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Review

A survey of image processing techniques for plant extraction and segmentation in the field

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ABSTRACT

In this review, we present a comprehensive and critical survey on image-based plant segmentation techniques. In this context, "segmentation" refers to the process of classifying an image into plant and non-plant pixels. Good performance in this process is crucial for further analysis of the plant such as plant classification (i.e. identifying the plant as either crop or weed), and effective action based on this analysis, e.g. precision application of herbicides in smart agriculture applications.

The survey briefly discusses pre-processing of images, before focusing on segmentation. The segmentation stage involves the segmentation of plant against the background (identifying plant from a background of soil and other residues). Three primary plant extraction algorithms, namely, (i) colour index-based segmentation, (ii) threshold-based segmentation, (iii) learning-based segmentation are discussed. Based on its prevalence in the literature, this review focuses in particular on colour index-based approaches. Therefore, a detailed discussion of the segmentation performance of colour index-based approaches is presented, based on studies from the literature conducted in the recent past, particularly from 2008 to 2015. Finally, we identify the challenges and some opportunities for future developments in this space.

Contents

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1. Introduction

1.1. Background and motivation

Weeds are one of the big challenges in agriculture because they appear everywhere randomly, and compete with the plant for resources. As a result of this competition for resources, crop yields suffer. Yield losses depend on factors such as weed species, population density, and relative time of emergence and distribution as well as on the soil type, soil moisture levels, pH and fertility (Papamichail et al., 2002). Numerous researchers have identified a strong link between weed competition and crop yield loss, with a wide range of crop varieties. For example, according to the study by Stall (2009), an annual loss of 146 million pounds of fresh market sweet corn and 18.5 million pounds of sweet corn for processing occurred in the United States from 1975 to 1979 due to weed competition, which corresponds to revenue losses of $13,165,000 and $9,155,000 respectively. Besides, the dry and head weight of crop yield are measured to evaluate losses. Based on a study carried out in 1996/1997 and repeated in 1997/1998 in central Jordan (Qasem, 2009), it was found that the average reduction in shoot dry weight and head yield were 81% and 89% respectively. An effective and efficient weed management system is necessary to minimise yield losses in valuable crops. The critical period for weed control must be taken into account to enhance weed management strategies (Swanton and Weise, 1991), as the duration of co-existence of weed and crop is an important indicator of yield losses due to weed competition (Kropff et al., 1992).

Zimdahl (1988, 1993) defined the critical period of weed control (CPWC) as "a span of time between that period after seeding or emergence when weed competition does not reduce crop yield and the time after which weed competition will no longer reduce crop yield". A more quantitative definition is as the number of weeks after crop emergence during which a crop must be weed-free in order to prevent yield losses greater than 5% (Hall et al., 1992; Van Acker et al., 1993; Knezevic et al., 1994).

A number of studies have been carried out in many different locations, under different environmental conditions in an attempt to establish the CPWC. The studies are generally conducted by keeping the crop free from weeds for a fixed period of time, and then allowing the weeds to infest. Another approach used is growing weeds with the crop for certain predetermined durations, after which all weeds are removed until the growing season ends (Nieto et al., 1968). Some studies have reported that weeds that emerge at the same time as the crop, or slightly after, cause greater yield loss than weeds emerging later in the growth cycle of the crop (Dew, 1972; O'Donovan et al., 1985; Swanton et al., 1999). Most studies recommended that crops should keep weed-free within the CPWC in order to minimise yield loss (e.g. Karkanis et al., 2012).

Manual methods for weed control include hand weeding and use of simpler hand tools. Hand weeding is a conventional weed removal method that has been successfully used to control weeds for many centuries, before any other methods existed, but is not practical for large scale commercial farms because it is extremely labour intensive, costly, tedious, and time consuming (USDA, 1996).

Mechanical methods for weed control (by tillage or cultivation of the soil) are mostly applied in large areas for row crops such as sugar beet, wheat, and corn for inter-row weed control. A number of studies have been carried out to evaluate the efficacy of mechanical weed control methods. Forcella (2000) reported that rotary hoeing yielded approximately 50% weed control alone without using other weed control methods such as herbicides and manual labour. Donald (2007) found that inter-row mowing systems for controlling both winter annual and summer annual weeds may reduce the use of herbicides by approximately 50%.

Mechanical weeding is particularly suited to organic fields for weed control and can also be helpful in conventional fields. On the other hand, the use of machinery may also have negative effects on crops and the environment by causing damage and erosion (Nelson and Giles, 1986; Eyre et al., 2011). Chemical weeding is the most widely used method for weed control in agriculture since the introduction of synthetic organic chemicals in the late 1940s, and farmers now rely heavily on herbicides for effective weed control in crops (Gianessi and Reigner, 2007; Grichar and Colburn, 1993; Bridges, 1992), particularly on large scale commercial farms. Many studies have documented that the use of herbicides is a more economical method for controlling weeds compared to hand and mechanical weeding. With the help of herbicides, farmers in Mississippi were estimated to have saved $10 million per year compared to the cost of labour (Gianessi and Reigner, 2007). Demand for chemicals by farmers has increased the market size; according to a report carried out in 2014 by BCC Research Chemical Report (2014), the biopesticide and synthetic pesticide market are expected to reach up to $83.7 billion by 2019.

Although herbicides are very effective at controlling weeds, they have negative impacts on both the environment (through pollution) and plant biology (development of resistance). Groundwater and surface water pollution has been reported in many cases in recent decades, and excessive use of herbicide has often been found to be the cause (Liu and O'Connell, 2002; Spliid and Koeppen, 1998). To counteract these catastrophic environmental effects, most European countries have introduced legislative directives to restrict the use of herbicides in agriculture (Lotz et al., 2002). If there are means to accurately detect and identify weed spatial distribution (weed patches), it is possible to limit herbicide quantities by applying them only where weeds are located (e.g. Lindquist et al., 1998; Manh et al., 2001; Berge et al., 2012; Christensen et al., 2009; Jeschke et al., 2011). Heisel et al. (1999) demonstrated a potential herbicide saving of 30–75% through the use of appropriate spraying technology and a decision support system for precision application of herbicides. This drives the need for systems for more accurate identification of weed patches, and has provided one motivation for development of image processing methods for identification of weeds. Colour-index based segmentation methods have demonstrated a particular utility for weed identification, and hence are a particular focus of this paper.

Besides identification of weeds to permit precision weeding, plant segmentation is also useful for other proposes, and applied in several applications such as plant species recognition (Lei et al., 2008), growing phase determination (Kataoka et al., 2003), and plant disease detection (Camargo and Smith, 2009). While weeding remains the most important motivator at present, these other applications are growing in importance with increasing interest in smart agriculture.

1.2. Image processing challenges

Most recent studies have focused on chemical technology and its applications for targeting weeds at close range to avoid disturbing crop plants, and these studies have demonstrated that it is feasible to accurately target weeds within 1 cm of crop plants. Slaughter et al. (2008) considered image processing techniques for detection and discrimination of plants and weeds in some detail. Plant has to be segmented from background soil, considering all field conditions, because mis-segmentation could seriously affect the accuracy of plant/weed detection. Among other things, Slaughter et al. concluded that natural illumination plays a crucial role in effective plant segmentation, and poor illumination contributes to poor plant segmentation. They also found that most of the available machine vision techniques are not robust for real time conditions. High segmentation performance is required for precision chemical application, and with good performance, the volume of herbicides that are applied to the fields can be minimised.

In this survey, we focus on recent studies that consider image processing techniques that used for plant extraction and segmentation under various field conditions and consider their performance. Fig. 1 shows a block diagram of a general scheme for segmentation, including a broad framework for evaluation of segmentation algorithms. This typically includes a pre-processing stage, followed by the core segmentation stage, which can be done using a variety of approaches (indicated by the "Algorithms" box on the left hand side of Fig. 1). Evaluation is typically carried out by comparing the output of the segmentation algorithm with a reference image that is treated as a "gold standard", and by using a suitable performance or quality metric. These steps will be described in the following sections of this paper.

1.3. Paper organisation

This survey is organised as follows: a brief overview of image processing approaches and a discussion of the pre-processing stage are given in Section 2; Section 3 describes colour index approaches, the most prevalent approach in the literature thus far; a comparison of segmentation performance for colour index-based approaches, based on recent studies from the literature, is given in Section 4. Section 5 briefly discusses threshold-based and learning based-approaches. An overall discussion and conclusions are given in Section 6, which also considers remaining challenges, limitations, and recommendations.

