RECOGNITION AND CLASSIFICATION OF WEEDS IN SUGARCANE USING THE TECHNIQUE OF THE BAG OF WORDS

Wesley E. Santiago, Antonio R.Barreto, Danilo G.Figueredo, Rodolpho C. dos R.Tinini, Neucimar J.Leite andBárbara J.Teruel

Engineer Agriculture Faculty - UNICAMP
Mechanical Engineer Faculty - UNICAMP
Institute of Computation - UNICAMP

ABSTRACT

The production of sugar and ethanol in Brazil is very prominent economically and the reducing costs and improving the production system being necessary. The management crops operations of sugarcane and the control of weed is one of the processes that cause the greatest increase in production costs; because the competition that exists between cane plants and weed, for water, nutrients and sunlight is big, contribute to the loss of up to 20% of the useful cane. The use of image processing techniques has proven to be a tool to aid the decision, reducing production costs, because through the early recognition of infestation, it is possible to make the localized application of herbicides, reducing the impact on losses during cutting and harvesting of cane. Applying bag of words technique for recognizing weeds plants is proposed. The method is divided into three stages: vocabulary of visual words, training and classification. Were defined six varieties of weeds that have significant occurrence in cane fields infestation in the São Paulo State, which is the largest producer of sugar and ethanol in the country. The varieties of harmful plants chosen were: *Panicum maximum, Euphorbia heterophylla; Brachiaria decumbens; Brachiaria plantaginea; Quamoclit Ipomoea; Ipomoea hederifolia*. As main class was defined sugarcane (*Saccharum officinalis*). Digital images were obtained weekly between September and November 2013, using a digital camera (Nikkon Coolpix P510). The recognition of the images was developed in MATLAB R2012a. On classification stage was used the Support Vector Machine (SVM), which is a non-probabilistic binary classifier, being the methodology tested with a set of 105 images of seven kinds of plants (six weeds plants and sugarcane). The proposed method gotten average accuracy of 90.68% in the recognition, showing is more sensible in identification of plants Brachiaria plantaginea and Ipomoea hederifolia.

Keywords: Precision agriculture, image processing techniques, machine vision

INTRODUCTION

The weed control is a crucial step in all farming systems. In sugarcane, the occurrence of weeds can reduce productivity to about 46% (Rolim and Christoffoleti, 1982; Silva et al 2009.). Among the different tools available for weed control, control by herbicides has been the most used in recent decades.

Currently, the decision-making about the sprayed of herbicide considers the historical and distribution of seedlings on field, however the kind of sprayed is defined like before and after planting, when after planting can be pre-emergent and post-emergent. As the analyses of field are based on visual assessments of covered area by weeds and time growing of the crop, the success of weed control depends directly of skills of the manager. Due subjectivity that there is on conventional method, in many cases, are sprayed quantities above or below that required.

Knowledge of management techniques associated whit technological management tools, allows the practice of modern agriculture that strives for economic and environmental sustainability (Biller, 1998; Brookes and Barfoot, 2012; Li et al 2012). Oerk et al (2010) argue that by adopting techniques from the AP, localized management of weeds in agricultural crops has enormous potential in the environmental impacts reduction from agriculture, besides collaborating with reduction in production cost.

The high rates success reached by some methods for weeds identification per image indicate high possibility its use to applications in real time or in the infestation maps construction. With success rates from 80%, work Feyaerts and Gool (2001) was able to reduce by 90% the volume of herbicide applied. Gerhards et al. (2002) achieved up to 98% reduction in herbicide use for weed control in sugar beet cultivation by localized application. In this work we propose a system of recognition and classification plants using bag of words technique.

