CFW RESEARCH

Use of Imaging Methods for Assessment of Asian Noodle Color

MUHAMMAD A. SHAHIN,[1,2] DAVID W. HATCHER,[1] AND STEPHEN J. SYMONS[1]

ABSTRACT

Color is the most important factor affecting the appearance and market acceptance of Asian noodles. A scanner-based imaging method was developed to assess noodle color in terms of CIE color scale (L^*, a^*, b^*) using neural networks. The neural networks' predictions based on image measurements correlated well with the spectrophotometric measurements, with an overall R^2 of 0.99, 0.92, and 0.93 for L^*, a^*, and b^*, respectively. Mean error for L^*, a^*, and b^* was 1.35, 3.68, and 2.96%, respectively.

Asia represents a major component of the wheat export market for Australia, Canada, and the United States. Depending on the Asian country, 35–40% of the imported wheat is used for the production of a wide variety of noodles (6). Fresh yellow alkaline and white salted noodles are very popular, and consumer purchasing is initially determined by product appearance (21,22). Noodle appearance can be influenced by flour protein content (23), degree of flour refinement (18), enzyme levels (1), flour particle size and the degree of starch damage (8), the presence of degrading factors (7,13), the type of alkaline reagent used (21,24), enrichment (16), and even the amount of water used in noodle production (9). The most common problem in noodles is speckiness due to the presence of small wheat bran particles in the flour. Wheat bran is a natural component of flour, but its presence and the size of the particles is a function of the degree of flour selection and sieving during the milling process. In many Asian countries, noodles are manufactured daily in small plants and transported to various vendors. The time, elevated temperature, and humidity after production all influence the changing appearance of the noodle product. Bran particles are very rich in a wide variety of phenolic compounds that undergo oxidation by enzymes and yield undesirable colored byproducts (4). Over time (24 hr), large areas of discoloration are produced that cause the consumer to reject the product. Image analysis methods can measure the degradation in noodle appearance.

Image analysis of raw noodles can effectively discriminate a large number of factors influencing final product appearance (14). For example, image analysis can effectively discriminate and quantify the degree of bran contamination and its impact on noodle appearance in both major noodle types (12). Initial research utilized costly CCD cameras to detect undesirable features on noodle surfaces. Refinements in imaging technology, in combination with advances in scanner technology, have resulted in the use of inexpensive scanner systems capable of providing noodle manufacturers with a high degree of appearance assessment and discrimination (28). Continuous advancements in the associated software for the analyses of captured images provides manufacturers with the ability to customize their quality control practices to meet the demands of their market niche (15,26). This technology also allows noodle manufacturing firms to stipulate quality specifications to their suppliers. An operator has the ability to quantify noodle appearance in seconds on the basis of number of specks, size of speck, and discrimination from the background matrix. While the use of inexpensive color scanners provides a wide variety of essential noodle quality information critical to the manufacturer for meeting the continually changing needs of consumers, concurrent color assessment from the captured images will greatly benefit the noodle industry.

The current procedure for assessing the noodle color under either commercial or laboratory conditions is through the measurement of CIE L^*, a^*, and b^* values on a small piece of noodle, usually <2.5 cm in diameter. A series of readings taken across the entire noodle sheet is averaged to quantify noodle color. The use of commercial colorimeters, while objectifying color measurement, does not offer any means to integrate and measure consumer perception of speckiness. An imaging system could potentially measure noodle color as perceived by humans. The captured images of noodles show the overall noodle color represented by the distribution (histogram) of individual color channels. Histograms have been widely used to represent, analyze, and characterize images for pattern recognition and content-based image retrieval from databases (5,25,30). The fundamental task that remains is to somehow relate image color histograms to the CIE L^*, a^*, and b^* values measured with a colorimeter.

