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Automatic segmentation of trees in dynamic outdoor environments☆

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ABSTRACT

Segmentation in dynamic outdoor environments can be difficult when the illumination levels and other aspects of the scene cannot be controlled. Specifically in orchard and vineyard automation contexts, a background material is often used to shield a camera's field of view from other rows of crops. In this paper, we describe a method that uses superpixels to determine low texture regions of the image that correspond to the background material, and then show how this information can be integrated with the color distribution of the image to compute optimal segmentation parameters to segment objects of interest. Quantitative and qualitative experiments demonstrate the suitability of this approach for dynamic outdoor environments, specifically for tree reconstruction and apple flower detection applications.

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1. Introduction

Segmentation is a key step in many object detection contexts, and when the result is accurate, can reduce the amount of information presented to subsequent steps of an autonomous computer vision system. This paper describes a method for segmentation of a mobile background unit from tree regions in an orchard setting as part of an automated pipeline to reconstruct and measure the shape of leafless trees for robotic pruning and phenotyping [1–3]. Since the images are acquired outdoors, illumination conditions are not stable and may change rapidly and widely. Furthermore, the entire tree reconstruction and measurement process is automated, and hundreds of images must be acquired per tree. Hence, the segmentation method must be robust and not require manual parameter tuning. Since our goal is to use the segmentation step as part of a real-time automation application, the method must also be fast.

The ability to robustly extract the silhouettes of objects of interest is generally an important step in the generation of three-dimensional models of complex objects such as trees [1] and may form a preprocessing step for other tasks, such as flower detection [4]. Existing silhouette extraction techniques based solely on thresholding and morphological characteristics of the object of interest, however, tend to generate unsatisfactory results, particularly with respect to segmentation. This problem, as with most computer vision tasks, is further aggravated in dynamic environments, which include situations such as drastically varying illumination conditions. Hence, we propose a novel method to segment an object (in this case a tree) from a low-texture background, which is robust to significant illumination changes.

The segmentation method proposed in this paper assumes an item of interest in a image is positioned in front of a background material of homogeneous color. It locates the low texture regions of the image using superpixels and models them using a Gaussian mixture model (GMM). Pixels in the image are classified according to the GMM and a mask of the background material region is created. The method is fully autonomous and does not require user input or training, other than initial setting of thresholds. The main contribution of this work is an unsupervised method to segment foreground objects in images that is sufficiently robust to operate with various models of cameras under natural outdoor illumination conditions and is fast enough to be used in automation contexts. The method is verified through quantitative and qualitative experiments as well as comparisons to alternative approaches based on Otsu's method [5] and adaptive thresholding mechanisms.

The remainder of this paper is organized as follows. Section 2 presents a brief overview of methods for the segmentation of

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foreground objects with a particular focus on agricultural applications. Section 3 describes our proposed approach. A comprehensive evaluation comparing the performance of our methods to alternative approaches to foreground object segmentation is given in Section 4. Finally, Section 5 concludes the paper and discusses possible future research directions.

2. Related work

There is a significant amount of related work on segmentation in dynamic environments for the purposes of foreground detection as recently reviewed by Bouwmans [6]. Traditionally, in foreground detection, the assumption is that the background can be

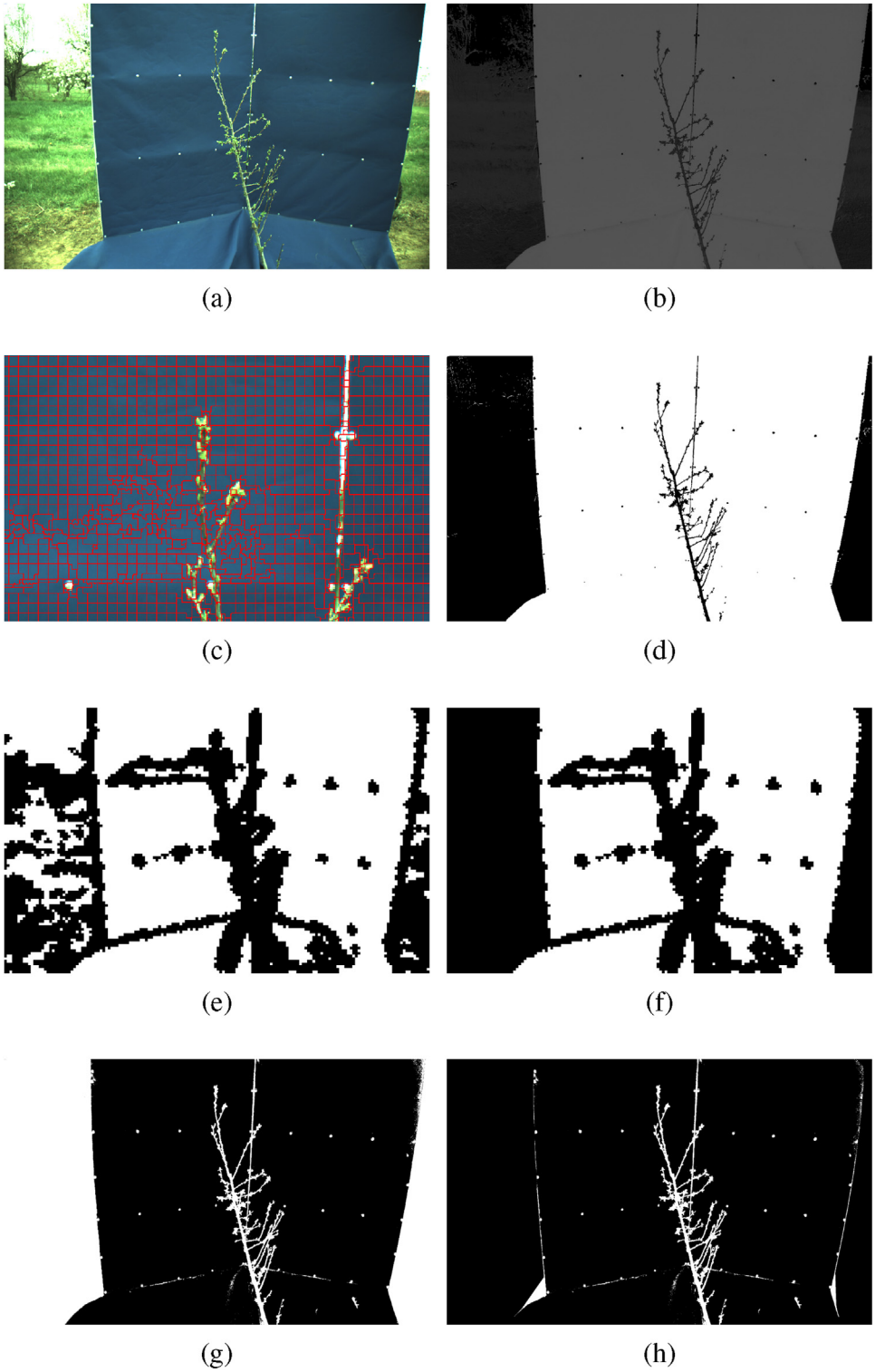

Fig. 1. (a) Original RGB image showing the object of interest (tree) in front of the background object. (b) Hue channel. (c) Close-up of portion of the original image (top portion of branch) with superpixels overlaid in red. (d) Threshold result from step 2 (T). (e) The set of superpixels $\mathbb{R}$ is shown in white, indicating low texture regions. (f) Set of superpixels B, where white pixels indicate locations where the GMM is estimated in the hue image. (g) Label image L after label assignment step. (h) L after application of the mask in step 5.