Using social media photographs to monitor changes in aesthetic value at tourist destinations

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Abstract

Introduction

Monitoring environmental change is of concern to destination managers. However, scientific monitoring is costly and in often logistically challenging. Recent advances in technology and data processing provide opportunities for cost-effective collection of data. Such technology can extract useful information from data generated purposefully by citizen science projects or collected incidentally by visitors to natural attractions (Becken et al., 2017).

Of particular interest here is the need of stakeholders to monitor the aesthetic value of sites in vulnerable ecosystems. The perceived beauty of natural sites is the key attractor for visitors, contributes to the generation of memorable experiences, and in turn leads to environmental protection. The value of such aesthetic experiences is reflected in the numerous photographs that visitors take and share via social media, such as Twitter, Instagram or Flickr. The photographs provide an untapped resource that can be used to assess changes in the environmental conditions.

This paper presents findings from research that developed a method to use visitor's photos to monitor the aesthetic value of the Great Barrier Reef (GBR) in Australia. The aesthetic value of the GBR (Johnston et al., 2013) is changing rapidly as a result of deterioration of water quality, coral bleaching, and biodiversity loss.

Objectives

This project addressed the need to monitor the aesthetic value of the GBR by:

1. Developing algorithms that automate the recognition of key objects within photographs or videos.
2. Developing algorithms for automatically assessing the aesthetic value of images.

Method

Following complementary research into key attributes of Reef beauty (fish, coral, turtle and contrast) (Scott et al., 2018) and an online survey (Becken et al., 2018), this research developed a computer-based system for the automated identification of marine species (N= 50 species) and assessment of the image's aesthetic value.

A total 27,000 images were downloaded from Flickr, of which 2,500 were deemed suitable for this research. In addition, video footage of selected GBR species was used to train the machine for automated species identification (Borland et al. 2017). The dataset of annotated picture frames for the detection of 50 species was divided into training (70%), validation 10%), and test (20%) sets. "Gold standard" data were used to train the model by pairing the input with the expected output. In the validation phase, additional data were used to assess model performance. Test data were used for calculating the test performance of the system.

A Deep Convolutional Neural Network (CNN) based method was used for image aesthetics assessment. The Deep CNN structure for image aesthetics assessment consisted of three Inception modules and connected intermediate local layers to the global layer. More detail can be found in Becken et al. (2018).

Results

The results show relatively high precision of species identification, as measured through the mean average precision. Figure 1 illustrates the identification of 'Regions of Interest' with subsequent determination of species. The machine can only recognise those species for which training material has been provided.

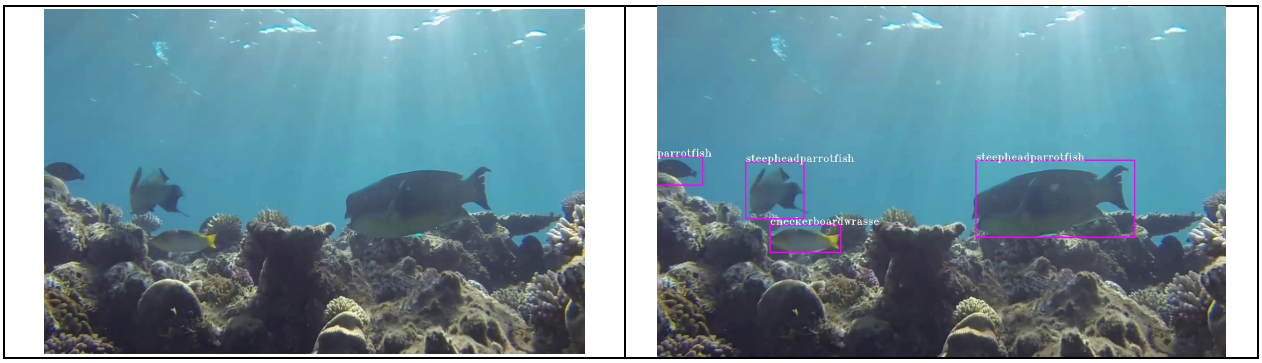


Figure 1. Example of input image to the left and output image after species detection on the right.

Table 1 presents the mean Average Precision (mAP) results obtained for the ten most frequent marine species in the dataset, and from three network architectures considered in our experiments. Compared with the two other models, the VGG-16 network (Simonyan & Zisserman, 2014) outperformed in terms of precision. For the VGG-16 network a mAP of 82.4% was achieved, and the average time taken for processing an image for detection during testing process was 0.2 seconds (i.e. 5 frames per second). For the ZF (Zeiler & Fergus, 2013) and CNN-M (Chatfield et al., 2014) models the processing time was 0.1 seconds (i.e. 10 frames per second) for network models, which implies that these systems are capable of processing videos in real-time scenario. The VGG-16 CNN had also performed well in related research on the aesthetics of landscapes (Seresinhe et al., 2017).

Table 1. Results from the experiment on the fish species datasets, comparing the three different models. AP = Average Precision, mAP = mean Average Precision.

Species	AP on VGG16	AP on CNN-M	Ap on ZF
Blue spotted flathead	1	0.818	0.831
Sand whiting	1	0.945	0.909
Smooth golden toadfish	1	1	1
Southern herring	1	0.947	0.867
Smooth nose Wedge fish	0.996	0.989	0.892
Painted grinner	0.986	0.951	0.972
Reticulate whip ray	0.909	0.909	0.909
Starry pufferfish	0.909	0.899	0.807
Swallowtail dart	0.909	0.838	0.994
Common stingray	0.906	0.995	0.97
mAP (whole sample)	0.824	0.769	0.75

The automated scoring of beauty of new images was compared with average scoring obtained from participants in an online survey (Table 2). The results show relatively high correlation,

although the findings differ for particular types of images. These images deserve further attention, as beauty scoring by humans might be disproportionally influenced by specific parameters (e.g. existence of charismatic species such as a turtle).

Table 2. Examples of the aesthetic score results obtained from humans and the machine

Image Name	Image	Human score	Machine score
Q1043_1.jpg		5.833	5.832
Q1125_1.jpg		6.833	6.828
Q2_887_1.jpg		7.727	4.628

Recommendations

This research delivered a proof-of-concept method for an automated species identification system, and an aesthetic assessment model. For both systems, the detection and assessment scores were high, despite some limitations such as comparatively small datasets for training. With some additional expert input and resources, the systems presented in this report could serve as a robust basis for the future implementation of an automated monitoring system of key aspects of the GBR. The concept is also transferrable to other nature-based destinations or even to urban contexts where aspects of crowding, building aesthetics (e.g. graffiti) and other destination attributes could be monitored.

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