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Density Weighted Connectivity of Grass Pixels in image frames for biomass estimation

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ABSTRACT

Accurate estimation of the biomass of roadside grasses plays a significant role in applications such as fire-prone region identification. Current solutions heavily depend on field surveys, remote sensing measurements and image processing using reference markers, which often demand big investments of time, effort and cost. This paper proposes Density Weighted Connectivity of Grass Pixels (DWCGP) to automatically estimate grass biomass from roadside image data. The DWCGP calculates the length of continuously connected grass pixels along a vertical orientation in each image column, and then weights the length by the grass density in a surrounding region of the column. Grass pixels are classified using feedforward artificial neural networks and the dominant texture orientation at every pixel is computed using multi-orientation Gabor wavelet filter vote. Evaluations on a field survey dataset show that the DWCGP reduces Root-Mean-Square Error from 5.84 to 5.52 by additionally considering grass density on top of grass height. The DWCGP shows robustness to non-vertical grass stems and to changes of both Gabor filter parameters and surrounding region widths. It also has performance close to human observation and higher than eight baseline approaches, as well as promising results for classifying low vs. high fire risk and identifying fire-prone road regions.

1. Introduction

Biomass, which is typically defined as the over-dry mass of the above ground portion of a group of vegetation in forestry (Vazirabad & Karslioglu, 2011), is one of the most important parameters of roadside vegetation, such as grasses and trees. Automatic estimation of grass biomass can be useful in various real-world applications, including monitoring roadside grass growth conditions, enforcing effective roadside management, and evaluating road safety. One typical example regarding the use of biomass is to identify the level of fire risk due to the presence of high, dense and dry roadside grasses, which are often characterized by high biomass. From the perspective of the transport, roadside grasses of high biomass can potentially become a big fire threat to the safety of vehicles, particularly in remotely located rural regions. Enforcing regular and frequent checks on roadside grass conditions by humans in a large state road network is often a big burden for transport authorities in terms of labour, cost, and time investments. Thus, it is of great significance to develop systems that are capable of automatically estimating the biomass of roadside grasses and precisely identifying those roadside regions with high fire risk, whereby necessary actions can be carried out to prevent possible fire threats such as burning or cutting the grasses.

A typical method of calculating biomass is to conduct field surveys, which often include destructive plant sampling within a sampling region and calculating the weight after over-drying them (Royo & Villegas, 2011). It is one of the most accurate ways for obtaining biomass. Obviously, this method is heavily dependent on human efforts and requires extensive time, labour and cost, as well as expertise and equipment support. More importantly, it is unsuitable for automatic processing of data from large-scale fields.

The vast majority of existing solutions to automatically estimating the above-ground biomass of vegetation have been investigated using remote sensing methods (Lu et al., 2016). The basic assumption of remote sensing methods for biomass estimation is that the mass of biomass is proportional to the volume of the vegetation and accordingly existing methods mainly base the biomass estimation on the upper layer of the canopy. The remotely sensed data can be captured using different types of sensors mounted on airborne, space-borne or terrestrial platforms. Optical spectral sensors are one of the most common ways of acquiring remotely

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sensed data with various spatial, spectral, radiometric and temporal resolutions. Typical examples of optical measurements are Vegetation Indices (VIs) (Schaefer & Lamb, 2016), spectral bands (Sibanda, Mutanga, & Rouget, 2016) and spatial image texture (Lu et al., 2016). However, it is often difficult to obtain high quality optical data in frequent cloud conditions, and the optical measurements are prone to be affected by variations in solar radiation. Not all vegetation indices are closely related with biomass. The widely used Synthetic Aperture Radar (SAR) (Santi et al., 2017) and LIght Detection And Ranging (LIDAR) (Andújar et al., 2016; Zhang & Grift, 2012) sensors offer a better tolerance to weather and light conditions and are capable of collecting three dimensional distribution of structures within vegetation. Thus, they allow precise analysis on the characteristics of vegetation including biomass. However, these sensors are largely dependent on satellite or airborne platforms in existing studies, which leads to high costs and low flexibility. To provide more economical and convenient ways for data collection, more recent advances have tended to adopt drone-based sensors (Fan et al., 2017; Kachamba, Ørka, Gobakken, Eid, & Mwase, 2016; Tang & Shao, 2015) or ground-based sensors such as ultrasonic sensor (Chang, et al., 2017; Moeckel, Safari, Reddersen, Fricke, & Wachendorf, 2017) and mobile laser scanner (Ryding, Williams, Smith, & Eichhorn, 2015; Li, Li, Zhu, & Li, 2016). Similar to satellite or airborne data, data collected using drone-mounted sensors reflect predominantly the upper canopy layers. Ground-based sensors can capture the whole above-ground structure of vegetation and thus they are suitable for biomass estimation in both large-scale and site-specific field surveys.

