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Weed and Crop Discrimination Through an Offline Computer Vision Algorithm

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ABSTRACT

With the recent global interest in organic farming and cultivation, many people are turning away from chemical-based herbicides and moving towards alternate methods to extirpate weeds living amongst their crops. Of the methods proposed, robotic weed detection and removal is the most promising because of its possibility to be completely autonomous. Several robust, fully-autonomous robots have been developed, although none have been approved for commercial use. This paper proposes a weed and crop discrimination algorithm that utilizes an excessive green filter paired with principal component analysis to detect specific spatial frequencies within an image corresponding to different types of weeds and crops. This method also works to reduce dimensions in data by representing an image as a small set of values obtained from a projection. This technique optimizes performance while allowing for simpler calculations. These calculations were used to develop thresholds for weeds, crops, and soil for discrimination purposes. The algorithm resulted in an overall classification rate of 77%. 46% of all crops were identified correctly; 78% of all weeds were identified correctly; and 91% of all soil was identified correctly. The low rate of correct crop classification was due to poor edge detection by the algorithm but could be improved in future research by applying one or more edge-detection algorithms. This technique can be adapted in the future with other image-analysis techniques to be used on low-cost systems.

INTRODUCTION

Weeding is one of the simplest, yet most time-consuming tasks given to farmers and gardeners around the world. Chemically-induced weed control is the most popular approach for small and large-scale farms, with the U.S. using over one billion pounds of pesticide and herbicide annually, 5.6 billion worldwide [1]. Slaughter et al.'s review of robotic weed control noted that although herbicide-based weed control systems reduce financial cost drastically compared to traditional weeding methods, "it is not without environmental costs" [2]. Because of the increase in pesticide and herbicide usage over the past decades, it has become evident that using these chemicals can spread toxic debris to regions far beyond their original target area. Most commonly, these chemicals remain in the soil for years and are eventually moved by water runoff to local water sources, which can harm aquatic systems and pollute drinking water [3]. The USDA estimates that fifty million people living in the United States obtain their drinking water from sources that could be contaminated by chemicals such as pesticides and herbicides [1]. Additionally, twenty-five million agricultural workers around the world are unintentionally poisoned by chemicals each year, with some of these chemicals being related to cancer [3]. With global population on the rise and food production demand increasing with it, solutions must be proposed to halt this toxic epidemic.

Organic farming has recently gained popularity because of its lack of genetically modified seed and herbicide use. However, organic farmers have had to revert to primitive techniques in weed control which can be inefficient, inaccurate, and costly [4]. For most small-scale organic farmers, hand labor is the weed control method of choice. Marty Gray of Gray Farms in Watseka, Illinois, claims that he hires multiple full-time seasonal employees for hand-weeding labor; however, this choice limits his farm in terms of net profit [5]. A study on weeding techniques for carrot farmers found that hand weeding yielded a net profit of $740/hectare (approximately 2.5 acres) while applying an herbicide yielded $1409/hectare in comparison [6]. For industrial-style farms that focus on maximizing production and minimizing cost, this job could be accomplished by a single machine that uniformly covers the plot with a weed-killing herbicide; however, hand weeding requires skilled laborers who can accurately identify the weeds and remove them completely without damaging the crop.

Robotics in Agriculture

In order to reduce the cost of labor in agriculture, the area of robotics has been proposed as a solution to not only weeding, but also various other farming-related tasks. Tasks such as site-specific herbicide application, mechanical intra row weed control, and individual seed planting have been tested because of the advancements in sensors, actuators, and electrical equipment over the past twenty years [7]. Although weeding sounds like a simple task, many variables must be taken into account in order to create a reliable weeding machine. Row guidance and control, GPS location, weed identification/classification, and weed removal are some of the major tasks that must be accomplished by a weeding robot.

The biggest challenge in developing a weeding robot is replicating human behavior. Humans have the capability of processing much information through the senses and making rational decisions based upon this information. In the context of weeding, humans can visualize the color of the plants, shape of the leaves, size of the leaves, and even crop spacing. However, this intuition must be learned by robotic systems in order to replicate the human process of manual weeding. A process like this can be learned by computer systems, but challenges still exist when trying to differentiate between minute details. For example, young broad-leaf weed sprouts can look very similar to young lettuce sprouts. A balanced robotic weeding system would have the ability to make fast-paced decisions based upon significant characteristics in data, but could also distinguish between minute details in similar-looking plants.

