Automatic classification of coral images using colour and textures

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Abstract. The purpose of this work is to address the imageCLEF 2019 coral challenge - to develop a system for the detection and identification of substrates in coral images. Initially a revision of the 13 classes was carried out by identifying a number of sub-classes for some substrates. Four features were considered – 3 related to greyscale intensity (1) and texture (2), and 1 related to the colour content. The Breiman's Random forest algorithm was used to classify the corals in one of 13 classes defined. A classification accuracy of about 49% was obtained.

Keywords: Image classification · classification methods · image processing.

1 Introduction

Coral reefs are large underwater structures composed of the skeletons of colonial marine invertebrates called coral. The coral species that build reefs are known as hermatypic, or "hard," corals because they extract calcium carbonate from seawater to create a hard, durable exoskeleton that protects their soft, sac-like bodies. Other species of corals that are not involved in reef building are known as "soft" corals. These types of corals are flexible organisms often resembling plants and trees and include species such as sea fans and sea whips, according to the Coral Reef Alliance (CORAL), a non-profit environmental organization [1].

Coral reefs support immense biodiversity and provide important ecosystem services to many millions of people, yet they are degrading rapidly in response to numerous anthropogenic drivers [2]. In fact, coral reefs are in danger of being lost within the next 30 years, and with them the ecosystems they support [3]. This catastrophe will not only see the extinction of many marine species, but also create a humanitarian crisis on a global scale for those who rely on reef services. By monitoring the changes and composition of coral reefs conservation efforts can be better implemented and prioritised [1]. The imageCLEF 2019 initiative addresses this issue, by proposing a challenge based on the detection and identification of substrates in coral images. The aim is to define a set of bounding boxes around the substrates found, and to make the identification of the classes to which they belong [4, 5].

In this paper, we propose to solve this challenge using a fully automatic process to identify coral substrates in digital images. The method developed uses colour and texture to identify regions of interest and, using the Breiman's Random forest algorithm [6] to classify a coral in one of 13 classes. The digital images used in this study are 3024×4032 pixels, in RGB (Red, Green and Blue) format.

2 Data

The data for the ImageCLEF2019 Coral task originates from a growing, large-scale collection of images taken from coral reefs around the world as part of a coral reef monitoring project with the Marine Technology Research Unit at the University of Essex [3]. Substrates of the same type can have very different morphologies, color variation and patterns. Some of the images contain a white line (scientific measurement tape) that may occlude part of the entity. The quality of the images is variable, some are blurry, and some have poor color balance. This is representative of the Marine Technology Research Unit dataset and all images are useful for data analysis. 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 [1, 4]. A more detailed description of the dataset is presented in [1].

The training set contains 240 images with 6430 substrates annotated. Two files are provided with ground truth annotations:

- one based on bounding boxes "imageCLEFcoral2019_annotations_training_task_1"
- and a more detailed annotation based on bounding polygon "imageCLEFcoral2019_annotations_training_task_2".

The test set contains 200 images [1, 4].

3 Methodology

The methodology proposed to detected and identify substrates in coral images is presented schematically in Figure 1. In a first phase, the training images are processed, and the regions that define each coral substrates are identified (Coral substrates). Then, the features of each of these substrates (Coral features) are used to train the classifier (Classification). In a second phase, the classifier is applied to the test images, thus obtaining images of classified corals. These images are post-processed and their corals (Connected components) are identified, a text file with the relevant information is produced.

