

Segmentation of low-cost remote sensing images combining vegetation indices and mean-shift

Moacir P. Ponti, Jr.

Abstract—The development of low-cost remote sensing systems is important on small agriculture business, specially in developing countries, to allow feasible use of images to gather information. However, images obtained through such systems with uncalibrated cameras, have often illumination variations, shadows and other elements that can hinder the analysis by image processing techniques. This letter investigates combination of vegetation indices (CIVE, VVI and the ExG) and the mean-shift algorithm, based on the local density estimation in the color space on images acquired by a low-cost system. The objective is to detect green coverage, gaps and degraded areas. The results showed that combining local density estimation and vegetation indices improves the segmentation accuracy when compared with the competing methods. It deals well with images in different conditions and with regions of imbalanced sizes, confirming the practical application of the low-cost system.

Index Terms—Image segmentation, Vegetation indices, Precision Agriculture.

I. INTRODUCTION

Precision agriculture is an important tool to assess and maintain crops on the agriculture business. However, one of the most important technologies in this context, satellite remote sensing, is expensive to medium and small farmers. For this reason, a low-cost remote sensing system was recently proposed, based on a helium balloon attached with an image acquisition equipment [1]. Low-cost systems are important in developing countries and small properties [2], [3]. The advantages of this method includes the height control (often 10–100m.), the need of just one or two operators, and the low cost. The drawbacks are the limitation in regions with trees and electric wires, and a low load support (2–4kg).

One of the most relevant information to be extracted from the image is the green coverage region. To address this task, previous studies includes method based on threshold Otsu's method [4] and on histogram [5]. Vegetation indices such as CIVE (color index of vegetation extraction) [6] and ExG (excess green) [7] were also proposed, among others, for this purpose. Segmentation based on the mean-shift was applied in the context of agriculture with cameras attached to vehicles [8] and to sort vegetable seedling [9].

This paper reports results based on the mean-shift segmentation [10], vegetation indices CIVE, ExG and VVI, and also the combination of segmentation and indices. Previous work showed that segmentation can be improved by preprocessing [11]. The main objective is to investigate the unsupervised

segmentation of images obtained by the low-cost system, offering a fast result concerning the green coverage, gaps and degraded areas, specially on small fields.

In section II we describe the methods, including: the low-cost remote sensing system, the vegetation indices, the mean-shift algorithm, the proposed method and its evaluation. Results are presented in section III, and the concluding remarks in section IV.

II. METHODS

A. Low-Cost Remote Sensing System

A system built with a helium gas baloon model Skyhook Helikite was used to acquire the images. A digital camera with a 10 megapixel CCD sensor of size (1/2.3)-in was attached to the baloon with a radiofrequency controller board. It was build to provide an inexpensive solution for remote sensing in Brazil [1]. For this study, a total of 12 images were obtained with an approximate height of 50 meters, from two different fields of common beans at 63 days after the emergence of the plants. The images were obtained in squared parcels, and resampled to 512×512 pixels, resulting in an aproximate resolution of 3.7cm/pixel. Figure 1 shows reduced versions of eight images used in the experiments. The difference between the two crops was the soil compaction, the second row of images were obtained from the crop with higher soil compaction.

B. Vegetation Indices

Vegetation index techniques often uses arithmetic operations on the available bands (visible light, near-infrared, etc.). The aim is to to enhance some features, obtaining an index-image in which, for example, it is possible to visualize better the vegetation, with a better contrast between the response models in the available channels. These indices are often used in order to segment the green vegetation regions in agriculture remote sensing images. Three of the most used indices, when only the visible light is available are the ExG:

$$\text{ExG} = 2G - R - B,$$

where G , R and B are normalized values of bands green, red and blue: $G = G/(R + G + B)$, $R = R/(R + G + B)$ and $B = B/(R + G + B)$, the CIVE computed by:

$$\text{CIVE} = 0.441R - 0.811G + 0.385B + 18.787,$$

The author is with the Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos-SP 13560-970, Brazil (email: moacir@icmc.usp.br)

This work was supported in part by the Fundação de Amparo à Pesquisa do Estado de São Paulo under Grant 2011/16411-4

