An Autonomous Imaging System for Argo Floats

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Abstract **– The Argo Float programme is a valuable instrument for monitoring the deep sea at global scale in space and time. Argo Floats equipped with imaging devices are candidate to become a new monitoring tool for studying macro- and mega- fauna in large areas and for extended periods, potentially providing monitoring results never attained before.**

I. INTRODUCTION

The Deep-Sea (>200 m depth) encompasses 95% of the ocean volume being largely unexplored and presenting important challenges for a highly science-based management of services [1]. Presently, networks of multi-parametric cabled observatories are effective tools for acquiring physical and bio-chemical information about the deep sea, for extended periods of time [2].
In such a technological development, video/image acquisition devices are shedding new light on ecosystems exploration and monitoring, disclosing important data on species behaviour and spatio-temporal variation of richness and evenness [3]. Nevertheless, the monitoring action is strictly limited to the seabed and in particular to the area surrounding the observatory itself, thus limiting the acquisition of information to small areas of interest.
In contrast, the Argo Float Programme in the last 15 years collected almost 1.5 millions of water column profiles down to 2000m depth all over the World Oceans [4] and at present more than 3800 floats are monitoring the deep sea, as shown in Fig. 1. Traditionally, the Argo Float profilers are equipped with instruments for the measurement of physical quantities like temperature, water conductibility and salinity. Recently new devices have been designed and experimented for the acquisition of ecological data as for example the chlorophyll and dissolved oxygen [4].
Despite of these new technological advances, very few attempts have been made for equipping the Argo Floats profilers with imaging devices capable of monitoring high complexity pelagic ecosystem components such as the deep macro- and mega- fauna, whose monitoring is strategic at a global scale being at the core of important services such as fisheries.
Within this context, the GUARD1 imaging device [5]

was appropriately designed to be installed on board the Argo Float profilers for the image acquisition and recognition of the macro- and mega- fauna populating the water column [6][7]. Both the hardware and the software components of the GUARD1 have been tested in several application contexts and experimented on board an ARVOR I vertical profiler and installed on the Acqua
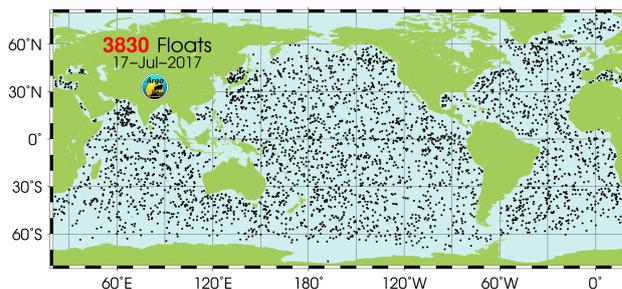

Fig. 1: Spatial distribution of the Argo Floats vertical profilers.

Alta oceanographic tower [8], as described below.

II. THE GUARD1 IMAGING DEVICE

The GUARD1 imaging device, was specifically designed as a stand-alone system capable of automatically process and recognize the content of underwater images. It is equipped with its own lighting system and it is capable to run image processing algorithms for the automate recognition of fishes and macro- and mega- gelatinous zooplankton (i.e. jellies). The relevant content extracted from the acquired images is encoded as textual information and stored on board the system or transmitted through a dedicated communication device. A detailed description of the hardware and software components of the device are presented in [6] [7].
A new image acquisition CMOS-based sensor, controlled by a Field Programmable Gate Array (FPGA), is currently under development with the double goal of (i) sensibly reducing the power consumption and (ii) incorporating image coarse-filters on board the FPGA, in order to automatically discard the not relevant images.

A PICO 96063 SBD Iridium transceiver is under test for transmitting the textual encoding of fishes and jellies abundance time series, extracted by the recognition algorithms. In order to allow the data communication, the GUARD1 was equipped with an iridium antenna appropriately reinforced with resin for resisting to the deep-sea high pressure and with a specifically designed wet/dry sensor for triggering the communication from the sea surface.

Beside the textual information, the GUARD1 can also transmit the acquired images, if appropriately resized and downgraded. For example, Fig. 2 shows two examples of gray level images scaled to 200 x 150 pixels and encoded through the JPEG protocol with quality 10. Fig. 2a) has a size of 610 Bytes, while Fig. 2b) has a size of 789 Bytes. These images need 3 and 4 SBD messages respectively (240 Bytes each) in order to be transmitted.
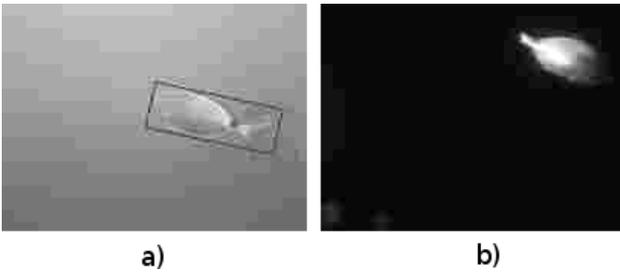

Fig. 2: Two examples of images ready to be transmitted through the SBD Iridium protocol.

III. THE GUARD1 EXPERIMENTED ON BOARD AN ARGO FLOAT

Fig. 3: The GUARD1 Imaging device on board the ARVOR I profiler.

