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Neural-Genetic Algorithm as Feature Selection Technique for Determining Sunagoke Moss Water Content

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Abstract

This study investigated the use of machine vision for monitoring water content in Sunagoke moss. The main goal is to predict water content by utilizing machine vision as non-destructive sensing and Neural-Genetic Algorithm as feature selection techniques. Features extracted consisted of 13 colour features, 90 textural features and three morphological features. The specificities of this study was that we were not looking for single feature but several associations of features that may be involved in determining water content of Sunagoke moss. The genetic algorithms successfully managed to select relevant features and the artificial neural network was able to predict water content according to the selected features. We propose neural network based precision irrigation system utilizing this technique for Sunagoke moss production.

[Keywords] features extraction, feature selection (FS), machine vision, neural-genetic algorithms, water content sensing.

I Introduction

Sunagoke Moss *Rachomitrium canescens* has been utilized as an active greening material to mitigate the urban heat island effect (Hendrawan and Murase, 2008). However, the supply of moss has not met the market demand because of the fact that moss grows very slowly. Therefore, there is need to develop controlled environmental system to make moss grow faster. In a protected plant production system, such as a plant factory, control applications are limited to environmental controls.

Water constitutes 80-90% of the living plant body and has a large heat capacity. Changes in water content drastically affect the growth and metabolism of plants (Murase et al., 1997). Relationships between CO_2 and water vapour exchange have shown that, in mosses, net CO_2 uptake is positively correlated to water loss (Heijmans et al., 2004).

There are many methods for sensing water condition in Sunagoke moss. Direct measurement of canopy parameters is considered to be relatively inefficient and destructive to the plants. One of the alternatives is the use of indirect measurement techniques. Here, it may be possible to recognize changes in some kind of indices that describe the water conditions from the appearance of wilting Sunagoke moss by machine vision. There have been many studies utilizing machine vision for detecting plant water stress. Kacira et al. (2002) and Yang et al. (2008) developed non-contact and quantitative detection of plant water stress with machine vision extracted plant features. The result of their study suggested that plant water stress detection using projected canopy area based features of the plants was feasible. Foucher et al. (2004) observed that artificial vision could indicate a modification of the state of a plant on the basis of shape analysis methods, allowing a diagnosis in the case of plants where water deficits were fairly high. Many studies have reported use of combination of colour, morphology and textural features to detect stress in plant (Ahmad and Reid, 1996; Escos et al., 2000; Leemans et al., 2002).

It is possible to extract many features from Sunagoke moss images, but it is difficult to determine which features or feature subsets are relevant to measure its water content. Feature selection (FS) techniques can be used to overcome these difficulties. FS techniques have become an apparent need in many bioinformatics applications (Saeys et al., 2007; Unay and Gosselin, 2007; Zapotoczny et al., 2008). FS is a process that chooses an optimal subset of features according to an objective function. It is used to reduce dimensionality and remove irrelevant features.

This study is part of on-going research aimed at developing machine vision-based precision irrigation system in a closed bio-production system for cultured Sunagoke moss. The main goal of this study is to predict water content of Sunagoke moss by utilizing combination of machine vision as non-destructive sensing (to extract colour features (CFs),

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morphological features (MFs), textural features (TFs)) and neural-genetic algorithm as FS techniques.

II Materials and Methods

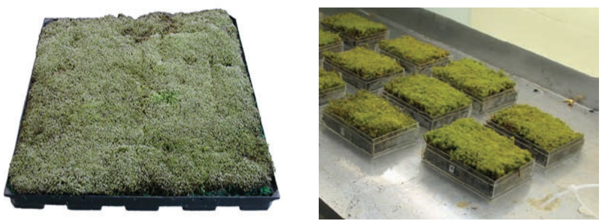
1. Materials and equipments

Study samples were made from living cultured Sunagoke moss mats (500 x 500 x 50 mm, M-3000, VARORE Co., Japan) growing in polyvinyl (PVC) netting and anchored in glass wool media, shown in Fig. 1(a). Ten samples shown in Fig. 1(b), placed in a 110 mm x 80 mm x 25 mm glass vessel were used in this study. Distilled water was given to the samples in the amount of 4 gg^{-1} (4 gram of water content per gram of initial dry weight). Water content (WC) was determined as:

$$WC = \frac{tw - dw}{dw} \quad (1)$$

where : WC is the average water content, tw is the total weight (wet weight) and dw is initial dry weight. Dry weight of moss was determined by drying it in the growth chamber (Biotron NK 350, Japan) with the environment parameters: air temperature = 15°C, RH = 65%, the CO_2 gas = 400 ppm, light intensity = 30 kflux, light duration = 12 h until the weight of the moss samples stabilized without any further decrement. The average initial dry weight of the samples was 12.5 g. Each sample was soaked with 4 gg^{-1} of WC and let to dry until it reached the initial dry weight (0 gg^{-1}).

