

Minimax-Based High Throughput Plant Phenotyping Analysis in Complex Wavelet Domain Using Adaptive Feature Extraction Algorithm

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Abstract

High throughput plant phenotyping that can identify plant traits and estimate yield is an important image processing requirement. Existing techniques capture plant components or objects and characterize the objects. Processing the plant data in the spatial domain is time consuming and has to address issues such as temporal variation, overlapping and the emergence of new objects. Image analysis in the wavelet domain has demonstrated advantages in extracting features, considering edge information. In order to improvise the feature detection process in the wavelet domain with additional orientations of edge features and to address shift variance in input data, a novel method is proposed in this work based on the Dual Tree Complex Wavelet Transform (DTCWT). In the proposed method, an adaptive algorithm is developed to accurately and adequately extract the features for processing plant phenotyping images. From the results obtained for metrics such as histogram, entropy and MSE, it is observed that there is an improvement in features by over 24% as compared with the conventional method and the adaptive algorithm is adjustable to meet the set requirements. The algorithm proposed in this work can enable plant phenotyping image analysis.

Keywords – Plant phenotyping, high throughput, DTCWT, plant traits estimation, yield estimation and quantification

Introduction

Morphological changes and functional traits of temporal variations in plant growth influenced by environmental conditions and regulated by plant genotypes provide information on plant yield and quality of yield. Plant phenotyping entails the study of plant structure and function, including growth, yield, biotic and abiotic stress responses, and quality. High throughput phenotyping is the process of analyzing a large number of phenotype images in a short interval of time with high accuracy and precision without human intervention [1]. Plants grow with changes in shape, appearance and structure. Continuous capture of plant images imposes challenges in phenotyping analysis as plant leaves position themselves in response to light interception. The growth of leaves leads to leaf cross over and occlusions. Image based phenotyping of plant data is also influenced by light illumination, background and camera properties [2]. From the images captured, it is required to quantify physiological processes that can aid in the measurement of environmental stress on plant parts and photosynthetic activity content in plant components [3]. It is also required to identify dynamic events in plants such as the emergence of new leaves, the time of emergence, the detection of germination, the time of germination, the emergence of fruits and flowers, and the timing of the emergence of fruits and flowers, which provide information on possible strategies to grow plants [4]. It is required to carry out a detailed study on structural variations in plants, considering plant phenotyping activities. In order to automate the process of image processing methods for plant phenotyping, it is required to develop a benchmark model based on conventional methods. In this work, a systematic approach is carried out in developing algorithms and methods for image based plant phenotyping activities.

Figure 1 presents the block diagram of the high throughput plant phenotyping model. In this model, image sequences are captured that are temporal variations, each of the image sequences will contain a group of

plants [5]. A Multimodal camera (images of visible light, fluorescent, near infrared, infrared and hyperspectral) is used to capture the images. These images were captured considering drought, salinity and variations in the thermal properties of the environment. Images are also captured in multi views, multimodal and temporal dimensions as required by the regulated standards of genotyping and environmental conditions. Visible images are used to compute structural changes or morphological variations in the plants. To capture chlorophyll, water and temperature changes in plants fluorescent images, near infrared and infrared images are considered. Leaf tissue structure, pigments, stress resistance and water composition in the plant is captured using hyperspectral images [6].

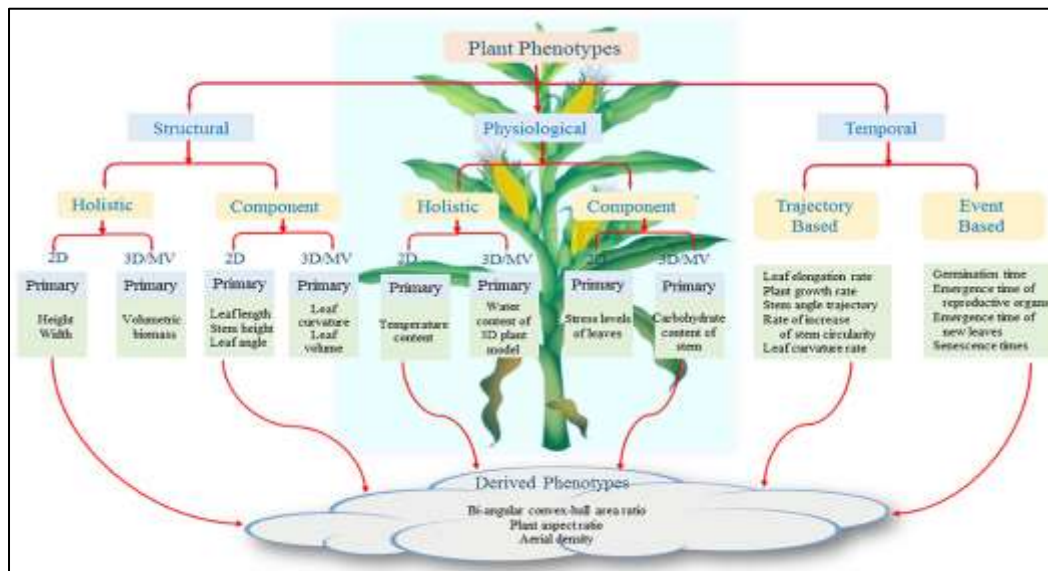


Figure 1 Plant phenotyping platform

Dellen et al. [7] have developed a phenotyping algorithm to track the growth of leaves and measure the trajectory of leaves by considering leaf shapes. Tracking of leaves is a complex task and use of Chamfer matching method is used to align and track the leaf [8]. The Emergence of new leaves and the timing of emergence, the number of leaves and the total number of emerged leaves are captured considering component phenotyping approaches [9]. Image processing methods with a combination of AI based approaches have also been used for high throughput applications [10]. A Convolutional neural network (CNN) model to identify and classify traits has also been developed by identifying features such as root tips, leaf tips and bases [11-13].

Functional dynamics in plants, water scarcity, and plant resistance to drought are assessed using hyperspectral images [14]. Drought analysis based on the volume maximization technique was developed by Romer et al. [15], considering hyperspectral images. Food quality, determination of salt content and stress due to salt content are analyzed considering hyperspectral images [16]. Abiotic stress levels, plant diseases and yield prediction are analyzed based on hyperspectral images [17,18]. Trajectories in leaf growth and leaf components such as length, skeleton area, mid-point in leaf, curvature of leaf, angle of stem and apex curvature that represent the temporal properties of plants are analyzed by Das Choudhry et al. [19].

