Overview of ImageCLEFcoral 2021: Coral Reef Image Annotation of a 3D Environment

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Abstract

This paper presents an overview of the ImageCLEFcoral 2021 task that was organised as part of the Conference and Labs of the Evaluation Forum - CLEF Labs 2021. The task addresses the problem of automatically segmenting and labelling a collection of underwater images that can be used in combination to create 3D models for the monitoring of coral reefs. The training dataset contained 882 images from 6 subsets from 4 locations. 1 subset was complete (containing all the images to build the 3D model) and 5 subsets containing a partial collection. The test data (491 images) contained the images required to complete 4 of the partial image sets from each of the 4 locations (the final partial subset is not used for testing, only training). 8 teams registered to the ImageCLEFcoral task, of which 3 teams submitted 8 runs. Participants' entries showed that although automatic annotation of benthic substrates was possible, developing a generic algorithm to work across multiple geographical locations will be difficult due to the variation of characteristics within and between classification types.

Keywords

ImageCLEF, image annotation, image labelling, classification, segmentation, coral reef image annotation, 3D photogrammetry

1. Introduction

Coral reef ecosystems are highly complex non-uniform structures that support a wide range of biodiversity; however, there has been a steady decline in coral reefs in recent years [1]. Currently, more than 85% of the reefs within the Coral Triangle region are at risk of disappearing [2, 3].

Coral reef community composition is an essential element for monitoring reef health and the importance of automated data collection, 3D analysis and large-scale data processing are increasingly being recognised [4]. In 2017, Chamberlain et al. at the University of Essex developed a novel multi-camera system to scale up previous data capture approaches [5] by acquiring imagery from several viewpoints simultaneously. The increasing use of large-scale modelling of environments has driven the need to have such models labelled, with annotated data essential for machine learning techniques to automatically identify areas of interest, assess community composition and monitor phase shifts within functional groups.

CLEF 2021 – Conference and Labs of the Evaluation Forum, September 21–24, 2021, Bucharest, Romania
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The composition of marine life on a coral reef varies globally. Within the Indo-Pacific Coral Triangle there are over 76% of all coral species and more than 3,000 fish species [2]. The Western Indian Ocean is also a centre of high diversity for hard corals and reef fauna [6] and forms an evolutionary distinct region. Coral reef fauna from the Caribbean within the Atlantic Ocean, is strongly delineated from the Indian Ocean [7].

Geographically distinct regions can contain the same species or genera with entirely different morphological features and traits. The variety in both environmental conditions and competitive niche filling can lead to changes in phenotypic expression, which makes the task of identifying them difficult without an extensive training image set. Typically, such training sets are developed from the region of interest; however, the utility of a generalised algorithm for identifying benthic fauna cannot be under-estimated as it would allow for rapid monitoring of invasive species and indicator species used to monitor climate change.

Previous ImageCLEFcoral tasks [8, 9] required participants to automatically annotate and localise a collection of images with types of benthic substrate, such as hard coral and sponge. Participants' entries showed that automatically annotating corals and benthic substrates was possible, despite this being a difficult task due to the variation of colour, texture and morphology between and within classification types. The results also showed that better performance was achieved when training on datasets similar to the test dataset, with some notable exceptions such as branching corals.

In its 3rd edition, the ImageCLEFcoral training and test data form the complete sets of images required to produce 3D reconstructions of the environment. This allows the participants to explore novel probabilistic computer vision techniques based around image overlap and transposition of data points. In addition, we encouraged the participants to train their algorithms with large-scale public datasets available from the National Oceanic and Atmospheric Administration (NOAA) and provided a conversion table from NOAA format to ImageCLEFcoral format. ImageCLEFcoral is organised as part of the Conference and Labs of the Evaluation Forum (CLEF Labs 2021) [10].

The paper is organised as follows: Section 2 presents the ImageCLEFcoral task and the participation; Section 3 describes the dataset; Section 4 the evaluation methodology used in the task; the results are presented in Section 5; and finally Section 6 discusses the lessons learnt and future directions.

