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A Review Analysis of Weed Detection in Crops by Computational Vision

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Abstract- In recent years, precision agriculture and precision weed control have been developed aiming at optimising yield and cost while minimising environmental impact. Such solutions include robots for precise hoeing or spraying. The commercial success of robots and other precision weed control techniques has, however, been limited, partly due to a combination of a high acquisition price and low capacity compared to conventional spray booms, limiting the usage of precision weeding to high-value crops. Nonetheless, conventional spray booms are rarely used optimally. A study by Jørgensen et al. (2007) has shown that selecting the right herbicides can lead to savings by more than 40 percent in cereal fields without decreasing the crop yield when using conventional sprayers. Therefore, in order to utilise conventional spray booms optimally, a preliminary analysis of the field is necessary. The major components of this system are composed of three processes: Image Segmentation, Feature Extraction, and Decision-Making. In the Image Segmentation process, the input images are processed into lower units where the relevant features are extracted.

Keywords : Weed detection, SVM, Kmeans, Image segmentation

I. Introduction

The aim of this project is to automatically detect and classify weeds in images from fields. This is the first step of an automated precision weed control system. Automatic detection of weeds is a well-established research area with a big potential in precision agriculture. Nevertheless, there has been limited success in the classification of multiple weed species under natural field conditions, including overlapping plants. With recent advances in convolutional neural networks, this dissertation demonstrates methods that can classify weeds in field-images that are collected using consumer cameras.

Controlling weeds is an important task in agriculture because weeds compete with crops in the field, contributing to a lower crop yield. The overall loss of yield due to weeds is estimated to be more than 30% for wheat, rice, maize, potatoes, soybeans, and cotton if weeds are not controlled (Oerke, 2006).

Today, the majority of Indian agricultural land is cultivated conventionally. Weeds are controlled chemically by applying herbicides to the field. Weeds can also be controlled mechanically or thermally, but it requires greater precision than chemical weed control, and consequently, the capacity is much lower. Moreover, the applicability of mechanical or thermalweed control is limited in cereal fields because the machines require a certain safety margin to the crops, which is not practical as the crop row distance is typically about 12 cm. Non-chemical treatment is, therefore, primarily utilised in organic farmland, which only represents 6.3% of the total agricultural area in india. As of 2011, India had a large and diverse agricultural sector, accounting, on average, for about 16% of GDP and 10% of export earnings. India's arable land area of 159.7 million hectares (394.6 million acres) is the second largest in the world, after the United States. Its gross irrigated crop area of 82.6 million hectares (215.6 million acres) is the largest in the world. India is among the top three global producers of many crops, including wheat, rice, pulses, cotton, peanuts, fruits and vegetables. Worldwide, as of 2011, India had the largest herds of buffalo and cattle, is the largest producer of milk and has one of the largest and fastest growing poultry industries. In madhya pradesh Agriculture is the mainstay of the State's economy and 74.73 per cent of the people are rural. As much as 49 per cent of the land area is cultivable.

Agriculture (Land Utilization) (2017-2018), Area according to village Papers (Lakh in Hect.) 231.29,Area under forest (Lakh in Hect.) 87.08, Culturable Waste Land (Lakh in Hect) 9.67, Total Fellow Land 10.29, Net Area Sown 151.91, Gross Cropped Area 251.14, Double Cropped Area 99.23, Net Irrigated Area 105.66, Gross Irrigated Area 113.94.

