Feature Extraction Technique using Discrete Wavelet Transform for Image Classification

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Feature Extraction Technique using Discrete Wavelet Transform for Image Classification

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***Abstract*-- The purpose of feature extraction technique in image processing is to represent the image in its compact and unique form of single values or matrix vector. Low level feature extraction involves automatic extraction of features from an image without doing any processing method. In this paper, we consider the use of high level feature extraction technique to investigate the characteristic of narrow and broad weed by implementing the 2 Dimensional Discrete Wavelet Transform (2D-DWT) as the processing method. Most transformation techniques produce coefficient values with the same size as the original image. Further processing of the coefficient values must be applied to extract the image feature vectors. In this paper, we propose an algorithm to implement feature extraction technique using the 2D-DWT and the extracted coefficients are used to represent the image for classification of narrow and broad weed. Results obtained suggest that the extracted 2D-DWT coefficients can uniquely represents the two different weed type.**

Index Term-- Feature extraction, Discrete Wavelet Transform, Coefficient, Weed

I. Introduction

Wavelet transform is widely used in machine vision as an image processing technique for object detection and classification. Wavelets have been applied in the past to analyze images [1] and are used in many applications in remote sensing, such as removing speckle noise from radar images [2], merging high spectral resolution images with high spatial resolution images, and texture analysis and classification [3]. In [4], wavelet transform has been used to classify EEG signal with integration of expert model. The concept of wavelet is closely related to multi-scale and multi-resolution application and it has been used in [5] to classify ground earth cover. Implementation of Discrete Wavelet Transform (DWT) as an image processing technique produces the transformation values called wavelet coefficient. The challenge here is how the coefficient can be interpreted to represent object for classification or detection. A common approach of feature extraction from wavelet transformation is the computation of coefficient distribution over selected mother of wavelet. In [4], expert model has been used as a feature extraction tool to analyze sub-band frequency of wavelet transform. The sub-band frequencies were used as an input to the expert model network. The common technique used for feature extraction of DWT coefficient is by using neural network [6], [7], [8]. In this study, wavelets will be used in the analysis of narrow and broad weed images since DWT allows decomposition of the image into different levels of resolution. By doing so, we introduce a new feature set that is based on the analysis of wavelet coefficient. This technique helps reduce the size of wavelet coefficient and produce a smaller size of feature vectors. As a result, simple linear classification tools can be used to categorize the two type of weed. Typically, the implementation of DWT uses the mother of wavelet such as Haar, daubechies, Coiflet, Meyer, Morlet and Mexican Hat. However, this study only considers the Haar mother wavelet in the preliminary attempt since the main objective is to extract a new set of features based on the DWT coefficients and to use linear discriminant analysis (LDA) to classify the weed.

II. Methodology

The research methodology adopted in this work can be graphically described in block diagram as shown in Fig. 1.

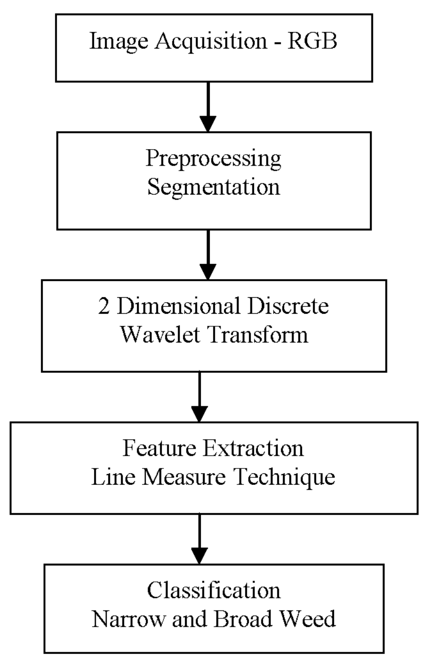

Fig. 1 - Process of narrow and broad weed classification

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The first step involves the image acquisition task. Weed images comprising of both narrow and broad weed types are captured on site in a palm oil plantation field using a CCD digital camera. The camera is set to capture images of standard size and resolution (e.g. 240x320 in JPEG RGB color format). An image dataset of more than 1000 samples were recorded. A total of 1000 images consisting of both narrow and broad weed types were used for the study. Next is the preprocessing task involving preprocessing step to convert RGB to gray scale. This is then followed by the feature extraction process. In this work, we have considered the structural approach employing the 2D-DWT. The images are transformed into their respective coefficients that separate the vertical, horizontal and diagonal sub-bands.

