HYPERSPECTRAL IMAGING FOR MUSHROOM (AGARICUS BISPORUS) QUALITY MONITORING

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ABSTRACT

A method for mushroom quality grading based on hyperspectral image analysis in the wavelength range 400-1000 nm is presented. Different spectral and spatial pre-treatments were investigated to reduce the effect of sample curvature on hyperspectral data. Algorithms based on chemometric techniques (Principal Component Analysis and Partial Least Squares Discriminant Analysis) and image processing methods (masking, thresholding, morphological operations) were developed for pixel classification in hyperspectral images.

Keywords— hyperspectral, imaging, mushrooms, chemometrics

1. INTRODUCTION

Mushrooms commonly exhibit surface browning due to physical impact during picking, preparation and distribution. Browning and bruising of the mushroom surface lead to reduced shelf life and lower returns to producers. Therefore there is a need for objective evaluation of mushroom quality to ensure that only high quality produce reaches the market. Conventional mushroom quality grading methods are based on the luminosity or L-value [1]. However, due to the contact nature of this approach it is not feasible for use as an online for routine quality measurement. Consequently, the mushroom industry relies on subjective and labor-intensive human inspection. Hyperspectral imaging (HSI) is an emerging technology for food quality monitoring which combines imaging and spectroscopy to provide pixel-level spectra of a scene. HSI thus expands the potential of RGB imaging, enabling a wider spectral range to be examined [2].

The objective of this work was to develop a mushroom quality monitoring system using hyperspectral imaging.

2. MATERIALS AND METHODS

In order to create groups of varying quality levels, mushrooms were subjected to vibrational damage. This was achieved by shaking 24 mushrooms in a plastic mushroom box (FP01, JF McKenna Ltd, N. Ireland) at 400 rpm for five time periods: 0, 60, 120, 300 and 600s. The mushrooms were then designated into respective quality classes as follows: undamaged = "U", 60s vibration = "D60", 120s vibration = "D120", 300s vibration = "D300", 600s vibration = "D600". The vibration of mushrooms in this manner induces development of browning on the mushroom surface. Twenty four mushrooms were examined per damage level, making a calibration set of 120 mushrooms (set 1); the experiment was repeated on an independent set of mushrooms 2 weeks later (set 2) giving a test set size of 120 mushrooms.

Colour measurements were performed using a diffuse CIE standard 'D65' illuminant, an angle of observation of 0º and a measurement area of 25 mm of diameter. Colour was measured from the middle region of the mushroom cap using a hand held tristimulus colorimeter (make: Minolta, Model CR 331, Osaka Japan). Three readings were taken at different positions on the cap per mushroom and average values were reported. Measurements were recorded in CIE Lab (1976) colour space, i.e. lightness variable L* and chromaticity coordinates a* (redness/greenness) and b* (yellowness).

The hyperspectral imaging system (Spectral Scanner, DV Optics, Padua, Italy) used in this research consisted of a high performance CCD camera (580 × 580 pixels), a spectrograph (Specim V10E) attached to the camera covering the spectral range between 400 and 1000 nm, a zoom lens, a tungsten halogen light source transmitted through fibre optics, a moving translation stage and a computer to acquire the images [3]. A two point reflectance calibration was performed; the bright response ('W') was obtained by collecting a hypercube from a uniform white ceramic the reflectance of which was calibrated against a tile

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of certified reflectance (Ceram Research (N.00608 of 28 May 2004)); the dark response ('dark') was acquired by turning off the light source, completely covering the lens with its cap and recording the camera response.

It may be desirable to employ spectral or spatial pre-processing in order to decrease spectral variability introduced by sample morphology as is the case for mushrooms. Spectra were subjected to two commonly used chemometric pre-treatments: multiplicative scatter correction (MSC) and standard normal variate (SNV) [4]. For the MSC pre-treatment the mean spectrum of the mushroom was used as a target spectrum. Mean and maximum image normalisation were also applied to the data; for these methods each image plane in the hypercube was divided by the mean and maximum image respectively.

Classification of spectral data was achieved using a selection of modelling approaches commonly found in the literature: Principal components analysis (PCA) combined with linear discriminant analysis (PCA-LDA); PCA combined with quadratic discriminant analysis (PCA-QDA); Partial least squares discriminant analysis (PLS-DA) and Spectral Angle Mapper (SAM) [5,6]. Models were built to discriminate between undamaged ("U") and impact damaged ("D") mushrooms. Mean pixel spectra (average spectra from 9 neighbours) randomly selected from the pooled hyperspectral data of mushrooms representing the "U" class and the "D60" (damaged by vibration for 60s) class were used for model building (number of spectra in calibration set ('cal')= 2,500; number of spectra in test set ('test')= 2,500).

