the problem of the automatic selection of the independent components that reflect the targets' contribution to the FVs. An ordinary practice to determine the optimal components for target detection is to rank them according to their kurtosis and use the ones with the higher values [15]. Kurtosis value of the components that emphasize targets shall be far larger than that of components reflecting larger scale seafloor characteristics (e.g. seafloor dynamics, morphology or sedimentology). The hierarchical cluster analysis (using correlation coefficient) and dendrogram interpretation is proposed as an additional way to have further insight into the interrelation of the generated components, toward judging which components are the proper ones in the context of target detection (Fig.2).

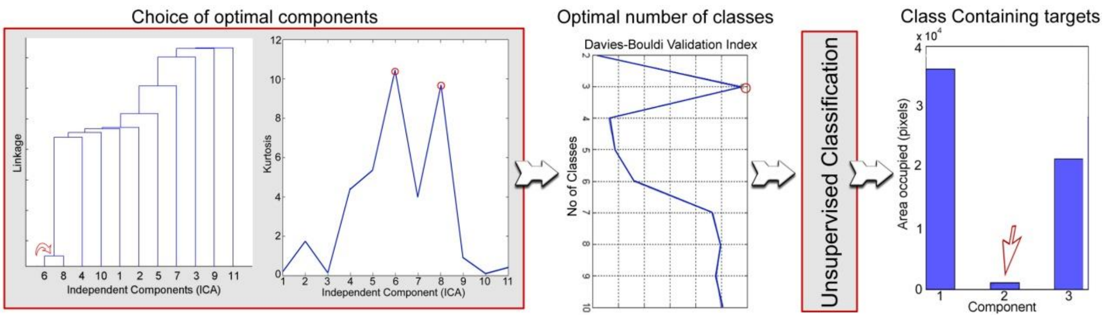
4. Unsupervised Classification Of Potential Targets

After the components highlighting the targets' contribution to the FVs have been determined, unsupervised classification is performed so that the reduced feature space is partitioned in meaningful clusters. Although simple thresholding techniques could be able to detect the targets, using unsupervised classification is more robust especially when more than one components have been selected. After ICA, generating just a few clusters should be enough to ensure that at least one of them will correspond to areas that include potential targets. SonarClass ACS software provides a large list of available unsupervised classification algorithms, including Gaussian Mixture Models (Bayesian), k-means, k-medoids, Fuzzy C-means, Fuzzy Gustafson-Kessel and Fuzzy Gath-Geva classifiers.

Bayesian and k-means classifier are the ones more often used is ACSs [12,14] owing to that the former has a statistical background that allows the calculation of posterior probabilities for each class and the latter is the least computationally expensive one.

A main drawback of unsupervised classification is that the number of classes must be a-priori determined manually. This can lead to overestimation or underestimation of the number of clusters with the former being the preferred case which is then combined with a cluster rejection-merging procedure. However, the use of cluster validation indexes that quantify the discrimination of the specified data clusters in the Euclidean space is a common practice among statisticians towards determining the optimal number of classes [4]. Specifically, the FVs are repetitively clustered (using a certain classificator) by sequentially increasing the number of clusters, then the validation index is estimated for each attempt and finally the number of clusters providing the maximum discrimination between the clusters is determined (Fig. 2). Although many cluster validation indexes are available in SonarClass software, the Davies-Bouldi index is proposed due to its computational speed and effectiveness.

Figure 2. Details of the proposed automatic target detection system that concern: a) choosing the optimal combination of components, b) choosing the optimal number of classes and c) selecting the class that most probably correspond to seafloor targets.



