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Evaluation of bag-of-features (BoF) technique for weed management in sugarcane production

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Abstract

Weeds interfere in agricultural production, causing a reduction in crop yields and quality. The identification of weed species and the level of infestation is very important for the definition of appropriate management strategies. This is especially true for sugarcane, which is widely produced around the world. The present study has sought to develop and evaluate the performance of the Bag-of-Features (BoF) approach for use as a tool to aid decision-making in weed management in sugarcane production. The support vector machine to build a mathematical model of rank consisted of 30553 25x25-pixel images. Statistical analysis demonstrated the efficacy of the proposed method in the identification and classification of crops and weeds, with an accuracy of 71.6% and a Kappa index of 0.43. Moreover, even under conditions of high weed density and large numbers of overlapping and/or occluded leaves, weeds could be distinguished from crops This study clearly shows that the system can provide important subsidies for the formulation of strategies for weed management, especially in sugarcane, for which the timing of weed control is crucial.

Keywords: Machine Vision, Weed Management, Pattern recognition, Image Processing, Precision Agriculture.
Abbreviation: PCD_Pixel Color Distance.

Introduction

Sugarcane, which is one of the most important energy crops, is cultivated in many countries around the world. The production of the sugar derived from this plant was expected to reach 185 million tons during the 2017/18 season; in Brazil, this was expected to be 40.2 million tons (USDA, 2017). Sugar is quite important in the Brazilian economic context, since it contributes largely to the Brazilian trade surplus, and its production is quite labor-intensive. However, better techniques in crop management should make it possible to improve productivity. One of the greatest challenges in the Brazilian production of sugarcane is weed control. Since weeds compete with the crop for water, light, nutrients and space, their presence reduces the productivity of the crop, as well as increasing the cost of production (Kuva et al., 2008; Silva et al., 2009; Vasconcelos et al., 2012). Nowadays, the main technique adopted by Brazilian farmers for the control of weeds in sugarcane is the use of herbicides (Barcellos Júnior et al., 2017). However, recent discussions have focused concern on their role in the quality and safety of the crops produced, as well as on the environmental risks arising from the use of this technique (Koller et al., 2012; Helander et al., 2012; Hernandezet al., 2013). The challenge is to increase production without damaging the environment. This has led to the development of various management tools, many focused on the limitation of the use and application of chemical products, as well as the reduction in production costs and the optimization of the agricultural processes involved (Le Bellecet al., 2015, Bajawa et al., 2015). One of these tools is process automation, especially in the area of weed control (Bakker et al., 2010; Burgos-Artizzuet al., 2011). Historically the detection of weeds in crops is conducted visually by a trained specialist; they are commonly classified by the shape of their leaves, whether narrow or broad (Santos and Cruvinel, 2008). The separation into these two classes is quite useful, since grass and broadleaf weeds tend to receive differential treatment due to the selectivity of certain herbicides for a specific class. In the past decade, several studies aimed at the optimization of weed management and a reduction in the use of herbicides through automatic weed detection and classification have been conducted. Camargo Neto et al., (2006) developed an algorithm to classify plant species using Fourier elliptical equations; they obtained an accuracy of 89.4%. Using the fast Fourier transform, Nejati et al., (2008) detected weeds in corn fields. Tellaeche et al., (2008) and Arasteh et al., (2012) presented a method based on the identification of weeds between the rows of crops.
Studies on the detection of weeds in crops on the basis of images has resulted in various approaches using the near infrared spectrum (Pérez-Ortiz et al., 2015; Strothmann et al., 2017) and colors in the visible spectrum (Pérez et al., 2000; Meyer and Camargo Neto, 2008), as well as shape

(Slaughter et al., 2008) and texture (Guijarro et al., 2011; Sujaritha et al., 2017). However, variations in lighting under field conditions and soil slope in relation to the camera provide challenges, as well as the stage of weed development; these have led to a limited accuracy rate for automatic detection systems.