On the contrary, chemical weed control is the preferred treatment by most conventional farmers. There is, however, a growing governmental pressure on farming, imposed through regulations, to limit the usage of herbicides, because of the unwanted impact that the herbicides potentially have on the environment. Additionally, the frequency of herbicide resistance is increasing (Gerhards and Christensen, 2003; Heap, 2014) while the number of approved pesticides in the EU has been reduced by more than 50% since 1998 (Bielza et al., 2008; Sanco, 2014). Therefore the farmer, according to The Council of the European Union (2009), has to inspect his fields before spraying and only use dosages targeted for the specific needs of his fields. Moreover, taxes have been imposed upon the herbicides in order to limit the usage. Spraying fields can, therefore, be a costly affair, as for winter wheat, the price of recommended treatments ranges from 202 to 922DKK/ha (27-124"/ha) depending on the weed coverage2,3(SEGES, 2016). Of these prices between 38% and 58% are taxes. The farmer therefore has a financial incentive to weigh the cost of spraying against the increased yield of his fields.

Spraying fields can be divided into three degrees of precision, where not only the herbicide savings, but also the complexity increases, the more precise the treatment becomes. The least precise treatment is uniformspraying of the whole field with the same herbicide dose. Uniform spraying is the typical approach used when controlling weeds, as this treatment requires a minimal inspection, and works with all sprayers. Even when spraying the field uniformly, however, herbicide savings are possible. By using conventional spraying methods combined with an optimised herbicide mixture, Gerhards et al. (1997) and Christensen et al. (2003) show that the pesticide usage can be reduced by 45 to 66% without reducing the crop yield.

The next degree of precision is patch spraying, where the field is divided into smaller regions, and the optimal treatment is determined per region. This approach is seldom used today, butmodern sprayers are able tomix herbicides on-the-fly, allowing for patch spraying of the field. However, this requires that a weed distribution map is available for the spray controller so that it knows the optimal herbicide dosage at a given location. Timmermann et al. (2003) show that by dividing fields into grid cells of 7.5-15m, savings of 54% can be achieved by turning the sprayer on and off based on the weed density in the cells. Likewise, Gerhards et al. (2012) show that 40% of three test fields have a weed density so low that the cost of weed control is higher than the crop value increase.

The most precise degree of weed control is a per-plant treatment, where each weed is detected and treated. This method will typically require an online weed detection systemand has nowhere near the capacity that the other solutions have. In return, herbicide savings of more than 99% can be expected (Graglia, 2004; Søgaard and Lund, 2007;).

Therefore,when the farmer is to spray his fields using a conventional sprayer, it is necessary to know which weeds are in the field, and the density of the different weed species, in order to determine what herbicides to choose. At the same time it can be a laborious task to inspect the fields and determine which weed species are present. Partly because it is time-consuming to go through the field, partly because it requires knowledge of biological traits of the individual weed species in order to distinguish themfrom each other. As a result, many farmers, choose to use an agricultural advisor to undertake this work. Yet, the decision on which herbicides to choose, is often based on a regional recommendation by the local agricultural advisory centre.

In recent years, various projects have dealt with automated recognition of weeds using cameras with the aim of developing new farmingmachinery that can control the weeds more intelligently. This puts heavy demands on automatic image analysis, which must be able to operate under uncontrolled field conditions.

The variance within the same weed species is a big challenge in the domain of automated plant recognition. Plants are soft and sensitive to factors such as wind, light, and nutrition, which have a visual impact on the plants. Some species also change significantly through the different early growth stages, making themhardly recognisable, as the plant will show only little resemblance between the early and later growth stages, as can be seen for the scentlessmayweed in Figure 1.1. Moreover, at early growth stages, different plant species often look alike as the plants have not yet grown their true leaves, which are the leaves carrying most of the “visual identity” of the plants. Therefore, the classification of weeds is further complicated.

Figure 1: Single scentless mayweed that has been tracked for the first two weeks of growth (after Dyrmann and Christiansen (2014)).

