Automated Weed Classification using Local Binary Pattern for Selective Herbicide Applications

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Abstract—**Concerns regarding the environmental and economic impacts of excessive herbicide applications in agriculture have promoted interests in seeking alternative weed control strategies. In this context, an automated machine vision system that has the ability to differentiate between broadleaf and grass weeds in digital images to optimize the selection and dosage of herbicides, can enhance the profitability and lessen environmental degradation. This paper presents an efficient and effective texture-based weed classification method using local binary pattern (LBP). The objective is to evaluate the feasibility of using micro-level texture patterns to classify weed images into broadleaf and grass categories for real-time selective herbicide applications. Two well-known machine learning methods, template matching and support vector machine, are used for classification. Experiments on 200 sample field images with 100 samples from each category show that, the proposed method is capable of classifying weed images with high accuracy and computational efficiency.**

Keywords-weed classification; selective herbicide applications; local binary pattern; template matching; support vector machine;

I. Introduction

In conventional cropping systems, one of the major concerns is to reduce the abundance of unwanted plants or weeds, as they disturb farm productivity and quality by competing with crops for resources like water, light, space, and soil nutrients [1, 2]. In 2006, the estimated potential loss due to all pests was about 40%–80% worldwide, varying for different crops, and the potential of yield losses due to weeds was found to be about 34%, which is the highest of all pests [3]. Therefore, better weed control strategies are critical to sustain crop productivity. In most cases, weed control strategies extensively rely on the application of chemical herbicides. More than 60% of the pesticides developed worldwide are the herbicide products to control weed population [4]. Although herbicides application allows producers to effectively suppress weed infestations and attain higher profitability, it should be minimized because of the adverse impacts of herbicide chemicals on environment, human health, and other living organisms. In addition, repeated application of same types of herbicides in a field often induces the emergence of herbicide resistant weed species. According to International Survey of Herbicide Resistant Weeds [5], 365 herbicide resistant biotypes that belonged to 200 species (115 dicots and 85 monocots) are spread over 450,000 fields worldwide. At present, uniform spraying is the most common method for herbicides application [6]. However, this method is inefficient and cost-ineffective as weeds distribution is usually non-uniform and highly aggregated in clumps or patches within the arable field [7, 8]. There could be many parts of the field that have none or insignificant volume of weeds.

In post-emergence applications, the amount of herbicides applied can be reduced through site-specific weed control, where herbicides are sprayed only in the weed infested areas of a field. In site-specific applications, different selective herbicides with corresponding application rates are applied to control broadleaf and grass weeds differently [9]. In this context, if the spatial distribution of broadleaf and grass weeds could be sensed locally with an efficient image processing method, then automated selective herbicides application could be applied to optimize the selection and dosage of herbicides. Moreover, classification of weeds into broadleaf and grass categories is more feasible than individual weed species classification approach [10] as this method provides computational efficiency and consistency with current herbicides applications [11].

In this paper, we have proposed a texture-based weed classification method using local binary pattern (LBP) [12]. LBP provides a simple and efficient approach for gray-scale and rotation invariant texture classification, which has attained significant popularity for describing the texture of an image [13]. The objective of this work is to present a computationally efficient algorithm based on LBP to effectively classify weeds with varying canopy size. We empirically study the feasibility of using the LBP operator to extract texture features from field images and to use these feature representations to classify weeds into broadleaf and grass categories. Two well-known machine learning methods, template matching (TM) and support vector machine (SVM), are used for classification. Experimental results show that, the classification rate of the proposed method is appreciable.

II. Related Work

Research on weed classification and plant identification basically falls into two categories: shape-based analyses and color or texture-based analyses. Early methods for weed classification were mostly based on geometric features, such as leaf shape or plant structure. In addition, some color and texture-based classification methods were also introduced.

Figure 1. Sample broadleaf and grass weed images used for this study. Images were obtained at diiferent times of a day

Shape analyses techniques were studied by Guyer et al. [14, 15] for automated leaf and plant identification. Experiments were conducted on images of juvenile plants taken in a controlled laboratory environment. Shearer and Jones [16] developed a photo sensor-based plant detection system that can detect and spray only the green plants. Later, Woebbecke et al. [17] conducted shape feature analyses on binary images originally obtained from color images. The objective was to differentiate between 10 common weeds, along with corn and soybeans. Zhang and Chaisattapagon [18] proposed a combination of color, shape and texture features for the classification of weeds and wheat crop. Recently, Søgaard [19] introduced active shape models for weed classification and reported accuracy between 60% to above 90% in identifying young weed seedlings of 19 different species. Weis and Gerhards [20] presented a review on different shape features for identifying weed species in digital images. In our previous work [21], we evaluated a combination of color features with a set of rotation and scale invariant shape features to classify some commonly seen weed species in Bangladesh.