From the literature studies, it is identified that plant phenotyping activities considering the structural, temporal and physiological properties of plants will provide information on yield and quantify plant traits. The determination of timing information of plant components such as germination, sequence of leaves, emergence of leaves, fruits and flowers provides details of biotic and abiotic stress in plants. With dynamic changes in plant components that are time driven, processing temporal images gives rise to variations in the positions of plant components when the images are captured at different time intervals. Any change in the positions of plant components in a given sequence of images that are captured at different time intervals will lead to complexity in image processing algorithms. Promising methods for feature extraction from plant images use Discrete Wavelet Transforms (DWT) sub bands to identify the objects and extract the

features of the objects for plant phenotyping analysis. The limitations of DWT are that they are shift variants and to overcome these limitations, shift invariant methods have been developed. In this paper, new methods for plant phenotyping and feature extraction is developed based on shift invariant transformation techniques.

DTCWT for Plant Phenotyping

Nick Kingsbury demonstrated the use of the Dual Tree Complex Wavelet Transform (DTCWT) to overcome the limitations of DWT [20]. In DTCWT, two filter structures are used in place of a single filter bank structure, as in DWT, the two filter bank structures form a Hilbert transform pair. One of the methods to achieve shift invariance is to use dyadic filters without decimation by 2. Decimation by 2 in the sub band filtering method eliminates redundancy in wavelet coefficients. Without decimation to avoid shift variance, the computation complexity increases and generates highly redundant sub bands. With every level generating redundant coefficients, the multi-level decomposition becomes complex and highly redundant. To overcome these limitations, Nick Kingsbury [20] introduced the Dual Tree Complex Wavelet Transform (DTCWT) that satisfied the properties of shift invariance and improved directional orientations in the sub bands generated. The DTCWT also had satisfied a perfect reconstruction property with a limited redundancy of $2^m: 1$ (m -number of dimensions) and a limited number of computations of 2^m times higher than the DWT. In DWT, the input image is first processed along the rows and then along the columns, similarly for computing DTCWT sub bands input image is processed along the rows first and then along the columns, capturing positive frequencies. However, in DTCWT, while processing along the rows and columns using wavelet filters, another pair of filters that form complex conjugate of the real filters is used to generate additional sub bands that capture negative frequencies. This gives rise to 4:1 redundancy in the generated wavelet sub bands. DTCWT generates three sub bands in each of the quadrants, generating six sub bands all together. The six sub bands capture features in six orientations of $\pm 15^\circ$, $\pm 45^\circ$ and $\pm 75^\circ$. As both positive and negative frequencies are captured by the real and its complex conjugate filters in DTCWT, strong orientations in both vertical and horizontal directions are present in the sub bands. Figure 2 presents the DTCWT and DWT sub bands. There are six sub bands generated in DTCWT with real and imaginary filters with directional orientations varying from 75° to -75° .

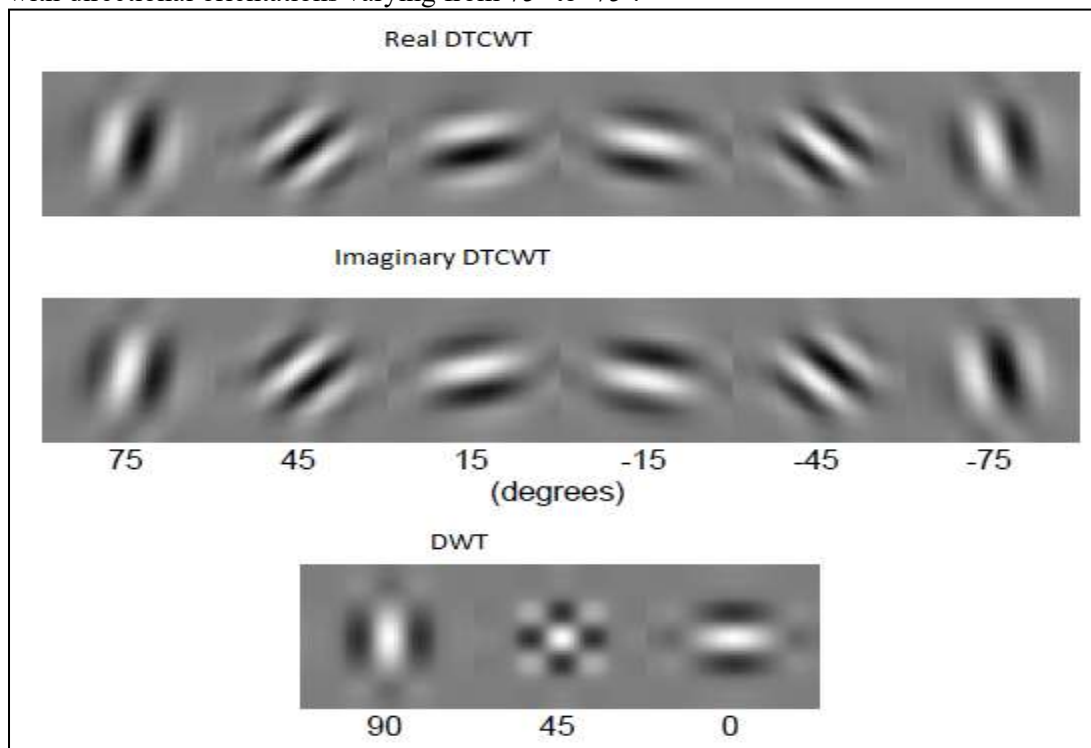


Figure 1: DTCWT and DWT sub bands

The orientations along the 45° and -45° are very distinct and when compared with the DWT sub band the orientations along the 45° are combined. The advantages of wavelet transform are the localization of features in each of the sub bands that are clearly visible in the sub bands of DTCWT as compared with DWT sub bands.

DTCWT is computed using two real DWT trees that are used to compute the real and imaginary parts of the wavelet sub bands. DTCWT decomposes the input data based on complex shifted and dilated mother wavelet functions (ψ) and scaling functions (ϕ). The wavelet functions and scaling functions for one dimensional wavelet are expressed as in Eq. (1) and Eq. (2) for the real (r) term and the corresponding imaginary (i) term for wavelet function and scaling function is expressed as in Eq. (3) and Eq. (4) [20].

$$\psi_r(t) = \sqrt{2} \sum_n H_a(n) \phi_r(2t - n) \quad (1)$$

$$\phi_r(t) = \sqrt{2} \sum_n L_a(n) \psi_r(2t - n) \quad (2)$$

$$\psi_i(t) = \sqrt{2} \sum_n H_b(n) \phi_i(2t - n) \quad (3)$$

$$\phi_i(t) = \sqrt{2} \sum_n L_b(n) \psi_i(2t - n) \quad (4)$$

The parameters L and H represent the low pass and high pass filters respectively. The complex wavelet function $\psi_c = \psi_r + j\psi_i$ is represented by combining the real wavelet and imaginary wavelet functions. The analysis filter coefficients for computing the real and imaginary wavelet sub bands are presented in Table 1 for the first level of decomposition. Table 2 represents the filter coefficients for the second level and higher [21].

