

RECOGNIZING THE RICE DISEASES DETECTION BASED ON SVM BASED TECHNIQUES

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Abstract— Rice leaf diseases can be detected and recognized automatically. The propose a new method, combining super pixels, expectation maximization (EM) algorithm, and logarithmic frequency pyramid of histograms of orientation gradients (PHOG), to recognize rice diseases. The proposed method is first, the super pixel operation is used to divide a diseased leaf image into a number of compact regions, which can dramatically accelerate the convergence speed of the EM algorithm that is adopted to segment the diseased leaf regions and obtain the lesion image. Second, the logarithmic frequency PHOG features are extracted from the segmented lesion image. Finally, Support Vector Machines (SVMs) are performed to classify and recognize different rice diseases. Conducted on a database of rice diseased leaf images, experimental results show the proposed method is effective and feasible for recognizing rice diseases.

Keywords— Expectation Maximization, Pyramid of histograms of orientation gradients, Support Vector Machines component

I. INTRODUCTION

Rice (*Oryza Sativa*) is one of the important crops in India. The majority of the land area is under the cultivation of the rice crop and is one of the main sources of economic development. Every year farmers face a loss of yield and financial losses due to the pests and the diseases on the rice plants. Bacteria, fungi, and viruses are the main reasons of the rice diseases. There are many rice diseases, out of which four diseases have been studied in this paper namely Rice Bacterial Blight (RBB), Rice Blast (RB), Rice Brown Spot (RBS) and Rice Sheath Rot (RSR). These diseases have some similar symptoms which confuse the human vision while detecting them. Early symptoms of some diseases cannot be detected by the farmers. Farmers require continuous monitoring by experts in order to diagnose diseases at an early stage which are very expensive and time-consuming. This creates a need for image processing techniques to detect diseases automatically. Image processing techniques help not only to diagnose the diseases accurately but also to classify diseases. Early and accurate identification of the diseases is also possible. This will increase the productivity and quality of the rice yield. With image processing techniques, human efforts are reduced in great extent. Image processing techniques are widely used for different agricultural applications ranging from identification of the leaflet of the plant to categorization of different diseases. Rice disease recognition based on diseased leaf images has become an increasingly important and challenging research topic in the community (Kiran and Ujwalla, 2014). Along with the development of image processing, computer vision and pattern recognition, many rice disease recognition methods have been proposed. Tian et al. (2008) proposed a method of recognizing rice leaf disease based on leaf image processing and SVM, where the features, such as texture, shape and color, were extracted from disease spot images. Experimental results indicated that rice diseases could be recognized more accurately and faster based on color features. Zhang and Zang (2010) carried out a number of the comparative tests of rice disease recognition using SVMs with radial basis function (RBF), polynomial function and sigmoid kernel function, respectively. They pointed out that the SVMs with

RBF and taking each spot image as a sample can achieve better classification performance. Pixia and Xiangdong (2013) mainly studied the rice diseases about downy mildew, powdery mildew and anthracnose using leaf image processing and recognition technologies. They extracted features, such as color, shape and texture using gray level co-occurrence matrix, and identified the diseases by the nearest neighbor classifier. Guo et al. (2014) segmented the rice disease images and obtained the lesions, and extracted the features of color and texture from the representative lesion with maximum area. Zhou et al. (2015) proposed a rice disease detection method by extracting 11 characteristic parameters from RGB model and HSV model to describe the color feature of images in rice disease area, including gray level statistics; RGB color characteristics of r, g, b; HSV color features, tonal H, saturation S, brightness V; gray level co-occurrence matrix texture feature, energy, correlation, inertia moment.

II. PROPOSED METHODOLOGY

2.1. Image preprocessing

Image are Caused by collective device, environment and so on, blurry edge of disease spots and spots of disease leaf always occur in color image of rice disease. Vector median filter had been taken to enhance image, stress some useful information and get rid of or weaken harmful information. A rice disease recognition method by fusion of super pixel, EM algorithm and PHOG. Major contributions of this paper are summarized as follows.

