CONTENT BASED LEAF IMAGE RETRIEVAL (CBLIR) USING SHAPE, COLOR AND TEXTURE FEATURES

B.SATHYA BAMA[1]

Department of Electronics And Communication Engineering, Thiagarajar College Of Engineering, Madurai,Tamil Nadu,India

S.MOHANA VALLI [2]

Department of Electronics And Communication Engineering, Thiagarajar College Of Engineering, Madurai,Tamil Nadu,India

S.RAJU [3]

Department of Electronics And Communication Engineering, Thiagarajar College Of Engineering, Madurai,Tamil Nadu,India

V.ABHAI KUMAR [4]

Department of Electronics And Communication Engineering, Thiagarajar College Of Engineering, Madurai,Tamil Nadu,India

Abstract

This paper proposes an efficient computer-aided Plant Image Retrieval method based on plant leaf images using Shape, Color and Texture features intended mainly for medical industry, botanical gardening and cosmetic industry. Here, we use HSV color space to extract the various features of leaves. Log-Gabor wavelet is applied to the input image for texture feature extraction. The Scale Invariant Feature Transform (SIFT) is incorporated to extract the feature points of the leaf image. Scale Invariant Feature Transform transforms an image into a large collection of feature vectors, each of which is invariant to image translation, scaling, and rotation, partially invariant to illumination changes and robust to local geometric distortion. SIFT has four modules namely detection of scale space extrema, local extrema detection, orientation assignment and key point descriptor. Results on a database of 500 plant images belonging to 45 different types of plants with different orientations scales, and translations show that proposed method outperforms the recently developed methods by giving 97.9% of retrieval efficiency for 20, 50, 80 and 100 retrievals.

Key Words: Plant Image Retrieval, Scale Invariant Feature Transform, Log Gabor Filter, Saturation Band and Retrieval Efficiency.

1. Introduction

The content-based image retrieval (CBIR) systems have proven to be very useful in many fields to browse and search very huge image databases. Botanists are usually brought to use large collections of plants images. They need automatic tools to assist them in their work. This paper presents a plant retrieval system which takes as input the image of a plant and returns the most similar images from a database. The system is intended to be used as an e-commerce service where users can send images of their house plants (which they often do not know by name) to find their Latin names and care instructions. The problem involves identification of the matching plant, as well as retrieval of related varieties which may be also of interest to the user.

1.1 The Problem in Plant Species Recognition

Plants are basically identified according to their morphological features such as number of ovaries in the fruit or number of stamens in the flower. A number of Manual and computer-aided keys for plant identification using morphological features[1] are available in the literature. Identifying plants using such keys is a very time consuming task and has been carried out only by trained botanists. There are several other drawbacks in identifying plants using these features such as the unavailability of required morphological information and use of botanical terms that only experts can understand. Fortunately, in addition to the structures of reproductive organs, shape, size, texture and colour of the leaves also play an important role in plant identification[2].

Plant leaves are approximately two-dimensional in nature and the shape of plant leaf is one of the most important features for characterizing various plants species. Therefore, it is necessary for us to develop an easy and automatic method that can correctly discriminate and recognize leaf shapes of different species[3-4]. Some research work has been done on this problem[5-7] .Two basic approaches to shape analysis exist: region based and boundary-based (contour-based). Region based systems typically use moment descriptors[9] that include geometrical moments, Zernike moments and Legendre moments[8]. Boundary-based systems use the contour of the objects and usually give better results for images that are distinguishable by their contours.

Even though shape features are extremely powerful in recognizing plant species through the leaf, it will be failed when identifying different plants with similar leaf shape like beetle and pepper. In such cases the method should consider extra characteristics to make the system reliable. According to plant recognition, the second most vital interpretation element is color. By combining texture with the shape feature discrimination capability of the method can be improved. Most of the existing plant recognition methods are based on both the global shape feature and the intact plant leaves. However, for the non-intact leaves largely existing in practice, such as the deformed, partial and overlapped leaves, the global shape features are not efficient and these methods are not applicable.

The effectiveness of a shape-based image retrieval system depends on the types of shape representation used, the types of queries allowed, and the efficiency of the shape matching techniques implemented.