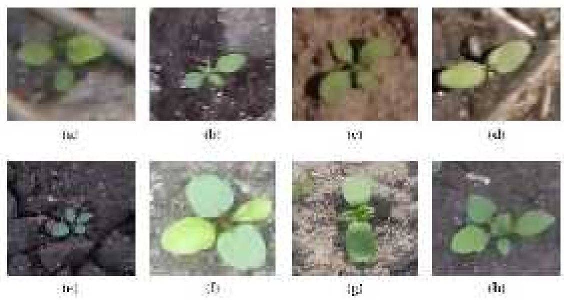

Figure 2: Different species that have many visual similarities at early growth stages. (a) Field-pansy. (b) Chickweed.(c) Shepherd's purse. (d) Speed-well. (e) Fat hen. (f) Dead-nettle. (g) Hemp- Nettle. (h) Common Poppy.

Figure 1.2 shows examples of eight different species at early growth stages that might be hard to discriminate for an untrained person. When controlling weeds, it is necessary to apply herbicides at an early growth stage in order to decrease the amount of herbicide needed. According to Aitkenhead et al. (2003), an automated system for weed detection

II. RELATED WORK

In this section describe about the existing work those Many different approaches are employed for weed control in Precision Agriculture (PA). Most of the identification of the weed regions use the concepts of Computer Vision, Pattern Recognition, and Machine Learning. In other cases, the use of Feature Extraction like that of shape, aspect ratio, and length ratio is used to determine the presence of weeds in fields [4]–[8]. Color, for instance, has been used for separating diseased and damaged plants in fields. Researchers have even made use of different classification algorithms for discerning weeds from plants [9], [10]. Gerhards et al. used the Fuzzy Logic algorithm for planning Site-Specific herbicide applications [11]. Clustering algorithms also be used in Remote Sensing environments; like in paper [12], where region-based clustering is performed to locate the agricultural fields. Schirrmann et al. [13] used three different clustering algorithms (K-Means, Partition Around Methods (PAM), and Fuzzy C-Means) to detect the spatial changes of biomass in wheat fields.

Another common Machine Learning algorithm that is used in recent research papers is the Support Vector Machine (SVM) for identifying regions of weeds or infected regions in an agricultural field. In Tellaeche and Shi's studies [14] [15], input images of the crop fields are subdivided into different cells than Support Vector Machine (SVM) is used to identify those regions that consist only of crop plants. The method stated in that paper is that images are split into grid cells where each cell is analyzed to determine whether to spray pesticides or not. This cell-based analysis is not suitable when the high precision treatment is required as it is computationally inefficient. Other papers used classifiers like Fuzzy Clustering [16], Artificial Neural Networks [17] (ANN), and Bayesian Classifier [18] as classifiers for weed area identification in farmlands. Furthermore, Hamuda et al. [19] paper discussed numerous approaches that are used for weed identification.

In any agricultural fields evaluating individual leave is not commercially suitable and will not have any significant impact in cultivation. Therefore, priority should be given to performing Remote Sensing in agricultural fields where weed density is high [20]. On the other hand, in the PA classification of plants from weeds need to be performed at ground level [21]. That means images generated from the fields consist of inter-mixed of plant and weed leaves. Haug et al. [3] performed weed and plants regions identification without segmenting any of the regions. Neto et al. [22] performed leaf segmentation that is convex in shape and that methodology cannot be applied to any other form of leaves. Thus, this methodology is ineffective for commercial usage.

In this paper, we evaluated two recent unsupervised deep clustering algorithms in two real weed datasets. The results achieved in these datasets indicate a promising direction in the use of unsupervised learning and clustering in agricultural problems. Using more clusters than the number of classes allowed the clustering algorithms to group images of same class into different clusters using extra information in the images, such as lighting and background. Our modified Unsupervised Clustering Accuracy has proven to be a robust and easier to interpret evaluation clustering metric for cases where cluster and class numbers differ. It was also possible to see how transfer learning and data-augmentation can greatly improve the unsupervised learning.The proposed usage of semi-automatic data labeling in weed discrimination achieved great performance in Grass-Broadleaf and presented as an alternative to major challenge of Deep Learning in agriculture: the need of large amounts of labeled data. Since itsperformance is directly related to the quality of clustering method used, given the recent advances in

Unsupervised Deep Clustering, it's expected that semi-automatic data labeling can achieve results similar to Grass-Broadleaf dataset in more complex agricultural datasets such as DeepWeeds, in the near future. Moreover, this technique is simple and straightforward to be reproduced in arbitrary datasets, in addition to the agricultural scope, with almost no modifications[1].