III. Wavelet Theory

The fundamental idea behind wavelets is to analyze signal according to scale. It has gained a lot of interest in the area of signal processing, numerical analysis and mathematics during recent years [9] [10].Generally, the wavelet transform is an advanced technique of signal and image analysis. It was developed as an alternative to the short time Fourier [11] to overcome problems related to its frequency and time resolution properties. The basic idea of DWT is to provide the time-frequency representation. The 2D-DWT represents an image in terms of a set of shifted and dilated wavelet functions $\psi^{LH}, \psi^{HL}, \psi^{HH}$ and scaling functions ϕ^{LL} that form an orthonormal basis for $L^2(R^2)$. Given a J-scale DWT, an image $x(s,t)$ of NxN is decomposed as

$$x(s,t) = \sum_{k,i=0}^{N_J-1} u_{J,k,i}\phi^{LL}{}_{J,k,i}(s,t) + \sum_{B\in \mathrm{B}} \sum_{j=1} \sum_{k,i=0}^{N-1} w^{B}{}_{j,k,i}\psi^{B}{}_{j,k,i}(s,t)$$

(1)

with

$$\phi^{LL}{}_{j,k,i}(s,t) \equiv 2^{-j/2}\phi(2^{-j}s-k, 2^{-j}t-i),$$

$$\psi^{B}{}_{j,k,i}(s,t), \psi^{B}{}_{j,k,i}(s,t) \quad (2)$$

$$\equiv 2^{-j/2}\psi^{B}(2^{-j}s-k, 2^{-j}t-i), B \in \mathrm{B}, \mathrm{B}$$

{LH,HL,HH}, and $N_j = N/2^j$. In this paper LH, HL and HH are called wavelet or DWT sub-bands. $u_{J,k,i} = \int\int x(s,t)\phi_{J,k,i}dsdt$ is a scaling coefficient and $w^{B}{}_{j,k,i} = \int\int x(s,t)\psi^{B}{}_{j,k,i}dsdt$ denotes the (k,i)th wavelet coefficient in scale j and sub-band B. Fig. 2 shows the scaling concept in wavelet transform.

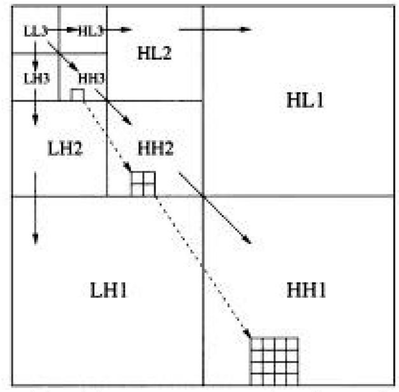

Fig. 2 - Joint spatial and frequency representation of a 2-D three-scale DWT.

IV. Image Classification

Classification of weed commonly found in palm oil plantations is carried out according to its respective category of either broad or narrow weed type. It is very important to distinguish narrow and broad weed in weeding strategy since different type of pesticide is used for different weed type. In the plantation sector, weeding strategy plays significant role in managing productivity and controlling palm oil quality. Currently, most plantation companies adopt manually sprayed herbicide as their weeding strategy which is known to be inefficient, labor intensive and also hazardous to the environment and the plantation workers. As a result, an intelligent system for an automated weeding strategy is greatly needed to replace manual spraying system in order to protect the environment and produce better and greater yields. In view of this, we have developed an intelligent system using machine vision to automate the weeding process. The core components of machine vision for this intelligent weeding system is the image recognition and classification. In this work, we report the image processing techniques that have been implemented which focused on the feature vector extraction and selection of the weed images. As mentioned earlier, weeding strategy is an important part in palm plantation industry to ensure palm oil production quality control. In this work, we will focus on the commonly found weed types in oil palm plantations which are classified and identified as narrow and broad weed. Fig. 3 shows the narrow and broad weed type in different image condition. These types of images will be processed using 2D-DWT and its coefficient features will be extracted using line measure technique (LMT).

