Color Texture Analysis of Rice Leaves to Diagnose Deficiency in the Balance of Mineral Levels Towards Improvement of Crop Productivity

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Abstract

Rice is one of the most widely cultivated food crops throughout the world. But due to deficiency in the balance of mineral levels, the production of rice often gets severely affected. Also, some destructive and sporadic rice diseases such as blast and brown spot are closely related with this loss of balance of mineral levels. Such deficiencies in the balance of mineral levels can be identified by detecting the change in the appearance of rice leaves. In the present article, we present our recent study on the use of image analysis based techniques for detection of possible changes in rice leaves indicating deficiency in the balance of mineral levels in rice fields. Such an attempt is a pioneering one and the ultimate goal of this study is the development of a prototype system, which may be embedded in camera phones for its convenient and effective use by the farmers. Simulation studies presented in this paper are based on images of rice leaves obtained from the International Rice Research Institute (IRRI), Philippines.

1. Introduction

Rice is one of the important cash crops in the world. Demand for rice as a major food item continues to increase and it is estimated that we will have to produce 50% more rice by the year 2025. To meet this challenge, studies are continuing in different fronts.

Often production of rice is severely affected due to a number of reasons. Such reasons include deficiency in the balance of level of one or more of several minerals such as sodium, potassium, boron, silicon, zinc, copper etc. and these often limit the health, quality and production potential of this important crop. Also, outbreak of some deadly diseases of rice plants such as brown spot, blast diseases or rice stem diseases are closely related with this deficiency in the balance of mineral levels [1]. Among these, blast is a very deadly disease of rice plants and it has widespread distribution in more than 80 countries including India. It has the potential to cause up to 50% yield loss when environmental conditions are favorable for its occurrence [2]. Often farmers use fertilizers providing mineral nutrition towards maximizing yield and promoting good market quality of rice. For example, in California Sacramento Valley, responsible for 95% of state rice production, fertilizer nitrogen (N) and phosphorus (P) are universally applied each year [3]. But several studies have confirmed that the chance of stem rot disease of rice plants increases due to excess of nitrogen. In fact, researchers have shown that maintenance of balance in mineral levels of rice plants reduces its chance of getting affected by some deadly disease. Thus, timely diagnosis of deficiency in the balance of minerals in rice plants is important.

Researches on this mineral neutralization mainly concern correct identification of the mineral or the dynamics of the deficiencies or determination of empirical damage functions due to such mineral deficiency [4, 5]. However, to the best of our knowledge, no study of some automatic system for determination of such mineral deficiency in crops exists in the literature. An advantage of designing such a system is that in near future it may be possible to embed the same in camera phones. In this connection, it may be noted that the increasing availability of high performance, low priced, camera phone devices has already become popular among the very common people all over the world including India. Thus, in future, a farmer with the help of such a camera phone will be able to investigate on some regular basis whether his crops are suffering from loss of balance of mineral levels and if necessary can take required measures without intervention of a plant pathologist.

Due to lack of balance in mineral levels, some specific changes appear on rice leaves. In the present approach, we consider automatic analysis of color texture of images of rice leaves captured by digital camera towards determination of any possible deficiency in the balance of mineral levels affecting the plants. Although our preliminary simulation results based on the available samples (obtained from International Rice Research Institute (IRRI), Philippines [1]) are encouraging, it needs more elaborate study based on a large volume of representative sample data.

In the present study, we have considered classification of color texture of images of rice leaves with respect to deficiency in the balance of levels of six important minerals such as Nitrogen, Iron, Magnesium, Potassium, Boron and Manganese. Thus, the present classification problem is a seven-class problem, which includes the normal situation when levels of all the concerned minerals are in balanced state. To the best of our knowledge, no such attempt has been reported before in the literature. In this classification task, multilayer perceptrons (MLP) are used as the classifiers. Instead of any predefined high-level features, low-level pixel values in a neighborhood of each pixel are used as the feature vector. However, high-level features are computed in the hidden layer of the concerned MLP classifier and these are not transparent to the user. This feature selection approach seems to have some similarity with the human visual system since we do not consciously use any predetermined feature set for recognition of texture. In [8], similar low-level features had been studied towards segmentation of grey level texture images.

