RICE CROP PHENOLOGY USING TEXTURE ANALYSIS ON TIME-SERIES IMAGES OBTAINED FROM STILL CAMERA

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ABSTRACT: In this study, an algorithm is proposed to determine the duration in a rice crop cycle based on texture analysis. During an observation period in 2013, daily images were acquired from a still camera installed at a paddy field. Given a set of time-series images, the texture analysis is used to classify different stages of the rice growing. Regarding the hypothesis, the rice crop cycle can be separated into three paddy stages; starting (coarse texture), midpoint (fine texture) and ending (no texture). The texture analysis is based on Gray Level Co-occurrence Matrix (GLCM) with multi-distances. The proposed diagram can be described as follows. Initially, the paddy region is selected as an area of interest (AOI). The selected AOI is computed for a vegetation index, Excessive Green (ExG), and enhanced by using histogram equalization method. Then, the enhanced image is used for generating co-occurrence matrix in order to describe the texture feature. Statistical property (contrast) is analyzed and measured on the co-occurrence matrix for paddy stage classification. The results show that our proposed diagram can be efficiently used to determine the duration of paddy stages. To obtain more efficient results, our perspective work will consider other features such as color, edge, shape, etc.

1. INTRODUCTION

Recent advances in image processing have seen rapid growth and they are applied for several purposes. In Thailand, agricultural application is one of the most important tasks required by various users; policy maker, investor, planning agency, farm operator, etc. The efficient applications would be possible to support; for example, farm monitoring, disaster warning, yield prediction and others. According to the potential for agricultural export products in Thailand, rice is one of the significant economic crops. Based on image processing techniques, a monitoring diagram used to separate and determine status of paddy is proposed in this paper.

The study focuses on a set of time-series images obtained from a paddy field located in Central part of Thailand (Suphanburi province). The time-series images were acquired from a still camera attached to an equipment called field server (Soontranon, 2014; Sritarapipat, 2014). An image of 720x480 pixels is recorded in JPEG compression format. The daily images were automatically taken at 10:30 a.m. (and 2 p.m. used as a redundant image) commanded by a controller unit. To observe a side-view along the rice field, the camera was attached on a mounting which is approximate 2 meters high from the ground level. The objective of our study is to monitor and determine the duration of paddy stages, which can be separated to: starting, midpoint and ending.

The time-series images once obtained can be used to monitor the changes of paddy for a period. Referring to literatures, color feature approaches are often used to compute the phenology which is measured amount of live green plant on the observed area (Richardson, 2009; Sonnentag, 2012; Sritarapipat, 2014; Soontranon, 2014). The color feature is efficiently used for monitoring on agricultural fields, forest, broadleaf, etc. However, there are few studies based on other features e.g. texture, edge, shape, etc. Texture feature, which is one of the useful information extracted from the images, has been studied in (Haralick, 1973). In this work, the texture feature is demonstrated that it can be also used to track and monitor the changes of paddy stages.

2. RELATED WORK

Texture is a well-known feature used to classify different regions (urban, forest, river). A well-known study is referred to Gray Level Co-occurrence Matrix (GLCM) (Haralick, 1973). An evaluation of texture analysis (Sharma, 2001) showed that the co-occurrence approach provided better performance than other techniques such as autocorrelation, edge frequency, primitive length. The GLCM approach is a type of second-order statistical measures. Given an image with a range of gray levels, a quantization method is usually required in order to reduce the number of gray levels (128, 64, 32, 16, 8 levels), each local image patch (e.g. 5x5, 7x7 pixels) is considered for constructing a co-occurrence matrix. The statistical properties of a co-occurrence matrix are computed by using the relationships of neighborhood pixels. Then, they are used for texture analysis by measuring contrast, correlation, energy, entropy, etc. Some statistical properties can be computed as listed in table 1.

Table.1 Statistical properties and formulas are listed as follows.

Statistical property	**Formula**
Contrast	$\sum_{i,j}^{i=N,j=N} (i-j)P_{ij}$
Correlation	$\sum_{i,j}^{i=N,j=N} \frac{(i-\mu_r)(j-\mu_c)P_{ij}}{\sqrt{\sigma_r^2\sigma_c^2}}$
Energy	$\sum_{i,j}^{i=N,j=N} P_{ij}^2$
Entropy	$-\sum_{i,j}^{i=N,j=N} P_{ij}\log(P_{ij})$
…	…

Where P_{ij} is the normalized co-occurrence matrix.
$\mu_r, \mu_c, \sigma_r, \sigma_c$ are the means and variances of row and column.

