A SIFT-based software system for the photo-identification of the Risso's dolphin

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Abstract

Photo-identification is a commonly used and non invasive technique that has been profitably employed in biological studies during the years. It starts from the assumption that a single individual can be recognized in multiple photos captured at different times by exploiting its unique representative and visible physical qualities such as marks, notches or any other definite feature. Hence, photo-identification is performed to infer knowledge about wild species spatial and temporal distributions as well as population dynamics, providing valuable information especially if the species being investigated is ranked as data deficient. Also, the technological improvements of the last decades and the large availability of devices with powerful computing capabilities are driving the research towards a common goal of enriching bio-ecological studies with innovative computer science approaches. In this scenario, computer vision plays a fundamental role because it can successfully assist researchers in the analysis of huge amounts of data. In fact, the aim of this paper is to effectively provide a computer vision approach for the photo-identification of the Risso's dolphin, exploiting specific visual cues with a feature-based approach based on SIFT and SURF feature detectors. The experiments have been conducted on image data acquired in the Gulf of Taranto from 2013 to 2017 performing a comparative analysis of the performance of both SIFT and SURF, as well as a comparison with the state-of-the-art software DARWIN, proving the effectiveness of the proposed approach and suggesting its application to large scale studies.

Keywords: Photo-identification, Cetaceans, Risso, Computer Vision, SIFT Features

1. Introduction

Photo-identification (photo-ID) of single individuals is a non-invasive technique generally applied to investigate spatio-temporal distributions and population dynamics of highly moving wild species. It is based on the general hypothesis that each individual is unique because of several specific physical characteristics and natural marks suitable for its unequivocal discrimination. This technique has been successfully applied in a great array of studies addressing invertebrates (Caci et al., 2013; Frisch & Hobbs, 2007) amphibians (Caorsi et al., 2012; Moya et al., 2015), sharks and rays (Marshall & Pierce, 2012), as well as terrestrial (Anderson et al., 2010) and marine mammals, resulting a promising tool when applied to understand migrations and residency patterns of dolphins and whales (Hastings et al., 2008; Ingram & Rogan, 2002; Falcone et al., 2009; Mizroch et al., 1990). Starting from these considerations, results of a research investigation, carried out by means of photo-ID technique, are reported in this study providing evidence of applicability and information on one of the least-known cetacean species on Mediterranean and global scale: the Risso's dolphin *Grampus griseus* (Cuvier, 1812). Remarkably, in the Mediterranean Sea it is categorised as Data Deficient by IUCN Red List (Gaspari & Natoli, 2012). Up to date, the knowledge about the presence and distribution of *G. griseus* in the Mediterranean Sea is mainly referred to its westernmost regions (Canadas et al., 2005, 2002; Gannier, 2005; Azzellino et al., 2008) and to the Greek area (Azzolin et al., 2010; Frantzis et al., 2003; Frantzis & Herzing, 2002), resulting heterogeneous and lacking in large areas of the Central-eastern basin, where information is limited to stranding data retrieved from the MEDACES database (http://medaces.uv.es/) and the Italian Stranding Network (http://mammiferimarini.unipv.it/) (Bearzi et al., 2011).

Thus, the need of a more comprehensive understanding of its habitat use and spatial-temporal distribution is crucial mostly considering the requirements under the UE Habitat Directive, Marine Strategy Framework Directive (MSFD) and Maritime Spatial Planning Directive (MSPD). Risso's dolphin is well known for its typical long-lasting identifiable natural marks, which include patterns of scarring, distinctive nicks and variations in dorsal fin shape (Bearzi et al., 2011; de Boer et al., 2013; Mariani et al., 2016). In fact, the body of an adult individual has a base colour of grey with white scars, which increase with age, to the

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point that oldest individuals can appear almost completely white (Bearzi et al., 2011; de Boer et al., 2013). These unique characteristics that allow the individual recognition of Risso's dolphins, could make photo-ID studies strategic to point out new knowledge on its distribution, habitat use and site fidelity.