The rest of the paper is organized as follows. Section 2 describes the background of the present work. Section 3 describes our classification approach in some details. Experimental results are discussed in Section 4. Section 5 concludes the paper.

2. Background

2.1 Effects of deficiency in the balance of levels of different minerals on rice leaves

Production of rice can be enhanced by timely diagnosis of loss of balance in mineral levels. For example, Leaf N status of rice is closely related to photosynthetic rate and biomass production and it is a sensitive indicator of changes in crop N demand within a growing season [6]. Maintenance of an optimal leaf N content is vital for achieving high rice yield with effective N management. To guide the farmers towards achieving the above and to find the plant N status, leaf color chart (LCC) is used [7]. The IRRI developed a Leaf Color Chart (LCC) shown in Figure 1 and guidance of using LCC is provided in [9].

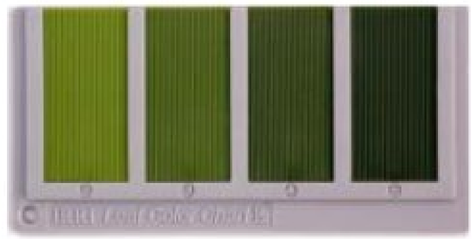


Figure 1. Leaf Color Chart (LCC) developed by IRRI (Courtesy: IRRI, Philippines)

Brief descriptions of effects on appearance of rice leaves in regard to deficiencies in the levels of six important minerals are described below. Parts of rice leaves affected by similar situations are shown in Figure 2.

Boron: Symptoms of the imbalances in boron nutrition appear first at the tips of older leaves, where a high boron concentration leads to chlorosis and necrosis, extending down the leaf margins.

Iron: The primary symptom of iron deficiency is interveinal chlorosis, the development of a yellow leaf with a network of dark green veins. In severe situations, the entire leaf turns yellow and the outer edges may scorch and turn brown as the plant dies.

Magnesium: Symptoms of the deficiency of magnesium include pale-colored plants with orange-yellow interveinal chlorosis on older leaves and later on younger leaves. In severe cases, chlorosis progress to yellowing and finally necrosis in older leaves.

Manganese: Due to manganese deficiency pale grayish green interveinal chlorosis spread from the tip to the leaf base. Later necrotic brown spots develop and leaf becomes dark brown.

Nitrogen: Due to nitrogen deficiency older leaves or whole plant turn to yellowish green. Sometimes chlorosis appears at the tip of the leaf.

Potassium: Potassium is the most important macronutrient in plant growth and development. Due to potassium deficiency, dark brown necrotic spots appear on leaves along with yellowish brown leaf margins. When severe potassium deficiency occurs, the leaf tips turns to yellowish in color.

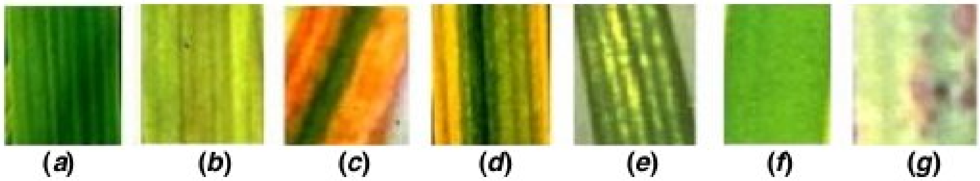


Figure 2. (a) Healthy rice leaf (b) turns to yellowish due to deficiency of boron (c) leaf margin with thick orange-yellow and middle thin green patch (chlorosis) due to deficiency of iron (d) leaf margin with thin yellow patch and middle broad green strip (chlorosis) due to deficiency of magnesium (e) scattered yellow patch on leaf due to deficiency of manganese (f) leaf turns to yellowish green due to deficiency of nitrogen (g) dark brown necrotic spots appear due to deficiency of potassium (Courtesy: International Rice Research Institute, Philippines)

2.2 Brief review of color texture segmentation approaches

Segmentation is a major problem in automated image analysis tasks. Texture and color information is often considered to be two useful features for classification of color texture images.