Black and Panozzo (2) compared two techniques to predict the color of grains and wheat flour (L^*, a^*, b^*) based on near-infrared reflectance (NIR) spectra. They found that the standard CIE method for computing color (Standard E308-95) performed better than calibrations derived from the spectra and reference colorimeter data. An earlier study (3) showed that a neural network model for converting a device-dependent color space (red, green, blue [RGB] and hue, light, saturation [HLS]) to a device-independent color space (CIE L^*, a^*, b^*) outperformed statistical as well as optimization approaches in terms of lowest error. Neural networks have been widely used for modeling complex problems where input-output relationships are not readily discernible (17,19,27,29). The objective of this study was to incorporate existing noodle imaging refinements with the development of a fast, reliable, and relatively inexpensive imaging method to concurrently predict the color of Asian noodles.

MATERIALS AND METHODS

Wheat Milling and Flour

For this study, 206 samples of different classes of Canadian wheat were received

[1] Grain Research Laboratory, Canadian Grain Commission, Winnipeg, MB, Canada.
[2] Corresponding author. Grain Research Laboratory, Canadian Grain Commission, 303-1404 Main St., Winnipeg, MB R3C 3G8, Canada. Phone: 204/984-7776; Fax: 204/983-0724; E-mail: mshahin@grainscanada.gc.ca.

DOI: 10.1094/CFW-51-0172

from different sources (plant breeders, co-ops); the samples varied greatly in color, ranging from white to red. Each sample was milled on a GRL tandem Buhler mill, as in Martin and Dexter (20), to yield straight-grade flour with an extraction rate of 73–75%.

Noodle Preparation

Flour (50 g) and (1% w/w) kansui solution (9:1 Na to K carbonates) were mixed in a pin mixer for 30 sec (3,000 rpm) using an asymmetrical speed mixer (model DAC 150 FV, FlackTec, Inc., Landrum, SC) according to the method of Hatcher and Preston (11). The dough was sheeted on a laboratory noodle machine (Ohtake, Tokyo, Japan) with an initial gap setting of 3.0 mm, folded longitudinally, and resheeted to duplicate the lamination process employed by commercial noodle manufacturers. The resulting sheet underwent seven further reductions on an Ohtake noodle machine at gap settings of 3.0, 2.55, 2.15, 1.85, 1.57, 1.33, and 1.1 mm, incorporating a 45-sec delay between each pass. The rolls were maintained at 28°C using a circulating water bath. The resulting dough sheet was used for color measurement and image analysis. Two noodle sheets were prepared from each sample.

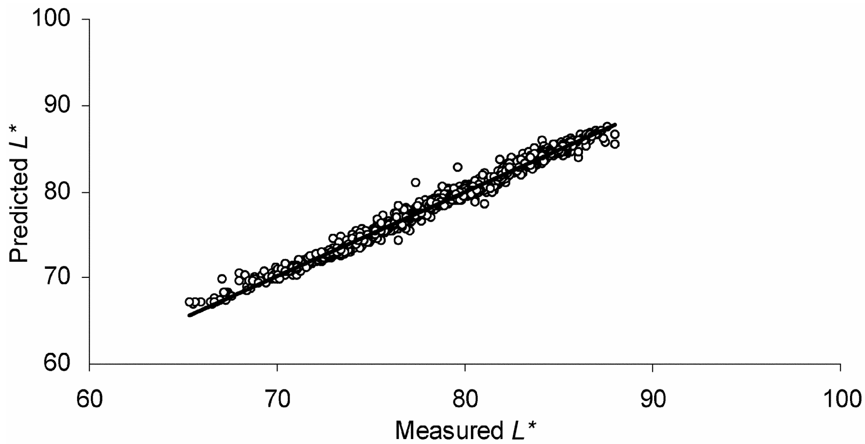

Fig. 1. Overall noodle color (L^*) prediction from image measurements.