2. Materials and Methods

The overview of the system is shown in Fig.1. The leaf image is first converted from RGB to HSV color space. Then image processed in saturated band is applied to Log Gabor wavelet. The filtered output image is given as the input to Scale invariant feature transform (SIFT) algorithm to make it scale, rotation invariant. Keypoints/extremas are extracted from SIFT and Key point elimination is done using corner detection approach. Finally Leaf images are retrieved using Descriptor Ratio Matching.

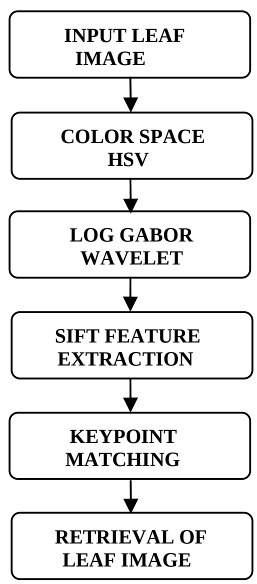

Fig .1 Overall Block diagram

2.1. Color Space Selection

For color feature extraction the HSV space is quite similar to the way in which the colors are defined as human perception, which is not always possible in the case of RGB. Interestingly, it is found that it is best to discard the hue, and represent each pixel with saturation and value only. This is because in field tests in the forest, it is found that the light has a greenish hue that dominates the hue of an otherwise white background. It is experimented with other representations, and colored paper backgrounds of different hues, but found that there are some problems in separating leaves from small shadows they cast. Thus saturation gives the amount of white/gray paint given with the hue[10]. It gives the fading up of colors with their raise and fall in their value. Though leaf image is recognized green in color, there are different shades of the same color due to the presence of chlorophyll. Hence processing SIFT in HSV color space gives the exact color feature matching which is more useful for picking up the damaged or dried leaves or of special colored variety which possess different shades of color.

2.2. Texture feature extraction

Texture of a plant may be due to having many veins in different directions or parallel lines of different colors. Classical Gabor filters give rise to important difficulties when implemented in multiresolution[11-12]. Filters overlap more importantly in the low frequencies than in the higher ones yielding a non-uniform coverage of the Fourier do- main. Moreover Gabor filters have no zero mean; they are then affected by DC components[13]. Hence, we use Log-Gabor method for texture feature extraction.

2.2.1. *Log-Gabor filters*

Log-Gabor wavelets show excellent ability to segregate the image information (e.g. the contrast edges) from spatially incoherent Gaussian noise by hard thresholding. Exact reconstruction is achieved using the same filters in both the direct and the inverse transforms (which means that the transform is self-invertible) a promising tool for processing natural images[13]. Log-Gabor functions match better with edges of natural images (yielding a stronger statistical differential response between edge and noise features) .Log Gabor filters are affine invariant[14-16]. An additional advantage is that they can appear more “natural looking” to human observers.

Log-Gabor filters are defined in the log-polar coordinates of the Fourier domain as Gaussians shifted from the origin[17]:

$$G_{(s,t)}(\rho,\theta) = \exp\left(-\frac{1}{2}\left(\frac{\rho-\rho_s}{\sigma_\rho}\right)^2\right)\exp\left(-\frac{1}{2}\left(\frac{\theta-\theta_{(s,t)}}{\sigma_\theta}\right)^2\right) \tag{1}$$

(ρ,θ) are the log-polar coordinates (in log2 scale indicating the filters organized in octave scales)

With

$$\left\{\begin{array}{l} \rho_s = \log_2(n) - s \\ \theta_{(s,t)} = \left\{ \dfrac{\pi}{n_t} \text{if s is even} \right. \\ \qquad\qquad \left\{ \dfrac{\pi}{n_t} \text{if s is odd} \right. \\ (\sigma_p, \sigma_\theta) = 0.996 \left(\sqrt{\dfrac{2}{3}}, \dfrac{1}{\sqrt{2}} \dfrac{\pi}{n_t} \right) \end{array}\right\}$$

Where, n_s= 5 is the number of scales of the multiresolution scheme and n_t is the number of orientations (n_t will range between 3 to 20. 8 orientations will be used as a typical value). s $\in\{1,\ldots, n_s\}$ and t $\in\{1,\ldots, n_t\}$ indexes the scale and the orientation of the filter, respectively; (ρs ,$\theta(s,t)$) are the coordinates of the center of the filter; and ($\sigma\rho$,$\sigma\theta$) are the bandwidths in ρ and θ, common for all filters[13].

