Chapter 1

Introduction

1.1 Shadow Removal

1.1.1 The Context

Video analytics have seen a rise in popularity in many application fields, such as surveillance, data collection, and smart-city infrastructure. Some of these applications, e.g., pedestrian and traffic counting (Danner et al.'s) [**??**], perform classification and analysis on moving objects. In order to detect and extract moving objects in an environment, foreground pixels are differentiated from those of the background through the use of statistical techniques, including Mixture of Gaussians, and Multi-Modal Mean [**??**, **??**]. These strategies establish a model of the background of a scene, which changes over time. This background model is then compared directly to a frame. By finding the difference between a frame and its background model, a mask containing the foreground pixels is created. Foreground pixels are then grouped together and segmented as a moving object, which is analyzed according to the needs of the application.

Applications that analyze moving objects rely on the accuracy of the extraction of foreground pixels. These applications are disadvantaged by the fact that shadows are often mischaracterized as foreground objects, and are included as part of a moving object. This is often due to shadows possessing similar movement patterns and brightness compared to non-shadow foreground objects [**??**]. Figure **??** illustrates the effect shadows have on the segmentation of foreground objects.

The inclusion of shadows in foreground objects may hamper detection and tracking in several ways. Prominent issues, noted by Sanin et al. [**??**], include the distortion of an object's appearance model (required to properly track an object), and the erroneous joining of multiple objects into one labeled connected-component. Additional details regarding a shadow's effect on tracking can be found in [**??**]. The removal of shadows from foreground objects is thus a vital step in accurately segmenting moving foreground objects.

Classifying shadow pixels within moving foreground objects has been approached in numerous ways, including color-based attenuation models, geometric projective models, and texture-matching models [**??**, **??**, **??**]. Machine-learning has also been employed to attempt to learn the appearance of cast shadows in an unsupervised manner [**??**, **??**, **??**]. A taxonomy of shadow

