Weed Detection Using Image Processing By Clustering Analysis

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Abstract – Agriculture plays one of the most important role in economy and therefore lowering the costs and improving the quality of agricultural products is highly demanded. A weed is a plant which grows in wrong place at the wrong time and doing more harm than good. Weed competes with the crops for water, light, nutrients and space, and therefore it reduces crop yields. In olden method, the weeds can be destroyed by using the controlled spray of herbicides. A major problem is that the heavy herbicide usage causes some of more prolific weeds becoming more resistant to the regular herbicides and therefore more powerful and more expensive options are being pursued. To overcome such problems with aiming at the reduction of herbicide usage, this proposed system focuses on developing a robotic system which can detect and mapping the weeds and then clearing of the weeds. And by this view, our proposed system provides a key solution to improve its quality by means of controlling the weeds and to increase the yield of crops in the farm field by mechanical cropping. The work is performed using 5 images and in this work the image is classified into pre-processed image and test image. Thereby, the needed solution is recovered in our proposed system. The proposed system can detect the early level of weeds in the farm fields with the accuracy of 75%. And so on, our system provides the following operation to cut the weeds in the farm field.

Index terms – Graphical User Interface

1. INTRODUCTION

Agriculture plays one of the most important roles in economy of countries. This fact has led to different approaches toward lowering the costs and improving the quality of products in agricultural industry. One of the most important and also costly labors in this industry is controlling weeds. As weed can be defined as every plant which has grown in an inappropriate place, weed controlling can be extended from farms to lawns, golf fields, and sport fields. Every year a large amount of herbicide is used for removing weeds from agricultural fields which is not only expensive, but also a source of environmental pollution. Hand labor is also weed is a plant which grows in wrong place at the wrong time and doing more harm than good. Weed competes with the crops for water, light, nutrients and space and therefore reduce crop yields. so our system provides the following operation to cut the weeds in the farm field. Therefore, many researches have been done to utilize computer vision and robotics to develop robotic cultivators for instantaneous weed detection and removal. The goal of site-specific weed control is the precise application of herbicides in highly infested areas of a field. Since the distribution of weeds is heterogeneous in most cases and stable across years (GERHARDS et al. 1997, MORTENSEN et al. 1998, GERHARDS & CHRISTENSEN 2003), site-specific weed control can reduce the amount of herbicides used. The spraying has to be controlled by the actual weed infestation. This way the selection and dosage of the herbicides can be optimized for each part of the field. In areas where the weed infestation is below the economic threshold no herbicides are used, in areas with a weed infestation above the threshold different herbicides in be used in varying dosages, adapted to the weed species. The first step therefore is to get information about the distribution of the different species.

Manual weed sampling is time- and cost-intensive and therefore cannot be economic in a wider practice. SLAUGHTER et al. (2008) give an overview of the techniques for weed detection and find, that the robust weed detection remains the primary obstacle toward commercial develop-Image Analysis for Agricultural Products and Processes Bornimer Agrartechnische Berichte • Heft 69 ISSN 0947-7314 Leibniz-Institut für Agrartechnik Potsdam-Bornim e.V. (ATB) 139 ment and industry acceptance of robotic weed control technology. Therefore a system was developed to measure the weed infestation

1.1. Existing System

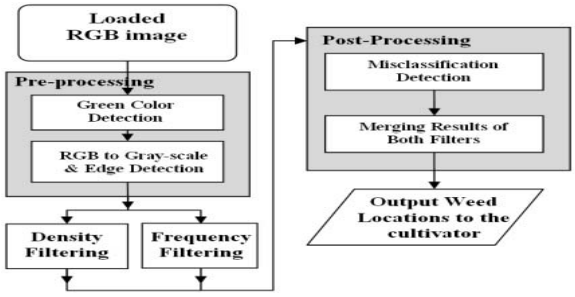

Figure 1: Existing System Block Diagram

2. PROPOSED SYSTEM

In this paper we proposed a real-time weed detection method for corn fields which benefits Fast Fourier Transform (FFT) to separate weeds from crops. Although this method has similarities with , they have major differences. Firstly, fields of weed detection in these two works are different (a lawn and a corn field), as field-specific parameters such as ground surface shape and field-specific weeds are important for classification purposes. Additionally, in the current work frequency of edges are also considered in addition to their densities. Finally, an error correction method is applied to present better results. This algorithm has been tested using images from corn fields showing 92% accuracy. The resulting application is then compiled to a dynamic linked library (dll) and used in a graphical user interface (GUI) to be used further by a cultivator robot in a real field (refer to "Conclusion And Future Works section)