Many robots have already been developed and proposed with several agricultural functions ranging from weeding to soil sampling. Of the published works on weeding robots, Deepfield Robotics' 'Bonirob' is one of the most developed. It has the capability to perform soil measurement, plant phenotyping, precision pesticide application, and more [8]. Although there are no early estimates of its costs, the price of the machine will undoubtedly be steep because of its robust research applications and advanced technology.

A recent article discussed a group of engineers in India that have developed a robot called the Greenbot that uses simple computing techniques to identify weeds in a vineyard. The Greenbot is a solar-powered autonomous bot run by a Raspberry Pi computer that handles the calculations for weed detection [9]. Its program is designed for the robot to travel under grape vines while detecting green values, target where those values are, and use a device to uproot the weeds. The Greenbot's calculations detect green values by using a segmentation technique that amplifies green values and creates a global threshold to binarize the image into plant and background [9]. The only issue with this system is that it is not able to discriminate between weeds and crops; it only detects plant life.

The scope of this project was to create an algorithm that will be able to discriminate between plant life in order to identify weeds in a crop field while using computationally efficient techniques. In the future, this system can be implemented on a small-scale robot that utilizes low cost materials like the Raspberry Pi ($40) to offer a more affordable robotic weeding solution.

Computer Vision Systems

Typically, computer vision systems use one of two mechanisms to identify weeds: shape analysis or color analysis.

Shape Analysis: In general, algorithms using shape analyses tend to be more robust and require more computing power than other techniques [2]. Another important drawback to shape-based analysis is that it is hindered by occlusion of weed and plant leaves; if the leaves are overlapping, then a program can find it difficult to determine which leaf belongs to which plant [10]. To overcome this obstacle, most shape analysis occurs during the early stage of life for both crop and weed, so the leaves do not overlap each other like they do when fully grown. Accuracy rates for the shape analysis procedures found ranged from 75 to 100%, depending on occlusion and lighting [10] [11] [12] [13].

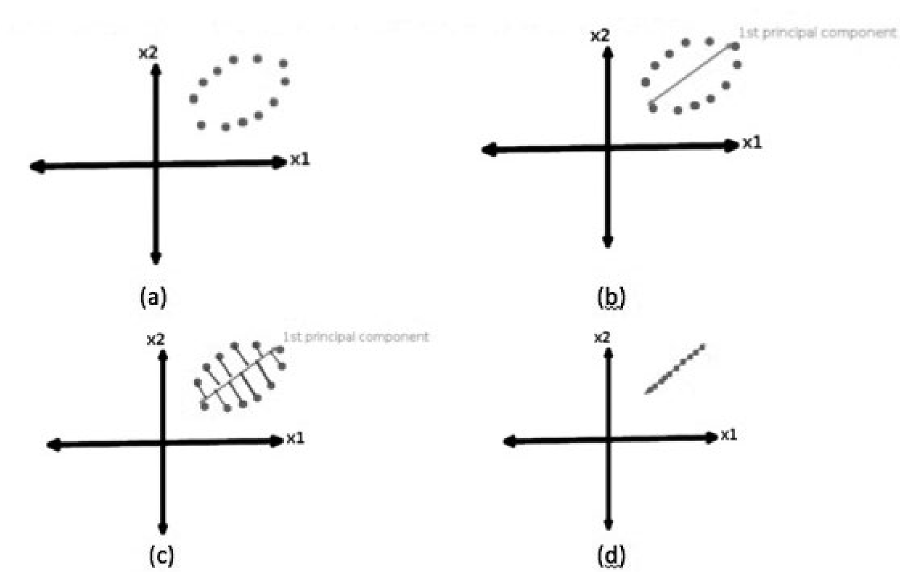


Figure 1:Two dimensional PCA. (a) represents the data plotted on an XY plane. (b) represents the first principal component line being draw through the data. (c) shows the variance of each point from that principal component. (d) Projects each data point onto the principal component [17].