In this paper, we present a new approach to the problem of automatic classification of weeds and crops from digital images. Frequently used for the diagnosis of images in medical research (Xu et al., 2011; Rocha et al., 2012; Wang et al., 2011; Zare et al., 2013) is the machine learning method known as Bag-of-Features (BoF). This technique is generally independent of image resolution, color space, distance of image acquisition, lighting and size of objects of interest, and it seemed a promising approach for weed identification. Our objective was to evaluate if the performance of the BoF approach would be satisfactory for use as a tool in making decisions in weed management.

Results and Discussion

Index of overall performance of the models

The proposed system was tested and validated on images of different stages of growth and intensity of competition. During the experiments, input images of 25×25 pixels were used. These images were first segmented to remove soil information so that feature extraction would be possible. A total of 30553 images were employed for the experimentation, 8566 of weeds and 21987 of crops.

For training the system, 18331 samples were used (5139 images of weeds and 13192 of crops), with a cross-validation approach adopted to select the most promising parameters. The testing of the approach was conducted with the remaining 12222 samples (3426 images of weeds and 8796 images of crops).

The performance of the system for the discrimination of crops from weeds using seven codebook models was evaluated on the basis of four indices derived from a confusion matrix: overall accuracy, producer precision, user accuracy and Kappa index. The results of the overall accuracy and Kappa index for the seven models are summarized in Figure 3.

The overall accuracy tends to increase with an increase in codebook size. Of the codebooks presented in Figure 3, the seventh achieved the greatest accuracy. This is due to the fact that larger codebooks have more samples to check; however, finding the optimal point becomes more difficult, and more time and processing capacity are required. For Sikka et al., (2012), the increase in codebook size is limited in relation to improvement in performance for the BoF technique. Using this technique, Long et al., (2014) showed that the power of discrimination between categories depended heavily on the learning approach used to create the codebook, as well as the encoding strategy adopted. The importance of the definition of codebook size is clear when one looks at the range between the best and worst results for overall accuracy and the Kappa index, (Yang et al., 2007; Chatzichristofis et al., 2013; and Guo et al., 2013).

Despite the moderate performance of the proposed system, the results are quite promising, because the images used here come from a complex scenario, i.e., crops and weeds are distributed randomly in the same image (Fig. 4). The results suggest that some of the problems resulting from partial occlusion and overlapping of leaves, such as reported by Lamm et al., (2002), Golzarian and Frick et al., (2011) and Hiremath et al., (2012) have been reduced.

Performance of each model

The Kappa index (Cohen, 1960) evaluates how much the results in classification differ from a random classification, as well as informing the level of agreement in classification; the first two models achieved an index considered reasonable (Kappa < 0.4), similar to the results obtained by Silva et al., (2013) in a classifier of areas cultivated in citrus fruit; for the other models, the index was considered moderate to good (0.4< Kappa <0.6).

The performance of the Kappa index and the overall accuracy was not exceptional, but when considered globally in relation to others, such as Foody (2002), Shind et al., (2014) and Lottes et al., (2016), these results do indicate a great potential for improvement over the traditional approach to weed management in Brazil. The system proposed here seems useful for the recognition and identification of weeds species, as well as for taking decisions about herbicide dosage and the specification of a map for spot spraying, or even the elaboration of phytosociological studies of crops.

Table 2 provides the results of the performance of producer and user for all models in relation to the categories of weeds and crop (sugarcane). The user accuracy reflects the degree of agreement of the classifier with manual classification, i.e, it indicates the number of images classified by the proposed system that are in agreement with those based on manual classification, with the results expressed as a percentage (Olofsson et al., 2014; Tso and Mather, 2009). Producer precision indicates the percentage of images that were manually classified that have been attributed to the same class as they were by the proposed system (Tso and Mather, 2009; Abdel-Rahman et al., 2014).

