Lightweight Computer Vision System for Automated Weed Mapping

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***Abstract*—Automatic weed mapping based on perception systems permits understanding weeds behaviors over-seasons. Acquiring accurate maps of weeds position encourages the adoption of driver-less vehicles (Airborne or Ground-vehicles) for autonomous spray operation. Unmanned Aerial Vehicles (UAV) have been tested as a replacement for satellites for large field surveying. However, images of UAVs suffer from low spatial resolution, producing a challenge for vision-based systems to locate the infested spots in the field, especially in high density of plants. In this paper, we propose a robust and lightweight detection process to generate weeds maps under high-density soybean fields. Our mapping system takes advantage of machine learning and features engineering abilities to provide an accurate position of the infested spots in each retrieved image within an acceptable time window. Results demonstrate that leaf orientations compromise promising features to use for discriminating weed-crop in clusters. The proposed system design can efficiently locate infested zones with an accuracy of 93.19%, allowing by that an estimated saving of 75% of the expensive herbicides.**

***Keywords*—Machine vision, Neural network, Automated weed mapping, Site-specific weed management, Remote sensing, HOG**

I. Introduction

Over decades, farmers have been struggling to maximize their products regardless of environmental factors. This problem consists of a challenge for stockholders and agribusinesses to maximize their profits while reducing costs [1]. Invasions of weeds are one of these factors, which negatively impact the crop [2]. A conventional approach that deals with weeds consist of manual inspection of the field, and manual spray. Farmers generally use Argo-chemicals to eliminate the weed plants, and the treatments are broadcasted uniformly across the field. This increases the risk of intoxication, and harm the natural resource. One way to deal with this issue is to intelligentize the agricultural activities to achieve a site-specific treatment, where only weed plants are sprayed. Consequently, agribusiness and stockholders can have more control over their production, while reducing costs and risks of the treatments [1].

Computer vision represents a potential candidate to enhance the surveying process of fields and approach site-specific management. By acquiring digital images of a field or field regions, it is possible to apply computer vision techniques to locate weed spots within a few milliseconds [3]. Various detection procedures and AI models have been explored for weed detection and plants classification. Some works use hand-designed features to discriminate between crop and weeds [4] [5] [6]. These features can be simple colour features or more complex features such as textural features or shape features. The use of each feature is application dependent. For instance, it is only possible to use colours as indicators, when the target plants show different colour appearances. Nevertheless, weeds and crops in some cases (e.g. soybean field) exhibit similar colours proprieties, making them less favoured to use. In which concerns textures and shape features, it is essential for the studied plants to be well-separated, to correctly extract the features. However, in the case of dense plants, the shapes fail to represent different plant species, resulting in lower prediction performance [2]. The selection of an adequate detection method depends on several factors, for instance, plants distribution and density in the field. Having weeds and crop in clusters, represent the difficult case for shape-based approaches [7].

Henceforward, we aim through this work to provide adaptive features that can represent plants in clusters regardless of their species, to improve weed detection performance. We assume that each cluster of specific plant species has a unique leaf orientation. Thus, we compute the statistical features of leaves orientation and use it to discriminate between weeds and crops in dense crop fields. We characterize the orientation of leaves with the Histogram of Gradients orientation (HOG).

The remainder of this paper is organized as follow: In section.II, we explain the proposed vision-based system. In section.III, we evaluate the classifier and the mapping system in weeds and crop discrimination. Finally, we discuss and conclude the work in section.IV.

II. Vision-based weed mapping

A. Overview of the system

To generate spraying maps we propose a vision based system that use UAV images to identify weeds spots (zones to spray). The acquired images suffers from low spatial resolution due to the altitude of the camera sensor. This emphasis on the use of region-based classification, to identify the infested spots. Therefore, we simplify the complex images using Simple Linear Iterative Clustering (SLIC). This process consist of splitting each image into regions that share similar color properities called Superpixels (i.e. segments). Extracted segments are then classified into crop or weeds. Finally, weed segments coordinates are stored for further use in the spraying phase.

The recognition of weeds is based on the orientation of its leaves. We represent the orientation using HOG descriptor. We start the feature extraction process by spliting the image into grids with square sizes. Next, we compute the HOG descriptor for each grid, and then compute statistical features for all computed descriptors. These statistical features form the features vector that will serve as an input of the Neural Network (NN) classifier for weed-crop discrimination. Fig.1 shows the pipeline of the proposed system.