2. Task and Participation

The ImageCLEFcoral task followed the same format as in previous editions [8, 9]. Participants were asked to automatically annotate regions in a collection of images containing 13 types of benthic substrates such as fire coral or algae. As in previous editions, the overall task comprises two sub-tasks:

1. Coral reef image annotation and localisation
2. Coral reef image pixel-wise parsing

The first sub-task uses bounding boxes for the annotation, with sides parallel to the edges of the image, around identified features. The second sub-task uses a series of boundary image coordinates which form a single polygon around each identified feature; this has been dubbed *pixel-wise parsing* (these polygons should not have self-intersections). Participants were invited to make submissions for either or both tasks.

The annotation task is different from other image classification and marine substrate classification tasks [11, 12, 13]. Firstly, the images are collected using low-cost action cameras with a fixed lens and firing on timelapse or extracted as stills from video. The effect of this on the imagery is that there is some blurring, the colour balance is not always correct (as the camera adjusts the white balance automatically based on changing environmental variables) and final image quality is lower than what could be achieved using high-end action cameras or DSLRs. However, the images can be used for reconstructing a 3D model and therefore have useful information in the pipeline. Low cost cameras were used to show this approach could be replicated affordably for future projects.

In the 2021 edition 8 teams registered to the ImageCLEFcoral task, of which 3 teams submitted 8 runs. Table 1 presents the three teams participating on the task. Teams were limited to submit 10 runs per subtask.

Table 1
Participating groups of the ImageCLEF 2021 Coral task. Teams with previous participation are marked with an asterisk.

Team	Institution	Runs T1	Runs T2
UAlbany [14]	University at Albany, Albany, USA	1	-
Pilsen Eyes [15] *	Faculty of Applied Sciences, University of West Bohemia, Pilsen, Czechia	2	1
MTRU [16] *	Marine Technology Research Unit, University of Essex, Colchester, UK	-	4

3. Data Set

The images were captured using an underwater multi-camera system developed at the Marine Technology Research Unit at the University of Essex (MTRU), UK.[1] The images contain annotations of the following 13 types of substrates: Hard Coral – Branching, Hard Coral – Submassive, Hard Coral – Boulder, Hard Coral – Encrusting, Hard Coral – Table, Hard Coral – Foliose, Hard Coral – Mushroom, Soft Coral, Soft Coral – Gorgonian, Sponge, Sponge – Barrel, Fire Coral – Millepora and Algae - Macro or Leaves.

The ground truth annotations of the training and test sets were made by a combination of marine biology MSc students at the University of Essex and experienced marine researchers. All annotations were double checked by an experienced coral reef researcher. The annotations were performed using a web-based tool, initially developed in a collaborative project with London-based company Filament Ltd and subsequently extended by one of the organisers. This tool was designed to be simple to learn, quick to use and allows many people to work concurrently (full details are presented in the ImageCLEFcoral 2019 overview [8]).