2. Image processing overview

Machine vision technology has been widely used and studied in agriculture to identify and detect plants (crops & weeds). It has shown a potential for success in a number of case studies in robotic weed control systems despite some serious challenges that will be

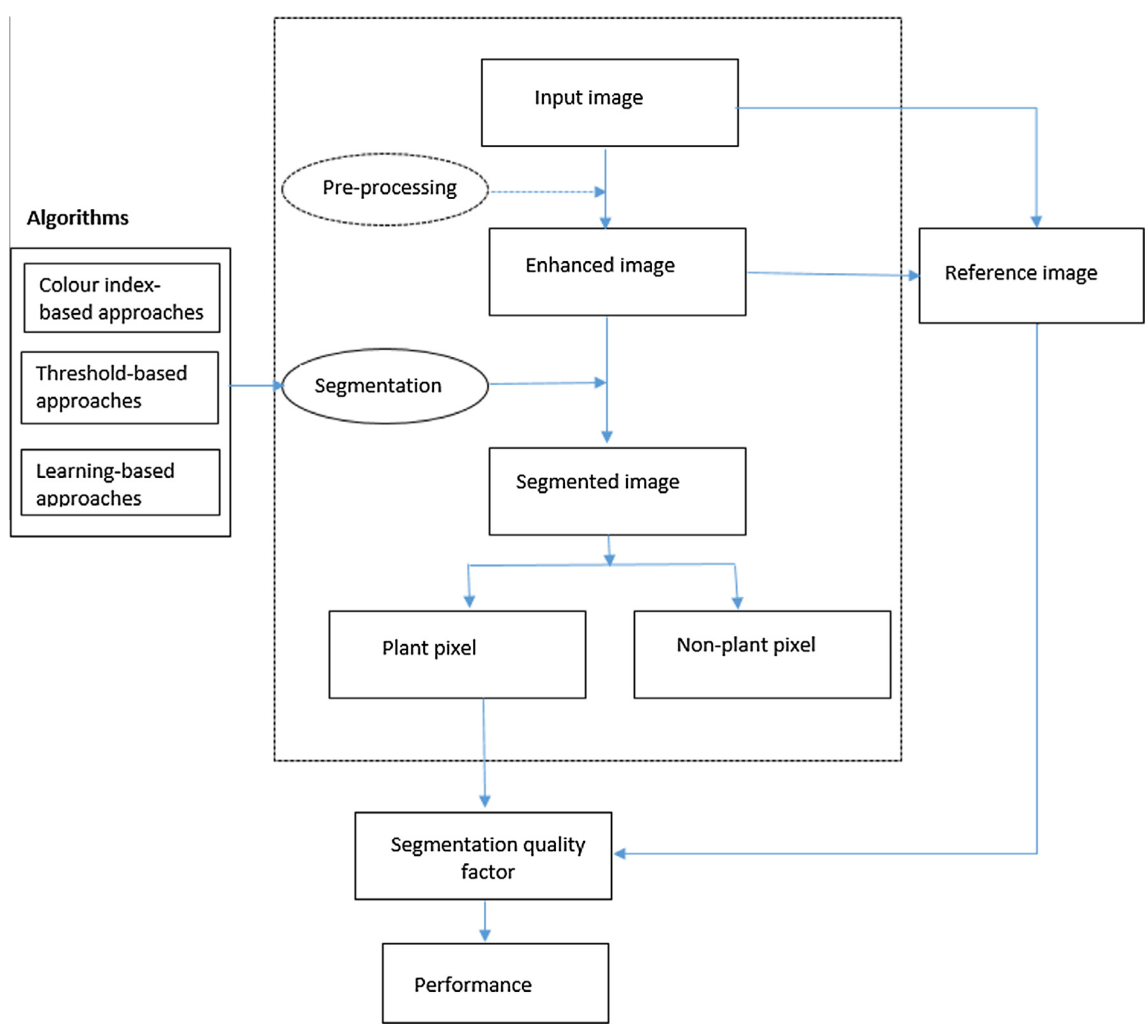

Fig. 1. General scheme for segmentation and its evaluation.

discussed below. After many decades of study, machine vision has improved the quality management of weed control systems (Meyer et al., 1998; Onyango and Marchant, 2003; Søgaard, 2005; Schuster et al., 2007). Machine vision technology has also been applied in other agricultural applications such as grading and harvesting fruits (Slaughter and Harrel, 1989; Van Henten et al., 2003; Abbasgholipour et al., 2011). As summarised in Slaughter et al. (2008), many researchers have developed image processing methods as guidance for machine vision, working in different fields and environments (under controlled and uncontrolled conditions). Image-based segmentation techniques mostly involve two main stages: pre-processing and pixel classification.

2.1. Pre-processing

Pre-processing involves some important initial processing on the original image from the camera such as contrast enhancement and removing noise.

Image enhancement is one of the important steps in computer vision and it has played a significant role in various applications such as medical imaging, industrial inspection, remote sensing, and plant disease detection. Image enhancement is a process used for enhancing and adjusting the contrast of the acquired image to address the variability of luminance issues such as sunlight and shadow (Jeon, 2014). Colour conversion is used to address lighting problems in the scene of an image. For example, Perez et al. (2000) applied Normalised Difference Index (using only green and the red channel) to reduce the illumination effect and discriminate between plants and background. Filtering is also one of the important parts in image enhancement; in agricultural application, colour conversion and histogram equalization are used for plant leaf disease detection (Thangadurai and Padmavathi, 2014). For instance, Homomorphic filtering is a technique that has the ability to minimise illumination issues and has been successfully applied in outdoor images under various environmental conditions (Pajares et al., 2005).

2.2. Segmentation

The initial goal in almost all image processing plant detection approaches is to segment the different pixels which appear in image into two classes: plant (crops and weeds) and background (soil and residues). Background removal is an essential stage, and it has to be done in an appropriate way to avoid any mis-classification. Several methods have been developed for segmenting crop canopy images. The common segmentation technologies used for this purpose are: colour index-based segmentation, threshold-based segmentation, and learning-based segmentation. The next two sections consider colour index-based methods, while Section 5 discusses threshold-based and learning-based approaches.

3. Colour index-based approaches

Colour is one of the most common methods used to discriminate plants from background clutter in computer vision. Several researchers have used colour to separate plant from soil e.g. colour characteristics were used to distinguish green plants from soil and estimate the leaf area (Rasmussen et al., 2007; Meyer and Camargo-Neto, 2008; Kirk et al., 2009).

The colour of a region of interest can be accentuated, so the undesired region (soil background region) will be attenuated. For the majority of conventional visible spectrum cameras, the images are output in the conventional RGB colour space. According to Tian and Slaughter (1998), converting the RGB values into greyscale did not result in good segmentation because plant and soil background pixels had similar greyscale values. Therefore, in order to demonstrate good segmentation, the RGB space is often converted to alternative colour spaces. Several common green indexes (listed according to date of publication) are as follows.

3.1. Normalised Difference Index (NDI)

The Normalised Difference Index was proposed by Woebbecke et al. (1992). They tested three methods to distinguish plant material from soil background in an RGB image. A range of difference indices based on the R, G and B channels was evaluated e.g. $G-R$, $G-B$, and $G-R/G+R$, with the third one demonstrating the best separation of plant from background. This index is applied to all pixels in the image, providing values ranging between -1 and +1, but to display the image, these values must range between 0 and 255. Therefore, the index was further processed by adding 1 to it and then multiplied by a factor of 128 to provide a greyscale image (0–255). Thus, the final formula for NDI is as follows:

$$NDI = 128 * \left(\left(\frac{(G-R)}{(G+R)} \right) + 1 \right) \tag{1}$$

The NDI index produces a near-binary image.

3.2. Excess Green Index (ExG)

Woebbecke et al. (1995) examined several colour vegetation indices that were derived using chromatic coordinates and modified hue in separating green plant from bare soil (corn residue and wheat straw residue). The colour vegetation indices that were used include:

$$r-g \tag{2}$$

$$g-b \tag{3}$$

$$\frac{g-b}{r-g} \tag{4}$$

$$2g-r-b \tag{5}$$

where r, g, and b are the chromatic coordinates:

$$r = \frac{R^*}{(R^*+G^*+B^*)}, \quad g = \frac{G^*}{(R^*+G^*+B^*)}, \quad b = \frac{B^*}{(R^*+G^*+B^*)} \tag{6}$$

where R^*, G^* and B^* are the normalised RGB values ranging from 0 to 1, and are computed as follows:

$$R^* = \frac{R}{R_{max}}, \quad G^* = \frac{G}{G_{max}}, \quad B^* = \frac{B}{B_{max}} \tag{7}$$

where R, G and B are the actual pixel values from the images based on each channel and $R_{max} = G_{max} = B_{max} = 255$ for a 24 bit colour image ($3 * 8$-bit channels).

Among selected colour vegetation methods, Woebbecke et al. found that the modified hue ($2g-r-b$), referred to as the Excess Green Index (ExG), was the best choice for separating plants from bare soil. This is because ExG provided a clear contrast between plants and soil, and produced near binary images. The ExG index has been widely used and has performed very well in separating plants from non-plants (Meyer et al., 1998; Lamm et al., 2002; Ribeiro et al., 2005; Guerrero et al., 2012).

3.3. Excess Red Index (ExR)

Meyer et al. (1998) inspired by the fact that there are 4% blue, and 32% green, compared with 64% red cones in the retina of the human eye, introduced ExR method and compared with ExG in the experiment to segment leaf regions from the background. Excess Red Index was able to separate the plant pixels from background pixels, but it was not as accurate as *ExG*. The formula for *ExR* is defined as follows:

$$ExR = 1.3R - G \tag{8}$$

3.4. Colour Index of Vegetation Extraction (CIVE)

Colour Index of Vegetation Extraction (*CIVE*) was proposed by Kataoka et al. (2003) based on a study carried out in soya bean and sugar beet fields. This method was proposed to separate green plants from soil background in order to evaluate the crop growing status. The formula for *CIVE* is as follows:

$$CIVE = 0.441R - 0.811G + 0.385B + 18.78745 \tag{9}$$

Kataoka et al. found that the *CIVE* has better plant segmentation than Near-infrared (*NIR*) method because it provides greater emphasis of the green areas.

3.5. Excess Green minus Excess Red Index (ExGR)

This method was introduced by Meyer et al. (2004), and combines two colour indices, namely, Excess Green Index (*ExG*) and Excess Red Index (*ExR*). These methods were applied simultaneously to separate plants from the soil and residue, with *ExG* used to extract the plant region and *ExR* used to eliminate the background noise (soil and residue) where green–red material (stems, branches, or petioles) may exist. The *ExGR* is defined as follows:

$$ExGR = ExG - ExR \tag{10}$$

where *ExG* and *ExR* are as previously defined.