In the performed experiment, the GUARD1 was configured only for acquiring images, without the execution of the recognition algorithms and without performing any communication of data.

The vertical profiler used was an ARVOR-I configured to reach a depth of 300 m. The experiment was performed in 2014, south of Sardinia and lasted for about 3 days, where 3 cycles of 24 hours each were executed by the Float. The GUARD1 was housed into a glass sphere and installed on the Argo Float through specifically designed clamps as shown in Fig. 3.

A total of 4020 images were acquired (one image every 2 min.) and although the majority of them do not contained any relevant subject, five of them contained specimens of jellies. Moreover, three images acquired from the sea surface contained plastic debris.

IV. AUTOMATED IMAGE RECOGNITION

Several experiments were performed for assessing the recognition performance of the algorithms developed for the GUARD1 imaging device as discussed in [7]. Recently, an experiment for testing the acquisition of images along the water column and for testing the performance of the image recognition algorithms were performed at the AcquaAlta oceanographic tower in the gulf of Venice [8].

In these test, images were acquired every 10 minutes from February 1st to May 20th. 2017 and the automated recognition was focused both on fish and ctenophora detection and counting.

The supervised machine learning approach based on the Genetic Programming presented in [7] was used for training a binary classifier that returns 1 if the input region of the analysed image contains a relevant subject (i.e. fishes or ctenophora), 0 otherwise.

Both the training, validation and testing phases were performed in the laboratory and not on board of the imaging device.

A. Automated Fish recognition

During the acquisition period, 12331 image were acquired by the imaging device. The 10% of these images (i.e. 1233 images), were randomly sampled from the whole datset for defining the training and the validation set used for learning the automated fish recognition algorithm.

The validation performance of the image classifier were estimated by computing the average and standard deviation of Accuracy: $ACC = (TP + TN) / (TP + FN + FP + TN)$, the True Positive Rate $TPR = TP / (TP + FN)$ and False Positive Rate $FPR = FP / (FP + TN)$, where TP, FP and TN represent True Positive, False Positive and
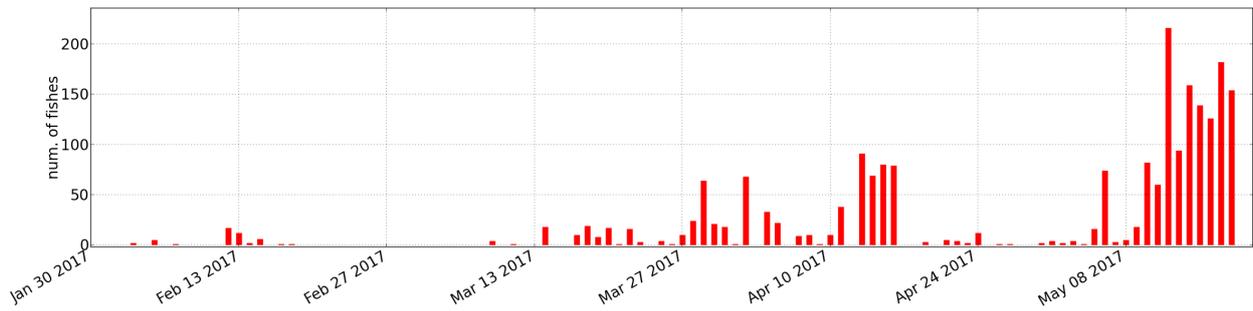
Fig. 4: *Daily fish abundance time series automatically extracted from the automated recognition algorithm.*

True Negative recognitions respectively (Table 1).

Table1. Mean and standard deviations (SD) of of the validation performance indicators. ACC=accuracy; TPR= true positive rate; FPR= false positive rate.

	Mean	SD
ACC	0.94	0.04
TPR	0.95	0.05
FPR	0.07	0.05

The images not involved into the training and validation phase (i.e. 11097 images) were used for testing the learnt automated fish classifier.

Some examples of automated fish recognition obtained during the test phase are shown in Fig. 5, where the red boxes contain the detected relevant subjects.
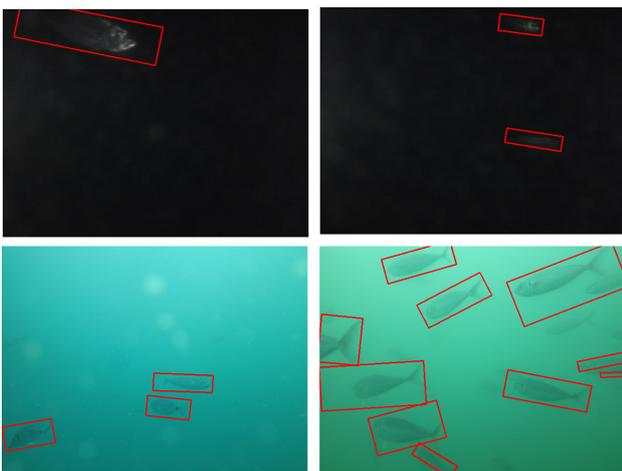

Fig. 5: Some examples of automated fish recognition

The recognition algorithm was then used for the automated extraction of the daily fish abundance time series in the reference period, as shown in Fig. 4.

