Application of Vector Agents to Weed detection from UAV imagery

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Abstract

In the remote sensing field, weed detection algorithms usually use the segmentation process to classify weeds in an image. In this context, the results are subject to user-defined parameters (e.g. scale) and predefined assumptions (e.g. uniform distribution of crop), limiting the usefulness of results. This paper presents a new approach based on Vector Agents (VAs) to extract weeds, more specifically boneseed, from Unmanned Aerial Vehicle (UAV) imagery. VAs are objects that can construct their own geometry and interact spatially with other VAs in the context of Geographic Automata Systems (GAS). The dynamic structure of VAs allows them to directly address real-world objects in an image, such as weeds. In this case, the method can automatically draw the boundary of the real world objects without setting any user-defined parameters, e.g. scale or compactness. We test the proposed model against the ones conventionally used in weed detection, e.g. mean shift and multiresolution. The preliminary results show 8% and 30% improvement in the correctness value of the VA model compared to the mean shift and multiresolution methods, respectively.

Keywords: Geographic Automata Systems, Segmentation, Unmanned Aerial Vehicle, Vector Agent, Weed Detection

1. Introduction

As a foreign plant species, weeds not only threaten local native species but also ecosystem processes (Reid, 1998). To detect weeds, there are various technologies that can be used, including Unmanned Aerial Vehicle (UAV) imagery. It is a cost-effective tool (Knoth et al., 2013), especially when the need is for a very high spatial resolution or for collection of data at a specific time (Pena et al., 2013). From this detailed imagery, the process of weed detection usually includes two main steps, segmentation and classification. In the former step, we usually use a set of parameters such as scale or color, depending on the segmentation method, to segment an image or create image objects. The information of these objects, such as shape or location, is then applied via a classification algorithm to identify weeds.

For example, Pena et al. (2013) used a multiresolution segmentation process to identify weeds. In the proposed method, they used objects ranging from very small to large scale to first find the orientation of crop rows, then extract weeds. Bah et al. (2017) used the spatial relationship between crop lines and segmented images (polygons) to discriminate between weeds and vegetation. Castro and et al. (2018) proposed a method formulated on multiresolution segmentation and the random forest classification algorithm to identify weeds between and within crop rows based on UAV imagery and a Digital Surface Model (DSM).

In the above methods, image objects or segmented images, have a critical role to detect weed objects. Because these methods lack the necessary ability to directly draw the objects, they use the segmentation process to create objects of interest, such as weeds. In this context, the results are strongly subject to the parameters (e.g. scale in the segmentation process). Moreover, these methods generally assume that the crops have uniform distribution.

In this paper, we propose a new approach for weed detection based on Vector Agents (VAs). The method uses the spatial and non-spatial characteristics of object of interest, namely boneseed, in extracting them from the UAV imagery without utilising a secondary process such as image segmentation. The next section provides some background to VAs, followed by an account of the VA implementation for weed detection. Finally, results are presented with discussion and concluding statements.

2. Vector Agent

A Vector Agent (VA) is an example of Geographic Automata (GA) (see Torrens and Benenson, 2005 for more details), entities that can represent (non)dynamic and (ir)regular vector boundaries of a wide range of geospatial phenomena, subject to geometric rules, along with state and neighbourhood information and rules. The application of the VA model to other domains is addressed in several studies (Hammam el al., 2007; Moore 2011; Borna et al., 2014). The main elements of the VA model as follows,

$$\mathbf{GA} \sim (\mathbf{K}; \mathbf{S}, \mathbf{T_S}; \mathbf{L}, \mathbf{M_L}; \mathbf{N}, \mathbf{R_N}), \qquad (1)$$

where:

- **K** is a set of automata types which are regarded as evolutionary, static, and elastic objects (Goodchild et al., 2007).
- $\mathbf{T_S}$ is a set of rules that allow the automata to update their own state, namely **S**,

$$\mathbf{T_S}: (\mathbf{S}_t, \mathbf{L}_t, \mathbf{N}_t) \rightarrow \mathbf{S}_{t+1} \qquad (2)$$

