Agricultural Water Management 151 (2015) 158–166

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Study and comparison of color models for automatic image analysis in irrigation management applications

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ARTICLE INFO

Article history:
Available online 1 September 2014

Keywords:
Color spaces
Automatic irrigation computation
Image processing in agriculture
Color classification

ABSTRACT

Image processing and computer vision are increasingly being used in water management applications in agriculture. Images can provide valuable information on the percentage of ground cover, which is essential in determining crop irrigation needs. Techniques based on color analysis allow classifying accurately and efficiently soil/plant regions in the images. Many color spaces have been proposed, among them: RGB, rgb, XYZ, $L^*a^*b^*$, $L^*u^*v^*$, HSV, HLS, YCrCb, YUV, I1I2I3 and TSL. Different possibilities to model the probability distribution of a given color class appear for each space; one of the most widespread non-parametric methods is modeling using histograms. This presents various alternatives in order to represent a color class: the number of channels, which channels to use, and the size of histograms. Using a wide and varied set of images of lettuce crops (*Lactuca sativa*)—previously classified manually in soil and plant pixels—a comprehensive analysis and comparison of the proposed color models has been conducted for the soil/plant classification problem. The experimental results demonstrate the superiority of models that separate luminance from chrominance. In particular, $L^*a^*b^*$ provides the best results with a^* channel, producing a 99.2% of correct classification. Further processing stages improve this performance up to 99.5% accuracy, taking less than 1/3 of a second per image in a normal laptop. These results can be applied to reduce water consumption by optimizing the accuracy and efficiency of automatic image analysis of crops.

1. Introduction

Automatic analysis of digital images of crops is an interesting and active research field where computer vision and agromotics converge. Color is an essential feature in many problems of this domain, although not all computer vision is based on the use of color; for example, a wide variety of alternative features could be helpful such as edges, shapes, texture, etc. However, color processing has great advantages for its simplicity, robustness, power and efficiency. So far, color has been used in applications related to crop monitoring (Lin et al., 2013), quality control of fruits and vegetables (Kodagali and Balaji, 2012), weed control (Slaughter et al., 2008), and in satellite crop imagery (Campos et al., 2010), among many others.

An important and ubiquitous image processing problem in agriculture is the segmentation of plant pixels from non-plant pixels (McCarthy et al., 2010), which is applied in the computation of the percentage of ground cover (PGC) of vegetation. According to Fernández-Pacheco et al. (2014), PGC is defined as "the proportion of land intersected by the vertical projection of vegetation" for a given image; other authors use the terms "top projected leaf area" (Giacomelli et al., 1998) or "vegetation coverage fraction" (Xu et al., 2010). This parameter has a key role in vegetation monitoring and is widely applied to determine crop water requirements using FAO-56 methodology (Allen et al., 1998). Moreover, many researchers have found a strong correlation with different parameters that are input for automatic irrigation systems. For example, PGC has been correlated with plant height (Fernández-Pacheco et al., 2014; Grant et al., 2012; Xu et al., 2010), with the crop coefficient Kc (Hanson and May, 2005; López-Urrea et al., 2009; Allen and Pereira, 2009), and with the depth of root in lettuce (Escarabajal-Henarejos et al., 2015), among other parameters.

Automatic estimation of PGC is achieved with specific computer vision systems that can work in indoors or outdoors conditions, from analysis of natural scenes to scenes conditioned by mechanical or optical components used to facilitate the problem (McCarthy

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http://dx.doi.org/10.1016/j.agwat.2014.08.010
0378-3774/

et al., 2010). For example, in early works simple thresholding methods were proposed. Giacomelli et al. (1998) estimated PGC of lettuce seedlings using a monochromatic camera; segmentation of plant was manually done with a threshold given by the human operator. Ling and Ruzhitsky (1996) measured PGC in tomato seedlings also from monochromatic images; segmentation was performed with automatic thresholding using Otsu's method. Blasco et al. (2002) developed a robotic system to eliminate weeds in lettuce fields; binary soil/plant classification in the RGB space was done in order to detect weeds in the captured images, reporting 96% classification accuracy.

More recently, Story et al. (2010) designed a system to detect calcium deficiency in lettuce crops using color and other features; the system works with RGB and HSL color spaces. In Åstrand and Baerveldt (2002), the normalized rgb color space is applied for weed control; they found that the green chromaticity value, *g*, was very effective in distinguishing crop from weed plants, with a 91% accuracy. Shiraishi and Sumiya (1996) extracted Q chrominance channel from the YIQ space, which is then thresholded to classify pixels as either plant or background. Similarly, Meyer et al. (1998) proposed the method called "excess green index", computed as: 2G–R–B, in order to obtain an image where segmentation can be done with a simple threshold. Some authors have extended the concept to the "excess red index", or have mapped the three-dimensional RGB color image data into one dimension (Woebbecke et al., 1995). A clustering method was proposed in Steward et al. (2004), in order to define the decision surfaces for the soil/plant classification in the RGB space; success rates range from 89.6% to 91.9% for cloudy and sunny lighting conditions, respectively. Some more samples of plant segmentation in agriculture can be found in recent reviews of the state of the art (Lin et al., 2013; McCarthy et al., 2010).

