ISSN:0975-9646

Sethulekshmi A V et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 8061-8066

Ayurvedic leaf recognition for Plant Classification

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***Abstract*-There are a lot of techniques relevant for the purpose automated leaf recognition for plant classification. Many algorithms have been introduced in the past decade and achieved good performance. Efforts have focused upon many other fields but properties of features have not been well investigated. A group of features is selected in advance but important feature properties are not well used to feature selection. In this paper the performance of different features extraction methods are compared, different combinations of features and a number of classifiers applied for leaf identification process are also discussed.**

***Keywords*-Feature extraction, leaf recognition, plant classification, classifier**

I. INTRODUCTION

Plants exist everywhere in the earth we lived, as well as places without us. Many of them carry important information for the development of human society. Many plants are at the risk of extinction. So it is very necessary to create a database for plant protection .The first step is to teach a computer how to recognize and classify plants. Classification based on leaf image is the first choice for leaf plant classification due to the easiness and accuracy. Sampling leaves and photoing them are economical and convenient. We can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques.

The problem of existing methods is some features are often preselected, but the properties of different features and combinations of feature are not well investigated in the leaf identification analysis. Second, these predefined features do not equally or positively contribute to the performance of identification. Also the leaf pattern varies with the age of plant, the region etc.

This paper presents a comparison between different leaf identification algorithm for plant classification based on color, texture and shape to solve the feature related problems in the leaf image identification. Application and image representation scheme is analyzed using a number of descriptors.

II. REVIEW OF DESCRIPTORS

A feature is a metric or some quantifiable value which is used to describe an image at high level perspective. Features related to color, texture, shapes, color blobs, corners are contained in an image. The first step is to detect interest points in the image having the property of repeatability, means the ability to detect the same physical interest points under different viewing conditions, followed by the description calculation of the interest points. The feature needs to be unique i.e. if similar point is being described in two or more images then that point should have similar description and it should be of proper dimensions, a large descriptor will makes the computation longer. But if the descriptor is small then it may discard some useful information.

A. Color Descriptors

Color is a basic feature for image representation, and is invariant with respect to scaling, translation and rotation of an image. Since most of the leaves have green color, color feature is not considered as an important feature for leaf recognition.

B. Texture Descriptors

Texture has no precise definition which has a tactile or visual characteristic of a surface. Texels are building blocks of a texture, small geometric pattern that is repeated frequently on some surface resulting in a texture. This descriptor provides measures of the properties such as regularity, coarseness, and smoothness .Statistical, structural and spectral methods which are used to measure the texture properties of an image.

1. Gray Level Co-Occurrence Matrix (GLCM)

It is for motion estimation of images; this can be used to extract second order statistical texture features. The four features named as, correlation, Inverse difference moment , Angular second moment, and Entropy are computed in GLCM extraction.

- *Angular Second Moment*
  Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM Angular Second Moment measures the image homogeneity. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar.
- *Inverse Difference Moment*
  Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.
- *Entropy*
  Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.
- *Correlation*
  Correlation measures the linear dependency of grey levels of neighboring pixels. When extracting the features of an image with GLCM approach, at the time

of RGB to GRAY level conversion the image compression time can be greatly reduced.

B. Haralick Texture Feature

The haralick textures are used for image classification. These features capture information about the patterns that emerge in patterns of texture. These kinds of features are calculated by using co-occurrence matrix, which is computationally expensive.13 features are belongs to this category. Once the co occurrence matrix has been established calculation of these features will begin .The 13 haralick features are: energy, correlation, inertia, entropy, inverse difference moment, sum average, sum variance, sum entropy, difference average, difference variance, difference entropy, information measure of correlation ,and information measure of correlation .

C. Frequency Domain Descriptors

It is having lower computational costs. The idea behind binary descriptors is that each bit in the descriptor is independent and the Hamming distance can be used as similarity measure instead of, e.g., the Euclidean distance .The four most recent and promising binary feature descriptors are Binary Robust Independent Elementary Feature (BRIEF), Oriented Fast and Rotated BRIEF (ORB) , Binary Robust Invariant Scalable Key points (BRISK) and Fast Retina Key point (FREAK) .