MATERIALS AND METHODS

Was used a digital camera (Nikon Coolpix P520) to take images of plants sugarcane in stage of sprouting and tillering, growing upon dry straw of previous harvest, well as six species of weeds cultivated in pots on Faculty of Agricultural Engineering of Campinas, the Figure 1 displays the plants utilized for each class. The images were taken in October of 2013, during the four first weeks of growth, in moment of capture of images was sought diversify randomically the position, center and height of camera to which the process were similar the variations possible of natural form of the land and light found in fields agricultural. Each image has just one plant, without overlap with leaves of other plants.



Brachiaria plantaginea *Brachiaria decumbens* *Panicum maximum*



Ipomoea hederifolia *Ipomoea quamoclit* *Euphorbia heterophylla*

Saccharum officinalis (Sugarcane)

Figure 1. Plants used to classification with bag of words.

The digital images were stored colorful with 24 bits and resolution of 1024 x 768 pixels, saved in space colors RGB and format of archive JPEG. Latter, the images were processed using the Digital Processing Images toolbox of Matlab 9.0 R2011 (Mathworks). In all were used 330 images divided in two groups, the first 225 images to training and 105 remainder images to test and validate the model. The algorithm shown here was implemented in a computer Intel Core 2 CPU, 2.13 GHz and 2 Gb Ram, running Windows operating system.

The approach introduced here takes into account the steps of processing, training and classification. The processing step includes the image capture, noises filtering, segmentation, conversion to gray-scale values, and key features extraction. The training process consists of identification and learning of the main features related to the plants discrimination. In the classification step, the training result is used to classify the new incoming images.

The segmentation performed before the features extraction aims at separating the soil regions from the plants. To do this, we considered the absolute green information in which the green value is obtained through the Euclidian distance, as follows (Nejati et al. 2008):

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

Where PCD is the pixel distance to absolute green, pixel (r) is the value given to pixel in red plan and pixel (g) is the value given to pixel in green plan. The PCD was applied in every pixels of image; those which had the Euclidian distance more than the threshold were assigned as background. The Figure 2 displays the result of this segmentation on test images.

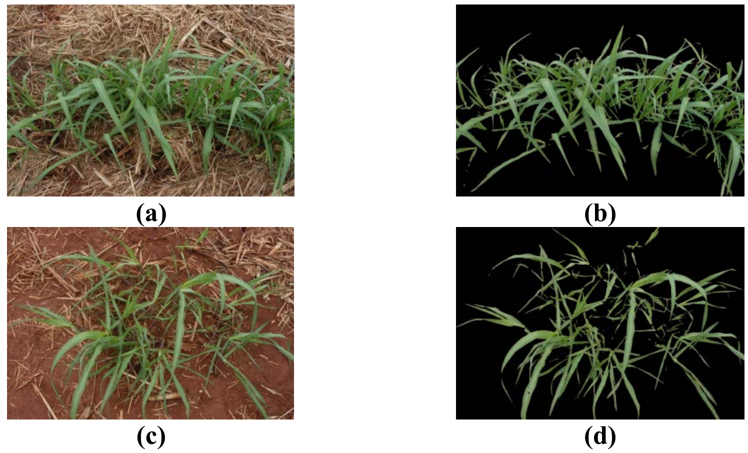

Figure 2. Segmentation using Equation (1) with a threshold of 0.73. (a) Image of sugarcane with straw in the background. (b) Segmented plants with background in black, (c) Image of sugarcane with mixed background (soil + straw), (d) Plant detected in the image and background in black.

After segmentation, the image is converted to a gray-scale representation where is applied a median filter to remove noise. Further, the SIFT (Scale Invariant Feature Transform, Lowe (1999)) was used as feature descriptor due to its property of defining features which are invariant to scale, translation, rotation and lightning conditions. Finally, with the key features extracted, the bag of words approach was used for training and classification, as shows the flowchart in Figure 3.