Table I. Noodle L^* prediction with a neural network for different datasets[a]

Dataset	R^2	MSE	% Error	Slope	y-Intercept
Training	0.994	0.123	1.02	0.986	1.129
Testing	0.986	0.339	1.66	0.973	2.186
Validation	0.983	0.352	1.71	0.965	2.802
Overall	0.989	0.235	1.35	0.977	1.860

[a] R^2 = coefficient of determination; MSE = mean squared error; % Error = 100 × (mean absolute error)/(range of L^* values); and slope and y-intercept of the linear curve fit.

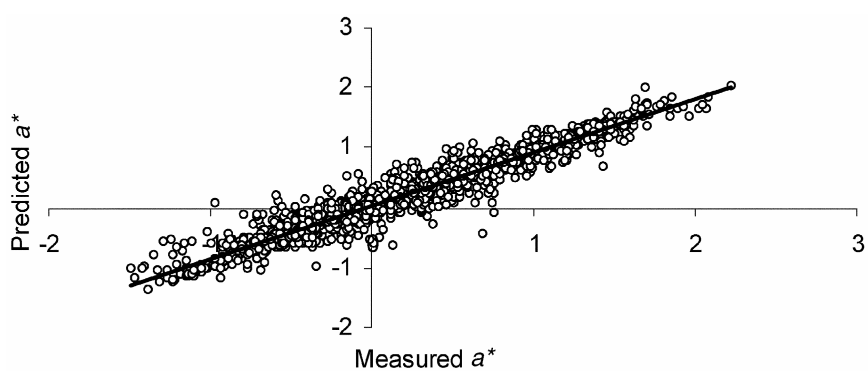

Fig. 2. Overall noodle color (a^*) prediction from image measurements.

Table II. Noodle a^* prediction with a neural network for different datasets[a]

Dataset	R^2	MSE	% Error	Slope	y-Intercept
Training	0.965	0.015	2.30	0.932	0.017
Testing	0.889	0.053	4.78	0.858	0.043
Validation	0.877	0.061	5.19	0.835	0.048
Overall	0.922	0.037	3.68	0.886	0.033

[a] R^2 = coefficient of determination; MSE = mean squared error; % Error = 100 × (mean absolute error)/(range of a^* values); and slope and y-intercept of the linear curve fit.

Raw Noodle Spectrophotometric Color Measurement and Image Capture

A spectrocolorimeter (Labscan XE, HunterLab, Reston, VA) equipped with a D65 illuminant using the CIE 1976 L^*, a^*, and b^* color scale, with a 10° viewing angle, was used to measure raw noodle color. A portion of the raw noodle sheet was folded to provide three layers of thickness and placed on the spectrocolorimeter port. The sheet was enclosed within a blackened container to remove ambient light. Measurements were made in triplicate at two locations on the noodle sheet surface for each sample.

The raw noodle sheet was immediately transferred to an inexpensive scanner-based (Scanmaker 8700, Micotek, Denver, CO) imaging system, where a 5 cm × 5 cm image of the noodle sheet was captured at 800 dpi. Spectrophotometric measurements and image capture were made at 0, 1, 2, and 24 hr, with two replicates at each time period. The raw noodle sheets were stored in a sealed plastic bag at 24°C over the 24-hr period. A total of 1,648 images of raw noodles (206 samples × 4 time periods × 2 replicates) were captured and analyzed.

Image Measurements and Noodle Color Prediction Models

The noodle images were analyzed with imaging software (KS400, Carl Zeiss, Echting, Germany) to measure image features of interest. A set of eight density histogram features per color channel was measured, including minimum, maximum, mean, variance, and gray values at 25, 50, 75, and 95 percentiles. Forty-eight features per image were recorded from the RGB and HLS channels. Using these image features as inputs and the respective spectrophotometric measurements (L^*, a^*, b^*) as the target values, three single-output neural network models were developed to predict noodle color. Each network predicted one of three color components (L^*, a^*, or b^*).