1. Scale Invariant Feature Transform (SIFT)

SIFT was originally introduced by Lowe as combination of a DoG interest region detector and a corresponding feature descriptor. However, both components have since then also been used in isolation. This descriptor aims to achieve robustness to lighting variations and small positional shifts by encoding the image information in a localized set of gradient orientation histograms.

2. SURF Descriptor/Detector

SURF approach, which is an effective alternative to SIFT. SURF combines its own gradient orientation based feature descriptor with a Hessian-Laplace region detector. For the internal computations, it uses 2D box filters (Haar wavelets). These box filters approximate the effects of the derivative filter kernels, and can be evaluated using integral images.

3. ORB (Oriented Fast and Rotated Brief)

A very fast binary descriptor based on BRIEF, called ORB, is proposed which is rotation invariant and resistant to noise. It evaluates the combination of oFAST and rBRIEF, which we call, ORB, using two datasets: images with synthetic in-plane rotation and added Gaussian noise, and a real-world dataset of textured planar images captured from different viewpoints.ORB is relatively immune to Gaussian image noise, unlike SIFT. If we plot the inliers performance vs. noise, SIFT exhibits a steady drop of 10% with each additional noise increment of 5. ORB also drops, but at a much lower rate.

4. BRIEF

BRIEF is a recent feature descriptor that performs simple binary tests between pixels in smoothed image regions. In many respects like blur robustness to lighting, and perspective distortion. Its performance is similar to SIFT. However, it is very sensitive to in-plane rotation.

5. BRISK (Binary Robust Invariant Scalable Key points)

BRIEF is a recent feature descriptor that uses simple binary tests between pixels in a smoothed image patch. Its performance is similar to SIFT in many respects, including robustness to lighting, blur, and perspective distortion. However, it is very sensitive to in-plane rotation.

The classic method for finding uncorrelated tests is Principal Component Analysis; it has been shown that PCA for SIFT can help remove a large amount of redundant information. However, the space of possible binary tests is too big to perform PCA and an exhaustive search is used instead.

Visual vocabulary methods use offline clustering to find exemplars that are uncorrelated and can be used in matching. These techniques might also be useful in finding uncorrelated binary tests. The closest system to ORB is, which proposes a multi-scale Harris key point and oriented patch descriptor. This descriptor is used for image stitching, and shows good rotational and scale invariance.

6. FREAK (Fast Retina Key Point)

Novel key point descriptor inspired by the human visual system and more precisely the retina, coined Fast Retina Key point (FREAK). A cascade of binary strings is computed by efficiently comparing image intensities over a retinal sampling pattern.

Many sampling grids are possible to compare pairs of pixel intensities. BRIEF and ORB use random pairs. BRISK uses a circular pattern where points are equally spaced on circles concentric. The testing environments rank FREAK as the most robust to all the tested image deformation. Surprisingly, SIFT is the worst descriptor in the first testing environment similar to what has been shown in BRISK. FREAK is faster than BRISK but BRISK is two orders of magnitude faster than SIFT and SURF.

The two main stages are training and query part. Images are first fed into the SURF function from training set. This will extract the interest points from each image. These points will then cluster into k clusters by k-means algorithm, Euclidean distance, with respect to their descriptors. In query part when a user submitted a query image, using SURF algorithm interest points and descriptors will be extracted.

First step in the evaluation is detecting key points in both the reference and query images. It uses a Ratio Test and Brute force matcher for feature matching in the second step. The next step in the evaluation is the random Sample Consensus (RANSAC).