3. RESULTS AND DISCUSSION

Colour images of the mushrooms subjected to different damage levels, obtained using a digital camera, are shown in Figure 1(a). It can be seen that there is a quite a large visible difference between the colour of the undamaged samples and those shaken for 5-10 minutes; however, mushrooms subjected to the lower damage levels show little visible difference compared with the undamaged ones. Mean intensity images of mushrooms (obtained from the hyperspectral image cubes) were pooled for each damage level and their corresponding pooled histograms are shown in Figure 1(b).

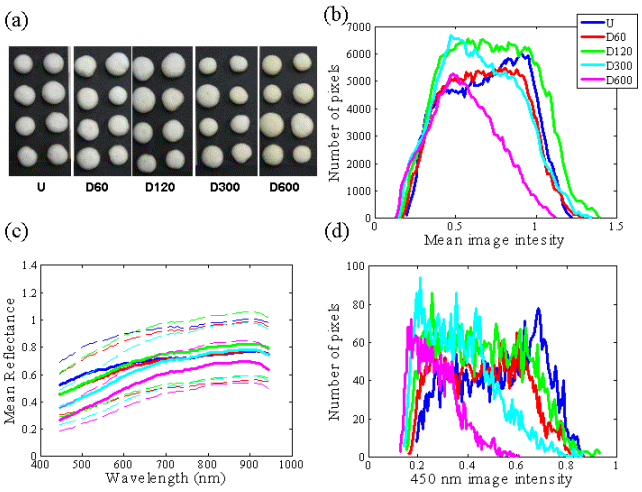

Figure 1. (a) Digital colour images, **(b)** Pooled histograms of mean intensity images, **(c)** Mean (solid lines) and mean ± standard deviation (dashed lines) spectra of mushrooms and (d) Pooled histograms of 4 subjected to different damage levels, where U = undamaged, Dn = damaged for n seconds (n = (60, 120, 300, 600)).

The histogram distribution of the undamaged mushrooms and that of mushrooms subjected to the lowest damage level (60s shaking) are very similar in shape to each other and overlapping. This indicates they exhibit similar mean hyperspectral responses. This is in agreement with the colour images (Fig 1(a)) from which differences between these groups are not readily visible. It is evident from these overlapping histograms that discrimination between the different mushroom quality levels would not be feasible using the mean intensity images. The mean reflectance spectra for each damage level (Fig. 1(c)) demonstrate their spectral similarity and the large variance in the spectral response. They do, however, indicate that the shorter wavelength region (450-500 nm) may be more useful for damage detection than the longer wavelength region, since the separation of mean spectra according to damage level is greatest here. Reflectance images obtained at 450 nm were pooled for each damage level and their corresponding pooled histograms are shown in Figure 1(d). Although there is less overlapping in these histograms than for the mean intensity histograms (Fig. 1(b)), there is still considerable overlap among classes, especially between the undamaged mushrooms and those subjected to the lowest damage level (D60). This indicates that single wavelength reflectance images would not be suitable for discrimination of the different damage levels and that more advanced data analysis is necessary.

In order to aid in the selection of the optimal pre-processing method, discriminant models were applied to both non pre-

processed reflectance spectra and to SNV, MSC and MNorm pre-processed spectra. The percentage misclassification rate for each model/pre-processing combination is shown in Table 1. The first two principal components (describing 99 % of the variance in the data) were used in the PCA-LDA and QDA models. Two latent variables were used in the PLS-DA model and a threshold of 0.5 was used for discrimination. The MSC pre-treatment was clearly optimal in terms of model performance and the PLS-DA model performed best for pixel classification, resulting in 100% correct classification for the calibration and test sets of data. Out of those tested, the SAM algorithm performed the worst. This seems reasonable since the SAM method relies on spectral shape differences among samples for discrimination; as previously stated the mean spectra for each damage level were very similar in shape (see also Fig. 1(c)).

PrP	**Data**	**Model**			
		PCA-LDA	*PCA-QDA*	*PLSDA*	*SAM*
None	cal	0.035	0.5	6.22	44
	test	8	50	7.5	39
SNV	cal	0.35	0.46	6.1	48
	test	30	47	10.3	47
MNorm	cal	0.14	0.15	5.8	40
	test	16.9	16.4	8	33
MSC	cal	0.28	0.28	0	29
	test	62.5	35.2	0	7

Table 1. Percentage misclassification for models applied to pixel spectra from calibration (cal) and test data sets, where PrP = Pre-processing method.

The PLS regression vector arising from the pixel-spectra analysis (described above) was applied to MSC pre-treated hyperspectral images of all mushrooms in the calibration and test set (in total 240 mushrooms) to create prediction maps. The mean predicted pixel value for each mushroom was calculated and is plotted in Figure 2 (a). The model performed similarly for the two independent test sets, indicating its robustness. The mean predicted pixel values tend to increase with damage level, indicating the model's potential usefulness for classifying mushrooms into different quality grades (as opposed to just classifying them into 2 groups (i.e. undamaged and damaged)). The good performance of the PLS model for higher damage levels (outside the range of the model) is surprising, since the model was developed on just 2 classes (U and D60).

