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Water Irrigation Control for Sunagoke Moss Using Intelligent Image Analysis

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Abstract: A novel technique suitable for noninvasive measurements of moss water content is presented. In this paper, colour image sensing is applied for measuring moss water content. Sunagoke moss *Rhacomitrium canescens* has been utilized as an active greening material to mitigate the urban heat island effect. The goal of this paper is to develop an intelligent image analysis system for water irrigation optimal control in Sunagoke moss. The combination of RGB components (green:red ratio, blue index, blue value and green index) using statistical pattern recognition can estimate water content and define the distribution of water condition in every pixel of Sunagoke moss images. The combination of colour image sensing and Artificial Neural Network (ANN) successfully described the relationship between water content and colour features *i.e.* average green index, average blue index, blue mean value, browning area index, green canopy index and average green:red ratio. This system is helpful to explore a new way of water spraying in Sunagoke moss plant factories based on computer vision. We propose a water irrigation technology of plant factory to realize the automation and precision farming. Precision water spraying system based on computer vision is important, not only for spraying the water scientifically, but also for improving the efficiency of spraying and decreasing the non- or off-target spraying to prevent over watering.

Keywords: Image analysis, artificial neural network, optimal control, plant factories, precision farming.

1. INTRODUCTION

High levels of pollution, population growth, and development in urban areas can increase the heat island phenomenon. The heat island effect can be counteracted slightly by using white or reflective materials. A second option is to increase the amount of well-watered vegetation. These two options can be combined in the implementation of green roof. Some of the benefits of green roof include, 1) reduce heating (by adding mass and thermal resistance value) and cooling (by evaporative cooling) loads on a building; 2) filter pollutants and CO_2 out of the air; 3) filter pollutants and heavy metals out of rainwater; 4) and dramatically improve the insulation value of a roof. Much attention is being paid to the use of moss as green roof materials because of the following characteristics: 1) moss can grow on inorganic materials such as concrete, because it does not need any soil and fertilizer for growing; 2) it also does not add too much extra load to the building roof structure; 3) it can survive under very dry condition; 4) and it is almost maintenance-free (Uemura *et al.,* 2003). In spite of these advantages, 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 a system to make moss grow faster in appropriate environment condition. Sunagoke moss *Rhacomitrium canescens* has been utilized as an active greening material to mitigate the urban heat island effect (Uemura *et al.,* 2003).

Computer vision is a novel technology for acquiring and analyzing an image of a real scene by computers and other devices in order to obtain information or to control processes (Mery *et al.,* 2005). The core technique in computer vision is always related to image analysis/processing, which can lead to segmentation, quantification and classification of images and objects of interest within images. Computer vision has proven successful for online measurement of several agricultural products with applications ranging from routine inspection to the complex vision guided robotic control (Gunasekaram, 1996).

The number of application using computer vision and digital image processing techniques in the agricultural sector are increasing rapidly. The quantification of the visual properties can play an important role to improve and automate agricultural management tasks. Non-destructive methods to analyze the growth and development of plants are becoming common and being applied in practice with the development of computers and electronics devices. Simple visible light digital cameras offer a potential for expanded forms of plant ecological research. A visible light digital camera can be used as a model for simple field estimations of photosynthesis and carbon gain (Graham *et al.,* 2006).

There are many methods for sensing water condition in Sunagoke moss. The direct measurement of canopy parameters is considered to be relatively inefficient, destructive to the plants (Ushada *et al.*, 2007) and can not always provide accurate results at the large scale production of Sunagoke moss in plant factory. In this paper, colour image sensing is applied for measuring Sunagoke moss water content. There are still a few applications of colour image sensing for controlling Sunagoke moss irrigation system. Colour image sensing provides a number of advantages: non-destructive method, non contact measurement and can be used for large scale production of Sunagoke moss in plant factory with more precision irrigation results.

Conventional irrigation for Sunagoke moss growth often apply a fixed water irrigation rate for the whole target and do not consider the variation in the spraying target area. The computer vision system can imitate the human eyes, and recognize the target object according to the extracted information from the real-time images. The researches on precision water spraying system based on computer vision are important, not only for spraying the water scientifically, but also for improving the efficiency of spraying and decreasing the non- or off-target spraying to prevent over watering.