Table 1: First level DTCWT filter coefficients

L_a	H_a	L_b	H_b
0	0	0.01122679	0
-0.08838834	-0.01122679	0.01122679	0
0.08838834	0.01122679	-0.08838834	-0.08838834
0.69587998	0.08838834	0.08838834	-0.08838834
0.69587998	0.08838834	0.69587998	0.69587998
0.08838834	-0.69587998	0.69587998	-0.69587998
-0.08838834	0.69587998	0.08838834	0.08838834
0.01122679	-0.08838834	-0.08838834	0.08838834
0.01122679	-0.08838834	0	0.01122679
0	0	0	-0.01122679

Table 2: Second level and higher level DTCWT filter coefficients

LL_a	LH_a	LL_b	LH_b
0.03516384	0	0	-0.03516384
0	0	0	0
-0.08832942	-0.11430184	-0.11430184	0.08832942
0.23389032	0	0	0.23389032
0.76027237	0.58751830	0.58751830	-0.76027237
0.58751830	-0.76027237	0.76027237	0.58751830
0	0.23389032	0.23389032	0
-0.11430184	0.08832942	-0.08832942	-0.11430184
0	0	0	0
0	-0.03516384	0.03516384	0

For computing DTCWT sub bands for the input image, the pair of trees are used for processing the rows and columns based on the separable property of filters. Figure 3 presents the decomposition structure of 2D DTCWT that generates six high pass and two low pass sub bands at level-1 decomposition.

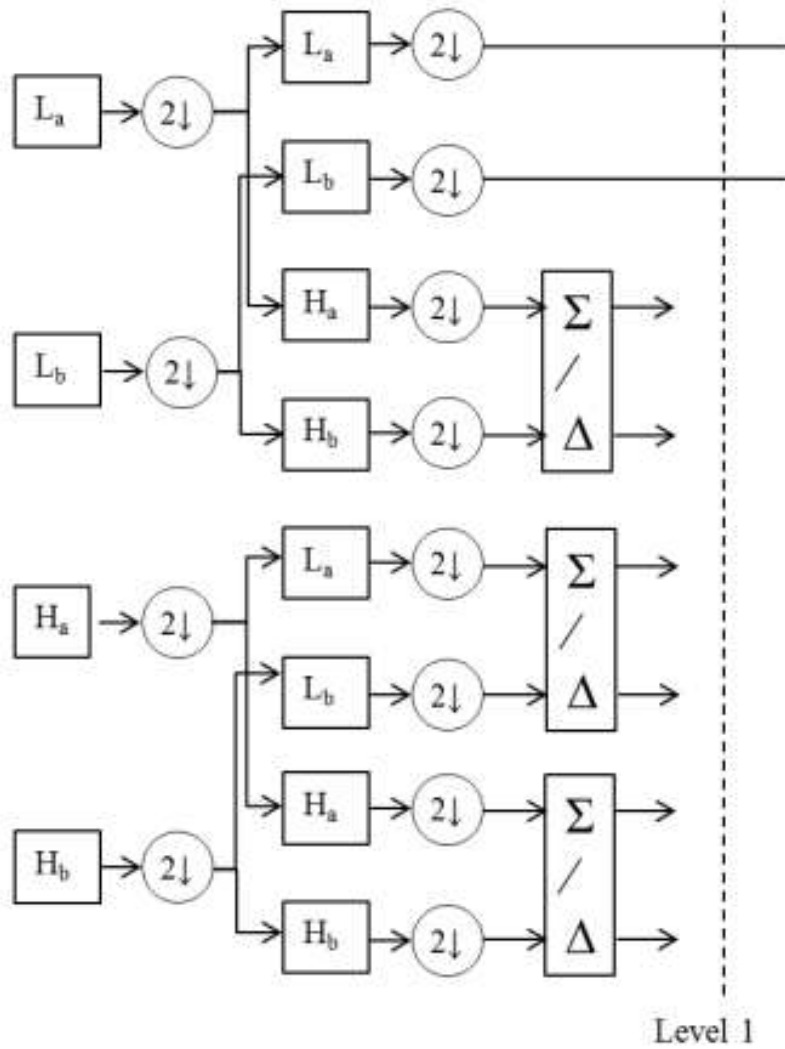


Figure 2: Level-1 2D DTCWT decomposition structure

The six sub bands that capture directional features along the $\pm 15^\circ$, $\pm 45^\circ$ and $\pm 75^\circ$ orientations are computed by performing the sum and difference operations of the LH, HL and HH sub bands. The mathematical operations to generate the six sub bands are computed based on the Eq. (5). The parameters a and b represent the filter pairs or trees.

$$\begin{array}{ccc} (LH_a + LH_b)/\sqrt{2} & (HL_a + HL_b)/\sqrt{2} & (HH_a + HH_b)/\sqrt{2} \\ (LH_a - LH_b)/\sqrt{2} & (HL_a - HL_b)/\sqrt{2} & (HH_a - HH_b)/\sqrt{2} \end{array} \quad (5)$$

For generating higher levels of sub bands the low pass sub bands are further decomposed into multiple levels by repeating the structure shown in Figure 2. For level-2 and higher levels of decomposition, the filter coefficients in Table 2 are considered. At every level of decomposition, there will be six high pass sub bands and two low pass sub bands generated. With additional directional information captured in these six sub bands overcoming the limitations of the shift variance property of DWT, image processing algorithms are to be designed for plant phenotyping images without loss of information.