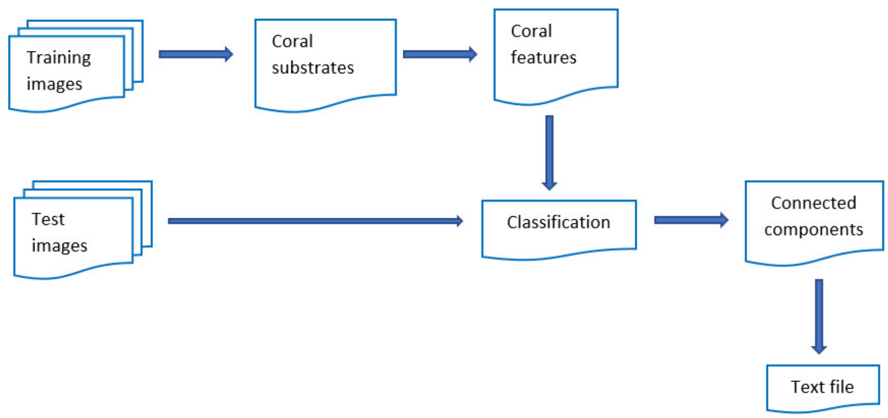


Fig. 1. Diagram of the proposed methodology.

The 13 types of substrates were identified in the 240 training images. A total of 6430 substrates annotations are availably, as listed in Table 1 and illustrated in Figure 2. A colour is assigned for each substrate, presented in the second column of Table 1. The number of occurrences of each substrate in the training images is presented in the third column of Table 1.

Figure 2 shows two training images and the number and type of substrates identified in these images. On the image on the left (2018_0714_11244_018), the following substrates were identified: "hard coral branching" (4 times), "hard coral boulder" (2 times), "hard coral encrusting" (3 times), "soft coral" (8 times), "sponge" (7 times), "sponge barrel" (1 time) and "algae macro or leaves" (3 times). For image 2018_0729_112525_048 (right): "hard coral branching" (4 times), "hard coral boulder" (4 times), "hard coral encrusting" (2 times), "soft coral" (11 times) and "sponge barrel" (1 time).

3.1 Coral substrates

By visual observation of several training images, it was verified that within the same substrate there are different types of corals, both in shape, colour and texture. Therefore, within each substrate different types (sub-classes) were identified. Another difficulty in the analysis of these images is the overlapping of the substrates identified in the training image. For example, in the left image of Figure 2, the substrate "sponge" (number 11 in green) is inside the region defined by the substrate "hard_coral_boulder" (number 0 in pink).

Table 1. Substrates annotated in training images.

Substrates	Colour bounding box representation	No. of occurrences
c_hard_coral_branching		777
c_hard_coral_boulder		1110
c_hard_coral_encrusting		331
c_hard_coral_mushroom		133
c_hard_coral_foliose		2
c_hard_coral_submassive		2
c_soft_coral		3353
c_sponge		531
c_sponge_barrel		7
c_algae_macro_or_leaves		11
c_fire_coral_millepora		1

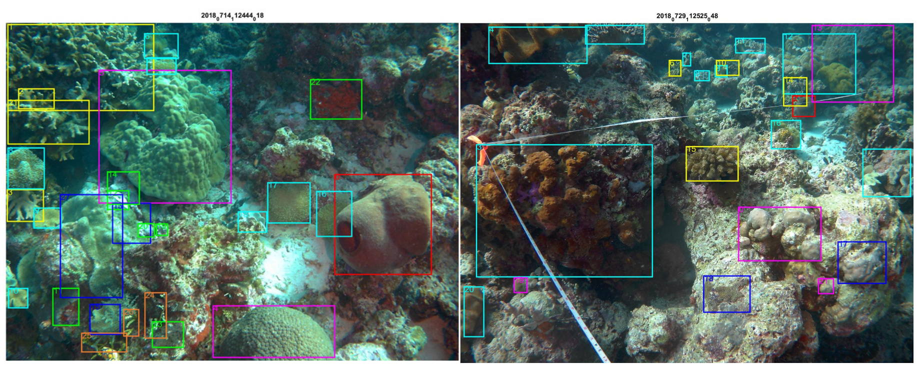
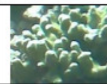
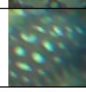
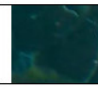
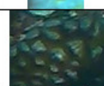
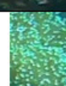
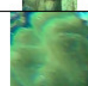
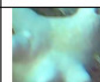
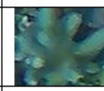
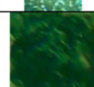
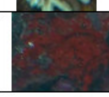
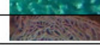


Fig. 2. Training images with bounding box of the substrates annotated in the respective color.