This research has proposed a practical way to detect weedsby image processing based on the characteristic of the area of each object in an image. Although research has been limited in that the size of the weed is smaller than that of the crop, high indices of sensitivity, specificity and positive predictive value have been achieved, contrary to the negative predictive value, which is lower than 50%. The proposed algorithm has the advantage of detecting weeds present between the plants in the crop lines. It also detects effectively as crop plants even those that are outside the crop lines, which is an objective difficult to achieve with other methods using computational vision [11]. However, the algorithm loses effectiveness when the sizes of the weeds are similar to the sizes of the plants of the crop, since the characteristic that is taken as variable of classification is the size of the plants. This problem can be solved by adding another characteristic as a classification method. The use of low level characteristics such as the color of the plants and the area is an advantage given that the specific characteristics of the weeds as texture or shape are not relevant, providing versatility for the application of the algorithm in different crops of vegetables. This advantage is important, due to the great variety and types of weeds that exist in crops. A specific database of weeds is not necessary to be able to train the algorithm and identify weeds, as an automatic learning algorithm would do. It was concluded that the proposed algorithm using low level characteristics and a threshold based on the area, have an improvement field in the specificity indexes and NPV, but the results are good enough to use the algorithm in practical applications of precision agriculture[2].

In this paper, we presented a novel approach for precision agriculture robots that provides a pixel-wise semantic segmentation into crop and weed. It exploits a fully convolutional network integrating sequential information. We proposed to encode the spatial arrangement of plants in a row using 3D convolutions over an image sequence. Our thorough experimental evaluation using real-world data demonstrates that our system (i) generalizes better to unseen fields in comparisonto other state-of-the-art approaches and (ii) is able to robustly classify crop in different growth stages. Finally, we show that the proposed sequential module actually encodes the spatial arrangement of the plants through simulation[3].
eural networks provide very powerful tools to deal with many problems in computer vision and pattern recognition in general. Recent advances in deep learning neural networks indicate that this trend will be even more prominent in the future. However, neural networks must be configured with a large number of parameters, such as number of neurons, layers, functions and input features. Setting the optimal configuration is a challenge for the system designers. In this paper, we have shown how metaheuristic algorithms can be applied to automate the optimal choice of the input features and the network configuration. In particular, a new computer vision based expert system has been proposed with the main objective of performing site-specific herbicide spraying of weeds for Precision Agriculture. This system is based on color and texture features classified with artificial neural networks. The metaheuristic cultural algorithm is used for selecting the most relevant features; while harmony search is applied for finding the optimal configuration of the network. The experimental results have clearly proved that this system is able to correctly identify potato plants and three kinds of common weeds, with an accuracy of 98.36% under outdoor light conditions and taking less than 0.8 s on an average PC. As a future research line, it would be interesting to study the extension of the proposed methodology to other kinds of crops and weeds, and other kinds of capture systems, such as drones. Since the method selects the most relevant features and parameters of the neural network in an automatic way, this extension should be straightforward. A weak point of the approach is that if the density of plants is very high, they cannot be segmented independently. In that case, the classifier can be applied to parts of the image instead of the whole object. Finally, another future work is the integration of the process with the hardware of the automatic spray system[4].

III. Method

The proposed system has taken these issues into account and performs selective spraying on plants.