Color Analysis: While the accuracy of shape-based analysis is difficult to match, an important part of this project was computational simplicity, and color-based analysis tends to be less taxing on computing systems [2]. In fact, in all of the research that has been reviewed, this is the only approach that has been used for segmentation between plant and soil. Sujaritha et al.'s Greenbot experiment mentioned earlier was done entirely with segmentation, since no weed/crop discrimination was needed. Through this process, Sujaritha et al. were able to segment the picture, removing 98% of the soil and leaving only the shape of the leaves [9].

Weed and crop discrimination can also be accomplished with the use of color analysis techniques as shown by Franz et al., Lamm, and Borregaard et al. with accuracies reaching 94% [14] [15] [16]. All of the data that is analyzed in these techniques is in the form of pictures that contain millions of pixels—the data points. In order to sort through these millions of data points in a computationally conservative manner, a matrix decomposition algorithm known as principal component analysis (PCA) was proposed. It is important to note that no one has previously applied matrix decomposition algorithms, such as PCA, to discriminate between weeds and crops in a ground level photograph.

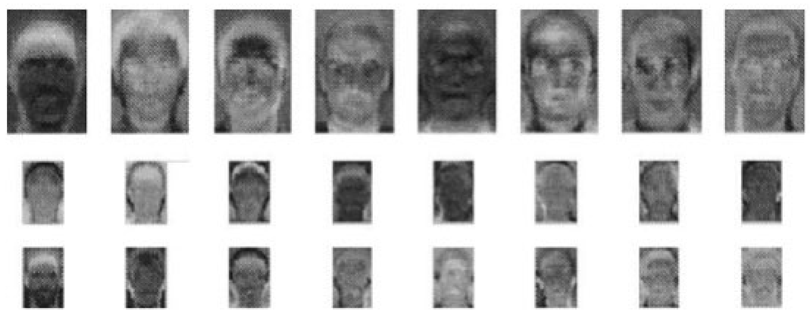
Principal Component Analysis

PCA takes large groups of data and simplifies that data as a projected value onto a principal component of the data. In Figure 1a we see a set of data in which each data point consists of both an X and Y value. If we then draw a line through that data and project each point onto that line, we are left with our first principal component. By doing this, we are able to reduce dimensions of the data from an X and Y value, to only one value along our first principal component line. This type of mathematics is called dimensionality reduction.

This same method of dimensionality reduction can be applied to image analysis and has been used by facial recognition software since the early 90s to reduce large quantities of data. Whereas the example above shows data being projected onto a line that represents a principal component, image analysis uses a matrix of values developed using the principal components, and data can be projected onto that matrix. An example of how this is accomplished in facial recognition can be seen in **Figure 2**. In this example, each face can be reconstructed by taking a weighted sum of the principal component values. This process is used to represent the data as a variance of known values, which reduces dimensions.

In this application of PCA, we will be detecting the most significant patterns in spatial frequencies within each image. By using PCA, we will be able to represent these patterns as different principal components; each principal component representing different spectral features of the image. The most significant patterns in spatial frequencies will be represented by the first principal component and the variance of the data from that component. The results of our experimentation showed that PCA can be used to simplify data in image analysis while retaining accuracy. After principal component analysis was used in this study, the proposed algorithm achieved 77% overall accuracy in image classification.

(a)



(b)

Figure 2: PCA in facial recognition. (a) the original dataset of images and (b) the resulting principal components represented as matrices of data. Each face in the original dataset can be represented as a weighted sum of the principal component values [18].

METHODS

Photos of various crop fields were obtained from Gray Farms in Watseka, Illinois, to use as data sets [5]. All images were taken with a five megapixel autofocus camera and included several types of lettuces and weeds. These photos were separated into two sets to be used in training and testing the discrimination algorithm.

