NONDESTRUCTIVE MONITORING OF CHICKEN MEAT FRESHNESS USING HYPERSPECTRAL IMAGING TECHNOLOGY

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ABSTRACT

This study investigated the capability of hyperspectral imaging technology for monitoring the freshness of chicken meat during storage. Fresh chicken meats were prepared and stored in a refrigerator at 4 °C for 8 days. Hyperspectral images were obtained every 24 hours for meat samples with ImSpector V10E, and the average spectral reflectance data for each sample were extracted. The bacteria in colony forming unit (CFU) for each meat sample was measured by the basic bacterial cultivation techniques. Simple correlation analysis and the two band vegetation index (TBVI) methods were used to develop the spectra-based CFU prediction models. Results indicated that the model with the TBVI based on the wavelengths 700 nm and 650 nm achieved the optimal estimation of CFU on meat surface (R^2=0.9328). The TBVI values based on the above two wavelengths were calculated for all pixels on meat images, and were visualized by displaying the TBVI values for all corresponding pixels on a new image. The predicted CFU for meat samples were then calculated and visualized by incorporating the model into the new TBVI image. The results demonstrated the promising potential of hyperspectral imaging technology for the detection of bacteria on meat surface.

Index Terms — hyperspectral imaging, colony forming unit (CFU), two band vegetation index (TBVI), monitoring, freshness

1. INTRODUCTION

Meat is an important part of a balanced human diet. It is a major source of protein, and helps build lean muscle mass in human body. Meat also provides high levels of iron and vitamins, as well as all of the nearly two dozen different types of amino acids that the human body requires on a daily basis [1]. Meat is edible raw, but is normally eaten after it has been cooked or processed in a variety of ways. Uncooked or unprocessed meat will easily spoil within hours or days. This spoilage is practically unavoidable because the infectious bacteria and fungi may be borne by the animal itself, the people handling the meat, and/or the implements [2]. Therefore, timely and accurate detection of the spoilage will help discriminate the quality and safety of meat products.

The concerns over pathogenic bacteria within meats have illustrated the requirement for a rapid and accurate detection system for microbial spoilage of meats. Many methods are currently available to detect the spoilage bacteria loads such as the standard colony-counting method [3], and several other modern molecular biological and immunological techniques [4,5]. However, these techniques still depend on destructive samplings and need follow a series of complicated procedures. This is not only costly but also time-consuming.

Hyperspectral imaging has been widely used to obtain and map the temporal and spatial variability in agricultural and food industry. Numerous studies have demonstrated the usefulness of hyperspectral imaging for estimating various agronomical parameters of crops within fields [6], and the quality of agro-products after harvest [7]. This study attempted to explore the potential of the hyperspectral imaging technology for estimating and visualizing bacterial contamination in meat products.

2. MATERIALS AND METHODS

2.1. Hyperspectral image acquisition

The present study chose to study the freshness of chicken meat, which is one of the most commonly consumed meat products in Japan. Fresh chicken meats were purchased from a local super market, and 16 samples (approximately 50~60g) were prepared and stored in a refrigerator at 4 °C for 8 days. During the storage, the hyperspectral images was acquired for 2 of the meat samples every 24 hours with ImSpector V10E (Spectral Imaging Ltd., Oulu, Finland) in the laboratory. All the obtained images cover the wavelength range from 350 nm to 1050 nm with a spectral resolution of 5 nm. The spatial resolution depends on the distance between the sensor and the object to capture, which slightly differs among the samples due to their different thicknesses.

2.2. Determination of number of viable bacteria on meat surface

Immediately after the hyperspectral image acquisition, the number of viable bacteria on the meat samples was measured every 48 hours using the basic bacterial cultivation techniques. In the experiments, 10g test specimen was prepared for each meat sample. The ready-to-use standard plate count agar media (Kenis, Ltd., Japan) were used to cultivate the viable bacteria in the test specimen with the dilution culture method. The prepared culture discs were incubated at 35°C for 48 hours. After cultivation, the number of viable bacteria was counted and recorded, and was finally calculated in terms of the colony forming unit (CFU) per gram.

2.3. Spectral data extraction, spectra-based viable bacteria prediction and visualization

The average spectral reflectance data for each meat sample were extracted with the software. The extracted reflectance data were then used to relate to the number of viable bacteria in each meat sample. Simple correlation analysis and the two band vegetation index (TBVI) were used to develop the spectra-based bacteria prediction models.