Several literatures (Bradley, 1995; Woodcock, 1989; Ferro, 2002; Mirowski, 2008) have studied texture analysis with multi-scales to obtain more accurate results of texture classification. The texture properties can be calculated based on either different window patches (with the similar scale of image) or different scales of images (with the similar patch).

Our approach is based on GLCM approach with multi-scales (distances) to measure the texture on time-series images. The images will be measured and analyzed at a fixed image resolution. Texture analysis with multi-distances can be used to classify the stages of paddy, which are represented by different texture patterns. According to the texture measured at varied distances and times, the proposed diagram is a type of 3D texture analysis.

3. HYPOTHESIS AND METHODOLOGY

In this section, we discuss about the hypothesis of texture analysis. Generally, the paddy stages can be classified as starting (seedling), midpoint (tillering) and ending (harvest or no crop).

3.1 HYPOTHESIS

A texture analysis approach shows to have potential to monitor the status of paddy from images in time-series. The paddy status can be separated to three main stages: starting (seedling), midpoint (tillering) and ending (harvest). Our hypothesis is shown in figure 1 and 2. Based on vertical texture, three stages can be determined on the paddy field. Relying on the daily images, the seedling stage can be represented by coarse texture. Meanwhile, the tillering stage can be represented by fine texture. For the harvest stage, there is no vertical texture represented on the images. To classify each stage, we, therefore, use a distant measurement of vertical texture as shown in figure 2. During the seedling stage, the maximum value occurs at the high distance. On the other hand, during the tillering stage, the maximum value occurs at the low distance. For the harvest stage, there is no distance measured on the area of interest. According to the hypothesis, the vertical texture measurement is based on GLCM approach by observing in a range of distance variation.

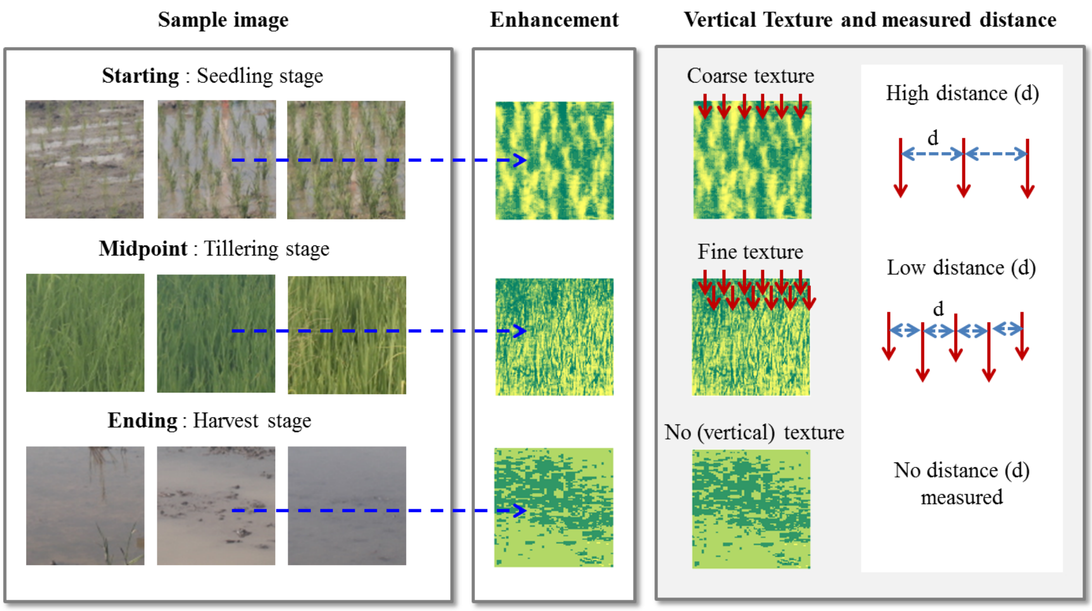


Fig.1 According to the distances of vertical texture, paddy stages can be classified (seedling, tillering and harvest).