2.3. Scale Invariant Feature Transform (SIFT)

Features are extracted by the use of the Scale Invariant Feature Transform (SIFT) as proposed by David G Lowe[14]. SIFT features are used rather than using shape based techniques as the feature robust, in the sense that they are invariant to translation, rotation, scale and affine transforms[18] .

2.3.1. *Detection of Scale-Space Extrema*

The scale space of an image is defined as a function, $L(x, y,\sigma)$ which is derived from the convolution of a variable-scale Gaussian, $G(x, y,\sigma)$ with an input image, I(x, y) [19,20].

$$L(x, y,\sigma) = G(x, y,\sigma) \otimes I(x, y) \tag{2}$$

Where, $\otimes$ is the convolution operation in x and y, and

$$G(x, y, \sigma) = \frac{1}{(2\pi\sigma^2)} e^{-(x^2+y^2)/2\sigma^2} \tag{3}$$

To efficiently detect stable keypoint locations in scale space, we compute the Difference of Gaussian (DoG). The difference of Gaussian $D(x, y, \sigma)$ is defined in equations 4 and 5. As an image enhancement algorithm, the Difference of Gaussians can be utilized to increase the visibility of edges and other detail present in the digital images.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \tag{4}$$

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{5}$$

Where k is a constant and is the same value over all scales and therefore does not influence extrema location. The pictorial representation of the approach to construction of $D(x, y, \sigma)$ is shown in Fig.2.

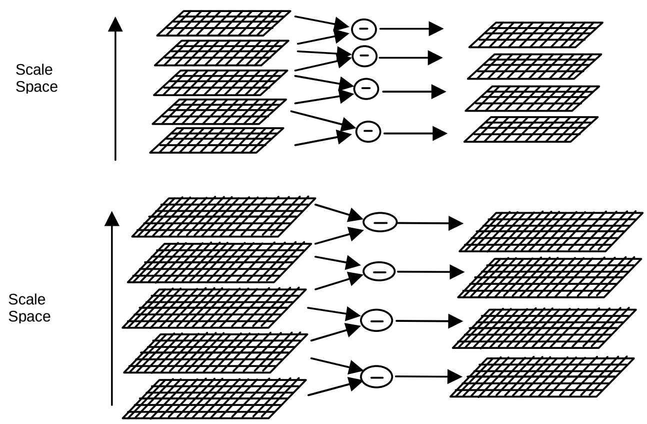

Fig 2. Scale space and Difference of Gaussian

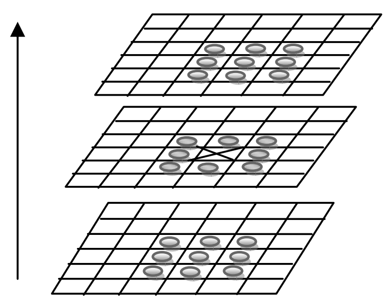

Fig.3 Neighbourhood for extrema detection

2.3.2. *Local Extrema Detection*

The next step is to detect the locations of all local maxima and minima (peaks) of $D(x, y, \sigma)$, the difference-of-Gaussian function convolved with the image in scale space. This can be done most efficiently by first building a scale space representation that samples the function at a regular grid of locations and scales. We check each sample point with the eight closest neighbours in image location and nine neighbours in the scale above and below, as shown in Fig .3. The defined neighbourhood size ensures high probability of detecting all local extrema.

2.3.3. *Orientation Assignment*

The next step is to assign an orientation value for each of the image samples. For each image sample, L(x, y), the gradient magnitude, m(x, y), and orientation, $\theta(x, y)$, is computed using the pixel differences as shown in equation 6 and equation 7.

$$m(x,y)=\sqrt{((L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2)} \qquad (6)$$

$$\theta(x,y)=\tan^{-1}\left\{\frac{L(x,y+1)-L(x,y-1)}{(L(x+1,y)-L(x-1,y)}\right\} \qquad (7)$$

An orientation histogram is formed from the gradient orientations of sample points within a region around the keypoint. The highest peak in the histogram is detected, and then any other local peak that is within 80% of the highest peak is used to also create a keypoint with that orientation.