Currently, several computer-assisted matching programs, able to support researchers performing photo-ID of cetaceans and analyse Risso's dolphin pictures, are available. Among them, the most notable are DARWIN (Stanley, 1995) and Finscan (Hillman et al., 2003), that can assist users working with image catalogues and help them to minimise subjectivity in the matching process. In particular, DARWIN uses a semi-automated process to create an approximation of the fin outline of a new dolphin. The researcher must trace a general outline of the leading and trailing edges of the dorsal fin with the cursor. Then, the fin outline is repositioned by using active contour and it is compared with a database of previously identified dolphin fins. The program presents to the researcher a ranked list of the possible matches for a comparison with the new fin image, with confidence limits for the nearest match to assist with the decision. Unfortunately, none of the existing algorithms takes into account the huge amount of information contained in the patterns of scars on the fin of the Risso's dolphins. Moreover, these tools present several limits: they are able to analyse only one image per time; substantial human expertise is required to discriminate an individual; the photo-ID process is very time consuming, limiting the amount of images they can analyse.

This study is aimed to develop a new software system, automatically performing the Risso's dolphin photo-ID process, dealing with the main difficulties of this task: 1) the background of images can be very noisy due to splashes and water, 2) the targets (dolphins) are constantly moving and 3) the image quality can be very poor depending on the atmospheric conditions. The software system consists in two main modules. The first one, targeting the computation and selection of distinctive feature descriptors, characterising the patterns of scars on the fin. The second one, focused at matching the feature descriptors between the new fin image and a collection of labelled dolphin individuals (models), providing us with the identity of the unknown dolphin.

In particular we use two different methods for features detection and description: Scale-Invariant Feature Transform (SIFT) (Lowe, 2004) and Speeded Up Robust Features (SURF) (Bay et al., 2008). It is known that the SIFT is invariant to rotation, scale changes and affine transformation, but it is slow and slightly sensitive to changing lighting conditions. The SURF is fast and has good performance as SIFT, but it is not stable to rotation and illumination changes (Juan & Gwun, 2009; Panchal et al., 2013). This study highlights which are the most suitable features to extract from fin images for performing reliable Risso's dolphin photo-ID with a comparative analysis of both approaches, as well as a comparison with the state-of-the-art software DARWIN.

The proposed photo-ID software system has been tested on a data collection of Risso's dolphin images, acquired in the Gulf of Taranto during the period 2013-2017. This data set has been collected thanks to the Citizen Science activities performed by our research team, on board of a 40 ft catamaran in the area of interest, involving citizens, tourists, students and decision makers in the research activities (see http://www.joniandolphin.it/wordpress/2017/).

The paper is organized as follows. In section 2 details about the study area, data collection and methodology are provided while in section 3 the experiments are described and results are discussed. Finally, section 4 concludes the paper.

2. Materials and Methods

2.1. Study area

The Gulf of Taranto situated in the Northern Ionian Sea (Central-eastern Mediterranean Sea) extends from Santa Maria di Leuca to Punta Alice covering an area of approximately 14000 km^2 (see Figure 1). A complex morphology characterizes the basin. A narrow continental shelf cut by several channels identifies the western sector while descending terraces delineate the eastern one, both declining towards the Taranto Valley, a NW-SE submarine canyon system with no clear bathymetric connection to a major river system (Capezzuto et al., 2010; Harris & Whiteway, 2011; Senatore & Pescatore, 2009; Rossi & Gabbianelli, 1978). This singular morphology involves a complex distribution of water masses with a mixing of surface and dense bottom waters (Sellschopp & Álvarez, 2003) and the occurrence of upwelling currents with high seasonal variability (Bakun & Agostini, 2001; Milligan & Cattaneo, 2007; Matarrese et al., 2011; Carlucci et al., 2014).

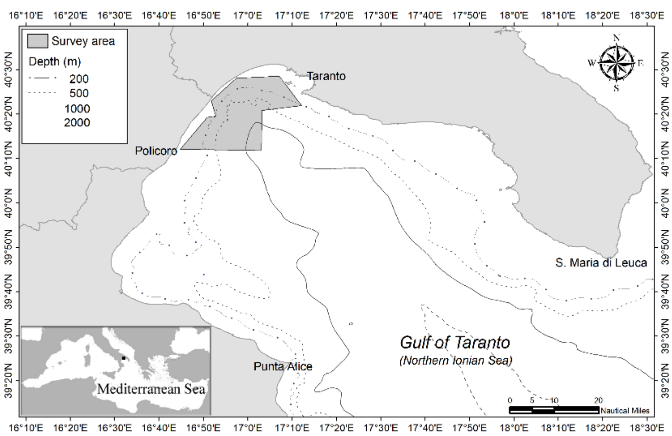

Figure 1: Map of the Gulf of Taranto (Northern Ionian Sea, Central-Eastern Mediterranean Sea) with indication of the survey area investigated from 2013 to 2017.

