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Invariant Feature Descriptor based on Harmonic Image Transform for Plant Leaf Retrieval

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ABSTRACT

Feature descriptor for image retrieval has emerged as an important part of computer vision and image analysis application. In the last decades, researchers have used algorithms to generate effective, efficient and steady methods in image processing, particularly shape representation, matching and leaf retrieval. Existing leaf retrieval methods are insufficient to achieve an adequate retrieval rate due to the inherent difficulties related to available shape descriptors of different leaf images. Shape analysis and comparison for plant leaf retrieval are investigated in this study. Different image features may result in different significance interpretation of images, even though they come from almost similarly shaped of images. A new image transform, known as harmonic mean projection transform (HMPT), is proposed in this study as a feature descriptor method to extract leaf features. By using harmonic mean function, the signal carries information of greater importance is considered in signal acquisition. The selected image is extracted from the whole region where all the pixels are considered to get a set of features. Results indicate better classification rates when compared with other classification methods.

Keywords: Feature descriptor, Harmonic image transform, Image processing, Leaf retrieval

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INTRODUCTION

Shape is an important element in describing an image. Retrieving the leaf imagery is a difficult task in image processing, since it is difficult to define the significant features and measure the dissimilarity between images. Particularly in leaf identification, there are huge leaf images with similar shapes and to distinguish them based on their shape can be challenging. Leaves of plants have varieties of shape, therefore the feature of the leaf including the shape and image pixel values are considered as the key element. In Im, Nishida, and Kunii (1998) used normalized shapes of leaves using the symmetry of each leaf with respect to the vein in order to recognize the different type of plants. Abbasi, Mokhtarian, and Kittler (1997) used the contour of leaves to form scale space images and Critical points as a representation technique. However, their work was not robust enough due to local variations of curvature.

Recently, there has been an expansion techniques of classification and recognition related to plant identification. Söderkvist (2001) classified the class of trees from an image of a leaf, and the first leaf database was constructed by Du, Wang, and Zhang (2007) and popularised the move median centres (MMC) hypersphere classifier based on morphological features. Kumar et al. (2012) created the first mobile application for identifying plant species using automatic visual recognition s called Leafsnap. In the past two decades, the problems of recognition and identification of leaf shapes have faced retrieval difficulties. A large amount of data stored in a system makes the retrieval process difficult. Leaf shapes normally have large intra class differences and high inter class similarity, these shortcomings make accurate retrieval challenging. Ling and Jacobs (2007) built insensitive shape descriptor to articulate and effectively capture some part of the structure, calling it inner-distance shape classification (IDSC). Instead of using Euclidean distance, they suggested inner-distance to be - the length of the shortest path between landmark points on the shape silhouette. However, the IDSC method using different parameter settings has not been tested on geometric transformed shapes. Multiscale shape representation emerged to develop an effective shape descriptor. Alajlan, El Rube, Kamel, & Freeman, 2007 proposed triangle area representation (TAR) by utilizing the area of the triangles formed with boundary points to measure the convexity and concavity of each point at different scales or triangle side lengths. Dynamic space warping (DSW) algorithm and dissimilarity distance were employed to search for the optimal correspondence between the points of two boundary shapes. The computation of TAR involves calculating the triangle area at each point of the boundary and the matching stage is evaluated separately. The TAR computation complexity is considered high enough which is O (N2). TAR is determined only to represent the different shape of triangles where determination of side length are not proper based on the size of triangle. In order to improve the TAR performance (Mouine, Yahiaoui, & Verroust-Blondet, 2013) have observed triangle side lengths and angle (TSLA). Unlike TAR and the other multiscale methods that computed each contour point on a triangle at different scales separately, TSLA introduced d (k) as the distance between the triangle points at scale k. In addition, TSLA only selects two sets of Ns points on both side of pi. In this case, Ns is the number of triangles and the number of scales and pi is represents the sample points distributed over the contour of the shape boundary. The eminence of TSLA is using the angles and side lengths is more appropriate than only the area for triangle description such as TAR, since the angular provides more precise information of description when it is used together with the triangle side lengths. Lately, Wang, Brown, Gao, and La Salle (2015) proposed the Multiscale hierarchical arch height features (MARCH) which focuses on extracting multiscale shape features to distinguish representation the shape of leaves. In addition they also proposed different chords spans to be extracted from each contour point in order to obtain the compact multiscale shape descriptor. Unlike, TAR and TSLA, MARCH uses log2N-1 scale levels, and arc height features than curvatures of leaf shape. MARCH utilizes a simple L1 norm based dissimilarity instead of a dynamic programming for shape comparison. Based on the results MARCH, achieved higher classification rate compared to TAR, TSLA and IDSC.

Most of the previous studies are based on the contour of the boundary of the shape and multiscale information. This paper uses a new technique called Harmonic Mean Projection Transform (HMPT) using region as an image transform where all the pixels in the image are considered and accumulated in order to get a set of features that represents the important information of an image.

MATERIALS AND METHODS

In order to classify and retrieve the leaf images automatically, region based method which has been proven to be superior from the other conventional methods (Jyothi, MadhaveeLatha, & Krishna, 2015) and the robust from affine invariant (Mei & Androutsos, 2009) are considered in this paper. The region based method takes into account all the pixels and the entity inside the region, so that, it more robust to transformation changes. Moreover, a new image transform known as Harmonic Mean Projection Transform (HMPT) which takes into consideration both region and contour information of an image is proposed in this study. Figure 1 presents the flowchart of the proposed plant leaf retrieval.

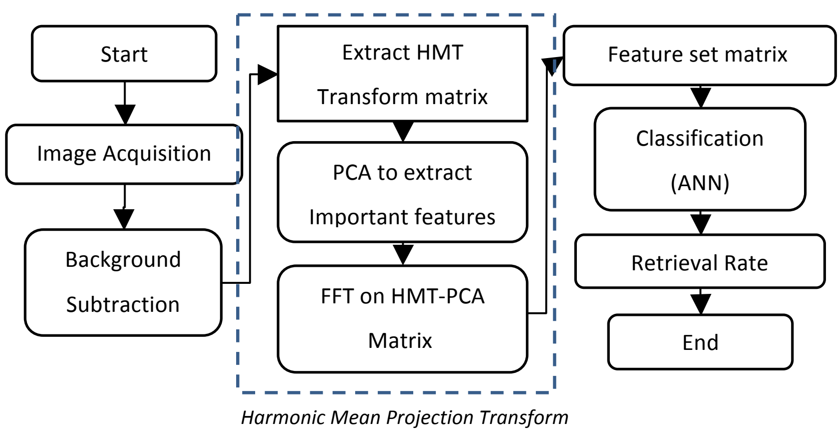

Figure 1. The plant leaf retrieval framework

The framework consists of sequential steps to achieve plant leaf retrieval. In the first step, after image acquisition, the background has been omitted in order to achieve the foreground including the pure leaf image. HMPT image transform was performed to extract the feature set matrix. Finally, a classification method based on artificial neural network was used to achieve the retrieval result. Figure 2 presents the new HMPT transform method to extract the important invariant feature vector from the leaf images.

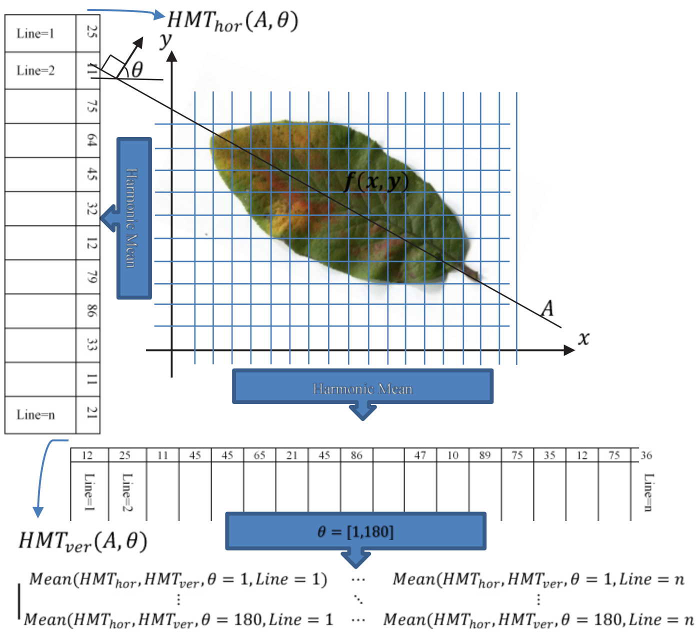

Figure 2. Image transform with HMPT

The harmonic mean in vertical and horizontal signal directions has been used to extract the first initial features for all the image rows and columns. Then, for each line, average values calculated in all image directions in $\theta = [0,180]$ in order to extract the feature vector from a raw image. In this region based feature extraction, sum of pixels in this shape is extracted vertically and horizontally and accumulated into sets of vector matrices, each of vector matrix contains set of sum in HMPT which is rotated from zero to 180 degrees. Considering the f(x,y) as the input image, the HMPT formulation is defined as:

$$Hf(L) = \iint_{-\infty}^{+\infty} Har(f(x))|dx|. \tag{1}$$

Equation (2) presents the HMPT applying the harmonic mean formulation.

$$HMPT = \iint_{-\infty}^{+\infty} \left(\sum_{i=1}^{i=n} \frac{1}{x_i}\right)^{-1} |dx|, \tag{2}$$

where x_i value is the pixel value in lication i in each line of the image signal in vertical or horizontal directions. In this concept, each image has 180 feature rows of vectors transform (see Figure 3). The dimension of the feature vector is reduced using Principle Component Analysis (PCA) and Fast Fourier Transform (FFT). Finally the feature vector is used to classify the input images using neural networks. Figure 2 portrays the image transform in order to obtain a set of feature vector using HMPT formula, while Figure 3 presents the initial feature set for all directions.

$\theta = 1°$	*hmpt* line1	*hmpt* line2	*hmpt* line3	*hmpt* line4	*hmpt* line5	………..	*hmpt* line *n*
$\theta = 2°$	*hmpt* line1	*hmpt* line2	*hmpt* line3	*hmpt* line4	*hmpt* line5	………..	*hmpt* line *n*
: : :	*hmpt* line1	*hmpt* line2	*hmpt* line3	*hmpt* line4	*hmpt* line5	………..	*hmpt* line *n*
$\theta = 180°$	*hmpt* line1	*hmpt* line2	*hmpt* line3	*hmpt* line4	*hmpt* line5	………..	*hmpt* line *n*

Figure 3. Feature set using HMPT in 180 degrees

As presented in Figure 3, each line contains the harmonic mean of pixels' region in both vertical and horizontal directions in order to calculate the HMPT matrix. Each row contains the value of hmpt from line 1 until line n, and each column escalated by rotating the image. Each degree rotation contains a set of feature vector metric value. A classification method based on ANN is performed to classify the images.

RESULTS AND DISCUSSION

In this study, Image CLEF dataset was used to measure performance. This dataset is a collection of 126 images of plant species. The scanned images contain white background and minimum shadow, photographs images with white background, and photograph images of the original image of leaves in h natural background. Each class is grouped into 6 species and presented in Figure 4.

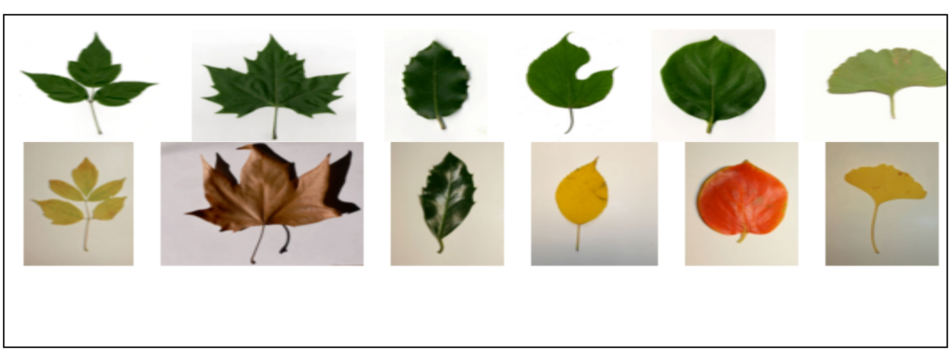

Figure 4. Image CLEF dataset sample images

The feature vectors are undergoing classification using neural network and compared with results from existing studies based on the same dataset. Table 1 presents the results of related methods with Scans images.

Table 1
Mean Average Precision (MAP) of different methods

Method	MARCH (Wang et al., 2015)	IDSC (Ling & Jacobs, 2007)	TAR (Alajlan et al., 2007)	Proposed
Mean Average Precision (MAP)	46.25	45.23	35.97	60.9

Based on the above results the proposed study was able to achieve higher rates of classification compared with previous researches, while the identical image dataset has been used for evaluation.

CONCLUSION

In this paper, we proposed a new feature descriptor method in order to achieve a higher classification rate for plant leaf retrieval. A region based technique using the entire pixels within a region was adopted instead of the boundary or edge information of the image. The output result indicates that the proposed method outperforms the existing techniques in leaf classification based on the mean average precision. In future works, other leaf image datasets such as Swedish and Flavia datasets can be considered for comparative purposes. Moreover, other invariant feature vectors including colour information can be considered in the feature extraction stage to achieve better performance.

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