It is clear that producer precision and user accuracy increase when the number of features in the model increase, here achieving maximum values of 72.8% and 74.1% for producer precision and user accuracy, respectively. Moreover, the proposed system is more efficient in the recognition of weed than crops, which may be explained by the complex characteristics of the situation of the experimental field where the images were taken. In some of the images, there is a great density of weeds and a large number of overlapping leaves, which make correct manual labeling difficult (Fig. 5).

State-of-the-art systems for the recognition of weeds and crops by image processing techniques show that the challenges include the identification of weeds and crops when they are close to each other and have overlapping leaves, as well as when weed species belong to the same botanical class as the crop (mono or dicotyledon) and when different stages in plant development and variations in natural light are involved (Lamm et al., 2002; Mccarthyet al., 2010; Jeon et al., 2011). Thus, given the complexity of the images used here, the results from our approach have proved to be quite promising, because the descriptors adopted include changes in invariants of lighting, rotation and/or scale.

Table 1. Performance evaluation of producer precision and user accuracy for all classifier models.

Codebook size	Class	Producer precision (%)	User accuracy (%)
Model 1	Weed	68.2	70.1
	Sugarcane	69.2	67.4
Model 2	Weed	69.0	71.9
	Sugarcane	70.7	67.7
Model 3	Weed	70.1	71.0
	Sugarcane	70.6	69.7
Model 4	Weed	71.0	71.1
	Sugarcane	71.0	70.9
Model 5	Weed	70.1	71.2
	Sugarcane	70.8	69.6
Model 6	Weed	70.4	71.7
	Sugarcane	71.2	69.8
Model 7	Weed	70.6	74.1
	Sugarcane	72.8	69.1

Fig 1. Segmentation of image using Pixel Color Distance and Otsu method. (a) Original image; (b) Plant image after segmentation process.

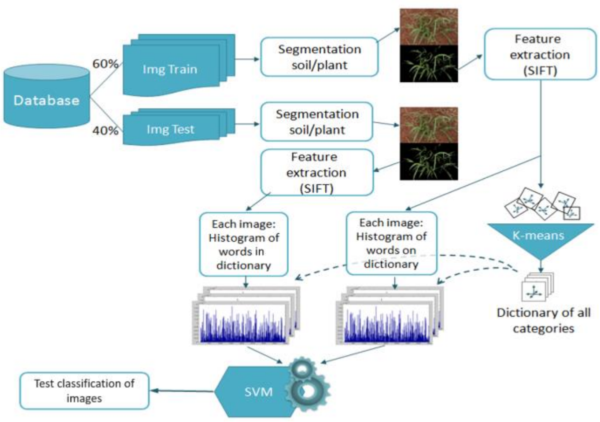

Fig 2. Flowchart of stages required for classification using the he Bag-of-Features.

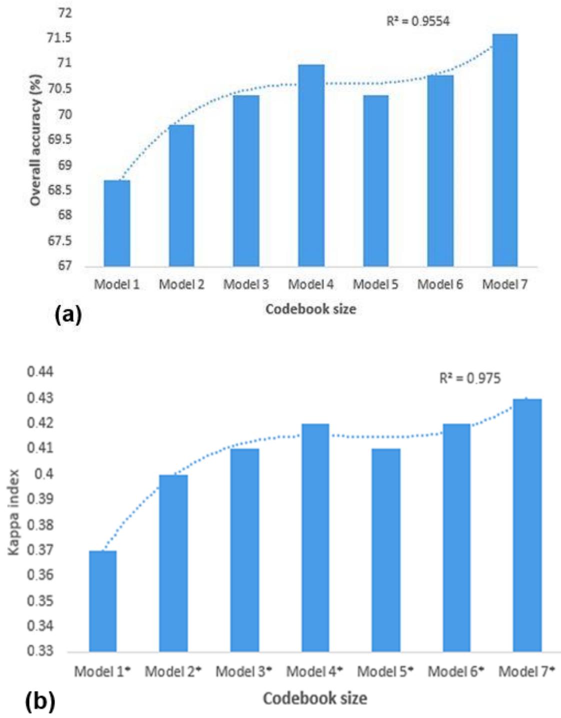

Fig 3. Comparison of weed and crop discrimination in relation to index of overall accuracy (a) and Kappa index (b) for all codebook models. *refers to results statistically significant at the 95% confidence level.