[1] https://essexnlip.uk/marine-technology-research-unit/

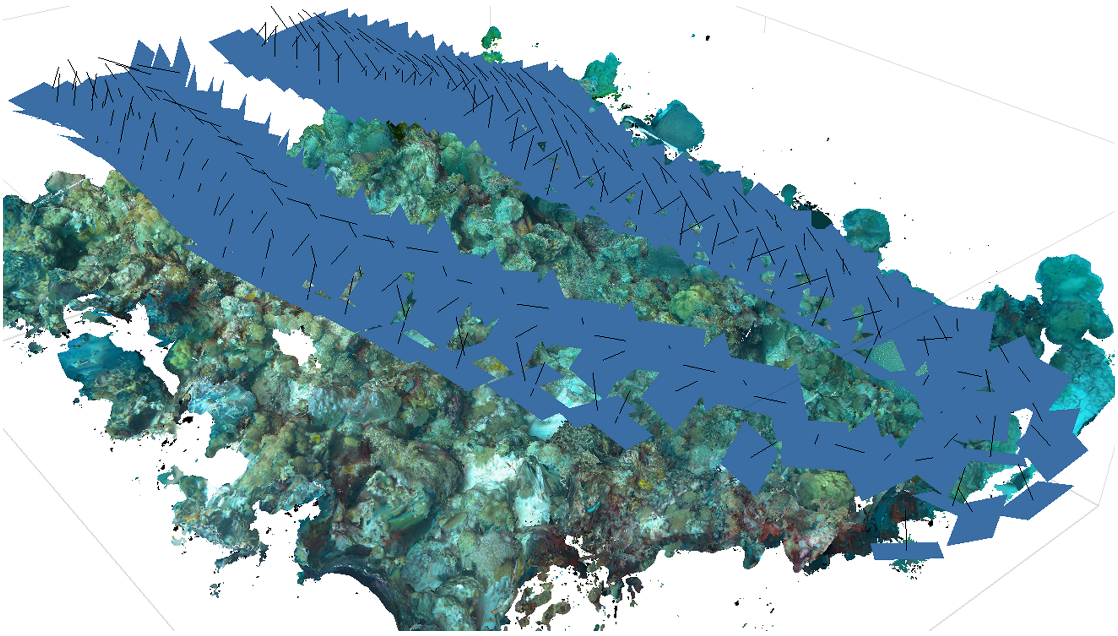

Figure 1: 3D reconstruction of a coral reef (approx. 4x6m). Each image in the subset to create this model is represented by a blue rectangle, with the track of multi-camera array clearly visible across the environment.

In this third edition, a complete set of images required to form a 3D reconstruction of the environment was provided with the training and test data. Figure 1 shows an example 3D reconstruction of one of the subsets of data (approx 4x6m). Each image in the subset to create this model is represented by a blue rectangle, with the track of multi-camera array used for data collection clearly visible across the environment. The .obj files were available to the participants and the 3D models can be visualised online.[2] The training dataset contained 882 images from 6 subsets from 4 locations. 1 subset was complete (containing all the images to build the 3D model) and 5 subsets containing a partial collection. The test data (491 images) contained the images required to complete 4 of the partial image sets from each of the 4 locations (the final partial subset is not used for testing, only training).

In addition, participants were encouraged to use the publicly available NOAA NCEI data[3] and/or CoralNet[4] to train their approaches. The NOAA NCEI data typically contains 10 annotated pixels per image, with a considerably larger classification scheme than the classes used in ImageCLEFcoral. A NOAA Translation processor to capture the classification types within the data set and translate them via an expert defined translation matrix into the ImageCLEFcoral classes was provided.

[2]https://skfb.ly/oo6VZ
[3]https://www.ncei.noaa.gov/
[4]https://coralnet.ucsd.edu/

Table 2
Distribution of classified pixels for training and test datasets.

Substrate	Training	Test
algae_macro_or_leaves	5.18%	12.28%
fire_coral_millepora	0.09%	0.03%
hard_coral_boulder	20.45%	10.83%
hard_coral_branching	17.34%	24.28%
hard_coral_encrusting	5.79%	4.30%
hard_coral_foliose	0.94%	0.03%
hard_coral_mushroom	0.30%	0.05%
hard_coral_submassive	8.50%	19.57%
hard_coral_table	3.16%	9.81%
soft_coral	27.84%	2.48%
soft_coral_gorgonian	0.71%	0.14%
sponge	7.68%	14.89%
sponge_barrel	2.02%	1.31%
unclassified	80%	77%

3.1. Collection Analysis

Table 2 shows the distribution of pixel classification between the training and the test datasets. The training dataset had a higher proportion of boulder coral and soft coral, compared to the test dataset which had more algae, branching coral, submassive coral, table coral and sponge. Both datasets had a similar amount of unclassified pixel areas. It was hoped the inclusion of additional large-scale public datasets from NOAA would allow the participants to address the lack of training examples for under-represented classes in the training data.

4. Evaluation Methodology

The performance of the participants' runs was evaluated on the unseen test data (see Section 3) using the popular intersection over union metric from the PASCAL VOC[5] exercise. This computes the area of intersection of the output of an algorithm and the corresponding ground truth, normalising that by the area of their union to ensure its maximum value is bounded.

We defined the following metric:

- *MAP 0.5 IoU*: the localised Mean Average Precision (MAP) for each submitted method using the performance measure of IoU >=0.5 of the ground truth.

5. Results

Tables 3 and 4 shows the results obtained by the participants for sub-task 1 and 2, respectively, and Table 5 shows a breakdown per class of each run for sub-task 2.