2.3.4. *Keypoint Descriptor*

A key point descriptor is created by first computing the gradient magnitude and orientation at each image sample point in a region of 16 X 16 around the key point location. These are weighted by a Gaussian window, indicated by the overlaid circle .These samples are then accumulated into orientation histograms summarizing the contents over 4 X 4 sub regions , with the length of each arrow corresponding to the sum of the gradient magnitudes near that direction within the region.

2.4. Keypoint Matching

The best candidate match for each keypoint is found by identifying its nearest neighbour in the database of keypoints from training images. The nearest neighbour is defined as the keypoint with minimum Euclidean distance for the invariant descriptor vector as was described in. However, many features from an image will not have any correct match in the training database because they arise from background clutter or were not detected in the training images. Therefore, it would be useful to have a way to discard features that do not have any good match to the database. A global threshold on distance to the closest feature does not perform well, as some descriptors are much more discriminative than others. A more effective measure is obtained by comparing the distance of the closest neighbour to that of the second-closest neighbour. If there are multiple training images of the same object, then we define the second-closest neighbour as being the closest neighbour that is known to come from a different object than the first, such as by only using images known to contain different objects. This measure performs well because correct matches need to have the closest neighbour significantly closer than the closest incorrect match to achieve reliable matching.

2.4.1. *Feature Matching*

Feature matching phase comprises of Descriptor Ratio matching method[21-22] of SIFT features extracted. The flow diagram of feature matching is shown in Fig .4.

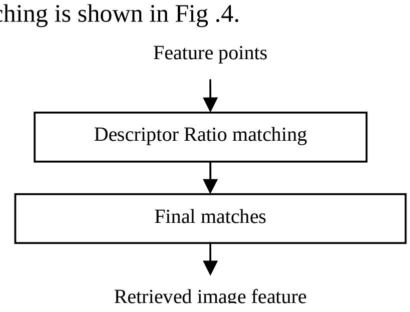

Fig.4 Feature matching

3. Data set

The required images for the proposed work are acquired with the help of digital camera. These images are captured in the close environment to maintain constant illumination and also they are taken in video graphics array mode (VGA). Database contains the reference image of all kinds of segmented leaves. The features of Query image and the reference images are extracted using the Scale Invariant Feature Transform. Then, the Query image of the leaf is matched with the reference images in database. Based on the matching of Query image and reference image, the leaf with highest matching ratio is given as output, which is tagged to the reference image. Matlab 10 is used for Simulation purpose. The database images that are considered for the simulation of the proposed work is shown in Fig.8.

The dataset which consists of more than hundred leaf images such as Neem, Beech, Cannabis, Pepper, Betel, Polygonum cuspidatum, Marijuana etc.

4. Results

a) b) c)

Fig. 5 a) Original image b) Gabor filter output c) Log-Gabor output.

The Gabor output which has DC component giving blur image and the third one is the Log Gabor output which has zero mean and hence no DC component giving a natural look. The Log-Gabor filters lack DC components and can yield a fairly uniform coverage of the frequency domain in an octave scale multi resolution.

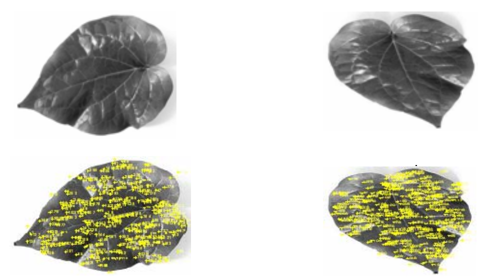

Fig. 6 Matching with Rotated version of same leaf

SIFT algorithm is rotation invariant and hence it is found to give 2105 matches in ratio method for Betel leaf and rotated Betel leaf as shown in fig.6

Fig .7 Matching with different shapes (Marijuana and Hydrastis)

Matching with different shapes (Marijuana and Hydrastis)which is of somewhat same kind of shape are found to be giving poor match of only 12 in ratio method on applying Log-Gabor in SIFT as shown in fig.7.

