Predict Ocean Health, One Plankton at a Time

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1. Introduction

Plankton are a crucial part of the earth's ecosystem, composing a large part of primary productivity and carbon fixed in the earth's global carbon cycle [3]. Since they are the foundation of aquatic food webs, loss of plankton populations could result in major ecological and social damage, particularly in indigenous cultures and the developing world [3]. Thus, plankton population levels are an ideal measure of the health of the world's oceans and ecosystems [3].

The Problem

Traditional methods for measuring and monitoring plankton populations are time consuming and lack the scope necessary for large-scale studies [3]. An alternative improved approach is through the use of an underwater imagery sensor. This towed, underwater camera system captures microscopic, high-resolution images over large study areas. The images can then be analyzed to assess species populations and distributions [3].

Manual analysis of the imagery to determine the class of species is infeasible – it would take a year or more to manually analyze the imagery volume captured in a single day [3]. Automated image classification using machine-learning tools is an alternative to the manual approach. Such an automated system will have broad applications for assessment of ocean and ecosystem health. We propose a system that will take as input images of a single organism and classify it into one of the classes from the list in Appendix A. This is a supervised learning problem, with a training set of labeled images that will be used to train the system.

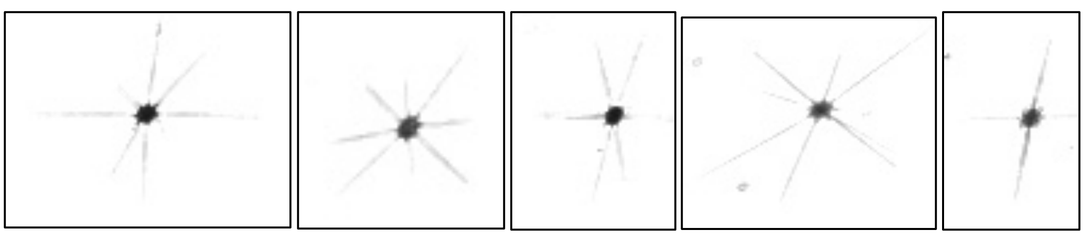
2. Learning Algorithm: Convolutional Neural Networks

Our problem is analogous to the famous character classification problem by Lecun et. al [4]. To solve this problem, Lecun et. al employ convolutional neural networks. Convolutional neural networks are "multi-layer architectures where the successive layers are designed to learn progressively higher-level features, until the last layer which produces categories. All the layers are trained simultaneously to minimize an overall objective function. The feature extraction is therefore an integral part of the classification system, rather than a separate module, and is entirely trained from data, rather than designed."[1] This significantly reduces the effort that has to be put for preprocessing and manual feature extraction, where accuracy in recognition of features of interest is largely determined by the ability of the designer to come up with an appropriate set of features [4]. The only basic preprocessing that will have to be done includes contrastive normalization and centering of the images. Feature extraction will be taken care of primarily (if not completely) by the machine-learning algorithm, which will be able to extract information meaningful to the algorithm, but not necessarily to a human. The implementation of the convolutional neural network will have to be tailored to the fact that we are dealing with amorphously shaped organisms, which can be distinguished primarily by shape and details, as shown in the images below the data section. Many more recent applications of convolutional neural networks in image feature recognition beyond character recognition has been in facial recognition and verification [2]. Similar applications have been tried on various other image classification problems, including medical imaging, satellite imaging, and astrological imaging, but little literature was found on a problem similar to this organism classification one.

3. Data

Our training data consist of approximately 30,000 images of planktons that are classified into 121 scientifically meaningful groups. Our test data contain additional 130,400 images of organisms. These data are provided by the National Science Bowl and are available on the Kaggle website [3]. The nature of the images and problem is such that, if need be, the data set can be doubled or tripled by a combination of reflections and translations of the images to provide more versions of each image to better train the algorithm.

The data for this project come from Oregon State University's Hatfield Marine Science Center, which collected nearly 50 million plankton images using an underwater imagery sensor over an 18-day period. Hatfield scientists ran each high-resolution raw image through an automatic processing to extract a smaller image containing a single plankton organism. Then they scientifically labeled a sample of the collection that populated our training data. Below are five different images of the Acantharia Protist contained in the training data.



4. Milestone Plan

By the milestone date (February 17th), we aim to achieve the following:

1. Size-normalize, center, and perform other processing of input images.
2. Research and evaluate the best networks for plankton recognition.
3. Make significant progress on writing a Matlab script that implements the Convolutional Neural Networks and produces preliminary results.