Table 2 shows different types of corals identified in each substrate. The types of corals defined in this table are due to the different textures and shapes that each one presents. For example, in the hard_coral_branching (first line) two different types were identified and in the soft_coral (line 7) six types because the latter substrate has a huge variety of types. This procedure was performed visually by the observation of different images with different types of substrates.

For each type of coral in each substrate, several replicates were identified in different training images by manual process. These replicates were identified, where possible, so that the substrate would fill the entire region defined. In the type of corals that appear more frequently more replicates were identified than in others.

Table 2. The type of corals defined for each substrates.

Coral substrates	substrate 1	substrate 2	substrate 3	substrate 4	substrate 5	substrate 6
hard_coral_branching						
hard_coral_boulder						
hard_coral_encrusting						
hard_coral_mushroom						
hard_coral_foliose						
hard_coral_submassive						
soft_coral						
sponge						
sponge_barrel						
algae_macro_or_leaves						
fire_coral_millepora						
hard_coral_table						
soft_coral_gorgonian						

3.2 Coral features

When we look at the coral images we find that they have different colours from green, blue, red, orange, brown and white. However, these colours are not unique identifiers of a substrate. The textures are also present on the substrates. Some corals are harder, rugged, sharper, and others smoother and softer. Hue is also a relevant characteristic of substrates.

With the replicates identified, the 4 most relevant features (by empirical way) were calculated, in a 5x5 neighbourhood of each pixel: mean (M), standard deviation (STD), entropy (E) of grayscale image and hue ratio (HR). The mean and the standard deviation of the neighbourhood identify the spatial arrangement of intensities in a selected region of an image and are represented in Equation 1 and Equation 2 respectively. This is

$$M = \frac{\sum p}{N} \tag{1}$$

$$STD = \sqrt{\frac{(p-M)^2}{N-1}}, \tag{2}$$

where p is the intensity of the pixels and N is the neighbourhood size. The Entropy is a statistical measure of randomness that can be used to characterize the image texture. Entropy (Equation 3) is defined as

$$E = -\sum p * \log_2(p), \tag{3}$$

where p is the intensity of the pixels.

The RGB image is converted to the HSV (Hue, Saturation, Value) colour model. Only values of Hue (H) below 0.34 or above 0.73 are considered for this feature. This threshold values were obtained by visual inspection of the training images. After that, the Hue ratio (HR) in equation 4 is calculated by dividing the number of pixels belonging to the range ($H < 0.34$ or $H > 0.73$) over the total number of pixels in the neighbourhood region.

$$HR = \frac{\#\text{pixels}(H < 0.34 \text{ or } H > 0.73)}{\#\text{pixels}}. \tag{4}$$

Table 3 shows the type of corals defined for each substrate, the number of replicates identified in each type and their features (mean, standard deviation, entropy and hue ratio). In hard_coral_branching substrate the first and second types was defined by 24 replicates while in algae_macro_or_leaves substrate only 8 replicates are defined for the types.

The features are elements of each type that identify it individually in relation to the other types. With these elements it is intended to characterize each type in a unique way. In Figure 3 it is possible to observe the features of a test image (2018_0712_073252_024). In the first line we can observe the original image (a) on the left, the average image (b) in the center and the standard deviation (c) on the right. In the second line the entropy (d) on the center and hue ratio of the image (e) on the right.

3.3 Classification method

Using Classification learner app available in MATLAB [7] environment, it is possible to classify the training coral image using various algorithms and compare the results in the same environment. After training multiple models, they were compared, based on validation errors. The classification models available in this app are: decision trees, discriminant analysis, Support Vector Machines (SVM), logistic regression, nearest neighbors, and ensemble classification. With the data

Table 3. Features valuers for the substrates.