Table 1. Performance Analysis of the proposed Method

Test + Reference Image	Final Matches Using SIFT	Final Matches Using SIFT in HSV	Matches Using SIFT	Matches Using SIFT in HSV
Coleus hybridus+coleus blumeiverschaffeltii	1058	23	Good match	Poor match
Hydrastis+ Ipomoea batatas	2025	7	Good match	Poor match
Bay + ikmo	12	10	Poor match	Poor match
Astilboides + Hydrangea	5	4	Poor match	Poor match
Chestnet + chervil	36	3	Poor match	Poor match
Polygonum cuspidatum+ polygonum filiforme	2467	85	Good match	Poor match
Marijuana + Manihot esculenta	3241	104	Good match	Poor match
Betel +Betel	2105	2003	Good match	Good match
Betel +birch	20	6	Poor match	Poor match
Solenostemonscutellarioides+coleus scutellarioides	1054	27	Good match	Poor match
Tomato leaf + Neem	1	1	Poor match	Poor match
Neem + Neem	3001	2098	Good match	Good match
Sugar maple + Black maple	2009	12	Good match	Poor match
Chestnut + Big mama hosta	1	1	Poor match	Poor match
Astilboides + Alder	22	9	Poor match	Poor match
Aquifoliaceae + Neem	3	1	Poor match	Poor match

This table gives the dataset of matches found using SIFT and SIFT in saturation band. Here the highlighted test and the reference image (different colored leaf image) show good match when SIFT is applied to them. This considers only the shape features whereas SIFT in saturation band gives poor matching for the same by considering both shape and color. Thus SIFT in saturation band of the HSV color space discriminates the good and poor matches, hence giving the exact match.

Table 2. Comparision Table

PERFORMANCE MEASURE	Without applying Texture	GABOR	LOG GABOR
Precision	0.893	0.931	0.979
Recall	0.598	0.602	0.62
Error rate	0.107	0.069	0.021
Retrieval efficiency	89.3	93.1	97.9

In table 2 the results of performance evaluation of Gabor and Log Gabor Wavelet transforms are tabulated. It is inferred that the Log Gabor wavelet gives good retrieval efficiency than Gabor wavelet.

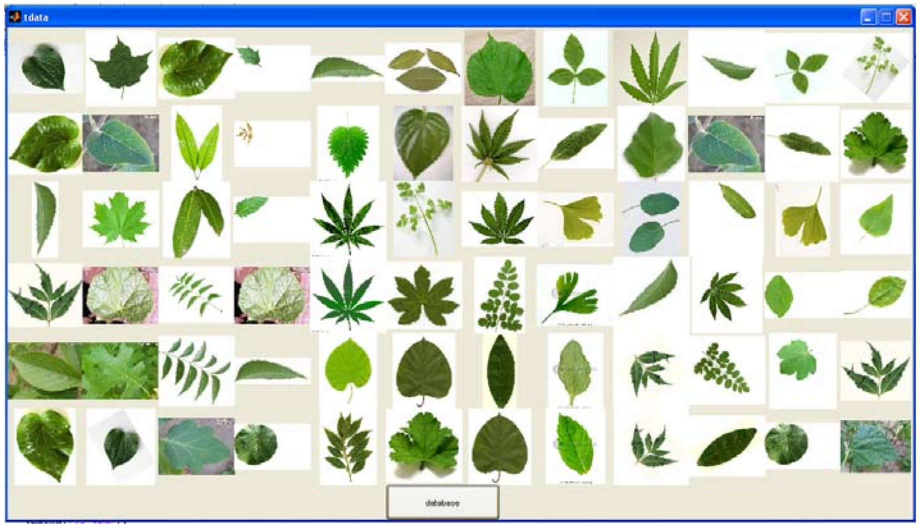

Fig. 8 GUI of the implemented system. (Database …)

