# Automated Weed Classification with Local Pattern-Based Texture Descriptors

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**Abstract:** *In conventional cropping systems, removal of weed population extensively relies on the application of chemical herbicides. However, this practice should be minimized because of the adverse effects of herbicide applications on environment, human health, and other living organisms. In this context, if the distribution of broadleaf and grass weeds could be sensed locally with a machine vision system, then the selection and dosage of herbicides applications could be optimized automatically. This paper presents a simple, yet effective texture-based weed classification method using local pattern operators. 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. Three widely-used texture operators, namely Local Binary Pattern (LBP), Local Ternary Pattern (LTP), and Local Directional Pattern (LDP) are considered in our study. Experiments on 400 sample field images with 200 samples from each category show that, the proposed method is capable of effectively classifying weed images and provides superior performance than several existing methods.*

**Keywords:** *Local pattern operator, machine vision system, support vector machine, template matching, weed classification.*

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## 1. Introduction

Weed control is a necessary management practice in agricultural systems, which is critical to sustain crop productivity and quality. In most cases, weed control strategies extensively rely on the application of chemical herbicides, which has had successes in attaining higher profitability by effectively suppressing weed infestations. However, concerns regarding the environmental and economic impacts of excessive herbicide applications have promoted increasing interests in seeking alternative weed control approaches [3]. At present, uniform spraying is the most common method for herbicides application [16]. 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 [19, 27]. There could be many parts of the field that have none or insignificant volume of weeds. This property of the weed distributions makes the development of site-specific management feasible.

In site-specific weed management, the amount of herbicides applied is reduced through spraying only the weed infested areas of a field, where different selective herbicides with corresponding application rates are applied to control broadleaf and grass weeds differently [17]. A prerequisite for this approach is the knowledge about the weed infestation and distribution within the field. Therefore, if the spatial distribution of broadleaf and grass weeds could be sensed locally with a machine vision system, then automated selective herbicides application could be applied to optimize the selection and dosage of herbicides. Classification of weeds into broadleaf and grass categories is more feasible than individual weed species classification approach [14] as this method provides computational efficiency and consistency with current herbicides applications [11].

In this paper, we have presented an effective texture-based weed classification method using local pattern operators. Local patterns provide a simple and efficient approach for texture analysis, which has attained significant popularity for describing the texture characteristics of an image. The objective of this work is to present a computationally efficient algorithm based on local texture patterns to effectively classify weeds with varying canopy size. We empirically study the feasibility of three widely-used local pattern operators, namely Local Binary Pattern (LBP) [18], Local Ternary Pattern (LTP) [24], and Local Directional Pattern (LDP) [10], to represent the texture features of field images and 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.

## 2. Related Work

Among the different techniques used for weed classification and plant identification, shape analysis and texture-based methods are widely investigated due to their performances. Early methods for weed classification were mostly based on geometric shape features, such as leaf shape or plant structure. In addition, some color and texture-based classification methods were also introduced.

Shape analysis techniques were adopted in [6, 7] for automated identification of leaf and plant. Experiments were conducted on images of juvenile plants taken in a controlled laboratory environment. A photo sensor-based plant detection system was introduced in [20] that can detect and spray only the green plants. In [29], shape-based feature analysis was conducted on binary images originally obtained from color images. The objective was to differentiate between 10 common weeds, along with corn and soybeans. Later, a combination of color, shape and texture features was proposed in [31] for the classification of weeds and wheat crop. Recently, active shape models were explored in [22] for identifying young weed seedlings of 19 different species and the reported accuracy was between 60% to above 90%. In [28], a review on different shape features was presented for identifying weed species in digital images. More recently, a combination of color features with a set of rotation and scale invariant shape features were evaluated in [2] in order 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 of individual plant or leaf [25]. This approach is also computationally inefficient. Therefore, current trends in the research on weed classification usually involve color and texture feature analysis to classify weeds in patch basis. Gabor wavelets-based texture features were introduced in [25, 26] for broadleaf and grass weed classification. Another classification method was proposed in [15], which is based on Weed Coverage Rate (WCR). Later, in [5], Gray-Level Co-occurrence Matrix (GLCM), Fast Fourier Transform (FFT), and Scale-Invariant Feature Transform (SIFT) were explored for a real-time weed control system in oil palm plantation. Recently, a study on wavelet transforms was performed in [4] for crop and weed discrimination. Both synthetic and real images were used in the experimental setup. A similar approach was adopted in [21], where wavelet decomposition technique was explored in a detailed manner. More recently, Haar wavelet transform via $k$-nearest neighbor algorithm has been introduced for broadleaf and grass weed classification [1].

