INTERNATIONAL JOURNAL OF AGRICULTURE & BIOLOGY
ISSN Print: 1560–8530; ISSN Online: 1814–9596
09–118/YHP/2009/11–5–559–565
http://www.fspublishers.org

Full Length Article

A Real Time Specific Weed Discrimination System Using Multi-Level Wavelet Decomposition

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ABSTRACT

The developed algorithm was used for the real time specific weed discrimination employing multi-level wavelet decomposition. This algorithm used four different types of wavelets i.e., Daubechies (bd4), Symlets (sym4), Biorthogonal (bior3.3) and Reverse Biorthogonal (rbio3.3) up to four levels of decomposition to classify images into broad and narrow class for real-time selective herbicide application using the Euclidian distance method. The lab, which have shown that the system to be very effective in weed identification, segmentation and discrimination. The test and analysis show that 97.26% classification accuracy over 350 sample images (broad & narrow) with 175 samples from each category of weeds and the proposed algorithm takes 29 ms as average time for the classification of the specific weeds.

Key Words: Real-time image processing; Specific weed discrimination; Image classification; Image processing

INTRODUCTION

Weed control is a critical farm operation and can significantly affect crop yield. Herbicides have vital importance in weed control and high crop yield however these have potential to produce harmful effects (Sunil, 2007). Herbicide are normally applied uniformly, because of which weeds are highly aggregated and tend to occur in clumps and or patches and also remain relatively stable in size and location year by year (Wilson & Brain. 1991; Stafford & Miller, 1993). Sunil (2007) reported that manual scouting for patch spraying consumed considerable resources and was not a feasible option for most farm operations. It had also been suggested that patch spraying considerably reduced herbicide use. Furthermore, on comparison with uniform application method the reduction of herbicide not only gives economic advantage but also it is friendly to environment.

The amount of herbicides in a control patch sprayer has been potentially reduced when real-time weed sensing is used. Patch spraying using remote sensing and machine vision are successful systems. Both the systems essentially require image acquisition and image processing (Tang *et al.*, 1999). Lee (1999) and Søgaard and Olsen (2003) have reported that image size ranged in the order of megabytes took 0.34s to 7 sec for its processing depending on image resolution, crop and weed type, algorithm used and hardware configurations. Further remote sensing can be employed on plot basis, while machine vision systems are more suitable on plant scale herbicide application.

Machine vision based weed sensing showed promise, because it not only it utilizes spectral information, but spatial and textural information as well (Tang *et al.*, 1999). Worked on selective sprayers with real-time weed sensing showed limited potential mainly, because of the difficulties in distinguishing weeds from crops (Stafford & Miller, 1993; Paice, 1995). Johnson (1997) compared two techniques of real-time weed sensing, one using photo detectors and the other using machine vision has been conducted. Photo detector weed sensing did not reach high-resolution levels, whereas machine vision could easily be set at a high resolution and larger sensing area was covered for spatial analysis.

Weeds could be separated from the crops by using color and geometric information (Tang *et al.,* 1999). The machine vision based approach uses shape, texture, color and location based features individually or jointly to discriminate between weed and crop but varied results were obtained for these features and their combinations (Åstrand, 2005). An imaging sensor is a key component of almost any weed detection and classification system and methods of using them are various but individual plant classification demonstrated success with either spectral (Vrindts, 2002) or color imaging (Hemming, 2003). However, the spatial resolutions of spectral systems are typically not accurate for individual plant or leaf detection. Thus, color-imaging methods with higher spatial resolution do not impart significant additional information (Pauli, 2007).

To cite this paper: Siddiqi, M.H., S.B.T. Sulaiman, I. Faye and I. Ahmad, 2009. A real time specific weed discrimination system using multi-level wavelet decomposition. *Int. J. Agric. Biol.,* 11: 559–565

One challenge in outdoor machine vision weed sensing is to overcome variable lighting conditions when using conventional CCD cameras and much research on machine vision weed sensing had been done on the controlled lighting conditions but a little attention has been paid to the issue of real-time operations (Woebbecke, 2005a). Tang *et al.* (1999) studied color indices in the image for weed segmentation with shaded and un-shaded plant surfaces and found that the best segmentation occurred with the modified hue and excessive green contrast index. However, leaf "hole" pixels were created due to converting images from 24-bit to 8-bit color representation. Further vegetation image segmentation methods were based on a clustering analysis model 9-10 with adapting to the lighting variation, which supervised color image segmentation using binary coded genetic algorithm identifying a region in hue-saturation-intensity color space for outdoor field real-time weed sensing and implemented to create a segmentation look-up table.