Fig.1. Growing Sunagoke moss in tunnel and the irrigation system

The goal of this paper is to develop an automatic intelligent image analysis for irrigation control of Sunagoke moss cultivation in tunnel. It was subdivided into three objectives *i.e.* 1) developing image analysis technique to determine optimum growth environment of Sunagoke moss based on the RGB colour components; 2) developing Sunagoke moss image analysis and processing software based on water content; 3) and modelling the relationship between water content and colour features using Back-propagation Neural Network. A computer vision system was used to collect red, green and blue (RGB) colour features interactively from slide images of Sunagoke moss.

2. MATERIAL AND METHODS

2.1 System building

As shown in Fig.2, the steps involved in image analysis are (Gonzalez & Wintz *et al.,* 1991):

1. Image formation, in which an image of Sunagoke moss under test is taken and stored in the computer.
2. Image pre-processing, where the quality of the digital image is improved in order to enhance the details.
3. Image segmentation, in which Sunagoke moss image is found and isolated from the background of the scene.
4. Measurement/image analysis, where some significant features of Sunagoke moss image are quantified.
5. Interpretation/water content estimation, where the extracted features are interpreted using some knowledge about the analyzed object.

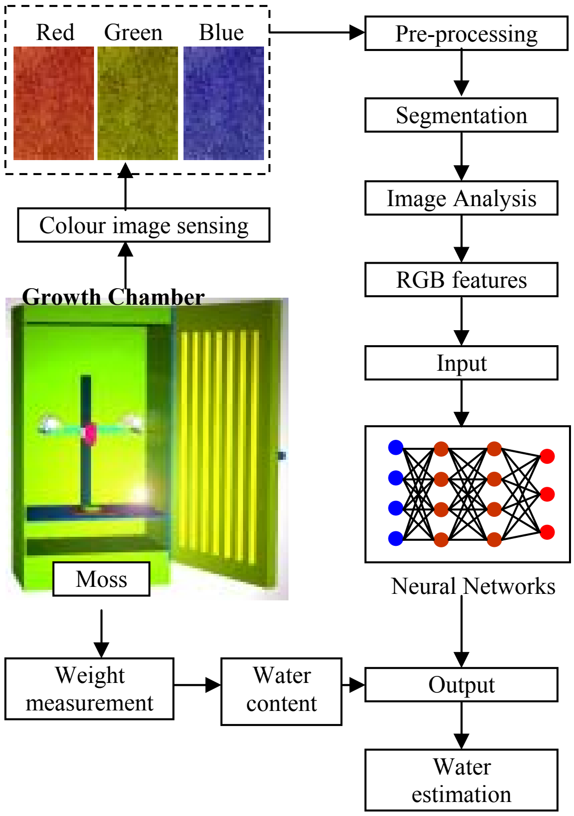

Fig.2. Schematic representation for Sunagoke moss intelligent image analysis

2.2 Growth environment

Sunagoke moss images were taken using a digital camera and processed by image processing algorithm with the image resolution of 400 x 565 pixels. In this study, samples of cultured Sunagoke moss were used. Growth chamber was used to control different variations of environment parameters. The temperature (T) in growth chamber was regulated at 10°C, 15°C and 20°C. Humidity (H) was regulated at 50%, 65% and 80%. Water was given in the amount of 1 gg^{-1} (1 gram water in every 1 gram dry weight of Sunagoke moss), 2 gg^{-1} and 3 gg^{-1}. The light was controlled at 30 kflux (12 hours) and the CO_2 gas was controlled at 400 ppm.

Photosynthesis rate was measured using Li6400 Li-Cor Biosciences Portable Photosynthesis System. Reference cell CO_2 was controlled at 400 μ mol CO_2 mol^{-1}, flow rate to the sample cell: 500 μ mol s^{-1}, leaf area: 88 cm^2, stomata ratio: 1 and external quantum sensor: 100 μ mol m^{-2} s^{-1}.