2.2. Data collection

The data collection contains images of Risso's dolphins fins cropped starting from larger pictures (see figure 2)

Figure 2: Examples of Risso's dolphins in which it is immediate to notice the white depigmentation on the whole body. The dorsal fin is cropped before being evaluated by the proposed software system.

acquired by our research team during specific acquisition campaigns in the Gulf of Taranto (Northern Ionian Sea, Central Mediterranean Sea) using a $40ft$ catamaran (Carlucci et al., 2016, 2017, 2018). The boat travels on random equally spaced transects that are daily generated in order to standardize the surveys, covering about 35 nautical miles in 5 hours (with a speed of about 7 knots) only in favorable weather conditions (Buckland et al., 2001) (see figure 1).
All the images have been taken by marine mammals observers on the boat with a Nikon D3300 camera with Nikon AF-P Nikkor $70 - 300mm$, $f4.5 - 6.3$G ED lens and have been manually labeled and organized in two distinct datasets:

D1 a dataset of 771 Risso's dolphin fin images, taken from 2013 to 2016, in which 60 different individuals have been recognized.

D2 a dataset of 126 Risso's dolphin fin images captured in 2017, in which 16 different individuals (among the ones observed in the past) have been recognized.

2.3. Methodology

The methodology proposed in this paper can be summarised as shown in figure 3: whenever a new image is fed into the system, it first goes through a *feature extractor* module in order to compute its distinctive features; then, the module *dolphin selector* is responsible for choosing the best matching model among a set of previously labelled models of dolphin dorsal fin. A model is a representation of one or more images of a specific dolphin in terms of relevant features. Once a specific feature extractor is chosen (e.g. SURF or SIFT feature detector), the same features must be computed for each model and stored in memory to be compared with new images. When a new fin image belonging to unknown dolphin is considered, the distinctive descriptors (e.g. SURF or SIFT feature detector) must be extracted from the image and compared with the models descriptors. The model image showing more similarities (best matching) with the query image returns the identity of the unknown dolphin depicted in the new image.

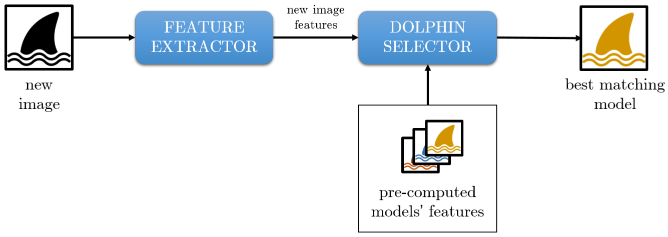

Figure 3: Overview of the proposed methodology.

2.3.1. Feature extractor

The *feature extractor* is a software module responsible for the extraction of the salient features belonging to the image. It takes a cropped fin image as input and returns a set of properly filtered features as output.

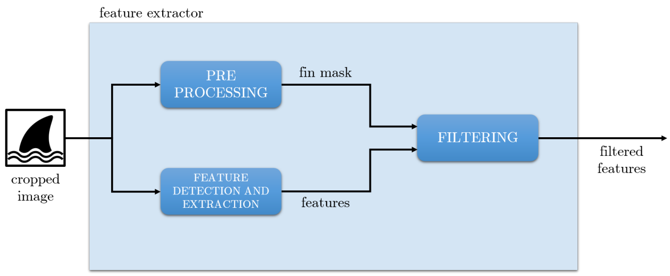

Figure 4: Block diagram of the *feature extractor* module.

With reference to figure 4, the input firstly goes through two different modules and then a filtering step follows before outputting the result. In more details:

Pre processing - this module performs the fin segmentation in the image, computing a binary image which represents the fin mask. Three steps are implemented to perform this task: the image is first converted from the RGB color space to the CIE-L*a*b* one, then a thresholding operation is done based on the Otsu algorithm, automatically establishing the threshold value that minimises the intra-class variance among background (the sea) and foreground (the fin) and finally a noise removal step by means of morphological opening and closing operations is performed. It is worth noting that the color space conversion is useful to model the information about a single pixel as a triple $(L*, a*, b*)$ that represents the lightness and the color opponents as perceived by the human vision system, thus resulting in a fruitful approach to separate the sea from the rest of the image.