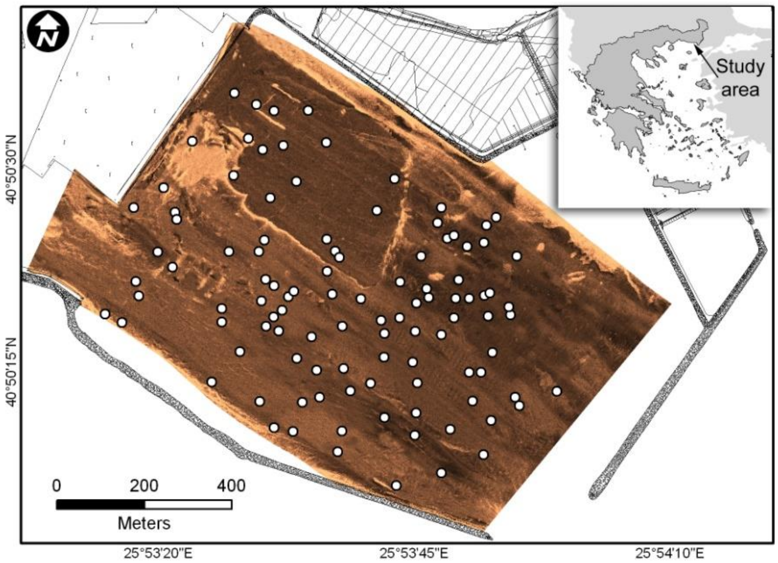
After the FVs have been clustered into the specified number of acoustic classes, the question is which class or classes refer to image windows containing potential targets. An obvious solution would be to visualize their spatial distribution in conjunction to the SSS imagery and visually judge which ones do correspond to image windows with targets, but this does not conform to the aspect of completely automated detection of potential targets. Tian [14] performed hierarchical analysis to the posterior probabilities of the generated classes in order to detect the most uncorrelated ones and associate them to SSS targets (coral reefs in that case). The proposed methodology does no restriction to exclusively use Bayesian classifiers and thus the above approach is not always feasible. Instead, the following approach is proposed as an alternative: the class occupying the least area (smallest number of raster cells) in the sonar image can be safely considered as the "potential targets" class (Fig. 2). Besides, visualizing the frequency of raster cells for each class towards judging which classes are meaningful and which should be merged with others or ignored is a widely documented practice [10].

5. Validation Of The Proposed System

The validation of the proposed system was performed by examining its performance to accurately detect numerous ground-truthed SSS targets and by comparing it to other common feature based acoustic classification procedures. The dataset that has been used for the validation of the proposed system was collected from the Igoumenitsa's Harbour, NE Greece (Fig. 3) and consists of 7 geo-referenced and geometrically corrected SSS images of 7 cm pixel sizing and the locations of 85 targets. These targets had first been visually detected in the SSS imagery and they were then ground-truthed, ensuring that all visually detectable targets are indeed man-made targets. The feature based acoustic classification schemes followed to classify the available SSS data are presented in Table 1. The accuracy rate for each experiment was estimated on the basis of comparing the number of occurrences between the areas classified as "potential targets" and the ground truthed targets (GT). The amount of the classified potential targets that do not eventually correspond to a real target is also provided as an indicator of the misclassification rate (NGT).

In general, the validation results in Table 1 show that the proposed methodological scheme (6th) outperformed the others as it has the higher GT and the minimum NGT. Additionally, by using ICA, the targets' information is concentrated in just a couple of independent components that need no more than 3 classes to be optimally separated in the Euclidean space.

Figure 3. Map showing theIgoumenitsa's harbour, NE Greece, whose SSS imagery has been used for the validation of the proposed automatic target detection system. Visually detected and ground-truthed targets are indicated with white circles..