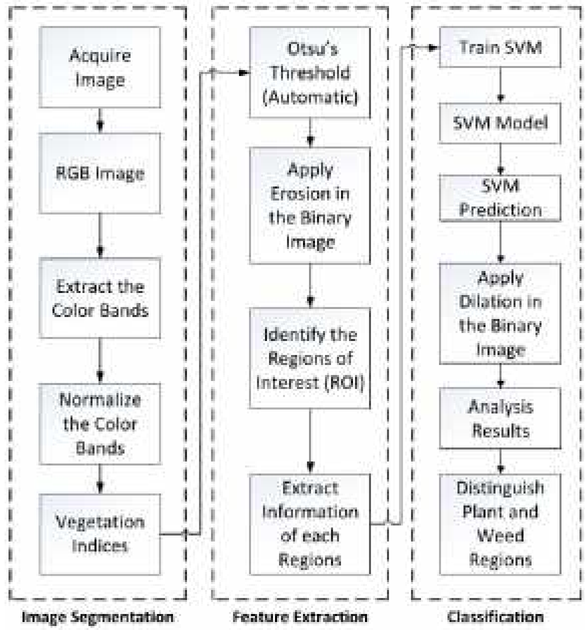

Figure 3. The flowchart of the proposed method for classifying and decision-making process.

Selective spraying minimizes the wastage of products required for the effective control of weeds, diseases, and pests to ensuring that plants receive adequate nutrients. The method uses SVM for decision-making, which has two main advantages. First, the model is robust that is numerous features can be included in the system which helps to maximize the width of the SVM margin.

This maximization directly improves the classification performance by reducing the chances of misclassification. Secondly, the employed SVM makes use of the Support Kernels which can model non-linear relationships. Non-linear relationships arise when multiple features are present within the system. The proposed approach considers three major features to maximize weed region identification: region area, perimeter, and convex area. These features are extracted from the input image and then used for analysis and classification by the SVM. Further improvement is been made on the proposed method with the addition of the K-Means clustering algorithm. This clustering approach by-passes the conventional methods of green region extractions. Then, the Feature Extractor Histogram of Oriented Gradients (HoG) is used to label the overlapping and non-overlapping regions. Finally, the SVM classifier detects the weed regions from the leaves both from the overlapping and non-overlapping regions within a field.

The system can be subdivided into three principal components: Image Segmentation, Feature Extraction, and Classification. These components are critical for region classification and discerning plants from weeds. The tasks carried out in each component is described in the following subsections.

Initially, an image database of color in-field images are used to produce viable training data. The set is created by highlighting greenness regions of plants and weeds. This is done by extracting each band of color from an RGB image and then normalizing each color components. This is done using the modified equations from Shi et al. [15].

$$\mathrm{NormalizedRed} = \frac{red}{red^2 + blue^2 + green^2} \quad (1)$$

$$\mathrm{NormalizedGreen} = \frac{green}{red^2 + blue^2 + green^2} \quad (2)$$

$$\mathrm{NormalizedBlue} = \frac{blue}{red^2 + blue^2 + green^2} \quad (3)$$

Equations 1 through 3 are used to find the value of each color band from an RGB image. Then, by using the set of equations below [15], the normalized component values of the image are calculated. These normalized values are then used as a means of highlighting the "greenness" regions.

$$r = \frac{\mathrm{NormalizedRed}}{\mathrm{NormalizedRed} + \mathrm{NormalizedBlue} + \mathrm{NormalizedGreen}} \quad (4)$$

$$g = \frac{\mathrm{NormalizedGreen}}{\mathrm{NormalizedRed} + \mathrm{NormalizedBlue} + \mathrm{NormalizedGreen}} \quad (5)$$

$$b = \frac{\mathrm{NormalizedGreen}}{\mathrm{NormalizedRed} + \mathrm{NormalizedBlue} + \mathrm{NormalizedGreen}} \quad (6)$$

The "greenness" part of the image relies on the common Vegetation Color Index (VCI) [27] in Equation 7 to further emphasize the greenness part of the plant. This equation applies more weight to greener regions of the plant and removes other color bands from the image.

$$\mathrm{ExcessGreen} = 2 * (g) - (r) - (b) \quad (7)$$

IV. Result

In this section we are detect weed. Here we take input from the agriculture land by any camera and process it in local system. Here we are classify image in RGB Then HSV to extract colour Region. Classify object with their property.