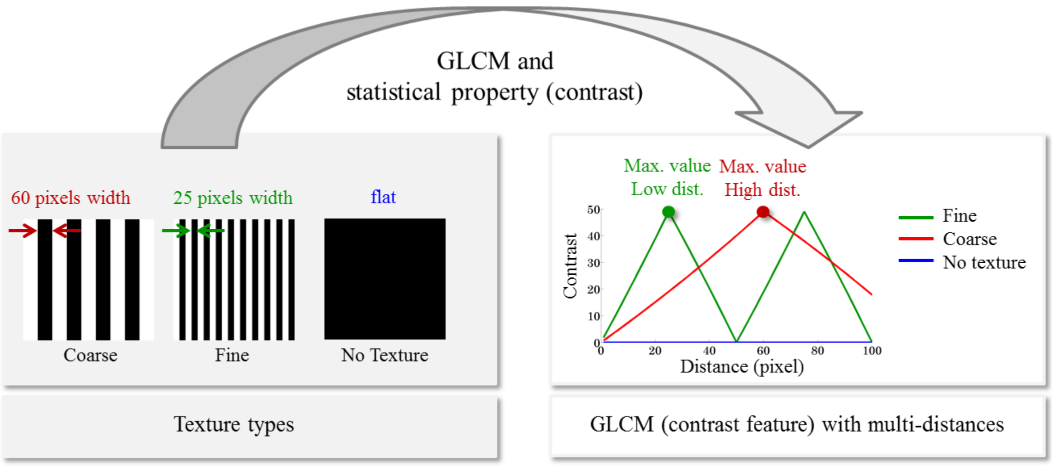


Fig.2 Relying on vertical direction, texture patches (coarse, fine and no texture) are computed for the statistical property based on GLCM.

3.2 METHODOLOGY

An overview diagram of the proposed method is shown in figure 3. It consists of area of interest (AOI), vegetation index computation, histogram equalization, GLCM with multi-distances and paddy stages analysis. Given a set of daily images obtained from the still camera, AOI is initially determined from a specified region in an image for texture analysis. Then, the vegetation index in the AOI is computed to describe the density of green levels on the paddy. The approach used to enhance the information is based on histogram equalization method. Given the enhanced images, GLCM with multi-distances is calculated and the statistical property (contrast) is measured. Finally, the phenology obtained from GLCM with multi-distances is observed and analyzed to determine the paddy stages.

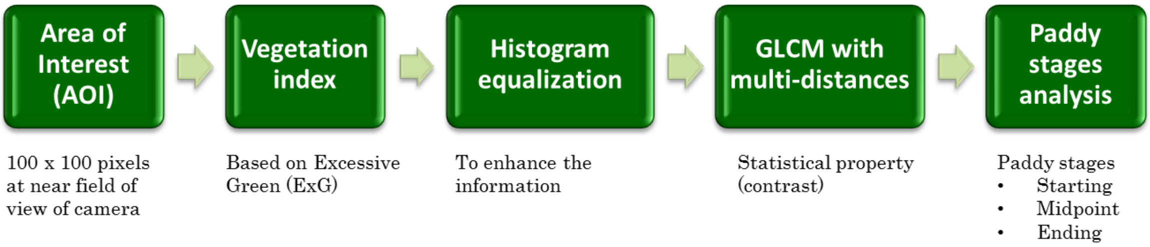
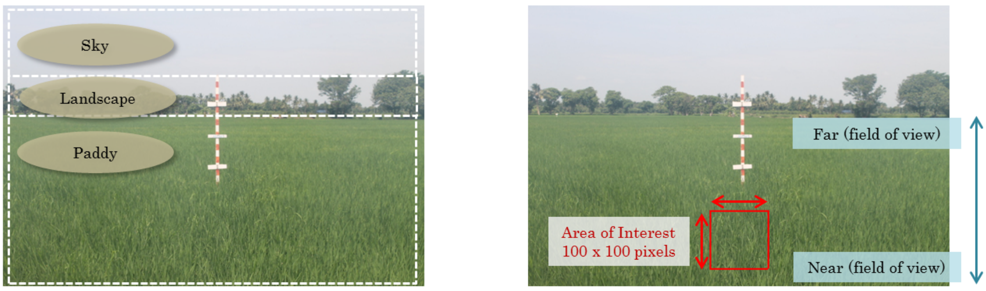


