

# Echo System: machine learning methods for classification of sonar targets

N. Amoroso<sup>1,2</sup>, L. Bellantuono<sup>1</sup>, A. Monaco<sup>2</sup>, M. Ricci<sup>3</sup>, P. Pesaresi<sup>4</sup>, M. Camilli<sup>4</sup>, V. Aprile<sup>4</sup> and R. Bellotti<sup>1,2</sup>

<sup>1</sup>Dipartimento Interateneo di Fisica “M. Merlin”, Università degli Studi di Bari “A. Moro”, I-70126 Bari, Italy

<sup>2</sup>Istituto Nazionale di Fisica Nucleare, Sezione di Bari, I-70126 Bari, Italy

<sup>3</sup>Direzione degli Armamenti Navali NAVARM, I-00175 Roma, Italy

<sup>4</sup>Engineering Ingegneria Informatica, I-00144 Roma, Italy

**Abstract** — ECHO System meets the need to acquire a technology to support the classification of marine self-propelled vehicles. The result of this project will be a prototypical platform for decision support, based on quantitative predictive models and algorithms, able to process audio tracks acquired in an underwater environment and perform the classification of objects.

## 1 Purpose

The ambition of the project is to realize a system which will be able to support the human operator in the classification of the acoustic signals in families (submarines, military vessels and cargo vessels) and deeper in the respective subsets of classes and subclasses.

## 2 Introduction

The acoustic signals detected by passive sonars are typically affected by such noise and distortion effects, that hinder the accurate classification of the acoustic target.

The problem can be solved supporting the human operator with a machine learning algorithm performing an accurate classification. Echo System is based on machine learning algorithms, that automatically learn the properties of audio tracks whose family is known a priori, and subsequently use such information to classify new signals.

## 3 Approach

The software includes a module that extracts a set of features from each track, following a multilevel approach, which exploits both local and global properties, passing through progressive generalizations.

In the first level of analysis, the signal is fractioned in time windows, and the algorithm computes 33 physical quantities, called short-term features (STFs) related to each window. The statistical distribution of each STF provides a useful insight about the signal.

The second level of analysis associates 10 statistical moments to the distribution of each of the 33 STFs: in this way, 330 mid-term features (MTFs) are obtained for each track. These quantities are used to train the classifier, such that it identifies reliable criteria to assign each observation to one of the three families, using the typical values of discriminating features.

To estimate the classification performance on unseen tracks, a cross-validation analysis follows the feature extraction step. Accordingly, the available database is randomly divided so that 80% of the tracks (training set) is used to train the algorithm, and the remaining 20% (test set) is used to evaluate its accuracy, namely the percentage of correctly classified tracks. This operation is repeated 500 times, to obtain performances not depending on the specific train and test set.

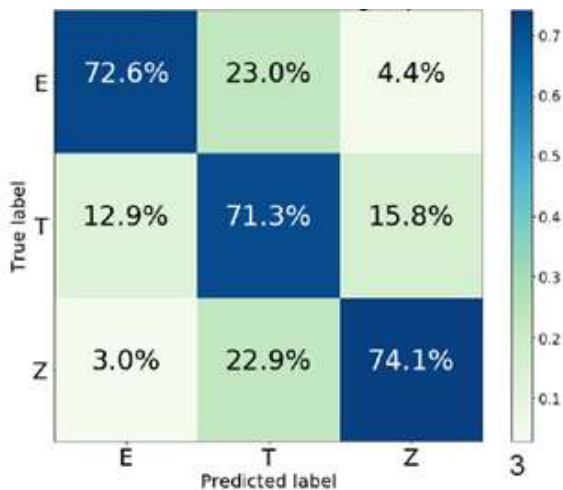
A Random Forest with 1000 decision trees was used, this choice being motivated by specific analysis performed during the design phase. Two specific optimizations were performed: (i) the first one addressed the problem of inhomogeneity of the available dataset; (ii) the second one reduced the number of false positives: to focus on this issue we have studied the effects of a threshold on the confidence level of the classification output.

## 4 Results and discussion

The developed algorithm, improved through this configuration, provides classification performance balanced on the three families, with accuracies exceeding 70%. The employment of this automatic system can significantly help the human operator contributing to reduce decision times and errors.

A machine learning tool that can be used to show the performance of the classification algorithm is the confusion matrix: a table in which rows and columns correspond, respectively, to the actual labels of the input instances and to the predictions provided by the model. In particular, the element located on line  $i$  and on column  $j$  of the confusion matrix represents the number of cases in which the algorithm has classified with the label  $j$  an object of type  $i$ . The elements on the main diagonal ( $i = j$ ) identify the correctly classified instances, while the other matrix entries identify the different circumstances in which the model has provided erroneous outputs. The confusion

matrix is so called because it yields a synthetic representation explaining which were the most common errors and the most “confused” categories.



**Fig. 1** Combined normalized confusion matrix for families using a probability threshold

The results obtained with different configurations of the classifiers have shown a satisfying robustness and accuracy of the classification performance.

To appreciate the goodness of the obtained results, it is worth noting that the baseline value (random classification) of a three-class classifier is 33% accuracy per class, while for a two-class classifier is 50% (essentially the probability that it comes out head or cross in tossing a fair coin).

## 5 Lessons learned and Conclusions

A lesson we learned is the importance that each audio track, classified by the algorithm under test, is associated with a level of confidence providing a measure of how reliable a prediction should be considered. A way to increase the performance of the algorithms, by lowering the probability of error, is to put a threshold on the confidence level provided by the classifier. In this way, for all those events whose confidence level is lower than the established threshold, the classifier will warn the operator, thus reducing the possibility of a classification error.

The classifier stability made it possible to minimize the decision error on the analysed families. To investigate the subsequent levels (classes and subclasses) is fundamental to design a multi-layer classification; besides, a confidence level has to be measured for each layer, giving the operator the possibility to accept/reject the classification according to his own experience, thus obtaining the most effective gain from this decision support system. With this goal, novel features extracted from the signal have to be investigated. Specifically, this feature extraction has to be performed on the most informative temporal portion of the signal, e.g. around the minimum distance point.

## Future Work

Future work will not only concern with the classification algorithms, but also with the realization of the software and hardware platform, its testing and validation.

Next steps are:

- design and technological implementation of the platform. It will lead to the following actions: (i) implementation of the algorithms, (ii) definition of technical and architectural specifications for both the hardware and software components, (iii) implementation of the software modules and their deployment. This step is ongoing and is expected to end in June 2020;
- testing and validation in *in vitro* and real environments, leading to the release of a working prototype. This step is expected to last 10 months.

## Author/Speaker Biographies

**Nicola Amoroso** graduated cum laude in Physics at the University of Bari, Italy in 2010 and obtained his PhD in Applied Physics. He is a researcher at the university. His research activities includes over 30 publications. He collaborated with the United Nations (UN) for the development and statistical assessment of the e-Government Development Index (EGDI). **Loredana Bellantuono** is a PostDoc fellow in Applied Physics at the University of Bari, working currently on the application of machine learning techniques to audio signal analysis and classification. She obtained a PhD in Theoretical High-Energy Physics in 2017. She spent a period as a visiting scientist at the Jagiellonian University in Krakow. Her research activity already includes 12 papers. **Lt Cdr Marina Ricci** is an Italian Navy Officer. She graduated in Telecommunication Engineering at the Naval Academy in April 2008. She is specialized in Mines and Mine Counter Measures and Underwater Electroacoustics. Since September 2014 she is working at the Italian Naval Armament Directorate in Rome in the Underwater Systems Division.