Substrates	# replicate	Classes	Mean	Standard deviation	Entropy	Hue ratio
algae_macro_or_leaves	8	1	98.43	32.30	5.47	0.59
fire_coral_millepora	16	1	48.08	8.23	3.72	0.92
hard_coral_boulder	24	1	112.22	5.24	3.50	0.38
	24	2	93.91	8.07	4.04	0.00
hard_coral_branching	24	1	68.05	13.38	4.75	0.22
	24	2	108.12	19.94	4.60	0.33
hard_coral_encrusting	24	1	111.83	22.85	4.87	0.37
	24	2	115.77	22.69	4.99	0.54
	24	3	119.96	2.37	3.03	0.64
hard_coral_foliose	8	1	89.85	34.76	6.11	0.08
hard_coral_mushroom	24	1	85.71	33.68	6.43	0.16
hard_coral_table	12	1	126.10	25.59	5.44	0.39
hard_coral_submassive	8	1	121.59	45.96	5.31	0.00
	4	2	163.32	38.99	6.51	0.35
soft_coral	24	1	140.54	41.08	6.82	0.32
	24	2	83.48	9.97	3.97	0.00
	20	3	191.92	26.25	5.13	0.29
	24	4	89.74	32.38	5.58	0.00
	24	5	86.53	23.60	5.35	0.00
	24	6	106,82	21.17	5.99	0.51
soft_coral_gorgonian	16	1	128.44	28.00	5.51	0.36
sponge_barrel	24	1	119.98	41.87	6.67	0.00
sponge	24	1	119.96	2.37	3.03	0.64
	12	2	165.77	30.55	5.91	1.00
	20	3	166.64	29.60	6.37	1.00
	24	4	115.77	22.69	4.99	0.54

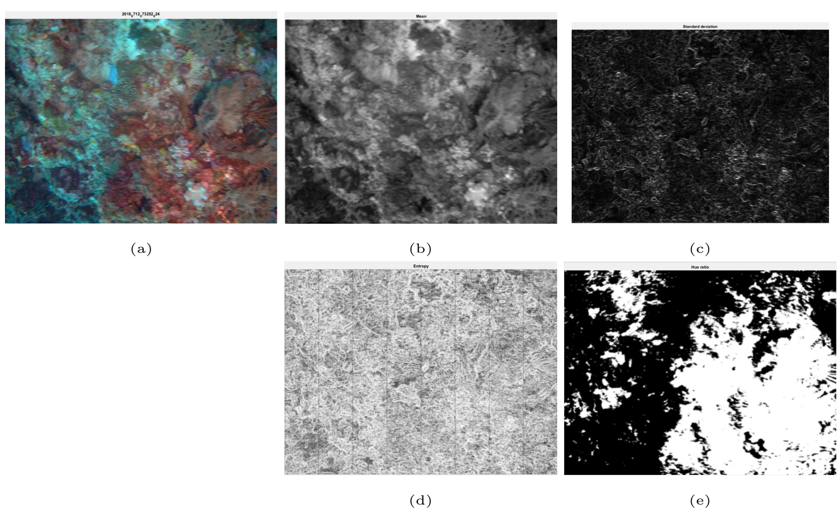


Fig. 3. : Original image (a) and its features: mean (b), standard deviation (c), entropy (d) and hue ratio (e).

described previously and the 4 features used, the best model was Random Forest which obtained a classification accuracy score of about 49%.

Random Forest consists of a collection of classifiers based on decision trees in which each tree gives rise to a vote for the output forecast. Random Forest produces a model consisting of n decision trees (ensemble), where each tree is based on a number of randomly selected instances of the training set. Each node of each tree is constructed from a random subset of the attributes. Upon receiving a test instance each tree will decide (vote) on which class it belongs to. The most voted class will be the class provided by the model. The most widely reported Random Forest algorithm is the Breiman algorithm [6].