Image Pre-Processing

Images were pre-processed in order to prepare the spectra for matrix decomposition. Initial pre-processing used the application of an excessive green filter, like the one used by Jeon et al. in their study using artificial neural networks to segment crops and weeds [19]. The filter works by applying the equation below to each pixel in the original image; the resulting image can be seen in **Figure 3a**. This green filter was used in the same way that humans would detect different hues of green and use them to identify crops and weeds.

$$EXG = (2G-B-R)/(R+G+B) \qquad (1)$$

Where,

EXG= excessive green normalized value
R= red pixel value
G= green pixel value
B= blue pixel value

Images were then separated into an overlapping grid of blocks and analyzed one block at a time. This block-based analysis approach has been used by other researchers who stress the importance of block size. If the block size is too small, there may not be enough information to use, and if it is too large, both crop and weed could exist in a block, skewing data [4]. The block size used in this experiment was 100 x 100 pixels with an 80% overlap, which was selected based upon average plant size and maximum computing power.

(a)

(b)

Figure 3: EXG filter. (a) is the original image and (b) is the resulting image after applying the excessive green image filter.

Once the image was divided into blocks, a fast-Fourier transform was applied to each block, transforming the data from a two-dimensional image space into a two-dimensional spatial frequency domain that can be used in the applications of PCA.

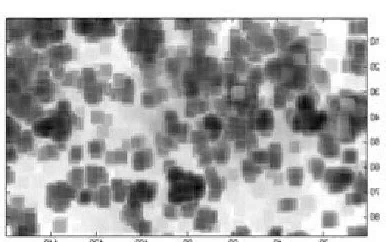
Principal Component Analysis

Principal component analysis was then used to derive a set of principal component values using the pre-processed spectra. Each matrix of principal component values can be remapped into the shape of the original image. By doing this, the values can visually represent different spectral features shown by crops, weeds, and soil. These values were taken from the matrices produced by the singular value decomposition function in MATLAB. After all matrices were collected, a projection matrix was created by using the code below:

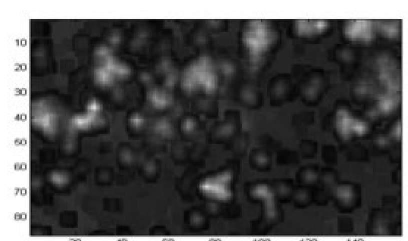
```
[U, S, V] = svd(spectra);
Vectors = V;
Values = U*S;
Projection_Matrix = inv(Vectors');
```

The first three principal component value matrices were then derived by multiplying the original spectra by the projection matrix and remapped to represent the dimensions of the original image. These values are shown below in **Figure 4.**

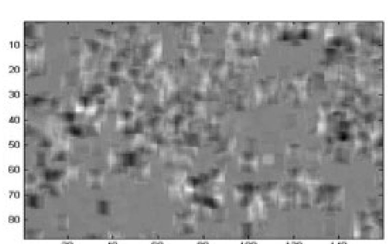
As shown in Figure 4, PCV1 represents the most variance in its values, and thus represents the most information about what is in that image. Although the other two matrices do contain information, there is not enough visible variance to help in the discrimination between crops and weeds.



(a)



(b)



(c)

Figure 4: The first three principal component value matrices taken from the training image. When multiplying the spectra by the projection matrix, the resultant matrix contains values that correspond to each principal component. These principal component values can be remapped into the size of the original image and used to represent crops, weeds, and soil within the image. (a) PCV1 (b) PCV2 (c) PCV3.

Training Image

In order to train the algorithm, a duplicate image **(Figure 5)** that was manually marked with the locations of all weeds and crops was projected onto the first principal component value matrix. This duplicate image was divided into six different categories/colors represented by three types of lettuce, two types of weeds, and soil.