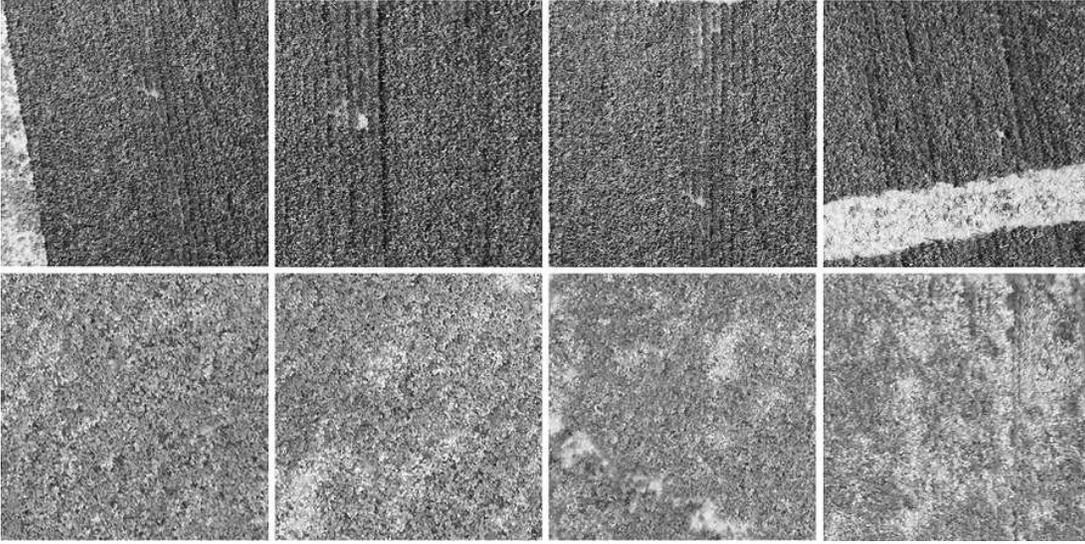


Fig. 1. Examples of images obtained from two different crops of beans (first and second row of images with different soil compaction) using a low-cost remote sensing system.

where R , G and B are the values of the color channels, and also the VVI (visual vegetation index), given by:

$$VVI = \left[\left(1 - \left| \frac{R - R_o}{R + R_o} \right| \right) \times \left(1 - \left| \frac{G - G_o}{G + G_o} \right| \right) \times \left(1 - \left| \frac{B - B_o}{B + B_o} \right| \right) \right]^{1/w}$$

For the VVI index, RGB_o is the vector of the reference green channel and w is a weight exponent to adjust the scale. Tests with color-calibrated images found the standard values of $RGB_o = [40, 60, 10]$ and $w = 1$ for 24-bit images. To avoid division by zero, it is also necessary to add an amount of 10 to the RGB channels.

The output images (index-images) are 255 gray level images. However, they can be easily binarized in order to obtain a mask for the green coverage areas.

C. Mean-shift

Mean-shift is an iterative procedure to segment color images, proposed by Fukunaga and Hostetler [12], and later generalized by Cheng [10] with the inclusion of a kernel function. The paper of Comaniciu and Meer [13] includes a detailed description of the method. The general idea is to define each pixel by its color in a feature space using an empiric probability density function, in which dense regions corresponds to a local maximum or modes of the distribution. It essentially applies a gradient ascendant in a region, where the stationary points, that represent the modes of the distribution, are used to classify pixels that are associated with them, and considered part of the same region. In order to control the segmentation resolution, the method includes parameters for the kernel function.

D. Index over Mean-shift Approach

In this paper the mean-shift is proposed to help the detection of green coverage by the pre-segmentation of the images. The

segmentation is followed by the computation of one vegetation index. The idea is to take advantage of the local maxima find by the mean-shift, that removes texture and small irregularities of the image and, afterwards, extract the vegetation index. Figure 2 illustrates the processing steps:

- 1) Run the mean-shift with minimum size of final regions = 10% of the image lateral resolution.
- 2) Compute vegetation index image using as input the mean-shift segmented images,
- 3) Apply an Otsu's threshold to the resulting image,
- 4) Smooth the binary image using a opening morphology operation.