3.6. Normalised Green–Red Difference Index (NGRDI)

The Normalised Green–Red Difference Index (*NGRDI*) was proposed by Hunt et al. (2005) and tested on digital photograph of crops such as corn, alfalfa, and soybeans, which were captured by a digital camera mounted on the bottom of an aircraft fuselage. The method of *NGRDI* was used to overcome the differences in exposure settings selected by the digital camera when acquiring aerial photography of the field. These differences may cause large differences in colour bands that have the same reflectance. The formula for *NGRDI* is as follows:

$$NGRDI = \frac{(G - R)}{(G + R)} \tag{11}$$

The $G - R$ component is used to discriminate between green plants and soil, and $G + R$ is used to normalise for variations in light intensity between different images.

3.7. Vegetative Index (VEG)

This was proposed by Hague et al. (2006) to separate plant (cereal and weeds) pixels from soil pixels. The study was conducted under field conditions, and the image was captured by a CCD camera. To achieve segmentation, an RGB image was converted to greyscale by using the following formula:

$$VEG = \frac{G}{R^a B^{(1-a)}} \tag{12}$$

where a is a constant value equal to 0.667. Hague found that this transformation demonstrated good contrast between plant and soil. In addition, the *VEG* has a significant advantage because it is robust to lighting change.

3.8. Combined Indices 1 (COM1)

Guijarro et al. (2011) selected four greens indices, *ExG, CIVE, ExGR*, and *VEG*. These methods were applied simultaneously rather than individually to improve segmentation quality:

$$COM1 = ExG + CIVE + ExGR + VEG \tag{13}$$

Guijarro showed that the combined method demonstrated better results than when the approaches were applied separately. The method has been tested in barley and corn fields and demonstrated high reliability under various illumination conditions in outdoor environments.

3.9. Modified Excess Green Index (MExG)

Modified Excess Green (*MExG*) Index was developed by Burgos-Artizzu et al. (2011) and is defined as follows:

$$MExG = 1.262G - 0.884R - 0.311B \tag{14}$$

Burgos-Artizzu conducted experiments under uncontrolled lighting in real time. The proposed method successfully converted the colour image into greyscale image, which was very easy to binarise with a fast automatic threshold method. The discrimination between plant and soil region was effective because the *MExG* method was very robust to the changing illumination conditions. Burgos-Artizzu found that *MExG* method demonstrated better segmentation results then *ExG*.

3.10. Combined Indices 2 (COM2)

This was introduced by Guerrero et al. (2012) for analysis of maize plants, and is quite similar to *COM1* in the combination of three colour Indices: *ExG*, *CIVE*, and *VEG*; *ExGR* was excluded because it classified the shadow of the maize plant as part of plant. Normalised Difference Index was also excluded because it may segment soil regions as plant. The contribution of each selected method is controlled by a weighting factor, with the weights summing to 1. The combined method is defined as follows:

$$COM2 = 0.36ExG + 0.47CIVE + 0.17VEG \tag{15}$$

4. Evaluation of plant extraction based on colour indices

Segmentation-based colour indices have been widely used as a benchmark by other researchers to evaluate the performance of

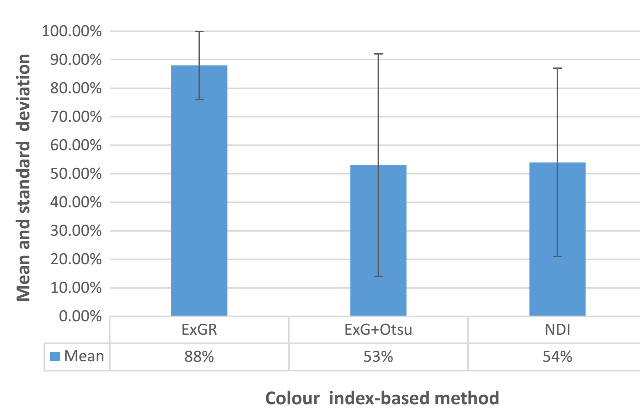

Fig. 2. Comparison of the performance of selected colour indices: *ExGR*, *ExG* + Otsu, and *NDI* – Otsu under greenhouse conditions. SD is indicted by error bar in the plot (Meyer and Camargo-Neto, 2008). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

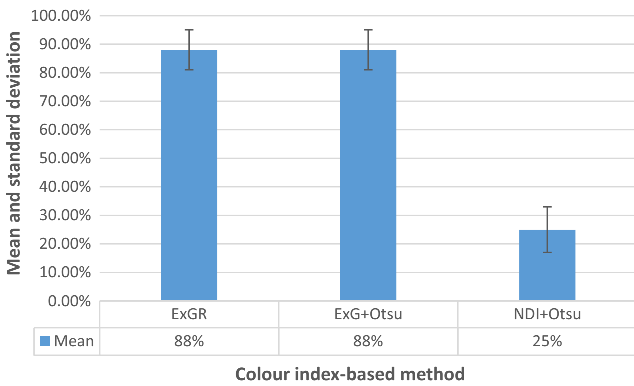

Fig. 3. Comparison of the performance of selected colour indices: *ExGR*, *ExG* + Otsu, and *NDI* + Otsu under actual field conditions. SD is indicted by error bar in the plot (Meyer and Camargo-Neto, 2008). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

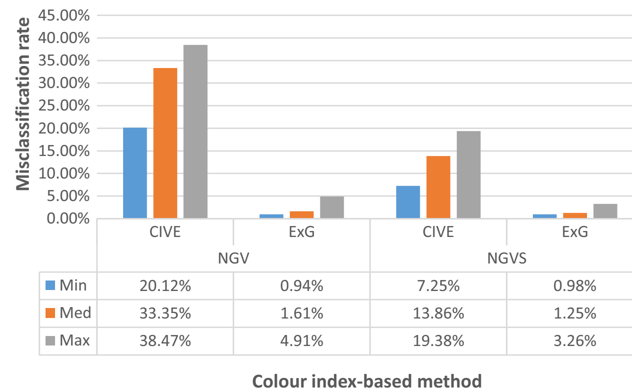

Fig. 5. Comparison of mis-classification of *CIVE* and *ExG* for both image types (NGV & NGVS) (Zheng et al., 2009).

their proposal methods for improving plant segmentation quality against various lighting conditions and complex background. This section draws together various recent studies that have used colour-index based methods, and in particular, focuses on the comparative performance of these methods. The discussion is constrained by the selection of colour indices that have been selected by the authors of the different studies considered; however, all of the colour index methods have been evaluated in at least one study.

In previous studies, evaluation has generally been done by calculating the mean and standard deviation of an appropriately defined segmentation quality factor. A high mean value and low standard deviation of segmentation quality factor corresponds to high demonstrated segmentation performance; a value of 1 for the mean, and 0 for standard deviation represents perfect plant segmentation. Meyer and Camargo-Neto (2008) compared three green indices, namely, Excess Green minus Excess Red Index (*ExGR*), Excess Green Index (*ExG*), and Normalised Difference Index (*NDI*). The segmentation quality has been tested and compared for both greenhouse and actual field of soybean images. In addition, various backgrounds (bare soil, corn stalks, and wheat residue) were considered. The segmentation quality for each applied method was evaluated according to the approach described in Bhanu and Jones (1993). The input parameters of the evaluation method are two different binary images: one is extracted manually using Photoshop as the annotated "gold standard", and other extracted by the colour index-based method under evaluation. Thus, the evaluation method measures the segmentation accuracy based on how similar the segmented image is to the annotated image and gives the result as ratio of correct classification of pixels. The greenhouse sets were analysed using *ExGR* with a fixed threshold of zero, *NDI* with a threshold of zero, and *EXG* with threshold calculated according to Otsu's method (Otsu, 1979). The field images were examined with *ExGR* with a threshold of zero, *NDI* with an Otsu threshold, and *ExG* with an Otsu threshold.

The mean and standard deviation of the quality factor for the colour indices considered for green house and field sets are shown in Figs. 2 and 3 respectively.

From Fig. 2, it can be seen that *ExGR* with zero threshold presented the best segmentation performance, with mean quality factor of almost 90% with low standard deviation, while the segmentation quality for *ExG* + Otsu and *NDI* – Otsu were quite similar, around 50%. According to the results in Fig. 3, the performance for *ExGR* and *ExG* + Otsu were similar at approximately 90%, while *NDI* + Otsu has the lowest performance.

Overall, *ExGR* demonstrated very good segmentation quality for the images that were taken under different environments (green house and field conditions), with various backgrounds. In addition, *ExGR* was superior in plant separation over the *ExG* and *NDI*. *ExG* also performed well in segmentation of plants in field conditions. *NDI* gave the lowest accuracy.

Zheng et al. (2009) proposed an algorithm using a Mean-Shift method and Back Propagation Neural Network (MS-BPNN) to improve the segmentation quality of plant. To assess the performance of the algorithm, two index-based methods (*ExG* and *CIVE*) were used as a benchmark. The study was conducted in outdoor environments, including variety of plant species, different

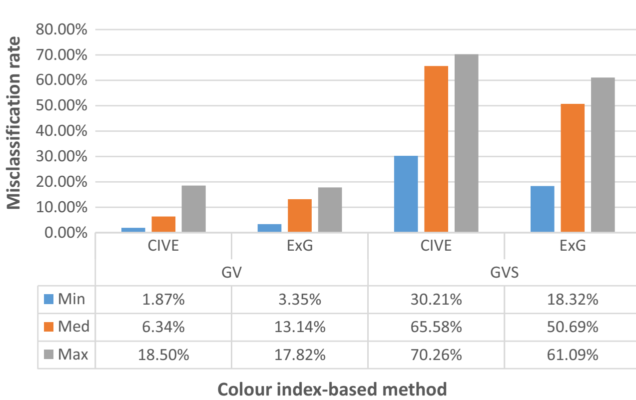

Fig. 4. Comparison of mis-classification of *CIVE* and *ExG* for GV and GVS image types (Zheng et al., 2009).