Fig.3 An overview Diagram of texture analysis for paddy stages monitoring

- **Area of Interest (AOI)**

Considering the images obtained from field server, taken from side-view along the camera perspective, the images consist of three regions: paddy, landscape and sky shown in figure 4a. An AOI is defined by a region of 100×100 pixels which is manually chosen from the paddy region of an image. The example of AOI is shown in figure 4b. Regarding to field of view (FoV) of the camera, the selected area located in near FoV can represent the image information better than the area in far FoV.



(a) (b)

Fig.4 (a) Image acquired from a still camera. (b) Area of interest (in red box) is used for texture analysis.

- **Vegetation Index**

The vegetation index can be used to measure levels of green plant on the observed area (Richardson, 2009; Sonnentag, 2012; Sritarapipat, 2014; Soontranon, 2014). A well-known vegetation index is referred as Normalized Difference Vegetation Index (NDVI). It is computed from NDVI = (NIR–Red)/(NIR+Red), when NIR is a near-infrared band and Red is a red reflectance band. Due to the lack of near-infrared information from filed server, we used another vegetation index called Excessive Green (ExG) to measure levels of green plants from RGB images (Sonnentag, 2012; Soontranon, 2014). The ExG index is computed from ExG = 2g – r – b when r, g, and b are normalized of red, green and blue, respectively.

- **Histogram Equalization**

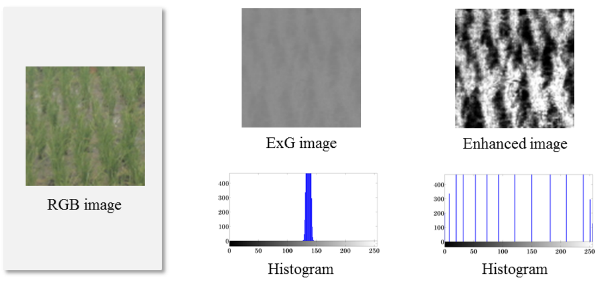


Fig.5 RGB (left), ExG (middle) and Enhanced (right) images by using histogram equalization.

Each pixel located on AOI is represented by ExG index which is normalized from 0 to 255. In figure 5, a histogram equalization approach is used to enhance the ExG images.

- **GLCM with Multi-distances**

GLCM is used for texture analysis at varying different distances. According to the paddy images, the rice texture is analyzed and measured only in vertical direction. Based on the measured distances, GLCM property (contrast) can be used to classify different textures.

- **Paddy Stage Analysis**

To separate paddy stages, a property (contrast) of vertical texture is measured on the AOI by applying a range of distance variation. Paddy stage classification is summarized in table 2 and figure 6. The contrast property computed from texture analysis is plotted on different times (Day of Year) and distances as shown in figure 7. The different stages can be classified by considering the value of contrast property on multi-distances. Using our tested images, the range of observed distance can be determined from 1 to 14 pixels. If the value of distance is more than 14 pixels, the 3D plot represents the repeat cycle (see also figure 7- view 2). It should be noted that an analysis of 3D surface (for example local maximum region detection) is still required in order to obtain an automatic process of paddy stage classification.

Table.2 Paddy stage classification is based on the GLCM with multi-distances.

GLCM (contrast property)	Texture type	Low distance	High distance	Paddy stage
Max. region	Coarse		●	Seedling
Max. region	Fine	●		Tillering
Min. region	No texture	●	●	No crop