Although a lot of work has been done, classification using shape features is difficult to accommodate in uncontrolled environment as it requires accurate detection and analysis of individual plant or leaf [22], which is also computationally inefficient. Therefore, recent approaches for weed classification usually involve color and texture feature analysis to classify weeds in patch basis. Gabor wavelets-based texture features were introduced by Tang et al. [22, 23] for broadleaf and grass weed classification. Another classification method was proposed by Naeem et al. [24] based on weed coverage rate (WCR). Later, Ghazali et al. [25] introduced gray-level co-occurrence matrix (GLCM), Fast Fourier Transform (FFT), and scale-invariant feature transform (SIFT) for a real-time weed control system in oil palm plantation. Recently, a study on wavelet transforms was performed by Bossu et al. [26] for crop and weed discrimination in both synthetic and real images. A similar approach was adopted by Siddiqi et al. [27], where wavelet decomposition technique based on four different sub-wavelets was used for weed classification. More recently, Haar wavelet transform via k-nearest neighbor algorithm has been introduced for broadleaf and grass weed classification [28].

From the above discussion, it is evident that, little research effort exploring micro-pattern based texture analyses for weed classification has been documented up to date. However, this approach has potential for real-time applications as micro-pattern based feature descriptors provide rotation invariance and robustness against illumination variation. In addition, micro-pattern based analyses are computationally more efficient than the wavelet based classification approaches. These considerations provided the motivation for this study.

III. MATERIALS AND METHODS

A. Image Database

In this study, we have used weed images that has only one dominant weed category: broadleaf or grass. The sample images were acquired in the field. The image database comprises 200 color image scenes of broadleaf and grass weeds with 100 samples from each class. Weeds with varying canopy size were selected to increase the difficulty of the classification problem. The images were taken at an angle of 45 degree with the ground in natural lighting conditions with a digital camera. The camera was mounted on top of a tri-pod in order to maintain a fixed height of 1.5 meter from the ground. During image acquisition, the resolution of the camera was set to 1200×768 pixels. In the experimental analysis, all the images were normalized to a resolution of 320×240 pixels in order to reduce the computation time.

B. Image Pre-processing

Background feature minimization is an important pre-processing step in weed classification. Otherwise, soil and residue features will mix with those from weeds and the texture analysis will yield unreliable results [29]. As the LBP operator requires gray-scale images, all the color images were subsequently converted to gray-scale images first. In the conversion process, a special contrast operation was applied to minimize the background feature, namely modified excess green (MExG). This operation has been shown to greatly enhance the contrast of the green vegetation in the image scene with respect to the background [30, 31]. In the MExG operation, an indicator value I is calculated for each pixel in the image using (1).

$$I = \begin{cases} 0, \text{ if } G < R \text{ or } G < B \text{ or } G < 120 \\ 2G - R - B, \text{ otherwise} \end{cases} \quad (1)$$

Here, R, G, and B are the red, green, and blue color components of the RGB image, respectively. The indicator value of each pixel is then mapped to a gray-scale intensity value g within the range of 0 to 255 by linear mapping:

$$g = 255 \times \frac{I - I_{min}}{I_{max} - I_{min}} \quad (2)$$

Here, I is the indicator value of a pixel, I_{max} and I_{min} are the maximum and the minimum indicator values within the image, respectively. After the gray-scale conversion, morphological dilation was applied to all the images. A defined structural element (SE) of odd number of rows and columns was used for this operation. It has been shown that, morphological dilation has the effect of removing unnecessary details of the weed images [28].

C. Feature Extraction Using the LBP Operator

LBP is a gray-scale and rotation invariant texture primitive that describes the spatial structure of the local texture of an image. The LBP operator selects a local neighborhood around each pixel of an image, thresholds the P neighbor gray values with respect to the center pixel and concatenates the result binomially. The resulting binary value is then assigned to the center pixel. Formal definition of the LBP operator takes the following form:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P\text{-}1} s(i_p - i_c)2^p \quad (3)$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (4)$$

Here, i_c is the gray value of the center pixel (x_c, y_c), i_p is the gray value of its neighbors, P is the number of neighbors and R is the radius of the neighborhood.

In practice, the LBP operator considers the signs of the differences of the gray values of P equally spaced neighbors with respect to the central pixel in a local neighborhood, which is then represented using a P-bit binary number. If any neighbor does not fall exactly on a pixel position, then the value of that neighbor is estimated using bilinear interpolation. The LBP histogram of the encoded image block is then used as a texture descriptor for that block. The basic LBP encoding process is illustrated in Fig. 2.