A high-resolution weed map is necessary for weed infestation map-based patch spraying (Tang *et al.*, 1999). Machine vision-based automated high-resolution weed mapping shows advantages over conventional manual weed counting and statistical model-based weed mapping (Tang *et al.*, 1999). Manual counting is labor intensive, resulting in low sampling resolutions and impracticality in covering large field areas. To overcome these limitations, a system was integrated into this real-time patch sprayer to generate high-resolution weed maps from geo-referenced video images or directly from the data recorded at real-time operation (Tang *et al.*, 1999). This map was useful for the next season pre-emergence herbicide application when no weeds were present. Meanwhile, this high-resolution weed mapping system can be used for other weed control guided applications. Machine vision systems are also widely used for inspection of growing plants to recognize their diseases using trichromatic features of leaves (Boleslaw, 2005). With its goal to sort data into some groups according to the given parameters i.e., to solve segmentation problem.

One approach for segmenting agricultural landed-fields in digital aerial images is using a generalization of region growing techniques combined with deformable models (Margarita & Petia, 2000). This mixed approach is called Region Competition. The goal of this approach is to alleviate the tasks of digitizing the region contours to obtain the vector representation of the features that appear in an aerial photo. Region competition combines the best features of Snakes/Balloon models and Region Growing techniques. While in operation, time these techniques are applied to the case of having only two regions: the parcel to be segmented and its complementary (Doudkin *et al*., 2007).

An example of an application that involves a segmentation technique is spraying the roadside plant material with herbicide to prevent the weeds from becoming a fire hazard in summer season. The first step in identifying weeds within an image involves classifying the pixels by using a point operation in such a way that surrounding pixels will not bias a pixel's classification (Chris, 2003). Further the purpose of segmenting the image into plant and background pixels is to detect the amount of plant material within a specific area. Moreover, if the amount of plant material reaches a specific threshold, then the area is targeted for herbicidal spay application (Chris, 2003). The spray threshold is limited by the fraction of background pixels that are misclassified as plant material. If the spray threshold is set too close to the background misclassification rate, then herbicide will be wasted spraying background. Therefore, a larger misclassification rate limits the smallest plant that can be detected without targeting the background for spray (Chris, 2003).

The real-time operation on machine vision weed sensing, herbicides delivery system that can perform patch-spraying for post-emergence herbicide application in real-time and creates a weed map to handle pre-emergence herbicide application for the following season. This system enabled distribution of chemical more effectively and resulted in lower environmental loading with increased profitability for procedure (Tang *et al.*, 1999). The system could make use of the spatial distribution information in real-time with necessary amounts of herbicide applied to the weed-infested area would be much more efficiently owing to minimal environmental damage. Thus, a high spatial resolution, real-time weed infestation detection system seems to be the solution for site-specific weed management.

Many researchers have developed different vision systems to highlight weed plants in crops and to map the weeds in real-time for site-specific spraying of infested areas (Felton & McCloy, 1992: Blasco *et al*., 2002; Slaughter *et al*., 2007). These systems were based on optical sensors (photodiodes) and used for the classification/discrimination between plants (narrow plants & broad plants) from their reflection spectra. Among the best-known systems are the Weed Seeker and Spray Vision (Felton & McCloy, 1992). The limitations of these systems are that they cannot discriminate between crop and weeds. More recently (Åstrand & Baerveldt, 2002 & 2005) have developed a robot with two vision systems guided by crop rows, which aimed at mechanical removal of inter-row weeds. The drawback of this detection method was that it suited to crops sown by drilling methods such as salad or sugar beet (Bossu *et al.*, 2009). An off-line approach has also been investigated, where data were acquired in one pass and analyzed at the office. In a second pass, the weed mapping was used to control an agricultural engine in the crop field. For example Meyer *et al.* (1998) developed a multi-spectral imaging system embedded in a small aircraft, which over-flew a sunflower field crop. This discriminated between crop and inter-row weeds with spatial image processing based on Gabor filtering, which detected crop rows by their frequency. However, weeds within the crop row were not recognized.