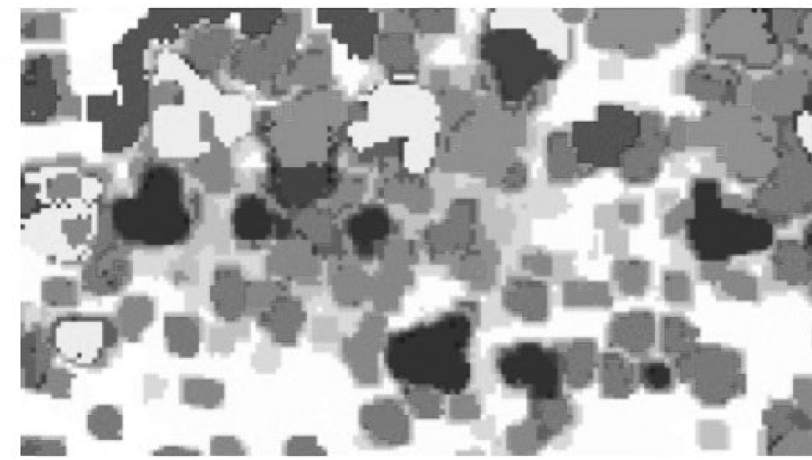


Figure 5: Training image mask. This image contains three different lettuces, two different weeds, and soil as the background. Each category was painted over with a different color to represent the location of weeds, crops, and soil in the image.

Once the mask was created, it was projected onto the first principal component image to associate each color with a range of principal component values. As shown in **Figure 6,** there is a clear region of values that can be represented as weeds, although the values separating each specific crop are not as clear. By separating the data into three categories, weed, crop, and soil, a clearer separation can be noticed in **Figure 7**. This information was used to develop two thresholds that represent each eigenvalue location as either weed, crop, or soil.

From the two thresholds developed by the data shown in the **Figure 7**, it can be assumed where values are < -0.063 there exists a lettuce crop, where values are < -0.035 but > -0.063 there exists a weed, and where values are > -0.035 exists the background/soil. These thresholds can be adjusted to hone the algorithm to be as general or as specific as needed in classification.

Classification

In order to classify an image, the same pre-processing steps were completed on every image to develop a matrix of spectra that can undergo calculation. Once the spectra were accumulated, the weighted principal component values were found by multiplying the spectra matrices by the projection matrix from the training image. Performing this image classification on our original training image should result in a figure similar to the mask that was created (**Figure 8**).

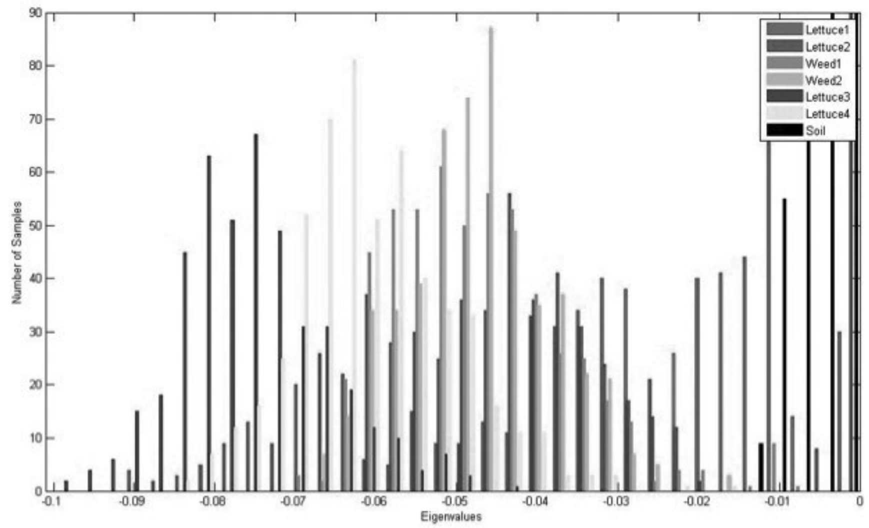


Figure 6: Categorical histogram of principal component values. Each category's values were plotted against the number of samples found within that value range. This was used to find specific ranges for each category in the image.