2.1 MODULE LISTS

On this feature selection basis, the entire algorithm is sectioned into three parts:

1. Pre-processing

2.Frequency and density filtering

3.Post-processing

Pre-processing includes tasks to prepare input RGB format image for filtering processes

by removing background, conversion to gray-scale image, and edge detection.

After preprocessing phase, filters are applicable to the derived image.

Each filter results image segmentation into three regions of crop, weed, and background.

At the last step, the postprocessing part re-checks the regions for any misclassifications and merges the results into a single image.

Weed location in this image are then reported to the cultivator in a matrix format

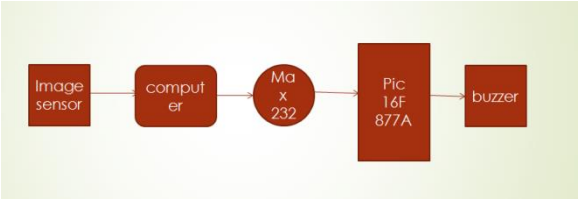

Figure 2: General Sub-Unit Process Flow Diagram

Agriculture plays one of the most important roles in economy and therefore lowering costs and improving quality of agricultural products is highly demanded. Controlling weeds is one of the most important and also expensive labors in agriculture which can be automated using robotic cultivators. These robots should be armed with a digital camera which uses a method to classify between weeds and crops based on captured image and then remove the weed by spraying herbicide accurately on the weed, cutting with blades or damaging with electric shock devices. Any of these methods reduce herbicide usage which also protects environment from side-effects of these chemical substances. In this article a method is proposed which utilizes fast Fourier transform and leaf edge density to classify between crop and weed leaves in corn fields in real-time. This method is based on specific shapes of these leaves and leaf vein structures. Testing the method on a sample set of corn field images showed more than 92% accuracy in detecting weedplants. The resulting application is finally compiled to a dynamic linked library (dll) and used in a graphical user interface (GUI) to be used further by a cultivator robot in a real field.

3. MATERIAL AND METHODS

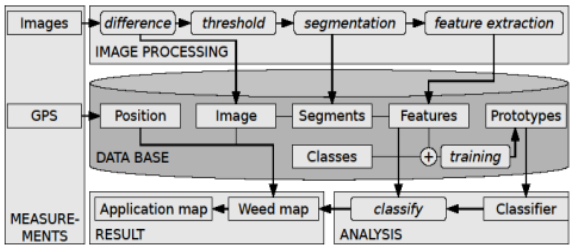

Figure 3: Result Generation

The difference image was analysed using digital image processing and the results are stored in a database (Figure 1). The first step is the binarisation with a grey level threshold that segments the foreground objects (white) from the background (black). A segmentation step identifies single foreground objects as objects, which are surrounded by background. Noise can be suppressed in this step, if small regions are filtered out with a size criterion. For the remaining objects features are computed, which characterise the shape of the plants. Geometric features are based on the object pixels, contour features, which are derived from the border pixels (fourier descriptors, curvature), and features based on the skeleton of the regions were computed. Size, compactness and Hu moments (HU 1962) are typical examples for the group of geometric features. The skeletonization was combined with a distance transformation of the regions and lead to a distance vector. Statistical measures from this vector describe then the thickness of the segments. With this step the image processing was complete and the features were used for the following analysis.