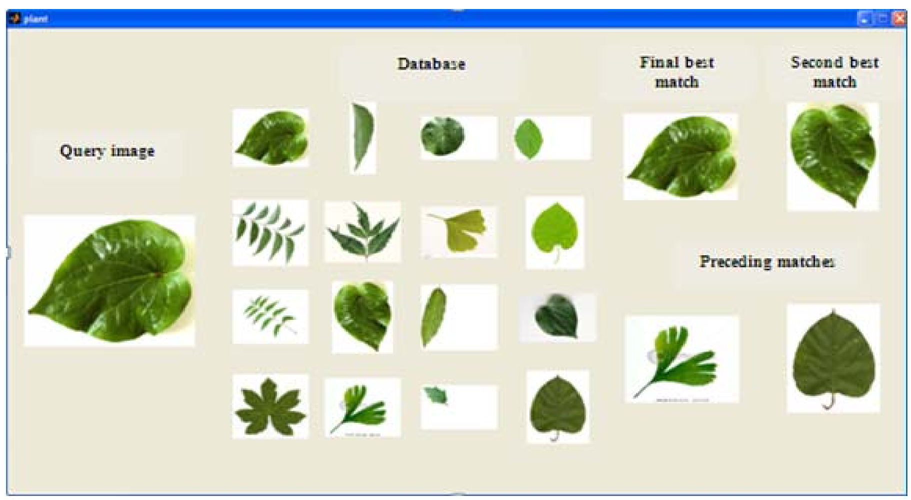

Fig.9 The image in the top left corner is the original query. The rightmost columns give the final best match and the preceding matches.

5. Performance Analysis of the proposed Method

Performance of CBIR System can be evaluated using Precision and recall. Considering the database that consists of different leaf samples, the performance analysis has been calculated from the parameters such as Precision, Recall and Error rate. Precision in terms of the percentage of precision is said to be the retrieval efficiency. These parameters characterize the performance of the image retrieval system.

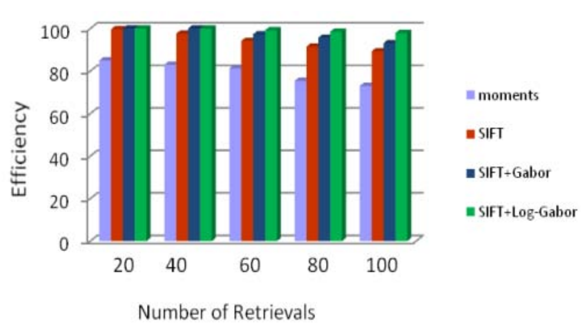

Fig.10 performance evaluation

This graph gives the retrieval efficiency of SIFT, Log Gabor + SIFT, HU's moments for shape feature extraction. From the performance analysis we obtain very high retrieval efficiency for shape with texture based algorithm (Log Gabor in SIFT). Shape with texture based algorithm (Log Gabor in SIFT) has better performance than the (SIFT) shape algorithm. Both these methods are proved to be efficient than the existing methods. Whereas HU's moments gives very less retrieval rate than the SIFT and SIFT applied to texture as shown in fig.10.

6. Conclusion

A leaf shape based plant recognition system has been proposed to identify the required leaf from the database. The proposed algorithm uses the efficient feature extraction methods like scale invariant feature transform (SIFT) for shape based feature extraction and color based feature extraction is done by applying SIFT in the saturation band of the HSV color space and texture based feature extraction is done on applying Log Gabor wavelet in SIFT. Then the matching is achieved by incorporating descriptor ratio method. The performance of the proposed method is proved to be more efficient than the existing algorithms by providing classification accuracy. Combining different color, shape and texture features extracted from the images enhance the accuracy of the system. For the leaf recognition the segmented leaf image is taken as an input for simulation using Matlab R2010a. The proposed work can be applicable in the field of medicinal industry, botanical gardening, herbal cosmetic industry etc.

References

[1] Ashton, M. S., Gunatilleke, S., de Zoysa, N., Dassanayake, M.D., Gunatilleke, N., Wijesundera, S., 1997. A field guide to the common trees and shrubs of Sri Lanka. WHT Publications, Sri Lanka, pp. 43-50.

[2] K.K. Pahalawatta, Plant Species Biometric Using Feature Hierarchies, A Plant Identification System Using Both Global And Local Features Of Plant Leaves, Department Of Computer Science and Software Engineering University of Canterbury Christchurch 2008.

[3] Yunyoung Nam a, Eenjun Hwang b, Dongyoon Kim, A similarity-based leaf image retrieval scheme: Joining shape and venation features, Computer Vision and Image Understanding 110 (2008) 245–259.