Certain accurate methods for weed detection have been developed, which included wavelet transformation to discriminate between crop and weed in perspective agronomic images (Manh *et al.*, 2001) and spectral reflectance of plants with artificial neural networks (Fontaine & Crowe, 2006). Other researchers have investigated texture features (Meyer *et al.*, 1998) or biological morphology such as leaf shape recognition (Manh *et al.*, 2001). So in real time for the identification and classification of crop rows in images, a lot of fast methods have been implemented (Moshou *et al.,* 2001); some of them are based on Hough transform (Leemans & Destain, 2006), Fourier transform (Vioix *et al.*, 2002), Kalman filtering (Hague & Tillet, 2001) and linear regression (Søgaard & Olsen, 2003). The Hough transform is usually implemented for automatic guidance in crop fields (Marchant, 1996; Keicher, 2000). Consequently, there are various vision systems available on autonomous weed control robots for mechanical weed removal.

The objective of this research was to develop a vision algorithm. It was not an autonomous robot but a real-time machine vision system, which can recognize the absence of weed and differentiate the presence of broad leaf weed and narrow leaf weed and also to construct and evaluate a classifier that was capable of recognizing the presence and type of weeds and then the appropriate herbicides could be applied using the automatic sprayer control system based on the proposed algorithm (multilevel wavelet decomposition). The algorithm contained four different types of wavelets: Daubechies (bd4), Symlets (sym4), Biorthogonal (bior3.3) and Reverse Biorthogonal (rbio3.3). In this work, the automatic sprayer control system was used, which included CCD camera, central processing unit (CPU), decision box and two dc pumps for spraying (Fig. 1). The images were taken at a distance of 4 m and at an angle of 45 degrees with the horizontal in a selected agricultural field.

MATERIALS AND METHODS

General experimental details. By using a multilevel wavelet decomposition a set of coefficients from each level of decomposition was extracted, which were used to classify the broad and narrow leaf weeds. There are three stages in the proposed algorithm: preprocessing, feature extraction and classification process. The preprocessing stage was necessary to improve the quality of images and made the feature extraction phase more reliable for the enhancement of broad and narrow leaf weeds image pruning. For this purpose, histogram equalization techniques were adopted for the removal of background information and un-necessary and hidden details for fast and easy processing, while the histogram equalization stage dealt with enhancing the contrast of suspicious areas in the image. The database of broad and narrow leaf images were used to recognized and classify the plants.

Image preprocessing. The database of the images having revolution 240 pixel rows and 320 pixel columns and almost 50% of the whole images compressed of the background with a lot of noise. In this stage a cropping operation was applied to the image to remove the un-wanted and hidden details of the image and hence diminished the noise.

Wavelet decomposition. This algorithm dealt with monochromatic images i.e., gray scale images. An integer value communicated with each pixel of the image, as an index in an ordered table of colors, contained a matrix of integers. True color images often interacted with three matrices, for RGB coding. The wavelet decomposition could be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. Each vector consisted of sub-vectors like:

$$V_0^{2D} = V_0^{2D-1}, V_0^{2D-2}, \dots\dots\dots, V_0^{2D-n}$$

Fig. 4 shows that how a 2D image is decomposed. For example, we have an image x of 2D and the values are to be affected to the coordinates in V_0^{2D}. The 2D image x breaks up into a sum of orthogonal sub images corresponding to different visualization, so the following equation is generated.

$$x = A_1 + D_1 = \dots\dots\dots = A_j + D_j + \dots\dots\dots + D_2 + D_1$$

Decomposition along three directions of detail spaces implies that in 2D:

$$A_j - 1 = A_j + D_j = A_j + [(D_h)]_j + (D_v)_j + [(D_d)_j]$$

Where D_h, D_v and D_d are known as horizontal, vertical and diagonal details.

In this study, four different levels of decomposition based on four different wavelet functions, namely Daubechies (bd4), Symlets (sym4), Biorthogonal (bior3.3) and Reverse Biorthogonal (rbio3.3) wavelet functions were used. In each level of decomposition the biggest 100 coefficients were used to represent the corresponding feature vector. In the proposed algorithm the image preprocessing (Image Pruning) was applied for the purpose of removing the un-necessary information from the image. Then the wavelet transformation was applied using db4, sym4, bior3.3 and rbio3.3 wavelets. For the feature extraction 100 highest and average coefficients from each level of decomposition (4 x 100 values) were determined. The Euclidian distance was used to design the classifier in which for each class the class core vector was the mean of 25% of the class vectors. Thus for the classification of proposed algorithm uses the Euclidian distance method (Fig. 2).

