Classifying Maritime Vessels from Satellite Imagery with HyperNEAT

Phillip Verbancsics
SPAWAR Systems Center Pacific
53560 Hull Street
San Diego, CA, USA
phillip.verbancsics@navy.mil

Josh Harguess
SPAWAR Systems Center Pacific
53560 Hull Street
San Diego, CA, USA
joshua.harguess@navy.mil

ABSTRACT

Maritime data uniquely challenges imagery analysis. Such data suffers from degradation, limited samples, and varied formats. To this end, the Hypercube-based NeuroEvolution of Augmenting Topologies (HyperNEAT) approach is investigated in addressing such challenges for classifying maritime vessels in a satellite imagery data set. The results show that HyperNEAT learns to extract features that allows better classification than those from Principal Component Analysis (PCA) and robust to differences in presentation of data. Furthermore, HyperNEAT enables a unique capability to scale trained solutions to different image resolutions.

Categories and Subject Descriptors

I.5.4 [**Pattern Recognition**]: Computer Vision

Keywords

Image Classification, Artificial Neural Networks, HyperNEAT

1. INTRODUCTION

HyperNEAT has succeeded in visual discrimination tasks [9] and handwritten digits [6, 7] but has yet to be fully explored in real-world imagery. Imagery from the maritime domain presents barriers to learning in the form of small data sets, many image formats, and occlusions, distortions, or degradation [4], thus is a challenging problem [3, 4]. Results show that HyperNEAT creates feature extractors that outperform PCA and effectively learns with different preprocessing techniques. Interestingly, these different normalizations do impact the types of features learned and can aid in overcoming challenges in the data set (e.g. biases towards a particular class). Finally, indirect encoding allows solutions to be applied at any image resolution.

2. BCCT200

Maritime classification is an important goal for many security applications. Towards that goal, Harguess et al. [3] created the Barge, Cargo, Container, and Tanker (BCCT200) dataset (Figure 1) from the RAPid Image Exploitation Resource (RAPIER®), developed by the Space and Naval Warfare Systems Center Pacific [1]. The BCCT200 dataset was created by hand-labeling image chips into the vessel categories (4 classes / 200 images each), then they were rotated, cropped, and resized [3].

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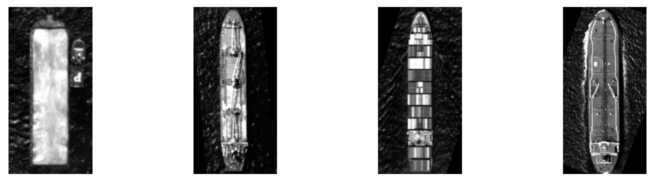

Figure 1: BCCT200 Data Set Examples.

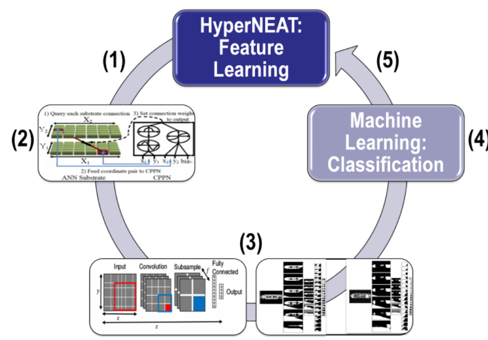

Figure 2: Feature Learning HyperNEAT. Evolved CPPNs (1) generate connectivity (2). The ANN extracts features (3). Features train another learning algorithm (4) to perform a task. Test performance determines fitness (5).

3. FEATURE LEARNING HYPERNEAT

HyperNEAT succeeds in challenging tasks [2, 8] by exploiting geometry, but is just beginning to address visual domains [6, 5, 7]. Conventional HyperNEAT trains a CPPN that defines an ANN that is the solution. However, Feature Learning HyperNEAT trains an ANN that transforms inputs into features that then are given to another machine learning approach to solve the problem. Performance of this learned solution then defines the fitness score of the CPPN for HyperNEAT (Figure 2). In this way, HyperNEAT acts as a reinforcement learning approach that determines the best features for a machine learning approach.