A false negative quantity was obtained for many of the images used in this experiment; this can be explained mainly by the difficulty in manual segmentation due to the overlapping of leaves (Fig. 6) Regions with a high density of narrow-leafed weeds not only lead to frequent cases of leaf overlap, but their great morphological similarity to the crop also inhibits the discrimination of weeds from sugarcane. In the future, it is suggested that the segmentation of images in such a complex scenario should be performed with complementary algorithms that eliminate overlap, such as those proposed by Lee and Slaughter (2004) and Lu et al., (2006), or they should be considered as a special class to be treated with different weights during classification.

Materials and Methods

This study was conducted on a single site of approximately 70 m^2 during the crop growing season of 2014. The study site was located in the proximity of 21º12' S, 47º52' W in the municipality of Ribeirão Preto, in the state of São Paulo in Brazil. It has been used continuously for the production of sugarcane for at least three growing seasons.The Koppen classification for the climate of Ribeirão Preto is Aw, i.e. a tropical climate; the average annual temperature is 23.2 ^{o} C, and the total annual rainfall is 1422 mm. The soil of the study site is classified as Udox (EMBRAPA, 2006). The variety IACSP95-5094 was used as the sugarcane ratoon, which was planted during the previous growing season (2012/13). The most common weeds contaminating sugarcane fields in the state of São Paulo were selected for the study: *Urochloa plantaginea*, *Urochloa decumbens*, *Panicum maximum*, *Euphorbia heterophylla*, *Ipomoea hederifolia* and *Ipomoea quamoclit*. Approximately 2 kg of a mixture of the seeds from all of these weeds were sown by hand, aiming for an approximate density of 60 seeds m^2. To ensure that the seeds would sprout directly from the soil, the residue of straw and sugarcane was removed, but after the sowing of the seeds, the residue was returned.

Image Acquisition

Daily images of the experimental plot were captured from the thirtieth to the forty-fifth day after the sowing of the weeds using an RGB digital camera (Nikon Coolpix P520) set for automatic focusing, exposure, shutter speed and lens opening. The camera was affixed to a tripod at a height of 1.5m. Each image covered an effective area of 2.20 by 1.65m (approximately an actual area of 3.63 m^2). Each image captured two rows of crops and the intervening space between them, whether or not it was occupied by weeds.

Vegetation segmentation

The images acquired were analysed with a customized Matlab program to separate the pixels indicating vegetation from the others, using the absolute green method described by Nejati et al. (2008), where the value of *Pixel Color Distance* is obtained by calculating the Euclidean distance applied to the normalized values of the red and green channels of each pixel. This distance is given by:

$$PCD = \sqrt{pixel\left(r^2\right) + \left[pixel\left(g\right) - 1\right]^2}$$

Where, PCD is the distance to absolute green of the pixels, pixel (r) the value of the pixel for the red channel and pixel (g) the value for the green channel. The PCD represents a new value for the pixel in a monochromatic image; this was calculated for all the pixels of the image. This Otsu method (Otsu, 1979) involves the iterative analysis of the histogram of the new image to automatically determine a threshold value; which is used to determine whether each pixel refers to a plant or background (Fig. 1). One hundred and twenty pictures were taken of the field and were manually subdivided into 25 x 25-pixel blocks, with each block labelled as to class (weed or crop). All of labelled blocks were then separated into two sets, the first for training (60% of the blocks or 18331 sub-images) and the second for the validation of the method (40% of the blocks or 12222 sub-images).

