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Segmentation of RGB images using different vegetation indices and thresholding methods

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ABSCTRACT: Image Segmentation is one of the fundamental aspects involved in image processing, which generally consists of discriminating objects of interest from its background. Thus, the objective of this study was to evaluate the effect of vegetation indices (VI) (ExG, ExGR, and NDI) on the performance of three automated thresholding methods (Otsu, Ridler, and Triangle) in terms of accuracy and processing time on image segmentation. A set of 30 images from an area cultivated with maize under different types of soil cover (conventional planting, no-tillage with coffee husk, and straw residue) were selected and processed. The images were processed through algorithms developed based on VI and thresholding methods. Then, the accuracy of the resulting images was evaluated through the ground truth image obtained by the K-means algorithm. The results demonstrated superior performance for the triangle method when preceded by the NDI (90.7%) and ExGR (90.23%) indices and the Otsu and Ridler methods when preceded by the NDI with 89.06% and 89.03% accuracy, respectively. The processing time was statistically equal among the evaluated methods. In general, the combined approach of VI and thresholding based methods were capable of separating with high accuracy the maize crop from the background.
Keywords: image processing, digital images, triangle method.

Segmentação de imagens RGB usando diferentes índices de vegetação e métodos de limiarização

RESUMO: A segmentação é um dos aspectos fundamentais envolvidos no processamento de imagens, que geralmente consiste na discriminação de objetos de interesse e fundo da imagem. O presente estudo objetivou avaliar o efeito de diferentes índices de vegetação (IV) (ExG, ExGR e NDI) no desempenho de três métodos de limiarização (Otsu, Ridler e Triângulo) em termos de precisão e tempo de processamento na segmentação de imagens. Para tal, foram utilizadas 30 imagens advindas de área cultivada com milho sob diferentes tipos de cobertura do solo (plantio convencional, casca de café e palhada). O processamento das imagens foi realizado através de algoritmos desenvolvidos com base nos IV e métodos de limiarização. A acurácia das imagens resultantes foi avaliada com a verdade de campo obtida pelo algoritmo K-*means*. Os resultados demonstraram desempenho superior para o método do triângulo quando precedido dos índices NDI (90,7%) e ExGR (90,23%) e dos métodos de Otsu e Ridler quando precedidos pelo NDI com 89,06% e 89,03% de acurácia, respectivamente. O tempo de processamento foi estatisticamente igual entre os métodos avaliados. De modo geral, a abordagem combinada de IV e métodos de limiarização foram capazes de separar com alta acurácia a cultura do milho do objeto de fundo.
Palavras-chave: processamento de imagens, imagens digitais, método do triângulo.

1. INTRODUCTION

Digital image processing is the application of several algorithms on the image to improve its quality by removing noise and other unwanted pixels and also to obtain more information on the image. Image Segmentation is one of the fundamental aspects involved in image processing, which generally refers to discriminating objects of interest from its background. According to Al-amri et al. (2010), this process is often a crucial step in the image analysis, where low-quality results may influence the entire process and lead to inaccurate and unsuccessful outcomes.

Technology advancement on the image segmentation technique has experienced tremendous growth both in theory and application. This technique is widely used in pattern recognition and image classification in many areas, such as agricultural (YANG et al., 2015), medicine (GROOTJANS et al., 2016) and forestry (TOCHON et al., 2015).

Among segmentation techniques, thresholding-based and clustering approach are the most used methods for segmenting images (ABDULLAH et al., 2012). In order to group image blocks/pixels associated with the pre-selected features, the best known and most influential clustering approach is the classical K-means algorithm (CLAUSI; DENG, 2005).

This technique is simple but effective for segmentation of images where it subdivides an image into meaningful non-overlapping regions or classes based on grey levels of images (SEZGIN; SANKUR, 2004). The grayscale image is used because it allows further exploitation on the image in an efficient and easy approach where it can consistently partition the image into two classes, which correspond to an object class and background class.

Otsu thresholding-based method is one of the most used. This method works on grayscale images and it automatically selects an optimised value from the image grey level histogram. The optimal threshold value is selected by maximising the between-class variance or minimising the within-class variance (OTSU, 1979).