Detect weed from the image

Figure 4 Input Image

Figure 4 is show input image. This image is capture by normal camera and process it on our proposed system. After the input image we are process it for color reorganization. We are separate select R, G and B color then convert it to HSV.

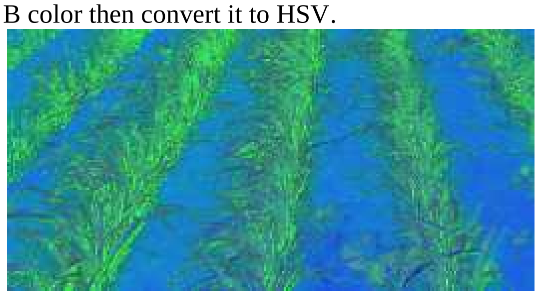

Figure 5 HSV Image

Figure 5 is show HSV image. This image is conversion of RGB to HSV and select separate color of H,S and V from the image.

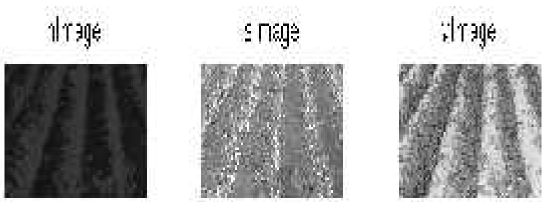

Figure 6 Separate image of H,S and V

Figure 6 is show image with separate color region . This is separate image of each color.

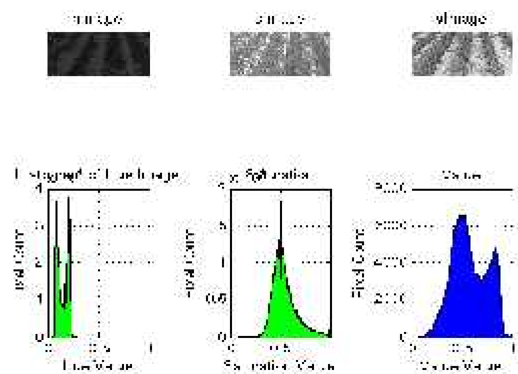

Figure 7 Histogram of Image

Figure 7 is show histogram value of separate image along with their histogram value.

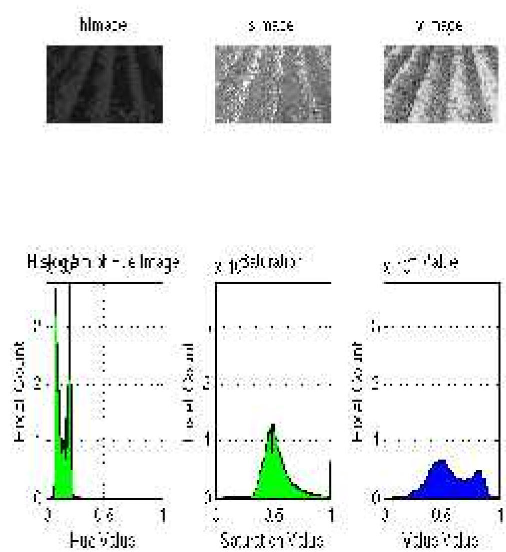

Figure 8 After Thresolding of image

Figure 8 is show thresolding output of color image. This is optimization graph of color image.

Figure 9 Output

Figure 9 show output of project.

IV. Conclusion

By proposed method is get best classification output through image segmentation, feature extraction and object classification. From proposed method we are classify any image which capture by any camera and detect weed. In proposed method is used Kmeans clustring algorithm to classify object from image and detect green color. Also used SVM to select weed from the image.

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