Proposed method

In order to identify the objects in plant data, it is required to identify significant features of the objects. To identify the object features, in particular the directional orientations, the plant images are transformed from a spatial domain to a complex wavelet domain. As shown in Figure 4, three levels of decomposition are carried out to generate DTCWT sub bands. The three levels of sub bands capture the DC or intensity, information of the input image and the directional features of the input image at three scales and resolutions. The focus of this work is estimating the object features without loss of information and hence it is required to consider the features captured in all these sub bands with utmost importance. In order to capture the features from all the sub bands three steps are proposed. In the first step, the real and imaginary sub bands are combined into a single sub band by computing the magnitude of the high pass sub band D_{Mag} is carried out as in Eq. (6) and the Eq. (7) for the low pass sub bands denoted by A_{Mag} .

$$D_{Mag}(i,m) = \sqrt{D_r(i,m)^2 + D_i(i,m)^2}, i = 1, 2, 3, 4, 5, 6 \text{ and } m=1, 2, 3 \quad (6)$$

$$A_{Mag}(i,m) = \sqrt{A_r(i,m)^2 + A_i(i,m)^2}, i=1, 2 \text{ and } m=1, 2, 3 \quad (7)$$

Combining the real and imaginary sub bands will reduce the number of high frequency sub bands from 12 to 6 and the low frequency sub bands from 4 to 2. In the second step, a gradient operation is carried out to find out the directional information. Considering the gradient operation that computes the first (∂) and second derivative (∇) along the x and y directions to enhance the edge information in the sub bands, the gradient of each of the sub bands is computed as in Eq. (8). From the gradients derived along the x and y directions of the six sub bands at each level, the magnitude of the gradient is computed as in Eq. (9).

$$\frac{\partial D_{Mag}(x,y)}{\partial x} = D_{Mag} \nabla_x = \frac{D_{Mag}(x+d_{x,y}) - D_{Mag}(x,y)}{d_x} \quad (8a)$$

$$\frac{\partial D_{Mag}(x,y)}{\partial y} = D_{Mag} \nabla_y = \frac{D_{Mag}(x,y+d_y) - D_{Mag}(x,y)}{d_y} \quad (8b)$$

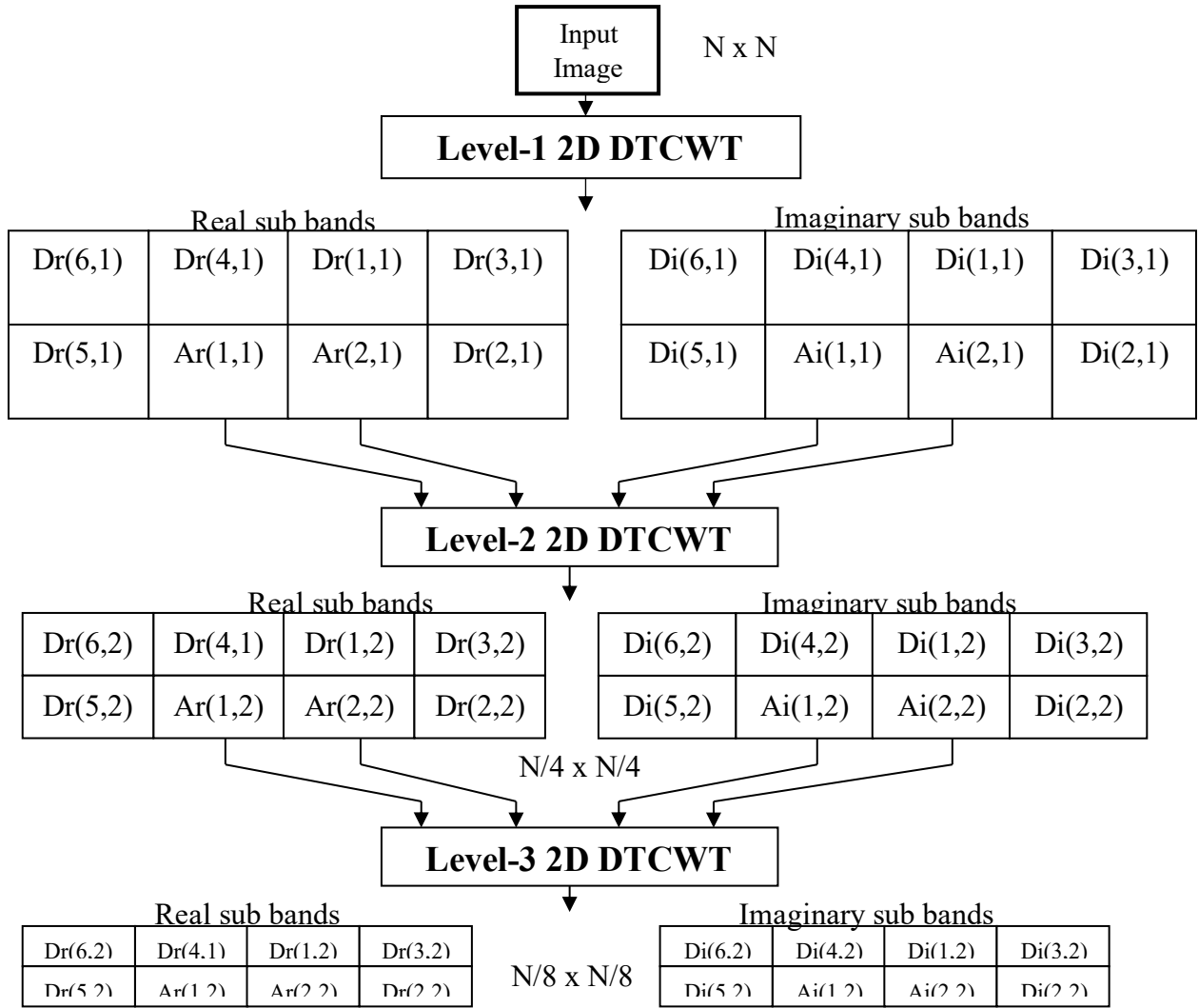


Figure 4: DTCWT sub bands after 3-level decomposition

In the magnitude operation, the square operation is replaced with the modulus operation to reduce the computation complexity. There will be six images that will hold significant directional features that will be localized in each of the six images that have been derived from the six sub bands.

$$DMagGrad = |DMag\nabla_x| + |DMag\nabla_y| \quad (9)$$

In the third step, the most significant directional orientations are retained. In order to retain the most significant edge information in each of the six images generated at every level, it is required to remove the insignificant edges. In order to identify insignificant edges or pixels, a threshold value is set. The threshold level is derived based on the expression presented in Eq. (10). The term β is a constant parameter that is set between (0.0001 and 0.001) and is incremented in steps of 10 depending upon the required performance metrics of image reconstruction. Each of the six images is considered in deriving the threshold levels. In order to achieve the best results, an adaptive algorithm is developed and is based on the expression in Eq. (10). After retaining the significant features and in order to find out that there is no loss of information, reconstruction of the original image is carried out. From the reconstructed image, the MSE is computed, if the MSE is not within the desired limits, then the constant β is varied (default is set to 0.001). This is an iterative process and at every level of threshold, the adaptive algorithm generates the sub bands and which are used in the reconstruction of the image at the transmitter section to compute MSE.

$$T_{Dthres}(m) = \beta \times \sqrt{\sum_{i=1}^6 \text{square}(DMagGrad(1, m))} \quad (10)$$

Based on the identified threshold level, each of the six images are quantized. Each pixel in the image is considered and retained at its original value if the pixel intensity is above the threshold value. If the pixel

intensity is less than the set threshold, the pixels are set to zero intensity levels. Figure 5 presents the proposed algorithm for plant phenotyping image analysis. The generated sub bands based on the adaptive algorithm are organized similarly to conventional methods.