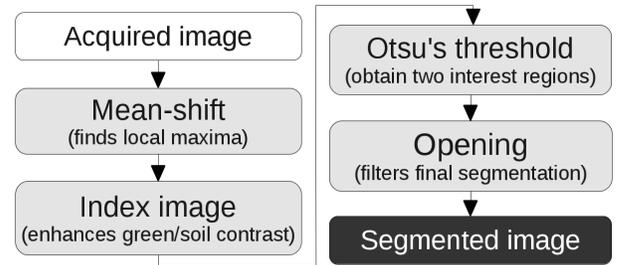


Fig. 2. Flowchart illustrating the steps of the proposed method

The mean-shift parameters used were the default parameters of the EDISON (2009 version) freeware package¹ used in the experiments (spatial bandwidth = 4, range bandwidth = 8).

E. Experiments

All images were manually labeled by three agronomists. These specialists segmented the images in two disjunct regions: i) green coverage and ii) vegetation gaps, soil, degraded areas and others. The agreement between the specialists was

¹<http://coewww.rutgers.edu/riul/research/code/EDISON/index.html>

of $91.5\% \pm 5.2$. The images labeled by the agronomist with the higher inter-agreement was used as ground truth. The acquired images with the ground truth, and also code and links to the packages used are available at the project webpage².

In order to detect the green coverage regions, the output of all methods was binarized using the Otsu threshold method and smoothed using an opening morphology operation using as structure element a disk of diameter equal to 0.5% of the lateral resolution of the image. Since the chances of detecting green coverage are higher than the chances of detecting gaps and soil, the evaluation was based on an accuracy value that takes into account the balance between the areas of the regions:

$$\text{Acc} = 1 - \frac{\sum_{i=1}^r E(i)}{2r},$$

where r is the number of regions, and $E(i) = e_{i,1} + e_{i,2}$ is the partial error of the region i , computed by:

$$e_{i,1} = \frac{FP(i)}{N - N(i)} \text{ and } e_{i,2} = \frac{FN(i)}{N(i)}, i = 1, \dots, r,$$

where $FN(i)$ (false negatives) is the number of pixels of region i incorrectly classified as belonging to other regions, and $FP(i)$ (false positives) represents the pixels of regions $j \neq i$ that were assigned to region i .

III. RESULTS AND DISCUSSION

The average accuracies (in percentages) for each method are presented in Table I. These results can also be visualized in Figure 3. A statistical test ANOVA was performed to compare the accuracies obtained by the methods: CIVE, ExG, VVI, MS (Mean-shift), MS+CIVE, MS+ExG and MS+VVI applied to the 12 images. The methods MS+CIVE, MS+ExG obtained significantly better results when compared with the other methods, according to the statistical test for $p < 0.01$. Note that (in Figure 3) these methods showed no outlier accuracy, indicating a stable performance when segmenting images from different regions of the two crops.

TABLE I
AVERAGE ACCURACY AND STANDARD DEVIATION FOR THE 12 IMAGES AND METHODS.

Methods	$\bar{x} \pm \sigma$
CIVE	66.1±11.9
ExG	78.5±8.6
VVI	70.4±10.5
MS	76.5±10.7
MS+CIVE	86.4±7.2
MS+ExG	85.0±8.4
MS+VVI	72.6±13.3

Samples of the obtained results are shown in Figure 4 and Figure 5, where the original image is composed with the regions in white, considered to be degraded or without green coverage. It is possible to see that the index method (ExG) and the MS oversegmented the image or also fail to find degraded areas, specially when the size of the regions are imbalanced (Figure 5). These unwanted effects are probably due to the