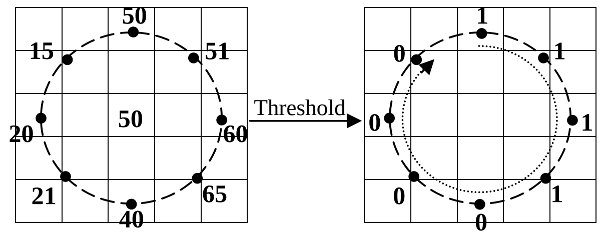

Figure 2. Illustration of the basic LBP operator. Here, the LBP binary code is 11110000 (decimal 240)

To remove the effect of rotation, each binary pattern generated by the LBP operator is converted into a rotation invariant pattern using (5).

$$LBP_{P,R}^{ri} = min\{ROR(LBP_{P,R}, i) \mid i = 0, 1, 2, ..., P-1\} \quad (5)$$

Here, $ROR(x, i)$ performs a circular bitwise right shift on a P-bit binary number x for i times.

One extension to the original LBP operator, known as the uniform LBP (ULBP), exploits certain LBP patterns, which appear more frequently in a significant area of the image. These patterns are known as the uniform patterns as they contain very few spatial transitions (bitwise 0/1 changes) in a circular sequence of bits, which is represented by a uniformity measure U. The U value of an LBP pattern is defined as the number of bitwise transitions from 0 to 1 or vice versa in that pattern. One example of a uniform pattern is 00011111. It has a U value of 1 as there is only one transition from 0 to 1. Ojala et al. [12] observed that, LBP patterns with U <= 2 are the fundamental properties of texture, which provide a vast majority of all the 8-bit binary patterns present in any texture image. Therefore, uniform patterns are able to describe significant local texture information, such as bright spot, flat area or dark spot, and edges of varying positive and negative curvature [12]. All the other patterns (U > 2) are grouped under a miscellaneous label. The mapping of $\text{LBP}_{P,R}$ to $\text{LBP}_{P,R}^{u2}$ (LBP patterns with U value <= 2) is implemented with a lookup table of 2^P entries.

D. Feature Representation Using LBP

After computing the LBP code for each pixel (x, y) of the input image of size $M \times N$, we will get an encoded image representation. Then, a histogram H is obtained from the encoded image using (6).

$$H(b) = \sum_{x=1}^{M} \sum_{y=1}^{N} f(LBP_{P,R}^{ri}(x, y), b), \quad f(a, b) = \begin{cases} 1, & a = b \\ 0, & a \neq b \end{cases} \quad (6)$$

Here, b is the LBP code value. The resulting histogram H is used as the feature vector that describes the texture information of the image. The length of the feature vector generated using the basic LBP operator is 2^P, where P is the number of equally-

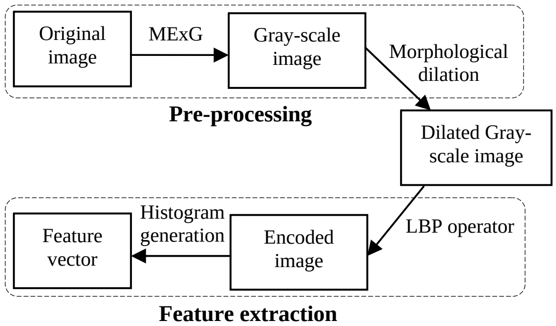

Figure 3. Proposed feature vector generation process using the LBP operator

spaced neighbors in the local neighborhood. The overall feature vector generation process is depicted in Fig. 3.

IV. Classification of Weed Images

A. *Classification using Template Matching*

During the training phase, LBP histograms of training sample images of the same class are averaged to generate the template model for that particular class. Using this method, two template histograms were formed to model the broadleaf and grass images.

The dissimilarity between the sample and the template histograms is a test of goodness-of-fit that can be measured using a non-parametric statistic test, such as chi-square statistic and log-likelihood ratio. After calculating the dissimilarity value for each class, the testing sample is assigned to the class with the smallest dissimilarity value. In our study, chi-square statistic is used to measure the dissimilarity value. The chi-square measure is defined as

$$D(S,M)=\sum_{n=1}^{N}\frac{(S(n)-M(n))\times(S(n)-M(n))}{S(n)+M(n)} \qquad (7)$$

where S is the LBP histogram of the testing sample, M is the model histogram of a category, and N is the number of bins in the histogram.