2.3 RGB components

The RGB components *i.e.* red index, green index, blue index, red mean value, green mean value, and blue mean value were analyzed using image analysis software built in Visual Basic 6. Average RGB index and RGB mean value can be described as:

$$Average\ Red\ index = \frac{\sum \frac{R}{R+G+B}}{\sum pixel\ area} \quad (1)$$

$$Average\ Green\ index = \frac{\sum \frac{G}{R+G+B}}{\sum pixel\ area} \quad (2)$$

$$Average\ Blue\ index = \frac{\sum \frac{B}{R+G+B}}{\sum pixel\ area} \quad (3)$$

$$Red\ Mean\ Value = \frac{\sum R}{\sum pixel\ area} \quad (4)$$

$$Green\ Mean\ Value = \frac{\sum G}{\sum pixel\ area} \quad (5)$$

$$Blue\ Mean\ Value = \frac{\sum B}{\sum pixel\ area} \quad (6)$$

3. RESULT AND DISCUSSION

3.1 Water content and photosynthesis rate

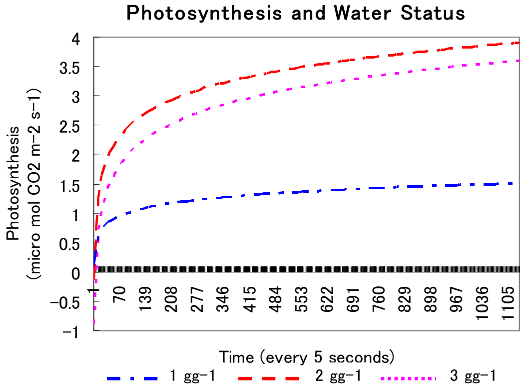

Fig.3. Water content and photosynthesis rate

As shown at Fig.3, Sunagoke moss at 2 gg^{-1} has the highest point of photosynthesis rate compare to Sunagoke moss in 1 gg^{-1} water and 3 gg^{-1} water conditions. From this observation we conclude that the optimum photosynthesis condition was reached when the water content of Sunagoke moss was between 2 gg^{-1} and 3 gg^{-1}. Lack of water and over watering condition can make the photosynthesis process decreasing. Therefore in this paper, we try to make irrigation system of Sunagoke moss using colour image sensing which can stabilize the amount of water between 2 gg^{-1} - 3 gg^{-1}.

3.2 Colour features and growth environment

As shown at Fig.4, at water condition of 2 gg^{-1}, the peak point of average green index and green mean value were at 65% of humidity. In this case, humidity does not directly influence colour features, but humidity affects the evapotranspiration process which influences photosynthesis, while photosynthesis has relation with colour features (Hendrawan *et al.*, 2007). The graphs of green factors and temperature condition show that the peak point of the graphs generally at 15°C of temperature. As the whole result of relationship between colour features and environment condition is that averagely the highest point of the green index (48.9%) and green mean value (169) were found at temperature of 15°C and humidity 65%. Therefore the observation of water content was conducted at this set-point of growth environment.

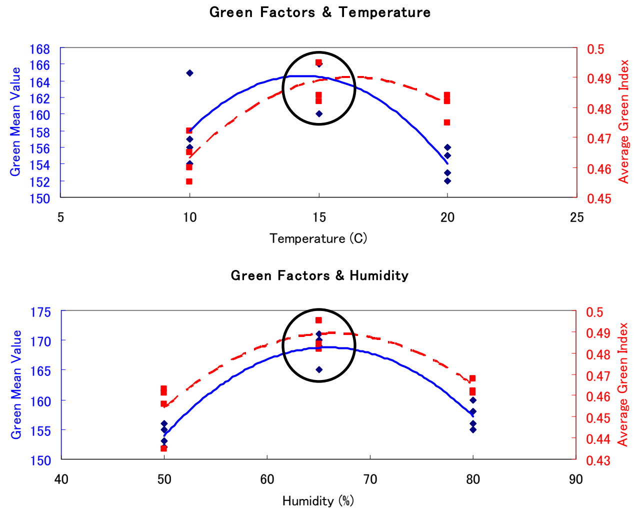

Fig.4. Green factors & growth environment

3.3 Image features and water content

From Fig.5, it is shown that as water content increases, average green index also increases up to peak point between 2 gg^{-1} - 3 gg^{-1} and then decreases until it stabilizes. From Fig.6, it is shown that as the water increases, red mean value decreases to the lowest point of 2 gg^{-1} - 3 gg^{-1} and then increases a bit until it stabilizes.