Feature extraction. Using the wavelet decomposition the images were enhanced and the features were extracted from those coefficients, which were produced during the process of the wavelet decomposition; thereby, making the classification of the specific weeds possible. The feature vectors (highest coefficients) that were extracted from the original images stored in the database and used to test the proposed algorithm. Euclidian distance method was used to

Fig. 1. Automatic Sprayer Control System

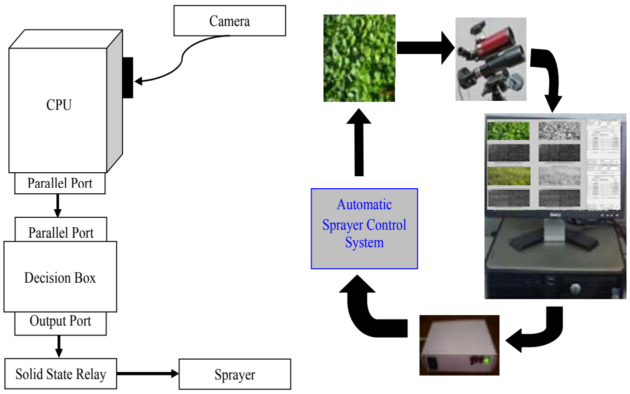


Fig. 2. Euclidian distance method used for the classification of the specific weeds

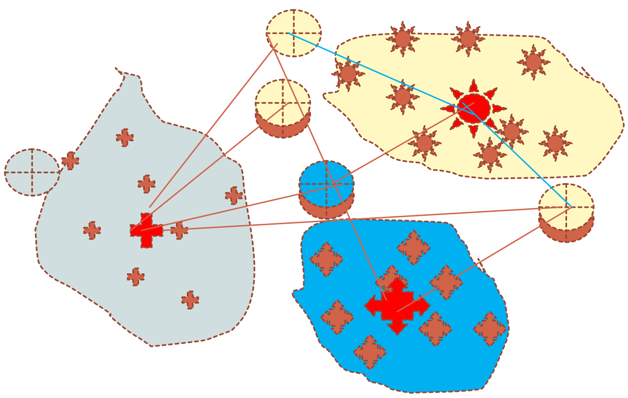


Fig. 3. Original Image- size = 320 x 240

design a classifier in order to recognize and differentiate between broad and narrow specific weeds for the real time automatic sprayer control system. For each class the core vector was the mean of 25% of the class vectors (Eq. 1). For a new feature vector the distance between feature vector and the class core vector is calculated using Equation 2. The system automatically classified the feature vector in the class for which the distance was smallest.

$$V_{core}^{i} = \frac{1}{N}\sum_{j=1}^{N} V_j^i \quad , i = 1, 2, 3......, k \qquad (1)$$

$$Dist = \sqrt{\sum_{i=1}^{k} (V_{core}^{i} - V_{test}^{i})^2} \qquad (2)$$

Where V_j is the coefficient vector for each training image, j is the index of vector; N is the number of the image in the class used for training, Dist is the calculated distance between the tested image and every core vector and k is the length of vectors. V_{test}^{i} Is the feature vector of the weeds to be classified and V_{core}^{i} is the vector core of each class. The weed images that were used in testing the effectiveness of the proposed system were decomposed into four levels of using sym4, db4, bior3.3, and rbio3.3. Table I, II, III and IV shows the distribution of used specific weed images over different classes. In every experiment a class core vector was calculated for each class using Equation 1 and then the feature vector (highest coefficients) was extracted from the database of specific weed images, which were employed in the testing phase including those used to produce the class core vector. Equation 2 is used to measure the distance between the coefficient vector and each class core vectors.

RESULTS AND DISCUSSION

Multilevel wavelet decomposition is a technique used in medical imaging. Bossu *et al.* (2009) proposed a complete approach for crop/weed discrimination based on wavelet transforms consisted of Daubechies, Mayer and Biorthogonal and compared it to a Gabor filtering. Among those the Daubechies and Mayer gave the best results (84.6% & 84.1%) and the Biorthogonal is the worst one, which gave the result 76.4% and Gabor filter gave the result 73.7%. So in this paper the proposed algorithm classified real-time specific weed discrimination based on wavelet transform consisted of Symlets, Daubechies, Biorthogonal and Reverse Biorthogonal and then to compared it with Bossu *et al.* (2009), so among those the Biorthogonal gave the best result (97.64%). This algorithm enabled to distinguish between broad and narrow according to their properties and then to classify them. By using this algorithm the right type of herbicides can be applied on the real time specific weeds. To build the class core vectors, 50 images are used for each class. The proposed algorithm uses the 4 different types of wavelets i.e., Daubechies (db4), Symlet (sym4), Biorthogonal (bior3.3) and Reverse Biorthogonal (rbio3.3). These wavelets are used in the decomposition process and four levels of decomposition are applied for the proposed algorithm.