A large number of research works are found in the literature on segmentation of image textures and also there exist a significant amount of works on segmentation of color images. Two works on each of the above two segmentation problems include [10, 11] using texture information and [12, 13] using color information. However, not enough work has been done on image segmentation using both the texture and color information present in the image. Consideration of both texture and color for the purpose of image segmentation is also challenging [14]. Usually, color based segmentation approaches provide inhomogeneous regions with sharp boundaries while textural feature based approaches produce more homogeneous regions with disturbed boundaries [15]. Thus, segmentation outputs from both the approaches may be combined to obtain improved results. In the literature, there are several methods [16, 17] combining color and texture information for segmentation of color texture.

2.3 Increasing availability of high-performance, low-priced hand-held devices with Internet connectivity

With the rapid advancement of mobile/wireless communication and camera technologies, cellular phones and Personal Digital Assistants (PDA's) are increasingly available with good enough built-in digital camera at affordable prices. Recent trends are embedding of various systems to extract desired information from images captured by the built-in camera of such devices. In this work, we consider image processing and pattern recognition techniques to extract nutritional information of rice plants from an image of its leaves captured by a camera attached to a mobile phone. The present study is only at a preliminary level and an ultimate system should be integrated with a suitable filter to enhance the image, a component to segment the leaf from the background, a suitable module to verify/identify the possible existence of a part of the leaf, which is affected due to imbalanced nutrition. Also, as commercially available PDA's or phone cameras have memory and processing power limitation, a client / server type architecture may be the preferred type of implementation. Client side consisting of a color camera attached to a cellular phone can be used to capture the image of the target leaf. Internet connection through some GSM modem may be used to allow the client to send the image and other necessary information to the server. Server side should consist of a server providing the system processing power and Internet connectivity.

3. Color Texture Classification

In the present study, we considered supervised classification of images of rice leaves in both gray level texture feature space and color feature space. Final classification results are obtained on combining the outputs in these two feature spaces.

3.1 Feature extraction

A color texture is regarded as a pattern described by the relationship between its structural and chromatic distributions. There are two basic feature extraction approaches [18] for segmentation of such color textures. In one approach, gray level texture feature is computed separately for each color band and, in the other, textural features are computed from the intensity image and color features are obtained separately. Both the approaches have been used in different existing color texture segmentation problems. Our approach belongs to the latter category.

3.1.1 Textural features

For gray level texture images, each pixel can be characterized by its spatial-interaction among its neighbouring pixels. Thus, for the present classification work in the gray level space, a *2D* neighbourhood square matrix of size $(2N + 1)$ of gray values around each pixel $(i; j)$ is considered. That is, the feature vector size here is $(2N+1)^2$. It is obvious that the optimal size of this matrix depends on the particular texture. If the size of the neighbourhood matrix is too small, certain textural information may not be captured and on the other hand, a large neighbourhood will cause more computational complexities. The present texture feature extraction approach does not involve computation of any high-level texture feature. In this approach, no parameter involving the shape aspects of the texture is computed explicitly.