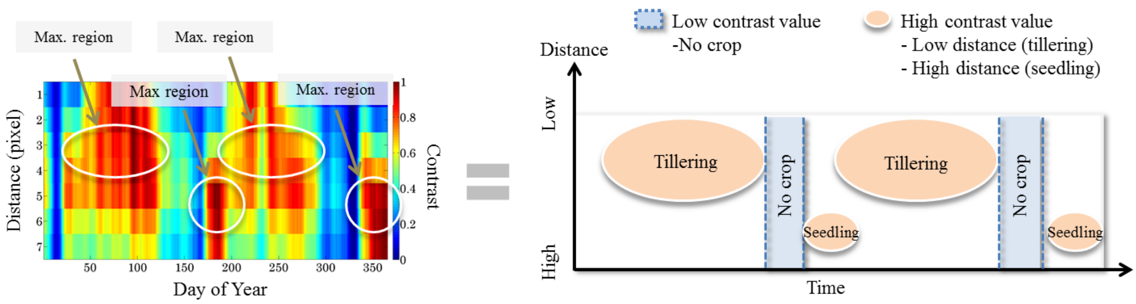


Fig.6 Paddy stages are analyzed by using a texture property (contrast).

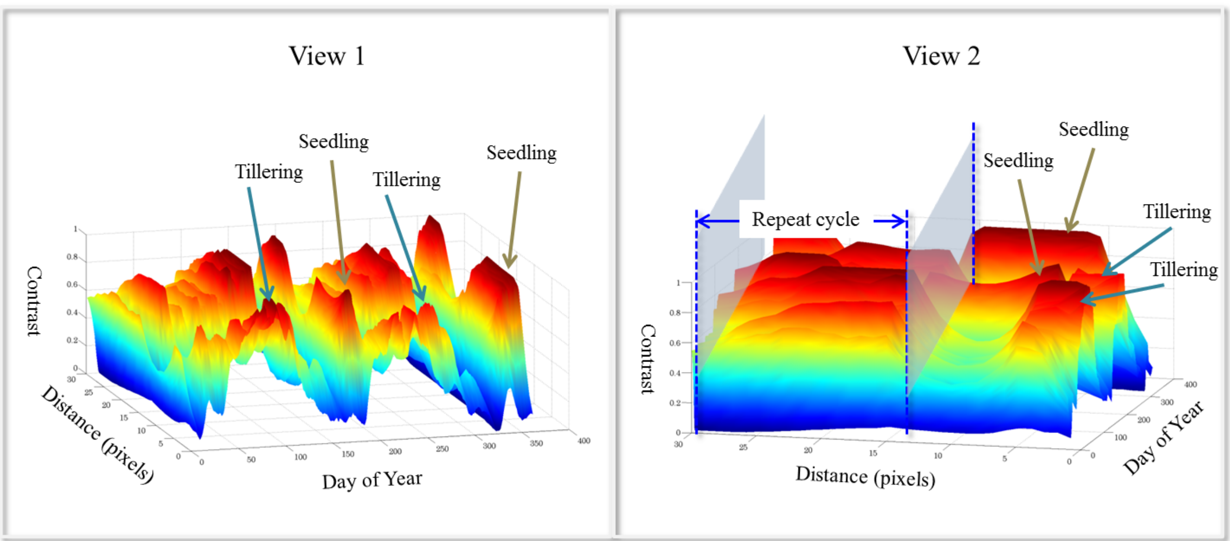


Fig.7 Based on GLCM (contrast property), 3D surface is computed for multi-distances. The maximum regions can be determined as seedling or tillering stages depending on (texture) measured distances.

4. CONCLUSIONS

Given a set of daily images obtained from the still camera, the diagram used for texture analysis was proposed for paddy stage classification. The paddy stages are separated into starting (seedling), midpoint (tillering) and ending (harvest or no crop). The diagram consists of the following: AOI selection, Vegetation index computation (ExG index), enhancement, GLCM with multi-distances and paddy stage analysis. The duration of paddy stages can be efficiently determined by using our proposed diagram. In this paper, the contrast property was used for texture analysis. However, the other statistical properties (e.g. correlation, energy, entropy, etc.) can be replaced by using the similar diagram.

According to this study, significant issues are listed as follows. Images recorded at a high resolution and raw format can provide efficient results for paddy stage monitoring. The selected AOI should be located on near FoV in order to obtain better information for texture analysis. To obtain more efficient system, in the future, we will combine texture feature with other features (e.g. color, edge, shape, etc.). The paddy stages information can be used as a parameter for yield estimation model, which is more useful for farm operator, manager and owner. The information is also used to compare with the other platforms such as satellite images in order to obtain the relation between each other, which would provide computation for the large-scale region (province, country,).

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