- $\mathbf{M_L}$ are rules and methods that enable VAs to construct and change their own geometry, namely **L**,

$$\mathbf{M_L}: (\mathbf{S}_t, \mathbf{L}_t, \mathbf{N}_t) \rightarrow \mathbf{L}_{t+1} \qquad (3)$$

- $\mathbf{R_N}$ are rules that enable VAs to perceive neighbouring objects at each iteration, namely **N**.

$$\mathbf{R_N}: (\mathbf{S}_t, \mathbf{L}_t, \mathbf{N}_t) \rightarrow \mathbf{N}_{t+1} \qquad (4)$$

This structure enables VAs to evolve dynamically in accordance with the nature of the real world objects, such as plants, in this case.

2.1. VA-Based Weed Detection

We develop an updated version of the VA model, proposed by Borna et al. (2014) in an imagery classification context, to detect weeds from the UAV imagery. In this way, the VA model utilises the geometry rules formulated in terms of a four-connected neighbourhood system to create objects (Figure 1).

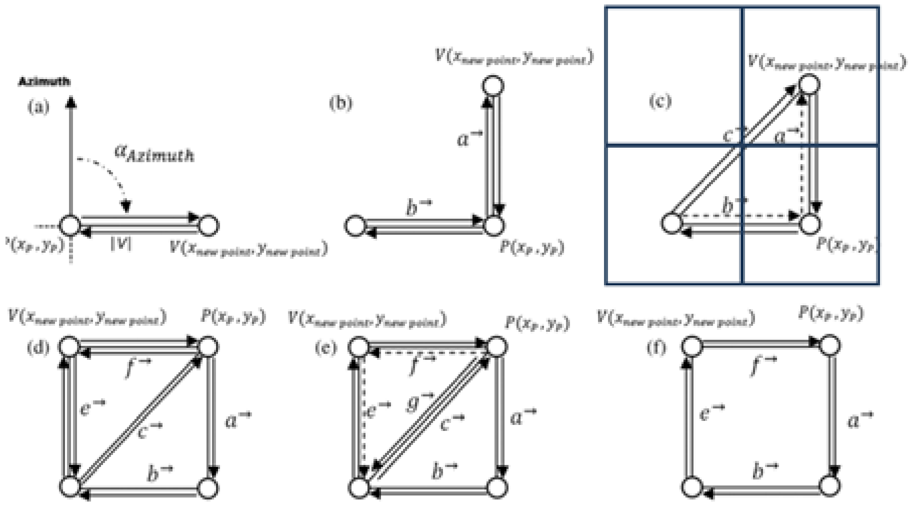


Figure 1. Four elementary operations are required to change the image objects geometry: (b) vertex displacement, (c) converging vertex displacement, (d) edge joining, and (e) edge remove. The spatial relationship of the lattice point to the raster cell it represents is also made clear in 1(a), Borna et al., 2014.

As VAs use a unified and dynamic geometric structure, they can simultaneously control and change internal and external rings. This structure enables the VAs to automatically implement a set of rules in terms of the geometry of the interest objects, e.g. boneseed. For example, here, VAs automatically remove the interior rings (blue polygons in Figure 2). That means there is no other object inside boneseed. This is because of the structure of the boneseed in the real world.

Figure 2. is an illustration of weed object where the red polygon displays the exterior boundary of weeds and the blue polygons show the interior boundary within weeds. The image is provided by The School of Science, Auckland University of Technology.

The VA model applies the Support Vector Machine (SVM) model to implement the transition rules (Borna et al., 2016). The SVM model enables the VAs to carry out the transition rules without setting any predefined assumptions, e.g. normal distribution (Srivastava et al., 2012). In contrast to the proposed VA by Borna et al (2014), where the VAs followed a stochastic algorithm to grow, each VA is here trained to geometrically grow toward the exterior boundaries. Figure 3 shows how the VA extracts the blue area from a synthetic image based on the new transition rules.