In recent years, the two band vegetation index (TBVI) has been developed as an alternative tool to the conventional normalized difference vegetation index (NDVI) to assess various agricultural crop characteristics [8]. In this study, the TBVI was used to identify the best two narrow band-based predictor of bacterial contamination. TBVI can be calculated by:

$$TBVI = \frac{R_{\lambda 1} - R_{\lambda 2}}{R_{\lambda 1} + R_{\lambda 2}} \quad (1)$$

where $R_{\lambda 1}$ and $R_{\lambda 2}$ are the reflectance values at the indicated wavelengths λ (nm). Since the hyperspectral data consists of 132 wavelengths in this study, TBVI can be calculated based on different combinations of the narrow band wavelengths.

Several analyses were sequentially carried out as follows: Firstly, simple correlation analysis was conducted between the calculated TBVIs and the number of viable bacteria. Secondly, the TBVI that has the best correlation with the number of viable bacteria was selected, and the wavelength used for calculation of this TBVI was identified. Thirdly, the TBVI values based on the above two wavelengths were calculated for all pixels on the meat images, and were visualized by displaying the TBVI values for all corresponding pixels in a new image. Finally, the predicted number of viable bacteria for the meat samples were then calculated and visualized by incorporating the model into the new TBVI image.

3. RESULTS AND DISCUSSION

3.1. Hyperspectral characteristics of meat surface

Figure 1 summarizes hyperspectral characteristics of the measured meat samples. The results indicate that there are significant differences in the spectral reflectance among the samples measured at different storage times during the experiment, though all the samples show a similar pattern along the wavelength range. This suggests that the spectral variations may provide useful information to estimate the number of viable bacteria on meat surfaces during the storage process.

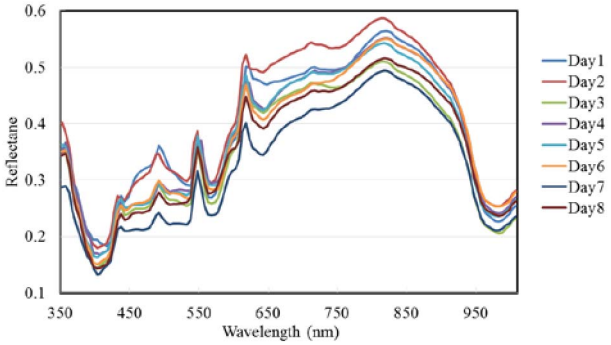

Fig. 1 – Average hyperspectral characteristics of meat samples stored for different time durations.

3.2. Change in the number of viable bacteria on meat surface during storage

Figure 2 shows the changing trend of the number of viable bacteria growth with the increase of refrigerator storage time (day). The number of viable bacteria on meat surface increased gradually in the two measurements on the first and the third days of storage, and then showed a sharp increase in the later measurements during the rest of storage days. The CFU values varied from 2.8 to 6.4 log10 CFU/g, showing a significant pattern of exponential growth.

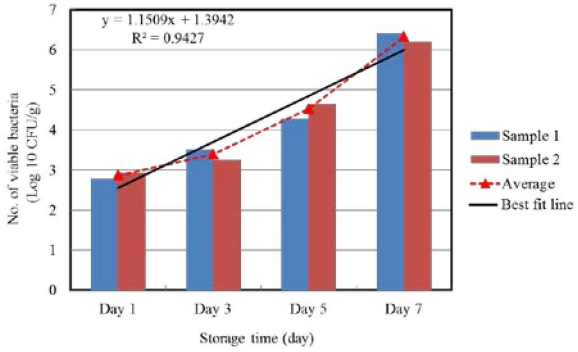

Fig. 2 – Change in number of viable bacteria on meat samples stored for different time durations.

3.3. Simple linear correlation between number of variable bacteria and reflectance of individual wavelength

Figure 3 shows the correlation coefficient spectrum between the number of viable bacteria and the average spectral reflectance at each wavelength for the meat samples. All the wavelengths individually showed a negative correlation with the number of viable bacteria. Among the wavelengths, the wavelength 360 nm, and the wavelength ranges 435~535 nm and 615~740 nm showed the highly significant correlations, with the negative correlation coefficients of less than -0.8.