B. Superpixel segmentation and simple linear iterative clustering algorithm (SLIC)

Superpixel segmentation can be defined as a tool used to reduce the complexity of image processing tasks by capturing the redundancy in the image [8]. The method splits the image into segments, which contain pixels that shares same color characteristics. This process produce segments that carry more information compared to single pixel. As result, we reduce the number of processing points from million of pixels to a couple of segments which improve the processing speed compared to pixel-based weed mapping approaches.

Superpixel segmentation generates segment pixels that shares same proprieties. This helps on getting more noise-free features of each class which improves the detection process in high density plants. We adopt the aforementioned segmentation method to overcome the limitation of region-based approaches in the case of overlapping plants. Herein, we use SLIC [9] method to extract the segments from the full complex image. SLIC generate superpixels by clustering pixels on $5D$ space. It takes into consideration similarities in lab color space, and proximity in image plane. Given a K superpixels (segments), the pixels are clustered based on their distance from centers C_k, where $k = 2, 3..K$. The distance is modified to encompass for different sizes of the image and it is computed as shown in Equation (3).

$$d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2} \quad (1)$$

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \quad (2)$$

$$D_s = d_{lab} + \frac{m}{S} d_{xy} \quad (3)$$

C. Features extraction

Assuming that the generated superpixels are homogeneous, it is not defined whether it contains weeds or crop. To distinguish between superpixels of crop and weeds, we adopt the HOG descriptor assuming that each plant cluster has a specific patterns of leave orientations. Besides, HOG is robust to scale, illumination changes, and artifacts. Thus, computing the features can be divided into two main steps:

- **Computing HOG:** The process start by computing the gradient magnitude and orientation for each cell. Next, those cells are grouped in blocks, and for each block we build an histogram of the gradient orientation normalized at block level. Later on, we extract each block's histogram separately to compute the statistical features.

  The size of cells here is 8×8 pixels, and the blocks are of size 2×2 cells. The orientation is fixed at 9 and the detector size is equal to the average of the superpixels sizes.
- **Statistical features:** The computed HOG descriptor is divided into grids with equal lengths. The number of using grids is equal to the number of blocks per superpixel. Next, we compute the statistical features in each grid, and combine it into 1 D feature vector called S_d. The reason of grids is to produce features that encompass for local information in different part of the image. This process reduce the HOG descriptor dimension, and carry more useful information on the distribution of leaf orientations.

The entire process of the vision-based system is summarized in Fig.2.

D. Neural Network

Back-propagation Neural Network (BPNN) with more hidden layers can provide good results compared to other conventional machine learning algorithm in weed detection [4]. To determine the topology of the model we use trial and error and the best model is the one that maximizes the F1-score. We find that BPNN with two hidden layer of 16 and 5 hidden units can provide good recall without affecting the precision. However, exploring more possibilities may provide better performance. The learning rate here was fixed on 10^{-5} without any decay. No dropout or regularization was used here as the number of samples for each class is important. Regarding the number of iteration, we use 100 as the initial number of iteration and we start adding 100 until the model is no longer improving. Hidden units with ReLU activation provide good results compared to other activation functions. Nonetheless, Sigmoid activation was used only in the output layer (binary classification). The weights were initialized using Glorot uniform initialization [10].

III. Experiments and Results

A. Soybean and weeds Data-set

Soybean is highly consumed world wide by humans and animals [11]. Soybean crop and its common invasive weeds (grass and broad-leaf) appears in clusters. This constitute a challenge for visual features. In this paper we choose to use a public data-set provided by [11], as it contains 11902

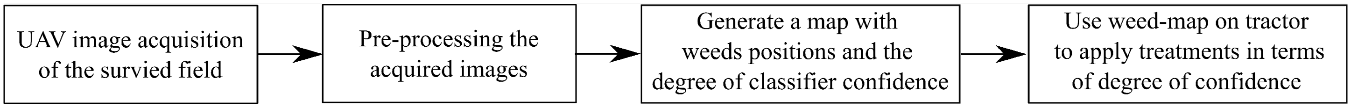


Fig. 1. Implementation steps of UAV-based weed detection in real fields.