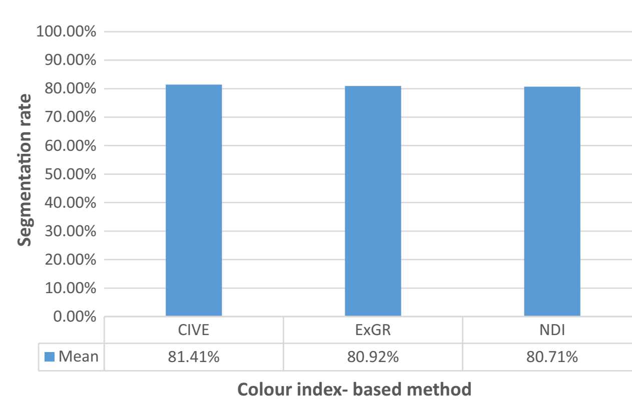

Fig. 6. The average segmentation quality for *CIVE*, *ExGR*, and *NDI* (Zheng et al., 2010).

illuminations, and different soil types. Before evaluating the segmentation performance, each region in the test image of size 2×2 pixels was labelled by hand with '1' for green region and '0' for background and then compared that with segmented image. The segmentation performance was assessed based on the mis-segmentation rate for green and background region, in particular the minimum (Min), median (Med), and maximum (Max) values were evaluated. Moreover, the mean running time per image (T) was used to evaluate the speed of MS-BPNN method. Four different image types were tested, including: green vegetation with shadow (GVS), green vegetation without shadow (GV), non-green vegetation with shadow (NGVS), and non-green vegetation without shadow (NGV).

For GV and GVS images, the MS-BPNN method gave the lowest Min, Med, and Max of mis-segmentation for GV: 0.19%, 2.53%, and 5.34%, respectively, and for GVS: 15.72%, 18.23%, and 34.13% respectively. Of interest here are the performance figures for *CIVE* and *ExG* shown in Fig. 4.

CIVE has lower mis-segmentation rate for GV images than *ExG*. Both *ExG* and *CIVE* based have very high mis-segmentation rate for GVS images. In general, *ExG* is more accurate for extracting plants with shadow than *CIVE*. For NGV images, the MS-BPNN method gives values of Min, Med and Max of mis-segmentation of 2.12%, 3.81%, and 5.26% respectively. These values are higher than those for NGVS, where the algorithm gives values of 0.12%, 1.28%, and 4.93%. Again, what is of interest here is the performance for the colour indices considered; the mis-classification performance for *CIVE* and *ExG* for NGV and NGVS images is shown in Fig. 5.

ExG demonstrated good segmentation results for NGVS images, whereas the *CIVE* exhibited poorer performance. In addition, *ExG* has shown lower mis-segmentation rate for NGV than the proposed MS-BPNN method.

Of further interest is the fact that although Zheng's proposed method demonstrated better segmentation performance overall than both *ExG* and *CIVE*, it gave the longest average computing time for both types of tested images, which were: 91.9 s and 10.8 s. By comparing the mean running time for colour index-based methods, *ExG* was given slightly lesser than *CIVE* for both types of tested images: (3.8 s and 0.5 s), (3.9 s and 0.6 s) respectively.

Zheng et al. (2010) introduced another method to improve the quality of crop image segmentation. The proposed method was based on the combination of two methods: one based on Mean Shift (MS) and another based on Fisher Linear Discriminant (FLD). The images that were used in the study were taken from different soybean fields, under actual field conditions, and at different times of day. As a benchmark, three colour index-based methods (*NDI*, *ExGR*, and *CIVE*) were compared with MS-FLD method to evaluate its performance. The method of Otsu was used to determine a threshold for use with all colour indices images for binarisation. In addition, an averaging filter was used to remove noise. To evaluate the performance of the MS-FLD method and the three colour index-based methods, each of the test images is labelled manually with '1' (white) for the green region, and with '0' (black) for background region. The study has shown that MS-FLD obtained the highest average segmentation rate, at 97.98%. The performance of the colour index methods (in terms of average value of correct segmentation rate) are presented in Fig. 6.

It can be seen that all three colour indices performed well, and average performance is quite high at approximately 80%. However, according to Zheng, the colour index-based methods were not stable for all tested images; some resulting images showed that *NDI* and *CIVE* gave better segmentation than *ExGR*, whereas others showed that *ExGR* produced better segmentation than *NDI* and *CIVE*.

Again, it is of interest to compare the computation time of the MS-FLD method with the simpler colour-index methods. While MS-FLD demonstrated better segmentation performance than colour index-based methods, its average running time was higher than that obtained by vegetation index-based methods: 3.3906 s and 0.0156 s (averaged over the three colour indices), respectively.

Guijarro et al. (2011) tested four green colour indices (*ExG*, *CIVE*, *ExGR*, and *VEG*) individually and simultaneously (using the *COM1* combined index described above) to assess their performance for better automatic segmentation of plant. As noted earlier, the study by Guijarro found that when used individually, these indices may create either over-segmentation or under-segmentation results; when combined through *COM1*, these problems can be overcome. The study was conducted in barley and corn fields under various illumination conditions. Two scenes were taken into account: one scenes contained plants and soil without sky and another one contained plants, soil, and sky. The combination method was proposed to increase the contrast between plant and soil, so the probability of distinguishing between plant and background image is increased. In order to accomplish this goal, the contrast was measured based on the grey level histogram (minimum uniformity). The uniformity was computed for each green image (U_{G_K}), and the weight was obtained for each one (W_{G_K}), where k = {*ExG*, *CIVE*, *ExGR*, *VEG*}. Besides, the combined greenness (G) was computed and the mean threshold was chosen instead of the Otsu threshold to separate the plant region from the background. The average error in pixel classification for segmentation of green areas for each colour index based method is displayed in Fig. 7.

The results of this study showed that the combination method (*COM1*) provided the lowest percentage of average error for

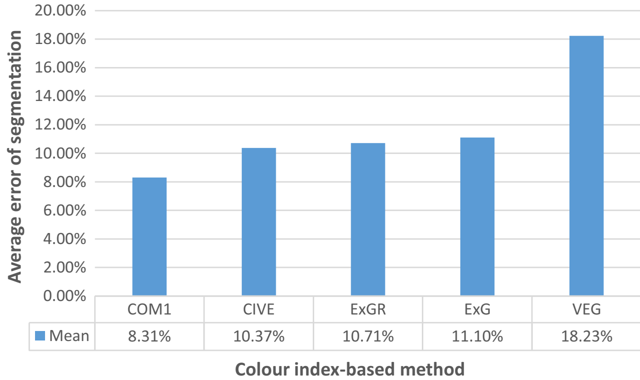

Fig. 7. Comparison of average error of greenness segmentation for *COM1*, *CIVE*, *ExGR*, *ExG*, and *VEG* (Guijarro et al., 2011).

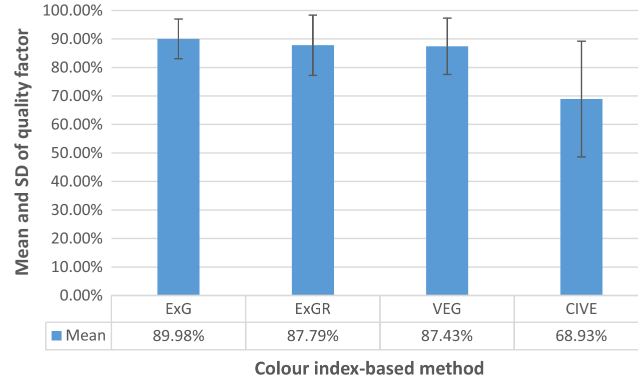

Fig. 8. Comparison of the mean and standard deviation of vegetation extraction for *ExG*, *ExGR*, *VEG*, and *CIVE*. SD is indicted by error bar in the plot (Yu et al., 2013a).

greenness segmentation, whereas *VEG* showed the highest. Each of *CIVE*, *ExGR*, and *ExG* method gave similar values of average error.

Guijarro calculated the average weight of the four selected indexes over the set of the 240 images to find out their contributions to the average percentage error. The average weights were given: 0.12, 0.25, 0.30, and 0.33 for $W_{G_{VEG}}$, $W_{G_{ExG}}$, $W_{G_{ExGR}}$, and $W_{G_{CIVE}}$ respectively. He found that there was a reverse correlation between the obtained average weights and the percentage of error for greenness. For example, *CIVE* has given the highest average weight (0.33) and resulted in the lowest average percentage error over the others, whereas *VEG* has given the lowest average weight (0.12) and caused the highest percentage error over the other methods.

In conclusion, if the colour indices are applied simultaneously, they produce better greenness segmentation quality rather than when they are applied separately. *CIVE*'s contribution to the combined method is greater than any other method while *VEG* was the lowest. Both of *ExG* and *ExGR* have nearly the same contribution.

There were one primary disadvantage associated with the combined method, which was increased computational time.

Yu et al. (2013a) proposed a new method for crop segmentation based on colour segmentation called Affinity Propagation-Hue Intensity (AP-HI). Five other algorithms were compared with it to judge its performance. Among these, three colour index methods, namely, *ExG*, *CIVE*, *ExGR* were used with Otsu threshold and a fourth (*VEG*) was used with mean threshold method. The fifth method was a supervised learning algorithm called Environmentally Adaptive Segmentation Algorithm (EASA) (Tian and Slaughter, 1998). Two experiments were carried out in two maize fields in China under different circumstances to identify the growth stages of maize. The image samples were acquired under various illumination conditions such as overcast, cloudy, and sunny days. Difficult backgrounds such as shadow, straws, pipes, and other equipment were included. The efficiency of each algorithm was evaluated through computing the mean and standard deviation (SD) of the quality factor defined in Xiao et al. (2011), based on mis-classification error.