From the above discussion, it can be noticed that, there has been little research to date on exploring micro-pattern based texture analysis for weed classification. However, as suggested in a previous study [3], this approach has potential for real-time applications. One of the main reasons is that, local texture patterns can be converted to rotation invariant features in order to provide robustness in uncontrolled environment. In addition, local pattern based analysis are computationally more efficient than the wavelet based texture analysis approaches. These considerations provided the motivation for this study.

## 3. Local Pattern Operators

In this section, we present a review on the local pattern operators used in our study.

### 3.1. Local Binary Pattern

LBP [18], 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:

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

$$s(v) = \begin{cases} 1, & v \geq 0 \\ 0, & v < 0 \end{cases} \tag{2}$$

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 Figure 1.

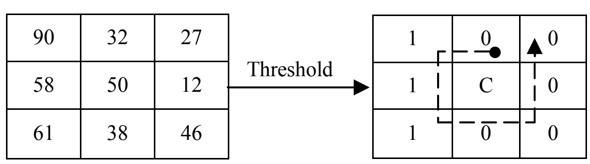


Figure 1. Illustration of the LBP encoding process (the LBP binary code for pixel C is 01110000).

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.* [18], 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 [18]. All the other patterns with $U>2$ are grouped under a miscellaneous label.

### 3.2. Local Ternary Pattern

The LBP operator thresholds at exactly the value of the center pixel. Therefore, LBP codes are sensitive to noise since a little variation can cause its value to alter with respect to the center value. To address this issue, LTP [24] was proposed, which extends LBP to a 3-valued code in order to provide more consistency in both smooth and high-textured regions under the presence of noise. In the LTP encoding process, gray values in a zone of width $\pm t$ about the center pixel are quantized to 0, and those above $+t$ and below $-t$ are quantized to +1 and −1, respectively. Hence, the indicator $s(v)$ in equation 2 is replaced by a 3-valued function:

$$s'(i_p, i_c) = \begin{cases} 1 & i_p \geq i_c + t \\ 0 & |i_p - i_c| < t \\ -1 & i_p \leq i_c - t \end{cases} \tag{3}$$

Here, $t$ is a user-defined threshold. Each LTP code is further split into its corresponding positive and negative parts, and treated as two separate binary patterns to reduce the number of features from $3^8$ to $2{\times}2^8$. The LTP encoding process is illustrated in Figure 2.

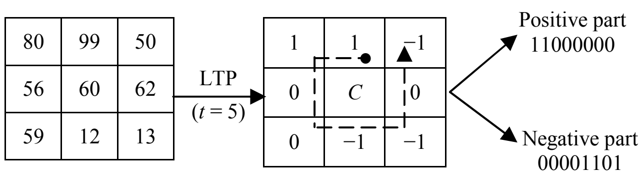


Figure 2. Illustration of the LTP encoding process (the LTPcode is 1100(−1)(−1)0(−1) and thecorresponding positive and negative patterns are 11000000 and 00001101, respectively).

### 3.3. Local Directional Pattern

Edge responses are more stable than intensity values [10, 12], thus, an encoding scheme that exploits the edge responses in different directions can retain more information of the local texture [12]. The LDP [10] operator assigns an 8-bit binary code to each pixel of an image, which is calculated by comparing the relative eight directional edge response values of a pixel. First, eight directional edge response values are computed by Kirsch masks centered on a pixel oriented in eight different directions as shown in Figure 3.

| | | |
|---|---|---|
| −3 | −3 | 5 |
| −3 | 0 | 5 |
| −3 | −3 | 5 |

a) E, S, W, N (rotated 90°)

| | | |
|---|---|---|
| −3 | 5 | 5 |
| −3 | 0 | 5 |
| −3 | −3 | −3 |

b) NE, SE, SW,NW (rotated 90°)

Figure 3. Kirsch eight directional edge response masks (different orientations are obtained by rotating these masks by 90°).

Here, N, S, E, and W correspond to North, South, East and West, respectively.

