DIGITAL IMAGE HANDLING BY FINITE ELEMENT RETINA FOR PLANT GROWTH MONITORING

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ABSTRACT

Objectives of this study were to develop an application method of a numerical retina using the finite element model and to investigate the performance of image features extraction in comparison to the textural analysis. Using a plant community of radish sprouts, excellent resolution of the finite element retina was revealed. The sensitivity analysis of the finite element retina from engineering point of view was discussed. The importance of sensitivity analysis of the finite element retina was pointed out in terms of extraction of effective image features of plant community. Technical details of maximizing the sensitivity of the finite element retina to populated plant canopy were also discussed.

Key Word : Image features, Finite element method, Numerical retina, Growth monitoring

INTRODUCTION

In a protected plant production system such as a plant factory, the control applications have been limited to its environmental controls. The feedback control technology for greenhouse environmental factors such as temperature, humidity, radiation intensity, carbon dioxide concentration and so forth has been developed and successfully implemented. The plant growth can be optimized or controlled by adjusting the environmental factors. Plants respond to the change of environmental parameters. For example, the stomata activity is sensitive to ambient humidity and CO_2 concentration. The plant tissue rigidity is affected by the availability of water at its root zone. Those environmental factors should be controlled based upon the plant status responding to the environmental conditions. The development of bio-response feedback control system has been a challenging task for plant production engineers and scientists. The bio-response feedback control concept known as speaking plant approach to environment control has been highlighted by Hashimoto, et al. (1985).

Changes in appearance of a plant canopy due to the growth reflect tonal variations over the community of plants. The tonal variation can be transformed into pictorial information electronically in retrieval form. The some kind of image features can be related to the tonal characteristics of the plant canopy that also substantially reflect the plant growth status. The textural analysis can be considered as one of applicable techniques for extracting image features[Murase *et al.*.(1994); Haralick *et al.* (1973)]. Some of problems in implementing the textural analysis are that there is too much flexibility to construct the co-occurrence matrix and the construction of the co-occurrence matrix requires impractical long calculation time. Broadly speaking, image features are any extractable measurement of use. Examples of low-level image features are pixel intensities or geometric distances between pixels. Features may also result from applying a feature extraction algorithm or operator to the image data. In this study, the finite element algorithm is use to extract image features (FE features;finite element features). In order to achieve the aim of developing such a bio-response feedback control system, the primary concern should be to develop a practical technique for monitoring plant growth

TEXTURAL FEATURES

The texture-contex information is adequately specified by the matrix of relative frequencies P_{ij} with which two neighboring resolution cells separated by distance d occur on the image, one with gray tone i and the other with gray tone j as shown in Fig. 1[Haralick *et al.* (1973)]. The joint probability density function is expressed by the notation $P_{(d,q)}(i,j)$.

In such a case that d=1 and θ=0, some of the textural features are calculated as follows:

(a)Contrast:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} (i-j)^2 P_{(1,0)}(i,j) \qquad (1)$$

(b)Homogeneity:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} P_{(1,0)}(i,j)^2 \qquad (2)$$

(c)Local Homogeneity:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \{P_{(1,0)}(i,j)\}/\{1+(i-j)^2\} \qquad (3)$$

The performance or specification of the co-occurrence matrix can be set by fixing d and θ values. The choice of d and θ values determines the sensitivity of the textural features.

FINITE ELEMENT FEATURES

Figure 2 shows a schematic representation of the finite element image processing grid proposed by Murase (1995) that converts pictorial image into non-geometric image features numerically. This non geometric image feature can be calculated based on the differences of gray level between every input node of the finite element grid. Each of input nodes serves as a photosensitive receptor (retinal cells). In practice, for instance, signals transferred from sensing elements of CCD area array should be given to these input nodes. Nodal values of the output nodes (Optic nerve cells) become the finite element features. Other nodes are boundary nodes (Choroidal cells) on which boundary conditions are specified.

The algorithm to relate input and output signals of the finite element image processing grid can be a linear mapping as described by a linear finite element equation. In this research work, 2-D Poisson's equation was utilized as a governing equation given by Eq.(4). The finite element equation used here is expressed as Eq.(5). The basic mechanism of finite element image processing grid for generating image features is the conversion of incident light intensity distribution projected over the area comprising of finite element input nodes into a vector form of image features distributed over the output nodes.

$$K_x \frac{\partial \phi^2}{\partial^2 x} + K_y \frac{\partial \phi^2}{\partial^2 y} = Q \qquad (4)$$

