

CHAPTER 4

DESIGN OF LEAF IMAGE ENHANCEMENT METHOD

A major factor that influences the quality of leaf image data is noise. The presence of noise often reduces the amount of information that can be gained from the image and sometimes obscures important image regions. According to www.wikipedia.org, image noise is defined as the random variation of brightness or color information in images produced during acquisition. Noise in leaf image is the consequence of various types of errors caused due to various factors like environment and equipment used and is introduced due to errors occurring during acquisition, transmission, compression and storage of images. It is considered as an undesirable by-product that is introduced into the image by any one of the following scenarios.

- Scanner : When a leaf photograph made on film is scanned, noise may be introduced as the result of damage to the film or by the scanner itself and is generally shown as grains in the image.
- Digital Equipment : If the leaf image is captured directly in digital format (for example using a CCD camera), noise is introduced by the equipment itself.
- Transmission : The leaf image is also degraded by noise acquired during transmission
- Storage : The method used for compression that makes efficient use of storage resources also introduces noise and artifacts into the leaf image.

Regardless of the source of noise, they are generally regarded as an undesirable by-product. Identifying and quantifying these factors is a difficult and challenging task. Due to these challenges, the field is still an active research area and generally integrates sophisticated image processing techniques with Human Visual System (HVS).

This chapter presents the methods and techniques which is used to remove noise from the leaf images. The main goal here is to enhance the leaf image in a manner that increases the visual quality of the leaf image so as to increase the efficiency of CAP-LR system. The design and development of a noise removal algorithm that meets the above goal is vital, as imprecise filtering might degrade the performance of leaf segmentation, feature detection and feature extraction which have a direct impact on plant recognition end result. Leaf images are normally degraded by the presence of Gaussian noise which causes low or high contrast, occurring both in the edge area and the image area. In general, preprocessing an image includes the removal of noise, edge or boundary enhancement, automatic contrast adjustment and segmentation. In this chapter, an approach that simultaneously removes noise, adjusts contrast and enhances boundaries is presented. The proposed denoising algorithm is termed as ‘Enhanced Wavelet based Denoising with inbuilt Edge Enhancement and Automatic Contrast Adjustment Algorithm (WEC Method)’.

4.1. BASIC CONCEPTS

As mentioned previously, leaf images are widely used by botanists and researchers interested in plant life to identify and recognize plants to which it belongs. Contrast adjustment, noise removal and edge enhancement are operations that are mandatory in pre-processing steps for the successful design of CAP-LR system. The Proposed WEC algorithm proposes to enhance the leaf image using a novel amalgamation of the existing algorithms to increase the quality of the image. It performs three operations namely

- Contrast adjustment
- Noise removal
- Edge Enhancement

4.1.1. Contrast Enhancement

Contrast generally refers to the difference in luminance or grey level values in an image and is an important characteristic during image enhancement. It can be defined as the ratio of the maximum intensity to the minimum intensity over an image

and this ratio has a strong bearing on the detectability and resolving power of an image. Larger this ratio, the more easy it is to interpret the image. Leaf images used to identify a plant, generally, lack adequate contrast and, hence, require contrast improvement.

Contrast enhancement technique expands the range of brightness values in an image so that the image can be efficiently displayed in a manner desired. The density values in an image are expanded over a greater range. The effect of contrast enhancement increases visual contrast between two areas having different uniform densities. The resultant image enables the researcher or analysts to differentiate easily between areas initially having a small difference in density.

4.1.2. Noise Removal

Leaf images are generally degraded by Gaussian noise, where each pixel in the leaf image is changed from its original value by a (usually) small amount. A histogram is defined as a plot that exhibits the amount of distortion of a pixel value against the frequency with which it occurs, shows a normal distribution of noise. This type of noise is a major part of the “read noise” of an image sensor, that is, of the constant noise level in dark areas of the image (Nakamura, 2005; http://en.wikipedis.org/wiki/Image_noise-cite_note-3). The standard model of amplifier noise is additive Gaussian, dependent at each pixel and dependent on the signal intensity which is primarily caused by thermal noise (Johnson–Nyquist noise), including the reset noise, also called as ‘kTC noise’, which comes from the capacitors. It is in the form of white noise and is caused by the random fluctuations in the signal (Ohta, 2008). In color cameras where more amplification is used in the blue color channel than in the green or red channels, there can be more noise in the blue channel. Amplifier noise is a major part of the noise appearing on an image sensor, that is, of the constant noise level in dark areas of the image.

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution or Gaussian distribution [1]. While other distributions are possible, the Gaussian (normal) distribution is usually a good model,

due to the central limit theorem that states that the sum of different noises tends to approach a Gaussian distribution.

Some examples of leaf images that are affected by Gaussian noise are shown in Figure 4.1.