The application of Random Forest pixel to pixel classifier in a test image with 3024 x 4032 pixels has a large computational weight since 4 matrices of 3024 x 4032 are constructed for the 4 features of each image pixel and another matrix with same size with confidence values. On the other hand, as it was necessary to classify 200 test images, the initial images were reduced by a factor of 4, so that the processing became faster.

3.4 Connected components

After classification it is necessary to find connected components of pixels belonging to the same substrate (area). As the areas of the substrates already identified in the training image are greater than 43,865 pixels, then in the classification of the test images, only areas with more than 500 (20 percent of one sixteenth of the average size of the substrates - $20\%(43,865/16) \approx 500$) pixels will be validated as substrate areas if the confidence valuer is greater than or equal to 0.5. With the regions identified in the images it is necessary to collect information about the image and class to which they belong, the degree of confidence of this classification and the position in the image of the bounding box that surrounds it (x minimum, y minimum, width and height). Finally, this information is placed in a text file as follows:

```
[image_ID];[substrate1][[confidence1,1]:][width1,1]x[height1,1]+[xmin1,1]+[ymin1,1],[[c
onfidence1,2]:][width1,2]x[height1,2]+[xmin1,2]+[ymin1,2],...;[substrate2] ...
```

4 Results

The 200 test images were processed according to the methodology described in section 3. Figures 4 and 5 show the results obtained for two different test images.

In Figure 4 the results for the image 2018_0712_073252_024 and in Figure 5 for the image 2018_0712_073534_067. The original image (a) and the classified image (b) and (c) where the pixels are identified within a substrate. The black pixels are not classified one of the following situations: substrate areas or confidence valuer (see section 3.4). The coral identified (d) with only the coral substrates presents in the test image. The colour shown in the images correspond to the colours identified for each substrate in the table 1. In the case of

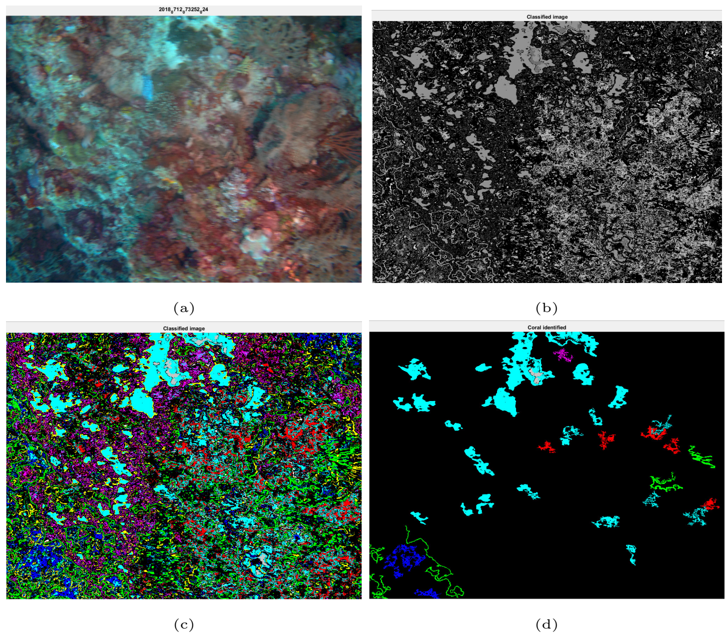


Fig. 4. : Original image (a), classified image in gray (b) and color (c) representation and the coral identified (c).