3.1 FEATURE SELECTION

Not all features have the same relevance for the classification. Each feature adds a dimension to the feature space, which is high dimensional. In our system up to 81 features were computed, which are all numerical. Therefore the prototypes

were located in a 81-dimensional feature space and it was necessary to reduce the number of dimensions. A feature selection or feature transformation can be used for this task. Selection algorithms weight features according to their discriminational abilities and select the ones that allow the best discrimination of the classes. The maximum number of features should not exceed 16 and the prototypes were used to select them. Selection algorithms can be grouped into two groups. One group uses the discriminative abilities of each feature or correlations of features to select the best ones. PCA weighting is one example, which uses the coefficients of a principal component analysis to weight the features. The other group of selection algorithms uses classification algorithms. Feature subsets are selected and the performance of a classifier, which uses only these subsets, is used. Two different algorithms for a weighted selection were used, which are implemented in the data mining program RAPIDMINER (MIERSWA et al. 2006). The selection process Image Analysis for Agricultural Products and Processes Bornimer Agrartechnische Berichte • Heft 69 ISSN 0947-7314 Leibniz-Institut für Agrartechnik Potsdam-Bornim e.V. (ATB) 141 consisted of a weighting using PCA weighting and info gain weighting with a following selection, that recursively did a (crossvalidated) nearest neighbor classification. The performance of the classification und therefore the feature subset was rated and feature subsets could be identified, which are optimized for the dicrimination of the classes.

3.2 CLUSTERING

A supervised classifier that uses the training data of the prototypes is used to assign classes to the objects. Unsupervised classification algorithms, also known as clustering, can be used, if no training data exists. These kind of classifiers were used before class information was available and before the manual selection of prototypes has taken place. These algorithms aggregate similar objects to clusters according to the feature information. In this context clustering is interesting in two ways: they can be used to support the training and they show similarities or differences between classes, giving hints on the seperability. Clustering was used here to group plants with similar shapes. In a second step classes can be set for these automatically derived clusters and prototypes can be selected. The advantage of the approach is, that classes with similar features can be identified. The training for classes which are difficult to separate can be optimized this way. If class has a multimodal distribution in the feature space, leading to two or more clusters (see clusters 0, 1 and 2 in Figure 4), then an additional classes may be defined. The same applies, if there are still noise objects left: a noise class can be used for them. The resulting prototype definitions are used for the classification.

3.3 DATA SET

The data for the clustering was derived from images taken in December 2007. The field had a size of 3.5 ha with a winter wheat (Triticum aestivum L.) crop. The crop was not emerged at that time and the weeds were grass weeds (mainly Alopecurus myosuroides Huds.) and dicotyledon weeds (Veronica persica L., Matricaria chamomilla L.).

The image series contains of 3367 images and their DGPS-coordinates. 160 images were selected from the series, which were near manual sampling points, and used for the training.

The number of weeds, separated for each species, were counted manually from the images and compared to the results of the image classification.

Additionally a manual field sampling was done using a frame to count the weed densities for each species. The position of the images and manual sampling points are not exactly the same, but differ up to two meters.

A map was created from the results of the supervised and unsupervised classification and the manual sampling. It can be seen that the weed patches can be found with each of the methods

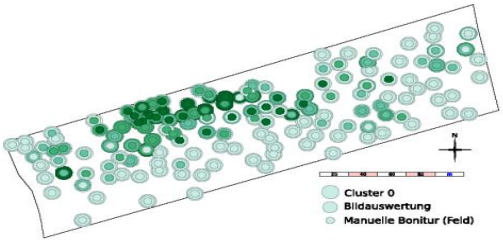

Figure 4: Clustering Network

Map of the weed densities using different measurements: outer rings contain results of unsupervised classification (Cluster 0), middle ring shows the supervised classification using prototypes, inner circle manual sampling results

4. RESULTS AND DICUSSION

The images were analysed following the schema from Figure 1, additionally there was the data of manual measurements from the images. The weeds were counted from the subset of the images, they were also used to select the prototypes. The result of the clustering can be compared to the training data. The clusters and object classes can be visualised in the feature space using three features. Figure 3 shows the trainingdata of the prototypes on the left and the result of the clustering on the right (clusters numbered from zero to four).