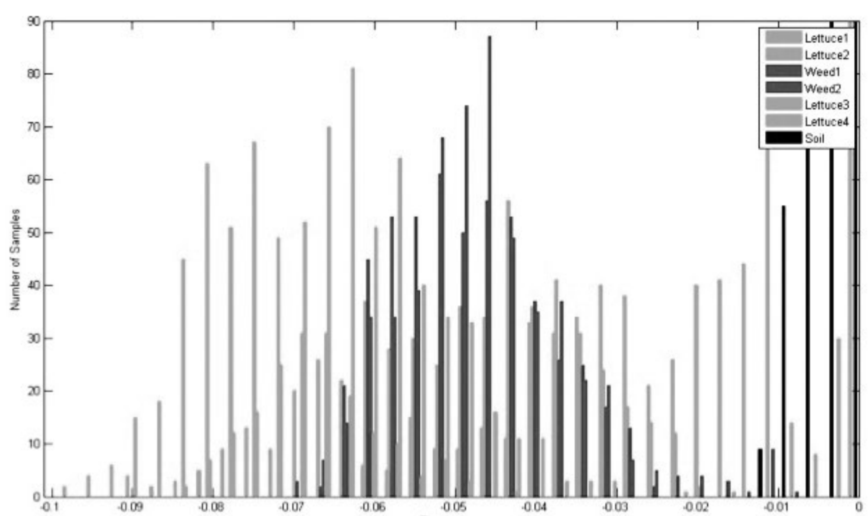


Figure 7: Segmented histogram of principal component values. By combining the categories into only three groups — weed, crop, and soil — a clear threshold of values was discovered.

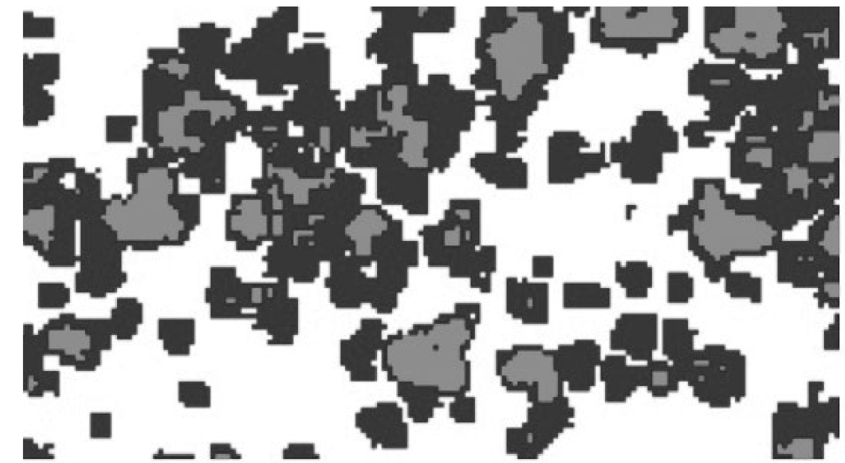


Figure 8: Training image classification. The classified representation of our original training image, where the light gray regions represent crops, the dark gray regions represent weeds, and the white regions represent soil. It should be noted that the purple cabbages were misclassified because of their lack of light gray values.

RESULTS

The results of the algorithm conducted on a new test image are shown in **Figure 9**. This image was also taken at Gray Farms but at a different section of the lettuce field. The classification image was obtained by performing the original pre-processing steps to obtain a matrix of spectra. The matrix of spectra was then multiplied by the projection matrix, which resulted in principal component values for the image corresponding to the values developed in the training image.

In order to test the results and accuracy of the classification image developed by the algorithm, a manual classification was created. To do this, the first principal component value matrix of the test image was opened in Microsoft Paint. Each region of the image was then manually classified by visual inspection and labeled as crop, weed, or soil. The resulting manual classification image was projected onto the algorithm's classification image to determine correlating values.

The result of this classification image was an overall accuracy of 77%. The contingency table show below displays a more in-depth analysis of the data. 45.6% of all crops were correctly classified, 77.8% of all weeds were correctly classified, and 90.8% of all soil was correctly classified.