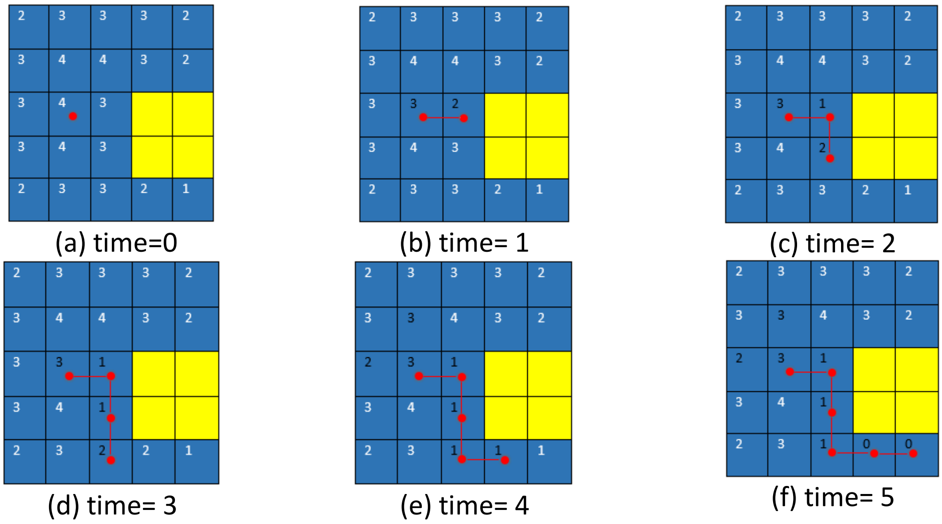


Figure 3. (a) shows a VA formed as a point in the pixel center. (b) constructs the first edge; the updated values are shown by the black color in each cell. (c), (d) and (e) show the growing process. (f) displays the event that a pixel value becomes zero.

In Figure 3, the value within each cell is determined based on the number of pixels which have class similar to the pixel centred in a local 3×3 window. The method applies a cardinal direction system to calculate the pixel values. It gives a number between 0 to 4 for each cell. To select a pixel, the VA uses the geometric rules defined by Borna et al. (2014) along with the following rules:

- A pixel is captured if the original vertex and candidate pixel are in the same class. Figure 3(a) displays that the VA can grow in four main directions.
- If there is more than one candidate vertex, a VA selects the pixel with the minimum value. For example, in Figure 3(a), there are two candidate pixels for the original vertex set to 3.
- VAs apply a clockwise direction to capture a candidate point. Figure 3(b) shows the VA uses the pixel which is on the right side to construct the first edge.
- A VA changes the start point to grow if the value of an active cell becomes zero, e.g. Figure 3(f). In this event, the VA starts growing from a vertex set to the minimum value. For example, in Figure 4(a) the minimum number is 1.
- If there is more than one starting point, e.g. Figure 4 (a), the VA selects the vertex that its immediate neighbours have the minimum value, orange point in Figure 4(a).
- If a vertex is within a polygon, its value becomes zero, the green pixel in Figure 4(f).

The use of the above rules enables a VA to geometrically grow toward the exterior boundary of the blue area where there is maximum heterogeneity. As can be seen in Figure 4(f), this algorithm allows the VA to ignore pixels with the highest value during the simulation process. This can reduce the computational time for the proposed approach compared to the VA applied by Borna el al. (2014). In the event that two VAs geometrically meet each other in the simulation space, the VA model utilizes the neighbourhood rules, e.g. shrinking/growing or merging/killing (Borna et al., 2016). As the VAs are in the same class, namely boneseed, the VA model only applies the merging/ killing process. In this event, two VAs are merging into each other. It yields a single VA with updated components **S**, **L** and **N** and the death of the other VA.