Pooled histograms showing the distribution of the predicted pixel values from the entire mushroom surface (Figure 2(b)) demonstrate excellent separation between the undamaged and damaged mushrooms. Comparing this with the histograms in Figure 1, in which the damage levels were largely overlapped, further highlights the usefulness of this model. It can also be seen that the threshold value of 0.5, used for classification of spectra into undamaged and damaged groups, is justified, since this point naturally separates the undamaged and D60 histograms. Each PLS prediction image was thresholded (pixels greater than 0.5 being assigned a value of 1 ("damaged") and those less than 0.5 being assigned a value of 0 ("undamaged)) and using a maximum voting rule (i.e. the predicted mushroom image was classified as undamaged or damaged corresponding to which class the majority of its pixels belonged) it was found that each model could correctly predict the class (i.e. "U" or "D") of all mushrooms tested.

In order to further test the model, it was applied to an independent set of 60 mushrooms imaged in plastic trays. This dataset included twenty mushrooms that were damaged for just 30s, which is 50% lower than the lowest damage level examined in the previous study. Prediction maps and corresponding histograms for this dataset are shown in Figure 3. The prediction maps (Fig. 3(a)) increase in intensity as the damage level is increased and the model performs well for classification even on the stalk regions of the mushrooms (which were not included in the model building). Some shading effects due to the edges of the container are evident at the edges of the mushrooms; however, these effects do not seem to greatly affect the model performance. The shaded regions manifest as humps on the left hand side of the image histograms (Fig 3. (b)). Examining the image histograms it can be seen that the model distinguishes very well between undamaged and D60 classes, and that a threshold of 0.5 would be suitable for discriminating these classes. It can also be noted that the predicted pixel values are similar to those for the same damage levels induced in the previous dataset (see Fig. 3(b)). The histogram of the intermediate damage level (D30) lies between the other two classes. While not entirely distinct from the undamaged class (i.e. some overlap exists between these classes, mainly in the shaded regions of the D30 image), the histogram peak is distinct enough from the undamaged class to suggest that this model can be used for detection of this low level using a new threshold (e.g. 0.4).

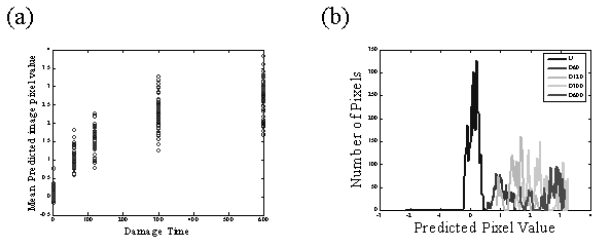

Figure 2. (a) Mean predicted pixel intensity and **(b)** pooled histogram of pixel intensity for PLS model applied to mushrooms subjected to different damage levels, where U = undamaged, Dn = damaged for n seconds (n = (60, 120, 300, 600)).

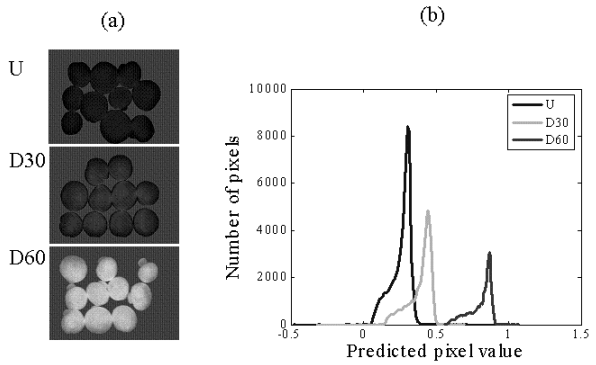

Figure 3. (a) Prediction maps and **(b)** corresponding image histograms for PLS model applied to independent set of mushrooms imaged in trays, where U =undamaged, Dn = damaged for n seconds (n = (30, 60)).

4. CONCLUSIONS

Spectral pretreatments could be used to decrease variability in hyperspectral images of mushrooms arising from curvature in the mushroom surface; multiplicative scatter correction was found to be the optimal pre-treatment in this respect. The use of pixel spectra is to be preferred over mean spectra in building classification models for identification of impact damage on mushrooms. Application of multiplicative scatter correction to mushroom hyperspectral images using the mean spectrum of the sample as a target, resulted in the best model performance with partial least squares discriminant analysis giving the best classification of mushrooms into undamaged and impact damaged groups. The developed PLS-DA model could identify mushrooms subjected to just 30s vibration damage.

5. REFERENCES

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