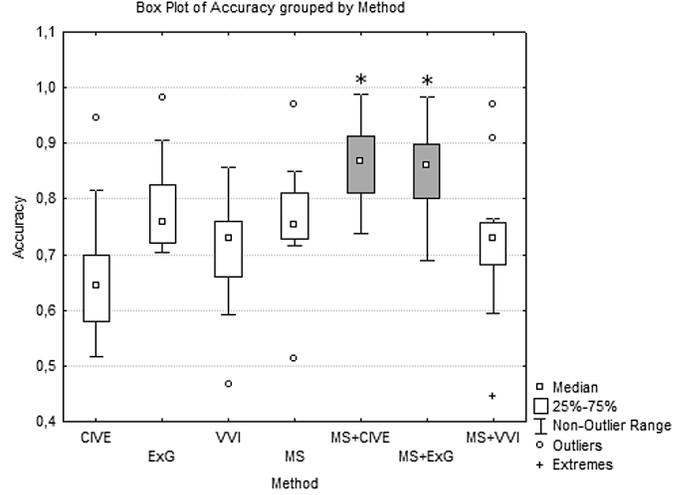


Fig. 3. Box plot of accuracies observed on the 12 images using the different methods. The gray boxes represents the methods that are significantly different from the others (* $p < 0.01$)

simplicity of the vegetation index. On the other hand, by using the mean-shift algorithm, the spectral response of green areas is ignored. The sequential combination of methods works by first smoothing out irrelevant features such as small textures, shadows and boundaries. Afterwards, the vegetation index can separate better regions of vegetation from the gaps and the soil, merging regions that can represent lack of nutrition in plants, irrigation deficiency and other factors that reduce the green coverage.

IV. CONCLUSIONS

The combined approach to detect green coverage regions on bean crop images showed promising results. The isolated use of vegetation indices often oversegments the images producing non-uniform regions.

Among the investigated indices, the ExG index appears to be the best choice when only visible band is available, since CIVE and VVI produced lower accuracies and unstable results when dealing with different acquired regions of the crop, showing higher variance and presence of outliers. When computed over the previously segmented image, both CIVE and ExG showed good results, without outlier results. The VVI, however, could not be improved by using a mean-shift pre-segmentation.

The MS+CIVE and MS+ExG methods are unsupervised and fast to compute. Besides, these approaches generate uniform regions removing small deviations in the culture lines, shadows and minor textures (as shown in Figure 5 (c) and (d)). Therefore it can give the specialist more meaningful information, that can be used to manage issues in the culture. In addition, the segmented images can be used in further machine vision methods in order to help estimate the yield, detect weed and other applications.

ACKNOWLEDGMENT

The author would like to thank Prof. L.B. Vieira and F.C. Martins, for providing the data, and to Prof. J. Oishi and Dr. P. Castro for helping in the statistical analysis.

²<http://www.icmc.usp.br/~moacir/project/lcrs>

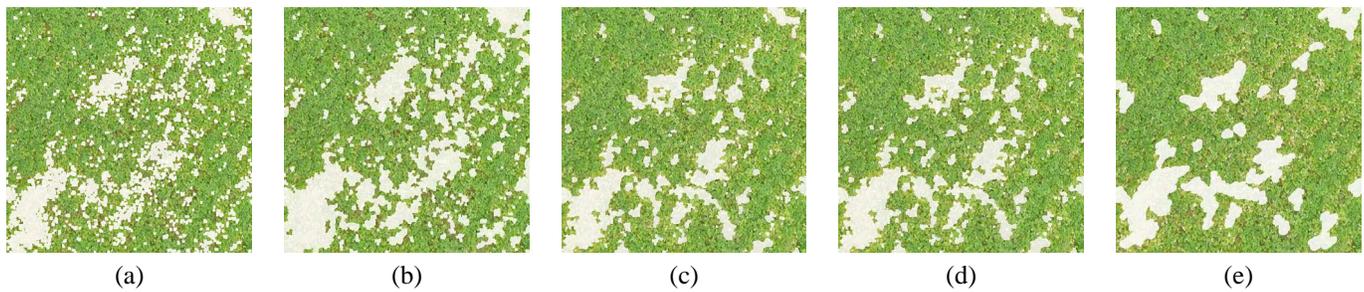


Fig. 4. Image 5 composed with the vegetation gaps or degraded regions detected by the following methods with corresponding accuracies: a) ExG (80.1%), b) Mean-shift (80.0%), c) Mean-shift + ExG (85.5%) and d) Mean-shift + CIVE (85.7%) e) Ground truth