K_x:information conductivity in x direction
K_y:information conductivity in y direction
ϕ :potential
Q :constant

$$[K]^{-1} \left\{ \begin{matrix} \vdots \\ A \\ \vdots \\ \vdots \\ B \\ C \\ \vdots \end{matrix} \right\} = \left\{ \begin{matrix} 1 \\ \vdots \\ 2 \\ \vdots \\ 3 \\ \vdots \end{matrix} \right\} \qquad (5)$$

$[K]^{-1}$: inverse matrix of stiffness matrix
{A} : input vector
{1} :output vector (image features)

The performance or specification of the finite element information processing grid can be set by fixing K values and the node arrangement. The choice of K values and the node arrangements determines the sensitivity of the grid. The K value is usually taken as the unity. The number of nodes is depending on allowable calculation capacity. The arrangement of nodes is arbitrary. However some trial procedure is usually required to optimize the grid performance.

EXPERIMENT

A growth of a community of radish sprouts was observed. The change of pictorial image due to the growth was recorded on a video tape. The digital image of the community of radish sprouts was used to calculate the cooccurrence matrix and also used for input data of a finite element retina. Fig. 3 shows the digital image of growing radish sprouts taken every 24 hours after seeding. The image feature was extracted from each of the five digital image frames shown in Fig.3.

Both of the finite element retina and the textural analysis were tested for comparison. Only three parameters of textural features were calculated. They were contrast, homogeneity and local homogeneity. One of the internal parameters (distance , d) for the co-occurrence matrix required to calculate textural features were set at three different values. They were 1, 5 and 10. The other parameter (angle, θ) was kept constant (θ=0). Five by five retinal array of the finite element was used. Three nodes were allocated for the output of the finite element retina. The nodal arrangement was varied to investigate the sensitivity and resolution of the finite element retina. The value of information conductivity, K, was kept one.

RESULT AND DISCUSSION

Figure 4 shows that the textural features obtained from the digital image data do not indicate any apparent consistency on the variation of plant pictorial image. The result shows that the textural features have some strong dependency on the internal parameter, d. Especially, the difference in behavior of the features due to the variation of d value from 1 to 5 is remarkable. It seems that the use of textural features for this particular problem will require to employ rather elaborate technique to relate input-output relationships.

The variations of the finite element features extracted from pictorial image of a community of growing radish sprouts as its appearance changed after seeding were plotted in Fig.5. The obvious variational factor of the pictorial image of growing radish sprouts is the increasing area of leaves. The change was fairly consistent as shown in Fig. 5. The course of image feature variables for the finite element retina seems reasonable. As indicated in Fig. 5, the arrangement of output node locations and number of choroidal cells may improve the sensitivity and resolution accuracy of the finite element features. In Fig. 5, the nodal arrangement of Retina 2 gives better resolution than Retina 1. In Retina 2, each output node is separated from other output cells by a choroidal cell. Retina 3 is much more sensitive than the Retina 2. The reduction of number of choroidal cells makes the boundary constrain less tight which increases the sensitivity of the retina. The comparison revealed that both methods can be considered one of means to quantize variation of pictorial image of plants. Their proportionality, resolutions and sensitivity depend on parameters involved in their calculation procedure. For instance, the distance and the angle which should be specified before finding the co-occurrence matrix affect the final result of the textural features. The values of information conductivities in finite element image processing grid should be also determined before finite element calculation.

CONCLUSIONS

Calculation of the textural features requires much more time than that of the finite element features. Optimized inverse stiffness matrix for the finite element image features can be constructed by arranging the location of choroidal cells and the optic nerve cells and the distribution of information conductivities in such a manner that the potential gradient over the retinal plane is made steep. The finite element retina has more advantages than the textural features in the application to monitoring for the growth of a community of plants (output stability, Sensitivity, resolution, comp-load)

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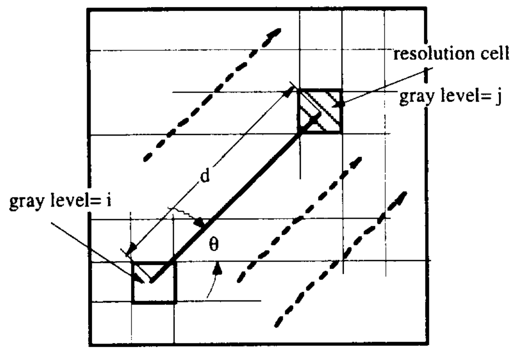

Fig. 1 Co-occurrence matrix.