B. Automated Ctenophora recognition

Tests was also performed for assessing the recognition performance for the ctenophora specimens. The body of these organisms is very transparent and can be correctly detected only if the water turbidity is very low. For this reason the experiment was restricted only to the images acquired in the month of February 2017. These images were used for training, validation and testing of the automated classifier.

Within this period 2688 images were acquired, and after the visual inspection, 145 ctenophora specimens were counted. The visual inspection of the images was performed through the use of an image enhancement tool specifically developed for incrementing the contrast of the ctenophora specimens. The Fig. 6 shows an image containing a ctenophore (left) and the corresponding enhanced image (right).
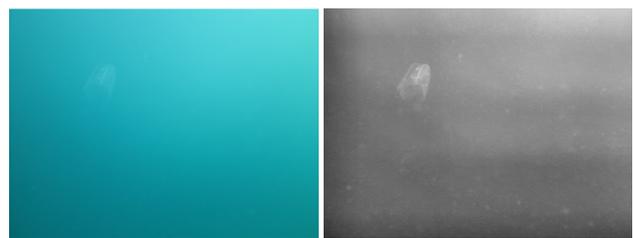

Fig. 6: Example of an image of a ctenophore (left) and the corresponding enhanced image (right).
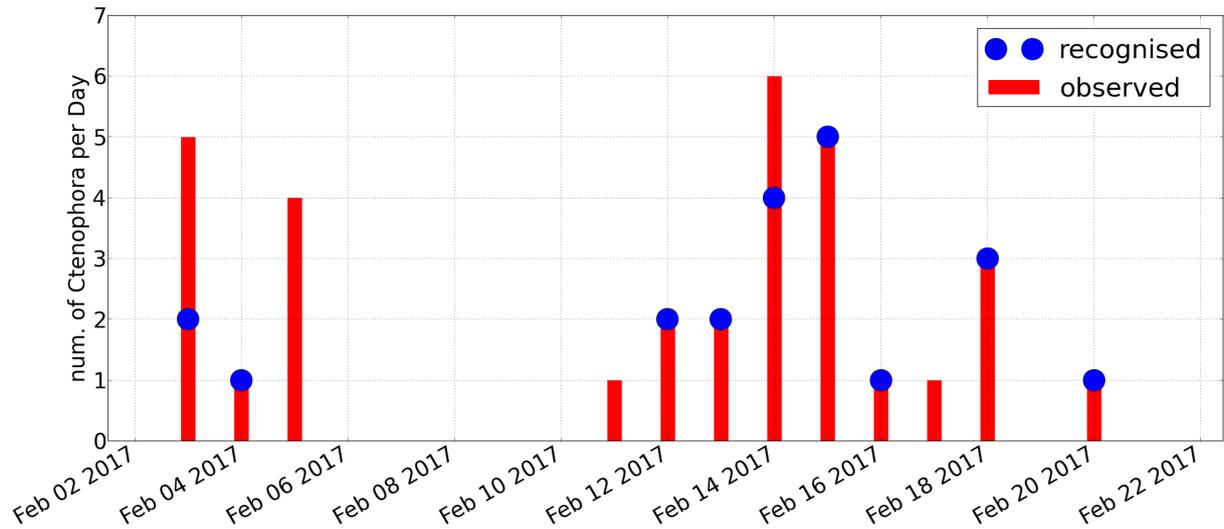
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Fig. 7: Daily abundance time series of ctenophora. Red vertical bars refer to the number of specimens observed through the visual inspection; blue circles refer to the number of automated recognised specimens.

The 50% of the images acquired in the reference period was used for the training and validation phase, the remaining images was used for testing the automated learnt ctenophora classifier. Analogously to the automated fish recognition assessment, the validation performance are shown in Table 2.

Table2. Mean and standard deviations (SD) of the validation performance indicators for the automated ctenophora classifier. ACC=accuracy; TPR= true positive rate; FPR= false positive rate.

	Mean	SD
ACC	0.90	0.06
TPR	0.81	0.2
FPR	0.08	0.07

Also in this case, the automated classifier was used for extracting the daily abundance time series of the ctenopora from the images not used in the training and validation phase, as shown in Fig. 7.
Coherently with the low TPR (and high SD) shown in Table 2, Fig. 7 shows that several specimens were not detected, probably due to their small size and to the very transparent body.

V. CONCLUSIONS

As human impacts and global climate change accelerates, one of the most urgent tasks for the coming decades is the development of technologies for continuously tracking and accurately predicting biological responses, in order to provide solid guidelines for management and conservation. In this context, measuring the deep pelagic biodiversity at different scales in time and space is of strategic importance for the management and conservation of important services. These goals can also be achieved by coupling the global monitoring capabilities of the Argo programme together with the technological advances provided by the Computer Vision and the Pattern Recognition communities, as proposed through the use of imaging devices like the GUARD1. In this case an array of Argo Floats insisting on a specific basin, like for the examples discussed in [9][10], would allow for the study of large areas and for extended periods, potentially providing monitoring results never attained before.

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