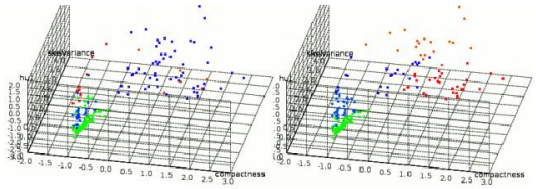

Figure 5: Classes Manually selected and Unsupervised Classification

Classes (manually selected prototypes) and clusters (unsupervised classification) in the feature space. The features are compactness, variance of the skeleton distance vector and the first Hu moment Image Analysis for Agricultural Products and Processes Bornimer Agrartechnische Berichte • Heft 69 ISSN 0947-7314 Leibniz-Institut für Agrartechnik Potsdam-Bornim e.V. (ATB) 143 The segments were labeled with colors according to the clusters and combined to label images. The combination of these with the (inverted) difference images is shown in Figure 4. Dicotyledon weeds can be found in cluster four, the monocotyledons are in cluster zero to three. The unsupervised classification can distinguish between these important weed classes. By assigning classes to the clusters the training step can be simplified, prototypes can be marked as belonging to that class. This way an efficient training is possible. It can also be seen, that the monocotyledon weeds have a multimodal distribution (single, elongated leaves, overlapped leaves). This can be taken into account in the class definitions for the prototypes, this class can be separated into two subclasses.

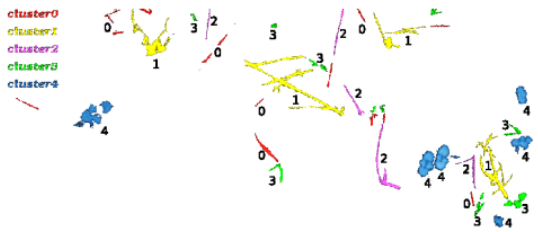

Figure 6: Cluster assignments in an example image, cluster 4 contains dicotyledonous, cluster 0-3 monocotyledonous weeds

Figure 7 relates the manual class assignments for Alopecurus myosuroides Huds. to cluster zero. There were some images without objects in the cluster (points on the ordinate), but in most of the images the numbers show the same tendency as the manually determined ones.

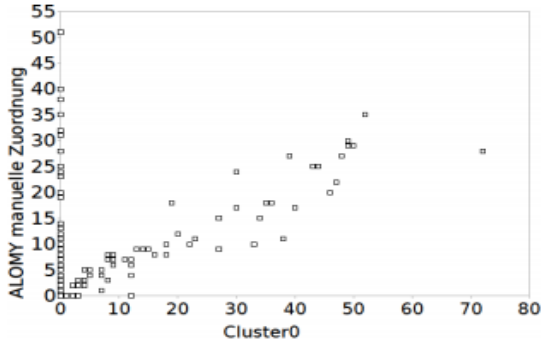

Figure 7: Correlation of the manual class assignments (ALOMY: Alopecurus myosuroides Huds.) and cluster zero of the unsupervised classification (clustering)

4. CONCLUSION

Weed sampling from camera images, as described in this approach, can be used to generate weed maps with high spatial density, which are necessary for a site-specific weed management. The approach uses bi-spectral images, which allow a good separation between plants and background. The analysis is based on the shape of single plants, which are parametrised using shape features. Supervised classifiers need training data, which are selected prototypes of weed and crop plants. The selection of the prototypes can be supported by unsupervised classification (clustering) by assigning classes to automatically derived clusters. This way the separability of the classes according to the shape features can be visually assessed already in the training step and the classes and training data can be adjusted to the situation. Unsupervised classification could be used to establish a fully automatic approach, if prior information about the weed species are introduced as starting values for the clusteringprototypes of weed and crop plants. The selection of the prototypes can be supported by unsupervised classification (clustering) by assigning classes to automatically derived clusters. This way the separability of the classes according to the shape features can be visually assessed already in the training step and the classes and training data can be adjusted to the situation. Unsupervised classification could be used to establish a fully automatic approach, if prior information about the weed species are introduced as starting values for the clustering.

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