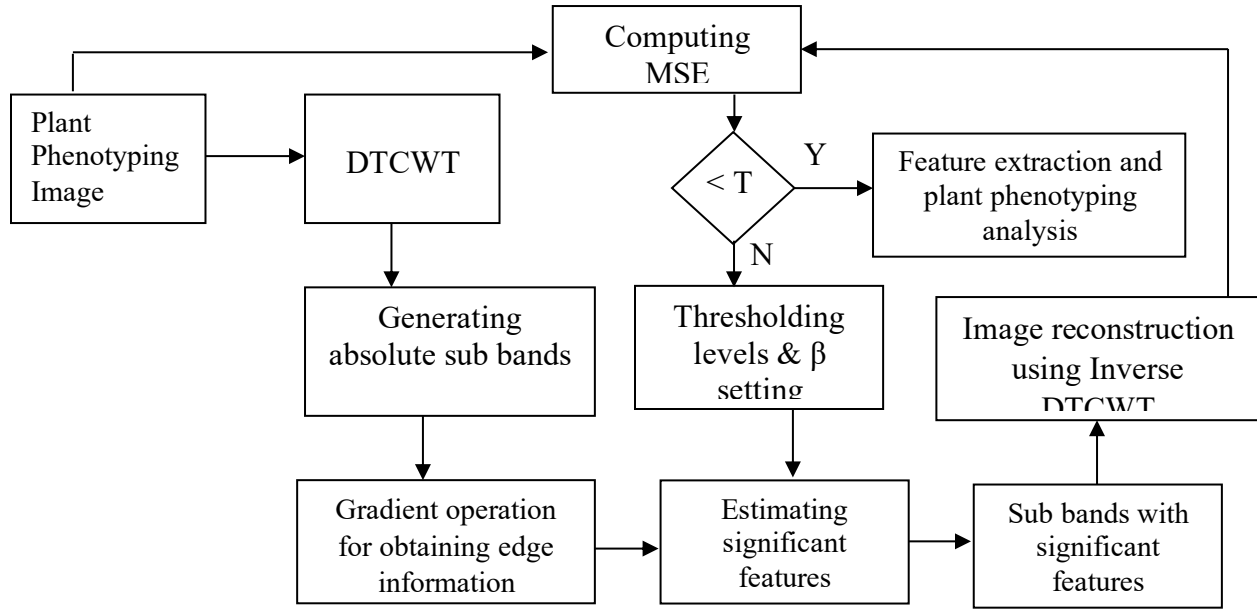


Figure 5: Proposed algorithm for feature extraction for plant phenotyping

In the proposed algorithm, the DTCWT sub bands are processed to identify the gradients and significant features in the gradient sub bands. The significant gradients that are identified are considered to be the best features, providing detailed information for identifying the features from the plant data. In order to justify that the identified features are the most appropriate data for further processing, inverse DTCWT is carried out to generate the original image. MSE is computed by comparing the original image and the output of the inverse transformation. If the MSE is less than a set threshold, indicating that the information in the reconstructed image captures all the significant information. If the MSE is greater than the threshold, the parameter β is adjusted and the process is carried out until the MSE is less than the given threshold. The proposed method is novel and is able to capture the significant features for identifying the objects for plant phenotyping applications.

Results & Discussion

Figure 6 presents the plant phenotype images of a single plant (*Arabidopsis*) captured using a visible camera at three different instances of plant growth over a few days [22]. The first picture shows the plant growth in the first 5 days of seed sown, the second picture was taken after 10 days and third picture was taken after 15 days. Considering the growth of plants in a controlled environment, phenotyping experiments are carried out by analyzing the information available in the plant data.

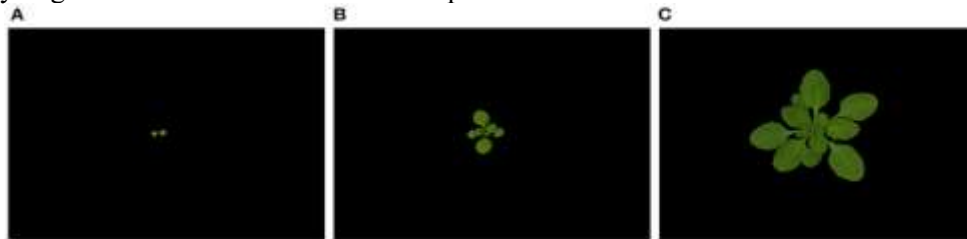


Figure 6: Growth of plant captured during phenotype experiments

Figure 7 presents the details of phenotyping experiments and analysis carried out with plant images. The plants that are placed in a tray comprise more than 10 pots of plants, each plant is segmented and from the segmented images, a leaf mask, leaf center, plant mask, leaf and plant bounding box are identified. High-throughput screening of quantitative plant traits upon perturbation of environmental and/or molecular-genetic factors is analyzed using these images [23].

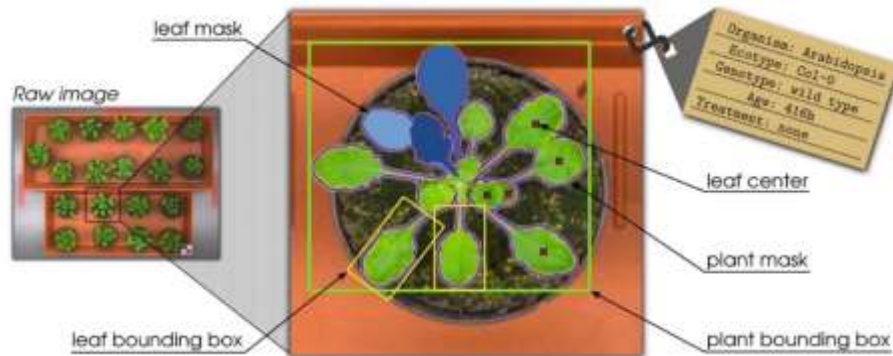


Figure 7: Image processing methods capturing plant information

Software that processes plant images detect and track the structural breaks in cells and organs of plants, model 3D geometries of whole plants, images of roots, tracking, flow and growth of plants. From these analyses, the impact of environmental changes on plant growth and yield is evaluated [23]. Figure 8 and Figure 9 present the tray of plants captured at different time intervals. As plant growth occurs, images are captured and processed to measure morphological, geometrical and color properties. Visible light imaging is used in the measurement of plant biomass, yield traits, panicle traits, leaf and seed morphology, coleoptile length and biomass, root architecture, seedling vigor and imbibition and germination rates of plants. Overlapping of leaf shadows in the image, brightness and color variation and variation of plants while cleaning cause challenges in processing visible images [24].