The results of the study have shown that AP-HI gave the highest performance, at 96.68%. The performance of EASA was in second place; it outperformed the colour index-based algorithms with mean of plant extraction equal to 93.20%. The performance of colour index approaches can be seen in Fig. 8.

It can be seen that *ExG* demonstrated the highest mean of greenness segmentation over the reminder of selected colour indexes, whereas *CIVE* has shown the lowest at 68.9%. *ExGR* and *VEG* showed similar performance.

Fig. 10. Comparison of the segmentation quality (Q_{seg} & S_r) of plant extraction for *ExGR*, *MExG*, and *ExG* for two different data sets under sunny conditions (Guo et al., 2013).

In conclusion, all colour indices demonstrated good adaptability in conditions of changing illumination (up to a certain degree of illumination) and complex environments, however *CIVE* did not perform as well as the other indices.

The AP-HI method was in dealing with various environment conditions and complex background up to certain degrees. However, this method has limitations especially during day light where some surfaces of the maize leaves acted like mirrors and reflected light.

Guo et al. (2013) introduced a new approach called Decision Tree based Segmentation Model (DTSM) for effective segmentation of vegetation from plant images. The study was conducted in wheat fields in Japan and the test images were taken under various light conditions. Three colour indices (*ExG*, *MExG*, and *ExGR*) were used as a benchmark to evaluate the performance of the proposed method. The accuracy of the segmentation methods is assessed by the same method that used in Meyer and Camargo-Neto (2008). Moreover, two tasks of segmentation quality were adopted in the study: one was based on the both plants and background regions (include plant pixels or background pixels) which was denoted as Q_{seg} and another was based only on the plant region (including only plant pixels) and was denoted as S_r. The training process was carried out based on acquired images which were taken over a period of two years under different illumination conditions (sunny and non-sunny) in 2011 and in 2012 (henceforth referred to as Data-2011 and Data-2012). Otsu's method was used with *ExG* and *ExGR* images for thresholding, while a zero threshold was applied with *MExG*.

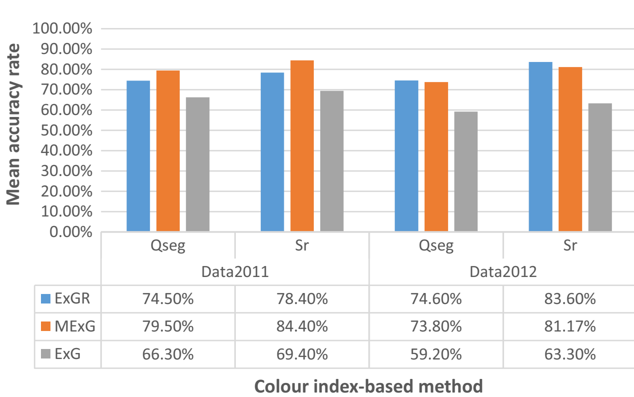

Fig. 9. Comparison of the segmentation quality (Q_{seg} & S_r) of plant extraction for *ExGR*, *MExG*, and *ExG* for two different data sets under non-sunny conditions (Guo et al., 2013).

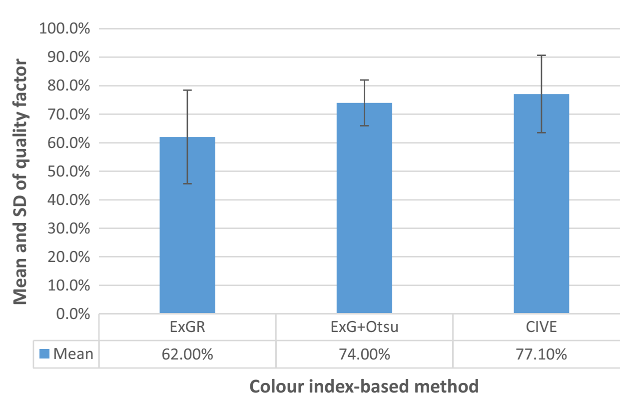

Fig. 11. Comparison of the mean and standard deviation of segmentation for *ExGR*, *ExG* + Otsu, and *CIVE* based on ATRWG metric. SD is indicted by error bar in the plot (Bai et al., 2013).

DTSM outperformed the three colour indices on segmentation quality. The mean value of Q_{seg} was 80.6% for the Data-2011 data set and 76.7% for the Data-2012 data set. In addition, DTSM gave the best mean of green segmentation quality (S_r) compare to the colour indices methods, with 83.3% for Data-2011 and 83.1% for Data-2012. The Q_{seg} and S_r for applied colour indices under non-sunny and sunny conditions are presented in Figs. 9 and 10 respectively.

According to the results presented in Fig. 9, the means of Q_{seg} and S_r for *ExGR* for the Data-2012 set are slightly higher than those of *MExG*, whereas the means of Q_{seg} and S_r of *MExG* were higher than those of *ExGR* for the Data-2011 data set. The *ExG* method produced the lowest segmentation quality (Q_{seg} & S_r) compared to *ExGR* and *MExG* in both years.

According to the results presented in Fig. 10, the means of Q_{seg} and S_r for *ExGR* in both data sets under sunny condition were higher than the other colour indices.

In conclusion, the three colour indices considered have better segmentation qualities for S_r than Q_{seg} under both conditions. Comparing the results in Fig. 9 to those of in Fig. 10, the colour indices performed better quality segmentation under non-sunny conditions than under sunny conditions. This suggests that colour index methods may in general perform more poorly under sunny conditions. The advantage of the DTSM algorithm proposed on Guo et al. (2013) is that no threshold adjustments are required for plant segmentation, unlike colour index methods. However, a disadvantage of DTSM is that it relies on training data.

Bai et al. (2013) introduced a new method for crop segmentation based on the CIE Lab colour space, using morphological modelling. The study was conducted in a rice paddy field in China, and the images were taken under various conditions for different growth status of rice plant. To verify the robustness of crop segmentation using the method under complex illumination, it was compared with six plant segmentation methods that included: three colour index based- methods (*ExG* with Otsu threshold, *ExGR*, and *CIVE*); Environmentally Adaptive Segmentation Algorithm (EASA) (Tian and Slaughter, 1998); colour image segmentation method using Genetic Algorithm with HSI colour space (GAHSI) (Abbasgholipour et al., 2011); and colour image segmentation method based on Affinity Propagation-Hue Intensity (AP-HI) (Yu et al., 2013a). Two well-known skin segmentation methods (segmenting colour pixels as either skin or non-skin classes) were also applied: Gaussian Mixture Modeling (GMM) (Bergasa et al., 2000; Jones and Rehg, 2002) and the Hue–Saturation–Intensity and B-Spline curve fitting method (HSI&B-Spline) (Kim et al., 2008). Two approaches were used to measure the segmentation quality

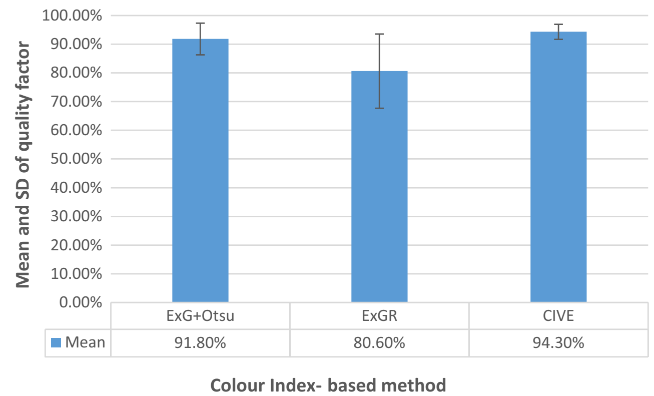

Fig. 13. Comparison of the mean and standard deviation of segmentation for *ExGR*, *ExG* + Otsu, and *CIVE* based on evaluated method which is defined in Xiao et al. (2011). SD is indicted by error bar in the plot (Bai et al., 2013).

for the applied methods: one defined by ATRWG (Neto, 2004) and other is given as in Xiao et al. (2011).

The segmentation performance for the referred methods was evaluated in three ways. Firstly, the tested image were taken under different light conditions and used ATRWG metric to measure the performance. The study showed that Bai's algorithm demonstrated the highest segmentation performance, with mean value of 87.2%, and standard deviation of 3.8%. The second highest performance of segmentation quality was given by GMM method with mean of 83.9%, and standard deviation of 7.2%. The performance of the three colour indices considered is shown in Fig. 11.

It can be seen that *CIVE* demonstrated the highest mean for segmentation quality whereas *ExGR* gave the lowest mean of segmentation quality. The method of *ExG* & Otsu also demonstrated good segmentation quality.

Secondly, the test images were sorted based on their imaging conditions; cloudy, overcast, and sunny. Each of set images was evaluated separately by using ATRWG metric. The experiment showed that Bai's method also gave better segmentation quality under different sky conditions than the other methods with mean of segmentation quality of 85.7%, 86.0%, and 88.6% for cloudy, overcast, and sunny conditions, respectively. The segmentation quality performance for *ExGR*, *ExG*, and *CIVE* are displayed in Fig. 12.

As can be seen from above figure, the best overall segmentation quality under the three conditions was obtained by *CIVE*, whereas the worst was obtained by *ExGR*. The *ExG* method demonstrated reasonably good segmentation quality under all three conditions.

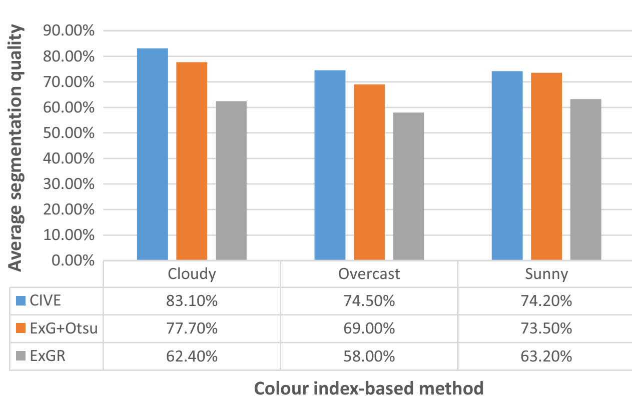

Fig. 12. Comparison of the mean plant extraction for *ExGR*, *ExG* + Otsu threshold, and *CIVE* under cloudy, overcast, and sunny conditions based on ATRWG metric (Bai et al., 2013).