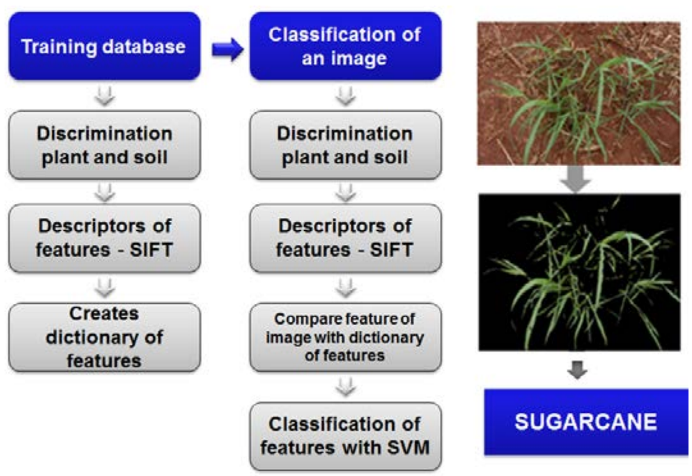

Figure 3. Flowchart of the proposed method for detection and recognition of plants.

The bag of words is a simple methodology and has been quite broadcast to categorization of images (Lazebnik et al. 2006; Yang et al. 2007; Chen et al. 2009; Ballan et al. 2009). In this methodology, is used a descriptor for extract the local features of image (visual words), then this features are grouped and the groups becomes in a description of category that image belongs. The set of several distinct groups creates a vocabulary of words which is the base to classification process in categories different, in this case, plants different. As explained to Yang et al. (2007), the stage of classification ignores or minimizes the disposition of words (spatial information in image) and classifies with base just in one histogram of frequency of visual words on image. For this work, were tested groups of 50 until 650 words to create a dictionary by cluster algorithm of K-means (Jain et al, 1999). So, driven by simply and low computational cost, was adopted like sorter the Support Vector Machine developed by Chang and Lin (2011).

Order to prevent the occurrence of the problem of over-fitting; we applied the technique of cross-validation data considering four folds. In cross-validation with four folds, the test set is divided into four subsets of equal size. Sequentially one of these subsets is used to test the classifier and the remaining three sets are used for training the classifier. The cross-validation is the average hit rate obtained when each subset was used in the classification test.

RESULTS AND DISCUSSION

In the first part of the experiments, we explored the importance of how the number of words considered to characterize the seven classes in the creation of the vocabulary influences the time and outcome of the rank. During the creation of vocabulary was identified that for amount of features extracted by descriptor would be necessary too much memory, disabling the use of method. So, we investigated if the random choice of a less number of features could affect the performance of rank. The results of classifier using the dataset training (225 images) are based on the average of a 4-fold cross-validation procedure (four independent evaluations of the full algorithm using at each time one fold as test and the remaining four as training).

Importance at vocabulary size choice is showed by several authors (Yang et al. 2007; Chatzichristofis et al. 2013; Guo et al. 2013), in accordance with Tsai (2012), the number of words at vocabulary is the most important factor on definition of accuracy of algorithm.Figure 3 shows the classification performance results for the random use of 20 and 50% of features on creation of vocabulary with the best and worst vocabulary sizes. For 20% of features extracted the best-performing vocabulary size consisted of 350 words and for 50% consisted of 550 and 650 words when used the training dataset. With the test dataset the best-performing vocabulary size consisted of 650 words for 50% and 350, 450 and 650 for 20% of features selected. For reference, with 20% of features, the system achieves 93.17% of accuracy using training dataset and 90.48% accuracy in test dataset, already with 50% of features; the system achieves 93.17% of accuracy using training dataset and 90.48% accuracy in test dataset. The worst performing vocabulary size was 50 words in both cases.

