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Automated classification of camouflaging cuttlefish

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HIGHLIGHTS

- An automated workflow is developed to classify images of camouflaging cuttlefish.
- Classification methodology is based on texture learning.
- System achieves a top performance of 94% accuracy as compared to human labels.
- Classifier output is used to propose a new model of cuttlefish camouflage.

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ABSTRACT

The automated processing of images for scientific analysis has become an integral part of projects that collect large amounts of data. Our recent study of cuttlefish camouflaging behavior captured ∼12,000 images of the animals' response to changing visual environments. This work presents an automated segmentation and classification workflow to alleviate the human cost of processing this complex data set. The specimens' bodies are segmented from the background using a combination of intensity thresholding and Histogram of Oriented Gradients. Subregions are then used to train a texton-based classifier designed to codify traditional, manual methods of cuttlefish image analysis. The segmentation procedure properly selected the subregion from ∼95% of the images. The classifier achieved an accuracy of ∼94% as compared to manual annotation. Together, the process correctly processed ∼90% of the images. Additionally, we leverage the output of the classifier

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to propose a model of camouflage display that attributes a given display to a superposition of the user-defined classes.

1. Introduction

Biological adaptive coloration has been observed in a diverse selection of animals, including moths, butterflies, spiders, chameleons, and a number of marine species (Stevens and Merilaita, 2009). Cephalopod camouflage has been of particular interest because of the breadth of possible body patterns these animals are capable of and the speed with which they can change (Barbosa et al., 2007). Laboratory experiments have suggested that the choice of particular camouflaging body pattern is fundamentally a visual process; cephalopods actively assess the surrounding ambient light field when camouflaging. A contemporary area of research is to unravel the complex physical and neurological processes underlying this impressive example of crypsis.

The Sub Sea Holodeck (SSH), an aquatic virtual environment, was developed to easily manipulate the visual environment experienced by a marine organism (Jaffe et al., 2011). The system allows control of the dynamic light field experienced by the animal using a combination of plasma display panels and digital projectors. An integrated camera records the subjects' response. Using the SSH, biologists are able to perform experiments to better understand the environmental stimuli that elicit changes in a cephalopods appearance.

The SSH, and other experiments that visually record the behavior of animals, generates large data sets. The data set from the single experiment analyzed in this work is comprised of nearly 12,000 images. Previous studies of cephalopod camouflage have analyzed data sets of similar size by hand. This process usually involves categorization according to some salient feature, or manually scoring each image based on 54 discrete body components followed by cluster analysis (Kelman et al., 2008). Additionally, the researcher must manually crop the animal from the background to prevent the type of background (e.g. sand versus black and white rocks) from affecting their scoring of body pattern. Besides being time consuming, manual processing is subject to errors resulting from short-term human memory, fatigue, boredom, and recency effects (Culverhouse et al., 2003).

In an effort to mitigate such problems, we propose an automated protocol to segment, register, and classify laboratory images of cuttlefish. The output of the classifier is further leveraged to quantify the probability that a given image belongs in each class. This capability will allow for the detection of subtle changes in an organism's body pattern that are difficult for a human observer to identify.

2. Prior work

Based on analysis of thousands of images of both terrestrial and aquatic animals, Hanlon (2007) posited that all animal camouflage can be classified into three basic patterns: uniform, mottle, and disruptive. Uniform (Fig. 1(a)) and mottle (Fig. 1(b)) patterns allow for general background matching whereas disruptive (Fig. 1(c)) patterns aim to obfuscate the outline of the animal and often include some aspects of the first two pattern types.

This generalization has been applied to studies of cuttlefish, providing a common language for classification. Previous studies have separated both laboratory and in situ images of cuttlefish into these three broad groups by grading the level of camouflage expression on 54 discrete chromatic, textural, postural, and locomotive body components as described by Hanlon and Messenger (1988). In this analysis, a pattern is defined as the combination of these components displayed by an individual. The "strength" of expression of each of these areas can be evaluated and used for classification.

A number of studies have made efforts towards improving the objectivity of the classification process. Images of disruptive and mottle displays were effectively separated by performing a principle component analysis on a manually generated matrix of body pattern grades (Zylinski et al., 2009).