Single-image semi-blind Gaussian Deconvolution of Coastal Aerial Imagery for Improved Rock Segmentation

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Introduction

Aerial imagery has wide-ranging coastal oceanography applications, including examining rates of coastal erosion and sea level rise, modeling concentrations of suspended sediment and coastal contaminants, and segmenting other features of interest such as rocks. A limiting factor to several of these applications is the sharpness of the available aerial imagery. Particularly, if imagery is blurry or noisy, it is difficult to quantify small-scale differences in sea level over time or to detect the precise position of edges of rocks in the ocean.

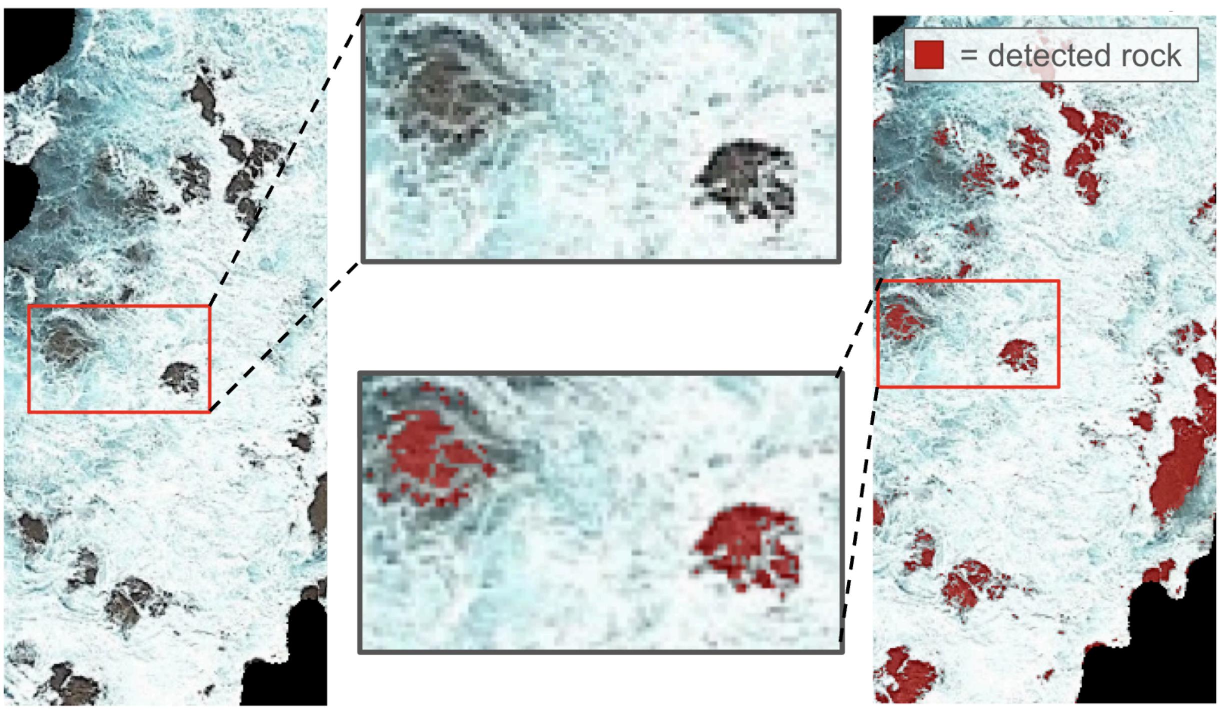

Figure 1. Example of blurry edges of surface-piercing rocks in the rocky shoreline and associated difficulty in segmenting these blurry rocks (shown in red).

In this project, we will focus on the task of improving image resolution to promote more accurate segmentation of rocks along rocky shorelines. Figure 1 shows an example of a blurry, pixelated edge of a rock, leading to difficulties in segmenting the rock accurately. In this project, we seek to determine whether this blur can be successfully reduced by applying an image reconstruction-based method to build a high-resolution image from a lower-resolution one.