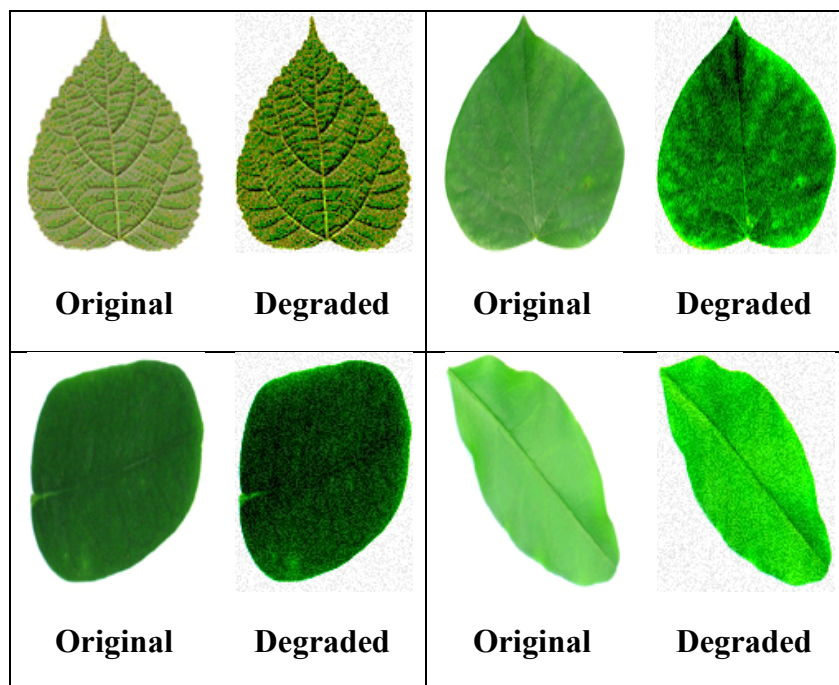


Figure 4.1 : Original and Gaussian Noise Degraded Images

4.1.3. Edge Enhancement

An edge in an image represents the objects of an image in a higher level of abstraction and forms the most fundamental primitive image characteristics. Edges are also one of the most important components of Human Visual System and are generally considered as color independent features used during object recognition and detection. Psychophysical experiments indicate that an image with accentuated or crispened edges often provides more information than the original image. The purpose of edge enhancement is to highlight the fine details in an image or to restore details that have been blurred due to errors that occur during image acquisition. Edge enhancement techniques sharpen the outlines of objects and features in an image with respect to their background.

Edge enhancement is an image processing filter that works by identifying sharp edge boundaries in the image, such as the edge between a background and a subject having contrasting color. After finding such an edge boundary, the contrast in that area is increased around the edge. This result in creating subtle bright and dark highlights on either side of any edges in the image, making the edge more defined.

The result of edge enhancement depends on different number of properties and some significant properties among them are listed below.

- **Amount.** This property controls the extent to which contrast in the edge detected area is enhanced.
- **Radius or aperture.** This property affects the size of the edges (to be detected or enhanced) and the area (surrounding the edge that will be altered by the enhancement). A small radius value results in enhancement applied only to sharper and finer edges and thus is confined to a smaller area around the edge.
- **Threshold.** This mechanism adjusts the sensitivity of the edge detection whenever required. A lower threshold results in more subtle boundaries of color being identified as edges. A threshold that is too low may result in some small parts of surface textures, noise or film grain being incorrectly identified as being an edge.

Unlike some forms of image sharpening, edge enhancement does not enhance subtle details that may appear in more uniform areas of the image, such as texture or grain, which appears in flat or smooth areas of the image. The advantage obtained is that the imperfections in the image reproduction, such as noise, or imperfections in the subject, such as natural imperfections, are not made more obvious by the process. An disadvantage to this is that the image may begin to look less natural, as the sharpness of the overall image increases the level of detail flat, smooth areas does not. As with the other forms of edge enhancement and image sharpening is only capable of improving the perceived sharpness of an image. The operation of enhancement is not

completely reversible and as such some detail in the image is lost as a result of filtering and has to be designed in a careful manner.

4.2. MOTIVATION

Most of the traditional edge enhancement filters that performs enhancement operations that consider the whole image as a single unit, and use enhancement operations to regions whose gray values vary largely. Because of the presence of noise in leaf images, these types of edge enhancers might enhance the noise and degrade the contrast of the original image. Moreover, traditional algorithms cannot differentiate a reverberation artifact that appears like an edge and accidentally enhances them also thus further reduce the quality of the image.

Contrast enhancement is usually achieved by histogram equalization in the spatial domain to redistribute gray levels uniformly. Existing techniques, however, while adjusting gray levels, lose some important information. Meanwhile, edge enhancement attempts to emphasize the fine details in the original image. But in spatial domain, it is hard to selectively enhance details at different scales. Further, in the spatial domain, applying operations for adjusting contrast and enhancing the edges in different orders may yield different enhancement results.

Wavelet-based image analysis provides multiple representations of a single image. It decomposes an image into approximated-coefficients and multi-resolution detailed-coefficients. To overcome the above spatial domain enhancement issues, this study proposes a wavelet-based image enhancement method combined with a noise removal procedure is proposed. Since the various enhancement procedures are applied on different components in the wavelet domain, they work independently and do not affect each other. Moreover, the order of applying both of them becomes irrelevant. A detailed description of the algorithm is presented in the following section.

4.3. THE WEC METHOD

The proposed denoising algorithm is termed as ‘Enhanced Wavelet based Denoising with inbuilt Edge Enhancement and Automatic Contrast Adjustment

Algorithm (WEC Method)'. The method combines the use of CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm with Discrete Wavelet coefficients for enhancing the contrast of the input leaf image. The Discrete Wavelet Transform (DWT) was used to obtain the edge and non-edge information of the image. Edge enhancement was performed using a sigmoid function and for noise removal a relaxed median filter was used. The various steps involved are shown in Figure 4.2 and are described in the following sections.

4.3.1 Step 1 : Color Space Transformation

A color model is an abstract mathematical model describing the way colors can be represented as tuples of numbers, typically as three or four color components (e.g. RGB and CMYK are color models) and the mapping of colors from the color model is the color space(Wyszecki,1982). The two most widely used color spaces for storing digital images are RGB color space and YUV color space. The RGB color space is defined by the three chromaticities of the red, green, and blue additive primaries, and can produce any chromaticity that is the triangle defined by those primary colors. RGB stores a color value for each of the color levels, Red, Green and Blue. That is, it uses 8 bits to each color level (thus the range 0-255 obtained from 28), thus using 24 bits to store color information.

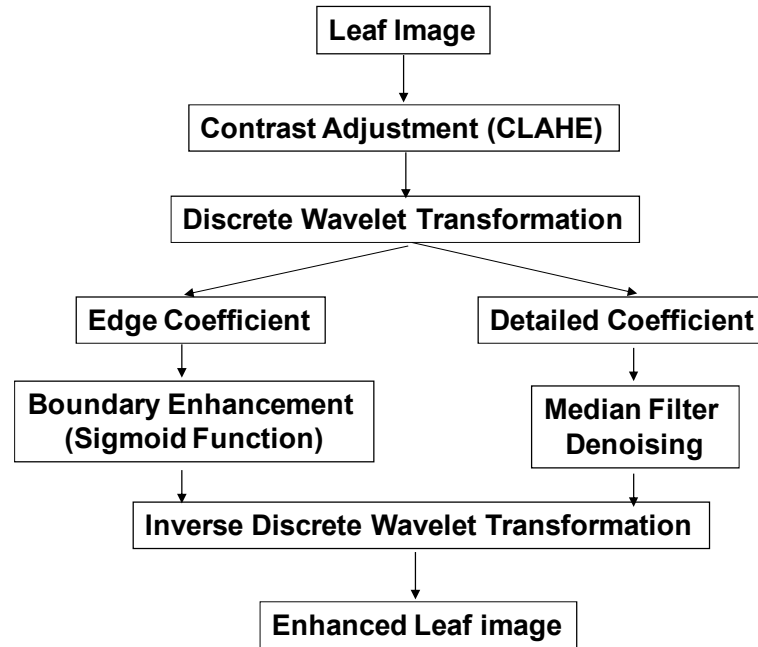


Figure 4.2 : Steps in WEC Method

YUV colorspace works on the principle that, as human eye perceives changes in brightness rather than changes in color and focuses more on brightness than the actual brightness level. There are three values while using YUV color space (<http://en.wikipedia.org/wiki/YUV>). They are,

- Luminance (Luma, which is the brightness level) is abbreviated as Y.
- U is the red difference sample
- V is the blue difference sample

YUV color space is stored using 16 bits, where 8 bits are used by Luma and 4 bits are used by U and V. Thus, YUV stores more relevant data at a lower accuracy than RGB. Moreover, it is well known that the RGB components of color images are highly correlated and if the wavelet transforms of each color component is obtained, the transformed components will also be highly correlated (Nobuhara and Hirota, 2004). Therefore, a color transformation that reduces the redundancy and correlation of the image is highly desired. Many linear transformations can be used such as the YUV, KLT, YCrCb or $L^*a^*b^*$. This study uses a YUV color transformation for the following reasons:

- (i) The YUV color model represents the human perception of color more closely than the standard RGB model used in computer graphics hardware, and ,
- (ii) The YUV color model stores more relevant data at a lower accuracy than RGB.

The equation used for converting or transforming the RGB components to YUV space is given in Equation (5.2).

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.200 & 0.587 & 0.114 \\ -0.418 & -0.289 & 0.437 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (5.2)$$

4.3.2. Step 2 : Wavelet Transformation

The purpose of this step is to apply Haar wavelet decomposition algorithm on a given image to obtain its wavelet coefficients. The given image is decomposed into several components in multi-resolution space by applying a forward wavelet transform. Different wavelet filter sets and/or different number of transform-levels results in different decomposition results. While any wavelet-filters can be used with the proposed scheme, the discussion is based on Haar wavelet. The application of Haar wavelet transform resulted in four subbands namely, LL (approximation coefficients) and HL, LH and HH (detailed coefficients).

4.3.3. Step 3 : Automatic Contrast Adjustment

The first step of WEC method is to adjust the contrast of the input leaf image automatically using CLAHE algorithm. CLAHE is a form of high-pass filtering where low-frequency information (large-scale intensity variation) is blocked and thus can improve the contrast and sharpen edges of an image simultaneously.

CLAHE (Wanga *et al.*, 2004) is a special case of the histogram equalization technique (Gonzalez and Woods, 2007), which seeks to reduce the noise and edge-

shadowing effect produced in homogeneous areas. CLAHE is a technique used to improve the local contrast of an image. This method is a generalization of adaptive histogram equalization and ordinary histogram equalization. The algorithm partitioned the images into contextual regions and applied the histogram equalization to each one. This evens out the distribution of grey values and makes the hidden features of the image more visible. The full grey spectrum was used to express the image. CLAHE is an improved version of AHE, or Adaptive Histogram Equalization, to overcome the limitations of standard histogram equalization. This section describes the working of CLAHE algorithm.

The traditional histogram equalization algorithm is a method used for adjusting contrast using the image's histogram. This algorithm works efficiently for smaller images or images where almost all of the different intensity levels are represented. Histogram equalization is a technique for recovering lost contrast in an image by remapping the brightness values, so that the brightness values are equalized or more evenly distributed. As a side effect, the histogram of its brightness values becomes flatter. The traditional histogram equalization algorithm is shown in below.

1. Read the input leaf image
2. Convert image to gray scale
3. Construct the histogram of the image ($H[x]$). This is a 256 value array containing the number of pixels with value x
4. Calculate the cumulative density function of the histogram ($cdf[x]$). This is a 256 value array containing the number of pixels with value x or less, that is, $cdf[x] = H[0] + H[1] + H[2] + \dots + H[x]$
5. Loop through the n pixels in the entire image and replace the value at each i^{th} point by $V[i]$, which is calculated as $\text{floor}(255 * (cdf[V[i]] - cdf[0]) / (n - cdf[0]))$

The result of step 5 is the contrast adjusted image. However, the major drawback of histogram equalization algorithm is the introduction of blocking artifacts introduced. This can be solved by using an Adaptive Histogram Equalization (AHE) algorithm. The pseudo code for adaptive histogram equalization algorithm is given in Figure 4.3 (Zhiming and Jianhua, 2006).

```

for every pixel i (with grey level L) in image
do
Initialize array Hist to zero;
for every contextual pixel j do
    Hist[g(j)] = Hist[g (j)]+1;
end
for i = 1 to I
    Hist[i] += Hist[i-1]
    L' = Hist[I]*L/W^2
end

```

Figure 4.3 : Pseudo Code for AHE

In Figure 4.3, L is the number of grey levels, W is the window size, L and L' are the old and new grey level respectively and g(j) is the intensity of the pixel j. Unlike traditional histogram, AHE operates on small data regions (tiles), rather than the entire image. The contrast of each tile is enhanced so as to cause the histogram of the output region approximately match the specified histogram. In order to eliminate artificially induced boundaries, a bi-linear interpolation algorithm is used to combine the neighboring tiles. To avoid amplifying the noise, which might be present in the image, the contrast is limited in homogeneous areas.

The time complexity of this algorithm is $O(M \times N \times (W^2 + n))$ where $M \times N$ is the number of pixels in the image, W is the window size and n is the number of bins. The time complexity of the AHE algorithm increases with window size. Thus, the window size has to be chosen carefully. A low size introduces noise, while a big size introduces artifacts. To solve this problem of AHE, CLAHE is introduced. Contrast enhancement can be defined as the slope of the function mapping from input to output intensity. With histogram equalization the mapping function m(i) is proportional to the cumulative histogram (Equation 4.1).

$$m(i) = (\text{Display_range}) * (\text{Cumulative_histogram}(i) / \text{region_size}) \quad (4.1)$$

Thus, the derivative of $m(i)$ is proportional to $\text{histogram}(i)$. So, the important task of CLAHE is to limit the histogram, which, in turn, limits the contrast enhancement. The algorithm is given in Figure 4.4 (Garg *et al.*, 2011). In the experiments, NB was set to 64, CL was set to 0.01 and tile size used was 8 x 8 and the histogram distribution was Bell-Shaped.

4.3.4. Step 4 : Edge Enhancement

Edge enhancement is one of the most fundamental operations in image analysis. Edges are considered as the outline of an object or as the boundary between an object and the background. An edge in an image is normally defined as the transition in the intensity of that image. If the edges in an image can be identified precisely, all objects can be located and basic properties such as area, shape and perimeter can be measured efficiently.

Input : Leaf Image, No. of bins (NB) of the histograms used in building image transform function (dynamic range), No. of regions in row and column directions, Clip Limit (CL) for contrast limiting (normalized from 0 to 1)

Output : Contrast Adjusted Image

1. Divide input image into 'n' number of non-overlapping contextual regions (tile) of equal sizes (8 x 8 used in experiments).
2. Process each contextual region (tile) thus producing gray level mappings, extract a single image region and perform the following:
 - a. Construct a histogram for each region using NB
 - b. Clip the histogram such that its height does not exceed CL (Histogram Redistribution).
 - c. Create a mapping (transformation function) for this region using Equation 4.1.
 - d. Interpolate gray level mappings in order to assemble final CLAHE image: Extract cluster of four neighbouring mapping functions, process image region partly overlapping each of the mapping tiles, extract a single pixel, apply four mappings to that pixel, and interpolate between the results to obtain the output pixel

Figure 4.4 : CLAHE Algorithm

Edge detection, in general, consists of two parts:

- edge enhancement - Process of calculating the edge magnitude at each pixel
- edge localization - Process of determining the exact location of the edge.

Once an edge is enhanced properly, the location of the edge can be identified accurately. Thus, the performance of edge detection depends on the enhancement of edges. Edge enhancement improves the quality of edges so as to help in the segmentation and recognition steps of CAP-LR system. Edge enhancement filters enhance the local discontinuities at the boundaries of different objects (edges) in the image. Fixed size edge operators, like the gradient operations, always enhance both

strong reflectors and speckle noise, spread the detected edges and decrease the contrast resolution of the image. Edge enhancement involves sharpening the outlines of objects and features with respect to their background.

This section is dedicated to enhance the edges of leaf images so as to improve the detectability of the leaf's borders. The main aim is to find edge structures and enhance weak borders of the leaf image. Most of the reported works have concentrated on edge detection (Bao *et al.*, 2005; Yu and Acton,2004) but report that have focused on edge enhancement of leaf images are sparse.

The proposed method enhances edges in two steps, namely, edge segmentation and edge enhancement. The steps in the proposed technique are outlined in Figure 4.5.

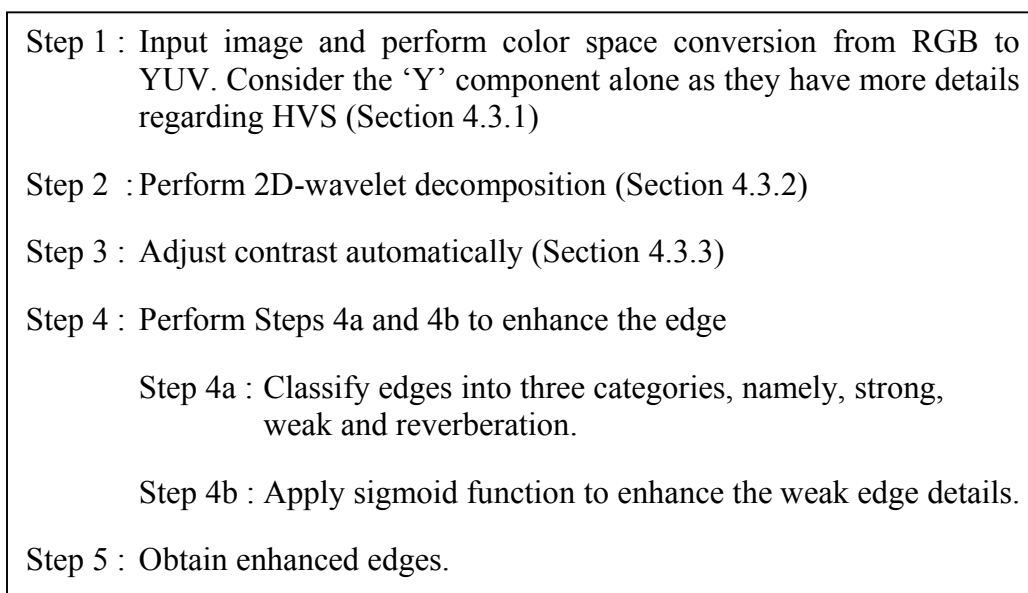


Figure 4.5 : Proposed Edge and Contrast Enhancement Algorithm

The edge enhancement was performed in two steps and was applied only to HL, LH and HH subband coefficients.

- Classify edges as strong edges, weak edges and reverberation artifacts
- Apply edge enhancement only to weak edges

To classify the edges into the selected three categories, the texture features of the image are used along with a simple rule-based procedure. The three texture features extracted are

1. Mean
2. Variance
3. Correlation

The above features were extracted using GLCM (Gray Level Co-Occurrence Matrix) procedure. Since its invention (Haralick, 1973), the GLCM has played a vital role in many texture based image analysis applications (Omaima, 2010; Caylak, 2010; Supriyanto et al., 2010; Selvan et al., 2010). The GLCM uses co-occurrence matrix to extract texture features of an image using statistical equations. A co-occurrence matrix is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset. The co-occurrence matrix can measure the texture of both grayscale or color image. As the co-occurrence matrices are large and sparse, a more useful set of features can be obtained.

The equations for calculating the mean and variance for the horizontal and vertical directions are given in Equations (4.2) and (4.3) respectively. Correlation is calculated using Equation (4.4).

$$\text{Mean} = \mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j}) \quad \mu_j = \sum_{i,j=0}^{N-1} j(P_{i,j}) \quad (4.2)$$

$$\text{Variance} = \sigma_i^2 = \sum_{i,j=0}^{N-1} (i - \mu_i)(P_{i,j}) \quad \sigma_j^2 = \sum_{i,j=0}^{N-1} (j - \mu_j)(P_{i,j}) \quad (4.3)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right] \quad (4.4)$$

The correlation texture is used to measure the linear dependency of grey levels on those of neighbouring pixels. GLCM correlation can be calculated for successively larger window sizes. The size of the window at which the GLCM correlation value

declines suddenly may be taken as one definition of the size of definable objects within an image. GLCM correlation is independent of mean and variance features and has a more intuitive meaning to the actual calculated values, that is, a 0 represents uncorrelated, 1 represents perfectly correlated features. The texture features thus extracted were quantized using the following simple procedure.

Let t_1, \dots, t_n be the set of feature values extracted for a particular feature. Initially, the maximum (Max), minimum (Min) and mean (μ) of this set is calculated, from which the size of quantization interval at left (Q_L) and right (Q_R) of the mean value obtained were estimated using Equation (4.5) with a total quantization level as 6.

$$Q_L = \frac{2(\mu - \text{Min})}{6} \quad Q_R = \frac{2(\text{Max} - \mu)}{6} \quad (4.5)$$

Using Q_L and Q_R , the ratio of quantization level can be calculated as

$$K = Q_L/Q_R \quad (4.6)$$

and the quantization Q_i of value t_i can be calculated as follows.

- $R = (t_i - \text{Min})/Q_R$
- If $R < 1/2$, then $Q_i = R$ else $Q_i = ((R-1/2)/K) + (1/2)$ ($l=6$)

Calculate Q_L and Q_R for the quantized values and group them into four ranges, namely, Large, Medium, Small and Very Small. Small values were from 0 to Q_L , medium values were from Q_L to Q_R and large values were all values greater than Q_R . All values which are less than 0 were considered very small.

Using the above quantized texture features the edges were classified as strong, weak and artifact using a rule-based procedure (Figure 4.6).

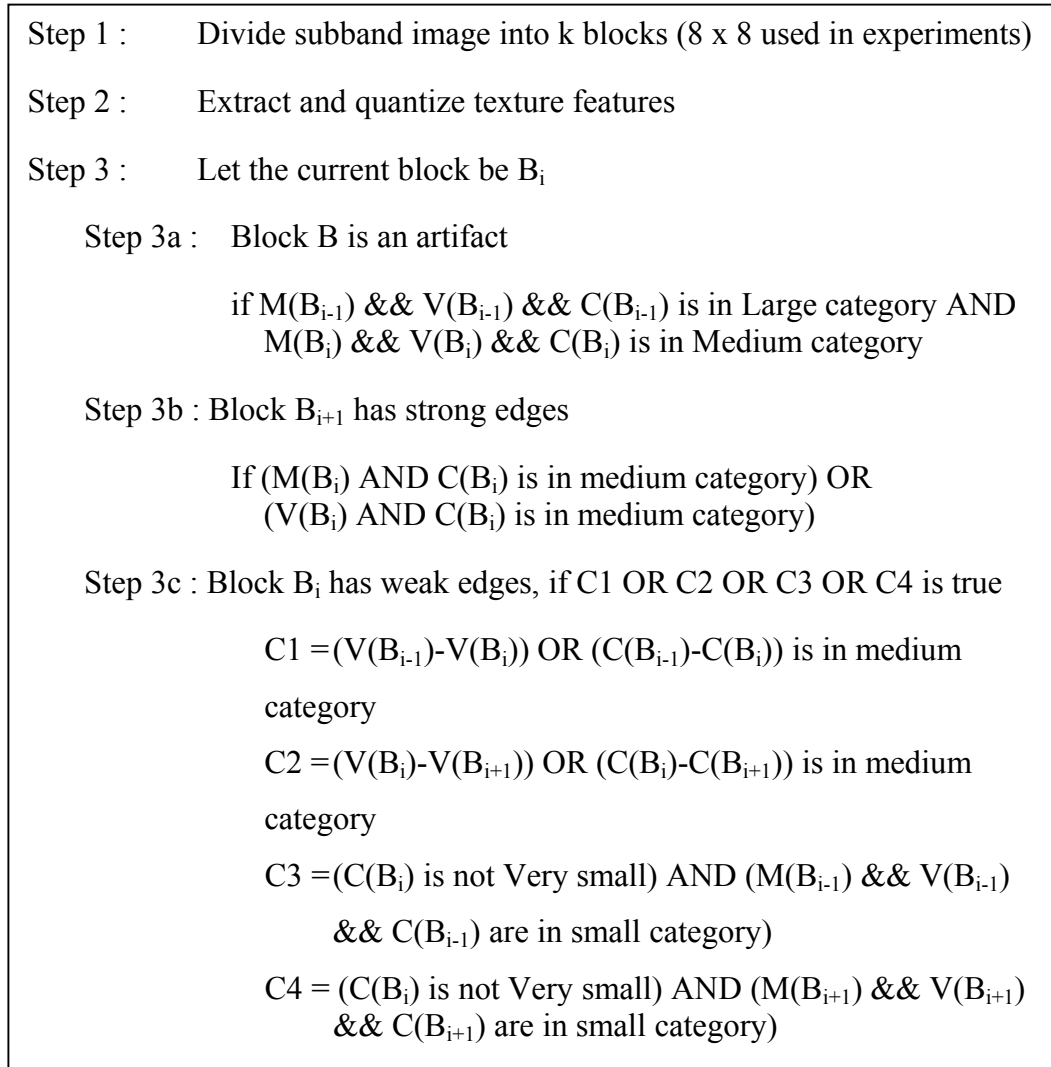


Figure 4.6 : Rule Based Edge Classification Algorithm

In the procedure, M, V and C represent the three features Mean, Variance and Correlation. After using the above procedure, the weak edges alone were enhanced using the sigmoid function Equation (4.7).

$$y(x) = \frac{M}{1 + e^{-\left(\frac{x-m-\Delta x}{a}\right)}} + \Delta x \quad (4.7)$$

where M is 255, m = 128 (for 8 bit image), x is the edge pixel, $-127 \leq x \leq +128$ and parameter 'a' refers to the speed of the change around the center. This process was

repeated for all detailed coefficients. The above procedure identified all high intensity, large variance and high correlation coefficients as strong edges and all coefficients with significant changes in variance and correlation as weak edges.

4.3.5. Step 5 : Noise Removal

The next step is to remove the noise from detailed coefficients. For this purpose, a relaxed median filter was used. Traditional median filter uses a window that slides across the image data and the median value inside the window is taken as the output value. The filter is efficient in noise removal. However, the filter sometimes removes sharp corners and thin lines, as they destroy structural and spatial neighbourhood information. To solve this several solutions have been proposed. Some of them include multilevel and multistage filters, weighted median filters, stack filters, nested median filters and rank conditioned rank selection filters. A relaxed median filter (Hamsa *et al.*, 1999) is proposed as another variant to solve the problems of the traditional median filter. The following paragraphs present details regarding the same.

Let $\{X_i\}$ be an m -dimensional sequence, where the index $i \in Z_m$. A sliding window is defined as a subset $W \subset Z_m$ of odd size $2N + 1$. Given a sliding window W , define $W_i = \{X_{i+r} : r \in W\}$ to be the window located at position i . If X_i and Y_i are the input and the output at location i , respectively, of the filter, then the standard median filter is given as

$$Y_i = \text{med}\{W_i\} = \text{med}\{X_{i+r} : r \in W\} \quad (4.8)$$

where $\text{med}\{\cdot\}$ denotes the median operator. Next, denote $[W_i]_{(r)}$, $r = 1; \dots, 2N+1$, the r^{th} order statistic of the samples inside the window W_i :

$$[W_i]_{(1)} \leq [W_i]_{(2)} \leq \dots \leq [W_i]_{(2N+1)}$$

The relaxed median filter works as follows: two bounds l (lower) and u (upper), respectively define a sublist inside the $[Wi]_{(c)}$ which contains the gray levels that are good enough not to be filtered. If the input belongs to the sublist, then it remains unfiltered, otherwise the standard median filter is used as the output. During experimentation, the lower limit was set to 3 and upper limit was set to 5 and the window size used was 3×3 .

4.3.6. Step 6 : Inverse DWT

Finally an inverse wavelet transformation was performed to obtain an enhanced leaf image that is contrast improved, edge enhanced and noise removed.

4.4. EXPERIMENTAL RESULTS

As mentioned earlier in Chapter 3, Methodology, four performance metrics, Peak Signal to Noise Ratio (PSNR), Pratt's Figure Of Merit (FOM), Mean Structural Similarity Index (MSSI) and enhancement speed (seconds) are used to evaluate WEC method. The images from Figures 3.2 and 3.3 representing sample images from standard and real datasets are used as test images and their results are depicted in figure 4.7, 4.8 and 4.9 respectively.

4.4.1. Peak Signal to Noise Ratio

PSNR is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. As many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. It is the most commonly used measure for analyzing the quality of reconstruction after enhancement. The PSNR values obtained during experimentation is projected in Figure 4.7.

The high PSNR obtained gives the understanding that the visual quality of the denoised image is good. On an average Wavelet produced 27dB and 30dB by WEC algorithm. The results prove that the proposed method is an improved version of the traditional algorithms.

4.4.2. Figure of Merit (FoM)

Figure 4.8 shows the Pratt's Figure Of Merit (FOM) obtained while using wavelet algorithm and proposed WEC method. This metric is used to measure the preservation capacity of the edges.

By the value nearing to unity achieved for the proposed model, it is clear that the proposed model is successful in removing maximum noise from the degraded image. To compare the performance of each filter with respect to FOM performance metric, the average value of the images was calculated. Wavelet showed 0.67 FOM and WEC method showed 0.72 FOM. This shows that the proposed WEC algorithm produces better FOM than all the other models indicating that the edge preserving capability is high.

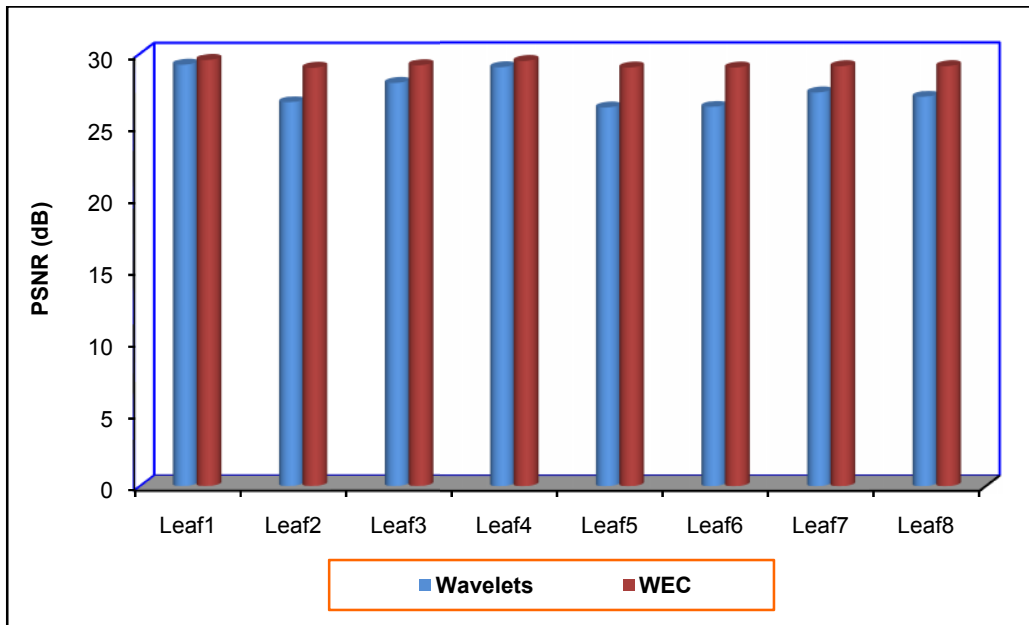


Figure 4.7 : PSNR (dB)