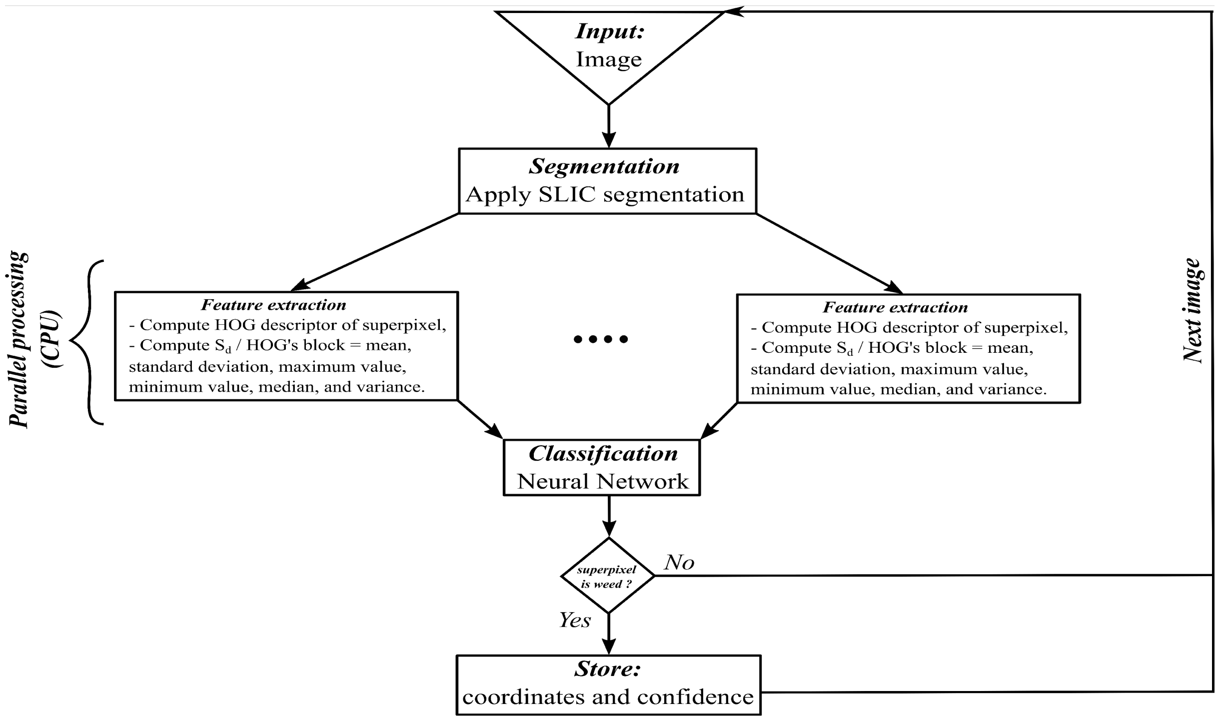


Fig. 2. Organigram of the proposed system

plants, 7375 of soybean, 3398 of grass, and 1129 of broad-leaf. These images are acquired using RGB camera mounted on a drone flying at an altitude of 4m.

B. Evaluation metrics and data splitting

The data-set is split into train and test sets. Out of 11902 images, 70% are used to train the model, and 30% for the test. In the parameters tuning, we take 10% from the train set for the cross-validation to prevent the model from overfitting the test set. The number of images in each plant class are shown in Table.I.

To evaluate the performance of the model we choose to compute ROC and Precision-Recall curves, which investigate the models performance across different thresholds. This is important in agricultural application as it shows the trade-off between treating all the weeds in the field (high recall and less precision) or avoid spraying the value crops (less recall and high precision). Moreover, we provide the execution time of the classical HOG and the proposed features to evaluate the computation efficiency .