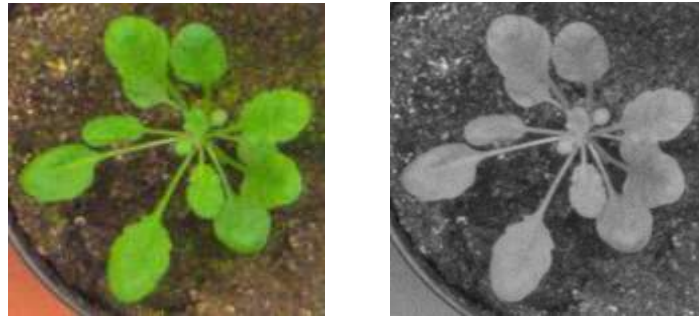


Figure 8: Images of plants captured at different time intervals



Figure 9: Group of plants (plant trays)

Figure 10(a) presents the plant image considered for analysis, titled “ara2012_plant002_rgb”. The input image is converted to a gray scale image for analysis. Figure 10(b) presents the gray scale image of the test data.



(a)Test image (b) Grey scale image

Figure 3: Test input from plant folder for analysis (ara2012_plant002_rgb)

The input image is processed by the DTCWT module to generate the real and imaginary sub bands of both low pass and high pass filters. Figure 11 presents the high pass sub bands generated by DTCWT considering level-1 decomposition. In level-1 decomposition, there will be 12 high pass sub bands and 4 low pass sub bands. The 12 high pass sub bands will capture the edge information along the $\pm 45^\circ$, $\pm 15^\circ$, $\pm 75^\circ$. The high pass sub bands with both positive and negative directions for both real and imaginary sub bands are captured and processed further for the compilation of sub bands.

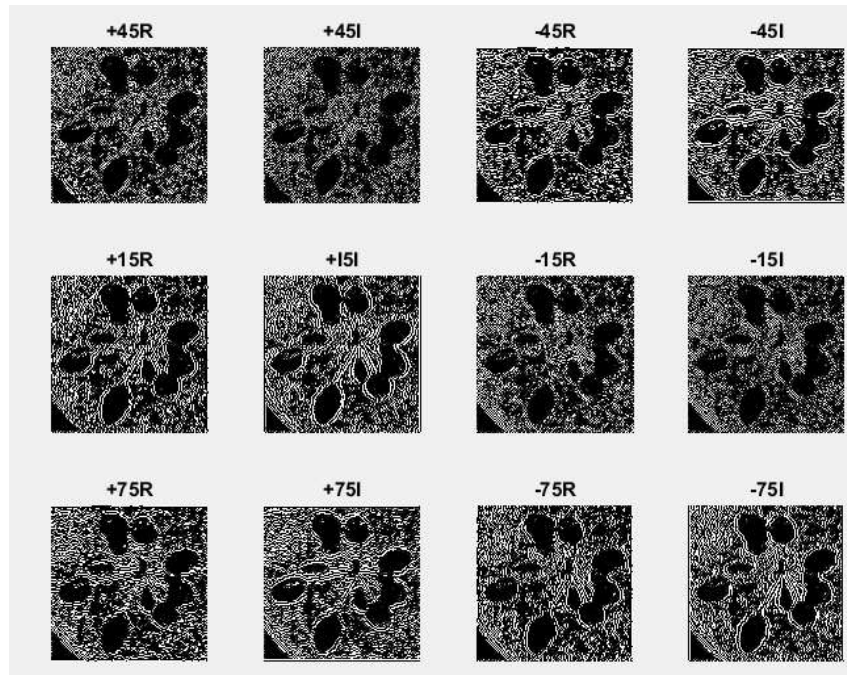


Figure 4: High pass sub bands of DTCWT at level-1

It is required to capture the directional edge information from all orientations from the outputs of DTCWT sub bands. In order to capture the directional information gradient operation is used, as discussed in the previous section. The gradient operation captures the edge information in both x and y directions. In addition to the directional information, the gradient operation is also used to capture the magnitude and direction information from all the 12 sub bands. Figure 12 to Figure 14 presents the sub band images with gradient information from real high pass sub bands at level-1.