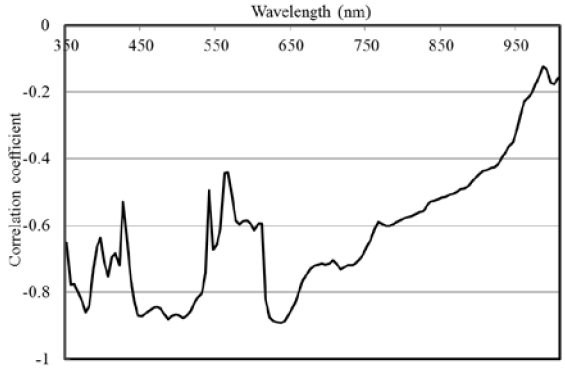

Fig. 3 – Correlation coefficient spectrum between number of variable bacteria and reflectance of individual wavelength.

3.4. Selection of the key wavelengths and calculation of the optimal TBVI

Figure 4 shows the 2-dimensional plot of the correlation coefficients between TBVI and number of variable bacteria on meat samples. TBVIs were calculated for 132 narrow bands spread across λ_1 (350 nm to 1050 nm) and λ_2 (350 nm to 1050 nm) from the hyperspectral data. It was found that the TBVIs calculated for the R-NIR range (635~850 nm) show a region of high correlations with number of viable bacteria. Further, the TBVI calculated for 700 nm and 650 nm wavelengths was found to have the highest correlation with number of viable bacteria (R^2=0.9328) (Fig. 4). Performances of the models based on the individual wavelengths 650 nm and 700 nm, and the TBVI calculated based on the above two wavelengths are shown in Figure 5. The results indicated that although the individual wavelengths 650 nm and 700 nm are not among the wavelengths that show the best correlations with the number of viable bacteria, the TBVI calculated based on these two wavelengths demonstrated the best prediction accuracy for estimating the number of viable bacteria.

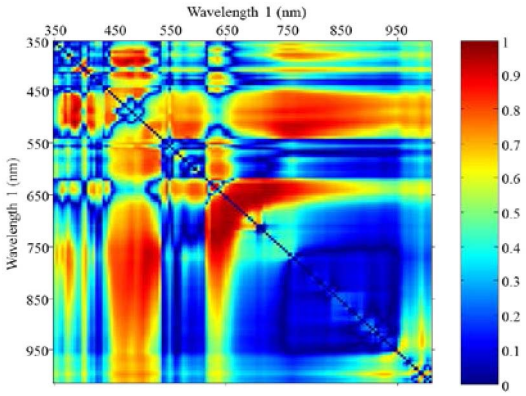

Fig. 4 – Correlation (r) between number of viable bacteria and narrow band TBVI values calculated for 132 narrow bands spread across λ_1 (350 nm to 1050 nm) and λ_2 (350 nm to 1050 nm) from the hyperspectral data.

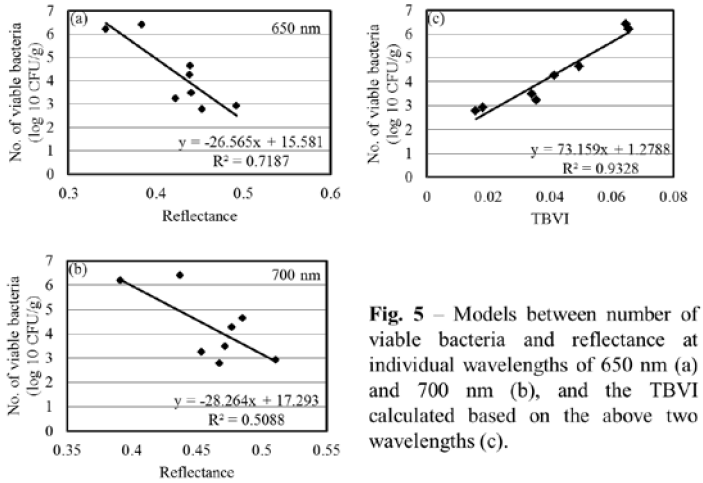

Fig. 5 – Models between number of viable bacteria and reflectance at individual wavelengths of 650 nm (a) and 700 nm (b), and the TBVI calculated based on the above two wavelengths (c).