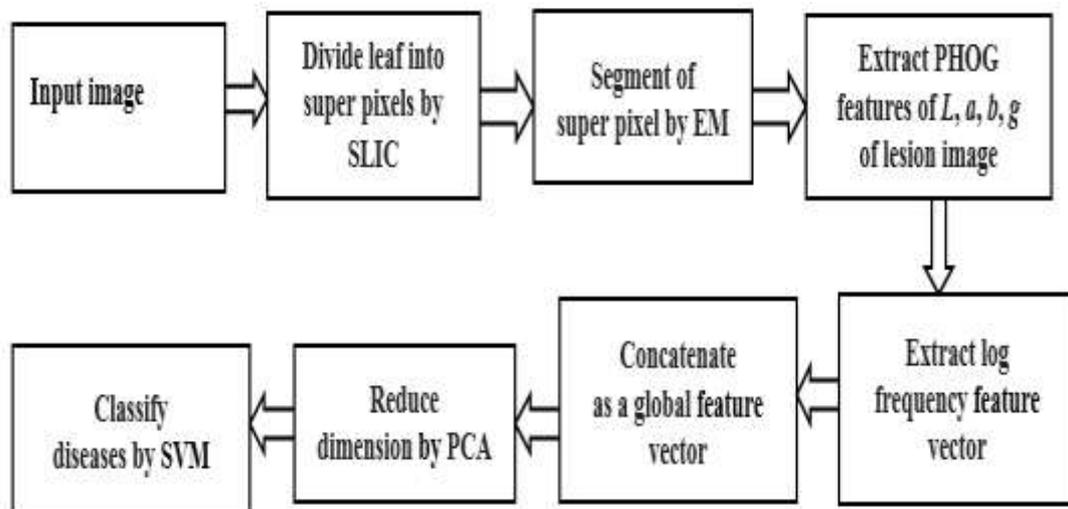


Figure 1 Proposed disease recognition method by combining super pixel clustering, EM algorithm and PHOG

2.2. SLIC segmentation algorithm

A super pixel is an image patch which is better aligned with intensity edges than a rectangular patch. Super pixels can be extracted with any segmentation algorithm; however, most of them produce highly irregular super pixels, with widely varying sizes and shapes. Super pixel is a group of connected pixels with similar colors or gray levels. Super pixel segmentation is dividing an image into hundreds of non-overlapping super pixels. SLIC is a simple and efficient method to decompose an image in visually homogeneous regions. It is based on a spatially localized version of k-means clustering. Similar to mean shift or quick shift, each pixel is associated to a feature vector.

2.3 Expectation-Maximization (EM) algorithm

The EM procedure is a powerful iterative technique suited for calculating the maximum-likelihood estimates MLEs. in problems where the observation can be viewed as incomplete data. The MLE of X based on the incomplete observed data Y is the log likelihood of Y given X . In many

applications, calculating the MLE is difficult because the log-likelihood function is highly nonlinear and not easily maximized. To overcome these difficulties, the EM algorithm introduces an auxiliary function along with some auxiliary random variables that has the same behavior as the log-likelihood function in that when the loglikelihood function increases, so does the auxiliary function but is much easier to maximize. Central to the EM method is the judicious introduction of an auxiliary random quantity W with log likelihood. The data W is referred to as the complete data because it is more informative than Y . The complete data W is not observed directly, but indirectly through Y via the relationship $Y = G(W)$, where G is a many-to-one mapping function. Those unobserved variables are referred to in the EM formulation as the hidden data and denoted by H . The EM approach calculates through an iterative procedure in which the next iteration's estimate of X is chosen to maximize the expectation given the incomplete data Y and the current iteration's estimate of X . The iteration consists of two steps:

- The E step computes the auxiliary function
- The M step finds $X^{[k+1]}$

The maximization here is with respect to X , the first argument of the function Q . Intuitively, the M step is designed to use the expected value of the hidden data H found in the E step as if it were measured data in order to obtain the ML estimate of X . The EM algorithm can easily be extended to a maximum a posteriori MAP estimator by imposing a prior model, $p(X)$, on the estimated quantity X during this step. With this modification, the M step finds the $X^{[k+1]}$ such that