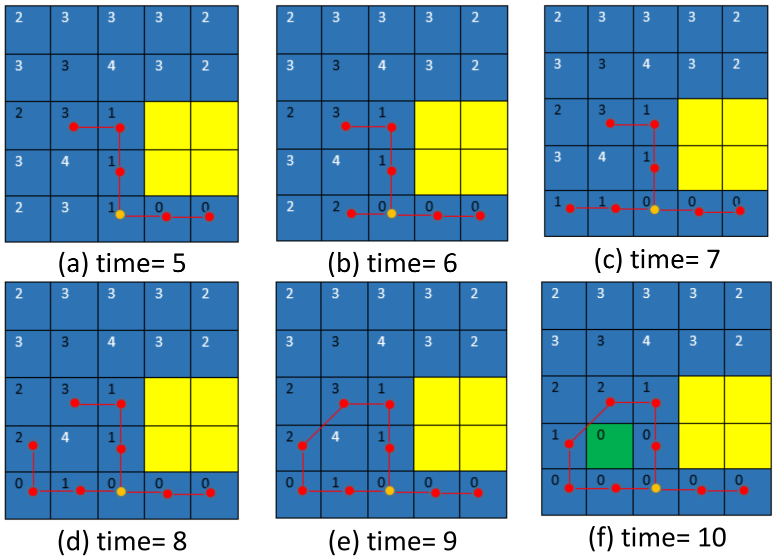


Figure 4. (a) shows the starting point, orange vertex. (b), (c) and (d) construct the VA's edges. (e) the VA creates a closed polygon through the half-edge joining method; in the event that a new vertex is diagonal neighbourhood to original vertex (d), the VA creates a new edge (e), Figure 1(c). (f) displays the event that a pixel placed within a polygon and its value becomes zero.

3. Implementation

Figure 5 shows the GUI of the VA model applied in this study. The GUI is defined and implemented through NetBeans, an integrated development environment for Java, along with a generic Vector Agent library developed by Moore (2011) to detect and model the weeds from the Unmanned Aerial Vehicle (UAV) images. As can be seen in Figure 5(a), the model has four main sections: Initialization, Implementation, Production and Tools.