D. Histogram Of Oriented Gradients (Hog)

The hog feature descriptors used for the purpose of object detection which counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. Local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within the cell

E. MPEG-7 Visual Descriptors

The MPEG-7 Visual Standard under development specifies content-based descriptors that allow users to measure similarity in images or video based on visual criteria, and can be used to efficiently identify, filter, or browse images or video based on visual content. More specifically, MPEG-7 specifies color, texture, object shape, global motion, or object motion features for this purpose

1. *Visual Color Descriptors*

   Color is the most widely used visual feature in image and video retrieval. Color features are robust to changes in the background colors and are independent of orientation and size of image and can be used for defining still images and video content.

2. *Visual Texture Descriptors*

   Texture refers to the visual patterns that have properties of homogeneity or not, that result from the presence of multiple colors or intensities in the image. It is a property of virtually any surface, including, bricks, trees, hair, fabric and cloud. It contains important structural information of surfaces and their relationship to the surrounding environment.

   - *Texture Browsing Descriptor*

   To characterize texture regularity (2bits), directionality (3bits*2) and coarseness (2bits*2), this compact descriptor requires only 12 bits. A texture may have more than one dominant direction and associated scale. For this reason, the specification allows a maximum of two different directions and coarseness values .The computation of this descriptor is as, the image is filtered using a bank of scale and orientation selective band-pass filters and the filtered outputs are then used to compute the texture browsing descriptor components

   - *Homogenous Texture Descriptor*

   This describes coarseness, a regularity and directionality of patterns in images and is most suitable for a quantitative characterization of texture that has homogenous properties. It can be used for similarity image-to-image matching for texture image databases.

   - *Non-Homogenous Texture Descriptor (Edge Histogram)*

   In order to provide descriptions for non homogenous texture images, MPEG-7 defined an Edge Histogram Descriptor. This descriptor captures spatial distribution of edges, somewhat in the same spirit as the Color Layout Descriptor. This is scale invariant, rotation sensitive and rotation-invariant matching is also supported. It is also very compact because using 3 bins each histogram bin is non uniformly quantized, results in a 240 bits descriptor size.

3. *Visual Shape Descriptors*

   In image data-base applications, the shape of image objects provides a useful hint for similarity matching. For image retrieval the shape descriptor wants to be invariant to scaling, rotation and translation.

- *3-D Shape Descriptor—Shape Spectrum*

  It can be described as the histogram of a shape index, computed over the entire 3-D surface. The shape index itself computes vexity of each local 3-D surface. Histograms with 100 bins each quantized by 12 bits are used.

- *Region-Based Descriptor—Art*

  The Region- Based Descriptor ART (Angular Radial Transformation) belongs to the class of moment invariants methods for shape description. This descriptor is well for shapes that can be best described by shape regions rather than contours. The idea behind moment invariants is to use region-based moments as the shape feature that are invariant to transformations,

- *Contour-Based Shape Descriptor*

  Objects for which shape features are best expressed by contour information can be described using the MPEG-7

- *Contour-Based Descriptor.*

  This descriptor is based on curvature scale-space (CCS) representations of contours and also includes eccentricity and circularity values of the original and filtered contours.

III. REVIEW OF CLASSIFIERS

Classifier identifies a new observation belongs to which of a set of categories (sub-populations), on the basis of a training set of data containing.

A. K-Nearest Neighbor

This classifier classifies a pattern x by assigning it to the class label that is most frequently represented among it's k nearest patterns. In the case of a tie, the test pattern is assigned the class with minimum average distance to it. Hence, this method is sensitive to the distance function and is a conventional nonparametric classifier that is said to yield good performance for optimal values of k.

B. Bayesian Classifier

The quadratic discriminant function using the Bayesian approach is the most general approach in the theory of supervised parametric classifiers. The decision boundaries obtained by these classifiers can be extremely complicated when dealing in d-dimensions. Though this method is highly computation intensive, most of the computation of generating the discriminant function is done off-line.

1. Probabilistic Neural Network

A probabilistic neural network **(**PNN**)** is a feed forward neural network In a PNN; the operations are organized into a multilayered feed forward network with four layers, Input layer, Hidden layer, Pattern layer/Summation layer, Output layer

C. Multi-layer Perceptron (MLP)

The multi-layer perceptron classifier is a basic feed forward artificial neural network. The hidden units were chosen differently for each data set. The number of hidden neurons was found out experimentally over a number of trials.. The neural network was trained using the back-propagation algorithm, According to [3], the multi-layer perceptron trained using the back-propagation learning algorithm approximates the optimal discriminant function defined by Bayesian theory. The outputs of the MLP approximate posterior probability functions of the classes being trained

D. Support Vector Machine Classifier

An SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. It can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

E. Self Organizing Map Classifier (SOM)

It generates two dimensional artificial neural networks and trains the network with given topic map associations. As a consequence topics with similar associations end up locating near each other in the neural network. The output from the winning neuron, feeds into a hidden layer and finally into an output layer. SOM is the front end, while the hidden and output layer of a multilayer perceptron is the back end. It is applied to machine vision systems for image classification and recognition

IV. STATE OF THE ART

In a system developed by A. Kadir Et.al [1], they include color information as features. The main reason is caused by a fact that they used green colored leaves as samples. Transform and three kinds of geometric features were used to represent shape features, color moments that consist of mean, standard deviation, and skewness were used to represent color features, texture features are extracted from GLCMs, and vein features were added to improve performance of the identification system. The identification system uses Probabilistic Neural Network (PNN) as a classifier

In another system, developed by Dalcimar Casanova, Et.al [2], they used a complex network-based approach for boundary shape analysis'. Instead of modeling a contour into a graph and use complex networks rules to characterize it. Leaf vein is a taxon characteristic used to plant identification proposes, and one of its characteristics is that these structures are complex, and difficult to be represented as a signal or curves and this way to be analyzed in a classical pattern recognition approach

In a system, developed Duaa Abu Maizer, Et.al [3], here plant type recognition depending on the morphology of the leaf. The plant leaf considered an obvious feature for recognition by implementing image processing techniques. The methodology is to group plants that have compound leaves according to the similarities and dissimilarities. Hierarchal clustering will be used to do the clustering process.

In the paper by Mohammad Faizal Ab Jabal, Et.al [4], the findings of this study are the types of leaf features that should be extracted, external factors that must be considered before the extraction process, types of extraction and classification methods that can be used for plant recognition and classification. The selected classifiers are Probabilistic Neural network (PNN) + Color and Texture as proposed, linear discriminant Analysis (LDA) + Nearest Neighbor (1-NN)

In a paper by Neeraj Kumar, Et.al [5], they developed a first mobile app for identifying plant species using automatic visual recognition. the leaf from an untextured background, extracting features representing the curvature of the leaf's contour over multiple scales, and identifying the species from a dataset of the 184 trees in the North eastern United States. The recognition process consists of Classifying, Segmenting, Extracting, Comparing and classifying images as leaves or not, obtaining fine-scale segmentations of leaves from their backgrounds, efficiently extracting histograms of curvatures along contour of the leaf at multiple scales, and retrieving the most similar species matches using a nearest neighbors search on a large dataset of labeled images.

In a content-based image retrieval system which is developed by Hanife Kebapci [6], a plant image consists of a collection of overlapping leaves and possibly flowers, which makes the problem challenging and introducing some new texture matching techniques and shape features. Feature extraction is applied after segmenting the plant region from the background using the max-flow min-cut technique. Common techniques are used in color and texture feature extraction steps: color histograms, color co-occurrence matrices, and Gabor filters.

In a paper by Abdul Kadir [7] color was not recognized as an important aspect to the identification. In this research, shape and vein, color, and texture features were incorporated to classify a leaf. In this case, a neural network called Probabilistic Neural network (PNN) was used as a classifier. In this research, we tried to capture shape, color, vein, and texture of the leaf. In implementation, we used Fourier descriptors of PFT, three kinds of geometrics features, color moments, vein features, and texture features based on lacunarity

V. SYSTEM IMPLEMENTATION

A. Feature Extraction Phase

Feature extraction is the first and important stage of any classification and annotation problem.

1. BRISK / FREAK Feature Extraction

The proposed architecture uses BRISK/FREAK to extract the features of both training and testing images .These extraction methods are scale and rotation invariant feature extraction method, which is faster than widely used feature extracting method (SIFT) and SURF.

2. *Color Feature Extraction:*

For color features RGB color histogram is used. Color histograms are flexible constructs that can be built from images in various color spaces, whether RGB, rg chromaticity or any other color space of any dimension. The histogram provides a compact summarization of the distribution of data in an image. The color histogram of an image is relatively invariant with translation and rotation about the viewing axis, and varies only slowly with the angle of view. By comparing histograms signatures of two images and matching the color content of one image with the other, the color histogram is particularly well suited for the problem of recognizing an object of unknown position and rotation within a scene.

3. *Texture Feature Extraction*

To determine texture features statistical texture measures is used. Without spatial or shape information, similar objects of different color may be indistinguishable based solely on color histogram comparisons. The feature vector for texture analysis of a particular image is computed by calculating following ten features: Variance (Var), Uniformity, Average Entropy, Relative Smoothness, Skewness

4. *Vein Feature Extraction*

Leaf vein extraction is a key step of modeling plant organs and living plant recognition. An efficient leaf vein extraction method is proposed in this paper by combining snakes technique with cellular neural networks (CNN). The active contours technique based on CNN provide high flexibility and control for the contour dynamics of the snakes. This approach has the advantage of applying a priori knowledge, puts similar characteristics from both the implicit and parametric models, to improve the precise and robustness of the segmentation

B. Training and Testing Phase

In this phase the extracted feature values are orthogonally classified by using a technique called principal component analysis(PCA),which s a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables The process of feature extraction is the same as the feature extraction method described in the training phase.

1. Feature Extraction

Feature extraction is the first and important stage of any classification and annotation problem.

- *BRISK/FREAK Feature Extraction*

  The proposed architecture will use the same frequency domain feature extraction procedure as done in the training phase.

- *Color Feature Extraction*

  For color features RGB color histogram is used. Color histograms are flexible constructs that can be built from images in various color spaces, whether RGB, rg chromaticity or any other color space of any dimension. The histogram provides a compact summarization of the distribution of data in an image. The color histogram of an image is relatively invariant with translation and rotation about the viewing axis, and varies only slowly with the angle of view . By comparing histograms signatures of two images and matching the color content of one image with the other, the color histogram is particularly well suited for the problem of recognizing an object of unknown position and rotation within a scene.

- *Texture Feature Extraction*

  GLCM (Gray Level Co Occurrence Matrix) is used as the texture feature in our method. By using this we can extract second order statistical texture features for motion estimation of images. The Four features namely, Angular Second Moment, Correlation, Inverse Difference Moment, and Entropy. The results show that these texture features have high discrimination accuracy, requires less computation time and hence efficiently used for real time Pattern recognition applications. By extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other DWT Techniques.

- *Vein Feature Extraction*

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C. Classification Phase

The tested values are compared within the convolutional neural network, which s a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in the visual field. Convolutional networks were inspired by biological processes and are variations of multilayer perceptrons which are designed to use minimal amounts of preprocessing.

After classification the input image is matched with most suitable image in the data set as well as the name of the plant is also displaye

VI. CONCLUSION

This paper presents a comparative study of global and local feature descriptors and classifiers used in leaf recognition algorithm. The comparative study considers both theoretical and experimental aspects, and checking for efficiency and effectiveness. The main feature descriptor for leaf recognition is texture and shape identification, because leaf shape and texture are promising identifier in a leaf. Overall, the semantic gap continues to be a big challenge for leaf images feature descriptors, especially in the context of similar leaf images.

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