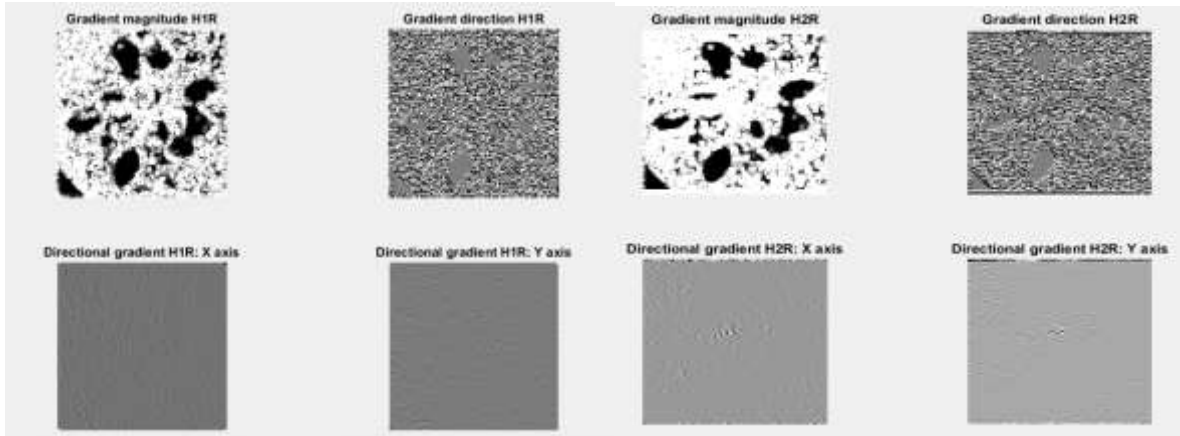


Figure 5: Directional information in the H1R sub band H2R sub band

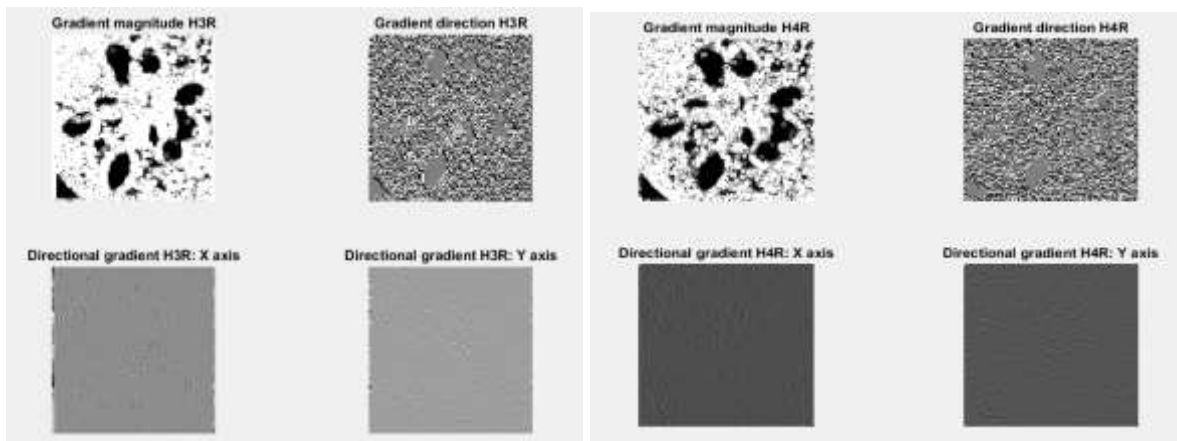


Figure 13: Directional information in the H3R sub band and H4R sub band

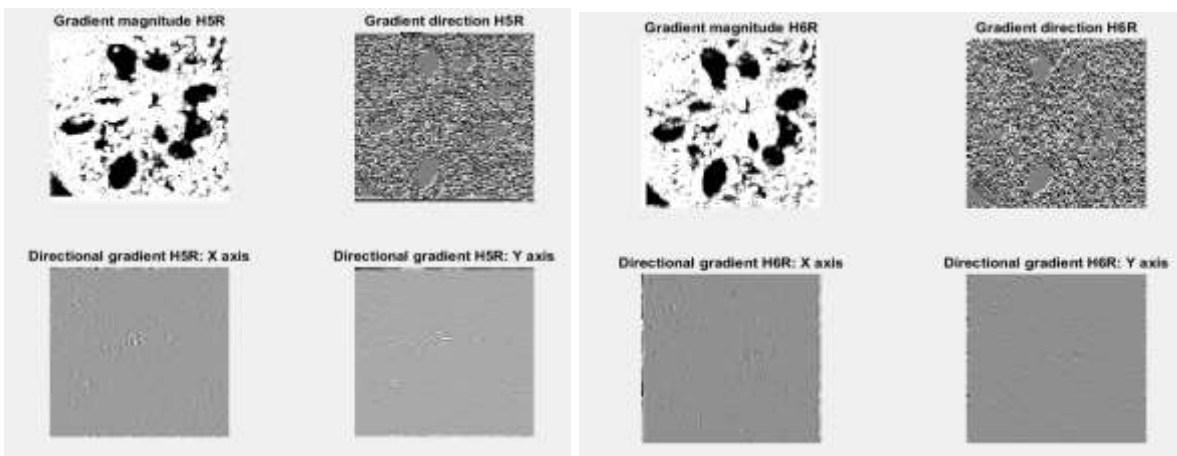


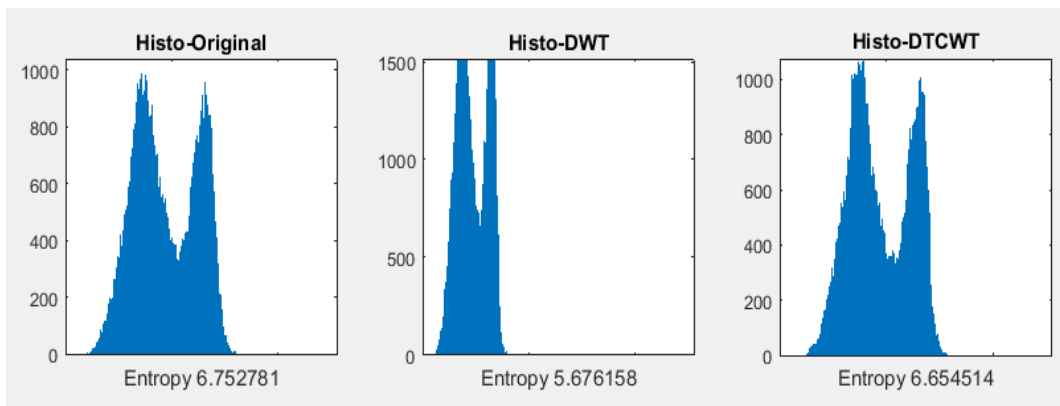
Figure 14: Directional information in the H5R sub band and H6R sub band

From the features identified and in order to justify that the features extracted are significant and sufficient enough for plant phenotyping process, the images are reconstructed using both the methods, such as DWT and DTCWT. Entropy information is also captured from both methods and is compared. Figure 15(a) presents the reconstructed image using the DWT method and Figure 15(b) presents the reconstructed image using the proposed DTCWT method. Figure 16 and Figure 17 presents the results of two image data sets.