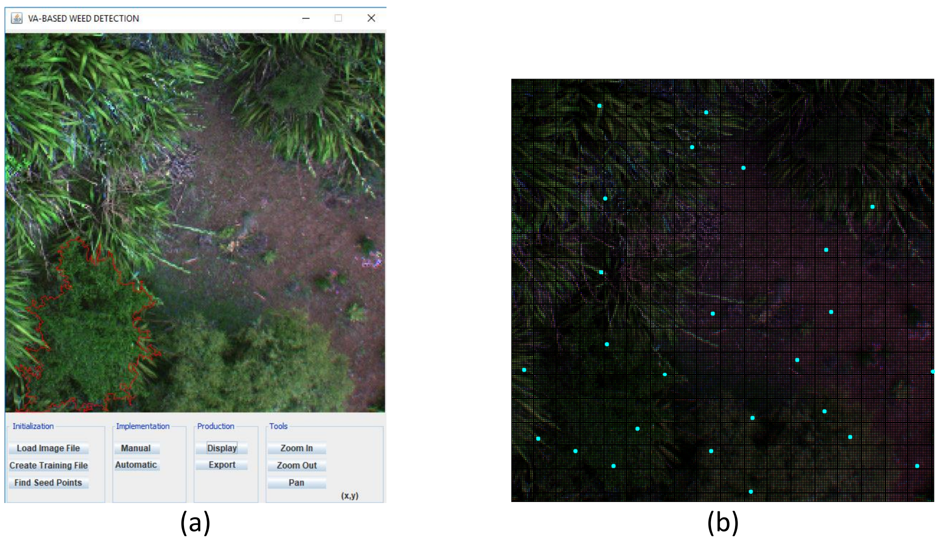


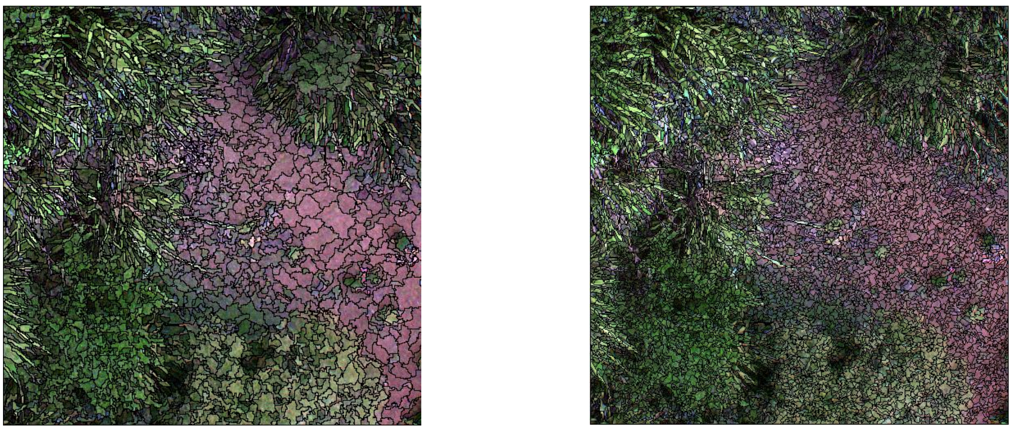
Figure 5. (a) The GUI designed for the Boneseed detection (b) shows the training samples including 7 pixels for soil, for boneseed, living vegetation and vegetation 5 pixels per class, and 3 pixels for flower.

In the Initialization step, the image is first normalized between 0 and 1 and displayed. An operator then applies the Create Training File to import or create training samples. The VA uses the training samples to train the SVM model in order to implement the transition rules. The method applies the stratified random sampling algorithm to generate training samples. In this context, random samples are taken, in proportion to the interest class, from each of the classes, Figure 5(b). In the implementation section, the operator can use manual or automatic mode to identify weeds. In the manual mode, the operator can visually follow the process of growing a VA weed. In the automatic mode, the VA model automatically finds and extracts the weeds. In the production section, the results are shown through the display button (e.g. red polygon in Figure 5 (a)).

3.1. Testing

The proposed approach was experimentally tested on a resampled subset image (264×264 pixels) with 2.00cm resolution, including 5 bands (Blue, green, red, red edge, near-IR), obtained from MicaSense RedEdge camera which covers a vegetation area at New Zealand. The test area contains 5 classes including, boneseed, flower, living vegetation, soil, vegetation.

In order to assess the performance of the proposed approach, the extracted objects provided by the VA-based approach were compared with corresponding objects created manually by a human expert (the red polygon in Figure 2). The results were also compared with the maps provided based on two different segmentation methods (Figure 6). In the first case, we apply the multiresolution segmentation algorithm in eCognition to segment the image. The method utilises the geometric, e.g. scale and compactness, and spectral information, e.g. color, of real-world objects to segment an image (Hay et al., 2005). As weeds and vegetation objects are the main targets in our scenario, the weight of band 4, scale, shape and compactness parameters are set to 2, 10, 0.1 and 0.5, respectively. In the second method, the mean shift algorithm in ArcGIS is used to segment the image. The method uses the number of pixels and the Euclidean distance defined within a spectral space to segment an image. In this case, the spectral details, spatial details and minimum segment size parameters are set to 20, 10 and 20, respectively.



(a) (b)

Figure 6. (a) the segmented image by the multiresolution algorithm in eCognition and (b) The segmented image by the Mean shift algorithm in ArcGIS.

For both methods, there is no unique solution to determine the user-defined parameters, e.g. scale or spatial details. For example, spatial detail parameter in the mean shift algorithm can be a value between 1 and 20. In the event that it becomes 20, the algorithm segments an image into higher spatial detail. Thus it would be difficult for a classifier to define and apply the spatial rules in order to label the segmented image. The use of smaller values creates spatially smoother segments. In this case, the classifier would not be able to separate classes with similar spectral reflectance. This can reduce the accuracy of the classified map. Here, the spatial details parameter is set to 10 to obtain optimum results.

After the segmentation process, we manually select a set of image objects as training samples to train the SVM algorithm. Here, the SVM model uses the mean and standard deviation of each band to solve the SVM problem. The SVM model is then used to classify the image objects (Figure 7).

