Grape leaf disease detection from color imagery using hybrid intelligent system

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Abstract- **Vegetables and fruits are the most important export agricultural products of Thailand. In order to obtain more value-added products, a product quality control is essentially required. Many studies show that quality of agricultural products may be reduced from many causes. One of the most important factors of such quality is plant diseases. Consequently, minimizing plant diseases allows substantially improving quality of the products. This work presents automatic plant disease diagnosis using multiple artificial intelligent techniques. The system can diagnose plant leaf disease without maintaining any expertise once the system is trained. Mainly, the grape leaf disease is focused in this work. The proposed system consists of three main parts: (i) grape leaf color segmentation, (ii) grape leaf disease segmentation, and (iii) analysis & classification of diseases. The grape leaf color segmentation is pre-processing module which segments out any irrelevant background information. A self-organizing feature map together with a back-propagation neural network is deployed to recognize colors of grape leaf. This information is used to segment grape leaf pixels within the image. Then the grape leaf disease segmentation is performed using modified self-organizing feature map with genetic algorithms for optimization and support vector machines for classification. Finally, the resulting segmented image is filtered by Gabor wavelet which allows the system to analyze leaf disease color features more efficient. The support vector machines are then again applied to classify types of grape leaf diseases. The system can be able to categorize the image of grape leaf into three classes: scab disease, rust disease and no disease. The proposed system shows desirable results which can be further developed for any agricultural product analysis/inspection system.**

I. INTRODUCTION

Plant disease is one of the crucial causes that reduces quantity and degrades quality of the product. The ability of disease diagnosis in earlier stage is then very important task in order to be able to timely cure and control such disease for decreasing dissatisfactory products. There are numerous characteristics and behaviors of such plant diseases in which many of them are merely distinguishable. Hence, human expertise is normally required for disease diagnosis. This allows usage of many image processing and computer vision techniques to apply with plant diagnosis problem because disease diagnosis is commonly performed by visual inspection. In present, using such approaches can partially replace plant disease expert, providing usage of a diagnosis system without having any prior knowledge. For examples, techniques of using artificial neural network and image processing are utilized for detection and classification of orchid seed disease using co-occurrence matrix from gray-scale image [1]. This resulting matrix yields salient disease features which are composed of disease contents and color characteristics. Back-propagation network is applied to classify types of diseases. In [2], diagnosis system of lemon leaf disease is proposed. Both HSI color space and co-occurrence matrix are deployed for salient disease feature extraction. Discriminant statistic-based algorithm is then applied for disease classification. Cucumber leaf disease diagnosis system is presented in [3] using histogram processing for enhancement of affected tissue and suppression of non-affected tissue. Fuzzy C-mean clustering algorithm is then used with component labeling to extract salient disease features. Color, shape, and size information are fed to back-propagation neural network in the stage of disease classification.

The environments of systems presented above, however, are controlled in many aspects. For examples, no complex background and only single leaf are examined without considering different sizes, orientations, and light conditions. This work presents grape leaf disease diagnosis system using color imagery with complex background (i.e. the environment is not controlled). Multiple grape leaves are considered with different sizes, orientations and light conditions (normal, bright and dim). Details of the system are proposed in the following sections.

II. OVERALL SYSTEM STRUCTURE

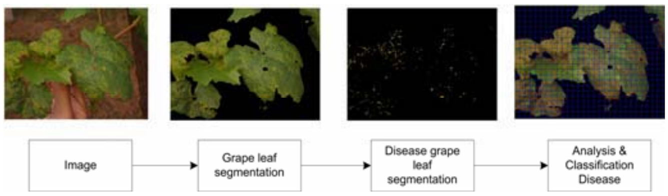


Fig. 1. Overall grape leaf disease diagnosis system.

The overall system is composed of three main parts: grape leaf color extraction from complex background, grape leaf disease color extraction, and grape leaf disease classification.

Fig. 1 shows diagram of the overall diagnosis system. Details of each part are described next.