V. Result and Discussion

As described in the previously, implementation of DWT produces coefficient values that follow the same size as original images. As such, the size of the wavelet coefficients produced will be the same as the images, which are 240x320 matrix pixel values. Based on wavelet coefficients, we develop a feature extraction technique called line measure technique (LMT). From the matrix of wavelet coefficient, the continuity of pixels values is measured inside the matrix. The continuity can either be 3, 5, 7 or 10 and the angle measurements are 0^0, 45^0, 90^0 and 135^0. LMT feature extraction is implemented as follows:

- Measure the continuity of pixel values using values of either 3, 5, 7 or 10
- If there is no continuity,, the pixel values is set to zero
- For example, if continuity = 3 with angle 0^0, the following step will be taken
    - If $X_n \& X_{n+1} \& X_{n+2} = 1$, remain the pixel value 1
    - If $X_n \& X_{n+1} \& X_{n+2} \neq 1$ all the pixel values set to 0.
    - $\sum_n Xn$

Fig 3 – Images of narrow and broad weed to be classified

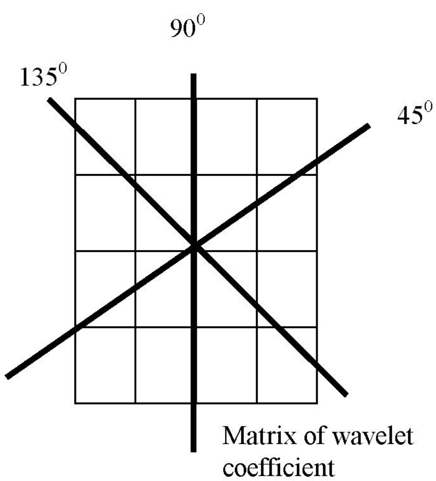

Fig. 4 – LMT technique with angle of direction

The 2D-DWT technique was applied to the narrow and broad weed image. Fig. 4 shows the original image and the output of wavelet with the basic mother wavelet function Haar. From the figure, we found that the wavelet coefficient of level 1 and level 2 has a different view of pixel values. The pixel values of level 2 have a bigger range of minima and maxima compared to level 1. All data coefficient information is very useful in order to extract its feature vector using LMT. Table 1 shows the feature vector of LMT for the wavelet coefficient of level 1 for both broad and narrow weed. The coefficients will be used as an input to classification tools to design the classifier system. Implementation of 2D-DWT produces three different sub-bands of wavelet coefficients called horizontal, vertical and diagonal sub-bands. The vertical and horizontal sub-bands are analyzed using LMT feature extraction technique and the extracted feature vector set is as shown in a scatter plot in Fig. 5. It can be seen that there are two unique clusters, each representing the narrow and broad weed type. It was also noted that the new feature set can be linearly separated and as a result, a linear classification tools can be used as a classifier system. A total of 1000 sample images were used in the testing of our proposed method and the classification rate of narrow and broad weed are shown in Table II, III and IV for line angle of 45°, 90° and 135° respectively. .

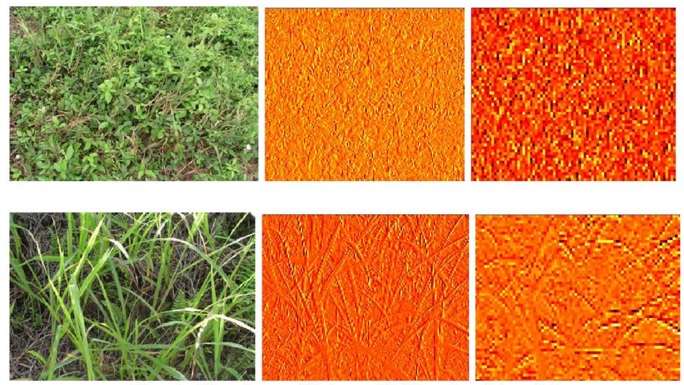

Fig. 4 - Wavelet coefficient with Haar level 1 and 2

TABLE 1
FEATURE VECTOR OF LINE MEASURE TECHNIQUE

Image	Broad	Narrow
1	271.00	582.00
2	210.00	573.00
3	219.00	473.00
4	219.00	619.00
5	267.00	509.00
6	219.00	617.00
7	210.00	614.00
8	267.00	614.00
9	210.00	511.00
10	210.00	945.00
11	199.00	511.00
12	240.00	525.00
13	386.00	668.00
14	210.00	584.00
15	150.00	769.00
16	219.00	683.00
17	210.00	597.00
18	267.00	558.00
19	210.00	703.00
20	219.00	1015.00

VI. CONCLUSION

The LMT with 7 continuity and angle of 45° obtained the best result with correct classification rate of 86.1% and 88.4% for narrow and broad weed respectively. Slight drop in the performance was noted when the continuity was set to 10 while maintaining the angle at 45°. We have found that the LMT with angle 45° is the most suitable angle since the best classification result is achieved when this value is used. In brief, it can be concluded that the LMT feature extraction technique has great potential since the extracted feature sets can uniquely represent the two different types of weeds and be used in distinguishing both narrow and broad weed with overall classification rate of 87.25%. Further work is ongoing to improve the technique either in the part of the feature extraction or classification.