From Table I and Fig. 5 the average accuracy of classification using Symlets (sym4) wavelet is 98.31% and the elapsed time for classification is 47.5 ms, from Table II and Fig. 6 the average accuracy of classification using Daubechies (db4) wavelet is 95.78% and the elapsed time is

Table I. Classification by using Symlet (sym4) wavelet

Levels	Accuracy of Classification (%)	Elapse Time (ms)	Error (%)
1	98.85	61	1.15
2	98.25	15	1.75
3	97.14	17	2.86
4	99.00	97	1.00

Table II. Classification by using Daubechies (db4)

Levels	Accuracy of Classification (%)	Elapse Time (ms)	Error (%)
1	99.00	25	1.00
2	97.71	17	2.29
3	99.00	31	1.00
4	94.86	23	5.14

Table III. Classification by using Biorthogonal (bior3.3)

Levels	Accuracy of Classification (%)	Elapse Time (ms)	Error (%)
1	99.00	25	1.00
2	97.71	17	2.29
3	99.00	31	1.00
4	94.86	23	5.14

Table IV. Classification by using Reverse Biorthogonal (rbio3.3) Wavelet

Levels	Accuracy of Classification (%)	Elapse Time (ms)	Error (%)
1	92.57	24	7.43
2	96.57	26	3.83
3	99.00	17	1.00
4	99.00	19	1.00

Table V. Comparison of different wavelets classification

Wavelets	Accuracy of Classification (%)	Elapse Time (ms)	Error (%)
Sym4	98.31	47	1.69
Db4	95.78	24	4.22
Bior3.3	97.64	24	2.36
Rbio3.3	96.79	21	3.21

24 ms, from Table III and Fig. 7 the average accuracy of classification using Biorthogonal (bior3.3) wavelet is 97.64% and the elapsed time for classification is 24 ms and from Table IV and Fig. 8 the average accuracy of classification using Reverse Biorthogonal (rbio3.3) wavelet is 96.79% and the elapsed time for classification is 21 ms.

Fig. 10 and 11 show the classification of broad and narrow weeds using different types of wavelets at different levels of decompositions. The proposed algorithm (Multilevel Wavelet Decomposition) is developed, which shows the original image, processed image and the results of the proposed algorithm. The images were taken at a 4 m long and at an angle 45^{o} with the horizontal, which gave a reliable accuracy to detect the presence or absence of weed cover. For areas, where weeds were detected, results show over 97.26% classification accuracy over 350 sample images within which 175 samples from broad category and 175 samples from narrow category (Table I, II, III & IV).

Fig. 4. Broad weed decomposition at level 1 (top), level 2 (middle) and at level 3 (bottom), the two graphs on the right shows the organization of the coefficients

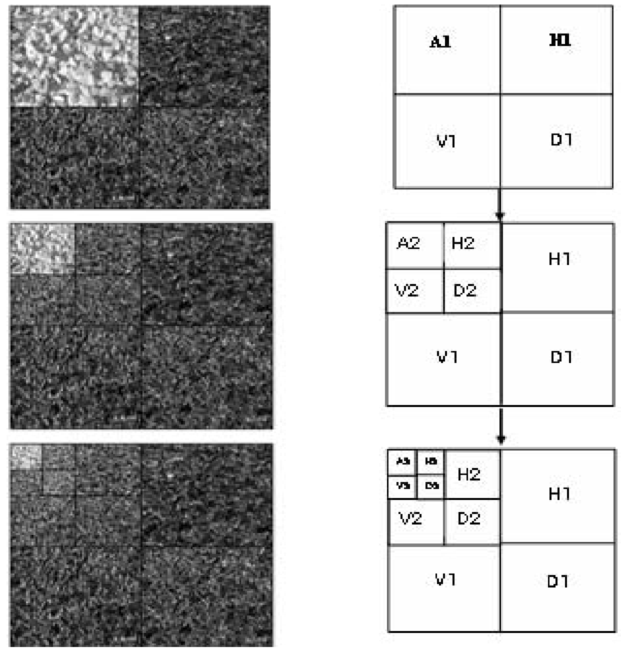
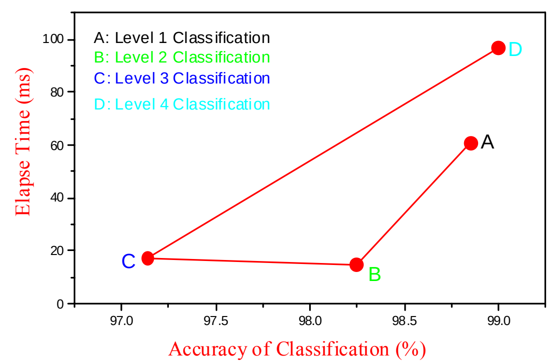