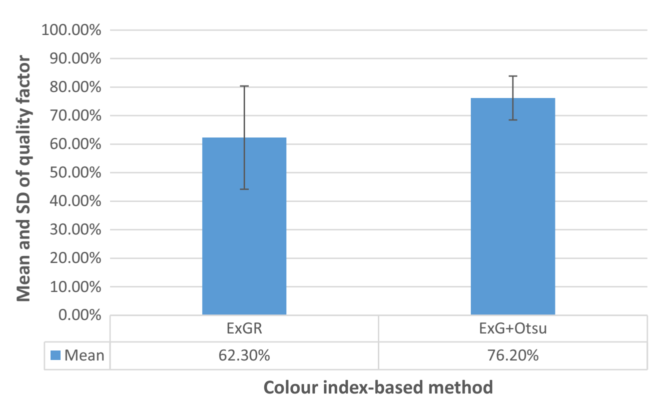

Fig. 14. Comparison of mean and standard deviation of plant extraction for *ExGR* and *ExG* + Otsu. SD is indicted by error bar in the plot (Bai et al., 2014).

Thirdly, the test images were taken under different lighting conditions and the method defined in Xiao et al. (2011) was used to measure performance. In this evaluation, the proposed method improved the mean of segmentation quality and reached up to 96.0% with standard deviation of only 1.5%.

The EASA, GAHSI, AP-HI, GMM, and HIS&B-spline gave mean of segmentation qualities as: 93.9%, 92.4%, 92.5%, 95.2%, and 87.7% respectively. The performance of the three colour indices considered is shown in Fig. 13.

It can be seen that *CIVE* demonstrated the highest mean for segmentation quality among applied colour indexes; *CIVE* also gave better performance that the other methods such as EASA, GAHSI, AP-HI, and HIS&B-spline. *ExGR* gave the lowest mean of segmentation quality. The method of *ExG* with Otsu threshold also demonstrated very good segmentation quality, at 91.80%.

Bai et al. (2014) proposed a new plant segmentation approach based on Lab colour space and a clustering method, namely, Particle Swarm Optimization (PSO) based *k*-mean. The images that were used in the study were captured under real conditions, in rice and cotton fields. Three segmentation approaches (*ExG* and Otsu, *ExGR*, and EASA) were used for benchmark purposes. Also, two methods that had been previously applied for segmenting human skin (GMM and ColourHist) were applied to assess the performance of the Bai's method. The ATRWG method was applied to evaluate the quality of segmentation for each segmented image, and means and standard deviations of the segmentation accuracies were calculated. According to results of the study, Bai's method obtained the highest performance of segmentation quality over the others, achieving 88.1% for the mean and 4.7% for standard deviation.

The method of GMM demonstrated very good performance close to Bai's method, with mean of 86.9% and standard deviation of 6.9%. The method of ColourHist demonstrated good performance, 82.1% for the mean and 6.4% for standard deviation.

The method of EASA provided also good segmentation results, with mean of 80.2% and standard deviation of 7.8%. For the two colour index methods considered, *ExGR* and *ExG* with Otsu threshold, the means and standard deviations of are shown in Fig. 14.

As it can be seen from Fig. 14, *ExG* with Otsu threshold demonstrated higher mean of segmentation quality than *ExGR*.

The performance of colour index-based methods was poorer than the other algorithms in the study. Bai et al. suggested this poor performance was because *ExGR* and *ExG* with Otsu threshold usually resulted in over-segmentation or under-segmentation. A disadvantage of Bai's method is that it requires a number of processing steps, which may affect real time application.

Torres-Sánchez et al. (2014) measured the accuracy of vegetation fraction (VF) mapping for wheat fields at different numbers of growing days after sowing from 35 to 75. The images of the fields were taken by a camera mounted on a UAV at different flight altitudes (30 m, 60 m). Six colour indices (*ExG*, *ExGR*, *CIVE*, Woebbecke Index as given in Eq. (4) (Woebbecke et al., 1995), *NGRDI*, *VEG*, and two combined colour indices, *COM1* (Guijarro et al., 2011) and *COM2* (Guerrero et al., 2012), were applied to evaluate the VF mapping. The VF is the percentage of pixels classified as vegetation in a given area. The mean accuracy (*A*) and standard deviation (SD) were calculated for every index based on three factors: threshold, flight date, and altitude. In addition, the coefficient of variation was calculated to get the best average accuracies of every vegetation index along the six tested flight dates. According to the results of the study, the highest mean accuracy was obtained from the images that were captured at 30 m flight altitude, so only results obtained at that altitude are considered here. The mean and standard deviation of all colour indices are shown in Fig. 15.

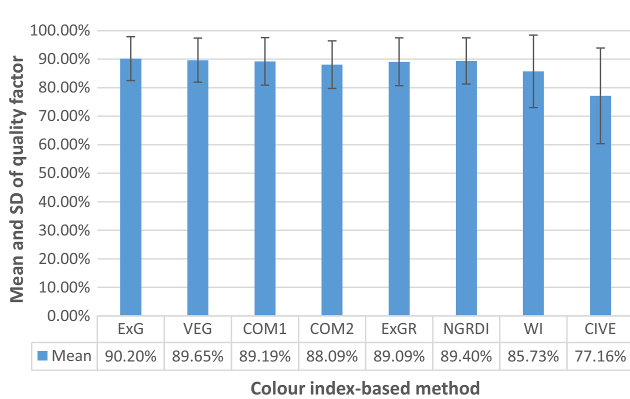

Fig. 15. Comparison of the mean and standard deviation of plant extraction for *ExG*, *VEG*, *COM1*, *COM2*, *ExGR*, *NGRD*, *WI*, and *CIVE* of images were captured at 30 m flight altitude (Torres-Sánchez et al., 2014).

ExG gave the highest mean accuracy over the other Vegetation Index (VI) methods, at 90.20%, however, most of the other indices gave quite similar levels of performance. *CIVE* has the lowest mean accuracy over the other VI methods, at 77.16%.

Ye et al. (2015) introduced a novel method to improve the quality of crop image extraction under strong illumination conditions such as shadow and highlighted region due to sunshine. Ye suggested reasons for misclassification of crop extraction under a variety of illumination such as cloudy, sunny, and over-sunny weather. In cloudy weather, there are two factors that cause classifying of soil pixels as crop. One is the reduction in the red component in the image because of lack of illumination, the other one is that the colour of soil is close to dark green. In sunny weather, shadows generated depending on the relative position of the sun and the object cause classification of shadow pixels as plant pixels. In over-sunny weather, the dense sunshine produces specular reflection (white light spots) in the leaf or soil. This leads to mis-classifying of those pixels. Ye proposed a segmentation method based on Probabilistic Superpixel Markov Random Field (PFMRF). This was based on the assumption that colour gradually changes of hue intensity between highlighted areas of crops and neighbouring non-highlighted areas.

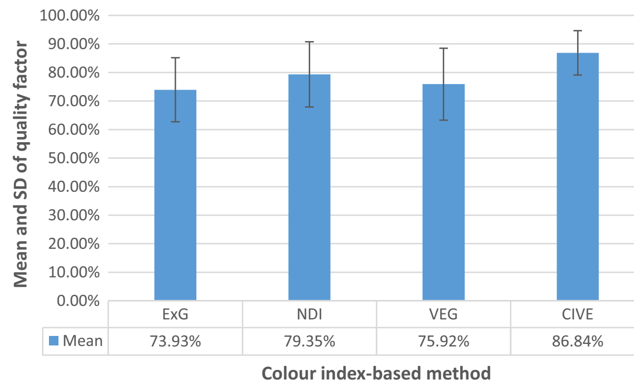

Fig. 16. Comparison of mean and standard deviation of crop extraction for *ExG*, *NDI*, *VEG*, and *CIVE*. SD is indicted by error bar in the plot (Ye et al., 2015).

The images that were used in the experiment were taken from two different crops (cotton and corn) at different stages of growth, under actual field conditions including on dark and bright days. To evaluate the performance of the PFMRF method, seven common algorithms were selected for comparison. Among them, four colour index-based methods (*ExG*, *NDI*, *VEG*, and *CIVE*) were applied. In addition, two learning-based segmentation methods (EASA and HI-AP) were applied. Hue Intensity and Probabilistic Super-Pixel Markov Random Field (HI-MRF) proposed by Yu et al. (2013b)

Table 1
Comparison of plant segmentation methods based colour indices.