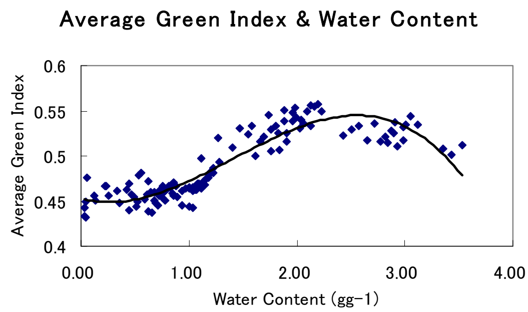

Fig.5. Water content and average green index

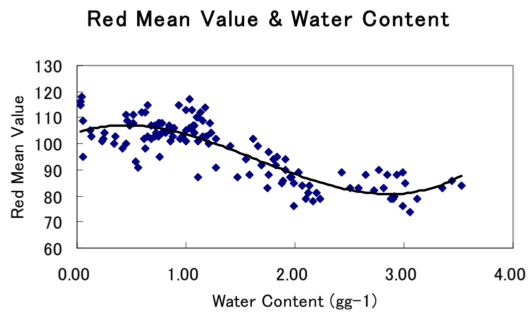

Fig.6. Water content and red mean value

3.4 Image analysis for water content estimation

Visible light photography has been to be effective in determining the percentage of maximal net CO_2 uptake using green:red ratio (Graham *et al.*, 2006). Red referred to a broad band of wavelength (600-699 nm) and green to a broad band of wavelength (500-599 nm). During the photosynthesis process, plant absorbs red wavelength that makes it reflect red wavelength less than green wavelength, so the more it absorb red wavelength the higher green:red ratio value, while photosynthesis has relation with appropriate water existence. If Sunagoke moss does not have enough water or it has too much water, then photosynthesis process will not be optimum. Photosynthesis of Sunagoke moss will be optimum if it has appropriate water content (Fig.3). The graph of different levels of water content (Fig.7) shows that generally Sunagoke moss at 2 gg^{-1} water has higher green:red ratio than Sunagoke moss at 1 gg^{-1} water or 3 gg^{-1}. Fig.8 shows that blue value has a linier correlation with water status. It means that as water content increases, the blue value decreases.

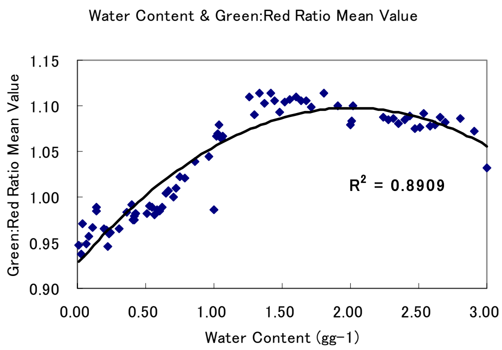

Fig.7. Water content and green:red ratio mean value

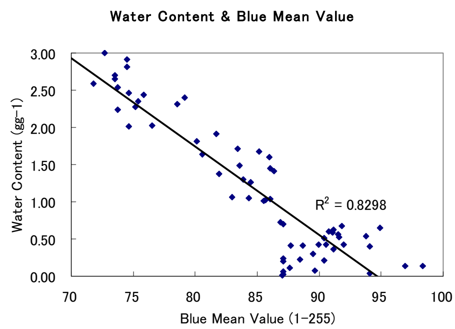

Fig.8. Water content and blue mean value

Using the combination of green:red ratio, average blue index, blue mean value and average green index features we can determine the water content of Sunagoke moss using statistical pattern recognition. The image analysis program was built in Visual Basic 6. From the data obtained from green:red ratio, average blue index, blue mean value and average green index, we can estimate the water condition and classify each pixel of the image into 4 categories of water content *i.e.* dry (water content: 0-1 gg^{-1}), medium wet (water content: 1-2 gg^{-1}), wet (water content: 2-3 gg^{-1}) and over wet(water content: >3 gg^{-1}).