3.1.2 Color features

The pixels in a color image is commonly represented in the RGB space, in which the color at each pixel is represented as a triplet (R, G, B), where R, G and B are respectively the red, green and blue output values from a color image capturing device. However, there exist other color spaces [19] also such as HSI, CMY etc. In the RGB space, the color and intensity at a pixel is not represented independently. But this is achieved in HSI (hue, saturation and intensity) space. However, the HSI space does not seem to be suitable from the computational aspect because of the circular nature of its hue component. Similar independence of intensity and color are also achieved in other spaces such as Yuv and YQQ spaces, where

$$Y = \frac{R+G+B}{3}, \quad \text{and}$$

$$u = \frac{1}{2}\left(\frac{R-G}{R+G+B}\right), \quad v = \frac{1}{2\sqrt{3}}\left(\frac{2G-R-B}{R+G+B}\right)$$

$$Q_{RG} = R/(R+G), \quad \text{and} \quad Q_{RB} = R/(R+B)$$

However, in the present work, we consider a more simple approach to obtain the color at a pixel minus its intensity. In fact, for this purpose, we computed the following two quantities representing the color at a pixel independent of the intensity.

$$P_{RB} = \frac{R}{B}, \quad \text{and} \quad P_{GB} = \frac{G}{B}$$

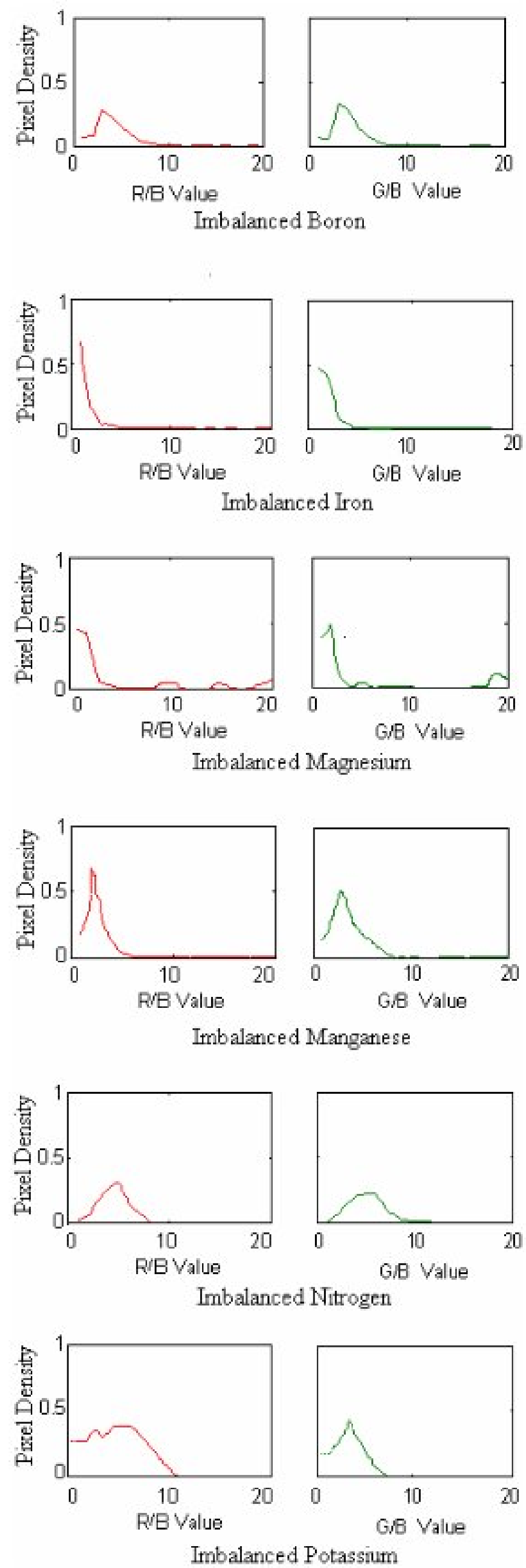


Figure 3. Histograms of the two features P_{RB} and P_{GB} in the six situations under considerations

Histograms of these two color feature values computed from one sample image for each of the six categories of imbalance of nutrition are shown in Figure 3. In the present approach, for segmentation using the color information, we consider a *2D* neighbourhood square matrix of size $2N + 1$ of the above pair of color values of each pixel similar to the textural features at the gray level. That is, the feature vector size here is $2(2N+1)^2$. Here also, it is obvious that the optimal size of this matrix depends on the particular color texture and in the present implementation we use the same size of this neighbourhood both in the gray level textural space and in the color space.