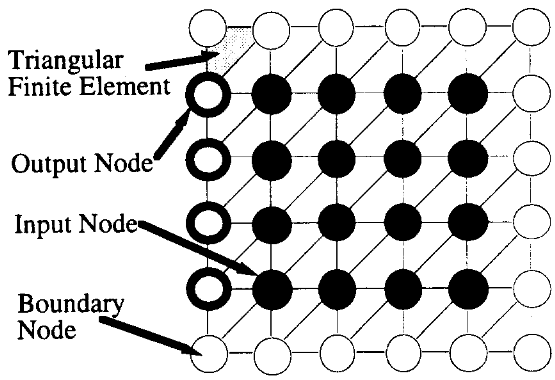

Fig. 2. Finite element image processing grid.

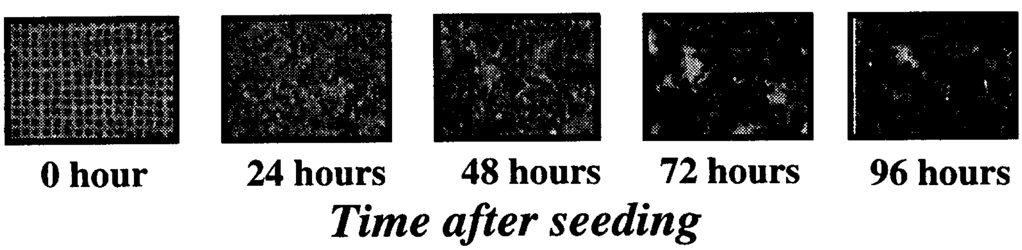

Fig. 3. Digital images showing change in appearance of a community of radish sprout.

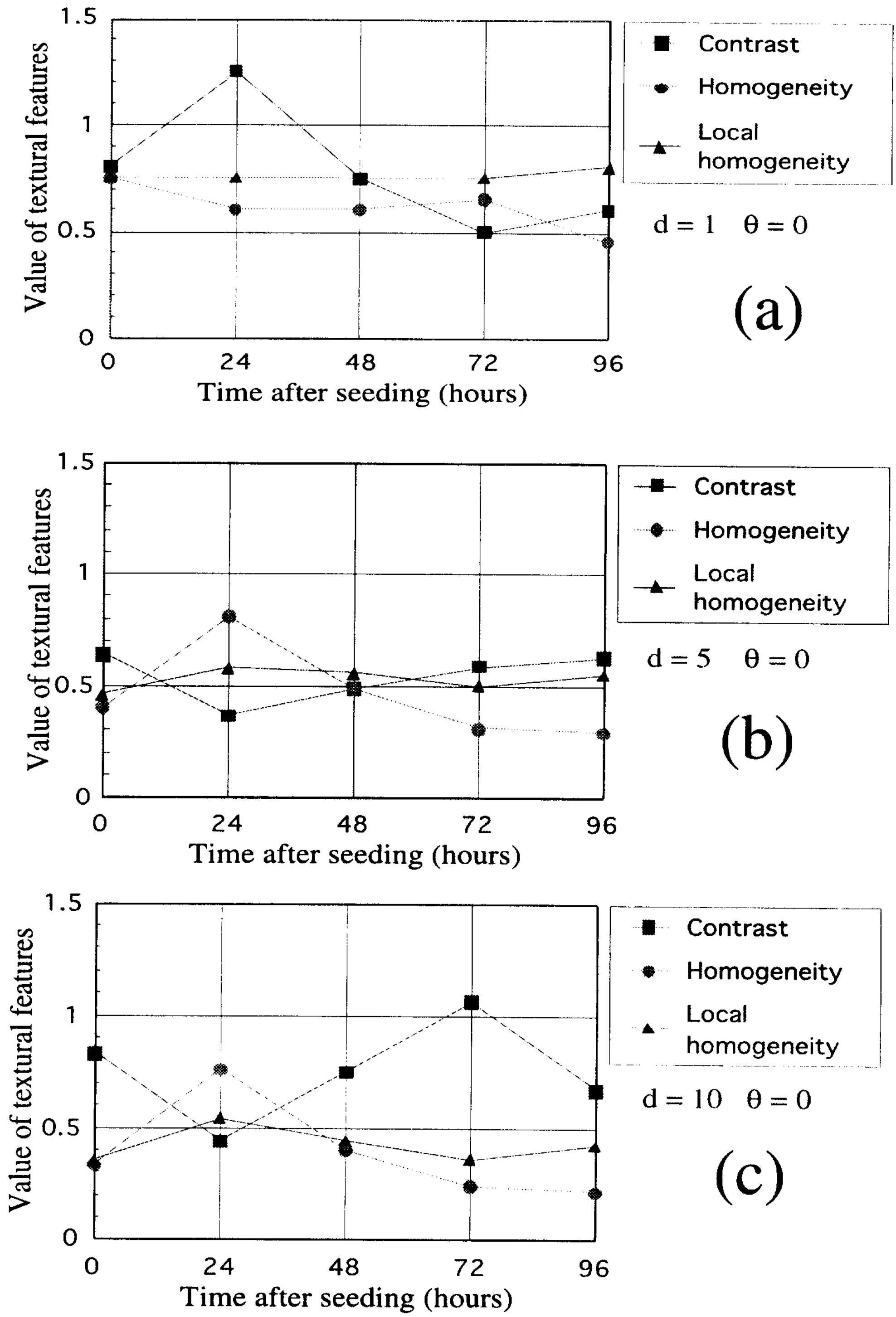

Fig. 4. Variation of textural features due to the change in appearance of a community of radish sprouts.