The submission from the Pilsen Eyes team [15] achieved the best results in both sub-tasks. Their approach was based around the Mask R-CNN model, pre-trained on the ImageNet database. Images were re-sized to 1000×1000 pixels and the model trained with batch size 2 and

[5]http://host.robots.ox.ac.uk/pascal/VOC/

Table 3
Performance in terms of all submitted runs for the ImageCLEF 2021 coral reef image annotation and localisation subtask.

Group Name	Submission Run	MAP 0.5 IoU
Pilsen Eyes	138115	0.121
Pilsen Eyes	137821	0.105
UAlbany	139118	0.001

Table 4
Performance in terms of all submitted runs for the ImageCLEF 2021 coral reef image pixel-wise parsing subtask.

Group Name	Submission Run	MAP 0.5 IoU
Pilsen Eyes	139084	0.075
MTRU	138389	0.021
MTRU	138443	0.018
MTRU	138411	0.017
MTRU	138449	0.011

Table 5
Coral reef image annotation and localisation performance in terms of the pixel-wise Intersection over Union (IoU) per benthic substrate

Team	Run id	algae-macro-or-leaves	fire-coral-millepora	hard-coral-boulder	hard-coral-branching	hard-coral-encrusting	hard-coral-foliose	hard-coral-mushroom	hard-coral-submassive	hard-coral-table	soft-coral	soft-coral-gorgonian	sponge	sponge-barrel
Pilsen Eyes	139084	0.000	0.000	0.054	0.111	0.026	0.000	0.000	0.027	0.000	0.504	0.000	0.016	0.003
MTRU	138411	0.000	0.000	0.076	0.005	0.007	0.000	0.000	0.010	0.000	0.002	0.000	0.000	0.000
MTRU	138449	0.000	0.000	0.088	0.056	0.024	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MTRU	138389	0.000	0.000	0.096	0.011	0.000	0.001	0.000	0.030	0.004	0.000	0.000	0.000	0.000
MTRU	138443	0.000	0.000	0.128	0.023	0.026	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000

accumulated gradient 4 using a SGD optimiser; the initial learning rate was 0.005 with a step decay of 0.0005 after 3 epochs. The training imagery were partitioned into a training set (80%) and validation set (20%). Augmentation of the training data employed random horizontal flips and brightness and contrast variations.

The MTRU [16] team only participated in the pixel-wise parsing subtask. The team employed the DeepLabV3 model from a previous submission, based around ResNet-101. Features extracted via ResNet undergo atrous convolution, which increases the field of view in the last layer by inserting 0-values at a particular rate, then atrous spatial pyramid pooling to assign a label to each pixel using different atrous convolution rates. The latter stages essentially make sure the network has seen different fields of view of the data.

As well as working with only the ImageCLEF dataset, the MTRU team explored augmenting the dataset with NOAA NCEI data on runs 138411 and 138449, which provided 3032 images and classifications at 10 pixels per image. Perhaps surprisingly, incorporating these annotations generally reduced the accuracy of classifications.

The UAlbany [14] team emphasised the importance of spatial relationships in analysing feature classes such as fire coral and branching coral, which have similar spatial patterns. This motivated them to make use of wavelet transforms in their approach, resulting in an over-complete decomposition across multiple scales known as Wave-CLASS. Multiple training phases were used. The first employed 120 images and 405 annotations across all 13 feature types while the second employed 96 images and 515 annotations. There appears to have been some manual intervention between first and second phases to ensure correctness.

6. Conclusion

The results of both sub-tasks were not as high as previous years. However, the 2020 task asked participants to train on a single geographical location and test on multiple locations. This year, the training set was from multiple locations, as was the test set. This multiplication of complexity compounds the known difficulty of varied morphology and distribution of substrates across different datasets and locations. This suggests that trying to develop a single generic algorithm to detect coral reef substrate type will be challenging, even with the incorporation of considerably larger datasets from other sources as training corpora.

The next steps for this work are to leverage the image overlap of the data to develop probabilistic labelled models in 3D and develop cross-compatibility in large datasets for use in this task.

Acknowledgments

The authors would like to thank the participants who have invested substantial amounts of time and effort in developing solutions to this task. The images used in this task were able to be gathered thanks to funding from the University of Essex and the ESRC Impact Acceleration Account, as well as logistical support from Operation Wallacea. We would also like to thank the MSc Tropical Marine Biology students who participated in the annotation of the test set.

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