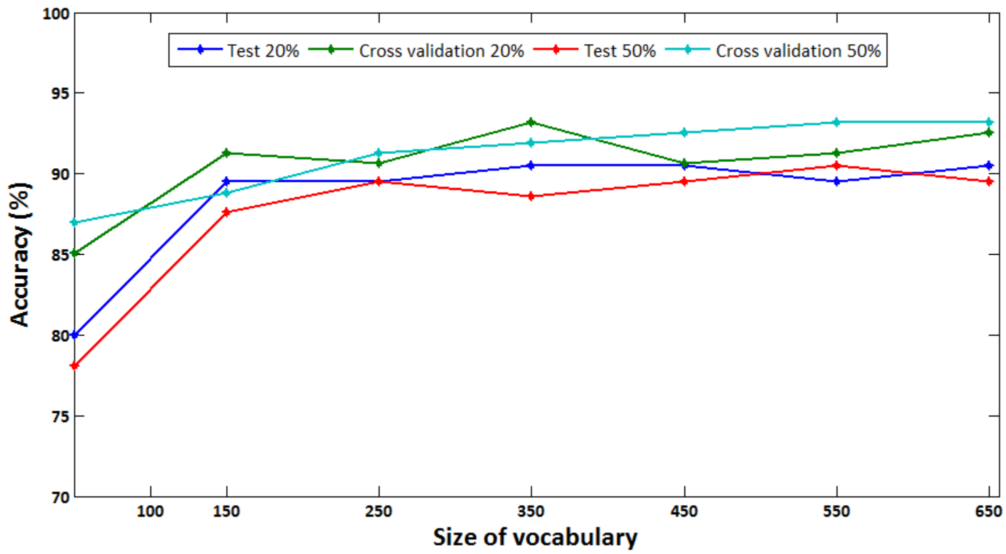

Figure 3. Performance results for classification using different sizes

The second part of our experiments consisted of analyze the confusion matrix of test in the best-performing vocabulary size using 20% of features. Was used the same dataset of images to test compound by 105 images, the who has 15 images per class.

During training, the parameters of the SVM were analyzed manually on try of find the best parameters of tuning of algorithm (Duan et al. 2003). The best SVM parameters were: SVM regularize C = 100 and the kernel RBF parameter = 8. The Table 1 displays the confusion matrix with the amount of images given to each class of plants. The columns mean the predicted results by method and row the actual category of image.

Table 1. Confusion Matrix

	S. Officinalis (SO)	B. plantaginea (BP)	B. decumbens (BD)	E. heterophyla (EH)	I. hederifolia (IH)	I. quamoclit (IQ)	P. maximum (PM)
SO	13	0	0	0	0	1	1
BP	0	15	0	0	0	0	0
BD	0	0	14	1	0	0	0
EH	1	0	0	14	0	0	0
IH	0	0	0	0	15	0	0
IQ	2	0	0	0	0	13	0
PM	2	0	1	1	0	0	11

Measures performance derived from the confusion matrix were established to identify classes where the method has a lower ability to identify, precision, (PC), accuracy (AC), sensitivity (SE) and specificity (SP). The performance of the classifier for each class is shown in Table 2.

Table 2. Performance of classification to each class

	S. Officinalis (SO)	B. plantaginea (BP)	B. decumbens (BD)	E. heterophylla (EH)	I. hederifolia (IH)	I. quamoclit (IQ)	P. maximum (PM)
Precision	72.2%	100.0%	93.3%	87.5%	100.0%	92.9%	91.7%
Accuracy	93.3%	100.0%	98.1%	97.1%	100.0%	97.1%	95.2%
Specificity	86.7%	85.7%	86.4%	86.3%	85.7%	87.3%	89.0%
Sensibility	86.7%	100.0%	93.3%	93.3%	100.0%	92.9%	73.3%
Accuracy (Cross Validation) = 90.68%							

The analysis of derivates of confusion matrix showed in Table 2 reveals that the model got high accuracy to identify plants of Ipomoea hederifolia and Brachiaria plantaginea (100% for measures accuracy and precision). However, in accordance with Davis and Goadrich (2006), high accuracy not mean that sorter is good, because can have happened problem like over-fitting of datas or the precision, specificity and/or sensibility the same class be low.