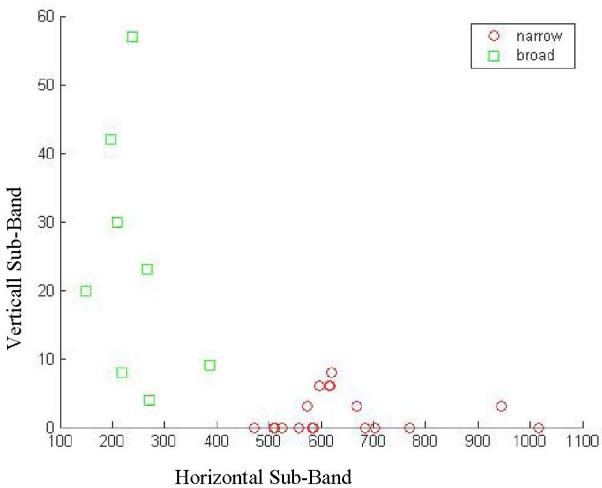

Fig. 5 – Feature vector of horizontal and vertical sub-band

TABLE II
CORRECT CLASSIFICATION RATE WITH LMT ANGLE 45^0

Continuity	45^0	
	nrw(%)	brd(%)
3	80.0	80.4
5	82.9	83.7
7	86.1	88.4
10	86.3	87.9

TABLE III
CORRECT CLASSIFICATION RATE WITH LMT ANGLE 90^0

Continuity	90^0	
	nrw(%)	brd(%)
3	70.8	71.2
5	73.7	74.2
7	74.5	75.8
10	74.4	74.9

TABLE IV
CORRECT CLASSIFICATION RATE WITH LMT ANGLE 135^0

Continuity	135^0	
	nrw(%)	brd(%)
3	80.4	81.0
5	80.9	82.3
7	82.4	84.7
10	82.2	83.9

VII. REFERENCES

[1] E. Virginie, S. Alfred, M. Steven and B. Johan, “A wavelet characterization of high-resolution NDVI patterns for precision agriculture”, JAG l Volume 3 - Issue 2 - 2001

[2] G. Horgan, “Wavelets for SAR image smoothing.

[3] C. Zhu and X.. Yang, “Study of remote sensing image texture analysis and classification using wavelet”, International Journal of Remote Sensing 19: pp. 3197-3203, 1998

[4] S. Abdulhamit, “EEG signal classification using wavelet feature extraction and a mixture of expert model”, Expert system with applications 32(2007) 1084-1093

[5] G. Ping, X. Fei and J. YuGang, “Stellar Data Classification Using SVM with Wavelet Transformation”, IEEE International Conference on Systems, Man and Cybernetics, 2004

[6] I.N Tansel, C. Mekdeci, O. Rodriguez and B. Uragun, “Monitoring Drill Conditions with Wavelet Based Encoding and Neural Networks”, Int. J. Machine Tools and Manufacture, vol 33, pp 559-575, Aug 1993

[7] A. Laine and J. Fan, “Texture Classification by Wavelet Packet Signatures”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 11, pp 1186-1191, 1993

[8] S. Livens, P. Scheunders, G.V de Wouwer, D.V. Dyck, H.Smets, J.Winkelmans and W. Bogaerts, “Classification of Corrosion Images by Wavelet Signature and LVQ networks, Computer Analysis of Images Patterns”, V.Hlavac and R. Sara, eds , pp. 43-48 1990

[9] I. Daubechies, “Orthornomal bases of compactly supported wavelets,” Comm. On Pure and Applied Mathematics, vol. XLI, pp 909-996, 1998

[10] J.O Stromberg, “A modified Franklin sustem and higher order splines as uncontditional basis for Hardy spaces” in Proc. Conf. in Harmonic Analysis in Honor of Antoni Zygmud (Beckner W. et al., ed.), vol II, Wadworth Mathematical Series, 1983

[11] S.G. Mallat, “A theory for multiresolution signal decomposition: the wavelet representation”, IEEE Transactions on Pattern Analysis and Machine intelligence 11: 674-693, 1989 Photogrammetric”, Engineering and Remote Sensing 64: pp. 1171-1177, 1998

VIII. BIOGRAPHIES

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