The steps involved in the experimental design were: (1) image acquisition; (2) features extraction (CFs, MFs and TFs); (3) FS using Genetic Algorithms (GAs) for selecting relevant feature subset; (4) Back-propagation Neural Network (BPNN) training for predicting Sunagoke moss WC. The number of features extracted was: 13 CFs, 3 MFs and 90 TFs. During the drying process, 30 moss image data were collected from each sample in various WC conditions.



(a) (b)

Fig. 1 Cultured Sunagoke: (a) moss mat (b) study samples.

The images were captured using digital camera (Nikon Coolpix SQ, Japan) placed at 330 mm perpendicular to the sample surface as shown in Fig. 2. The image size was 1024 x 768 pixels. Imaging was done under controlled and well distributed light conditions. Light was provided by two 22W lamps (EFD25N/22, National Corporation, Japan). Light intensity over the moss surface was at 100 µmol $m^{-2}s^{-1}$ PPF (Photometer, Li6400, USA) during image acquisition.

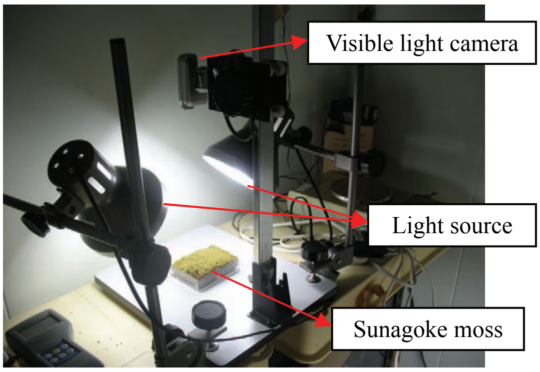


Fig. 2 Image acquisition.

2. Colour features (CFs)

Visible light photography has been effective in determining optimum photosynthesis of moss using green/red ratio (Graham et al., 2006). During the photosynthesis process, plant absorbs red wavelength that makes it reflect less in this wavelength than in the green wavelength. Thus, the more it absorbs in red wavelength the higher the green/red ratio, while photosynthesis is influenced by the plant water status (Hendrawan and Murase, 2009). In computer vision, an image of the sample is digitized into pixels, containing levels of the three primary colours *i.e.* red-green-blue (RGB colour system). The RGB CFs (Hendrawan and Murase, 2009) were described as:

$$average\ red\ index = \frac{1}{M}\sum_{i=1}^{M}\frac{R}{R+G+B} \quad (2)$$

$$average\ green\ index = \frac{1}{M}\sum_{i=1}^{M}\frac{G}{R+G+B} \quad (3)$$

$$average\ blue\ index = \frac{1}{M}\sum_{i=1}^{M}\frac{B}{R+G+B} \quad (4)$$

$$red\ mean\ value = \frac{1}{M}\sum_{i=1}^{M}R \quad (5)$$

$$green\ mean\ value = \frac{1}{M}\sum_{i=1}^{M}G \quad (6)$$

$$blue\ mean\ value = \frac{1}{M}\sum_{i=1}^{M}B \quad (7)$$

$$green/red\ ratio\ mean\ value = \frac{1}{M}\sum_{i=1}^{M}\frac{G}{R} \quad (8)$$

$$green/red\ ratio\ variance = \frac{1}{M}\sum_{i=1}^{M}(x\_gr_i - \overline{x\_gr})^2 \quad (9)$$

where: R (red value); G (green value); B (blue value); M is the total number of pixels; x_gr_i is green/red ratio value and $\overline{x\_gr}$ is green/red ratio mean value.

Hue-saturation-value (HSV) and hue-saturation-lightness (HSL) colour space were developed from RGB colour space using equations 10 to 14.