B. *Classification using Support Vector Machine (SVM)*

Support vector machine (SVM) is a state-of-the-art machine learning approach based on modern statistical learning theory. It has been successfully applied in different classification problems. SVM performs classification by constructing a hyper plane in such a way that the separating margin between positive and negative examples is optimal. This separating hyper plane then works as the decision surface.

Given a set of labeled training samples $T = \{(\boldsymbol{x}_i, l_i), i = 1, 2, \ldots, L\}$, where $\boldsymbol{x}_i \in \mathbf{R}^P$ and $l_i \in \{-1, 1\}$, a new test data $\boldsymbol{x}$ is classified by

$$f(\boldsymbol{x})=\mathrm{sign}\left(\sum_{i=1}^{L}\alpha_i l_i K(\boldsymbol{x}_i,\boldsymbol{x})+b\right) \qquad (8)$$

where α_i are Lagrange multipliers of dual optimization problem, b is a threshold parameter, and K is a kernel function. The hyper plane maximizes the separating margin with respect to the training samples with $\alpha_i > 0$, which are called the support vectors.

SVM makes binary decisions. To achieve multi-class classification, the common approach is to adopt the one-against-rest or several two-class problems. In our study, we used the one-against-rest approach. Radial basis function (RBF) kernel was used for the classification problem. The function K can be defined as

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\exp(-\gamma\,\|\boldsymbol{x}_i-\boldsymbol{x}\|^2),\quad \gamma>0 \qquad (9)$$

$$\|\boldsymbol{x}_i-\boldsymbol{x}\|^2=(\boldsymbol{x}_i-\boldsymbol{x})^t(\boldsymbol{x}_i-\boldsymbol{x}) \qquad (10)$$

Here, γ is a kernel parameter. A grid-search was carried out for selecting appropriate parameter value, as suggested in [32].

V. Results and Discussion

To evaluate the effectiveness of the proposed method, we carried out a ten-fold cross-validation scheme to measure the classification rate against 200 sample images (100 images from each class). In a ten-fold cross-validation, the whole dataset is randomly partitioned into ten subsets, where each subset comprises an equal number of instances. One subset is used as the testing set and the classifier is trained on the remaining nine subsets. The average classification rate is calculated after repeating the above process for ten times. As the instances of the testing subset are unknown to the classifier, the success rate of classifying an independent testing dataset is reflected by the prediction accuracy obtained from this unknown subset. Therefore, cross-validation testing procedure is able to prevent over-fitting and the result generalizes better to the actual operating environment.

The classification rate of the proposed method can be influenced by adjusting two parameters: the number of selected neighbors P and the radius R of the local neighborhood. Therefore, we have evaluated the performance of the proposed method for different parameter values in order to find the optimal parameter setting. TABLE I shows the performance of the proposed feature representation scheme for different parameter settings using template matching. It can be observed that, the best classification rate is achieved using rotation invariant uniform LBP patterns with $(P, R) = (8, 1)$. Applying the $\mathrm{LBP}_{8,1}^{riu2}$ operator yields a feature vector of length 10, which is plausible for real-time decision making. The $\mathrm{LBP}_{16,2}^{ri}$ operator also yields high classification accuracy. However, in this case, the length of the feature vector is very large, which causes a higher computation time than the $\mathrm{LBP}_{8,1}^{riu2}$ operator. In all cases, for the same parameter settings, rotation invariant LBP patterns achieve higher classification rate than basic LBP.