An important aspect observed in this study was that a digital camera used only the visible spectrum, without any structure for correction of variations in illumination and height obtained classification rate (90.68% accuracy in cross-validation) similar to results from other methods found in the scientific literature, especially the work of Feyaerts and Gool (2001) Which starting que described in 80% of accuracy is possible decreasing until 90% the volume of herbicide applied. Gerhards et al. (2002) got reduce until 98% the herbicide use on weeds control in sugar beet fields by localized application.

Although the conditions are different, a comparative analysis of the performance achieved by the proposed method and three different classification approaches to weed through digital RGB images can be viewed in Table 3. The method used by Ahmed et al. (2012) considered a vector of nine characteristics that encompassed color information, regardless of size and shape invariant moments. Hiremath et al. (2012) uses texture features to build an array of co-occurrence of gray levels (GLCM). In the method of Liu et al. (2010) morphological and wave energy characteristics were used to classify images of weeds and corn.

Table 3. Analyse of accuracy between approaches different

Approaches	Number of class	Number of samples	Misclassify	Accuracy (%)
Approach proposed	7	105	10	90.68
Ahmed et al. (2012)	6	224	6	97.30
Hiremath et al. (2012)	2	92	9	90.00
Liu et al. (2010)	2	68	3	95.59

It is believed that the performance of the method is primarily due to the characteristics of the descriptor which has the scale invariance, rotation and lighting, the latter being one of the most characteristic for plants classification undertake real-time systems because the natural light environment generates shadows and artificial lighting can promote noise and difficulty design (Huang et al 2012; Peteinatos et al 2014).

CONCLUSION

The method proposed was able of discriminate weed species and sugarcane. The algorithm was more effective in the detection of broad leaf plants of the genus Ipomoea and genus Brachiaria for narrow leaf. The results show that the algorithm has potential to use as a tool for precision agriculture, especially for construction of infestation maps.

ACKNOWLEDGEMENTS

The Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) and the Fundação de Amparo a Pesquisa do Estado de Sao Paulo (FAPESP) by support this research.

REFERENCES

AHMED, F., AL-MAMUN, H. A., BARI, A. S. M. H., HOSSAIN, E. and KWAN, P. (2012). Classification of crops and weeds from digital images: A support vector machine Approach. Crop Protection 40 (2012) 98-104.

BALLAN, L., BERTINI, M., BIMBO, A. and SERRA, G. (2009).Video Event Classification Using Bag of Words and String Kernels, Proceedings of the 15th International Conference on Image Analysis and Processing, Vietrisul Mare, Italy.

BILLER, R. H. (1998).Reduced Input of Herbicides by Use of Optoelectronic Sensors. Journal of Agricultural Engineering Research, Volume 71, Issue 4, Pages 357–362, December 1998.

BROOKES, G., and BARFOOT, P. (2012). Global impact of biotech crops: Environmental effects, 1996–2010. GM Crops and Food: Biotechnology in Agriculture and the Food Chain 2012; 3:129 – 137.

CHANG, C. C., and LIN, C. J. (2011). LIBSVM: a library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2:27:1--27:27.

CHATZICHRISTOFIS, S. A., IAKOVIDOU, C., BOUTALIS, Y. and MARQUES, O. (2013). Color Visual Words Based on Non-Predefined Size Codebooks. Cybernetics, IEEE Transactions on, On page(s): 192 - 205 Volume: 43, Issue: 1.

CHEN, X., HU, X. and SHEN, X. (2009). Spatial Weighting for Bag-of-Visual-Words and Its Application in Content-Based Image Retrieval, Proceedings of the 13th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining, Bangkok, Thailand.

DAVIS, J. and GOADRICH, M. (2006).The Relationship between Precision-Recall and ROC Curves.Proc. 23rd Int. Conf.On Machine Learning.