In 1978, Ridler; Calvard proposed an iterative threshold-seeking segmentation method. This method known as Ridler achieves an initial threshold by calculation of the average of the foreground and background class means. The process is repeated iteratively until the change of updated thresholds is sufficiently small (LU; LU, 2017). Also, there is the Triangle method, which consists of a line construction between the histogram peak and the farthest end of the histogram. The optimal threshold is the point of maximum distance between the line and the histogram (ZACK et al., 1977).

All these methods were widely used in the last years. However, this process has become a challenging issue because of the complex background and changeable illumination on the images. These illumination variations greatly affect the Red, Green, and Blue (RGB) pixel values of acquired field images and lead to the inconsistent colour representation of plants (SOJODISHIJANI et al., 2010; TEIXIDO´ et al., 2012). In addition, shadows often create illumination contrast, causing substantial luminance differences within a single image scene.

Thus, using only threshold-based methods to separate plants and soil may not lead to accurate results. Several methods have been proposed for segmenting crop canopy images, specifically oriented towards green segmentation. The typical methods are those based on visible spectral-index, such as the Excess Green Index (ExG) (WOEBBECKE et al., 1995), the Excess Green minus Excess Red Index (ExGR) (MEYER; NETO, 2008) and the Normalized Difference Index (NDI) (WOEBBECKE et al., 1992).

All these methods address the problem of greenness identification under the assumption that plants display a clear high degree of greenness, and the background is just the bare soil. However, brightness and contrast of outdoor images are seriously affected by weather and illumination conditions. Moreover, the colour of the plant is not always bright greenness either. It can be affected by several factors, such as plant health, nutrition deficiency, diseases, etc.

The above mentioned complicating environmental factors always make these visible spectral-index based methods unable to work correctly. Consequently, it needs to fix a threshold value for final segmentation. Thus, the objective of this study was to evaluate the effect of different vegetation indices (ExG, ExGR, and NDI) on the performance of three automated thresholding algorithms (Otsu, Ridler, and Triangle) in terms of accuracy and processing time on natural images segmentation.

2. MATERIALS AND METHODS

2.1. Study Area

This study was performed in the Agricultural Engineering department of the Federal University of Viçosa (UFV), in Viçosa, Minas Gerais, located between the geographical coordinates of 20º45'35 "S and 42º52'29"O.

In order to evaluate the effect of different vegetation indices (ExG, ExGR, and NDI) on the performance of three automated thresholding-based methods (Otsu, Ridler, and Triangle), two steps were carried out in this study. The two steps were: image acquisition and pre-processing and image processing.

2.2. Image Acquisition

The camera used for this study was a Sony® model DSC-H200, with CCD sensor of 1/2.3". Moreover, camera settings were set to automatically control contrast, saturation, sharpening and white balance as conditions changed. There were captured 30 images for this study and all of it belonged to maize crops, which were grown under different soil cover conditions, such as conventional planting system, a no-tillage system with coffee husk and with straw residue.

The digital images were captured at a height of 1.5 m from the ground and then stored as 24-bit colour images with resolutions of 2592 x 1944 pixels saved in RGB (Red, Green, and Blue) colour space in the jpeg format. Data acquisition was performed twice, providing some images with different growth state and different conditions of illumination. Lastly, all images were resized to 950 x 350 pixels in order to have standard pixel intensity values for all images as shown in Figure 1.

Figure 1. Examples of images used to represent the three conditions of soil cover: a) conventional planting; b) no-tillage with coffee husk; and c) straw residue.

Figura 1. Exemplos de imagens usadas para representar as três condições de uso do solo: a) plantio convencional; b) plantio casca de café; e c) plantio com palhada.

2.3. Image Processing

First of all, to discriminate between the object of interest (crop canopy) and background (soil) different algorithms were developed to combine the proposed vegetation indices with each threshold method. Details of the vegetation indices are described below.

2.4. Excess Green (ExG)

The ExG index was computed using Equation 1.

$$ExG = 2g - r - b \qquad \text{(Equation 1)}$$

where: r, g, and b are the chromatic coordinates.