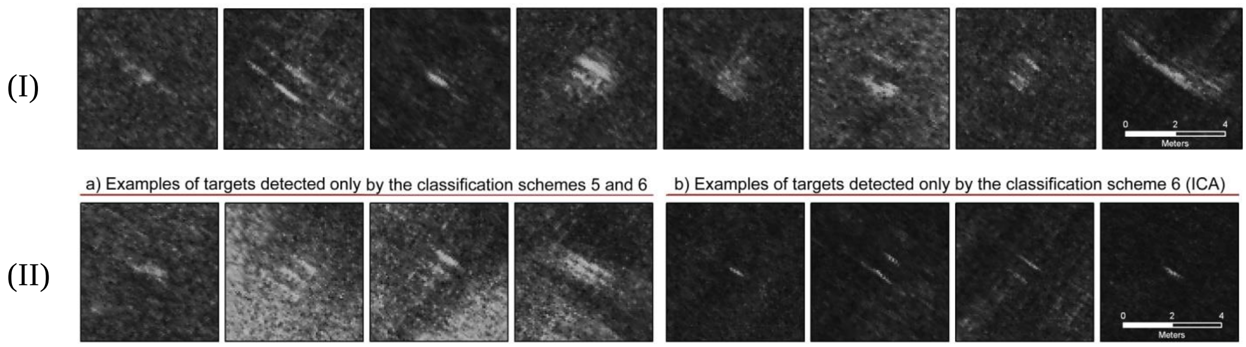


Classification scheme 1 consists of feature selection and calibration using the SonarClass's dedicated module (see section 2) and supervised classification using image samples from a set of randomly selected ground-truthed targets. It exhibits low GT and low NGT, indicating that although supervised classification can lead to relatively few misclassifications, only those targets that have almost the same characteristics as the training set are going to be detected. Schemes 2 and 3 indicate that unsupervised classification without a preceding data decomposition/reduction stage, leads to the requirement of a large number of classes to be considered, which in turn reduces the system's accuracy and robustness.

Table 1. Details and accuracy statistics for the 6 classification procedures considered for the validation of the proposed target detection system. The scheme 6 corresponds to the proposed approach utilizing ICA and component selection prior to classification. GT is the amount of the ground-truthed targets that were detected by the system (true positives) while the NGT is the amount of classified regions that were not related to a ground-truthed target (false positives).

	Acoustic Classification schemes (details)					Accuracy statistics	
	Features Used	Reduction Method	Components considered	Classifier	No of Classes	GT	NGT
1	Corr, Std	-	-	Discriminant	-	**28%**	**33%**
2	Corr, Std	-	-	Bayessian	6	**56%**	**67%**
3	All	-	-	K-means	10	**62%**	**65%**
4	All	PCA	1,2,3	Bayessian	9	**54%**	**70%**
5	All	PCA	8,11	Bayessian	8	**72%**	**51%**
6	All	ICA	6,8	Bayessian	3	**77%**	**13%**

Figure 4. Examples of ground -truthed SSS targets used for the validation of the proposed methodology, that were detected (I) by all the available classification schemes (see Table 1) and II) by (a) only the 5th and 6th classification schemes or b) exclusively the proposed.



The 4th scheme reflects the most widely used procedure in the literature that includes PCA to reduce the FVs to the 3 major principal components and unsupervised classification. This scheme performed even worse than the 2nd and 3rd ones, confirming that targets are subordinary image information that cannot be captured in the first few components using PCA. However, the 5th approach that concerns PCA instead of ICA in the proposed approach is the second more successful one, giving adequate results and indicating that appropriate component selection is essential after any kind of component analysis towards successful target detection. Fig 4 shows that although many targets lying on a uniform background were detected by all the tested approaches, the detection of targets lying on a background with higher variability was only feasible by the ones concerning component analysis coupled with component selection while very small targets were exclusively detected by the proposed scheme that makes use of ICA.

4. Conclusions

In this paper, an attempt to detect targets in SSS imagery by coupling traditional feature based ACS and Independent Component Analysis has been presented and validated. The core of the implemented system consists of the SonarClass ACS and a well validated approach in anomaly detection and blind source separation studies, called ICA. ICA is a powerful data decomposition technique able to separate the image information into anomalies (i.e. targets) and background. An efficient technique based on the kurtosis of the independent components is proposed so that only those independent components that emphasize targets are used, leading to more accurate and unbiased classification results. The validation of the proposed approach was conducted on the basis of comparing its effectiveness to detect numerous ground truthed targets against other more common approaches in ACS. The proposed methodological scheme outperformed all other approaches and although coupling PCA with the same component selection criterion has also proved to be a satisfactory approach, the superiority of utilizing ICA is still evident. Despite methodological and computational improvements that the presented system may need, it represents a fair demonstration of using ICA towards the extraction of targets from SSS images and it signifies that it may worth further attention by ATR system researchers and developers.

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Conflicts of Interest

The author declare no conflict of interest”.

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