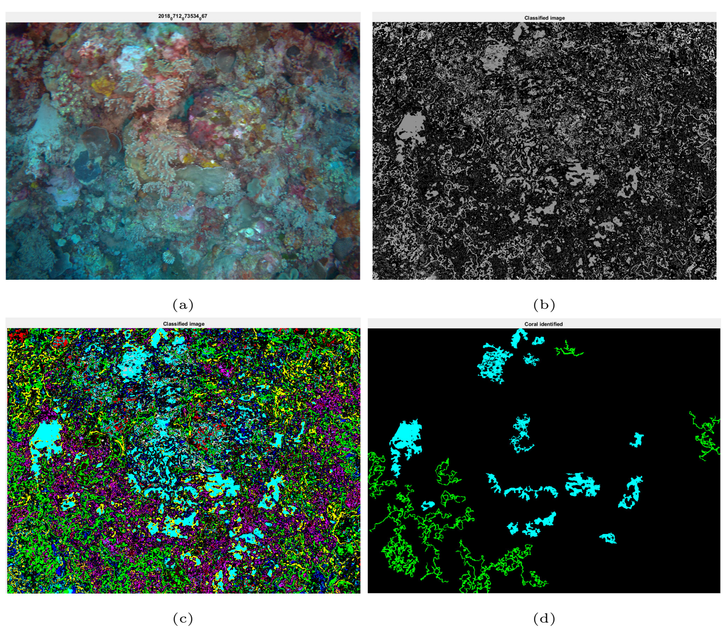
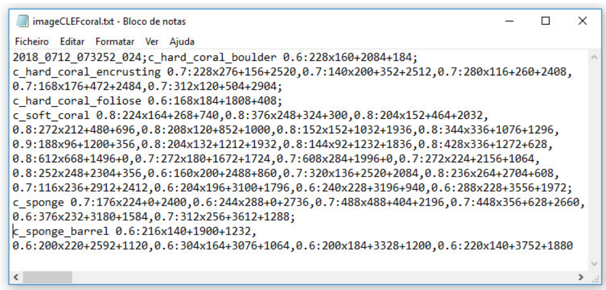


Fig. 5. : Original image (a), classified image in gray (b) and color (c) representation and the coral identified (c).

Figure 4, the substrates identified are: ”soft coral” (light blue), ”sponge barrel” (red), ”sponge” (light green), ”hard coral encrusting” (dark blue), ”hard coral boulder” (pink) and hard coral mushroom” (white). With this classification obtained, the relevant information is exported to a text file. An example (for image 2018_0712_073252_024) is presented in Figure 6.




```
2018_0712_073252_024;c_hard_coral_boulder 0.6:228x160+2084+184;
c_hard_coral_encrusting 0.7:228x276+156+2520,0.7:140x200+352+2512,0.7:280x116+260+2408,
0.7:168x176+472+2484,0.7:312x120+504+2904;
c_hard_coral_foliose 0.6:168x184+1808+408;
c_soft_coral 0.8:224x164+268+740,0.8:376x248+324+300,0.8:204x152+464+2032,
0.8:272x212+480+696,0.8:208x120+852+1000,0.8:152x152+1032+1936,0.8:344x336+1076+1296,
0.9:188x96+1200+356,0.8:204x132+1212+1932,0.8:144x92+1232+1836,0.8:428x336+1272+628,
0.8:612x668+1496+0,0.7:272x180+1672+1724,0.7:608x284+1996+0,0.7:272x224+2156+1064,
0.8:252x248+2304+356,0.6:160x200+2488+860,0.7:320x136+2520+2084,0.8:236x264+2704+608,
0.7:116x236+2912+2412,0.6:204x196+3100+1796,0.6:240x228+3196+940,0.6:288x228+3556+1972;
c_sponge 0.7:176x224+0+2400,0.6:244x288+0+2736,0.7:488x488+404+2196,0.7:448x356+628+2660,
0.6:376x232+3180+1584,0.7:312x256+3612+1288;
c_sponge_barrel 0.6:216x140+1900+1232,
0.6:200x220+2592+1120,0.6:304x164+3076+1064,0.6:200x184+3328+1200,0.6:220x140+3752+1880
```

Fig. 6. : Line information in text file.

5 Conclusions

The methodology developed allows to identify substrates of different classes in digital images of corals. The preliminary results are not very favourable, but there are many potential improvements that can be implemented. The most promising lines of work forward would be to focus on a better identification of sub-classes, and the use of additional features related to both colour and texture.

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