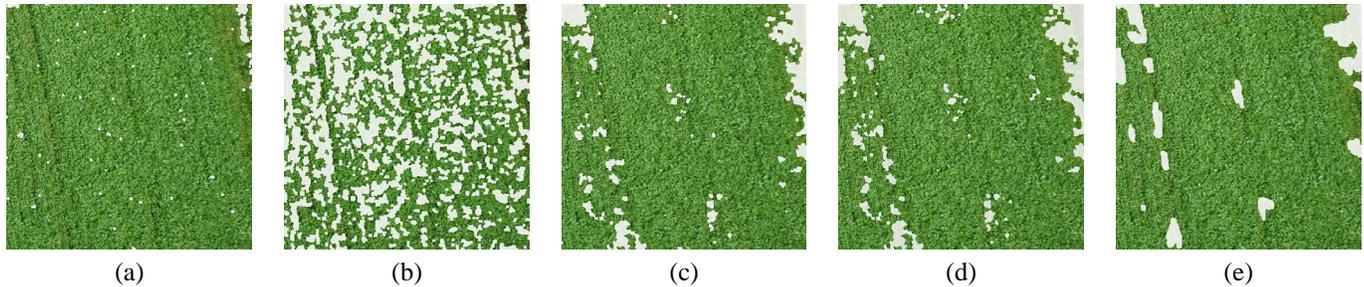


Fig. 5. Image 10 composed with the vegetation gaps or degraded regions detected by the following methods with corresponding accuracies: a) ExG (71.0%), b) Mean-shift (51.2%), c) Mean-shift + ExG (94.3%) and d) Mean-shift + CIVE (94.1%) e) Ground truth

REFERENCES

- [1] F. C. M. Martins, "Evaluation of compact areas in the bean culture using remote sensing techniques (in portuguese)," Master's thesis, Universidade Federal de Viçosa, MG, Brazil, 2010.
- [2] T. Seang and J.-P. Mund, "Geo-referenced balloon digital aerial photo technique a low cost high-resolution option for developing countries," in *5th Annual Int. Conf. Exhib. Geographical Info. Tech. & Appl. (Map Asia 2006)*, Thailand, 2006.
- [3] K. Swain, S. Thomson, and H. Jayasuriya, "Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop," *Transactions of the ASABE*, vol. 53, no. 1, pp. 21–27, 2010.
- [4] D. Shrestha, B. Steward, and S. Birrell, "Video processing for early stage maize plant detection," *Biosystems Eng.*, vol. 89, no. 2, pp. 119–129, 2004.
- [5] A. Tellaache, X. P. Burgos-Artizzu, G. Pajares, A. Ribeiro, and C. Fernandez-Quintanilla, "A new vision-based approach to differential spraying in precision agriculture," *Comput. Electron. Agr.*, vol. 60, pp. 144–155, 2008.
- [6] T. Kataoka, T. Kaneko, H. Okamoto, and S. Hata, "Crop growth estimation system using machine vision-based," in *IEEE/ASME Int. Conf. Adv. Intell. Mech.*, vol. 2, 2003, pp. b1079–b1083.
- [7] C. Gée, J. Bossu, G. Jones, and Truchetet, "Crop/weed discrimination in perspective agronomic images," *Comput. Electron. Agr.*, vol. 62, pp. 49–59, 2008.
- [8] L. Zheng, D. Shi, and J. Zhang, "Segmentation of green vegetation of crop canopy images based on mean-shift and fisher linear discriminant," *Pattern Recogn. Lett.*, vol. 31, pp. 920–925, 2010.
- [9] Y.-C. Liao and Y.-C. Chuang, "Vegetable seedling sorting based on mean-shift," in *2009 Joint Conf. on Pervasive Comp.*, 2009, pp. 191–196.
- [10] T. Cheng, "Mean shift, mode seeking and clustering," *IEEE Trans. PAMI*, vol. 17, no. 8, pp. 790–799, 1995.
- [11] M. P. Ponti-Jr, "Microscope volume segmentation improved through non-linear restoration," *Int. Journal of Natural Computing Research*, vol. 1, no. 4, pp. 37–46, 2010.
- [12] K. Fukunaga and L. Hostetler, "The estimation of the gradient of a density function with applications in pattern recognition," *IEEE Trans. Inf. Theory*, vol. 21, no. 1, pp. 32–40, 1975.
- [13] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," *IEEE Trans. PAMI*, vol. 24, no. 3, pp. 603–619, 2002.