[4] Ji-Xiang Du, Xiao-Feng Wang, D.S. Huang, Automatic plant leaves recognition system based on image processing techniques, Technical Report, Institute of Intelligent Machines, Chinese Academy of Sciences, October, 2004.

[5] Ji-Xiang Du a,b, Xiao-Feng Wang b, Guo-Jun Zhang , Leaf shape based plant species recognition , Applied Mathematics and Computation 185 (2007) 883–893

[6] Xiao-Feng Wang a,b,c, De-Shuang Huang a, Ji-Xiang Dua,b, Huan Xu a,b, Laurent Heutte, Classification of plant leaf images with complicated background, Applied Mathematics and Computation 205 (2008) 916–926.

[7] C.L. Lee, S.Y. Chen, Classification for leaf images, Proc. 16th IPPR Conf. Comput. Vision Graphics Image Process. (2003) 355–362.

[8] El-ghazal, A., Basir, O. A., and Belkasim, S. Shape based image retrieval using pair-wise candidate co-ranking. In Kamel, M. S. and Campilho, A. C. (eds.), ICIAR, Lecture Notes in Computer Science, 4633, pp. 650–661. Springer-Verlag. (2007)

[9] Park, J. S. and Kim, T.-Y. Shape-based image retrieval using invariant features. In Aizawa, K., Nakamura, Y., and Satoh, S. (eds.), Advances in Multimedia Information Processing – PCM(2004), Berlin / Heidelberg Lecture Notes in Computer Science, pp. 146–153. Springer-Verlag.

[10] Shamik Sural, S. (2005). Histogram generation from the HSV color space using saturation projection. In S. Deb (Ed.), Multimedia systems and content-based image retrieval.Hershey, PA: Idea Group Publishing.

[11] Dengsheng Zhang, M.I., Aylwin, W. and Lu,G.Content Based Image Retrieval Using Gabor Texture Features". Proc.1st IEEE Pacific Ri.(2004)

[12] Fischer, S., Cristobal, G., and Redondo, R.'Sparse over complete Gabor wavelet representation based on local competitions'. IEEE Trans. on Image Proc., 15(2):265–272.m Conf. Multimedia December(2006), pp. 392–395

[13] Sylvain Fischer, Laurent Perrinet, 'Self-Invertible 2D Log-Gabor Wavelets', International Journal of Computer Vision 75(2), 231–246, 2007

[14] S.R. Fountain, T.N. Tan, "efficient rotation invariant texture features for content-based image retrieval", Pattern Recognition 31 (11) (1998) 1725–1732

[15] Gui-Song Xia , Julie Delon , Yann Gousseau, 'Shape-based Invariant Texture Indexing', Int J Computer Vis. November (2009), DOI 10.1007/s11263-009-0312.

[16] C. Ballester, M. GonzSalez, "Affine invariant texture segmentation and shape from texture by variational methods", J. Math. Imaging Vision 9 (1998) 141–171.

[17] Chi-Man Pun and Moon-Chuen Lee," Log-Polar Wavelet Energy Signatures for Rotation and Scale Invariant Texture Classification IEEE transactions on pattern analysis and machine intelligence, vol. 25, no. 5, may (2003)

[18] Lowe, D. G.Distinctive image features from scale invariant keypoints. International Journal of Computer Vision, 60, 91–110. (2004)

[19] Wang, J., Zha, H., and Cipolla, R. Combining interest points and edges for content-based image retrieval. IEEE International Conference on Image Processing., (2005). ICIP 2005, Sep., pp. 1256–9.
[20] Koenderink,J.J.The structure of images. Biological Cybernetics,50:363-396.Lindeberg, T. 1994. Scale-space theory: A basic tool for analysing structures at different scales. Journal of Applied Statistics, 21(2):224-270. (1984)
[21] Brown, M. and Lowe, D.G. Invariant features from interest point groups. In British Machine Vision Conference, Cardiff, Wales, pp. 656-665.(2002)
[22] Kamarul Hawari Ghazali, Mohd. Marzuki Mustafa , Aini Hussain "Feature Extraction Technique Using SIFT Keypoint Descriptors" Proceedings of the International Conference on electrical engineering and informatics, june 17-19 ,(2007)