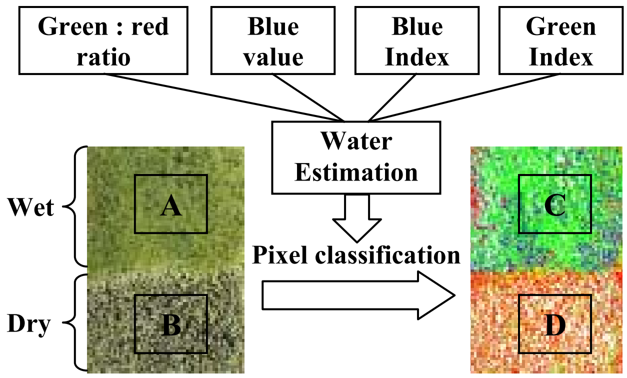

Fig.9. The result of pixel classification on wet and dry Sunagoke moss

Fig.9 shows the image of Sunagoke moss in which half part was given water [A], and another part left in dry [B]. Using the combination of green:red ratio, average blue index, blue mean value and average green index, we can determine the distribution of water content level of each pixel. The result is shown at the pixel classification image *i.e.* blue colour (15.73%) as over wet pixel, green colour (37.33%) as wet pixel, yellow colour (22.88%) as medium wet pixel, red colour (24.05%) as dry colour and white colour as background colour. The pixel classification image (Fig.9) shows the different colour distribution in Sunagoke moss, the wet part [C] was dominated by green and blue colour, and the dry part [D] was dominated by red and yellow colour.

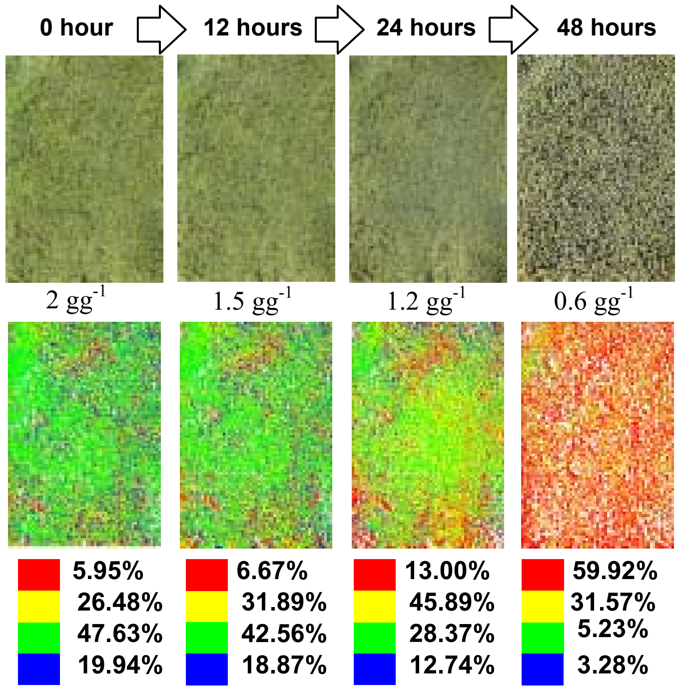

Fig.10. Water content estimation and pixel classification

Using this combination, we can classify pixel into 4 categories *i.e.* dry pixel (red colour), medium wet pixel (yellow colour), wet pixel (green colour) and over wet pixel (blue colour). From the image in Fig.10, it shows the condition of Sunagoke moss after giving water at different periods of time *i.e.* after 12 hours, after 24 hours, and after 48 hours. The process shows that dry and medium wet pixel are increasing from 5.95% and 26.48% to 59.92% and 31.57%, respectively, while wet and over wet pixel decreasing from 47.63% and 19.94% to 5.23% and 3.28%, respectively. The water content is also decreasing from 2 gg^{-1} to 0.6 gg^{-1}. From the validation process (20 validation data) using statistical pattern recognition model, the combination of green:red ratio, average blue index, blue mean value and average green index features can describe the water content of Sunagoke moss with the root mean square error (RMSE) of 0.05.

3.5 Determining water content using back-propagation neural network

Back-propagation supervised learning neural networks were used to develop the relationship between water content and colour image features. These neural networks used 6 inputs (*i.e.* average green index, average blue index, blue mean value, browning area index, green canopy index and average green:red ratio) and water content as the output. Browning process on Sunagoke moss can be influenced by virus, fungi, water content or environment condition. From the chart shown in Fig.11, it shows that water content influences the browning process. When Sunagoke moss stays in dry condition, browning area index is increasing and it will reach minimum point at water level approximately 2 gg^{-1}. The browning process will also increase a bit in over watering condition. Browning area index can be determined using green:red ratio value. The threshold point of browning area index is 0.93-1.13 of green:red ratio value (Hendrawan *et al.*, 2007).