Motivation

Comprising 75% of coastline worldwide, rocky shores can be considered the "jungles" of the ocean, supporting diverse ecosystems of invertebrates, intertidal plants, and algae. The stability and connectivity of these ecosystems depends on wave breaking and the subsequent water circulation it generates. Rocks located in the surf zone (the region of wave breaking) are hypothesized to control wave breaking and circulation patterns. Therefore, to understand the impact of rocks on wave breaking and circulation patterns in the rocky shoreline environment, an accurate identification of characteristic morphological features on rocky shores near the region of breaking waves is necessary. Precise rock segmentation, allowing us to compute important statistics such as the density of surface-piercing rocks, is an important component of this.

Background and Related Work

Single-image blind Gaussian deconvolution is a popular post-processing technique in computational imaging when a sharper image is desired and blur in a known image can be constrained as Gaussian. Differing from pure blind convolution—where no knowledge of the blur kernel is known, making the problem severely ill-posed—semi-blind deconvolution makes the assumption that the blur is a point spread function (PSF), but the parameters thereof such as the variance must be estimated (Xue and Blu, 2012). The deconvolution process can be modeled an inverse problem:

$$y = Hx + \eta$$

Where $y \in R^N$ is the observed (blurry and noisy) image of an unknown clean image $x \in R^N$ that we seek to obtain which is blurred by a PSF h. $H \in R^{NxN}$ is the convolution matrix of h, and $\eta \sim \mathcal{N}(0, \sigma^2 I)$ is additive Gaussian noise. H can represent many blurs, including defocus and motion blurs (Lam and Goodman, 2000), and therefore typically requires many variables to parameterize. Solving this class of blind deconvolution problems is typically done two ways: first, if the specific blurring operator is assumed to be gaussian yet the variance of the Gaussian blur is unknown, H can be estimated by itself first, followed by non-blind deconvolution (with H as the estimated PSF) to obtain a sharper image (Xue and Blu, 2012). A second approach involves a joint optimization problem, allowing for the identification of blur and image restoration simultaneously (Cai et al. 2009; Chan and Wong, 1996; Molina et al., 2006).

While single-image blind Gaussian deconvolution has been widely applied in the field of computational imaging, this post-processing technique has not yet been applied directly to coastal satellite imagery.

Overview of project and objectives

In this project we seek to explore whether improvements in the accuracy of rock segmentation in the surf zone from high-resolution Google Earth pro aerial imagery off the coast of Northern California. To do so, we aim to reduce image blur through deconvolution, by estimating an initially unknown Gaussian PSF. We assume a simple case in which Gaussian blur is isotropic, implying that it is only parameterized by σ. In reality this is likely not the case for aerial imagery which is subject to directional motion blur (Wade et al., 2025).

To solve for the PSF and a resulting cleaner image, we plan to use an isotropic Total Variation (TV) regularizer, which has been shown to be effective for solving blind deconvolution inverse problems by promoting sparse gradients in the reconstructed image, making it appear realistic (Chan and Wong, 1996). We may incorporate the use of different regularizers depending on the success of the TV approach.

The success of our method will be quantified by comparing the estimated segmented area of rocks from both the blurry input image and the output clean image to manually-outlined ground truth estimates of rocks from Washburn (2026). This is defined as:

$$Segmentation\ success_{image} = \frac{\Sigma\ detected\ rock\ area}{\Sigma\ ground\ truth\ rock\ area}$$

Where the detected rock area only includes the area that overlaps with the ground truth, i.e. false positives are omitted.

A simple segmentation algorithm will be used to segment rocks in the surf zone based on thresholding. An rgb-based index is created to separate bright whitewater and darker rocks, and Otsu's thresholding method is used to separate pixels into whitewater and rock categories.

Timeline (including milestones and intermediate goals)

1. Week 1: develop a simple algorithm for sharpening aerial images by estimating the PSF and in turn the cleaner image.
2. Week 2: fine-tune this model by changing thresholds and trying different regularizers if needed. Evaluate the approach on one single aerial image at Garrapata State Park, CA.
3. Week 3: evaluate this approach on other images along the coast of Northern California and increase the generalizability of the model. Prepare materials for presentation and report.

References

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