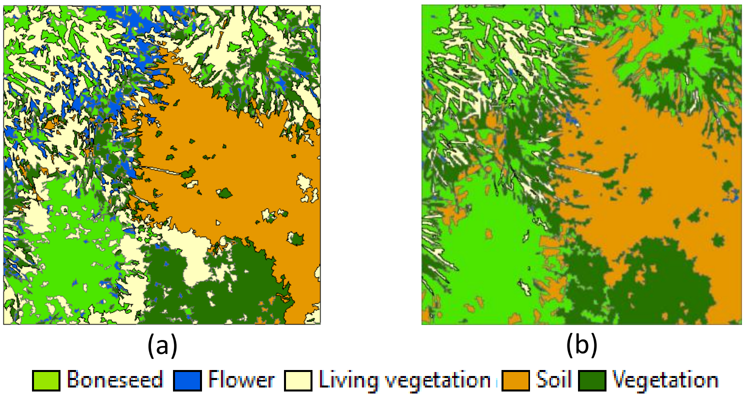


Figure 7. (a) and (b) Classified image objects after using the SVM model, (a) mean shift algorithm (b) multiresolution algorithm.

4. Discussion and Results

Figure 7(a) and Figure 7(b) show the results of the segmentation step based on the multiresolution and the mean shift algorithms, respectively. As can be seen in Figure 7(a) and Figure 7(b), there are some polygons of the Living vegetation and soil classes within the weed polygons. This is because of the shadow effect and the spectral similarity between weed and vegetation objects. To remove these polygons, we develop a set of rules based on the geometric characteristics of boneseed objects (e.g. bushy shape and size), in the classification step. For example, if the Living vegetation or shadow polygon, blue polygons in Figure 2, is within the weed polygon, it changes into the weed polygon. Figure 8(a) and Figure 8(b) display the results of the classification step applied to multiresolution and mean shift algorithms, respectively.

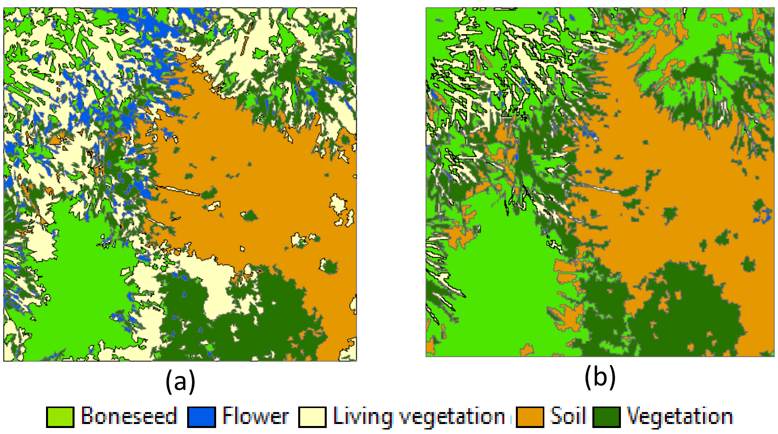
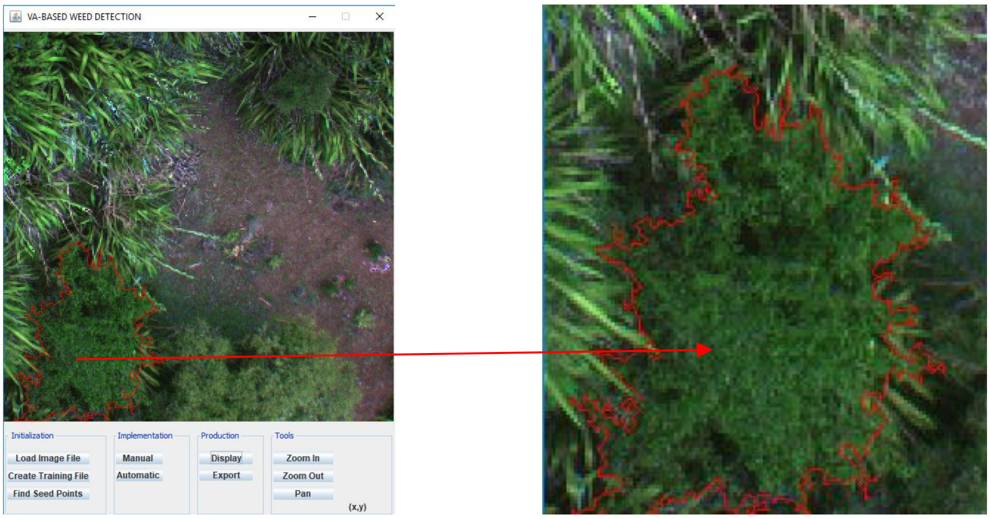


Figure 8. (a) shows the updated weed polygon based on Figure 7(a), and (b) displays the classified map after using classification rules on Figure 7(b).