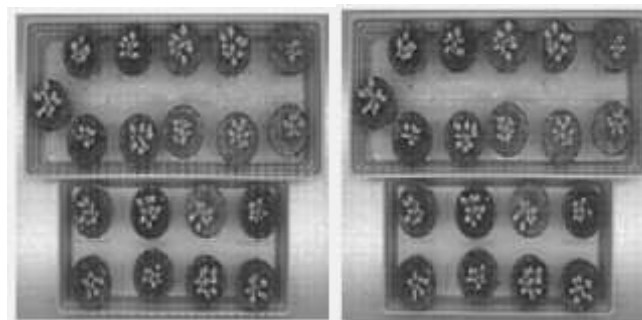


(a) DWT method

(b) DTCWT method

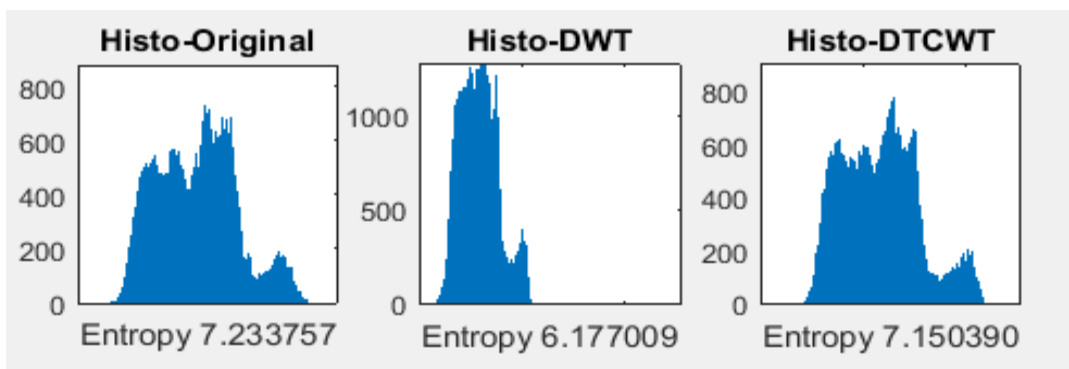


(c) Entropy and histogram of plant image 1

Figure 15: Reconstructed images test image 1 from plant data set

(a) DWT method

(b) DTCWT method



(c) Entropy and histogram of plant image 2

Figure 16: Reconstructed images test image 2 from tray data set

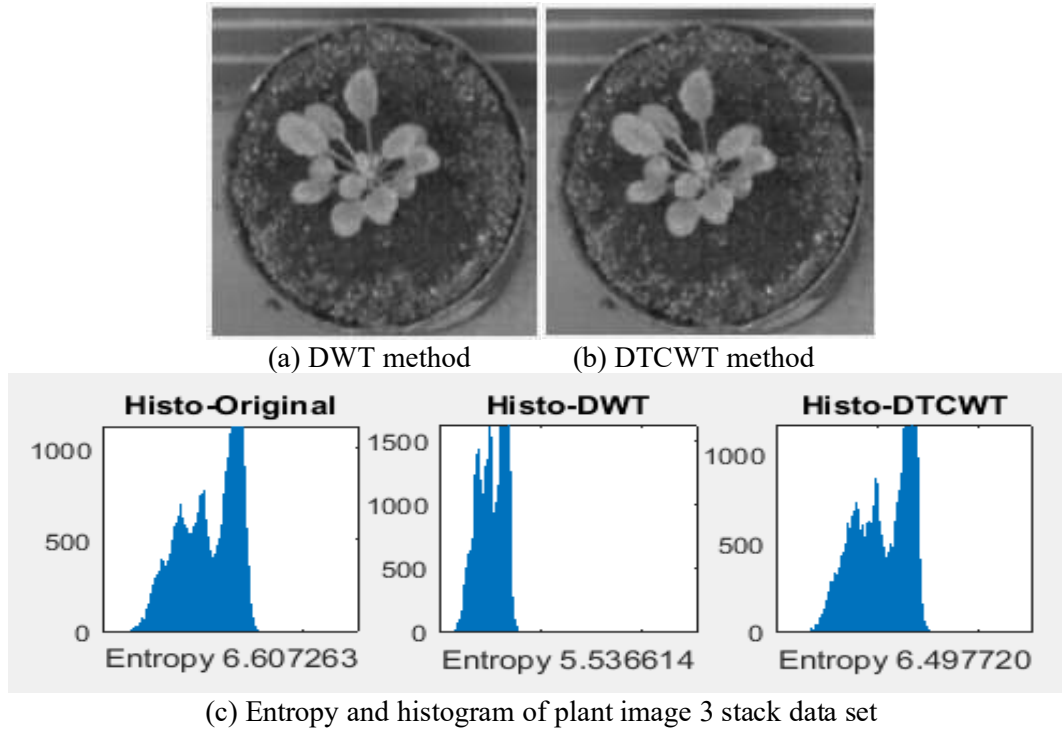


Figure 17: Reconstructed images for test image 3 from stack data set

Nine different images from three data bases are considered for the analysis of the MSE metric. The input data is decomposed into DTCWT sub bands considering level 1 to level 5. From each of the levels, the proposed algorithm is used for the reconstruction of images. From the reconstructed images, the MSE is computed in comparison to the original image. From the comparison results presented in Table 3, it is observed that the averaging method generates better images considering the MSE metric.

Table 3: MSE metric for reconstructed images from companded sub bands

Data base	Image	Iteration 1		Iteration 2		Iteration 6	
		DWT method	DTCWT method	DWT method	DTCWT method	DWT method	DTCWT method
Plant	Test Image 1 - ara2012_plant01_rgb	6.21	8.28	4.37	5.11	1.33	1.45
	Test Image 2 - ara2012_plant05_rgb	7.92	9.39	4.98	5.20	1.43	1.60
	Test Image 3 - ara2012_plant16_rgb	7.29	9.34	5.10	5.98	1.51	1.72
Stack	Test Image 1 - ara2012_plant01_frame02_rgb	10.20	12.73	6.98	7.40	1.91	2.10
	Test Image 2 - ara2012_plant01_frame12_rgb	13.90	14.83	7.29	8.92	1.89	1.98
	Test Image 3 - ara2012_plant01_frame23_rgb	14.98	16.34	7.73	8.39	1.9	2.28
Tray	Test Image 1 - ara2012_tray02_rgb	16.18	18.84	12.19	13.29	6.41	7.39
	Test Image 2 - ara2012_tray08_rgb	18.67	19.48	13.98	15.93	6.3	7.69
	Test Image 3 - ara2012_tray14_rgb	20.91	22.92	13.92	15.67	6.29	7.66

With iterations varying from 1 to 6, the MSE metric is reduced, indicating that the proposed algorithm is able to capture more edge information from lower sub bands. Considering the MSE metric, the threshold level is set for data encoding. From the test results, it is observed that after 6 iterations, the MSE levels are minimized, demonstrating the extracted features are optimum for plant phenotyping image analysis.

Summary

High throughput plant phenotyping is an important process to estimate plant yield and accurately predict plant traits. Identifying the traits in plants requires detecting plant objects such as leaf diameter, leaf center, leaf position and leaf growth rate. With dynamics and temporal variations in plant data, it is required to extract the features accurately. In this proposed work, temporal changes in plant objects are captured with additional directional orientations using complex wavelet transforms. The real and imaginary sub bands are processed to identify the significant orientations and from these orientations shift invariant features are estimated for object or component detection. The proposed method is adaptive and capable of processing plant data at high speed for high throughput applications with higher accuracy in information capture.

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