Presence of edge or corner will cause high edge-response values in their respective directions. Likewise, uniform or smooth regions will provide edge response values of same or similar magnitudes in different directions. Therefore, The LDP operator sets the most prominent $k$ directions to 1 and others to 0 in order to obtain a binary pattern based on the relative strength of the edge response values in different directions. Formally, the LDP code is derived by:

$$LDP_k = \sum_{i=0}^{7} b_i (m_i - m_k) \times 2^i \tag{4}$$

$$b_i(a) = \begin{cases} 1, & a \geq 0 \\ 0, & a < 0 \end{cases} \tag{5}$$

Here, $m_k$ is the magnitude of the $k$-th most significant directional response. Since the edge responses are less sensitive to illumination and noise than intensity values, the resultant LDP feature retains more information and characterizes the texture primitives of an image in a more stable manner, including different types of curves, corners, and junctions. The LDP encoding process is illustrated in Figure 4.

| | | |
|---|---|---|
| 90 | 32 | 27 |
| 58 | 50 | 12 |
| 61 | 38 | 46 |

a) Original image.

| | | |
|---|---|---|
| 348 | 100 | 524 |
| 580 | *C* | 412 |
| 164 | 68 | 324 |

b) Magnitude of eight directional edge responses.

| | | |
|---|---|---|
| 0 | 0 | 1 |
| 1 | *C* | 1 |
| 0 | 0 | 0 |

c) k=3, LDP binary code=00100011 for center C.

Figure 4. Illustration of the LDP encoding process.

## 4. Materials and Methods

### 4.1. Image Database

In our experiment, we use weed images that has only one dominant weed category: broadleaf or grass. The sample images were acquired in the fields. The image database comprises 400 color image scenes of broadleaf and grass weeds commonly seen in Bangladesh with 200 samples from each class. Images were obtained at different times of a day. In addition, 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 Canon EOS 550D digital camera. An 18 to 55 mm lens was used during image acquisition. 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. Figure 5 shows sample images of broadleaf and grass weeds obtained from the fields.

a) Broadleaf weeds.

b) Grass weeds.

Figure 5. Samples of weed images used in the experiments.

## 4.2. Image Pre-Processing

Background feature minimization is an important pre-processing step in weed classification problem. Otherwise, soil and residue features will mix with those from weeds and the texture analysis will yield unreliable results [13]. As the LBP operator works on 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 with respect to the background [30, 23]. In the MExG operation, an indicator value $I$ is calculated for each pixel in the image using equation 6:

$$I = \begin{cases} 0, & if\ G<R\ or\ G<B\ or\ G<120 \\ 2G-R-B, & otherwise \end{cases} \quad (6)$$

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:

$$g = 255 \times \frac{I - I_{min}}{I_{max} - I_{min}} \quad (7)$$

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 [1]. Figure 6 illustrates the image pre-processing steps applied on a sample weed image.

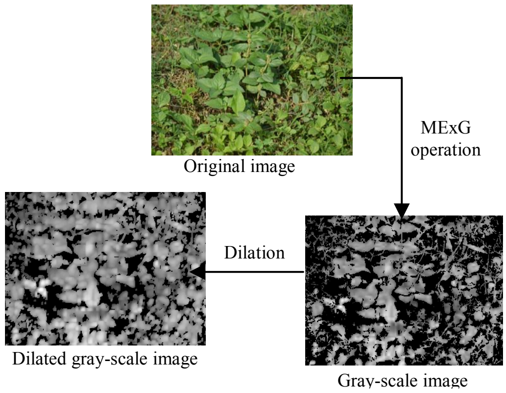


Figure 6. Pre-processing of a sample broadleaf weed image.

## 4.3. Rotation Invariant Feature Representation

To remove the effect of rotation, each binary pattern generated by the local pattern operators is further converted into a rotation invariant pattern using equation 8:

$$LP = min\{ROR(LP, i)\},\ i = 0,1,2,...,P-1 \quad (8)$$

Here, $ROR(LP, i)$ performs a circular bitwise right shift on a $P$-bit binary number $LP$ for $i$ times. After computing the rotation invariant local pattern code for each pixel $(x, y)$ of the input image of size $M \times N$, a histogram $H$ is obtained from the encoded image using equations 9 and 10:

$$H(b) = \sum_{x=1}^{M} \sum_{y=1}^{N} f(operator(x, y), b) \quad (9)$$

$$f(a,b) = \begin{cases} 1 & a = b \\ 0 & a \neq b \end{cases} \quad (10)$$

Here, $b$ is the local pattern code value and operator $(x, y)$ is the local pattern operator operating on the pixel $(x, y)$.