For neural network development, image measurements combined with the respective L^*, a^*, b^* data (patterns) were randomly portioned in three datasets: a training set, a testing set, and a validation set. The training set contained 824 patterns, 50% of the total measurements. The test set contained 330 patterns, 20% of the total measurements. The validation set contained 496 patterns, 30% of the total measurements. In each dataset, an equal number of patterns representing noodle color at 0, 1, 2, and 24-hr time intervals were maintained.

Neural networks were developed with a software package (NeuroShell 2, release 4.0, Ward Systems Group, Inc., Frederick, MD). The generalized regression neural network (GRNN) architecture was employed due to the continuous nature of the color values. The training set, with the appropriate color component (L^*, a^*, or b^*) marked as target output, was used to train the networks with a generic algorithm. While training, network performance was continuously monitored on the test set to avoid overfitting. Training was stopped when a network achieved minimum error on the test set based on the Euclidean distance metric.

Performance of all three networks was evaluated on the three datasets by comparing network predictions with the respective photospectrometric measurements in terms of their correlation. Coefficient of determination (R^2), mean squared error (MSE), slope, and y-intercept of the linear curve fit were used as the performance criteria. Performance on the validation set was considered as a test of robustness, which is a network's ability to generalize to new data not previously seen by the network.

RESULTS AND DISCUSSION

The neural network model successfully predicted noodle brightness (L^*) based on image measurements, with an overall R^2 approaching 0.99 (Fig. 1). The model predictions correlated very well with the values measured for all three datasets (Table I). Very low MSE was shown for the training (0.123), testing (0.339), and validation (0.352) sets. Maximum mean absolute error (MAE) of 0.428 was observed for the validation set, which translates to an error of ≈1.7% on a scale of 65–90 (Table I, Fig. 1). Slope and y-intercept values for the linear curve fitting are comparable for all three datasets.

Figure 2 shows a plot of neural network predictions for a^* (redness) against the spectrophotometric measurements. Network predictions based on image measurements correlated fairly well with the measured values of a^*, with an overall R^2 of 0.922. The network performance on the individual datasets is presented in Table II. R^2 for

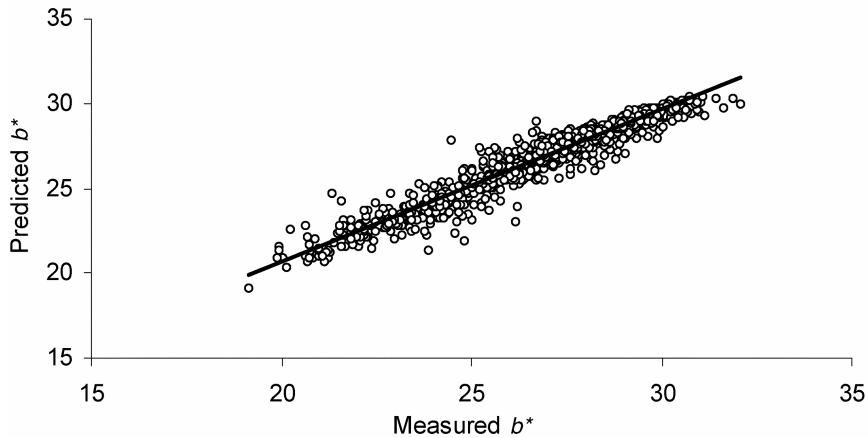

Fig. 3. Overall noodle color (b^*) prediction from image measurements.

Table III. Noodle b^* prediction with a neural network for different datasets[a]

Dataset	R^2	MSE	% Error	Slope	y-Intercept
Training	0.979	0.093	1.66	0.951	1.329
Testing	0.904	0.477	4.03	0.876	3.291
Validation	0.878	0.609	4.43	0.838	4.300
Overall	0.932	0.324	2.96	0.90	2.67

[a] R^2 = coefficient of determination; MSE = mean squared error; % Error = 100 × (mean absolute error)/(range of b^* values); slope and y-intercept of the linear curve fit.