A. Grape Leaf Color Extraction

In this part (see system diagram in Fig. 2), the input image is enhanced by using anisotropic diffusion technique [4] to preserve information of the affected pixels before extracting grape leaf color from the background. H and B components from HSI and LAB color space, respectively, are used to reduce effect of illumination and distinguish between grape and non-grape leaf color efficiently. The resulting color pixels are clustered by the unsupervised SOFM network [5]-[6] to obtain groups of colors in the image (see Fig. 3). The back-propagation neural network (BPNN) is then applied to extract grape leaf color from other background color as can be seen in Fig. 4. There are 200 samples of grape leaf color pixels and 210 samples of non-grape leaf color pixels used in BPNN training stage.

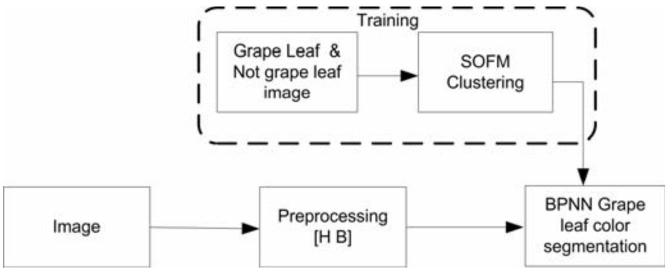
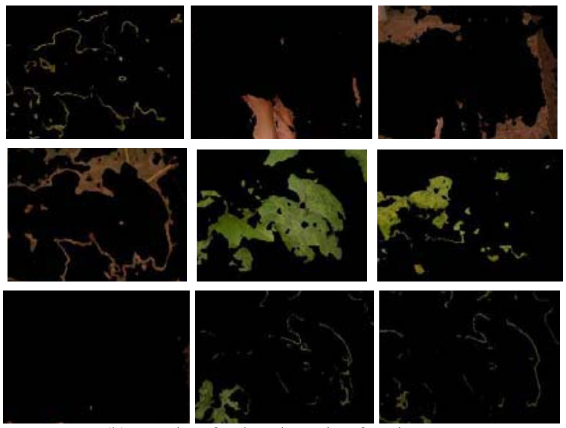


Fig. 2. Grape leaf color extraction system diagram

(a) Original grape leaf image



(b) Results of color clustering for nine groups

Fig. 3. Example of color clustering

Original image

Grape leaf color extracted image

Fig. 4. Example of grape leaf color extraction

B. Grape Leaf Disease Color Extraction

The image background is additionally processed to remove edge pixels in order to preserve the actual affected pixels as many as possible. In additions, A, U, and Cr components from LAB, UVL, and YCbCr color space, respectively, are applied for affected-leaf color extraction with the purpose of less illumination effects. The remaining color pixels are then extracted for grape leaf disease color. By using modified self-organizing feature map (MSOFM) [7], the clustering process does not require any training nor predefined number of color groups. This network is also adjustable allowing similarity of each color group to be fine tuned. The suitable number of color groups can lead to the better color extraction. The grape leaf disease color extraction system diagram is shown in Fig. 5. Examples of different number of color groups are displayed in Fig. 6.

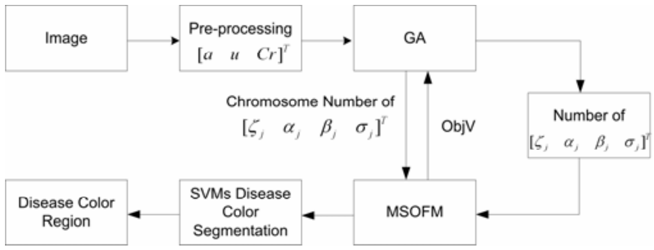
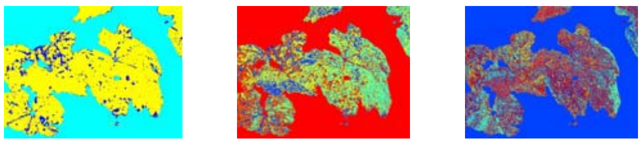


Fig. 5. Grape leaf disease color extraction system diagram

Original image



2 groups 23 groups 106 groups

Fig. 6. Examples of different numbers of color groups from MSOFM

In order to obtain optimal number of color groups, genetic algorithm (GA) [8] is deployed to search for optimal parameters of MSOFM by using the objective functions in (1)-(3). Fig. 7, shows results of using optimal number of color groups from GA for MSOFM used in this work.