However, despite this extensive literature, there is a significant lack of comparative studies to select the optimum color spaces and color representation techniques for the plant segmentation problem. In most of the works afore mentioned, color processing is performed in a manual, supervised or semi-supervised form. Classification is done by means of thresholding, linear discriminants, Gaussian models, fuzzy logic, neural networks, and others, using a predefined color space; different spaces are not assessed and compared. Those kinds of studies are more common in other domains, particularly in image indexing and retrieval, and human face and skin detection. For example, Shih and Liu (2005) comparatively assessed 12 color spaces in face retrieval applications, and concluded that optimal configurations were obtained with Y–V and Y–I in YUV and YIQ spaces, respectively. Luszczkiewicz-Piatek (2014) focuses on the proper choice of color space for image retrieval in large, heterogenous databases; color is represented using Gaussian mixture models, and 11 color spaces are studied. Terrillon and Akamatsu (2000) introduced the TSL space, and compared 9 color spaces for the problem of human face detection. Human skin color (Kakumanu et al., 2007), and automatic driving systems (Kumar et al., 2002) are other areas where numerous comparative studies of color can be found.

Therefore, the purpose of this work is to perform a complete and thorough analysis of the optimal color spaces and color distribution representations in agriculture. More specifically, the problem of PGC computation in natural, outdoors and unconstrained images is addressed, by automatic binary classification of pixels in soil/plant classes. A total of 11 color spaces are assessed in the experiments, along with all possible combinations of their channels.

The rest of this paper is organized as follows. In Section 2, the set of available images, the color spaces compared, and the methodology for color classification are described in detail. The experimental results are presented and discussed in Section 3, which includes a proposal of some pre- and post-processing techniques to improve the accuracy and efficiency of the method. Finally, Section 4 draws the main conclusions.

2. Materials and methods

2.1. Experimental plot and images used

The images available for the experiments correspond to lettuce (*Lactuca sativa*) cultures, located in Cartagena (37°46′N, 0°58′W), Spain, with a commercial planting density (16.5 plants m^{-2}). Two series of photographs were taken in different seasons. The first series took place between October 2010 and January 2011, and the second one between October and December 2012. In each of both, four small plots were photographed at intervals between 2 and 4 days. The images were taken with a compact digital camera Nikon Coolpix S3300 at high resolution, and present an overhead view of the terrain from a height of about 1.5 m from the ground, as shown in Fig. 1. The first series contains a total of 108 photographs, and the second series 61. Capture was done in daylight, so illumination conditions were uncontrolled, in some cases receiving direct sunlight and in other cases taken on cloudy days.

Before color analysis, the images were trimmed and normalized with respect to a rectangular pattern that was physically located on the floor; thus, each set corresponds to exactly the same position along time. The normalized images from the first series have a resolution of 1500 × 1500 pixel, and 3600 × 2000 pixel the second one.

After trimming, the images were manually segmented by experts using the ENVI® (Environment for Visualizing Images) software (Research System Inc., Boulder, CO, USA) version 4.0. Starting from a manual selection of some regions of interest, this program helps the user to perform a supervised classification of the images. The result is a set of binary images where all pixels are classified either as soil or plant. Some samples are shown in Fig. 2.

In total, there are available 169 high quality images that are very varied in terms of lighting conditions, shadows, percentage of ground cover, soil types, white balance settings, etc. And, more importantly, the soil/plant classification that should ideally produce a *perfect* automated system is also available as provided by human experts. In the tests described below, the first series of 4 plots is used to train each color model, and the second series of 4 plots is used for the experimental validation of models.

2.2. Color representation and classification

The color of a particular pixel can be observed as a stochastic event within the *n*-dimensional space defined by the color space used; there exists a probability distribution for the *soil class*, and another one for the *plant class*. In the first case, the color distribution is determined by the type and composition of soil, lighting conditions at the time of taking the picture, soil moisture, and specific camera parameters (for example, the white balance setting). Similarly, the presence of chlorophyll in vegetation implies the predominance of green tones in the plant class, but is also affected by intrinsic and extrinsic factors of the acquisition process.

Suppose that the probability distribution functions of soil color, $p_{soil}(color)$, and plant color, $p_{plant}(color)$, are known, where *color* is a tuple in some color space; i.e. $p_{soil}(color)$ and $p_{plant}(color)$ represent the probability of observing *color* if the pixel corresponds to soil or to plant, respectively. For example, in the well-known RGB color space, *color* is a 3-valued tuple (r, g, b), with $0 \le r, g, b \le 255$.

On the other hand, the a priori probability of soil, $P(soil)$, and plant, $P(plant)$, can also be defined. These probabilities are determined by the expected predominance of soil or plant pixels in the images. As shown in Fig. 2, there is not a clear a priori predominance in all images; in some cases, crop cover is less than 4%, while in other