Figure 9(a) and Figure 9(b) display the extracted weed polygon by using the VA model. The method is implemented by the NetBeans using an Intel CPU at 2.67 GHz and 4 GB of memory. In the first scenario, using a single VA, it took 25 Seconds for the VA to identify the boneseed object with 802 vertices in an image with the size of 264×264.



(a) (b)

Figure 9. (a) shows result in the GUI, (b) shows the extracted weed object.

For assessing the proposed method, the correctness index is applied through the following equation:

$$correctness = \frac{True\ Positive}{False\ Positive + True\ Positive} \quad (5)$$

where True Positive (TP) is the number of pixels that have the same class in both datasets (ground truth map and classified map). False Positive (FP) represents pixels that belong to another class, but are classified belonging to the weed object. Table 1 displays the results of the applied methods.

Method	TP	FP	Correctness(%)
Multiresolution	30287	15857	66.63
Mean shift	28093	3677	88.42
VA-based	26448	1206	95.63

Table 1: Comparison between Multiresolution, Mean shift and VA-based approaches.

The results show the VA-based method improves the correctness value more than 8% compared to the mean shift method. This is because the mean shift approach applies a static geometry. In this way, it would be difficult for the method to deal with the classes which have similar spectral reflectance, e.g. boneseed, Living vegetation and vegetation. Table 1 represents that the correctness value of the VA-based method is significantly better than the multiresolution method, 30% improvement. There are two reasons for this. Firstly, the multiresolution method applies a static geometry. Secondly, the number of heterogonous image objects are more than the mean shift approach (Figure 6). Image objects are larger than ones created by the mean-shift approach. This can decrease the correctness value, especially where boneseed, Living vegetation and vegetation objects are connected to each other in image space.

5. Summary

To find the weeds in an image space, conventional weed detection algorithms use segmented images to identify weeds. The use of segmented images allows the methods to overcome the problems such as salt-and-pepper effects which usually originates from the pixel-based approaches. Moreover, the image objects allow the algorithms to use the additional information such as shape and size and spatial relationship between objects in order to identify weeds from an image. This information has a vital role to find weeds, especially in which the classes, e.g. weeds and living vegetation, have similar spectral reflectance. For example, in Figure 8, we used this information to remove the living vegetation polygons within the weed objects. Despite the advantage that image objects offer, the outputs are strongly subject to the results of the segmentation process. However, there is no single solution for the image segmentation problem. For example, Figure 6 displays different results based on two different image segmentation methods. Moreover, such image segmentation is highly subjective in terms of the parameters which are usually defined based on trial and error by an operator. Whereas the VA model offers a dynamic geometry without setting any user- defined parameters, such as scale.

In the conventional methods, the segmented images are first classified through the SVM model. The classified objects are then merged into each other, Figure 7. This step is automatically performed by the VA model through the neighbourhood rules. As the proposed method does not need to find the other classes, the merging/killing method between weed objects is the only interaction between objects. We then developed a set of rules based on spatial and non-spatial information of the boneseed objects to remove vegetation objects within the boneseed object, Figure 8. As this process is manually performed, it is usually a time-consuming process. Moreover, depending on the selected features for defining classification rules, we may have different results. Whereas the VA model enables the proposed method to automatically remove the interior rings during the growing process.

The experimental results demonstrate the desirable performance of the new approach. VAs proved that they can draw weeds in an image without setting any parameters (e.g. scale) or predefined assumption (e.g. uniform distribution of crop). In other words, to identify the weed objects from an image, an operator needs to only determine training samples. In this context, further research needs to be done to find reliable samples in order to increase the accuracy and robustness of the VA model. Developing an algorithm to reduce the processing time on a large remote sensing data would also be interesting to study.

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7. References

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