Fig. 5. Classification using sym4 wavelet



It is obvious form the Table V and Fig. 9 that the classification through Symlets (sym4) wavelet is more efficient, due to least error (1.69%) and highest accuracy 98.31%, but it took more time for classification (47 ms) and the classification through bior3.3 wavelet is the most efficient as it took half of the time (24 ms) as of the sym4. The accuracy of classification through db4 (95.78%) and rboi3.3 (96.79%) are comparable to sym4 and bior3.3 and took less elapse time for classification (24 ms & 21 ms, respectively) but higher in term of error (4.22% & 3.21%, respectively).

The db4 wavelet, which is used by Ferreira and Borges (2003) for the purpose of mammogram classification using a multilevel wavelet transform, sym4 and rbior3.3 may not be used for the classification of the specific weed in term of error and elapse time. The results indicate that

Fig. 6. Classification using db4 wavelet

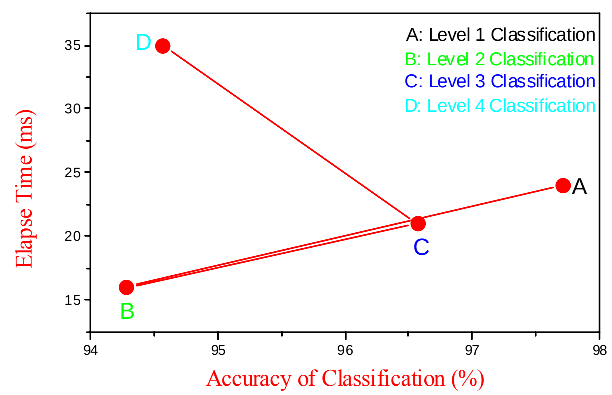


Fig. 7. Classification using bio3.3 wavelet

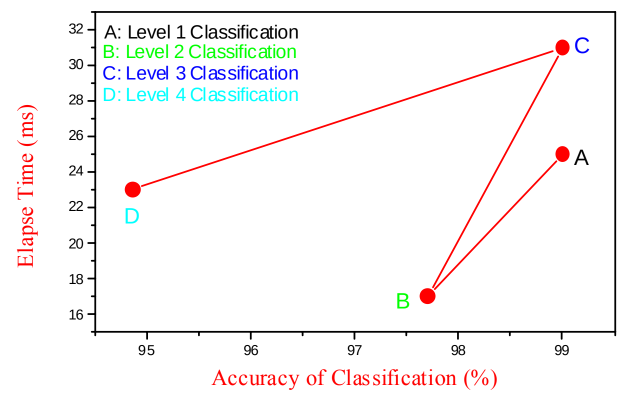


Fig. 8. Classification using rbio3.3 wavelet

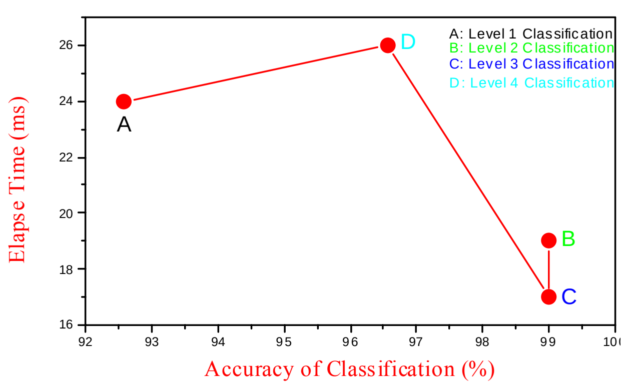


Fig. 9. Comparison of different wavelets classification

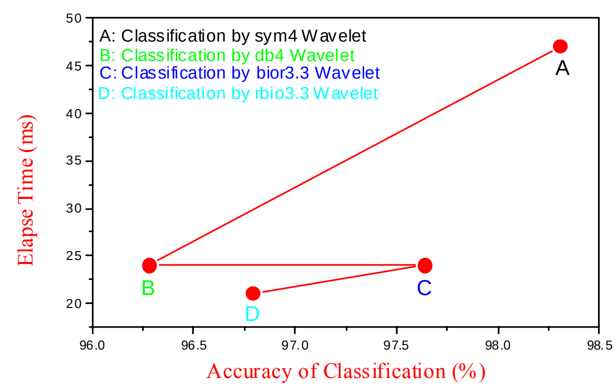


Fig. 10. Broad Weeds decomposition using bior3.3 wavelet

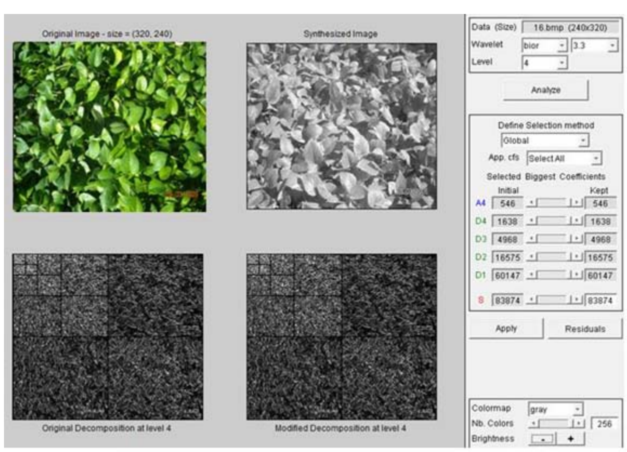
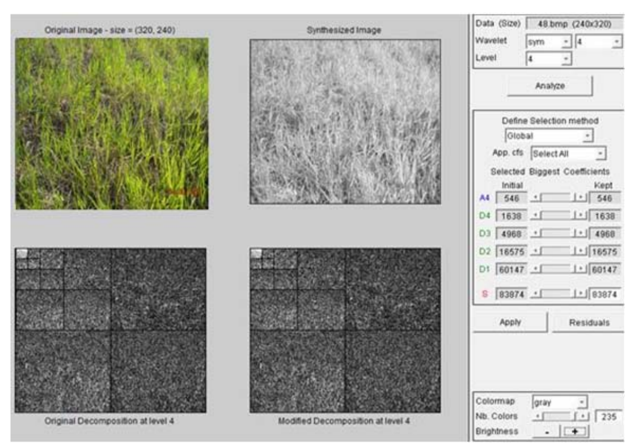


Fig. 11. Narrow Weeds decomposition using sym4 wavelet



