Content Based Leaf Image Retrieval (CBLIR) Intended for e-commerce

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ABSTRACT

This paper proposes an efficient computer-aided Plant Image Retrieval method based on plant leaf images using Shape and Texture features intended for e-commerce particularly in medical industry, botanical gardening, house plant identification etc. Log-Gabor wavelet is applied to the input image for texture feature extraction. 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. 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.

KEYWORDS

Plant Image Retrieval, Scale Invariant Feature Transform, Log Gabor filter, 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. Particularly Botanists need automatic tools to assist them in their work. Identifying plant using morphological features [1] are available in the literature. There are several other drawbacks in identifying plants using these methods such as, the unavailability of required morphological information and use of botanical terms. And also using such keys are very time consuming task and has been carried out only by trained botanists. 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].

There are several methods which uses contour and moment based descriptor to identify the plant features. Region based systems typically use moment descriptors [3] that include geometrical moments, Zernike moments and Legendre moments [4]. Boundary-based systems use the contour of the objects and usually give better results for images that are distinguishable by their contours. Even though these methods are extremely powerful in recognizing plant species through the leaf, it will be failed when identifying different plants with similar leaf shapes. In such cases the method should consider extra characteristics such as texture feature extraction to make the system reliable. 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.

Hence this paper presents a plant leaf retrieval system which uses SIFT for shape feature extraction and Log-Gabor for texture feature extraction.

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2. MATERIALS AND METHODS

The overview of the system is shown in Fig.1.The leaf image 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.

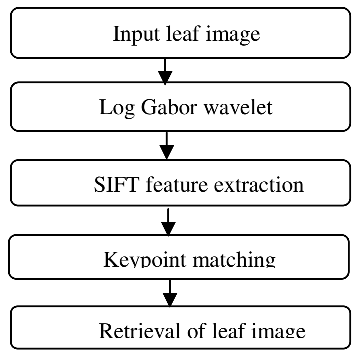

Fig .1 Overall Block diagram

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. Moreover Gabor filters have no zero mean; they are then affected by DC components [5, 6]. 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. Log-Gabor filters are defined in the log-polar coordinates of the Fourier domain as Gaussians shifted from the origin [7]:

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

$(\rho,\theta)$are the log-polar coordinates (in log2 scale indicating the filters organized in octave scales)

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. 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 [8]

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) [9].

$$L(x, y,\sigma) = G(x, y,\sigma) \otimes I(x, y) \qquad (2)$$

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

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

To efficiently detect stable keypoint locations in scale space, we compute the Difference of Gaussian (DoG).

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

2.3.2. Local Extrema Detection

We check each sample point with the eight closest neighbours in image location and nine neighbours in the scale above and below. The defined neighbourhood size ensures high probability of detecting all local extrema.

2.3.3. Orientation Assignment

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 5 and equation 6.

$$m(x, y) = \sqrt{((L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2)} \qquad (5)$$

$$\theta(x, y) = \tan^{-1}\left\{\frac{L(x, y+1) - L(x, y-1)}{(L(x+1, y) - L(x-1, y))}\right\} \qquad (6)$$

2.3.4. Feature Matching

Feature matching phase comprises of Descriptor Ratio matching method [10] of SIFT features extracted. The flow diagram of feature matching is shown in Fig .2.

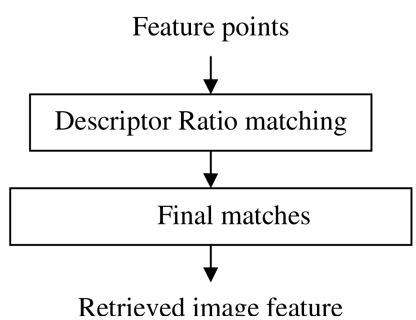

Figure 2 Feature matching

4. RESULTS

(a) **(b)** **(c)**

Fig. 3 a) Original image b) Gabor c) Log-Gabor

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.

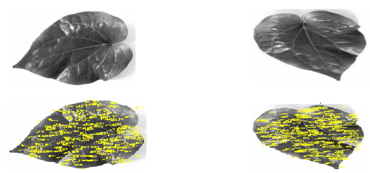

Fig. 4 Matching with Rotated version of same leaf
(SIFT algorithm is rotation invariant and hence it is found to give 2105 good matches)

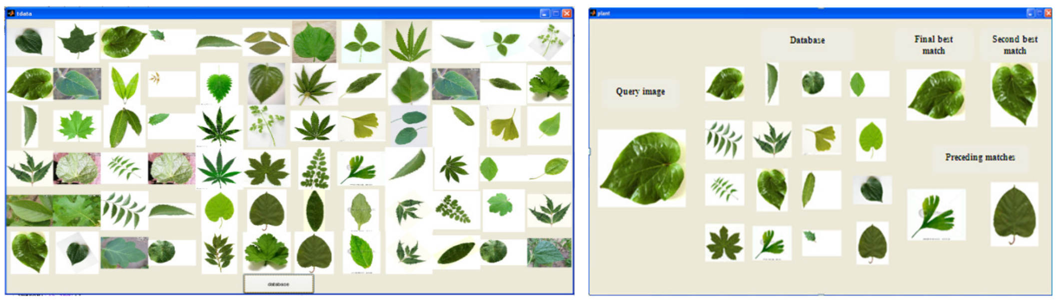

Fig. 6 GUI of the implemented system. (Database …) is given in the left and the image to the right gives the best retrieved image and preceding matches.

5. Performance Analysis Of The Proposed Method

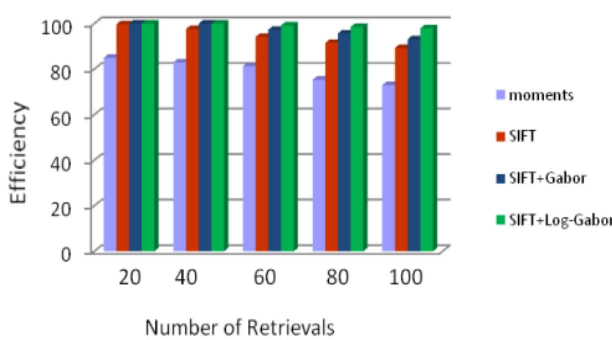

Fig.7 performance evaluation

From this graph we can infer that the retrieval efficiency of Log Gabor + SIFT gives the best retrieval rate compared to all other methods.

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 texture based feature extraction is done on applying Log Gabor wavelet in SIFT. The performance of the proposed method is proved to be more efficient than the existing algorithms by providing classification accuracy.

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]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)

[4]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.

[5] 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

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

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

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

[9] Brown, M. and Lowe, D.G. Invariant features from interest point groups. In British Machine Vision Conference, Cardiff, Wales, pp. 656-665.(2002)

[10] 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)