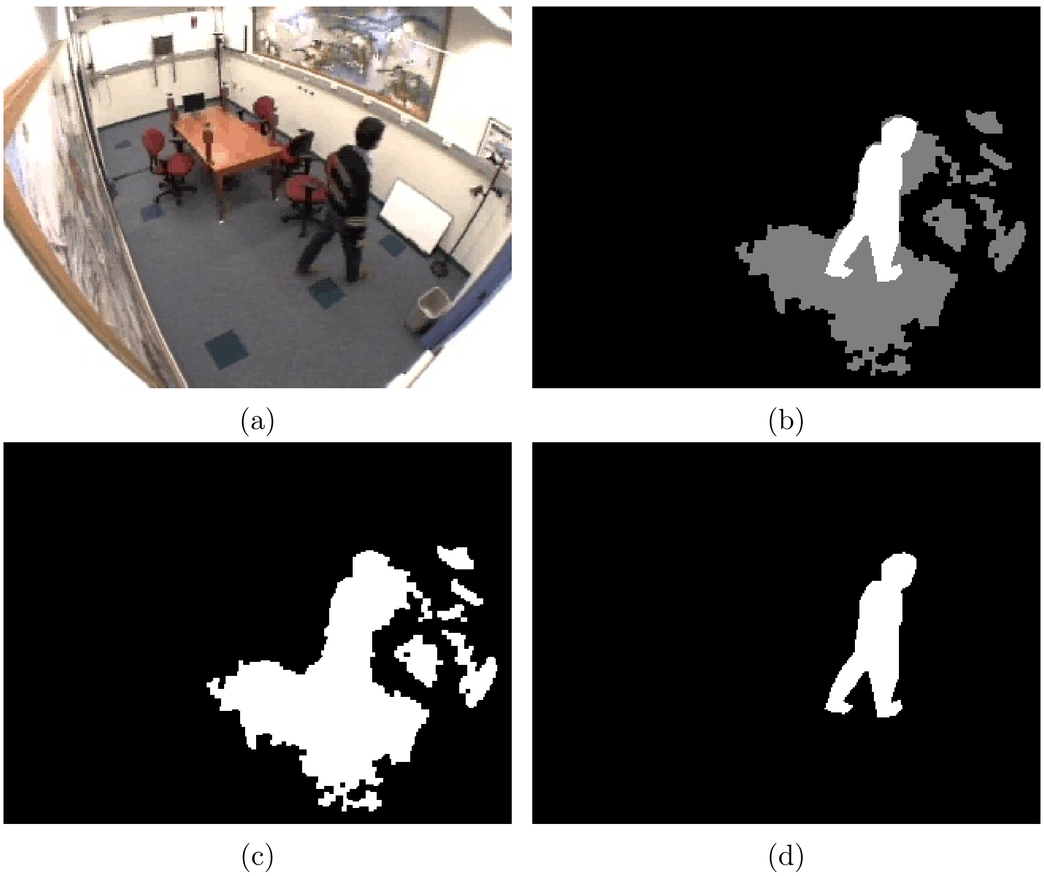


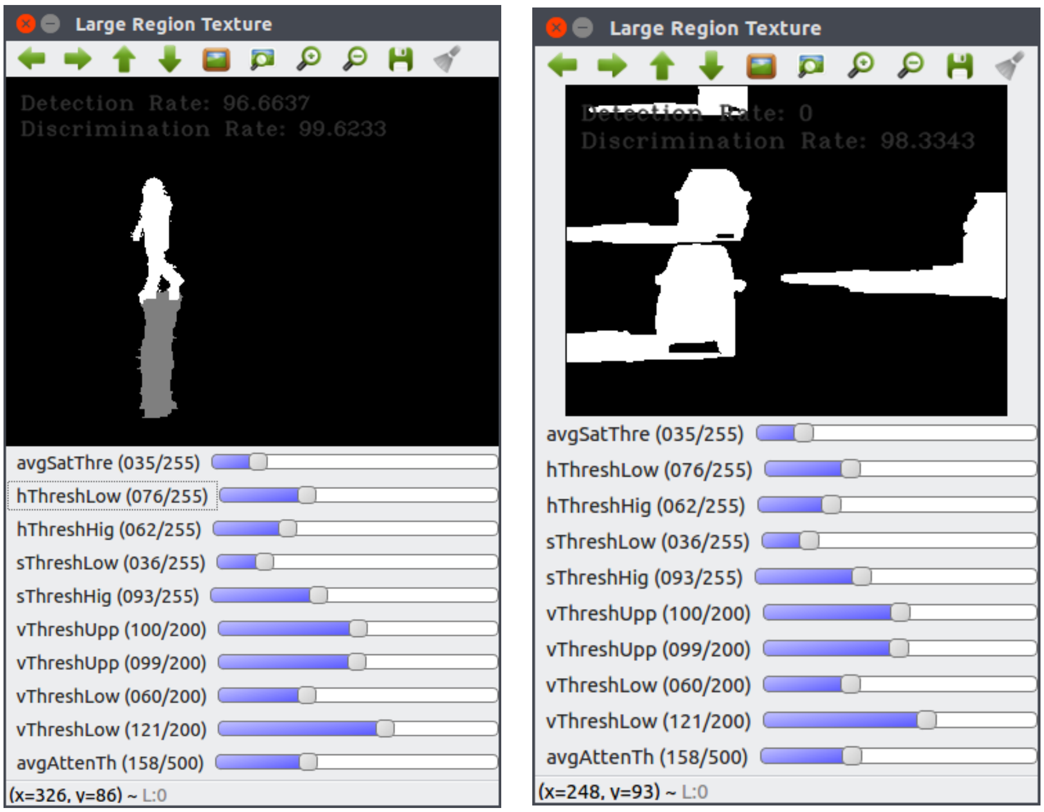
Figure 1.1: (a) Original frame, from the aton_room dataset. (b) The foreground mask is provided, and segmented. Shadow pixels are shown in gray, and foreground object pixels in white. (c) Improper segmentation of the foreground due to shadows. (d) Proper segmentation with the removal of shadows.

removal methods produced by Prati et al. summarizes and evaluates four contemporary method classes: Statistical Nonparametric, Statistical Parametric, Deterministic Nonmodel-based and Deterministic Nonmodel-based 2 [2]. The study concluded that the simpler methods were more suited for general practice, but "to detect shadows efficiently in one specific environment, [adding] more assumptions yield better results." A second algorithm survey conducted by Sanin et al. in [1] evaluated more modern methods (catalogued as Chromacity, Geometry, Physical, Small Region Texture, and their own contribution, Large Region Texture) on the same datasets as above, yielding similar results concerning the generalization of shadow removal to an arbitrary scene. Mitra et al. provides a survey of threshold selection strategies for identifying shadows in moving foreground objects [3].