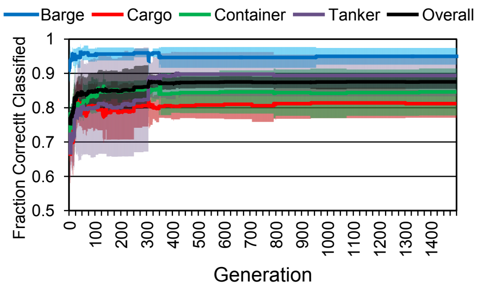

Figure 3: Max Bipolar Normalization.

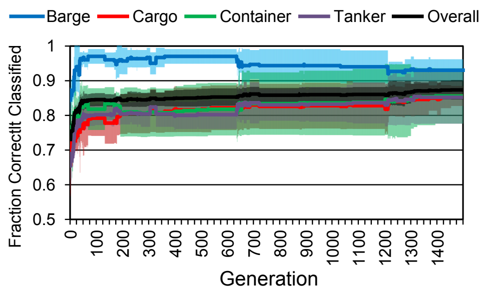

Figure 4: Mean Per Image Bipolar Normalization.

4. EXPERIMENTAL SETUP

BCCT200 is scaled down to 28×28 pixels and split into three sets: Training (400 images), Evaluation (200 images), and Testing (200 images). KNN ($k = 3$) learns from the training set, evaluation determines fitness, and testing is data unseen during evolution. The ANN has no hidden layers to match PCA's linearity. Image normalization is varied in three ways. (1) Normalization is varied between dividing by the max value, mean normalization, and deviation normalization. (2) Normalization is varied between all the pixels from all the images, within a single image, and at a particular location. (3) Range is set to either unipolar or bipolar. Scaling is implemented by applying a solution trained at the 28×28 to 20×20, 50×50, and 100×100.

5. RESULTS

PCA provides baseline performance of 86% training and 75% testing. Peak training performance is 92% with [deviation; all images; unipolar] normalization and peak testing performance is 80% with [max; bipolar]. Peak combined performance is [max; bipolar] normalization (89% training, 80% testing). All normalization approaches except [mean; all images; bipolar] exceed PCA's training performance. However, HyperNEAT only exceeds PCA's testing performance with: [deviation; per image; unipolar], [max; bipolar], and [mean; all images; bipolar]. Figures 3, 4 show performance per class over time of [max; bipolar] and [mean; per image; bipolar]. [Max; bipolar] converges to correct classifications 95% (barges), 89% (tankers), 85% (container), 81% (cargo). [Mean; per image; bipolar] differs by finding classification rates of 97% (barges), 82% (container), and 80% (tanker, cargo), but then learning balanced classification, with rates of 93% (barges), 86% (cargo, container), and 85% (tankers).

Classification performance at the trained resolution is 90% for training and 75% for testing. Scaling to different resolutions does degrade training and testing performance to 81% and 65%, 82% and 64%, and, 81% and 63% for the 20, 50, and 100 scales, respectively. Note, these results have *no* further training. Traditional computer vision [4] performance drops by more than half under similar scale changes.

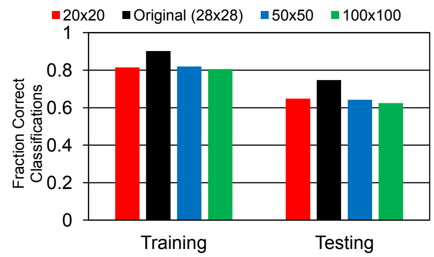

Figure 5: Scaling to Different Resolutions.

6. DISCUSSION & CONCLUSION

Feature Learning HyperNEAT was invesitgated in the challenging classification maritime vessels from satellite imagery represented by the BCCT200 data set. Results showed that HyperNEAT discovers superior linear feature extractors versus PCA under different manipulations of the data. Furthermore, the correct pre-processing allows HyperNEAT to overcome a strong bias present that can be present in small data sets. Finally, HyperNEAT demonstrates an ability to scale to different image resolutions. Thus HyperNEAT presents a unique approach to feature learning for imagery that can enable capabilities that are difficult for current approaches.

7. ACKNOWLEDGMENTS

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