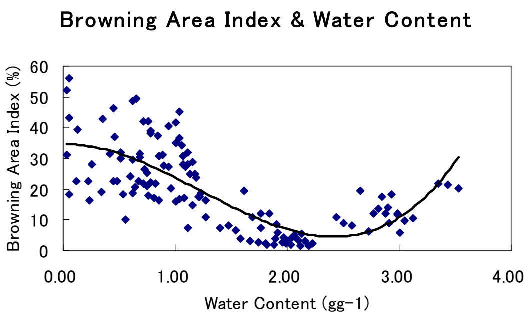

Fig. 11. Browning area index and water content

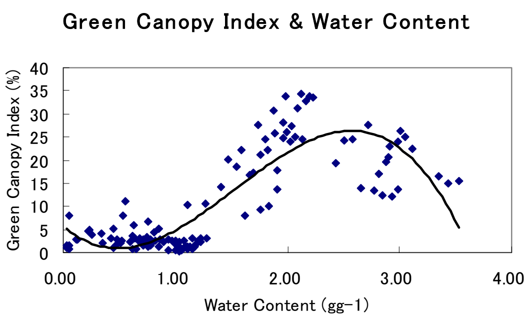

Fig.12. Green canopy index and water content

The threshold point of green canopy index can be determined using green:red ratio value. Green canopy index has relation with water content of Sunagoke moss (Fig. 12). Green canopy index reaches the optimum point at 2 gg^{-1} - 3 gg^{-1} of water content. Sunagoke moss in dry condition has less green canopy index than Sunagoke moss in wet condition (Fig.13). As shown at Fig.14, the threshold point of green canopy index is above 1.71 of green:red ratio value.