TABLE I
NUMBER OF SAMPLES USED TO TRAIN AND TEST THE MODEL

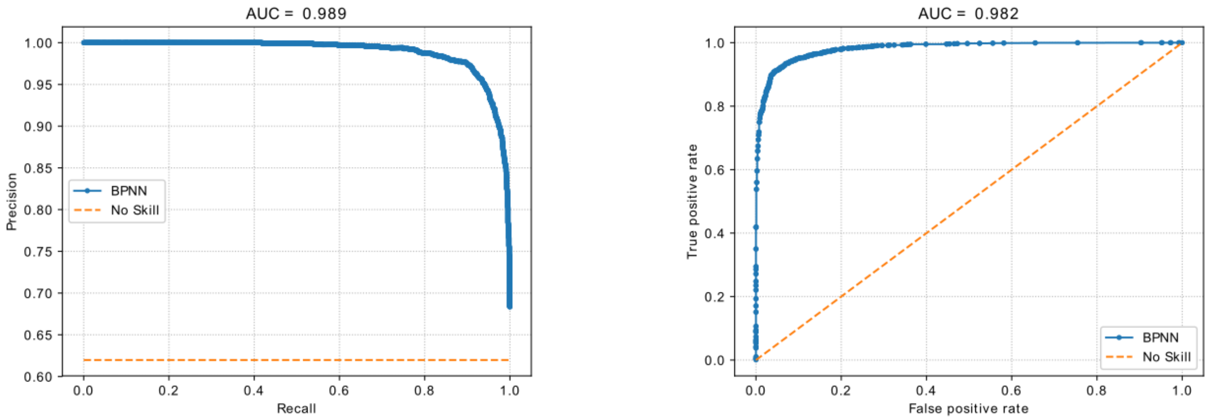
Plant's specie	Train	Test
Soybean	5163	2212
Grass	2380	1018
Broad-leaf	790	339

C. Performance of the mapping system

Weed mapping systems should be able to identify the location of the infested spots for specific treatment. The system need to provide good detection rate and can run under low-cost architectures to be commercially viable.

Speaking of the spraying maps, the priority for farmers is to treat all the weeds in the field. This means that the system need to provide 100% recall. In the same time, the system should avoid as much as possible classifying crop spots as weeds to avoid wasting the herbicides. The precision-recall curve and ROC curve of the system are shown in Fig.3.

Using the statistical features of gradient orientation,



(a) Precision and recall curve.

(b) ROC curve

Fig. 3. curves of the system performance under different probability thresholds. The no-skill curves refer to the worst case, when the model is randomly predicting or have a constant prediction.

BPNN can provide up to 93% of true positive rate with 5% of the false positives rate as can be seen in Fig.3-(b). This means that 93% of the system decisions (i.e. spray or not) will be correct with the possibility of spraying 5% of the crop spots. This can be adjusted by changing the probability threshold to extract as much as possible of the weeds zones. As can be seen from the Fig.3-(a), to get 100% of the weed spots, decreasing the probability threshold can help the system achieves the corresponding recall with about 80% of precision which is good for agricultural applications. Computing features on the HOG descriptor gives better results, with less impact on the computational efficiency Table. II.

D. Weed mapping on new samples

By preserving an image for the test, we can observe how the model will perform on new examples. The image was randomly selected for weed mapping. After fixing the topology and the parameters of the model, we train the BPNN using the same training samples mentioned in section.III-B. Next, we save the trained model for further use. The detection process is similar to the one described in Fig.2. After classifying all the segments, we color the weeds zone in green with intensity proportional to the confidence of the classifier. Dark green means that the corresponding zone is classified as weed with high probability, and the absence of green means no weeds is detected. The results of the system are shown in Fig.4.

The proposed system can differentiate between weeds and crop/bare soil, with good performance. Regions that contains broad-leaf, and grass were detect with high confidence (Fig. 4). The system can also avoid the non-weed area, helping in conserving the expensive herbicides. Some crop regions were misclassified as weeds, but with lower probability, and it can be avoided by setting an adequate threshold to filter these misclassifications.

E. Estimated saves of herbicides

Eliminating weeds while saving herbicides is the main reason for adopting Site Specific Weed Management (SSWM) and perception systems. In this section, we provide a simulation of the advantages of the proposed system compared to the conventional practice (uniform application).
Considering the acquired images that present 4000×3000 pixel resolutions, each pixel represent 1cm of ground sampling distance. This means that each image represent a field surface equal to $1200m^2$. The weeds are in their pre-emergence, thus we assume that we are applying Flumetsulan herbicides. According to authors in [14], the conventional application rate is about 1.44 $kg\ ai\ ha^{-1}$. Treating the whole area that appears in the image with same application rate will cost 0.1728 kg of herbicides.
Now lets assume that we are adopting the mapping system and will only treat the green spots (weeds or zone identified as weeds). For the same image, regions marked as weeds represent a total number of pixels equal to 3000000 pixels. This is equivalent to $300m^2$ spatial surface. Thus, treating only the marked area will cost 0.0432 kg of the herbicides. Hence, by comparing both spraying approaches, using the proposed mapping system will result on an estimated save of 75% of the herbicides (0.1296 kg) in each $1200m^2$ area.