bior3.3 is a promising wavelet due to it high accuracy, less error and less elapse time as compared to the rest of the wavelets tested. This finding is significant when determining the suitable wavelet to be used in real-time specific weed discrimination system (Fig. 1).

CONCLUSION

In this study, we proposed a complete approach for real-time specific weed discrimination from image processing using multilevel wavelet decomposition. The developed algorithm was successfully tested in the lab for weed detection/classification in order for selective spraying of herbicide using vision recognition system. It used four different types of wavelets, namely Symlets (sym4), Daubechies (db4), Biorthogonal (bior3.3) and Reverse Biorthogonal (rbio3.3). The accuracy of discrimination for sym4 is higher and produced less error but it took more elapsed time. Db4 and rbio3.3 wavelets produced higher accuracy and less elapse time but the highest in terms of error. The algorithm shows an effective and reliable classification of images using Biorthogonal (bior3.3) wavelet. The environmental parameters greatly affect the performance of currently developed weed classifier. Lighting conditions, wind and other natural environment parameters degrade the performance of algorithm. Further research is needed to perform environmental adaptive weed recognition and classification to develop such classifier, which will detect natural environment parameters and classify weed images according to these parameters to enhance the result of weed classifiers.

Acknowledgment. We thank Mohamed Meselhy Eltoukhy for improving algorithm and manuscript.

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(Received 14 April 2009; Accepted 23 May 2009)