1.1.2 The Problem

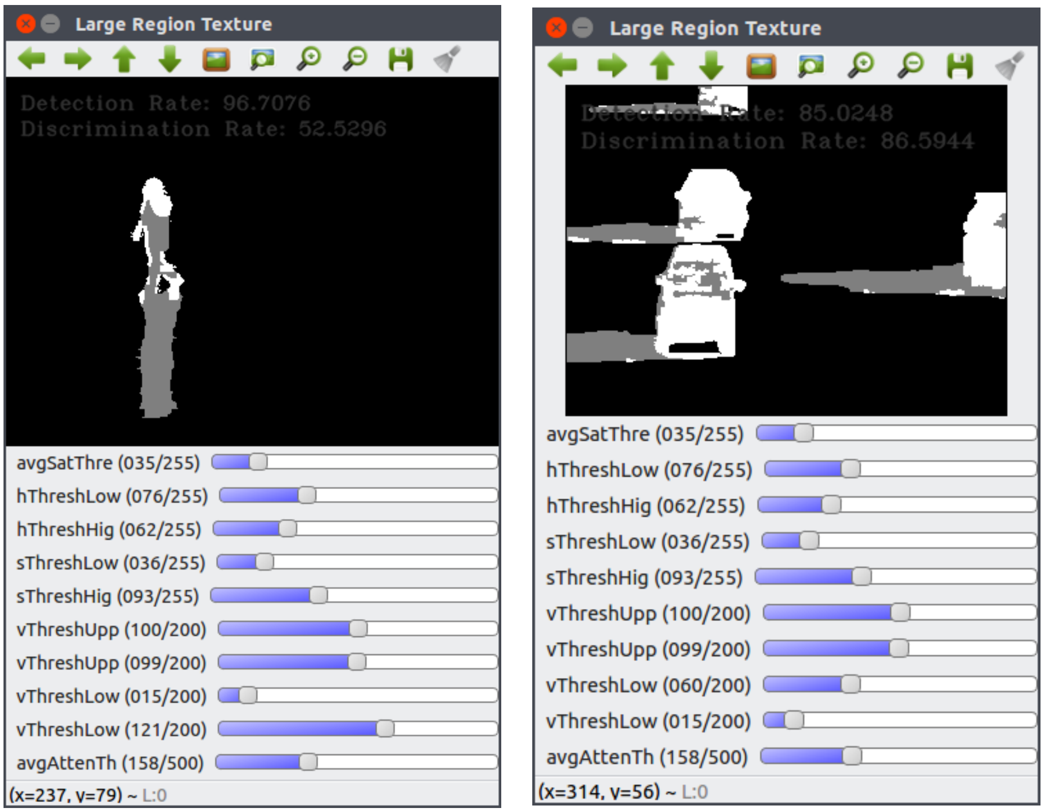
These surveys indicate that existing shadow removal algorithms fail to optimally adapt to various environmental properties; these methods quantifiably benefit from assumptions made about key factors of a scene, including illumination constancy, color content, and shadow intensity. In order to facilitate optimization, shadow removal methods possess algorithm parameters that are manually tuned to an environment. The reliance on environmental assumptions affects shadow removal in two ways: firstly, shadow removal performs suboptimally when deployed in an arbitrary environment, and secondly, even when manually calibrated, shadow removal fails to adapt to environmental parameters that change over time. From an application context, a surveillance system that monitors a sun-lit environment 24 hours a day will possess a wide range of shadow qualities when comparing shadows cast at dawn to shadows cast in the evening. Shadows cast in the same location may vary in darkness, size, orientation, and shape depending on the time of day. Therefore shadow removal must adapt not only to diverse environments, but continually adapt as environmental properties vary over time.

We quantitatively demonstrate several cases that indicate the need for adaptation. Shadow removal is judged by its detection rate and its discrimination rate, further detailed in section **??**. Detection rate indicates the number of shadow pixels correctly identified, while discrimination rate indicates the number of foreground object pixels that are correctly identified. Figure **??** modifies a parameter belonging to Large-Region Texture (LRT) shadow removal, which controls the chromacity range in which a shadow can lie. The parameter (*vThreshLower*) causes LRT shadow removal to perform optimally in the CAVIAR frame at its default value, 121. Similarly, the same algorithm performs poorly in the included dataset aton_highway1 with the default parameters. However, if *vThreshLower* is modified from 121 to 15, CAVIAR experiences a 47% loss of discrimination, while aton_highway1 gains 85% detection in exchange for a 13% loss of discrimination. Geometry shadow removal was found to also showcase different results on the same scene, but with differing parameters (Figure **??**).