TABLE 1

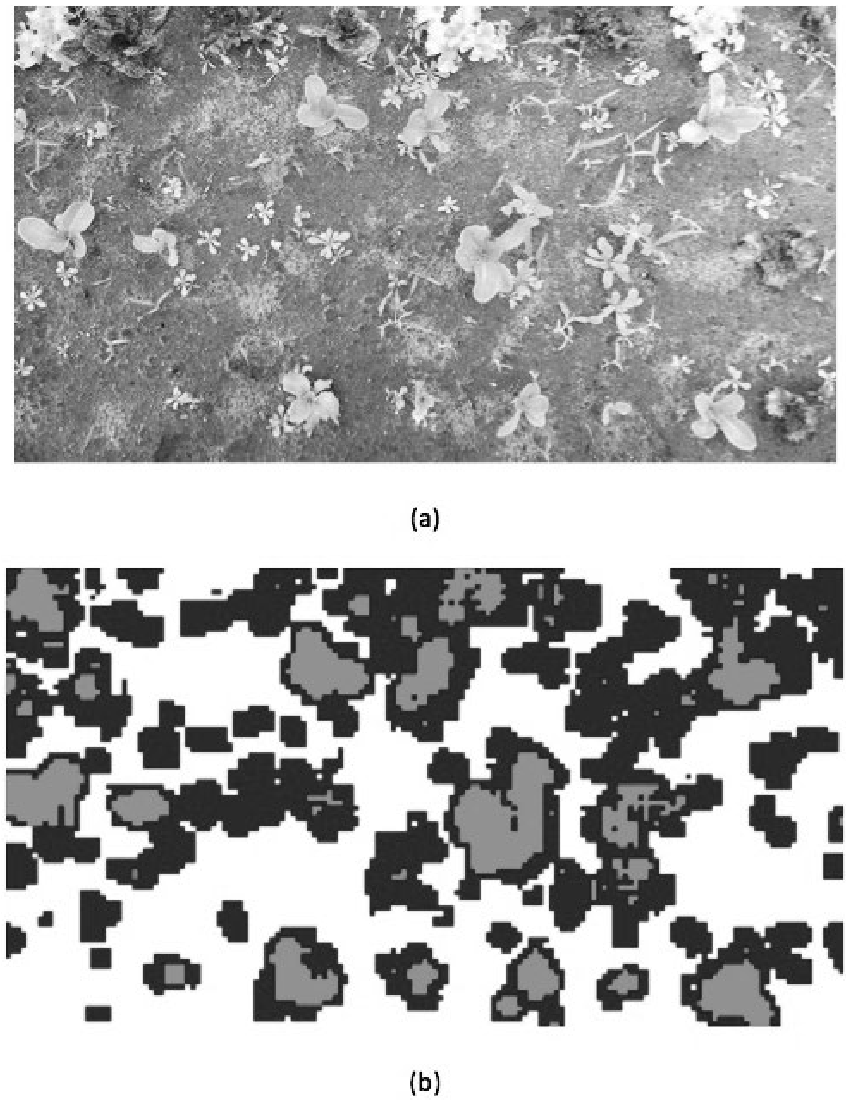


Figure 9: Classification of plant type on a new image using the discrimination algorithm. The test image (a) and the resulting test classification image, where the light gray regions represent crops, the dark gray regions represent weeds, and the white regions represent soil (b). This represents an overall classification accuracy of 77%.

Classification Contingency Table

This table shows the number of blocks that were correctly classified by the algorithm (shown in light gray) versus the number of blocks that were misclassified by the algorithm (shown in dark gray).

Actual \ Predicted	Crop	Weed	Soil
Crop	1221	1085	373
Weed	339	3936	787
Soil	6	528	5269

The overall results of this experiment demonstrated that dimensionality reduction techniques can be paired with image processing to discriminate between weeds and crops in a ground level photograph. With a total accuracy of 77%, an analysis of misclassification must be made. The largest type of misclassification that occurred was crop/weed misclassification. To clarify, 1085 out of 2679 known crop regions were classified as weed instead of crop. This 40% misclassification rate is oddly high in comparison to other misclassifications of weed/crop at 7%, weed/soil at 15%, soil/weed at 9%, and soil/crop at 0.1%. To further analyze this high misclassification rate, the crop/weed misclassifications were binarized and plotted as shown in **Figure 10**. Nearly all of these misclassifications were found bordering sections of crops. By taking