Except for remote sensing methods, another relatively less investigated method for biomass estimation is to use ground-based digital image or video data captured using ordinary cameras. Compared with remotely sensed data, ground-based images or video are relatively easier to collect using everyday devices such as ordinary cameras, smart phones and tablets, and can be operated by general people without requiring specialized knowledge. For the purpose of this paper, our industry partner – Department of Transport and Main Roads (DTMR), Queensland, Australia collects roadside video data from main state roads in Queensland using vehicle-mounted cameras, thereby human are employed to visually assess roadside conditions, such as vegetation species, height, fuel load, and potential safety threats to roads. For real-world applications where only ground-based video data are available, it is crucially important to develop automatic systems capable of estimating biomass from video frames.

Estimating biomass from ground-based digital image or video data is still a seldom investigated field. Studies (Juan & Xinyuan, 2009; Sritarapipat, Rakwatin, & Kasetkasem, 2014) exploited the way of estimating the height of vegetation from ground-based digital images. The height was calculated by measuring the distance between reference markers, which were pre-set manually on different parts of vegetation. Thus, these methods cannot be directly used for automatic applications. In our previous work (Verma, Zhang, & Stockwell, 2017), we have proposed the Vertical Orientation Connectivity of Grass Pixels (VOCGP) approach to automatically predict roadside grass biomass based on the grass height in images. The VOCGP approach segments brown grass pixels using an Artificial Neural Network (ANN) classifier with color and texture features, and detects the dominant texture direction at every pixel by performing Gabor-based votes on local texture. It then obtains the length of continuously connected grass pixels along every image column and takes an average length as the predicted biomass. However, the approach estimates the biomass predominantly based on the grass height and has largely ignored the contribution of the grass density to the biomass. The grass density is also an important for determining the grass biomass.

To solve the drawbacks in existing methods, this paper proposes Density Weighted Connectivity of Grass Pixels (DWCGP) to automatically estimate the biomass of roadside grasses in ground-based images. The DWCGP extends the VOCGP approach by jointly considering both grass height and density in the estimation of biomass, and thus it is expected that the DWCGP can produce more accurate estimation results. The main novelties in this paper are (a) a novel concept for determining the grass pixel orientation, height, and density without using any reference object; and (b) a novel integrated framework based on grass region segmentation and vertical grass orientation for grass biomass calculation. To the best of our knowledge, this is one of the first attempts that estimate grass biomass on ground-based data using image processing techniques.

The original contributions of this paper are as follows:

(a) A concept of DWCGP for estimating grass biomass based on local texture features in a sampling image window is presented. The DWCGP measures both the grass height and density to quantify the fuel loads of grasses, leading to accurate prediction of the biomass.
(b) An integrated framework for DWCGP calculation based on the results of grass vs. non-grass pixel classification and vertical vs. non-vertical orientation detection is presented. Because the framework does not require manually setting up reference makers, nor the availability of specified equipment rather than a digital camera, it can be directly applied into site-specific analysis in a large-scale field.
(c) An evaluation of DWCGP is presented by conducting a large number of experiments and comparisons with ground truths of both objective biomass and subjective density of roadside grasses collected from field surveys. A comparative analysis to show the effectiveness of DWCGP in supporting fire-prone road identification is included as well.

The remainder of the paper is organized as follows. Section 2 discusses related work. Section 3 introduces the proposed DWCGP approach. Experimental results are presented in Section 4. Section 5 draws the conclusions.

2. Related work

This section reviews prior work on grass region segmentation and grass height estimation. Although intensive works (Hamuda, Glavin, & Jones, 2016) have been reported on vegetation or crop analysis and scene understanding, only few studies have specifically focused on roadside grass analysis. Compared with grassland vegetation, roadside grasses often have a more visible profile of the whole structure (e.g. appearance, geometry and length of grass stems), which is particularly important for analyzing tall grasses. By contrast, analysis of grassland vegetation is often restricted to the upper layer of grasses only.

2.1. Grass region segmentation

Existing work relevant to grass region segmentation can be approximately divided into two groups, including visible and invisible feature approaches.

(a) Visible feature approaches extract visual properties of vegetation such as shape, texture, geometry, structure and color in the visible spectrum to distinguish them from other objects such as sky, road and soil. They can be further divided into three groups: (1) approaches that extract features from a Region Of Interest (ROI) for object classification. Campbell, Thomas, and Troscianko (1997) adopted a self-organizing feature map for object segmentation using color and Gabor texture, and a multi-layer perceptron for classifying 11 outdoor objects.