Author	Method	Description	Advantages	Disadvantages
Woebbecke et al. (1992)	*NDI*	Normalised Difference Index	(1) Easy to compute (2) Somewhat robust to lighting, except for extreme values	(1) Does not perform well when the light is very high or very low (2) Many false positives
Woebbecke et al. (1995)	*ExG*	Excess Green Index	(1) Easy to compute (2) Widely used (3) Low sensitivity to background errors and lighting conditions (4) Showed good adaptability in outdoor environment	(1) Does not perform well when the light is high or low
Meyer et al. (1998)	*ExR*	Excess Red Index	(1) Easy to compute (2) Although it relies only on red component, it still extracts green pixels (3) Segment soil texture	(1) Does not perform well when the light is high or low (2) It is not as accurate as *ExG*
Kataoka et al. (2003)	*CIVE*	Colour Index of Vegetation Extraction	(1) Low running time (2) Showed good adaptability in outdoor environment	(1) Performs poorly when light is weak or strong (2) Has poor adaptability with shadow
Neto (2004)	*ExGR*	Excess Green minus Excess Red Index	(1) Showed good adaptability in outdoor environments (2) Can do two tasks: extracting green by *ExG* and eliminating background noise by *ExR*	(1) Does not perform well when the light is high or low (2) Segments the pixel of shadow as plants (over-segmentation)
Hunt et al. (2005)	*NGRDI*	Normalised Green–Red Difference Index	(1) Reduces the differences in exposure settings selected by the digital camera (2) Consists of two components (8): one is used to discriminate between green plants and soil, and other is used to normalise for variations in light intensity between different images	(1) Does not perform well when the light is high or low (2) Limited use
Hague et al. (2006)	*VEG*	Vegetative Index	(1) Invariant to the colour temperature of a black body illuminant (2) Insensitive to the amplitude of the illumination (3) Requires a single threshold	(1) Does not perform well when the light is high or low. Complex to implement
Guijarro et al. (2011)	*COM1*	Combined *ExG*, *ExGR*, *CIVE*, and *VEG* indexes	(1) Showed very good adaptability in outdoor environment	(1) Increase of computational time (2) Does not perform well when the light is high or low (3) Segments shadow as part of plant because of *CIVE*
Burgos-Artizzu et al. (2011)	*MExG*	Modified Excess Green Index	(1) Showed very good adaptability in outdoor environment	(1) Does not perform well when the light is high or low
Guerrero et al. (2012)	*COM2*	Combined *ExG*, *CIVE*, and *VEG* indexes	(1) Showed very good adaptability in outdoor environment	(1) Increased computational time, but less than *COM1* (2) Does not perform well when the light is high or low

was also applied. A performance measure (λ) (Xiang and Tian, 2011) based on the misclassification error was used.

The results of the study showed that the proposed PFMRF method gave the highest performance over all applied algorithms, with mean of 92.29%, and with the lowest SD, at 4.65%. The performance of HI-AP was in second place, at 88.52%, while the performance of EASA was almost the same, at 88.42%. The performance of HI-MRF was also high, at 87.74%. The performance of the four colour index-based methods can be seen in Fig. 16.

As it can be seen from Fig. 16, *CIVE* demonstrated the best performance among colour index-based methods, at 86.8%, whereas *ExG* showed the lowest. Both *NDI* and *VEG* demonstrated good performance. All colour index-based methods demonstrated good adaptability in light changing, but failed when shadow and highlight conditions occur.

A summary of the established colour index-based segmentation methods, highlighting their primary advantages and disadvantages, is presented in Table 1.

5. Other segmentation approaches

The previous two sections have considered colour index-based segmentation methods in some detail, including their performance. This section briefly discusses some of the other segmentation approaches that have been recently proposed, in particular based on thresholding, and machine learning.

5.1. Threshold-based approaches

Threshold techniques that are applied in plant/weed detection based on image segmentation have generally assumed a two class problem, namely, plant vegetation class and soil background class. Thresholding is generally applied to a transformation of the original image in order to determine the class; for example, many of the colour-index based approaches considered earlier used either zero threshold or a threshold based on Otsu's method. However, other more sophisticated approaches for threshold selection exist. Choosing the proper threshold plays an important role in segmentation. For example, if the threshold value is set too high, some important regions (plant pixels) may be merged with other regions (background pixels) which leads to under-segmentation, while a low threshold that is set too low may lead to over-segmentation. Thus, numerous researchers have applied different threshold technique to address these problems. These techniques are given as follows. Dynamic thresholding was applied in Reid and Searcy (1987). Hysteresis thresholding was applied in Marchant et al. (1998). Fixed threshold is also a technique which was utilised in many studies such as Hemming and Rath (2001) and Aitkenhead et al. (2003). Tellaeche et al. (2008) applied entropy of a histogram to

Table 2
Comparison of threshold based segmentation methods.

Author	Method	Description	Advantages	Disadvantages
Reid and Searcy (1987)	Dynamic threshold	Thresholds are dynamically set according to local rather than global characteristics. The approach is to partition the image into sub-images of size $m \times m$ pixels, and then choose a threshold for each sub-image	(1) Insensitive to shading or gradually changing illumination	(1) Increase in computation time since it requires several steps
Marchant et al. (1998)	Hysteresis threshold	Includes two thresholds, high and low. This leads to the creation of 3 classes: below low threshold (to be removed), above high threshold (to be retained), and between low and high thresholds (to be retained only if connected to a pixel above high threshold)	(1) Effective in handling overlap between the modes in the histogram of an image	(1) Various morphological operations were required to improve the segmentation, increasing computation
Hemming and Rath (2001) and Aitkenhead et al. (2003)	Fixed threshold	Empirical threshold selection	(1) Simple	(1) Sensitive to light changes
Tellaeche et al. (2008)	Entropy of a histogram	Can be chosen through the peaks of grey-level histogram of an image	(1) Easy to choose a threshold value when grey-level histograms are bimodal (plant and soil)	(1) It is hard to choose a threshold value when the peaks vary significantly in size and the distance between modes is relatively large
Otsu (1979)	Otsu threshold	Based on finding the threshold that minimises the weighted within-class variance	(1) Automatic method (2) Widely used	(1) Can produce under-segmentation, i.e. some green pixels were not identified in some circumstances (2) Slower than the mean intensity method
Gebhardt et al. (2006) and Gebhardt and Kaühbauch (2007)	Homogeneity threshold	Local homogeneity is calculated for an image pixel and used to obtain a homogeneity threshold value to derive binary images	(1) Helpful in recognising small objects (2) Since local information is considered, may be useful to address light changes	(1) Increase in computation time since it requires several steps
Kirk et al. (2009)	Automatic threshold	The threshold value is selected based on Gaussian distribution functions of intensities; the Gaussian distribution with the lower mean represents the soil and the one with the higher mean represents plant vegetation	(1) Good in handling light changes (2) Automatic method	(1) Increase in computation time since it requires several steps
Jeon et al. (2011)	Automatic threshold	The threshold value is determined by dividing the pixel distribution of the image into two groups by a pixel value ranging from 1 to 255. The pixel value that minimises the variance sum of two groups was used as the threshold value for each image	(1) Provides adaptive segmentation (2) Automatic method	(1) Requires threshold adjustment to update segmentation limit especially for high plant density (2) High computation time since it requires several steps

distinguish plant vegetation pixels from soil pixels. Otsu's method is a threshold technique widely used in many applications of image processing based-segmentation. According to a survey carried out by Sahoo et al. (1988) to compare the segmentation accuracy of nine threshold methods, Otsu's method demonstrated the highest accuracy value over the others. This has inspired numerous researchers to utilise it particularly in plant and weed segmentation. Otsu's method was applied by Ling and Ruzhitsky in (1996) to segment tomato seedlings from background. It was also applied in Shrestha et al. (2004) to separate the plant vegetation from the background; it was preferred to remove the noise pixels instead of using morphological dilation as it does not require as much computation as dilation operations. Gebhardt et al. (2006) and Gebhardt and Kaühbauch (2007) introduced an algorithm to segment weed leaves from grassland by converting RGB images into greyscale image intensity and then calculating local homogeneity images and obtaining a homogeneity threshold value to derive binary images. Finally, morphological opening was used to eliminate the remaining blades of grass in the binary images. Kirk et al. (2009) introduced a new algorithm for pixel classification (plant or soil pixels) to work under a variety of illuminations. The algorithm is based on greenness and intensity pixels, which are derived from the combination of *R* and *G* pixel values, and an automatic threshold was applied based on the assumption of two Gaussian distribution functions of intensities; the Gaussian distribution with the lower mean represented the soil distribution and the one with the higher mean represented plant vegetation distribution. Jeon et al. (2011) applied another threshold technique to automatically segment plant pixels from soil pixels based on transformed RGB image (nearly greyscale image).

Meyer and Camargo-Neto (2008) have examined the segmentation quality for some colour indices with using automatic Otsu threshold and zero threshold methods; in particular, *ExG* and *NDI* were tested with an Otsu threshold, and *ExGR* was tested with zero threshold. The results showed that the fixed zero threshold was sufficient for binarisation of *ExGR* images, so the Otsu's method was not required. Two different automatic threshold approaches were used and evaluated for vegetation segmentation in Guijarro et al. (2011): one was Otsu's method and the other was based on mean intensity. The results showed that the Otsu threshold produced under-segmentation, i.e. some green pixels were not identified. Besides, it was slower than the mean intensity method. Therefore, the automatic threshold adjustment approach (the mean intensity value) was adopted in the study as it produced fast and robust segmentation. On the other hand, the mean intensity value was not found suitable in Burgos-Artizzu et al. (2011) to binarise a grey image which was generated by the combined colour indexes, because its value was less than the threshold value received with Otsu method. Therefore, the combination of Otsu and a morphological operation were used instead. The advantages

Table 3
Comparison of learning based segmentation methods.