For LBP and LDP, we will get one histogram for each encoded image. On the other hand, for LTP, there will be two histograms for the positive binary code and the negative binary code, respectively. Therefore, for LTP, the two histograms are concatenated to form a single spatially combined histogram. The histograms obtained from the encoded images are used as the feature vector that describes the texture information of the image. The overall feature vector generation process is depicted in Figure 7. Figure 8 shows the encoded image representations obtained by applying different local pattern operators.

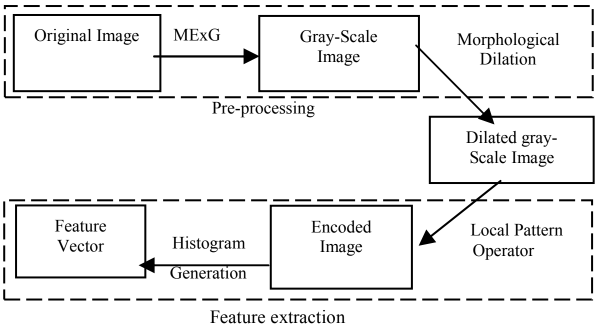


Figure 7. Illustration of feature vector generation process.

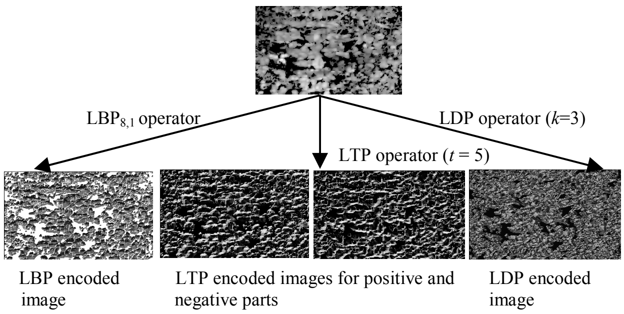


Figure 8. Encoded image representations obtained by applying different local pattern operators.

## 5. Weed Classification with Local Texture

For classifying weed images, different machine learning approaches such as template matching, Bayesian classifier, or SVM can be used. In our study, both template matching and support vector machine were used for the classification task.

### 5.1. Template Matching

During the training phase, histograms of training sample encoded images of the same class are averaged to generate the template model for that particular class. By 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:

$$D(S,M)=\sum_{n=1}^{N}\frac{(S(n)-M(n))\times(S(n)-M(n))}{S(n)+M(n)} \qquad (11)$$

Here, $S$ is the local pattern histogram of the testing sample, $M$ is the model histogram of a category, and $N$ is the number of bins in the histogram.

### 5.2. Support Vector Machine

SVM is a state-of-the-art machine learning approach based on the modern statistical learning theory. It has been successfully applied in different classification problems. SVM performs the 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 $T=\{(x_i, l_i), i=1, 2, \ldots, L\}$, where $x_i \in R^P$ and $l_i \in \{-1, 1\}$, a new test data $x$ is classified by:

$$f(x) = sign \sum_{i=1}^{L} \alpha_i l_i K(x_i, x) + b \qquad (12)$$

Here, $\alpha_i$ 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 with two different kernels, namely polynomial kernel and Radial-Basis Function (RBF) kernel. A grid-search was carried out for selecting appropriate kernel parameter values, as suggested in [9].

## 6. Experimental Results

To evaluate the effectiveness of the proposed method, we carried out a ten-fold cross-validation scheme to measure the classification rate against 400 sample weed images (200 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 accuracy of the local pattern operators can be influenced by adjusting different parameters. For LBP, we have used different settings for the parameters $P$ and $R$. Similarly, for LDP and LTP, the classification rate was calculated for various $k$ and $t$ values, respectively. Table 1 and Table 2 show the classification rate of LBP, LTP, and LDP feature representations for different parameter settings. All these experiments were carried out on rotation invariant patterns using both template matching and support vector machine, respectively.