$$d_{wx} = \frac{1}{N_w}\sum_{g=1}^{N_w}\frac{1}{N_g}\sum_{i=1}^{N_g}\sqrt{(x_{gi1}-w_{g1})^2+(x_{gi2}-w_{g2})^2} \tag{1}$$

$$d_{ww} = \frac{1}{N_d}\sum_{j=1}^{N_d}\sum_{i=j+1}^{N_w}\sqrt{\sum_{k=1}^{n}(w_{ik}-w_{jk})^2} \tag{2}$$

$$ObjV = d_{wx} + \frac{N_w}{d_{ww}} \tag{3}$$

Where

x = color component of input pixel

w = weight vector (center of color cluster)

N_w = Number of weight vectors (color groups)

N_g = Number of color pixels within the weight vector

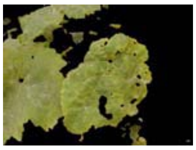
N_d = Number of measures between weight vectors

n = Number of input x

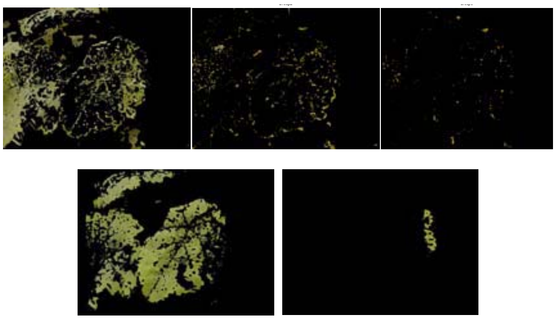
d_{wx} = distance between input and weight vector

d_{ww} = distance between weight vectors

$ObjV$ = objective value (fitness value)



(a) Original image



(b) Clustering of grape leaf pixels using 5 groups of color

Fig. 7. Examples of grape leaf pixel clustering using MSOFM with GA

After grape leaf disease colors are segmented corresponding to number of weight vectors (groups of color), information from segmented image (both disease and non-disease pixels) are used for training with support vector machines (SVMs) [9] for grape leaf disease segmentation (see Fig. 8). Using SVMs allow better segmentation of grape leaf disease pixels than using of neural network. In this work, SVMs are trained using only 20 grape leaf disease samples and 25 non-disease samples. The resulting segmented pixels are then processed for classification of grape leaf disease.

Original Segmented grape leaf disease pixels

Fig. 8. Example of grape leaf disease color extraction

C. *Grape Leaf Disease Classification*

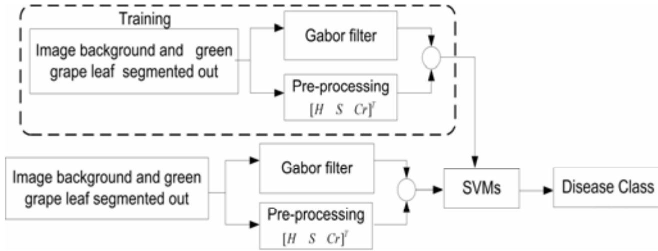


Fig. 9. Grape leaf disease classification system diagram

Before classification processes, some irrelevant pixels is eliminated using convolution and thresholding techniques. H, and S components (from HSI color space) and Cr component (from YCbCr color space) are applied to extract salient color features of grape leaf disease. Additionally, grape leaf color segmented image is processed using Gabor filter [10] to obtain different disease appearance features (see Fig. 10). All information from these processes is used for examining affected pixels within the image. Finally, multiclass SVMs are deployed for grape leaf disease classification.