3.2 Classifier selection

For segmentation of input color texture image, we use two different MLP classifiers for the two feature spaces. MLP is the most popular artificial neural network architecture and its details are available in the literature. Each of the two feature vectors is presented to the input layer of the respective MLP classifiers and segmentation mappings are obtained at their output layers. The above two segmentation results are basically probability like measures and they are combined by the sum rule.

3.2.1 Combination of multiple classifiers

For a given classification task, there usually exist several alternatives for designing a classifier using machine learning. However, the solution for choosing the best classification system for the problem at hand is not readily available. On the other hand, simulation studies have revealed that although one among several classifier designs usually provides the best results in terms of classification accuracies, the sets of correctly classified patterns by different classifiers usually differ. These observations led to the idea of combining an ensemble of classifiers to increase the robustness and performance of a classifier. There are several rules for such a combination of classifiers and in the present work we use the sum rule.

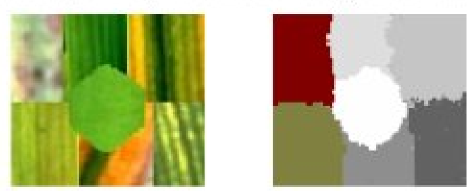
3.2.2 Selection of parameters for MLP and its training

The success of an MLP-based classification method largely depends on the choice of its hidden layer size and also selection of its learning parameter values. There exist several heuristics in the literature towards the selection of hidden layer size of an MLP. However, often these do not perform satisfactorily in real-life problems. So, we made a near exhaustive search for its optimal size and results are reported on the basis of this size.

The BP algorithm, used to train an MLP network, performs a gradient descent on a hyper surface, called error surface, in its connection weight space from a random initial position and there is no guarantee that the global minimum (even approximately) will be reached after a moderate number of presentations (sweeps) of the training sample set. In fact, an acceptable minimum on the error surface may be reached through an optimal selection of the learning rate parameter value. To tackle the problem Rumelhart et al. suggested [20] inclusion of a momentum term in its iterative weight adjustment rule. Though this suggestion is effective in solving different benchmark problems, we have observed that a non-zero momentum term in the weight modification rule is counter productive in the present texture segmentation problem and we have used certain self-adaptive learning rates [21] for BP training of MLP networks.

4. Experimental Results

We have performed training and testing of the present approach on sample images of leaves of affected and normal rice plants obtained from the IRRI, Philippines. Training samples were created from approximately 80% of these sample images while remaining 20% were used for testing purposes. Around each pixel of an image we have considered a 7×7 neighbourhood for computation of the feature vector. The MLP classifier used with texture feature consists of 40 hidden nodes while the MLP classifier used with color feature consists of 70 hidden nodes. Classification results on a few test samples (after applying a 5×5 median filter for removal of artifacts) are shown in Figure 4. These classification results correspond to a combination of outputs of the two MLPs corresponding to texture feature and color feature. A quantitative analysis of the results shows that 88.56% of the pixels are correctly classified.



(*a*) (*b*)

Figure 4. (a) An image mosaic consisting of parts of seven rice leaves corresponding to healthy and affected by loss of balance in six different mineral levels; (b) results of segmentation of the mosaic shown in (a)

5. Conclusions

In the present article, we have presented the result of our pilot study towards application of an image analysis (particularly, texture analysis) technique for diagnosis of deficiencies in the mineral levels affecting a rice plant. However, to study the robustness of the present scheme, a more extensive study on the basis of large training and test sets is necessary. But it is expensive to develop the required database. We look forward to getting such a database for further study. Also, we feel the requirement of studying several other feature extraction methods for the present classification job.

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