Reference	Method	Description	Colour model	Task	Advantages	Disadvantages
Tian and Slaughter (1998)	EASA	Environmentally Adaptive Segmentation Algorithm	RGB space	Detect plants	(1) Adapts to most daytime conditions in outdoor fields	(1) Only 45–66% of all the cotyledons were recognised under partially cloudy and overcast conditions (2) It requires sufficient training data to obtain good segmentation results
Meyer et al. (2004)	FC	Fuzzy Clustering	RGB space	Extract the plant region of interest from *ExG* and *ExR* images	(1) Identifying green plants from soil and residue	(1) When plant pixel coverage is less than 10% in the image, there apparently is not enough colour information to cluster them
Ruiz-Ruiz et al. (2009)	EASA	Environmentally Adaptive Segmentation Algorithm	Hue–saturation (*HS*) and only hue (*H*)	Plant image segmentation under complex field conditions	(1) Reduced the computation time (2) It is more robust to a variety of illumination than the EASA in Tian and Slaughter (1998)	(1) It is not effective to segment plants at early growing stage where the cotyledons start to appear
Zheng et al. (2009)	MS-BPNN	Mean-shift algorithm with Back Propagation Neural Network	RGB and HSI colour space	Classify between plant and non-plant region	(1) Demonstrate good segmentation performance under different illuminations	(1) It suffers from long run time (2) Suffers from low segmentation rate on the green parts with shadows
Zheng et al. (2010)	MS-FLD	Mean-shift algorithm with Fisher Linear Discriminant	LUV space	Separate green from non-green vegetation	(1) No longer suffers from the low segmentation rate on the green parts with shadows	(1) It suffers from long run time
Guerrero et al. (2012)	SVM	Support Vector Machines	RGB space	Classify between masked (soil and other materials) and unmasked (plants) plant regions	(1) The method is able to identify plants (weeds and crops) when they have been contaminated with materials coming from the soil, due to artificial irrigation or natural rainfall	(1) Relies on other steps (threshold)
Guo et al. (2013)	DTSM	Decision Tree based Segmentation Model	RGB space	Segment the vegetation form the background	(1) Addressing illumination problem such as shadow and specularly reflected regions (2) Not requiring a threshold adjustment for each image	(1) It relies on training data
Yu et al. (2013a)	AP-HI	Affinity Propagation-Hue Intensity	Hue–Intensity (*HI*) space	Separate the pixels of crop and background under light conditions and complex environment	(1) Robust and not sensitive to the challenging variation of outdoor luminosity and complex environmental elements	(1) Misclassifying highlighted region in leaves
Bai et al. (2013)	MM	Morphology Modelling	Lab colour space	Distinguishes the crop and background pixels under complex illumination conditions	(1) Robust to the variation of illumination in the field	(1) Despite utilizing different sizes of structure elements in the training phase, it did not give a significant improvement; the mean of segmentation qualities of MM was 87.2%
Bai et al. (2014)	PSO-MM	Particle Swarm Optimisation clustering and Morphology Modelling	Lab colour space	Distinguishes the crop and background pixels under complex illumination conditions	(1) Robust to variation of illumination in the field	(1) It suffers from long run time as it depends on many processing steps

and disadvantages of threshold based-approaches are summarised in Table 2.

5.2. Learning-based approaches

Although the colour-based approaches have demonstrated promising segmentation results, there are a few cases where it could not perform well particularly in sunny and overcast conditions. As a result, several studies have investigated more sophisticated approaches, including applied supervised and unsupervised machine learning approaches with simple transformation of colour features such as HIS, LUV, and LAB, or with colour index to extract the plant pixels from the background, and looked to improve the segmentation under variety of illumination conditions. For instance, Meyer et al. (2004) applied unsupervised learning approach called fuzzy clustering to extract the area of interest from *ExG* and *ExR* images. For supervised learning approaches, several researchers have also proposed several approaches. Tian and Slaughter (1998) proposed Environmentally Adaptive Segmentation Algorithm (EASA) and applied to normalised RGB images of outdoor fields to detect plants. Later, Ruiz-Ruiz et al. (2009) applied EASA with hue–saturation (*HS*) and only hue (*H*) instead of RGB colour space to produce robust and fast plant image segmentation under complex field conditions. Zheng et al. (2009) proposed a supervised mean-shift algorithm with Back Propagation Neural Network to classify images into plant and non-plant regions. The features used in the algorithm were RGB and HSI colour space. Zheng et al. (2010) applied a supervised mean-shift

Table 4
Suggested segmentation algorithms for use in different conditions.

Algorithms	Relative Complexity	Real-time performance	Accurate	Suitable application fields			Suggested algorithms
				Cloudy	Overcast	Sunny	
Colour index-based approach	Simple	Effective	Low accuracy if the light is strong or poor	Effective	Poor segmentation result	Poor segmentation result	– For cloudy day: *CIVE*, *COM1* – For overcast day: *CIVE*, *ExGR* – For sunny day: *COM2* or *ExG* because both are good for addressing shadow
Threshold-based approach	Fairly sample.	Somewhat effective	Fairly good accuracy	Effective	Threshold adjustments are required	Threshed adjustments are required	– For cloudy day: Otsu – For overcast and sunny days: Dynamic threshold or Homogeneity threshold
Learning-based approach	Complex	Expansive	High accuracy	Effective	Several training steps are required	Several training steps are required	– For cloudy day: EASA – For overcast day: AP-HI – For sunny day: DTSM because it is good in addressing problems such as shadow and specularly reflected regions

algorithm, but with Fisher Linear Discriminant to separate green from non-green plant; the colour space used in the algorithm was LUV instead of RGB and HSI. Support vector machines (SVM) have been applied as the learning method to classify between masked and unmasked plant regions by Guerrero et al. (2012). To address illumination problem such as shadow and specularly reflected regions, Guo et al. (2013) introduced a new method as learning approach based on decision tree model to segment plant region form the background in RGB images. The advantages and disadvantages of learning based-approaches are summarised in Table 3.

6. Discussion and conclusions

According to some of the studies considered above, colour index-based methods have some limitations: they may result in over-segmentation (excessive green) in one application and under-segmentation in another application, especially when a single index is applied by itself. This varies considerably with imaging conditions, and the fact that the same test data are not used in all studies makes direct comparison more difficult. Few comparative studies have been carried out using a common set of test data. One somewhat recent example was carried out by Meyer and Camargo-Neto (2008), to compare three green indices, namely, *ExGR*, *ExG*, and *NDI*. However, colour index-based methods have both advantages and disadvantages that can be summarised as follows:

Advantages:

- Simple methods that are easy to understand and implement.
- Easy to modify their formulas to create a new colour index.
- Generally do not require training.
- Generally require low computation which makes them suitable for real time use.
- They are effective in normal condition where the light is neither very high nor very low.
- Some of the colour index-based methods have shown results that are comparable to other more sophisticated methods e.g. see study by Bai et al. (2013).

Disadvantages:

- They require threshold optimisation to meet the particular target for final segmentation.
- They generally cannot perform good segmentation when the light is strong or poor.
- They are only suitable for segmentation where the dominant plant colour is green.

Threshold based-methods require several adjustments with different lighting conditions. Therefore, once change occurs, the segmentation error may increase. Moreover, some threshold techniques might be suitable for one case, but not for others.

The learning-based approaches demonstrated better performance over colour index-based methods under a variety of illumination conditions because they rely on a training phase, but this results increased computation time which is not preferable in real time applications. Moreover, in order to perform reliable segmentation results, substantial training samples are required.

While good segmentation performance has been achieved with the methods considered, several challenges remain:

- Lighting conditions: cloudy, overcast, and sunny conditions impact segmentation quality. For example, when the light is strong as on a sunny day, the surface of some leaf types such as corn leaf, acts as a mirror (specular reflection); as a result, it may be segmented into the wrong category.
- Shadow, including shadow caused by a plant itself or by other objects (cast shadow), may be extracted as foreground (plant vegetation); as a result, the mis-segmentation rate is increased.
- Complex background (scene of the image), including straws, stones, soil colour, water pipes, and other residues, can affect the segmentation quality particularly if a background element has a green colour such as green pipe; as a result, it might be mis-segmented as plant.

These factors still remain as serious challenges for the available segmentation approaches. Therefore, further research is required to fully optimise the technology of computer vision for the complex conditions that may occur in commercial agriculture fields.

In addition to the development of specific algorithms for processing colour images, a number of studies have also considered other factors associated with acquiring images, and the issues that need to be considered in order to obtain good performance. Woebbecke et al. (1994) considered the detection of plants using a range of sensors (thermal and optical) and determined that the location and coverage of target plant components within the field of view of the sensor can significantly influence performance and must be taken into consideration. This work was extended by Criner et al. (1999) who specifically considered the detection of bind weed and determined the maximum field of view for a given target size on bare soil. Both of these studies uses the Normalised Difference Vegetative Index (*NDVI*), which is the ratio of the difference between near infra-red reflectance and red components, and their sum. Criner et al. also emphasised the value of being able to configure the detection algorithm based on specific conditions, e.g. knowledge of field conditions or soil moisture can be used to adapt detection thresholds to maximise performance. Later studies reflected increasing use of digital visible spectrum cameras and relied on the indices based on *R*, *G* and *B* channels and their derivatives discussed in this paper. Meyer et al. (2004) described a system based on the use of a number of clustering algorithms using colour indices. Images were acquired using a camera that automatically set parameters such as focus, exposure time and white balance. More recent studies have also examined the specifics of the imaging sensor. For example, Dworak et al. (2013) used a low-cost single-chip camera again using *NDVI*, and compared it to a much more expensive specialised imaging device. Good performance was achieved by appropriately reconfiguring camera filters, coupled with algorithmic modifications. While the topic of the optimal camera parameters (such as field of view) is beyond the scope of this survey, previous studies suggest that the ability to adapt detection algorithm parameters such as thresholds can provide an advantage in ensuring optimal performance.

By way of conclusion, Table 4 summarises the key conclusions from the review, and in particular suggests specific algorithms that may perform well in particular conditions, based on analysis of their performance based on studies from the literature.

Based on prevalence in literature, the survey focused on colour index based-methods. While performing well in their own right, these methods are also widely used as a reference to evaluate the performance of other proposed methods. A detailed discussion of the performance of colour index based-methods, based on a number of recent studies, was presented. Threshold-based approaches were briefly discussed and their advantages and disadvantages were presented. In addition, the advantages and disadvantages of learning-based segmentation methods were briefly considered. The challenges and limitations that continue to hold for segmentation approaches were also highlighted. Finally, Suggested segmentation algorithms for use in different conditions were give.

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