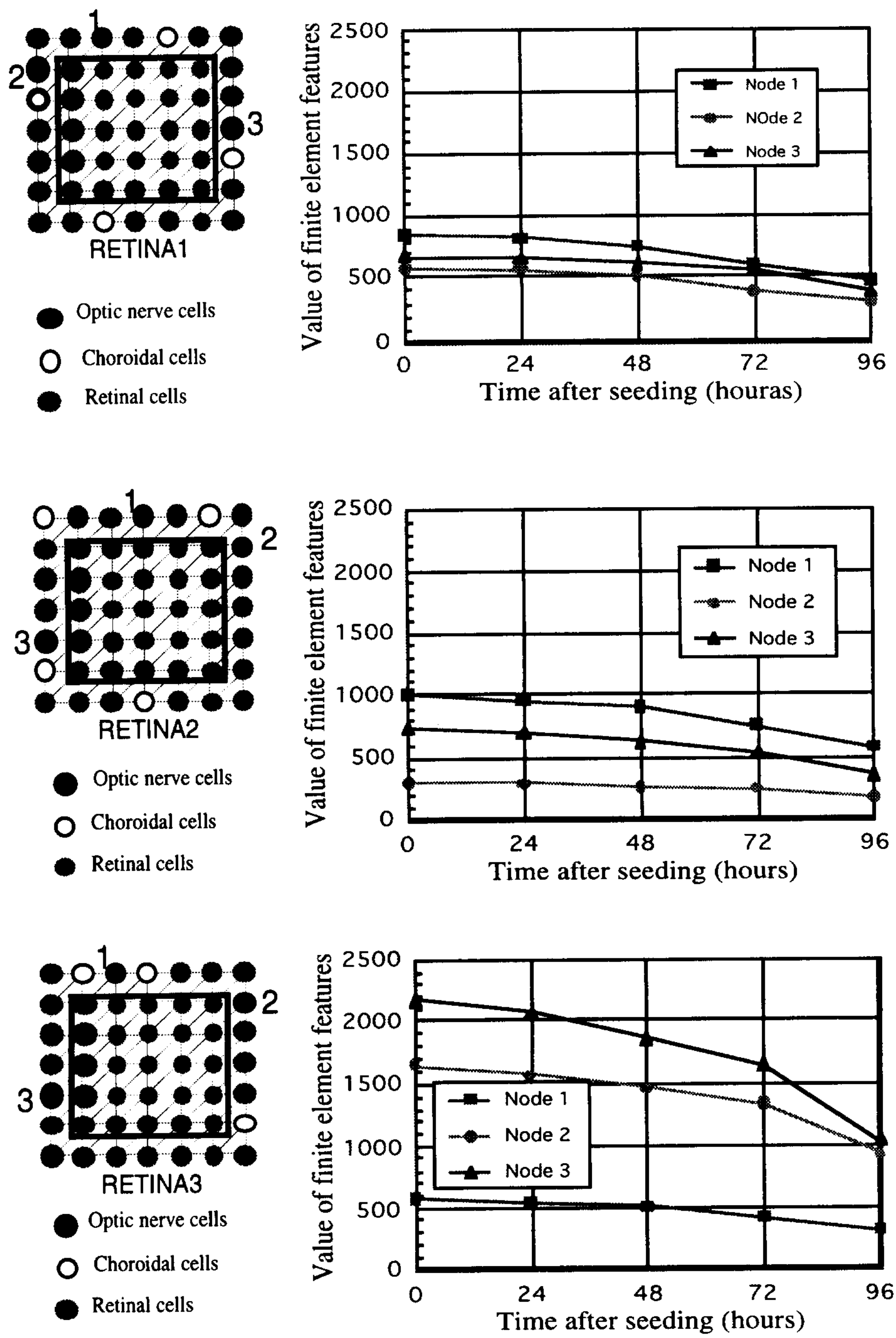

Fig. 5. Variation of finite element features due to the change in appearance of a community of radish sprouts.