These are the main explicit goals. Other "soft" goals include potentially exploring more algorithms that could complement or enhance the convolutional neural networks, including random forests, support vector machines, and other methods that have been implemented for similar image classification problems. It will be important to keep researching the literature for better understanding of the algorithms we are using and how they can be applied.

References

[1] F.-J. Huang and Y. LeCun, “Large-scale learning with SVM and convolutional nets for generic object categorization,” in Proc. Computer Vision and Pattern Recognition Conference (CVPR’06), IEEE Press, 2006.
[2] Lawrence, S., C.l. Giles, Ah Chung Tsoi, and A.d. Back. "Face Recognition: A Convolutional Neural-network Approach." IEEE Transactions on Neural Networks 8.1 (1997): 98-113. Web.
[3] http://www.kaggle.com/c/datasciencebowl
[4] Lecun, Y., L. Bottou, Y. Bengio, and P. Haffner. "Gradient-based Learning Applied to Document Recognition." *Proceedings of the IEEE* 86.11 (1998): 2278-324. Web.
[5] Y. LeCun, F.-J. Huang, and L. Bottou, “Learning Methods for Generic Object Recognition with Invariance to Pose and Lighting,” Proc. IEEE CS Conf. Computer Vision and Pattern Recognition, 2004.

Appendix A
Class List:

acantharia_protist_big_center	hydromedusae_bell_and_tentacles
acantharia_protist_halo	hydromedusae_h15
acantharia_protist	hydromedusae_haliscera_small_sideview
amphipods	hydromedusae_haliscera
appendicularian_fritillaridae	hydromedusae_liriope
appendicularian_s_shape	hydromedusae_narco_dark
appendicularian_slight_curve	hydromedusae_narco_young
appendicularian_straight	hydromedusae_narcomedusae
artifacts_edge	hydromedusae_other
artifacts	hydromedusae_partial_dark
chaetognath_non_sagitta	hydromedusae_shapeA_sideview_small
chaetognath_other	hydromedusae_shapeA
chaetognath_sagitta	hydromedusae_shapeB
chordate_type1	hydromedusae_sideview_big
copepod_calanoid_eggs	hydromedusae_solmaris
copepod_calanoid_eucalanus	hydromedusae_solmundella
copepod_calanoid_flatheads	hydromedusae_typeD_bell_and_tentacles
copepod_calanoid_frillyAntennae	hydromedusae_typeD
copepod_calanoid_large_side_antennatucked	hydromedusae_typeE
copepod_calanoid_large	hydromedusae_typeF
copepod_calanoid_octomoms	invertebrate_larvae_other_A
copepod_calanoid_small_longantennae	invertebrate_larvae_other_B
copepod_calanoid	jellies_tentacles
copepod_cyclopoid_copilia	polychaete
copepod_cyclopoid_oithona_eggs	protist_dark_center
copepod_cyclopoid_oithona	protist_fuzzy_olive
copepod_other	protist_noctiluca
crustacean_other	protist_other
ctenophore_cestid	protist_star
ctenophore_cydippid_no_tentacles	pteropod_butterfly
ctenophore_cydippid_tentacles	pteropod_theco_dev_seq
ctenophore_lobate	pteropod_triangle
decapods	radiolarian_chain
detritus_blob	radiolarian_colony
detritus_filamentous	shrimp_caridean

detritus_other diatom_chain_string diatom_chain_tube echinoderm_larva_pluteus_brittlestar echinoderm_larva_pluteus_early echinoderm_larva_pluteus_typeC echinoderm_larva_pluteus_urchin echinoderm_larva_seastar_bipinnaria echinoderm_larva_seastar_brachiolaria echinoderm_seacucumber_auricularia_larva echinopluteus ephyra euphausiids_young euphausiids fecal_pellet fish_larvae_deep_body fish_larvae_leptocephali fish_larvae_medium_body fish_larvae_myctophids fish_larvae_thin_body fish_larvae_very_thin_body heteropod hydromedusae_aglaura unknown_blobs_and_smudges unknown_sticks unknown_unclassified	shrimp_sergestidae shrimp_zoea shrimp-like_other siphonophore_calycophoran_abylidae siphonophore_calycophoran_rocketship_adult siphonophore_calycophoran_rocketship_young siphonophore_calycophoran_sphaeronectes_stem siphonophore_calycophoran_sphaeronectes_young siphonophore_calycophoran_sphaeronectes siphonophore_other_parts siphonophore_partial siphonophore_physonect_young siphonophore_physonect stomatopod tornaria_acorn_worm_larvae trichodesmium_bowtie trichodesmium_multiple trichodesmium_puff trichodesmium_tuft trochophore_larvae tunicate_doliolid_nurse tunicate_doliolid tunicate_partial tunicate_salp_chains tunicate_salp