

Deep Learning for Detecting Amphoras in Ancient Shipwrecks

by

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Bachelor Thesis in Computer Science

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Abstract

Consider this a separate document, although it is submitted together with the rest. The abstract aims at another audience than the rest of the proposal. It is directed at the final decision maker or generalist, who typically is not an expert at all in your field, but more a manager kind of person. Thus, don't go into any technical description in the abstract, but use it to motivate the work and to highlight the importance of your project.

(target size: 15-20 lines)

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1 Introduction

1.1 Motivation

1.1.1 Relevance of Amphoras

The name *amphora* is derived from the Greek word *amphoreus*, which literally means "two-handled" [1, 2]. It is the combination of two linguistic roots: *amphi* (on both sides) and *phoreus* (bearer) [1, 2]. Amphoras (or amphorae) were commercially used from 1500 B.C.E. to 500 C.E. to ship products throughout the Mediterranean, supplying the ancient Greek and Roman empires [2]. Amphoras were designed to ship large quantities of liquid (wine, olives, and oils) and dry products (grain, nuts, and salted fish) [2].

Like many measures that are named after the packages, amphoras were also a semistandard unit of liquid measure [2]. A cargo ship's capacity was measured by the number of amphoras it could carry instead of by weight [2, 3].

The structurally strong egg-like shape and the high volume-to-weight ratio made amphoras very efficient packages [2]. Amphoras were by far the most common cargo type in Mediterranean shipwreck analysis; more than half of the ships only carried amphoras [2, 4].

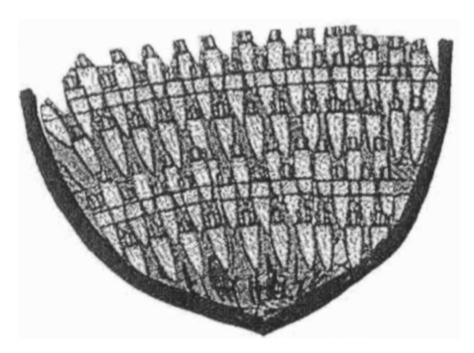


Figure 1: The egg-like shape enabled amphoras to interlock and minimize the waste of space on a ship. Source: [2].

Amphoras' various shapes and markings - which changed by time, region, producer, contents, and brand identity - were used to identify the package status and the different products inside [2].

Amphoras have great significance in archaeology. They can be used as evidence for the trade patterns throughout the Mediterranean [2]. As they were usually discarded at the destination of a trade and have been found in shipwrecks, archaeologists have been



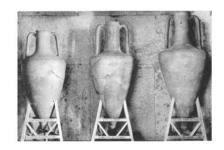






Figure 2: Amphoras have various shapes. Source: [2].

using them to recreate the transit routes [2]. Furthermore, researchers have been able to classify different amphoras, which also helps to date ruins and shipwrecks [2].

1.1.2 Computer Vision for Underwater Object Detection

Computer vision is the science of perceiving and understanding the world through images and videos [5]. There have been multiple exciting applications of computer vision, including image classification [6], object detection and localization [7, 8], art generation (neural style transfer) [9], image creation with Generative Artificial Networks (GAN) [10], face recognition [11], action and activity recognition [12], human pose estimation [13], and image recommendation system [14].

However, there is still limited research for the application of computer vision and machine learning in archaeology, especially underwater archaeology, compared to other domains [15, 16]. Computer vision, instead of visual inspection, could be used to automate the assessment and classification of artifacts [15].

Underwater computer vision has proven to be challenging, largely due to: 1) the distortion and attenuation caused by light propagation in water, and 2) the unrestricted natural environment with the abundance of marine life and suspended particles [16, 17, 18].

Despite the challenges, computer vision has lower cost [17] compared to sonar imagery [19] and laser scanning [20]. Plus, the abundance of visual data obtained through autonomous underwater vehicles (AUVs), unmanned underwater vehicles (UUVs) [18], and seafloor cabled observatories [16] enables us to utilize deep learning.

1.2.1	Artifical Neural Networks (ANN)			
1.2.2	Convultional Neural Networks (CNN)			
1.2.3	Deep Learning vs. Traditional Computer Vision			
1.3	Object Detection			
Define	object detection and introduce the sliding CNN approach.			
1.3.1	Fully Convolutional Networks (FCN)			
1.3.2	General Object Detection Framework Components			
Regio	n Proposals			
Network Predictions				
Non-Maximum Suppression (NMS)				
Metrics				
1.3.3	Region-Based Convultional Neural Networks (R-CNN)			
R-CNN	I			
Faster	R-CNN			
Faster	R-CNN			
1.3.4	Single Shot Detector (SSD)			
1.3.5	You Only Look Once (YOLO)			
YOLO				
YOLOv2				

1.2 Deep Learning

YOLOv3

YOLOv4

YOLOv5

2 Related Work

3 Data and Methods

This is the technical core of the thesis. Here you lay out your how you answered your research question, you specify your design of experiments or simulations, point out difficulties that you encountered, etc.

(target size: 5-10 pages)

- 3.1 Data
- 3.2 Model

3.3 Model Training

4 Evaluation

This section discusses criteria that are used to evaluate the research results. Make sure your results can be used to published research results, i.e., to the already known state-of-the-art.

(target size: 5-10 pages)

Number	Description
7	A lucky number in Western culture
8	A lucky number in Chinese and other Asian cultures
42	Answer to the ultimate question of life, the universe, and everything
404	Not found

Table 1: Useless insights I gained with no further meaning

4.1 Visual Evaluation

4.2 Metric Evaluation

5 Conclusions

Summarize the main aspects and results of the research project. Provide an answer to the research questions stated earlier.

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6 Future Work

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