2.4 Support vector machines (SVM)

A Support vector machine is a powerful tool for binary classification, capable of generating very fast classifier function following a training period. There are several approaches to adopting SVMs to classification problems with three or more classes. In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. SVM are inherently two class classifiers. The traditional way to do multiclass classification with SVMs is use one of the methods. The classifier evaluation consist the output value higher than the threshold area recorded as "true" and any SVM output value lower than the threshold are recorded as "false". The SVM classifier consist the binary classification of images

2.5 Principal component analysis (PCA)

Principal component analysis (PCA) is one of the statistical techniques frequently used in signal processing to the data dimension reduction or to the data de correlation. Presented paper deals with two distinct applications of PCA in image processing. The following are the steps needed to perform a principal component analysis (PCA) on a set of data are:

1. Give the input in matrix form (here DCT matrix)
2. Subtract the mean: For PCA to work properly, we have to subtract the mean from each of the data dimensions.

2.6 Pyramid histogram of oriented gradient features (PHOG)

Pyramid histogram of oriented gradient features (PHOG) with part based crescent like structure, whose simplicity combined with an original learning strategy leads to a fast and high accuracy detect results. Histogram of Oriented Gradient (HOG) can capture edge or gradient structure that is very characteristic of local shape, and gets better invariance to local geometric and photometric transformations by using gradient and histogram normalization (Zhang and Sha, 2013). This not only simplifies the classification procedure, but also removes the influence of botany conception that may change all the time.

1)These algorithms uniformly utilize fixed thresholds from diseased leaf image with gray level differences between the healthy pixels and spot pixels. In reality, however, the healthy part and spot part in a diseased leaf image are fuzzy, and the color of healthy part and spot part is often uneven and

unclear, as shown in Fig. 1A and B. The overlapping clearly makes it difficult to determine the uncertain lesion pixels from diseased leaf image by a fixed threshold, criteria or its grayscale histograms, as demonstrated in Fig. 1C, D, E and F.

- 1) The segmentation speed is usually slow due to randomly setting initial parameters in the whole diseased leaf image of EM algorithm for image segmentation (Deploures et al., 2007).
- 2) Many important features that can well represent the types of diseases, such as frequency-domain features, have not fully adopted and the recognition performances can be further improved for real-world applications.



Figure 2 Preprocessing of diseased leaf segmentation

A fast algorithm fusing super pixel clustering and EM algorithm for lesion segmentation is introduced in the section. Briefly speaking, the proposed segmentation algorithm is consisted of the following two parts,

(1) Applying SLIC to divide the original diseased leaf into several super pixels;

(2) Using EM to segment each super pixel and obtain the lesion image. The processing process is shown in Fig. 3.4. The steps of the proposed segmentation algorithm are introduced as follows. Feature extraction by PHOG Histogram of Oriented Gradient (HOG) can capture edge or gradient structure that is very characteristic of local shape, and gets better invariance to local geometric and photometric transformations by using gradient and histogram normalization. This not only simplifies the classification procedure, but also removes the influence of botany conception that may change all the time. Pyramid of Histograms of Orientation Gradients (PHOG) is a spatial pyramid extension of HOG. In this paper, we adopt PHOG descriptors to develop the frequency-domain feature representation of disease lesions. Basically speaking, a lesion image (I) is divided into $M \times M$ cells after preprocessing; each of the cell has a pixel size of $N \times N$. The gradient magnitude g and the gradient orientation h are computed for all the pixels in the block using Eqs.

$$g(\varphi, \omega) = \sqrt{g_x(\varphi, \omega)^2 + g_y(\varphi, \omega)^2}$$

$$\theta(\varphi, \omega) = \arctan \frac{g_y(\varphi, \omega)}{g_x(\varphi, \omega)}$$

The derivatives g_x and g_y of the image I are computed with pixel differences using Eqs.