3.5. Visualization of TBVI values and predicted number of viable bacteria

To illustrate the spatial difference in the identified TBVI on meat samples, the TBVI image for one sample on each day during the storage was calculated based on the hyperspectral image data. Figure 6a shows the raw image displayed in RGB (R: 660 nm, G: 560 nm, B: 460 nm). Figure 6b illustrates the TBVI image calculated based on 700 nm and 650 nm wavelengths. Finally, the number of viable bacteria on meat surface was visualized by incorporating the TBVI model (Fig. 5c) into the TBVI image (Fig. 6b). The generated images in Figure 6c shows the spatial distribution of viable bacteria on the surface of each meat sample. Simple visual inspection of the images for different storage days clearly shows an increase in the number of viable bacteria with increasing storage time, suggesting the deterioration of freshness and quality of the meats over storage time. In addition, a clear spatial variability in the

number of viable bacteria was also found on meat surface, and the extent of this variability on meat surface become more obvious as the storage time increases. Because the identified TBVI shows a highly significant correlation with the number of viable bacteria (R^2=0.9328), the generated TBVI image (Fig. 6b) and the image of viable bacteria distribution (Fig. 6c) looks very similar.

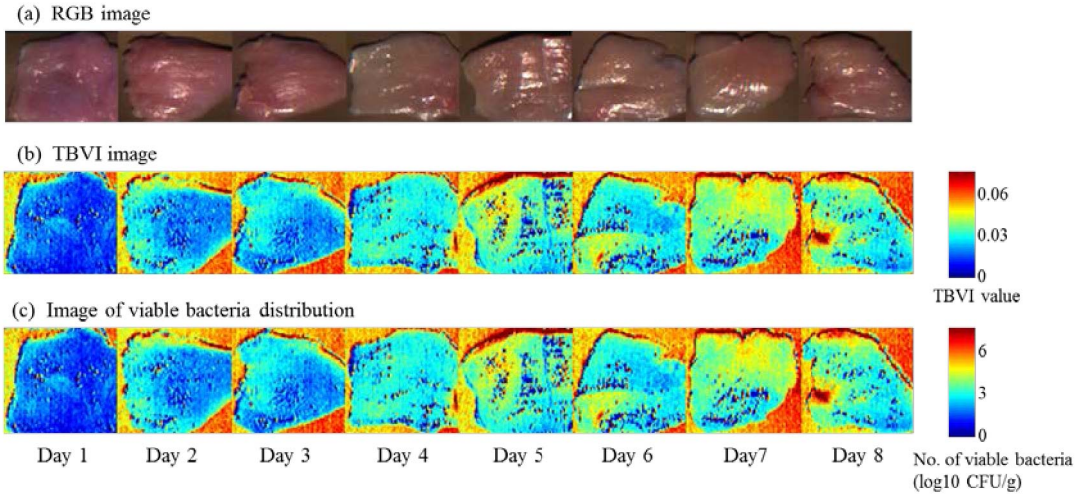

Fig. 6 – RGB image and the visualized TBVI values and predicted viable bacteria distribution for samples stored for different time durations.

4. CONCLUSIONS

This study examined the capability of hyperspectral imaging for estimating and visualizing the number of viable bacteria on chicken meat surface. Hyperspectral imagery data were obtained every 24 hours for meat samples under cold storage condition for 8 days. The bacteria in colony forming unit (CFU) for each meat sample was measured by the basic bacterial cultivation techniques. Simple correlation analysis and the two band vegetation index (TBVI) methods were used to develop the spectra-based bacterial prediction models. Results indicated that the model with the two band vegetation index (TBVI) based on the wavelengths 750 nm and 650 nm achieved the optimal estimation of bacterial contamination on meat surface (R^2=0.9328). The TBVI values based on the above two wavelengths and the predicted number of bacteria were calculated and visualized. The generated images clearly illustrated the increase in both TBVI values and number of viable bacteria over storage time, suggesting the deterioration of freshness and quality of meat samples. The results showed the potential of hyperspectral imaging in detecting the degree of bacterial contamination on meat surface. This technology provides a nondestructive approach for assessing the freshness of meats during storage, and could be possibly applicable to the online monitoring of meat products in food factory.

ACKNOWLEDGEMENTS

This research was supported by JSPS KAKENHI (B) (no. 23380147) and the NSFC (no. 61273062).

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