Enhanced HOG-LBP Feature Vector based on Leaf Image for Plant Species Identification

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Abstract. Plant species database has become essential as biodiversity is declining rapidly. With advance technology and technocrats, an attempt has been made of plant species identification based on leaf image is implemented. Leaf characteristics are used to prepare feature vector. HOG and LBP are used as feature vectors, LDA and SVM as classifiers. When HOG and SVM are concatenated and used as feature vector, accuracy of classifiers is enhanced as compared to individual HOG and SVM as feature vector. LDA is proved to be better classifier than SVM for database mentioned.

Keywords: Histogram Oriented Gradient, Local Binary Pattern, Support Vector Machine, Linear discriminant Analysis.

1 Introduction

Environment refers to surroundings to living beings, it affects their lives too. Environment's main components are organisms, soil, water, air, solar energy etc. Plants are important component of environment, without which earth's ecology will have no existence. Globalization and urbanization, has effect on environment, like deforestation on large scale. Climate change and many other are leading to plants at the risk of extinction. Plant database is a step towards conservation of earth's biosphere helping in protecting the plants and catalogue various types of flora diversities. Rapid and accurate plant identification is essential for effective study and management of biodiversity. Botanist use different characters of plants to identify the plant species. Limited number of experts and rapid declining biodiversity leads to significant challenges to biological study and conservation.

These challenges are leading to concept of using advanced technology and approaches of computer vision.

With an availability of high-end portable devices like digital camera, scanners concept of plant database can be implemented. Computer vision algorithms can be used for identification and categorization of plant species. A detail analysis of plant database and comparison of plant species classification techniques is done[1].With technology introduced in this field of plant species identification, a system is developed for plant identification is done based on leaf image. Leaf image is acquired by digital camera or scanner. These images will be pre-processed which includes RGB to grey conversion, filtering, noise removal, image enhancement, segmentation etc which makes them suitable for feature extraction. Extracted feature vector is passed on to classifier for classification.

1.1 Background

Major research work of plant identification is based on leaf analysis but flower, bark, fruit, full plant are also used [1]. Flowers are available in blooming seasons only, plant identification by flower using machine learning is difficult task because it is a three dimensional object. There is variation due to view point, scale, occlusion as compared to leaf images. Colour based analysis is easy. Shape based flower analysis is also possible. Individual shape of petals are considered but it is usually soft and flexible which makes them to curl, twist makes difficult to identify. Organ specific like, fruits, bark, full plant are also used for classification.

Feature reduces the dimension of the information by extracting the characteristics pattern of leaf. colour, texture, shape features for study can be categorized as general features which includes colour, shape, texture, veintion pattern.

Many researchers have worked upon various features mentioned above but there is no universal feature which can be implemented for all species. Different features or combination of features are also experimented and found to be successful. This is essential because leaf shape of some species may be same but colour/ texture of leaf may be different. Similarly, for flowers, flower may have same colour but different shape and texture. Overall, general features can be categorized as shape, colour, texture. Shape feature can be categorized as Region based shape features and Contour based shape features.

Main focus of this paper is Region based features. Simple and morphological shape features are described by diameter, major and minor axis, perimeter, centroid [2]. Based on these shape features morphological features are calculated like aspect ratio, rectangularity measure, circulatory measure, perimeter to area ratio, etc [3],[4],[5],[6],[7],[8],[9],[10],[11]. Leaf specific features like leaf width factor (LWF) and Area width factor (AWF)are used [12]and[13] respectively.

Region based descriptors, moments are used for object classifier, they are invariant to translation, rotation and scale. Hu has proposed six moments which is great contribution to this research [14]. These are combined with ZMI Zernike moment invariants and Legendre moment invariant LMI are used but their computational complexity is high [6],[15],[16].

Local Feature techniques SIFT, SURF, HOG are also used. SIFT Scale Invariant Feature Transform which is combination of feature detector and feature extractor. It is very robust against image scale, rotation, changes in illumination [17]. SURF speeded up robust feature is used for leaf classification [18]. HOG histogram of Orientated Gradient is used on large scale [19]. It is similar to SIFT. HOG is calculated for all over image and calculations are done for cells which overlaps between neighbor blocks.

HOG and MMC maximum marginal criteria are combined to form feature vector [19]. Disadvantage of HOG is its sensitivity to leaf petiole orientation. So pre-processing related to petiole orientation is essential [20],[21]. Performance of the identification system is evaluated using classifier accuracy. Many researchers have used parameters mentioned above but when multi features are used, accuracy increases than using single parameter. HOG is having lot of redundant information, dimension reduction is essential.

Availability of datasets is also important, Leafsnap dataset, Swedish Leaf dataset, Flavia dataset, ICL dataset, Oxfard Flower are used for analysis of above mentioned features etc.