DUAN, K., KEERTHI, S. S. and POO, A. N. (2003). Evaluation of simple performance measures for tuning SVM hyperparameters.Neurocomputing, Volume 51, April 2003, Pages 41-59, ISSN 0925-2312.

FEYAERTS, F., and GOOL L. V. (2001).Multi-spectralvision system for weed detection.Pattern Recognition Letters, v.22, n.6-7, p.667- 674.

GERHARDS, R., SÖKEFELD, TIMMERMANN, C. and KÜBAUCH.(2002). Site–specific weed control in maize, sugar beet, winter wheat, and winter barley. Precision Agriculture, 3, 25-35.

GUO, J., QIU, Z. and GURRIN, C. (2013).Exploring the optimal visual vocabulary sizes for semantic concept detection. Content-Based Multimedia Indexing (CBMI), 2013 11th International Workshop on, On page(s): 109 – 114.

HIREMATH, S., VAN DER HEIJDEN, G., VAN EVERT, F.K. and STEIN§, A. (2012). The role of textures to improve the detection accuracy of Rumexobtusifolius in robotic systems. Weed Research 52, 430–440.

HUANG, J., HUANG, N., ZHANG, L. and XU, H. (2012).A method for feature selection based on the correlation analysis. Measurement, Information and Control (MIC), 2012 International Conference on , vol.1, no., pp.529,532.

JAIN, A, K., MURTY, M. N. and FLYNN, P. J. (1999).Data Clustering: A Review. ACM Computing Surveys, Vol. 31, No. 3, September.

LAZEBNIK,S., SCHMID, C. and PONCE, J. (2006). Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories. Computer Vision and Pattern Recognition- IEEE Computer Society Conference on.v.2 p.2169 – 2178.

LI, X., PENG, L., and SUN, C. (2012).The Application and Forecast of Geospatial Information Technology in Agriculture Internet of Things. Remote Sensing, Environment and Transportation Engineering (RSETE), 2012 2nd International Conference on , vol., no., pp.1,5, 1-3 June 2012.

LIU, X., LI, M., SUN, Y., and DENG, X. (2010). Support vector data description for weed/corn image recognition. Journal of Food, Agriculture & Environment Vol.8 (1) : 214 – 219.

LOWE, D. G. (1999). Method and apparatus for identifying scale invariant features in an image and use of same for locating an object in an image. US Patent 6,711,293 (March 23, 2004). Provisional application filed March 8, 1999. Asignee: The University of British Columbia.

NEJATI, H., AZIMIFAR, Z., and ZAMANI, M. (2008). Using fast fourier transform for weed detection in corn fields. Systems, Man and Cybernetics, 2008.SMC 2008. IEEE International Conference on, pp.1215,1219.

PETEINATOS, G.G., WEIS, M., ANDÚJAR, D., AYALA, V.R. and GERHARDS, R. (2014).Potential use of ground-based sensor technologies for weed detection.Pest.Manag. Sci., v.70,(2), 190-199.

ROLIM, J. C., and CHRISTOFFOLETI, P. J. (1982).Período crítico de competição na cultura da cana-de-açúcar (Saccharum spp) - cana-planta de ano. Saccharum (São Paulo), Piracicaba, v. 5, n.22, p. 21-26.

SILVA, I. A. B., KUVA, M. A., ALVES, P. L. C. A., and SALGADO, T. P. (2009). Interferência de uma comunidade de plantas daninhas com predominância de Ipomoea hederifolia na cana-soca. Plantadaninha. vol.27, n.2, pp. 265-272

TSAI, C. (2012). Bag-of-Words Representation in Image Annotation: A Review. ISRN Artificial Intelligence, vol. 2012, Article ID 376804, 19 pages, 2012.

YANG, J., JIANG, Y.G., HAUPTMANN, A. G. and NGO, C. W. (2007).Evaluating bag-of-visual-words representations in scene classification. In MIR '07: Proceedings of the international workshop on Workshop on multimedia information retrieval, pp. 197-206.