The Bag-Of-Features (BoF) as machine learning method

The BoF approach was used to detect the classes of plants on image. This approach consist in represent an image as histogram of representative local features extracted from the image and called visual words (Upadhyay and Chandra, 2019), and a set of visual words is generally called a visual vocabulary or codebook. Figure 2 summarizes the stages required for classification using the BoF approach. Firstly, using the training sub-images interest point (keypoint) are extracted from image and coded as an image descriptor. Then, the dimension of image descriptors are reduced by an unsupervised clustering technique that connect the extracted set of features to cluster centers which form a visual word and then the codebook (Zhao et al., 2016). Each image is represented as a histogram of visual words and these histograms are used into classifiers to perform image classification (Nanni and Melucci, 2016). Basically, the BoF approach can be summarized as features description, codeword representation and classification (Tamaki et al., 2013; Nasirahmadi and Ashtiani, 2017).

Detection and codeword representation

All the sub-images were submitted to determination of features descriptor based on the SIFT operator - Scale Invariant Feature Transform (Lowe, 2004). The features identified using this operator refer to relevant points and make it possible to combine the information present in two images, even when changes such those involved in lighting, rotation and/or scale of objects are considered. The descriptors extracted from the training set are then grouped by similarity using the K-means clustering algorithm (Jain et al., 1999) to generate average descriptors for the group. Each average is considered to be a visual codebook word. The size of the codebook, i.e, the number of words generated during the grouping, is important in influencing the effectiveness of the approach, since the existence of only a small number of visual words can compromise the information about the distinctiveness of a class, while a large number can reduce the ability of generalization of the classifier (Rocha et al., 2012). For this study, we evaluated dictionaries with 50, 150, 250, 350, 450, 550 and 650 visual words. Based on these codebooks and the calculation of the Euclidean distance between the descriptors of a given image and the codebook of visual words, it was possible to define a corresponding histogram vector of the probability density function, which compares the visual words of the codebook to what is found in the image. This vector was then used as an input parameter of the classifier.

Classification

The classification was made using the Support Vector Machine (SVM) method (Cortes and Vapnik, 1995). In its original version, the SVM classifier is characterized as being linear and non-probabilistic based on the analysis of data from a hyperplane subdivided into two classes. The Library for Support Vector Machines 3:17 (LIBSVM 3:17) of Chang and Lin (2011) was used in the implementation of the SVM classification, and the Radial Basis Function (RBF) was selected as the core. This function requires two model configuration parameters: 'γ' and 'C' (Hsu et al., 2010). These parameters were determined by trial and error. A set of the values was defined in the SVM training phase, and the pair (γ, C) that provided the best accuracy was selected. The accuracy evaluation of each tuple was based on cross-validation of the training data, with this divided into four groups.

Each codebook gave rise to a decision model that was evaluated by a performance index derived from a confusion matrix. The indices used were overall accuracy, producer precision user accuracy, and Kappa index. The whole algorithm, including the subdivision of images into 25 x 25-pixel blocks and their labelling, as well as the Bag-Of-Features machine learning technique, was implemented using the tool box of Image Processing from Matlab 9.0 R2011 (Mathworks) software in a computer with an Intel Core 2, 2.13 GHz and 2 Gb Ram, run with the Windows operating system.

Conclusion

The system proposed for the identification and classification of crops and weeds has achieved a reasonable accuracy and Kappa index, even under conditions of high weed density and a large number of overlapping leaves. The results show that the system can provide important subsidies for the formulation of strategies for weed management, as well information for the development of a smart system for decision-making in weed management, i.e, the information provided by image-processing software can be used to make a map of the level of weed infestation, which can, in turn, serve as a guide for localized herbicide application. Despite its importance in the development of weed management technologies, the most important contribution of this paper resides in the increase in economic and environmental sustainability made possible for Brazilian agricultural production, since it will be possible to reduce the use of herbicides, which are so commonly applied to sugarcane fields.

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