Stephen Gang Wu, Forrest Sheng Bao, et al. (2007) have used geometrical, digital morphological features, PCA is applied to reduce the dimensionality [22]. Chaki, Parekh, et al. (2011) have used features like moment invarients, centroid-radii distances and given as input to Neural Network for classification [23]. Abdul Kadir, Lukito Edi Nugroho, et al. (2011) have used shape, texture features and neural net as classifier [6]. MinggangDu, Xianfeng Wang (2011) have used Histogram Oriented Gradient for representation of shape and used PCA and LDA combinely for dimensionality reduction [24]. Hang Zhang, paulyanne, et al. (2012) have used geometric features, Local and Global features along with Support vector machine as a classifier [25] E. Aptoula, B.Yanikoglu (2013) have used two descriptors. One is morphological covariance on the leaf contour profile and another is Circular Covariance Histogram considering leaf venation characteristics [26]. Tsolakidis, Kosmopoulos, et al. (2014) Have used Zernike moments and HOG feature and SVM as a classifier [27]. Trishen Munisami, Mahess Ramsurn, et al. (2015) have used Geometric features along with KNN classifier [28]. Aimen Aakif, Muhammad Khan, et al. (2018) have used various Morphological features along with SIFT and ANN is used as a Classifier to get the high rate of accuracy [3]. Many combinations of features and classifiers are worked upon.

Individually working with HOG as a feature is not giving satisfactory results so an attempt has been made to combine LBP (Local Binary Pattern) with HOG as a feature. Two types of classifiers are used LDA and SVM for classification. Paper is organized as: section 2 gives Feature Vector description, Section 3 explains about Classifiers Section 4 describes Performance Evaluation and experimental results and paper concludes with section 5.

2 Feature Vector Description

2.1 HOG (Histogram of Gradient) [29]

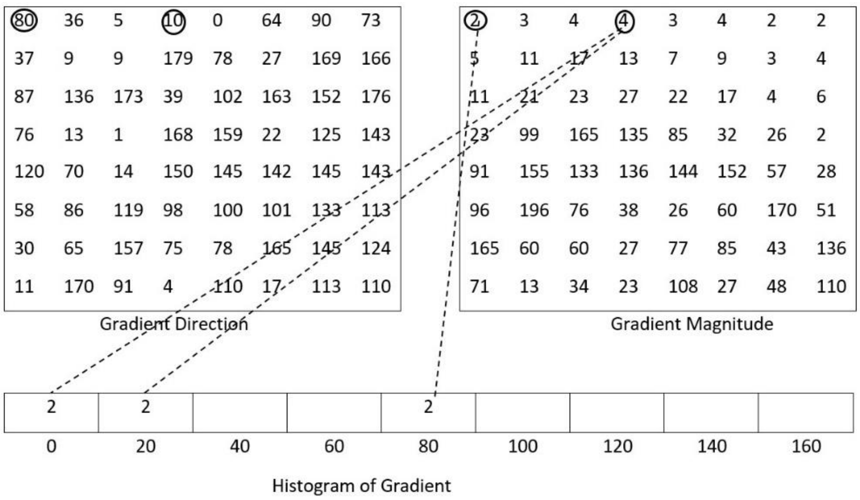
Image is divided into no of blocks and each block into no of cell. Cell size is 8x8,16x16,32x32,64x64 as per size of image. Gradient magnitude$G(x,y)$ and gradient direction$\theta(x,y)$ is calculated with given formula

$$G(x,y) = \sqrt{Gx^2(x,y) + Gy^2(x,y)} \qquad (1)$$

$$\theta(x,y) = \arctan\left(\frac{Gy(x,y)}{Gx(x,y)}\right) + \pi/2 \qquad (2)$$

Histogram of Oriented Gradient with 8×8 Cell size is shown below in figure 1

Fig. 1. Bin Formation in HOG



It is calculated for each pixel. Each pixel is taken into consideration while computing HOG so that even a minor change in images is enough to distinguish among two different images.

Image is divided into number of blocks and each block is further divided into number of cells for which the HOG is to be calculated. For 8x8 image patch, gradient of patch contains two values per pixel leading to total number of values to be 128. These many numbers are represented using a 9 bin histogram which is stored as an array of 9 numbers. Histogram vector consists of 9 numbers corresponding to angles 0,20,40…160.Bin in the histogram vector is selected based upon direction and value based upon magnitude, contribution of all pixels in 8x8 cells are added to generate 9 bin histogram.

2.2 LBP (Local Binary Pattern)

This operator gives information about texture better as compared to texture information provided by Gabor Co-occurrence and Wavelet approach [30].

It is used as local grey level structure representation. This operator considers adjacent pixels and thresholds the difference of grey level between them, generating binary values image patch as local image descriptor. Originally it was defined for 3x3 neighborhood leading to 8 bit codes as shown in figure 2. Mathematically it is represented as

$$LBP(p_c + q_c) = \sum_{r=0}^{n} 2^r s(i_r - i_c) \qquad (3)$$

Where ‘r’ runs over 8 neighbors of central pixel c, ir and ic are grey level value at c and n.

$$s(u) \ = \begin{matrix} 1, & u > 1 \\ 0, & otherwise \end{matrix} \qquad (4)$$

Fig. 2. Uniform LBP Operator

79	92	49
55	54	48
16	11	12

$\xrightarrow{\text{Thresholding}}$

1	1	0
1		0
1	0	0

This is uniform LBP. There are many extensions or modifications in Local Binary Pattern. We are using Uniform Local Binary Pattern because it is used for shape detection. Image is divided into region grid of cells and generated Local Binary Pattern of that cell, finally Local cell level LBP are concatenated continuously to generate Global Local Binary Pattern vector. Usually LBP vector is high dimensional.