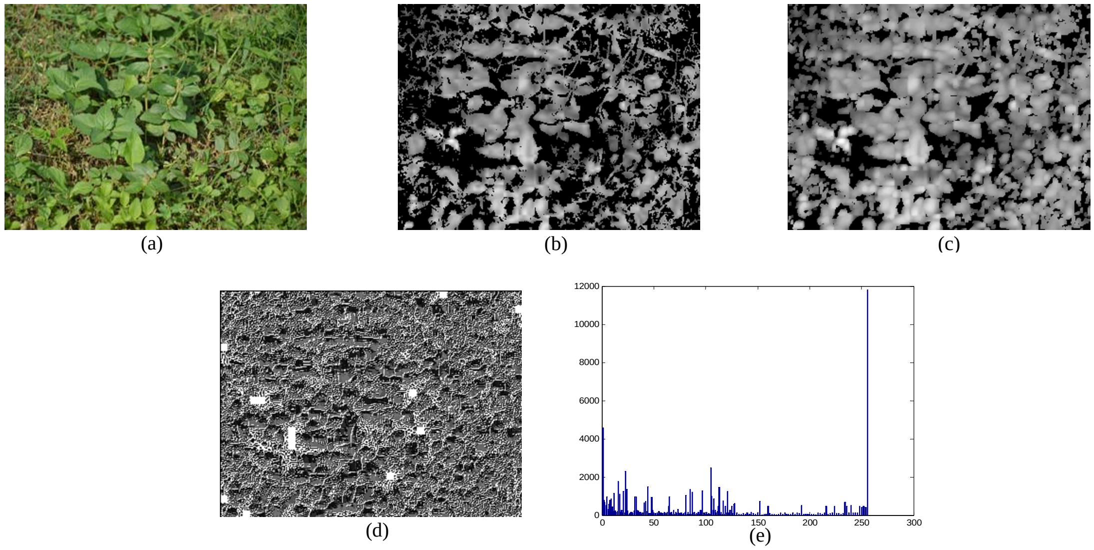

Figure 4. Illustration of feature vector representation, (a) Sample broadleaf weed image, (b) Gray-scale image obtained using MExG operation, (c) Gray-scale image after applying morphological dilation operation, (d) $\mathrm{LBP}_{8,1}^{ri}$ encoded image obtained from (c), (e) LBP histogram obtained from (d)

TABLE I. CLASSIFICATION RATE OF THE PROPOSED METHOD FOR DIFFERENT PARAMETER SETTINGS USING TEMPLATE MATCHING

Operator	Classification rate (%)
$\mathrm{LBP}_{8,1}$	77.28
$\mathrm{LBP}_{8,1}^{ri}$	85.56
$\mathrm{LBP}_{16,2}$	84.44
$\mathrm{LBP}_{16,2}^{ri}$	86.11
$\mathrm{LBP}_{8,1}^{riu2}$	88.33

TABLE II. CLASSIFICATION RATE OF THE PROPOSED METHOD FOR DIFFERENT PARAMETER SETTINGS USING SVM

Operator	Classification rate (%)
$\mathrm{LBP}_{8,1}$	92.50
$\mathrm{LBP}_{8,1}^{ri}$	96.00
$\mathrm{LBP}_{16,2}$	92.50
$\mathrm{LBP}_{16,2}^{ri}$	95.50
$\mathrm{LBP}_{8,1}^{riu2}$	98.50

To further evaluate the performance of the proposed method, we conducted the same experiments using support vector machine (SVM). SVM is a well-devised machine learning method that provides excellent accuracy for pattern classification. TABLE II shows the classification rate of the LBP operator using SVM for different parameter settings. From the results, it can be observed that, SVM yields better classification rate than template matching. Here also, the $\mathrm{LBP}_{8,1}^{riu2}$ operator provides the best classification rate. In addition, the $\mathrm{LBP}_{8,1}^{ri}$ operator also yields high classification accuracy. In both cases, the length of the feature vector is relatively small than the other operators. As mentioned earlier, there are only 10 features in the feature vector generated by the $\mathrm{LBP}_{8,1}^{riu2}$ operator. In case of $\mathrm{LBP}_{8,1}^{ri}$, the number of features is 256. As expected, in all cases, rotation invariant LBP patterns provide higher classification rate than the basic LBP for the same parameter settings.

Based on the experimental results, several potential improvements can be mentioned. First, the proposed method provides rotation invariance by converting rotation variant LBP patterns to rotation invariant ones. Therefore, this method is capable of providing stable performance in presence of orientation variation. Second, this method provides a computationally efficient approach to feature extraction and classification. Rather than using a time and memory intensive feature extraction method like Gabor wavelet that convolves the image with a bank of Gabor filters, the proposed method employs the LBP operator, which is able to generate the feature vector by performing only a single scan of the image. Third, in our study, we used weed images acquired in natural lighting condition. Moreover, no pre-processing step was applied to remove the effect of illumination variation. The reason is that, LBP based feature representation is robust against monotonic illumination variation, which yields high classification accuracy in uncontrolled environment. In fact, LBP itself is sometimes used as a lighting normalization stage for other methods [33]. As no pre-processing is required to handle variations in lighting changes, computational complexity is reduced.

VI. CONCLUSION

A weed classification method based on LBP-based feature descriptor was developed to classify broadleaf and grass weed images for real-time selective herbicide applications. Different parameter settings for the LBP operator were evaluated to find the optimal setting. Extensive experiments on 200 sample images show that, the proposed method is very efficient and effective for classification of weed images. The discriminative power of this method mainly lies in the utilization of rotation invariant micro-pattern based texture information to generate the feature vector. In future, we plan extend our work by introducing mix weed images and treating them as a separate category along with broadleaf and grass weeds.

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