In order to get the chromatic coordinates, the values of each spectral band (R, G and B) were normalised by dividing the highest value within the spectral band for the image being analysed. The normalised pixel values range in [0,1] according to Equation 2 to 4 (GÉE et al. 2008).

$$r = Rn / (Rn + Gn + Bn) \qquad \text{(Equation 2)}$$

$$g = Rn / (Rn + Gn + Bn) \qquad \text{(Equation 3)}$$

$$b = Rn / (Rn + Gn + Bn) \qquad \text{(Equation 4)}$$

where: Rn, Gn, and Bn are the normalised RGB coordinates ranging from 0 to 1.

Rn, Gn, and Br were obtained by Equation 5:

$$Rn = R / Rmax,\quad Gn = G / Gmax,\quad Bn = B / Bmax \qquad \text{(Equation 5)}$$

where: Rmax = Gmax = Bmax = 255.

2.5. Excess Green minus Excess Red Index (ExGR)

This method combines two colour indices, namely, Excess Green Index (ExG) and Excess Red Index (ExR). These methods were applied simultaneously to separate plants from the soil, with ExG used to extract the plant region and ExR used to eliminate the background noise. In order to get the ExGR, it was necessary to compute the ExR as can be seen in Equation 6.

$$ExR = 1.4r - g \qquad \text{(Equation 6)}$$

Then, the ExGR was computed using the Equation 7.

$$ExGR = ExG - ExR \qquad \text{(Equation 7)}$$

2.6. Normalized Difference Index (NDI)

This index is applied to all pixels in the image, providing values ranging between -1 and +1, although, to display the image, these values must range between 0 and 255. Therefore, the index was further processed by adding 1 to it and then multiplied by a factor of 128 to provide a greyscale image (0–255). The NDI was computed with Equation 8:

$$NDI = 128 * (((G-R)/(G+R))+1) \qquad \text{(Equation 8)}$$

where: G and R are the green and red bands.

Subsequently, the Otsu (OTSU, 1979), Ridler (LU; LU, 2017) and Triangle (ZACK et al., 1977) thresholding methods were applied to each image. As a result, all images showed some noise, which was removed using a median filter with a 3 x 3 window size.

Ground truth segmentation model for comparison of the three methods was developed from the K-means method. Generally, this method can be employed in different areas including image processing, where it can be used as a thresholding method based on data clustering.

This method partitions n pixels into k clusters, where k is an integer value that holds k < n. K-means algorithm classifies pixels in an image into k number of clusters according to some similarity feature like the grey level intensity of pixels and distance of pixel intensities from centroid pixel intensity (DASS et al., 2012).

The algorithm is based on six steps:

1. **1.** Selection of k clusters (k is a user defined parameter);
2. **2.** Calculation of the number of image pixels N;
3. **3.** Selection of k initial pixel intensity centroids μj;
4. **4.** Calculation of distances D_{ij} between pixel x_i and each centroid μj as given in Equation 9.

$$Dij = (xi - \mu j)^2 \qquad \text{(Equation 9)}$$

where: i = 1 ÷ N; and j = 1 ÷ k.

Particular pixel x_i is then classified to cluster c_j to which centroid it has the smallest distance.

1. Recalculation of centroid positions μ_j as a mean value of all pixel intensities which belong to cluster cj as shown in Equation 10.

$$\mu_t = (1/L_j) * \sum_{i=1}^{Lj} x_i \qquad \text{(Equation 10)}$$

where: L_j is a number of pixels that belong to cluster c_j.

2. Steps (4) and (5) are repeated until classification of the image pixels does not change or equivalently, centroids do not move.

In this study, the value of k (number of clusters) was defined as two, where the first represented the crop canopy and second the soil.

In order to validate the performance of each thresholding method, the accuracy index, proposed by Coy et al. (2016) was computed using Equation 11.

$$Accuracy = 100 * ((A \cap B)/(A \cup B)) \qquad \text{(Equation 11)}$$

where: A represents the set of pixels in the ground truth image that is marked as crop canopy, and B represents the set of pixels in the segmentation that is marked as crop canopy.

This measure of accuracy determines how closely the segmentation matches the ground truth, with 100% indicating an exact match and perfect segmentation.

Lastly, the nine combinations of vegetation indices and threshold methods were considered as treatments in a completely randomised experimental design with 30 replications (images processed). Thus, to verify the significance of the proposed methods, the accuracy means and processing were submitted to analysis of variance (ANOVA) and significant differences between the means were compared by the Tukey test at a 5% significance level (α <0.05).