Final feature vector consists of HOG and LBP feature concatenated.

3 Image Classifiers

3.1 Linear Discriminant Analysis

It is basically general form of Fisher’s linear discriminant. It is used in machine learning or pattern recognition when data is to be classified in more than two classes. In general mathematical steps for LDA implementation for a given dataset is as follows [31]

- Mean vector for given number of classes m is calculated
- Within class and between class scatter is calculated
- Eigen vectors E1, E2, E3....Em and corresponding eigenvalues for scatter matrix are calculated for m classes
- Sort the eigenvector and select eigenvector with maximum eigen value to form m x k dimensional matrix P, each column of P represents an eigenvector.

- This eigenvector matrix mxk is used to transform samples onto new subspace. It can be stated that, newly generated matrix Y=X x P is transformed to n x k dimensional samples in new subspace, where X is a n x d dimensional matrix representing n samples and yare transformed n x k dimensional samples in new subspace.

3.2 Support Vector Machine

Support Vector Machine is discriminative supervised type of classifier defined by separating hyperplane [32]. It creates a dividing hyperplane in the space, which establish a boundary between the two distinct datasets. In order to set up boundary it produces two hyperplane on each side of dividing hyperplane between the two datasets.

The separating Hyperplane can be defined in equation form as

$$W^T X + b = 0 \qquad (5)$$

Where W is Weight Vector, X is input Vector and b is bias. It can be rewritten as

$$W^T X + b \geq 0 \quad \ldots for\ d_i = +1 \qquad (6)$$

$$W^T X + b < 0 \quad \ldots for\ d_i = -1 \qquad (7)$$

Where d is margin of separation between the hyperplane and closest data point for weight vector W and bias b. With input X and Y it is represented as

$$F(x) = Y_i(W^T X + b) \qquad (8)$$

From above equation functional margin for classification is determined.

4 Performance Evaluation

Images for database can be obtain from following categories: Scan Images, Pseudo-Scan Images and Photographs. While choosing the Database background of leaf should also take in consideration. Most of the researchers use plain background and Images obtain by Scan and Pseudo-Scans to avoid Overlaps. Swedish Leaf Database, Flavia Database, LeafSnap dataset, ICL Database are some of the publicly available Database on which large research has been carried out. Swedish Leaf Database contains scanned Images of isolated leaf on plain background. It includes 15 Swedish Plant Species having 75 Leaf images per species. Flavia Database is sampled by using commonly available plants in China including 50-77 images per species of 32 different species. LeafSnap Database contains both, images taken by mobile camera with Controlled Light and other source is high quality lab images of pressed leaves. In an all 185 tree species are considered. ICL Database is a huge database consisting of 220 plant species having individually 26 to 1078 images per species. This is a Chinese database Collected by Intelligent Computing Laboratory (ICL). Here a computer vision system is developed for plant species identification based on LeafSnap image Database [33] and experimentation is carried out using MatLab 16a. Features used are HOG ,LBP individually and concatenated with LDA and SVM as classifiers. Performance is evaluated with accuracy of classifiers

Some examples of types of leaf images used from Database are shown in figure 3. All images given in above mentioned database are sequentially processed, HOG and LBP are calculated and passed on to Classifiers Learners App, a facility available in, Statistics and Machine Learning Toolbox of MATLAB for classification.

Fig. 3. Types of Leaf

In training the HOG and LBP with Classifiers like SVM and LDA, time complexity is based on the size of the Feature vector. Normally Classification Learner Application requires time of 1-2 minutes to train all parameters on well performing computer system.

S. No.	Feature	Classifier	Accuracy in %
1.	HOG	SVM	83
2.	LBP	SVM	85
3.	HOG	LDA	86
4.	LBP	LDA	88
5.	HOG+LBP (Concatenated)	SVM	91
6.	HOG+LBP (Concatenated)	LDA	93

Table 1. Table 2. Classifier Accuracy

5 Conclusions

Plant species identification system using leaf images is implemented with MatLab 16a software. Comparison of LeafSnap Database is not feasible since authors used varying subset of the dataset for their evaluation.

Two feature, HOG (Histogram of Gradient) and LBP (Local Binary Pattern) are used. HOG is calculated for whole image. It is calculated for cell with overlap in neighbor block. It has redundant information as well so use of LBP is suggested to improve the classification accuracy. HOG and LBP in concatenated form gives better results as compared to individual use of them.

LDA (Linear Discriminant Analysis) and SVM (Support Vector Machine) are used as classifiers. LDA is analytical solution. It focusses on data points to estimate the covariance matrix. It tries to minimize the within class scatter and maximizes between class scatter, whereas SVM is an optimization problem. It is optimized over data points which lie on separating margin. It performs better on two class problem whereas LDA handles multi class problem.

LDA as a classifier performs better as compared to SVM with same input data.

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