IV. Conclusion and discussion

In this work, we present a weed mapping approach based on novel features. The detection relies on the statistical measurements of the gradient orientation of plants leave in different part of the image. These statistical features are concatenated into 1D vector that represent the final descriptor. This modification aims to reduce noise in the HOG descriptors generated by the dynamic morphology of the plants. The proposed approach can detect weed in high plants density with an overall accuracy of 93.19%. The results demonstrate that weeds and crops in clusters, exhibit

TABLE II

COMPARING THE PERFORMANCE OF THE SYSTEM WITH DIFFERENT VISUAL-BASED METHODS FOR WEED DETECTION

Detection method	Overall Accuracy (0.5 threshold)	Computation efficiency of descriptor
Proposed approach	93.19%	0.026 s $\pm$ 8.3e^{-04}
HOG	70.69%	0.025 s $\pm$ 9.5e^{-04}
Color-based detection [4]	95-96%	0.0211 s
Spectral-based detection [12]	93-100%	N/A
Crop-row based detection [13]	90-95%	N/A

Fig. 4. Result of weed mapping using the proposed system, where a) represent the original image and b) is the resulting weed map, and c) is the ground-truth. Degree of the green intensity in the weed-map refer to the confidence of the classifier that the corresponding region is weed.

a unique leaves orientation pattern, that can be used for discrimination. Moreover, superpixel segmentation methods provide a solution for high density crops problem, and can enhance the detection process by simplifying the image into couple of regions with similar proprieties.

Regarding the application benefits, using the proposed system for automated weed mapping, will help increase farmers profit, by reducing costs of manual labors, and saving up to 75% of the agro-chemical products.

REFERENCES

[1] A. M. Hasan, F. Sohel, D. Diepeveen, H. Laga, and M. G. Jones, "A survey of deep learning techniques for weed detection from images," *Computers and Electronics in Agriculture*, vol. 184, p. 106067, 2021.

[2] S. Abouzahir, M. Sadik, and E. Sabir, "Bag-of-visual-words-augmented histogram of oriented gradients for efficient weed detection," *Biosystems Engineering*, vol. 202, pp. 179–194, 2021.

[3] A. Wang, W. Zhang, and X. Wei, "A review on weed detection using ground-based machine vision and image processing techniques," *Computers and electronics in agriculture*, vol. 158, pp. 226–240, 2019.

[4] S. Abouzahir, M. Sadik, and E. Sabir, "Enhanced approach for weeds species detection using machine vision," in *2018 International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*. IEEE, 2018, pp. 1–6.

[5] D. A. Kumar and P. Prema, "A novel wrapping curvelet transformation based angular texture pattern (wctatp) extraction method for weed identification." *ICTACT Journal on Image & Video Processing*, vol. 6, no. 3, 2016.

[6] A. Bakhshipour and A. Jafari, "Evaluation of support vector machine and artificial neural networks in weed detection using shape features," *Computers and Electronics in Agriculture*, vol. 145, pp. 153–160, 2018.

[7] M. Aitkenhead, I. Dalgetty, C. Mullins, A. J. S. McDonald, and N. J. C. Strachan, "Weed and crop discrimination using image analysis and artificial intelligence methods," *Computers and electronics in Agriculture*, vol. 39, no. 3, pp. 157–171, 2003.

[8] S. Abouzahir, M. Sadik, and E. Sabir, "Bag-of-visual-words-augmented histogram of oriented gradients for efficient weed detection," *Biosystems Engineering*, vol. 202, pp. 179–194, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1537511020303056

[9] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, "Slic superpixels," Tech. Rep., 2010.

[10] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, 2010, pp. 249–256.

[11] A. Dos Santos Ferreira, D. M. Freitas, G. G. da Silva, H. Pistori, and M. T. Folhes, "Weed detection in soybean crops using convnets," *Computers and Electronics in Agriculture*, vol. 143, pp. 314–324, 2017.

[12] R. S. Fletcher and K. N. Reddy, "Random forest and leaf multispectral reflectance data to differentiate three soybean varieties from two pigweeds," *Computers and Electronics in Agriculture*, vol. 128, pp. 199–206, 2016.

[13] M. D. Bah, A. Hafiane, and R. Canals, "Weeds detection in uav imagery using slic and the hough transform," in *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*. IEEE, 2017, pp. 1–6.

[14] C. Swanton, P. Sikkema, A. Hamill, F. Tardif, and R. Gulden, "Long-term effects of roundup-readytm compared to conventional herbicide systems in ontario," 2008.