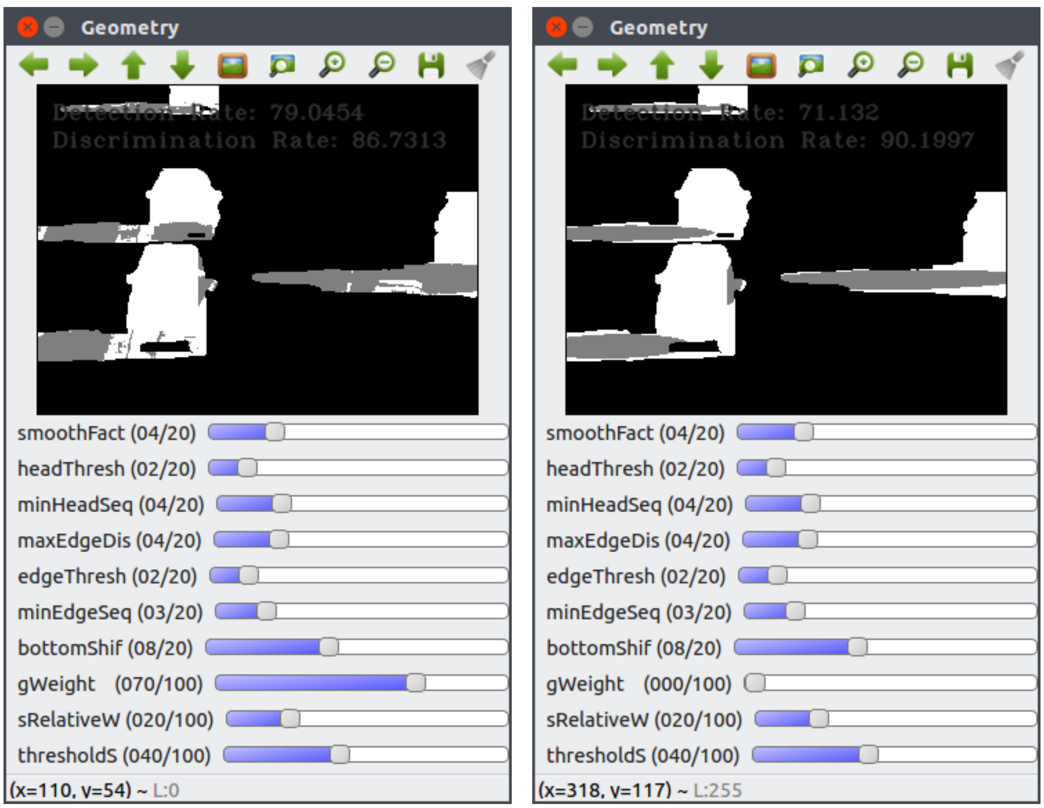
(a) (b)

Figure 1.2: Default parameters (Datasets provided by Sanin, et al. [**??**]) (a) Detection: 96.6637, Discrimination: 99.6233. (b) Detection: 0, Discrimination: 98.3343



(a) *vThreshLower: 121* (b) *vThreshLower: 15*

Figure 1.3: *vThreshLower* shifted from '121' to '15.' (Datasets provided by Sanin, et al. [**??**]) (a) Detection: 96.7076, Discrimination: 52.5296. (b) Detection: 85.0248, Discrimination: 86.5944



(a) *gWeight: 70* (b) *gWeight: 0*

Figure 1.4: *gWeight* shifted from '70' to '0.' (a) Detection: 79.0454, Discrimination: 86.7313. (b) Detection: 71.132, Discrimination: 90.1997

1.2 Objective and Contributions

Our research seeks to establish an understanding of environmental properties that affect shadow removal, and utilize that understanding to optimize shadow removal in an arbitrary environment. This is achieved by automatically calibrating an algorithm's parameters based on observed environmental properties. Furthermore, we seek to create an understanding of how these environmental properties change over time, in order to continuously adapt shadow removal algorithms. These objectives require the creation of an adaptive model which automatically configures a shadow removal method to optimally perform given the observed environmental properties.

Our research makes the following contributions. We perform a qualitative assessment of each algorithm's performance in various environments. We construct and utilize an interactive framework for evaluating the sensitivity of an algorithm with respect to its mutable parameters. We identify and quantify observed environmental properties, and correlate them to sensitive algorithm parameters. Finally, we demonstrate the construction of an adaptive model, capable of leveraging correlated environmental properties to automatically tune an algorithm's parameters. The demonstration is completed by constructing a proof-of-concept model for Physical shadow removal.

Our proof-of-concept adaptive model draws upon the correlation between brightness attenuation in shadow regions and one of the Physical algorithm's parameters, *coneR1*. It improves shadow detection by up to 10% and shadow discrimination by up to 28% on a range of standard datasets from ATON and PETS. Additional indirect environmental factors are found to modify the effectiveness of the adaptive model. Various brightness calculation methods are shown to influence attenuation correlation by 7% to 20%. A study of low-contrast feature keypoints in a scene was shown to occasionally improve attenuation-correlation by up to 12%.

The outline of this thesis is as follows. In Chapter 2, we detail the shadow removal algorithms utilized in this study, and outline the steps taken to produce an adaptive model. Chapter 3 assesses the shadow removal algorithms for their performance in diverse environments, as well as their sensitivity to parametric change. These assessments culminate in the construction of a proof-of-concept adaptive model for Physical shadow removal, using its *coneR1* parameter. Chapter 3 also explores indirect environmental properties and their potential impacts on the performance of the adaptive model. Chapter 4 quantifies and discusses the results of the adaptive model, and the indirect environmental properties' effects on the model. Chapter 5 concludes with analysis and future work.