Feature detection and extraction - this module detects and extracts interest points from the whole image and stores them in an appropriate data structure. Let $I \in \mathbb{N}^{h \times w}$ be the current image made of $(h \times w)$ pixels and $F : \mathbb{N}^{h \times w} \rightarrow \mathbb{R}^{k \times n_f}$ a specific algorithm that takes an image and computes its features, the computation of $F(I)$ produces k salient features centred in key points, each one described as a vector of n_f real numbers. For example, when F equals to the SURF or SIFT feature detector, $n_f = 64$ or $n_f = 128$.

Filtering - dolphin fin images are often affected by noise basically due to splashing water in the surroundings of a fin. This phenomenon acts as an unpredictable noise source, resulting in a misclassification of splashes as robust image features. For this reason, only the feature points that lie inside the dorsal fin are kept in memory and can go further to the next steps.

2.3.2. Dolphin selector

The *dolphin selector*, shown in figure 5, is the software module that performs the matching of the features extracted from the query image with all the pre-computed models' features in order to select the best matching dolphin, i.e. the estimated identity of the dolphin captured in the query image.

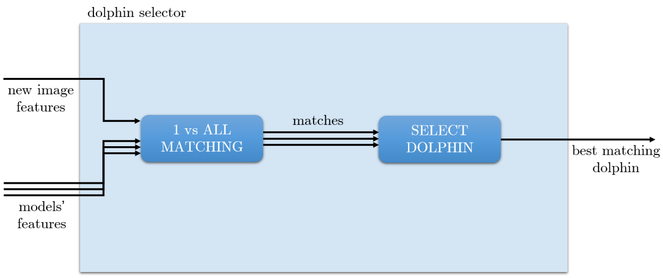

Figure 5: Block diagram of the *dolphin selector* module.

The first block, *1 vs. all matching*, iteratively executes a matching function and outputs a set of matching features between those computed from the query fin image and each fin model. Then, the model having the highest number of matching features with the query image is selected as the best matching dolphin. The choice is considered reliable if at least η valid matches have been computed.

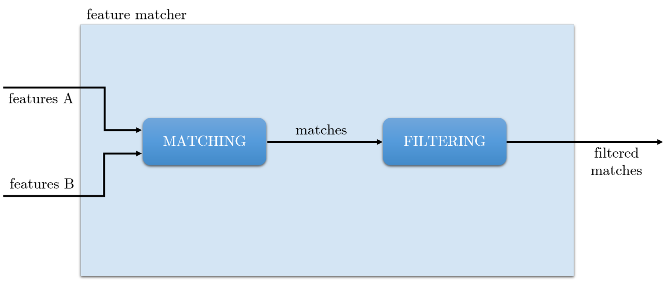

Figure 6: Block diagram of the feature matcher.

Details about the *feature matcher* are reported in figure 6, where it is immediate to see that two sets of features are compared at each iteration. More specifically, at the $i-th$ iteration:

A is the set of features computed on the new image, i.e. $F(I)$

B is the set of features computed on the $i-th$ model, i.e. $F(m_i)$

The matching algorithm computes the distance $\Delta(\cdot, \cdot)$ between each feature of A and each feature of B. Supposing that $|A| = n_A$ and $|B| = n_B$, a feature $f_a \in A$ matches a feature $f_b \in B$ if and only if

$$b = \underset{j=1 \dots n_B}{\operatorname{argmin}} \Delta(f_a, f_j) \text{ and } \Delta(f_a, f_b) < \tau$$

The "filtering" step depends on the specific feature that has been chosen because each algorithm can add specific information about the neighborhood of each feature. In fact, in the case of SIFT and SURF, the orientation $\theta(\cdot)$ of each feature is returned by the algorithm. In the proposed methodology the features are filtered with respect to their relative orientation. Let (i, j) be a match between the $i-th$ feature of the new image and the $j-th$ feature of the model, (i, j) is considered valid if and only if $|\theta(i) - \theta(j)| < 0.5\,rad$.

