# Chapter 103
# Machine Learning for Detecting Scallops in AUV Benthic Images:
## Targeting False Positives

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## ABSTRACT

*A large volume of image data, in the order of thousands to millions of images, can be generated by robotic marine surveys aimed at assessment of organism populations. Manual processing and annotation of individual images in such large datasets is not an attractive option. It would seem that computer vision and machine learning techniques can be used to automate this process, yet to this date, available automated detection and counting tools for scallops do not work well with noisy low-resolution images and are bound to produce very high false positive rates. In this chapter, we hone a recently developed method for automated scallop detection and counting for the purpose of drastically reducing its false positive rate. In the process, we compare the performance of two customized false positive filtering alternatives, histogram of gradients and weighted correlation template matching.*

## INTRODUCTION

Understanding the parameters that affect the habitat of underwater organisms is of interest to marine biologists and government officials charged with regulating a multi-million dollar fishing industry. Dedicated marine surveys are needed to obtain population assessments. One traditional scallop survey method, still in use today, is to deploy a dredge from a vessel and conduct several tow transects over an area. From the dredge material one extrapolates to arrive at an estimate of the local population density. In addition to being invasive to scallop habitat, these estimates are not necessarily accurate. There is a need for non-invasive and accurate survey alternatives.

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The availability of a range of robotic systems in form of towed camera and Autonomous Underwater Vehicle (AUV) systems offer possibilities for such non-invasive alternatives. Optical imaging surveys using underwater robotic platforms provide higher data densities. The large volume of image data (in the order of thousands to millions of images) can be both a blessing and a curse. On one hand, it provides a detailed picture of the species habitat; on the other it generates a need for extensive manpower and time to process the data. While improvements in robotic platform and image acquisition systems have enhanced our capabilities to observe and monitor the habitat of a species, we still lack the required arsenal of data processing tools. This need motivates the development of automated tools to analyze benthic imagery data containing scallops.

Computer vision, machine learning, and (big) data analytics become candidate fields for drawing ideas. In this chapter, we focus on reviewing an automated scallop counting method based on benthic images that we recently developed (Kannappan et al., 2014), and enhancing it so that the false positives rates is drastically reduced. Weighted Correlation Template Matching (WCTM) and Histogram of Gradients (HOG) are two techniques evaluated as possible candidates for this purpose, and their comparative performance is analyzed. The new false positive filter layer that is integrated into the scallop counting tool of Kannappan et al. (2014) offers a new paradigm for scallop counting in noisy underwater image datasets.

## BACKGROUND

The 2011 Research Set-Aside project (Titled: "A Demonstration Sea Scallop Survey of the Federal Inshore Areas of the New York Bight using a Camera Mounted Autonomous Underwater Vehicle.") was a proof-of-concept that successfully used a digital, rapid-fire camera integrated with a Gavia AUV (Figure 1(c)), to collect a continuous record of photographs for mosaicking, and subsequent scallop enumeration and size distribution assessment. In July 2011, data was collected over two separate five-day cruises (27 missions). Image transects were performed at depths of 25-50 m. The AUV continuously photographed the seafloor (see Figure 1(a)) along each transect at a constant altitude of 2 m above the seafloor. Spacing parallel sets of transects at 4 m gave excellent two-dimensional spatial resolution.

The camera on the AUV was a Point Grey Scorpion model 20SO (for details on the camera specification, see (Kannappan et al., 2014)). It was mounted inside the nose module of the vehicle, with its strobe light near the center of the AUV (see Figure 1(b)) and a horizontal viewing angle of 44.65 degrees. The camera focus was manually fixed at 2 m and the resolution was at 800×600 pixels. Given the viewing angle and distance to the object being photographed, each image captured an area of 1.86×1.40 $m^2$ on the seafloor. Images were saved in JPEG format, with metadata that included position information (including latitude, longitude, depth, altitude, pitch, heading and roll). This information enabled manual annotation and counting of the number of scallops (Walker, 2013).

Rosenkranz et al. (2008) have reported that the data processing time to review and analyze one hour of collected data is in the order of 4 to 10 hours. They also suggest that automated computer techniques would greatly benefit imaging surveys, but note that there exist no available automated tools. There has been anecdotal evidence of development of automated scallop assessment tools by HabCam group (Gallager et al., 2005), though there is no such tool available to the research community. Manual data processing time estimates from our own AUV data indicates that the counting can be performed by a team of 6 researchers at a rate of 2080 images/hour for scallops (Walker, 2013). If this were to be extended