Table 1. Classification rate (%) using template matching for different parameter settings.

| Operator | Parameter Setting | Classification Rate (%) |
|---|---|---|
| **LBP** | (P, R) = (8, 1) | 82.8 |
| **LBP** | (P, R) = (16, 2) | 83.3 |
| **Uniform LBP** | (P, R) = (8, 1) | 83.8 |
| **Uniform LBP** | (P, R) = (16, 2) | 85.0 |
| **LTP** | t = 5 | 87.0 |
| **LTP** | t = 10 | 86.3 |
| **LTP** | t = 15 | 85.5 |
| **LDP** | k = 2 | 87.0 |
| **LDP** | k = 3 | 89.3 |
| **LDP** | k = 4 | 87.8 |

Table 2. Classification rate (%) using support vector machine for different parameter settings.

| Operator | Parameter Setting | Classification Rate (%) | |
|---|---|---|---|
| | | Polynomial Kernel | RBF Kernel |
| **LBP** | (P, R) = (8, 1) | 87.8 | 90.3 |
| **LBP** | (P, R) = (16, 2) | 89.3 | 93.8 |
| **Uniform LBP** | (P, R) = (8, 1) | 90.5 | 94.5 |
| **Uniform LBP** | (P, R) = (16, 2) | 91.0 | 94.8 |
| **LTP** | t = 5 | 94.5 | 98.3 |
| **LTP** | t = 10 | 90.0 | 94.5 |
| **LTP** | t = 15 | 89.3 | 93.8 |
| **LDP** | k = 2 | 94.3 | 97.5 |
| **LDP** | k = 3 | 97.8 | 98.5 |
| **LDP** | k = 4 | 94.8 | 97.8 |

It can be observed that, LDP ($k$=3) provides the highest classification rate among the local pattern operators using both template matching and support vector machine. It is understandable that, the superiority of LDP encoding scheme is due to the utilization of robust edge response values in different directions for forming the binary pattern, where the other methods exploits intensity values of a local neighborhood. In our experiments, support vector machine provides higher classification rate than template matching for all local pattern operators. Based on the results, we can easily identify the optimal parameter setting for these operators. Table 3 shows the optimal parameter setting for the local pattern operators based on the experimental results.

Table 3. Optimal parameter setting for the local pattern operators.

| Operator | Parameter Setting |
|---|---|
| **LBP** | (P, R) = (16, 2) |
| **Uniform LBP** | (P, R) = (16, 2) |
| **LTP** | t = 5 |
| **LDP** | k = 3 |

The performance of the local pattern based feature representation is also compared with some other existing weed classification methods, namely Gabor wavelets [25] and Haar wavelets transform [1]. Figure 9 shows the comparison between the recognition rates of existing wavelets-based methods and LDP ($k$ = 3). It can be seen that, LDP outperforms the other methods in terms of classification accuracy.

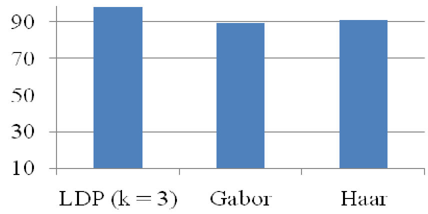


Figure 9. Comparison of existing methods against LDP in terms of classification rate (%).

## 7. Discussion

Based on the experimental results, several potential improvements can be mentioned:

- The proposed method provides rotation invariance by converting rotation variant local patterns to rotation invariant ones. Therefore, this method is capable of providing stable performance in presence of orientation variation.
- This method provides an efficient and effective approach to feature extraction and classification. Rather than using a time and memory intensive feature extraction method like wavelets that convolves the image with a bank of filters, the proposed method employs the local pattern operators, which are able to generate the feature vector by performing only a single scan of the image.
- In our experiments, we used weed images acquired in natural lighting conditions. Moreover, no pre-processing step was applied to remove the effect of illumination variation. The reason is that, some local patterns (such as LDP) are stable in presence of illumination variation and noise. In addition, LBP itself is sometimes used as a lighting normalization stage for other methods [8]. As no pre-processing is required to handle variations in lighting changes, computational complexity is reduced.

## 8. Conclusions

A weed classification method based on the local pattern-based texture descriptor was developed to classify broadleaf and grass weeds for real-time selective herbicide applications. Three widely-used local texture operators with different parameter settings were evaluated in our study. Extensive experiments on 400 sample images show the effectiveness of the proposed method in classifying weed images. The discriminative power of the proposed method mainly lies in the utilization of rotation invariant micro-pattern based texture information to form the feature vector, which facilitates robust performance in uncontrolled environment.

In our study, we used weed images that has only one dominant weed category: broadleaf or grass. Mixed weed images were not considered for this study. Therefore, future work includes studying local pattern based methods for classification of mixed weeds and introducing advanced methods for image pre-processing in order to achieve higher classification accuracy in real-world scenario.

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