3. Experiments and results

In order to effectively test and discuss the methodology described in the previous section, some restrictions need to be applied to the dataset D1. First of all, one fin model image per each individual should be selected, but acceptable images of at least one side of the fin in terms of perceived image quality (resolution, focus and size of the fin) are available for only 40 dolphins. This leads to the definition of a models set made of 45 different images due to the fact that pictures of both fin sides are available for only 5 dolphins. Secondly, whenever a fin model is chosen, all the pictures of that dolphin on the same date are deleted from the dataset. Moreover, a preliminary filter is applied to exclude from the experiments the images with less than 5 computed features or with height and width less than 200 pixels. Under these assumptions, 235 images of 21 different dolphins are kept in the dataset D1. These filters are applied before evaluating the outcomes of the algorithm, in order to compute its accuracy without introducing any bias.
Three experiments have been designed to test the methodology described in this paper, as follows.

1. The first experiment, run on the dataset D1, is devoted to the fine tuning of the parameters introduced in the previous section;
2. the second experiment, run on the dataset D2, is performed to validate the approach;

3. in the third experiment the performances of the proposed tool are compared with those of the state-of-the-art photo-ID tool, DARWIN.

The performances of the photo-ID tools are evaluated in terms of accuracy, defined as the percentage of correct matches with respect to the total number of tested images. In the experiments, both SIFT and SURF features are used to perform the photo-identification task. The proposed algorithm has been developed using MATLAB software (MathWorks, Natick, MA), while both SIFT and SURF implementations have been taken from the OpenCV library 2.4.10 linked to the Matlab environment.
The first experiment aimed to set the number of valid matches parameter η. The algorithm is executed on each image of D1 keeping track of the highest number of matching features per image. Figure 7 shows the percentage of images that are discarded if a specific number of valid feature matches η is selected. When $\eta = 0$ no images are discarded, meaning that each output of the *dolphin selector* module is considered as reliable (see section 2.3.2); when η increases, the percentage of discarded images increases accordingly. It is immediate to notice that both feature detectors show a similar behavior in the first part of the curve and then, after an intersection point for $\eta = 7$, the SURF curve increases more rapidly than the SIFT one. This means that for each $\eta^* > 7$ a SURF-based approach would discard a higher number of images with respect to a SIFT-based approach. For this reason, the parameter η has been set to the intersection value 7 (yellow line in the figure) keeping the number of discarded images comparable for both feature detectors.

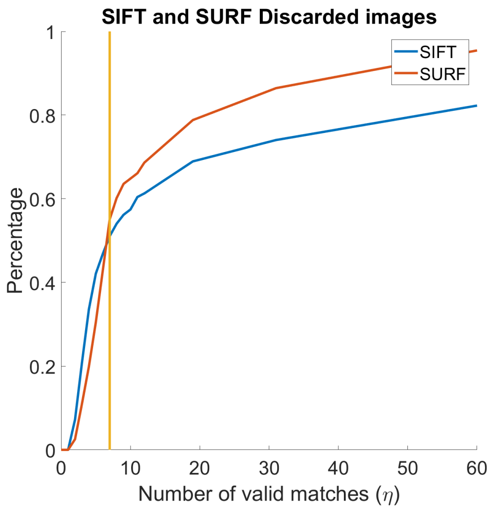

Figure 7: Percentage of images that are discarded by the proposed algorithm, when a specific number of valid feature matches η is selected. SIFT and SURF feature detectors are respectively plotted with a blue and an orange line.

Figure 8 shows the accuracy of the algorithm for each value of η and for both feature detectors. A first remark should be given to the similar shape of the two curves that reflects the common algorithmic basis of the two detectors. In fact, both SIFT and SURF approaches exploit the Laplacian of Gaussian of the image but with different approximations: the first generally finds more features while the second is computationally faster (Panchal et al., 2013). For $\eta = 0$ (no images discarded) there is a 10% difference in terms of accuracy between the two feature detectors with SIFT showing better results with respect to SURF, while both approaches are able to correctly recognize all the images that have at least 20 matching features. However, according to the result discussed before, the comparison between SIFT and SURF is performed when $\eta = 7$ reporting the details in table 1. The evidence is that SIFT outperforms the SURF feature detector achieving 99% accuracy on reliable images. On the contrary, SURF feature detector achieves 89% accuracy.