3. RESULTS

The results obtained in the image processing using the vegetation indexes and the thresholding methods are presented in Table 1.

The Triangle method, when preceded by the NDI and ExGR indexes, presented performance statistically equal to the Ridler and Otsu methods when preceded by the NDI index. However, only the NDI and ExGR indexes when combined with the Triangle method were superior to the other treatments, being observed the lower dispersion of the data when presenting the lowest values of the standard deviation with 1.24 for NDI and 2.03 for ExGR, respectively. In general, all the treatments had a high performance with a mean accuracy above 85%, maximum standard deviation of 5.01 and coefficient of variation (CV) of 4.14%.

Table 1. Average of Accuracy and processing time obtained from the proposed algorithms.
Tabela 1. Médias da acurácia e tempo de processamento obtido a partir dos algoritmos propostos.

	Algorithm	Accuracy (%)		Processing Time (s)	
	Treatments	μ (%)	σ	μ (%)	σ
9	NDI + Triangle	90.70 a	1.24	1.17 a	0.37
8	ExGR+Triangle	90.23 a	2.03	1.14 a	0.37
3	NDI + Otsu	89.06 ab	3.47	1.17 a	0.39
6	NDI + Ridler	89.03 ab	3.81	1.17 a	0.36
5	ExGR + Ridler	87.73 bc	4.99	1.13 a	0.34
2	ExGR + Otsu	87.58 bc	5.01	1.13 a	0.37
7	ExG + Triangle	87.31 bc	3.55	1.18 a	0.38
4	ExG + Ridler	85.92 c	4.23	1.20 a	0.39
1	ExG + Otsu	85.71 c	4.36	1.20 a	0.42
	CV (%)	4.14		32.38	

*Means followed by the same lower case letters in the lines do not differ significantly by the Tukey test (p < 0,05); CV: Coefficient of variation.

Regarding the processing time, ANOVA was significant, however, statistically, the time was the same for all treatments. The shortest processing time was 0,62s obtained in treatment 5 (ExG + Ridler) and the longest time was 1,99s, obtained in treatment 1 (ExG + Otsu). Although processing time was relatively low for all treatments, a high CV value is observed in this variable, which is due to the lack of uniformity in processing time.

Figure 2 shows three of the resulting images from the segmentation using the NDI combined with Otsu, Ridler and the Triangle methods for all types of soil cover. It can be seen that all methods could precisely separate the plant from the soil. However, it is possible to identify on the leaves some poorly segmented regions, mainly in the image C from the left to the right, which is the result of the Otsu and Ridler methods.

Normally, the histograms should exhibit a bimodal behavior in which most of the vegetation pixels values are clustered in one lobe, while the background pixels values are clustered in the other. This pattern is optimal for setting a discriminating thresholding value for separation of the two classes in the initial segmentation process. However, adverse factors, such as, different soil cover, shaded parts, and uneven illumination conditions make it harder to identify which distributions are related to vegetation or the image background.

Based on that, the result shown in Figure 2.C clearly demonstrates the effect these factors on the histogram distribution and in the segmentation accuracy. As a result, the lowest accuracies were obtained from images with maize crops cultivated under straw residue, which ranged from 67.18% to 84.03%. These results demonstrate that the spectral confusion caused by non-vegetation pixels which were misclassified as vegetation pixels directly affects the algorithm performance since it resulted in falsely extracted plant parts.