$$g_x(\varphi, \omega) = I(\varphi + 1, \omega) - I(\varphi - 1, \omega)$$

$$g_y(\varphi, \omega) = I(\varphi, \omega + 1) - I(\varphi, \omega - 1)$$

After gradient computation, each pixel within a cell casts a weighted vote for an orientation-based histogram, which is based on the gradient magnitude and orientation. Then we normalize all

cells' histograms in a block to reduce the influence of lamination and noise. We arrange the histogram in the same cell as a normalized descriptor vector V , where the normalization is conducted as follows:

$$V = \frac{V}{\sqrt{\|V\|_2^2 + \epsilon^2}}$$

Finally, the histograms of all the blocks consist of a whole HOG descriptor. In this paper, for example, a HOG descriptor extracted from a 64 64 image, a cell contains 8 8 pixels and a Block consists of 2 2 Cells, and the number of bins, K , is set to 9. As a result, there are total 64(8 8) cells and 49(7 7) blocks, so the dimension of overall HOG feature is 1746 (9 2 2 49). Considering the final classifier is the nearest neighbor algorithm, a further dimensionality reduction procedure is needed, which will be discussed later.

III. RESULT ANALYSIS

3.1. Fast lesion segmentation by adopting super pixels and EM

The rice diseased leaf images are complex and various, which are composed of diseased leaf regions, healthy leaf regions and complex background. Moreover, the symptoms of a diseased leaf are different while the plant diseases are developing; the color, size, shape and spot distribution of a diseased leaf symptom are not always the same, which makes the plant disease recognition.

3.2 Lab color space

Lab color space is a 3-axis color system with dimension L for lightness and a and b for the color dimensions. Working with the Lab color space includes all of colors in the spectrum, as well as colors outside of human perception. The Lab color space is the most exact means of representing color and is device independent. This accuracy and portability makes it suitable in a number of different industries such as printing, automotive, textiles, and plastics. Lab color is usually converted to less accurate color spaces, such as RGB and CYMK, because computer monitors and printers use either three or four colors to represent images.

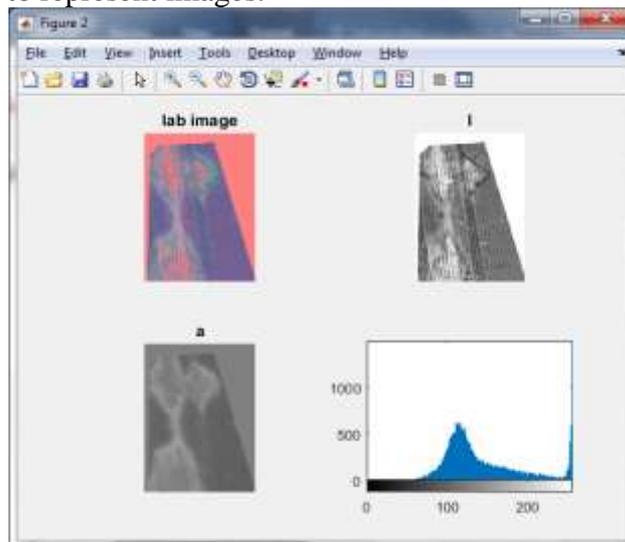


Figure 3 Lab color space

3.3 Histogram

A histogram is an accurate graphical representation of the distribution of numerical data. The bins are usually specified as consecutive, non-overlapping intervals of a variable. The bins (intervals) must be adjacent, and are often (but are not required to be) of equal size.