the test and validation sets (≈0.88) was slightly lower than that for the training set (0.965), which accounts for a relatively wider spread of data (Fig. 2). Considering the relatively shorter range of a^* values (–1.5 to 2.2), relatively larger values of MSE were noted for the test (0.053) and validation (0.061) sets. Some variations in the slope and y-intercept values exist for different datasets. The practical significance of these deviations has yet to be determined. Overall, the model was robust enough to accurately predict a^* values from an independent dataset previously not seen by the network. Maximum MAE of 0.192 was observed in the validation set, which translates to an error of ≈5.2% on a scale of –1.5 to 2.2 (Table II, Fig. 2).

For b^* (yellowness) values, neural network predictions based on image measurements correlated well with the measured values, with an overall $R^2 > 0.93$ (Fig. 3). The network performance on the individual datasets is presented in Table III. Low MSE values were observed for the training (0.093), testing (0.477), and validation (0.609) sets. Maximum MAE of 0.576 was observed in the validation set, which translates to an error of <4.5% on a scale of 19–32 (Table III, Fig. 3). Slope and y-intercept values for the linear curve fitting were comparable for all three datasets.

SUMMARY

The scanner-based imaging technique worked very well for predicting noodle color using neural networks. The network predictions correlated well with the measured values for the three color components (L^*, a^*, b^*). Observed error for the three color components was low: 1.7, 5.2, and 4.5% for L^*, a^*, and b^*, respectively. All three network models generalized well to new data previously not seen by the networks. This means that the proposed method can accurately assess noodle color using scanner-based imaging.

We have already developed an imaging system in our laboratory to discriminate and quantify degree of bran contamination in terms of noodle speckiness (10). The next step is to integrate the proposed method of color assessment with the existing speck counting system and evaluate its performance on multiple scanners. A scanner calibration method developed earlier in our laboratory (28) can be used to minimize scanner-to-scanner variations after modifications to deal with the narrow color range in noodles.

The integrated system will let the operator quantify noodle appearance on the basis of overall color (L^*, a^*, b^*), number of specks, and size and color of individual specks in seconds, eliminating not only the need for subjective visual color assessment and strenuous speck counting, but also the need for spectrophotometric color measurements. A single inexpensive imaging system doing both the noodle color assessment and the speck counting would be of particular importance to noodle manufacturers as it would enable them to customize quality control practices to meet the demands of their market niche. This technology will also allow noodle manufacturers to stipulate quality specifications to their suppliers.

CONCLUSIONS

Based on the results of this study, it can be concluded that scanner-based imaging coupled with a neural network technique can be used to assess noodle color accurately compared with spectrophotometric color measurements.

Acknowledgments

We thank M. Anderson and H. Facto of Asian Products, GRL, CGC, for their help in making, measuring, and scanning noodles.

References

1. Baik, B. K., Czuchajowska, Z., and Pomeranz, Y. Discoloration of dough for oriental noodles. Cereal Chem. 72:198, 1995.
2. Black, C. K., and Panozzo, J. F. Accurate technique for measuring color values of grain and grain products using a visible-NIR instrument. Cereal Chem. 81:469, 2004.
3. Cho, M. S., Kang, B. H., and Lou, M. R. Device calibration of a color image scanner digitizing system by using neural networks. Proc. IEEE Int. Conf. Neural Networks. 1:59, 1995.
4. Francis, F. J., and Clydesdale, F. M. *Food Colourimetry: Theory and Applications*. Avi Publishing, Westport, CO, 1975.
5. Funt, B., and Finlayson, G. Color constant color indexing. IEEE Trans. Pattern Anal. Mach. Intell. 17:522, 1995.
6. Hatcher, D. W. Asian noodle processing. Pages 131-157 in: *Cereals Processing Technology*. G. Owens, ed. Woodhead, Cambridge, 2001.
7. Hatcher, D. W., Anderson, M. J., Clear, R. M., Gaba, D. G., and Dexter, J. E. