Computer Science & Engineering: An International Journal (CSEIJ), Vol.1, No.4, October 2011

Automatic Recognition System Using Preferential Image Segmentation For Leaf And Flower Images

N.Valliammal[1] and Dr.S.N.Geethalakshmi[2]

[1] Assistant Professor, Avinashilingam Deemed University for Women, Coimbatore-641043,
e-mail: Valli.p.2008@gmail.com

[2] Associate Professor, Avinashilingam Deemed University for Women, Coimbatore-641043,
e-mail: sngeethalakshmi@yahoo.com

ABSTRACT

Plant is one of the most important forms of life on earth. Plant recognition is very demanding in biology and agriculture as new plant discovery and the computerization of the management of plant species become more popular. The recognition is a process resulting in the assignment of each individual plant to a descending series of related plants in terms of their common characteristics. The process is very time-consuming as it has been mainly carried out by botanists. Computer-aided plant recognition is still very challenging task in computer vision as the lack of proper models or representation schemes, a large number of variations of the plant species, and imprecise image pre-processing techniques, such as edge detection and contour extraction. The focus of computerized living plant recognition is on stable feature's extraction of plants. The information of leaf veins, therefore, play an important role in identifying living plants. The ultimate goal of this project is to develop a system where a user in the field can take a picture of an unknown plant, feed it to the system carried on a portable computer, and have the system classify the species and display sample images of the closest matches within a couple of seconds.

Keywords

Preferential image segmentation, Tree of shapes, Curve matching, pre-processing, Filters, feature extraction

1. INTRODUCTION

Automatic plant classification systems are essential for a wide range of applications including environment protection, plant resource survey, as well as for education. With the aid of advanced information technology, image processing and machine learning techniques, automatic plant identification and classification will enhance such systems with more functionality, such as automatic labelling and flexible searching. Image segmentation and object recognition are two aspects of digital image processing which are being increasingly used in many applications including leaf recognition. In this paper, the Preferential Image Segmentation (PIS) [3] method is used to segment an object of interest from the original image. A probabilistic curve evolution method with particle filters is used to measure the similarity between shapes during matching process. The experimental results prove that the preferential image segmentation can be successfully applied in leaf recognition and segmentation from a plant image.

Plant is important for environment protection. However, the problem of plant destruction becomes worse in the few years. We should train people to know plant, which in turn, to treasure

DOI : 10.5121/cseij.2011.1402

and protect plant. In addition to the limited number of expert botanists, automatic classification and recognition system for plant is necessary and useful since it can facilitate fast learning of plants.

Digital image processing is the use of the algorithms and procedures for operations such as image enhancement, image compression, image analysis, mapping, geo-referencing, etc. The influence and impact of digital images on modern society is tremendous and is considered as a critical component in variety of application areas including pattern recognition, computer vision, industrial automation and healthcare industries. Image processing can be roughly categorized as follows: imaging, image denoising, image restoration, image coding, image segmentation, image transformation, object representation and recognition, and content-based image retrieval. Typical tasks for computer vision are scene interpretation, object recognition, optical character recognition, registration, feature extraction and video tracking. Edge detection methods utilize intensity gradients to detect the boundaries of objects. However, edge detection methods usually generate edges that are not closed contours, and this causes difficulties for later processing such as object recognition. Curve evolution methods have been popular for image segmentation since the early 1990s. These methods evolve the initialized curve(s) to the boundaries of objects in an image. The evolution of the curves may be driven by image gradient information region information or their combination .These methods are theoretically solid and numerically stable. Moreover, these methods generate image segments enclosed by closed contours, which leads to straightforward post processing. When we wander around the fields, we can find lots of plant. However, we rarely know their names. We may consult their name with the book about plant but even such a book is on hand, it is not easy to find a proper section or an exact page showing the plant. It would be useful if we take a picture of the plant's leaf and feed the picture into a computer and the computer can aid recognition and classification of the plant. In addition, some knowledge about the plant can be obtained to facilitate learning. In this study, we try to analyze various leaf features so that some useful features can be extracted, which, in turn are used to achieve the goal of automatic classification of leaves. Plants are basically classified according to shapes, colors and structures of their leaves and flowers However, if we want to recognize the plant based on 2D images, it is difficult to analyze shapes and structures of flowers since they have complex 3D structures. On the other hand, the colors of leaves are always green; moreover, shades and the variety of changes in atmosphere and season cause the color feature having low reliability. Therefore, we decided to recognize various plants by the grey-level leaf image of plant. The leaf of plant carry useful information for classification of various plants, for example, aspect ratio, shape and texture. The system is user friendly. The user can scan the leaf and click the recognition button to get the solution.

There are many kinds of plants that exist on the earth. Plants play an important role in both human life and other lives that exist on the earth. Due to various serious issues like global warming, lack of awareness of plant knowledge, etc., the categories of plant is becoming smaller and smaller. Fortunately, botanists are realizing the importance of protecting plants and are discovering methods to protect them. In a similar fashion, there is also a need for recognizing a plant by its category, to help agriculturists / farmers during reproduction of extinct plants. The main challenge faced by them is the identification of the category to which a particular plant belongs to. To help them in this challenging venture, several researches (Man *et al.*, 2008; Lee and Chen, 2006) are conducted to automatically classify a plant into a category, when its leaf sample image is given as input.

Plant has plenty use in foodstuff, medicine and industry. And it is also vitally important for environmental protection. However, it is an important and difficult task to recognize plant species on earth. Designing a convenient and automatic recognition system of plants is necessary and useful since it can facilitate fast classifying plants, and understanding and managing them

(Tzionas *et al.*, 2005). The classification of plant leaves is a vital process in botany and in tea, cotton and other industries. Moreover, it can also be used for early diagnosis of certain plant diseases.

The paper is organized as follows. Section 2 describes the general architecture used by plant classifiers. Section 3 explains the preferential image segmentation, while section 4 summarizes the results and section 5 shows the conclusion and references.

2. GENERAL ARCHITECTURE

The general process for plant classification through leaf recognition is given in Figure 1.

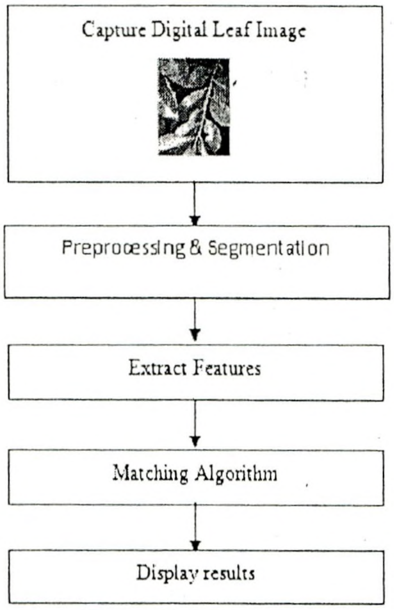


Figure 1 General architecture of Automatic Plant Classification system

The performance of object recognition depends on the performance of pre-processing and segmentation. Segmentation is defined as the process of partitioning a digital image into multiple segments, where the pixels inside each segment share certain visual characteristics such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristics. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze (Shapiro and Stockman, 2001). Image segmentation locates objects and boundaries (lines, curves, etc.) in images. After segmentation, the image is represented by a set of segments, which collectively represents the entire image. The process of plant identification through leaf recognition is explained below.

2.1 Capturing Leaf Image

In this paper the leaves samples are collected in the forest and the leaves are full-grown. Leaf image could be captured using a scanner or CCD camera, (shown in Figure. The acquired images are RGB color images, so we need to convert the colors from RGB to Gray, by which we can avoid the color disturbed.

Figure 2 Sample Leaf

The above figure 2 shows the sample plant leaf. Since classification is a complex operation that needs high memory usage normally, lossy compression format like JPEG / BMP / GIF is used. For convenience take all the leaf images to be of the same size and resolution. Plants are basically classified according to shapes, colors and structures of their leaves and flowers. In addition, the colors of leaves are always green shades and the variety of changes in atmosphere cause the color feature having low reliability. Therefore, to recognize various plants using their leaves, the obtained leaf image in RGB format will be converted to gray scale before pre-processing. The formula used for converting the RGB pixel value to its greyscale counterpart is given in Equation 1.

$$Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B \qquad (1)$$

where R, G, B correspond to the color of the pixel, respectively.

2.2 Pre-processing

The leaf image pre-processing refers to the initial processing of input leaf image to correct the geometric distortions, calibrate the data radiometrically and eliminate the noise and clouds that present in the data [15]. These operations are called pre-processing because they normally carried out before the real analysis and manipulations of the image data occur in order to extract any specific information. The aim is to correct the distorted or degraded image data to create a more faithful representation of the real leaf.

Various pre-processing techniques are then used to enhance the leaf image obtained. Several techniques like boundary enhancement, smoothening, filtering, noise removal, etc. can be applied to improve the quality of the leaf image. The following figure shows the pre-processing steps in leaf image.

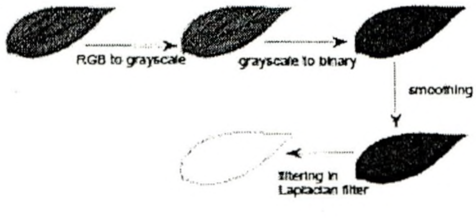
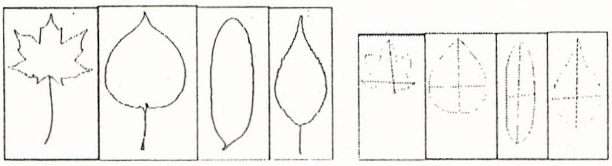


Figure 3 Pre-processing Example

2.3 Feature Extraction

Several feature extraction is performed to obtain the leaf contour. The image-threshold [3] operation is applied to the gray image to obtain the binary image of leaf shape. Then the binary image is traced to produce the contour of leaf by making use of the border tracing algorithm. The traced contour, length and width of leaf is shown in Figure 4.



(a) Leaf contour (b) Leaf length and width

Figure 4 Feature extraction

2.4 Image Segmentation

Image segmentation is a fundamental task in computer vision. Although many methods are proposed, it is still difficult to accurately segment an arbitrary image by any method alone. In recent years, more and more attention has been paid to combine segmentation algorithms and information from multiple feature spaces (e.g. color, texture, and pattern) in order to improve segmentation results. According to literature survey, segmentation algorithm is explained based on two properties such as, discontinuity and similarity. For leaf recognition, basic standard segmentation algorithms are taken and are discussed in this section.

Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels) (also known as super pixels). More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Several approaches to segmentation have been proposed which can be categorized into cluster based techniques (Pauwels and Frederix, 1999), histogram based techniques (Zwiggelaar, 2010) [9], compression based techniques (Ballester *et al.*, 2007) [15], edge detection, region growing methods (Chen and Georganas, 2008) [5], Graph partitioning methods (Sumengen and Manjunath, 2006), watershed transformation (Wenzhong and Xiaohui, 2010), etc. Another popular method used is the curve evolution methods (Farzinfar *et al.*, 2010). These methods evolve the initialized curve(s) to the boundaries of objects in an image. The evolution of the curves may be driven by image gradient information (Kichenassamy *et al.*, 1995; Caselles *et al.*, 1997), region information (Chan and Vese, 2001 [6]; Jehan-Besson *et* al., 2003) [2], or their combination (Tsai *et al.*, 2001)[4]. The image segments generated are enclosed by closed contours and are unsupervised which make it an ideal candidate for image post processing. These methods are more suitable for simple images and their performance degrades both in terms of segmentation and complexity, with complicated images (Paragios and Deriche, 2000). In such cases, the utilization of prior information is necessary for curve evolution methods in complicated image segmentation applications.

Several methods have been proposed that utilize prior information for supervised image segmentation. These methods usually propose new variational energy functions which integrate both the prior information and the gradient/region information in the image to be segmented. The minimizations of these functions can lead to segmentation results. Shape priors are utilized in (Cremers and Funka-Lea, 2005; Cremers *et al.*, 2002; Chen, 2002)[7,8] and (Leventon *et* al., 2000). Both intensity priors and shape priors are applied in Leventon *et al.*, (2000). Natural image using tree of shapes for car recognition proposed by Pan *et al.* (2009) is analyzed and applied for our test bench.

3. PREFERENTIAL IMAGE SEGMENTATION (PIS)

A novel preferential image segmentation method is proposed in this paper using techniques from mathematical morphologies. This method is motivated by the utilization of prior information in curve evolution models. However, image topologies may provide better results for complicated cases. The proposed method utilizes a tree of shapes to represent the image content.

This representation provides a hierarchical tree for the objects contained in the level sets of the image. The hierarchical structure is utilized to select the candidate objects from the image. The boundaries of the selected objects are then compared with those of objects selected from prior images. By means of the tree of shapes and curve matching, the proposed method is able to preferentially segment objects with closed boundaries from complicated images. It is more straightforward to utilize prior information in this way than with the curve evolution methods, and there is no initialization problem. Furthermore, the method is invariant to contrast change and translation, rotation and scale. The method has been shown to work in the presence of noise.

Tree of shapes provides a natural way to represent the spatial relationships of the shapes in an image. It represents images based on the techniques of contrast-invariant mathematical morphologies. This method is based on the theory of image representation using connected components of set of finite perimeters in the space of functions with Weakly Bounded Variations (WBV). It shows that an image, if taken as a function of weakly bounded variation is guaranteed to be decomposed into connected components with closed boundary this is an extension to classical methods where an image is taken as a piecewise- smooth function. The representation of an image using a tree of shapes utilizes the inferior or the superior of a level line to represent an object, and considers the boundary of the inferior area as the shape of the object. Therefore, only closed shapes are generated. This representation also provides a tree structure to represent the spatial relationship for the objects in an image. Concept of "shape" is introduced to generate a unique inclusion tree for an image. A shape is defined as the connected components of a level set and the holes inside them. The whole image acts as the root of the tree located at the top level. The shapes in the same level are spatially disjoint in the image. The shapes in the lower level are spatially included in the shapes in the next higher level. The tree of shapes, therefore, provides a natural way to represent the spatial relationships between the shapes in the image.

The tree of shapes is used as a candidate to obtain the intensity information in the priori image which is used in preferential segmentation. A common method used to construct tree of shapes to both images (Figures 3a and 3b), whose features are then compared to identify the ratio of similarity between the images. However, the main disadvantage of this approach is the amount of shapes (features) generated, which is very huge. For examples, the example picture produces 3832 shapes (Figure 2b). The closed curves in Figure 4 correspond to the boundaries of the shape in the tree of shapes. These discovered boundaries provide valuable information which can be utilized during shape similarity measure.

3.1. IMAGE REPRESENTATION USING THE TREE OF SHAPES

The tree of shapes represents images based on the techniques of contrast-invariant mathematical morphologies .This method is based on the theory of image representation using connected components of set of finite perimeters in the space of functions with weakly bounded variations (WBV), as introduced in .It shows that an image, if taken as a function of weakly bounded variation is guaranteed to be decomposed into connected components with closed boundary .This is an extension to classical methods where an image is taken as a piecewise- smooth function.

The representation of an image using a tree of shapes utilizes the inferior or the superior of a level line to represent an object, and takes the boundary of the inferior area as the shape of the object. Therefore, only closed shapes are generated. This representation also provides a tree structure to represent the spatial relationship for the objects in an image. For a gray image with, the upper level set of value and the lower level set of value are obtained. The above definitions have several advantages. First, they represent regions instead of curves in an image, which provide a way to handle the contents inside the regions. Second, they are invariant to the contrast changes in an image, which may be caused by the change of lighting .Third, closed boundaries are acquired for each upper level set or lower level set, which can be utilized for shape matching of the regions. As the number of shapes increases, the computational complexity also increases, thus necessitating to reduce the number of shapes used during segmentation and shape comparison.

3.2. PLANAR CURVE MATCHING

The method in defines the shape of a curve as a conjunction of shape elements and further defines the shape elements as any local, contrast invariant and affine invariant part of the curve. These definitions are oriented to provide invariance to noise, affine distortion, contrast changes, occlusion, and background. The shape matching between two images are designed as the following steps.

1) Extraction of the level lines for each image. The level set representations are utilized here for the extraction. The level line is defined as the boundaries of the connected components as shown before.

2) Affine filtering of the extracted level lines at several scales. This step is applied to smooth the curves using affine curvature deformation to reduce the effects of noise.

3) Local encoding of pieces of level lines after affine normalization .Both local encoding and affine normalization are designed for local shape recognition methods. This step will help to deal with occlusions in real applications.

4) Comparison of the vectors of features of the images. Euclidean Distance is utilized to compare the feature vectors. The performance of curve matching between two curves is calculated after affine filtering, Curve normalization and local en-coding is calculated.

This is performed using the intensity information that is contained inside the shape. The intensity information by means of the tree of shapes includes the following features.

1. The number of objects (Nd) contained directly in the shape, which corresponds to the number of direct children of the shape in the tree, Nd=2 for the indicated shape in Figure 2a.

2. The total number of objects (Nt) contained in the shape, which corresponds to the total number of children below the shape in the tree Nt=3 for the indicated shape in Figure 2a.

3. The relative area change between the shape and its direct children. Suppose the area of the shape is S, and the areas of its direct children are S_i, where $1 \leq i \leq Nd$, the relative area change is then defined as

$$A = \prod_{i=1}^{Nd} \frac{S_i}{S}$$

(IJCSIS) International Journal of Computer Science and Information Security,
Vol. 9, No. 11, November 2011

Enhancement Technique for Leaf Images

N.Valliammal
Assistant Professor, Department of Computer Science,
Avinashilingam Institute for Home Science and Higher
Education for Women, Coimbatore-641 043. INDIA
valli.p.2008@gmail.com

Dr.S.N.Geethalakshmi
Associate Professor, Department of Computer Science,
Avinashilingam Institute for Home Science and Higher
Education for Women, Coimbatore-641 043. INDIA
sngeethalakshmi@yahoo.com

Abstract— **Computer aided identification of plants is an area of research that has gained more attention in recent years and is proving to be a very important tool in many areas including agriculture, forestry and pharmacological science. In addition, with the deterioration of environments, many of the rare plants have died out, and so, the investigation of plant recognition can contribute to environmental protection. A general process of a Computer Aided Plant Classification through Leaf Recognition (CAP-LR) contains four steps, namely, building the leaf database, preprocessing, feature extraction and classification. This paper focuses on the preprocessing step of CAP-LR. In this paper, an approach that simultaneously removes noise, adjusts contrast and enhances boundaries is presented. Experimental results prove that the proposed method is an improved version to the traditional enhancement algorithms.**

Keywords: Contrast Adjustment; Discrete Wavelet Transform; Boundary Enhancement; Median filter.

I. INTRODUCTION

Plants are living organisms belonging to the vegetable kingdom that can live on land or in water. They are responsible for the presence of oxygen [1], which is vital for human beings. The ability to know or identify plants allows to assess many important rangeland and pasture variables that are crucial to proper management of plant life. To help botanists in this challenging venture, several researches (Man *et al.*, 2008; Lee and Chen, 2006) are conducted to automatically classify a given input plant into a category. A general process of a Computer Aided Plant Classification Through Leaf Recognition (CAP-LR) contains four steps [5],[6], namely (i) Acquisition of leaf images and creation of plant and leaf image database (ii) Preprocessing the acquired images (iii) Extract salient features and (iv) Cross examine these extracted features with the historical data to match the leaf with its associated plant. The plant that has the maximum match is the recognized plant

Out of these four steps, this paper focuses on the preprocessing stage of CAP-LR. Preprocessing is the technique of enhancing a leaf image in such a way that it increases the efficiency of the subsequent tasks of the leaf recognition system. Leaf images are normally degraded by the presence of noise and low or high contrast both in edge area and image area. Preprocessing an image include removal of noise, edge or boundary enhancement, automatic edge detection, automatic contrast adjustment and segmentation. For segmentation and classification processes [7, 8] CAP-LR is used. In this paper, an approach that simultaneously removes noise, adjusts contrast and enhances boundaries is presented.

II. PROPOSED METHODOLOGY

The proposed algorithm presented presents a novel amalgamation of the existing systems to increase the quality of the image. The method combines the use of CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm for enhancing the contrast of the input leaf image, Discrete Wavelet Transform (DWT) [2] to identify the edge and non-edge region of the image, edge enhancement using sigmoid function and noise removal using median filter. The various steps involved are shown in Figure 1.

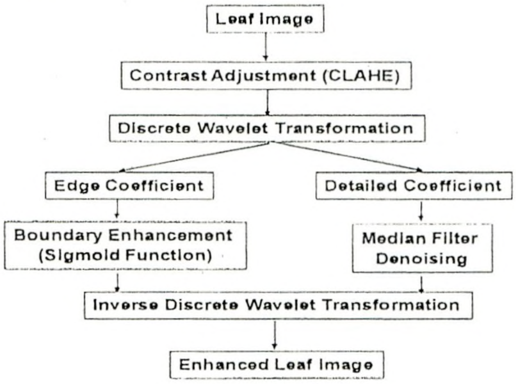


Figure 1. Enhancement Procedure

The algorithm begins by applying CLAHE to adjust the contrast of the leaf image. 01CLAHE (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. The algorithm is given in Figure 2. In the experiments, NB was set to 64, CL was set to 0.01, tile size used was 8 x 8, and the histogram distribution is Bell-Shaped. The contrast adjusted image is then decomposed using 2D Haar wavelet transform to obtain LL, LH, HL and HH subbands. It is known that the LL subband has the average details of the image, while LH contains horizontal edge details, HL has vertical edge details and HH subband elements contain diagonal edge details. Thus the detailed coefficients are selected. The edge enhancement procedure starts by dividing the wavelet coefficients into 8 x 8 blocks. The image features mean, variance and correlation are calculated for each block to obtain the local information in terms of texture pattern. Figure 2 shows the CLAHE algorithm.

Input: Leaf Image, No. of bins (NB), Clip Limit (CL);

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. For each region
   a. Calculate histogram for each tile using NB
   b. Clip the histogram such that its height does not exceed CL (Histogram Redistribution) (CL = 0.01 set in experiments).
   c. Use transformation function (Equation ---) to create a mapping for this region

Combine neigh-bouring tiles using bilinear interpolation and modify gray scale values according to the modified histograms

Figure 2. CLAHE Algorithm

Using this information the edges are categorized as strong and weak edges. The weak edges are then enhanced using a sigmoid function (Equation 1).

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

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

The next step is to remove the noise from detailed coefficients. For this purpose, a relaxed median filter is used. Traditional median filter is efficient in noise removal. However, the filter sometimes removes sharp corners and thin lines and destroys structural and spatial neighbourhood information. To solve this, this work uses a relaxed median filter (Hamsa *et al.*, 1999). During experimentation, the lower limit was set to 3 and upper limit was set to 5 and the window size used as 3 x 3. After enhancing the edges and removing the noise, finally an inverse wavelet transformation is performed to obtain an enhanced leaf image.

III. EXPERIMENTAL RESULTS

The performance metrics used as Peak Signal to Noise Ratio (PSNR), Pratt's Figure Of Merit (FOM) and enhancement speed. All the experiments were conducted in a Pentium IV machine with 2GB Memory and the proposed enhancement algorithm was developed using MATLAB 2009a. The proposed method was evaluated using several test images, three of which is shown as sample in Figure 3 (Leaf1-Leaf6). The manually corrupted images are also shown in Figure 3 (LeafN1-LeafN6)[3]. Fifty percent contrast was added with 10% uniform impulse noise. The results are compared with the traditional median filter and wavelet denoising filter [9]. To compute PSNR, the block first calculates the Mean-Squared Error (MSE) and then the PSNR (Equation 2).

$$PSNR = 10 \log 10 \left[\frac{R^2}{MSE} \right] \qquad (2)$$

where $MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$ and R(=255) is the maximum fluctuation in the input image data type, M and N, m and n in MSE equation are number of rows and columns in the input and output image respectively

To compare edge preservation performances of different speckle reduction schemes, the Pratt's figure of merit (Yu and Acton, 2002) is adopted and is defined by Equation (3).

$$FOM = \frac{1}{\max\{\hat{N}, N_{ideal}\}} \sum_{i=1}^{\hat{N}} \frac{1}{1+d_i^2 \alpha} \qquad (3)$$

where $\hat{N}$ and N_{ideal} are the number of detected and ideal edge pixels, respectively, d_i is the Euclidean distance between the i^{th} detected edge pixel and the nearest ideal edge pixel, and α is a constant typically set to 1/9. FOM ranges between 0 and 1, with unity for ideal edge detection.

Enhancement time is the execution taken by the proposed algorithm to perform the enhancement operation on the noisy image and obtain the reconstructed image. The time is measured in seconds. All the experiments were conducted in a Pentium IV machine with 2GB Memory and the proposed enhancement algorithm was developed using MATLAB 2009a. The proposed method was evaluated using several test image, four of which is shown as sample in Figure 3. The manually corrupted images are shown in Figure 4. Fifty percent contrast was added with 10% uniform impulse noise. The results are compared with the traditional median filter and wavelet denoising filter.

http://sites.google.com/site/ijcsis/
ISSN 1947-5500

The PSNR and Pratt's Figure of Merit (FOM) values obtained are projected in Table 1. Figure 3 shows the original and corrupted images.

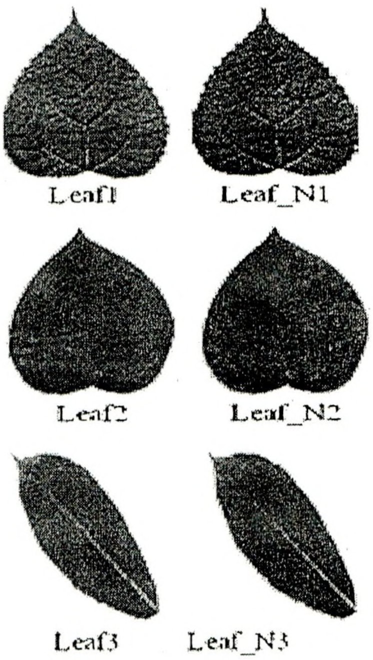


Figure 3. Original and Corrupted Images

TABLE 1. PSNR

Filter Model	Leaf_N1	Leaf_N2	Leaf_N3	Leaf_N4	Leaf_N5	Leaf_N6
Median	31	34	33	34	30	30
Wavelet	34	36	39	40	35	31
Proposed Method	42	46	44	45	41	40

The table 1 & 2 shows the PSNR and FOM value for the different method.

TABLE 2. FOM

Filter Model	Leaf_N1	Leaf_N2	Leaf_N3	Leaf_N4	Leaf_N5	Leaf_N6
Median	0.4004	0.3027	0.4212	0.3072	0.4120	0.4099
Wavelet	0.7399	0.6958	0.7199	0.6841	0.7001	0.7200
Proposed Method	0.7990	0.7437	0.7877	0.7892	0.7813	0.7363

The high PSNR obtained gives the understanding that the visual quality of the denoised image is good. On average the median filter [11] produced an PSNR value of 32 dB, Wavelet produced 35.83dB and 43dB by proposed algorithm. This shows that the proposed method is an improved version of the traditional algorithms. Similarly, while considering the FOM, by the nearing value to unity achieved by the proposed model, it is clear that the proposed model is successful in removing maximum noise [12] from the corrupted image. To compare each filter's performance with respect to FOM performance metric, the average value of the six images were calculated. The median filter based enhancement algorithm showed 0.38, wavelet showed 0.71 and proposed method showed 0.77 FOM. This shows that the proposed algorithm produces better FOM than all the other models indicating that the edge preserving capability is high.

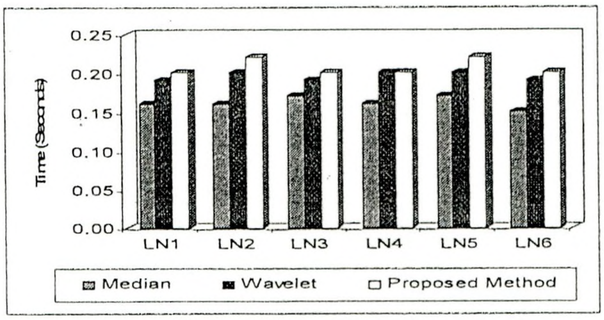


Figure 4. Enhancement Speed

The above figure shows the enhancement speed. While considering the execution time, the median filter was the quickest in enhancing the corrupted image, which was followed by wavelet. The proposed algorithm was the slowest of all the three algorithms. The reason might be because of the extra computations performed by the CLAHE algorithm. However, this difference is very small (0.05 and 0.01 seconds with median and wavelet filters respectively) and can be considered negligible. From the results, it is evident that the speed of the proposed denoising algorithms is faster and the PSNR value obtained is also high.

IV Conclusion

Leaf image enhancement is a vital preprocessing step in CAP-LR system. This paper 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 shows that the proposed method shows significant improvement in terms of noise removed, edge preservation and speed [11]. In future, the impact of the enhancement algorithm on leaf recognition for plant identification [4] is to be studied. Further, methods to automatically calculate the value of NB and CL in CLAHE will also be considered.

http://sites.google.com/site/ijcsis/
ISSN 1947-5500

REFERENCES

[1] Palmer, J.D., Adams, K.L., Cho, Y., Parkinson, C.L., Qiu, Y.L. and Song, K. (2000) Dynamic Evolution of Plant Mitochondrial Genomes: Mobile Genes and Introns and Highly Variable Mutation Rates, Proceedings of the National Academy of Sciences of the United States of America, Vol. 97, No.13, Pp. 6960-6966.

[2] Gu, X., du, J. and Wang, X. (2005) Leaf Recognition Based on the Combination of Wavelet Transform and Gaussian Interpolation , Lecture Notes in Computer Science, Springer Berlin / Heidelberg, Vol. 3644/2005, Pp. 253-262.

[3] Sathyabama, B., Mohanavalli, S., Raju, S. and Ahbaikumar, V. ((2011) Content Based Leaf Image Retrieval (CBLIR) Using Shape, Color and Texture Features, Indian Journal of Computer Science and Engineering (IJCSE), Vol 2, No. 2, Pp. 202-211.

[4] Wu, S.G., Bao, F.S., Xu, E.Y., Wang, Y., Chang, Y. and Xiang, Q. (2007) A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network, IEEE International Symposium on Signal Processing and Information Technology, Pp. 11-16.

[5] N. Valliammal , S.N.Geethalakshmi, Analysis of the Classification Techniques for Plant Identification through Leaf Recognition, CIIT International Journal of Data Mining Knowledge Engineering, Vol.1, No.5, August 2009.

[6] N.Valliammal, S.N.Geethalakshmi, Leaf Recognition for Plant Classification, IETECH, International Engineering and Technology Journal of Advanced Computations, Vol.3, No.3, 2009.

[7] N. Valliammal, S.N.Geethalakshmi, Performance Analysis of Various Leaf Boundary Edge Detection Algorithms, A2CWic'10, Proceedings of the First ACM-W celebration of Women in Computing in India,16-17, September 2010.

[8] N. Valliammal, S.N.Geethalakshmi, Hybrid Image Segmentation Algorithm for Leaf Recognition and Characterization, International Conference on Process Automation, Control and Computing, PACC 2011,20-22 July 2011.

[9] Li, Y., Zhang, Y., Zhu, J. and Li, L. (2010) Wavelet-based maize leaf image denoising method, World Automation Congress (WAC), Pp. 391-395.

[10] Ma, L., Fang, J., Chen, Y. and Gong, S. (2010) Color Analysis of Leaf Images of Deficiencies and Excess Nitrogen Content in Soybean Leaves, International Conference on on E-Product E-Service and E-Entertainment (ICEEE), Pp.1-3.

[11] El-Helly, M., Rafea, A. and El-Gammal, S. (2003) An integrated image processing system for leaf disease detection and diagnosis, 1st Indian International Conference on AI (IICAI-0), Hyderabad, India.

Zhang, J. (2010) An efficient median filter based method for removing random-valued impulse noise, Digital Signal Processing, Vol. 20, Issue 4, Pp. 1010-1018.

[12] Rubio, E.L. (2010) Restoration of images corrupted by Gaussian and uniform impulsive noise, Pattern Recognition, Vol.43, No.5, Pp. 1835-1846

http://sites.google.com/site/ijcsis/
ISSN 1947-5500