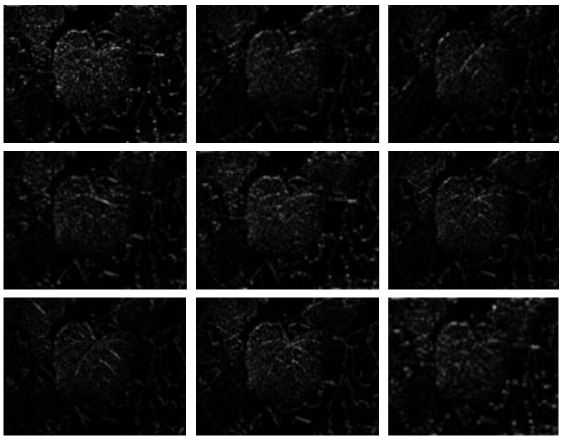
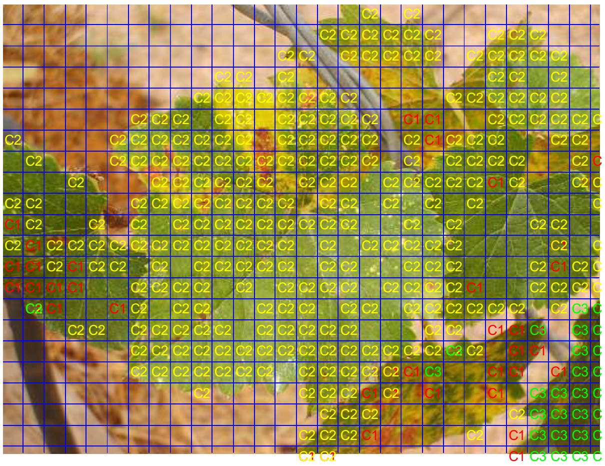


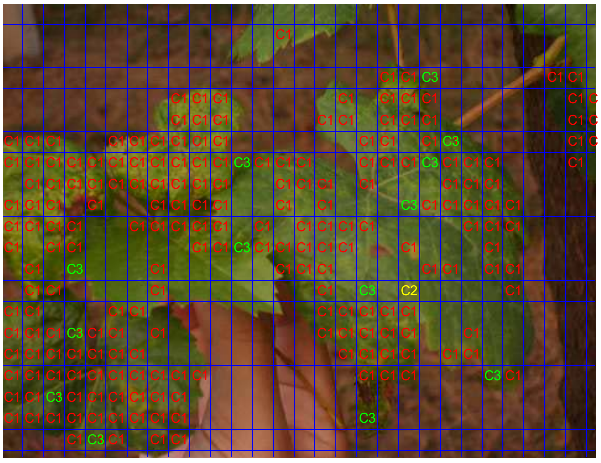
Fig. 10. Examples of disease feature extraction using Gabor filters (3 scales and 3 orientations)

III. Experimental Result

The proposed system is tested with images of 426x568 pixels. There are 497 scab disease samples, 489 rust disease samples and 492 non-disease samples used in training SVMs. For testing stage, there are 39 scab disease images (19,968 subimages) , 41 rust disease images (20,736 subimages) and 35 non-disease images (18,432 subimages). The results show that the system provides desirable performance as can be seen in Fig. 11. The notation C1, C2, and C3 represent scab disease, rust disease, and no disease, respectively. Table 1 demonstrates efficiency percentage of grape leaf disease diagnosis system.



(a) Example of rust disease detection



(b) Example of scab disease detection

Fig. 11. Example of grape leaf disease diagnosis results

IV. CONCLUSIONS

This work presents grape leaf disease extraction and classification system using color imagery. The system provides desirable results. BPNN gives efficient grape leaf color extraction with complex background while MSOFM & GA provides automatic adjustment for grape leaf disease color extraction. Grape leaf disease appearance features using Gabor filters and grape leaf color features using illumination invariant color components allows SVMs to achieve very efficient classification of diseases. Even though, there are some limitations of extracting ambiguous color pixels from the background of the image, the system, however, demonstrates automatic diagnosis capability with very promising performance for further agricultural product analysis/inspection system development.

Table 1
Diagnosis percentage of the system

Diagnosis	Disease Type : Number of subimages		
	Scab	Rust	No disease
Scab	16,689	2,251	614
Rust	2,060	17,122	901
No disease	462	770	16,917
False detection	757	593	0
Correction (%)	83.5	82.5	91.7
Average (%)	86.03		
Detection (%)	97.8		

ACKNOWLEDGMENT

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