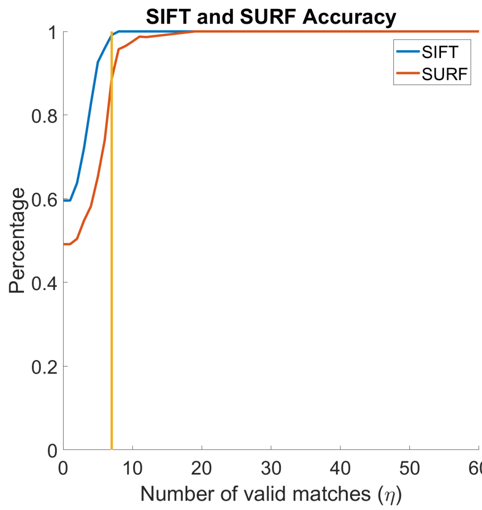

Figure 8: Accuracy of the proposed algorithm when a specific number of valid feature matches η is selected. SIFT and SURF feature detectors are respectively plotted with a blue and an orange line.

Table 1: Accuracy and discarded images on the dataset D1

$\eta = 7$	SIFT	SURF
Accuracy	99 %	89 %
Discarded images	51 %	55 %

In order to validate the proposed approach a second experiment has been conducted on the dataset D2 that contains only images captured in 2017. Table 2 summarizes the results of the experiment, showing 90% accuracy when using SIFT feature detector compared to 63% achieved with SURF. SIFT-based algorithm discards a higher number of images (62%) compared with that discarded by SURF approach (52%). This result is compatible with an expected performance drop in a validation experiment and suggests that the SIFT based approach is more robust for the specific application of Risso's dolphin photo-ID with respect to SURF.

Table 2: Accuracy and discarded images on the dataset D2

$\eta = 7$	SIFT	SURF
Accuracy	90 %	63 %
Discarded images	62 %	52 %

The third experiment has been conducted to compare the performances of the proposed methodology with DARWIN, in terms of accuracy and time required to perform the photo-ID task. At this end, a hard effort is required to build the reference database inside DARWIN: the models set has been imported and the fin outline has been manually extracted for each image. Successively, to test the performances of DARWIN, the researcher must preprocess a single test image per time, in a semi-automated way. The main steps can be summarised as follows: 1) the user must trace some key points on the fin; 2) starting from these points, the algorithm traces an approximate contour; 3) if needed, the user adjusts the contour. In our experiment we took about 4 minutes per image to do this task. Due to the high effort required in terms of time, a subset of only 50 images extracted from D1 has been used to test the algorithm. Each one of the 50 images is then manually preprocessed and given to DARWIN to predict the identity of the dolphin. A prediction is considered correct if the correct match is returned as the first rank prediction. Under these assumptions DARWIN accuracy is 68%, against the 99% computed by the proposed approach. Moreover, the time required to process an image makes DARWIN unusable for large scale studies.
In general, the experimental results achieved in all the three experiments here proposed, suggest that the novel photo-ID methodology can efficiently assists the researcher during the photo-ID task, especially when dealing with large amount of data.

4. Conclusion and future works

In this paper, a computer vision based software system for the photo-identification of Risso's dolphin was presented, whose dorsal fin shows evident distinctive signs that can be effectively exploited to identify a specific individual. The main contribution of this work is represented by the innovative application of a feature-based automated approach aimed to the selection of the best matching Risso's dolphin model whenever a new unknown image needs to be analysed. Comparative experiments on real data acquired during specific acquisition campaigns from 2013 to 2017 shown that the proposed methodology is able to achieve 90 % accuracy in the validation experiment, with an outperforming boost in terms of execution time if compared with the state of the art. In addition, results suggest that the novel photo-ID methodology can efficiently assists the researcher during the photo-ID task, especially when dealing with large amounts of data. Up to our knowledge, this is the first work that exploits computer vision in the particular challenging domain of cetacean analysis, providing a baseline for the widening of the automated approach to their photo-identification. Moreover, it highlights that applying a clever synergy between bio-ecological information on the species and innovative technological strategies, a more comprehensive understanding of spatial and temporal distribution, abundance, critical habitats of cetacean species. Future extensions of this work are strictly related to the data availability and will be devoted to the analysis of new images coming from both other researcher's collections or citizen science activities.

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