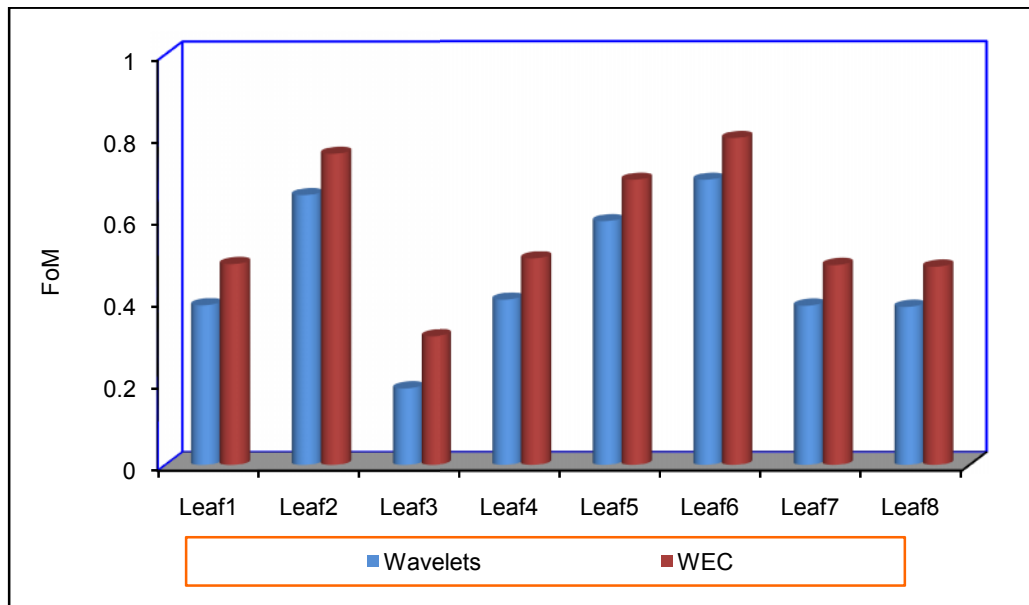


Figure 4.8 : Figure of Merit (FoM)

4.4.3. Mean Structural Similarity Index (MSSI)

Figure 4.9 presents the MSSI values obtained by wavelet and WEC enhancement algorithms.

The MSSI parameter was used to analyze the structure preserving capacity of the proposed WEC algorithm. This measure also showed that the WEC model is effective in preserving the structure when compared to the wavelet model.

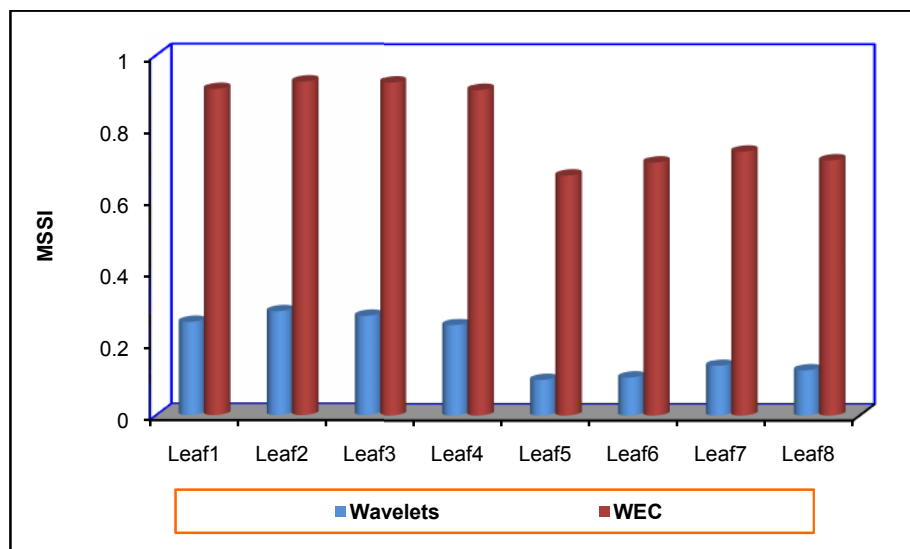


Figure 4.9 : Mean Structural Similarity Index (MSSI)

4.4.4. Speed

The proposed method was the quickest in enhancing the degraded image, which was followed by wavelet. The proposed algorithm makes it an attractive option for several advanced applications in the field of plant leaf processing algorithms.





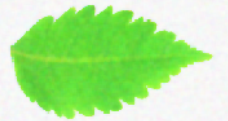







Original Images	Wavelet	WEC
		
Leaf 1		
		
Leaf 2		
		
Leaf 3		
		
Leaf 4		

Figure 4.10: Visual Results of Noise Removal (Standard Dataset)


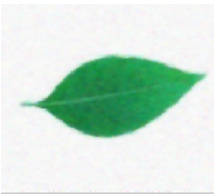










Original Images	Wavelet	WEC
		
Leaf 5		
		
Leaf 6		
		
Leaf 7		
		
Leaf 8		

Figure 4.11 : Visual Results of Noise Removal (Real Dataset)

4.4.5 Visual Results

The visual comparison of the enhanced image produced by the proposed algorithm for figure 3.2 and 3.3 is shown in Figure 4.10 and Figure 4.11 for the standard and real datasets respectively and the results of the entire dataset is shown in **Appendix B**. From the visual results, it is further confirmed that the enhancement operations are successful and have improved the conventional wavelet based method.

4.5. CHAPTER SUMMARY

Leaf image enhancement is a vital preprocessing step in CAP-LR system. This chapter introduced an automatic contrast adjustment, edge enhancement and noise removal algorithm. The algorithm used CLAHE, relaxed median filter and sigmoid function during the enhancement task. The experimental results showed that the proposed method shows significant improvement in terms of noise removal, edge preservation and speed. Thus, the various results of the experiments conducted clearly indicate that the images produced by the proposed algorithm are of good visual quality and therefore can be applied to CAP-LR system.