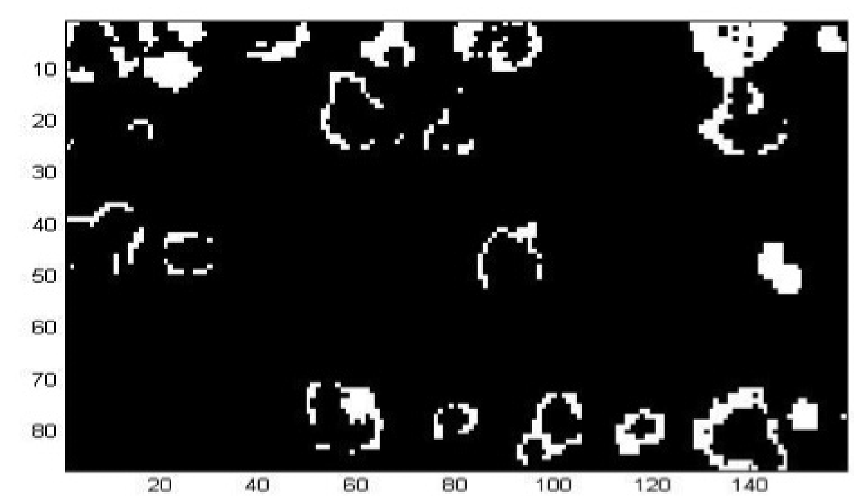


Figure 10: Crop/weed misclassifications due to insufficient edge detection. All instances of crop/weed misclassification, where the algorithm identified the block as a weed when it was actually a crop, are displayed in white. It can be noted that most of these misclassifications occurred at the edges of existing crop regions.

another look at the first principal component image, it can be noted that the values around the border of most crop regions were higher than the specific range of values that was used to identify crops. Many of these misclassifications could be eliminated by applying additional image-processing techniques in the future.

Edge detection is a very prominent sub-field of image processing and is used to define clear borders between objects in an image. Every image processing technique uses some form of edge detection to separate regions from one another and create borders. In this algorithm, the principal component values define a "fuzzy" edge that is not as useful for minute details but works well overall. In order to better discriminate between crops and weeds, an edge-detection algorithm could be applied during the pre-processing steps of our methods or applied directly to the principal component values to better separate regions and group them together as crops, weeds, or soil with strict borders.

Neighborhood and cluster-based approaches are two general ways to better classify edges within an image. The most notable techniques in image processing for edge detection are the Roberts Detection, Sobel Edge Detection, and Laplacian of Gaussian Detection [20]. However, because the proposed algorithm in this paper requires computationally efficient techniques, these methods would not be able to be used. Another approach to edge detection would be a fuzzy edge detection technique like the one described by Liang and Looney [21]. This type of edge detection classifies regions based upon gray level variation in multiple directions. When compared to other techniques, like the popular Canny edge detector, Liang and Looney's algorithm produced similar results at a much faster rate [22].

Because of the use of the excessive green filter shown in Figure 3, it can be noted that most of the purple lettuces in each picture were faded into the background of the image and classified as soil. These purple lettuces would most likely fall within the value range of > -0.03 and < -0.015. For the sake of accuracy, all purple lettuces were thrown out of our data and simply included in the value range for background. It can be concluded that this technique works most successfully with crops and weeds of a green color and that a separate image filter would need to be used in order to discriminate between crops and weeds of another color.

The overall accuracy reached by this algorithm was comparable to other research done by teams that used color analysis or shape analysis. Tian et al., Kiani et al., Cho et al., and Perez et al. were able to reach accuracies ranging from 75 to 100% using techniques like neural networks on cereal fields and tomato seedlings [10] [11] [12] [13]. Franz et al., Lamm, and Borregard et al. also had accuracy rates ranging from 75 to 100% while using spectral analysis of the images to analyze the colors of each plant [14] [15] [16]. Considering the lack of additional edge detection techniques, an overall accuracy rate of 77% is adequate when compared to similar research. If additional edge detection techniques were to be applied to this algorithm in future research, accuracy rates would be expected to rise.

Compared to other techniques currently being used, the results of this study showed a similar classification rate. This proves that the data from images can be reduced in dimension while maintaining a relatively high classification rate. As image processing technology and techniques evolve, this method can be adapted and used to more accurately differentiate between crops and weeds in an efficient manner. The future of image processing in weed and crop discrimination can use this work to simplify data calculations and develop smarter systems that work on smaller, more affordable platforms.

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