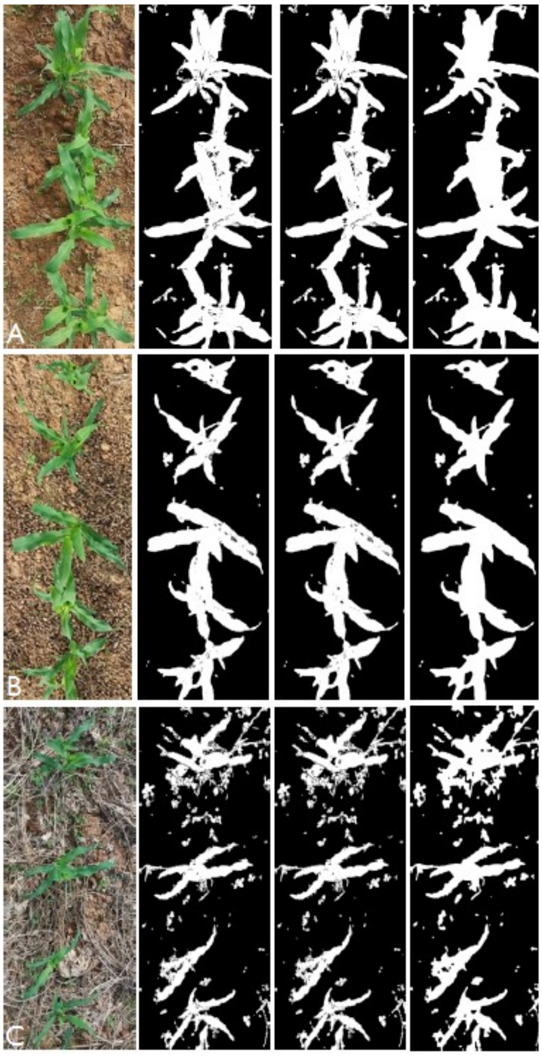

Figure 2. Processing results of images from the three conditions of soil cover: A) conventional planting; B) no-tillage with coffee husk; and C) straw residue.
Figura 2. Resultado do processamento de imagens das três condições de cobertura do solo: A) plantio convencional; B) plantio casca de café; e C) plantio com palhada.

4. DISCUSSION

The use of vegetation indices in addition to the thresholding methods was fundamental to improve the contrast between the plants and the image background. The superior performance of the NDI and ExGR indices occurred due to the greater adaptation to the field conditions, especially with respect to illumination. The three thresholding methods were efficient in identifying the ideal threshold when the images were preprocessed by both indices mentioned above.

However, the modification of the histogram after the application of vegetation indexes might have influenced negatively the results of the Ridler method, since iterative methods are more efficient when the histogram does not clearly define the peak between the two classes (BAHRGAVI; JYOTHI, 2014). On the contrary, the use of indexes was beneficial to the Triangle method, especially when combined with NDI and ExGR, since this method tends to be more effective when the objects of interest produce a weak peak in the histogram, an effect that was observed in the histograms with the creation of a lower intensity peak in the plant class (RAJU; NEELIMA, 2012).

ExG index presented lower performance when combined with the three thresholding methods, especially with the Otsu method. Moreover, insufficient segmentation results and the lowest accuracy values were observed in images covered with straw residue, as the index failed to highlight the plant in relation to the background. In general, the ExG and Otsu method performed an under-segmentation in several images as well as over-segmentation when compared to the ground truth image. Another point observed about the Otsu method is that the adopted threshold was always above the mean value in the histogram, which led to many pixels being discarded as green. The Otsu method often results in insufficient segmentation in images obtained under adverse lighting conditions, which directly affects its performance in field studies (BAY et al., 2013).

However, according to Meyer; Neto (2008), segmentation methods based only on vegetation indexes have limitations and may result in erroneous segmentations, especially when there is no control of lighting and shading. Thus, it becomes essential to use an automatic thresholding method to identify the ideal threshold. The results have shown that processing time did not affect performance in this case, and it did not require a high computational complexity, which is a measure of time convergence of an optimization technique that is variable with respect to different image processing methods (SHANNON et al., 2017), since for all proposed treatments it presented an average of low time.

Even though satisfactory performance has been achieved in the segmentation with all methods, there are still factors, such as the lighting conditions, plant shading and complex background that are challenges to the success of segmentation. In this study, illumination condition was one of the main factors that made segmentation more difficult, as the photos were taken on a sunny day, the surface of the corn leaf acted as a mirror (specular reflection), resulting in errors in the segmentation of several plants.

5. CONCLUSIONS

The combined approach of vegetation indices and thresholding based methods to detect green coverage regions on maize crop images was capable of separating with high accuracy the vegetation from the background. Furthermore, among the investigated indices, the NDI and ExGR proved to be the best choice when dealing with RGB images, since ExG produced lower accuracies and unstable results when dealing with adverse lightning conditions.

As a recommendation for future studies, the resulting binary image could be used to assist in the extraction of individual whole leaves for shape feature analysis and textural assessment of species characteristics.

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