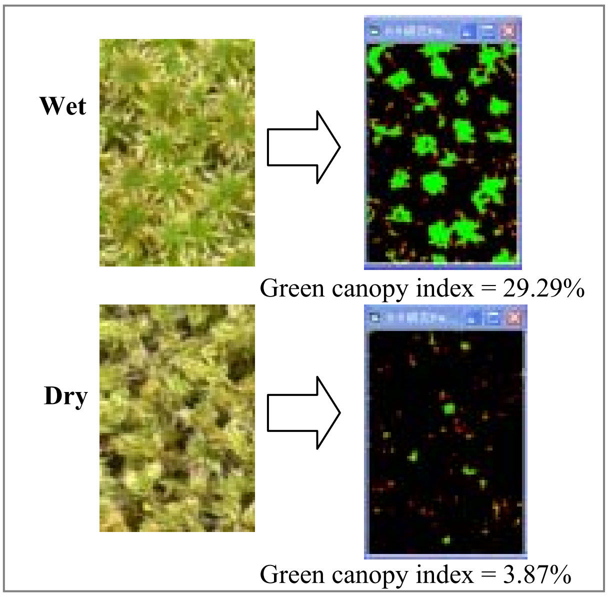

Fig.13. Green canopy index in different water condition

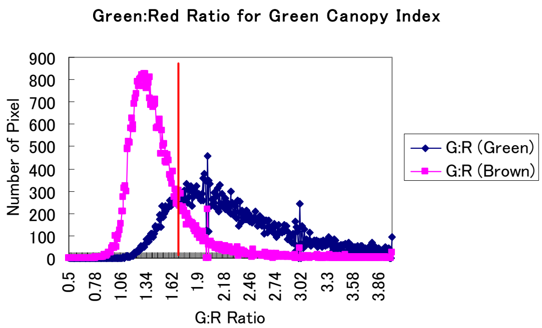

Fig.14. Green:red ratio to determine threshold point of green canopy index

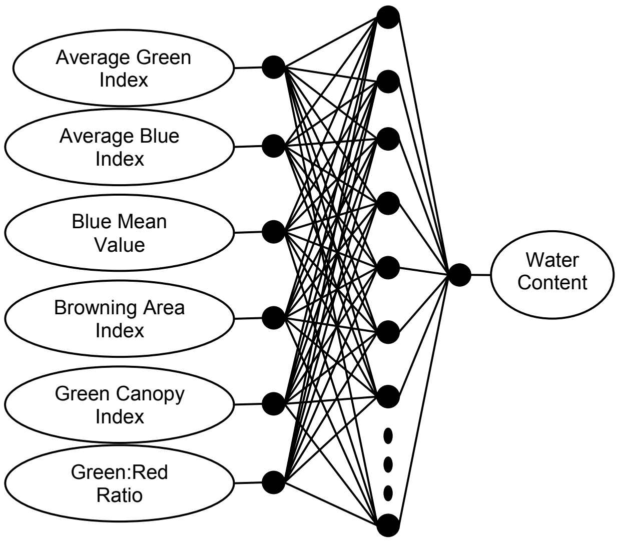

Fig.15. ANN model for water content estimation

The model of back-propagation neural network is shown in Fig.15. The training converged after approximately 40,000 iterations, learning coefficient of 0.1, momentum: 0.9, number of hidden nodes: 21, number of training data: 99 and number of validation data: 20. The training and validation root mean square error (RMSE) value were 0.012 and 0.008, respectively. ANN model performance was tested successfully to describe the relationship between water content and colour image features. The validation RMSE results show that back-propagation neural network method can estimate water content of Sunagoke moss better than statistical pattern recognition method with the efficiency improvement value of 84%.

3.6 Precision irrigation design based on colour image sensing

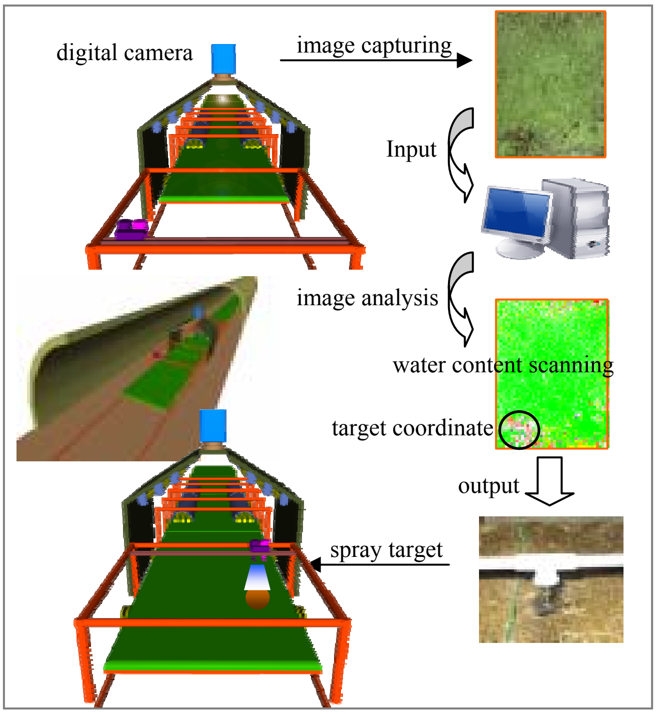

Fig.16. Proposed irrigation control design for growing Sunagoke moss in tunnel

Water content has relation with optimum photosynthesis. Therefore, if we can determine part of area which is lacking water through positioning (coordinate system), then we can automatically give appropriate water at that precise area, so the decrement of dry area can bring Sunagoke moss into optimum photosynthesis process. The proposed irrigation control design of Sunagoke moss is shown at Fig.16. Inside the image processing chamber, Sunagoke moss images are taken by digital camera as an input to be processed using image analysis software which detects dry area with coordinate position as output to be sent to water spray system to irrigate the dry part of Sunagoke moss in accurate places.

4. CONCLUSION

In this paper, a novel technique suitable for noninvasive measurements of Sunagoke moss water content has been suggested. Optimum growth environment of Sunagoke moss (temperature: 15°C, humidity: 65% and water content: 2 gg^{-1} - 3 gg^{-1}) can be described using RGB colour features. The combination of green:red ratio, average blue index, blue mean value and average green index features using statistical pattern recognition can estimate water content and define the distribution of water content in each pixel of Sunagoke moss images. The combination of computer vision and ANN method has successfully described the relationship between water content and colour image features (*i.e.* average green index, average blue index, blue mean value, browning area index, green canopy index and average green:red ratio) and increased the efficiency improvement value (84%).

This system is helpful to explore a new way of water spraying in Sunagoke moss plant factory based on computer vision. We propose water irrigation technology of the plant factory to realize automation and precision farming not only for Sunagoke moss product but also for other plant products.

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