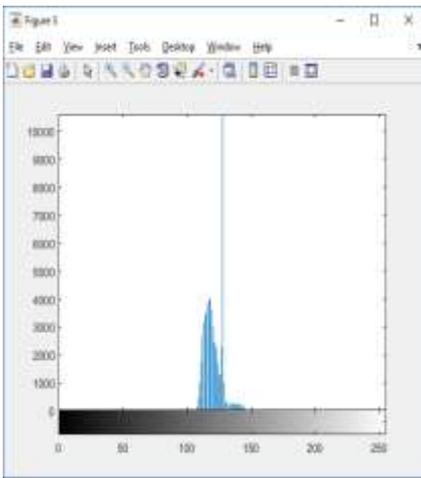


Figure 4 Histogram for L

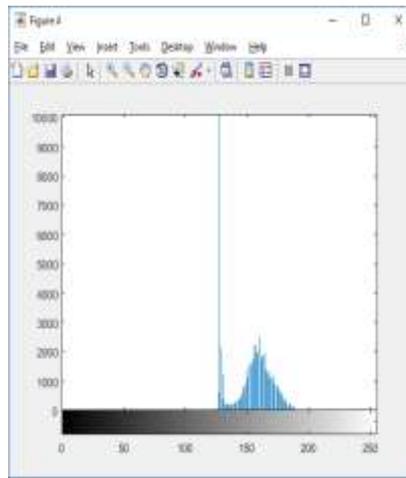


Figure 5 Histogram for A

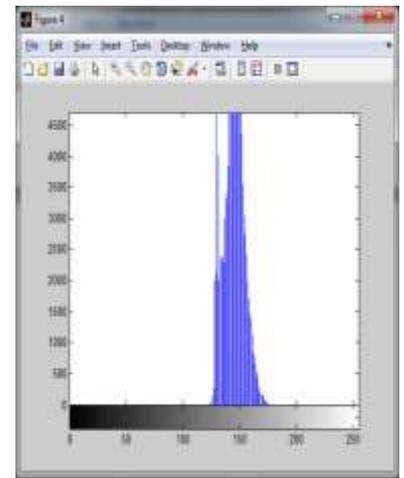


Figure 6 Histogram for B

3.4 Super pixel segmentation

A super pixel can be defined as a group of pixels which have similar characteristics. It is generally color based segmentation. Super pixels can be very helpful for image segmentation. to segment super pixels which doesn't require much computational power.

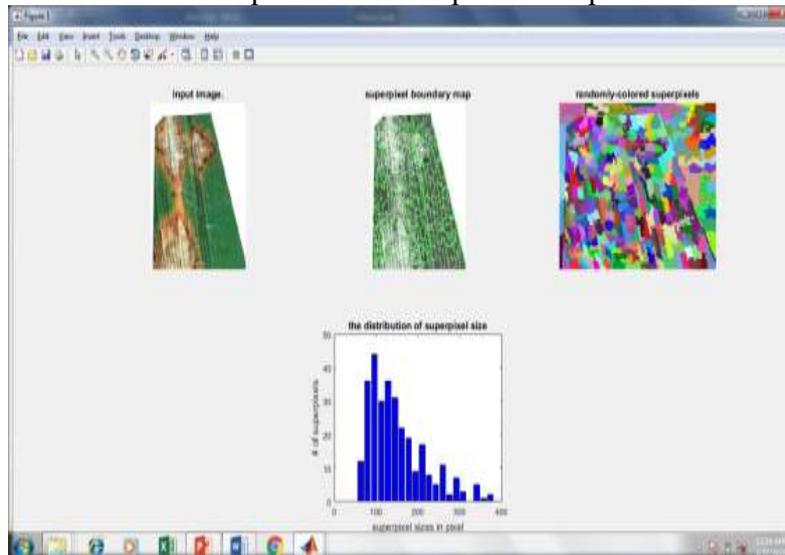


Figure 7 Super pixel segmentation

3.5 Segmentation of EM Algorithm

The method firstly Convert Image from RGB Color Space to HSV Color Space; Secondly we make use of a model of mixture K Gaussians, the Expectation Maximization (EM) formula is used to estimate the parameters of the Gaussian Mixture Model (GMM), which the desired number of partitions and fits the image histogram. The EM algorithm tends to get stuck less than K-means algorithm.



Figure 8 Segmentation of EM Algorithm

IV. CONCLUSION

The rice disease recognition method based on fusing super pixels, EM algorithm and PHOG. Super pixels are employed in preprocessing step to help EM clustering algorithm to initialize the parameters by greatly reducing the redundancy and complexity of the diseased leaf image processing. After the parameter estimation by EM, the lesion image is obtained by the conventional maximum likelihood method. The robust logarithmic frequency PHOG features are extracted and concatenated from the L/a/b/ image and corresponding grayscale image of the segmented lesion image. SVM is applied to disease recognition. The proposed method is validated on a rice diseased leaf database. The experimental results show that the proposed method is efficient and feasible for the rice disease recognition.

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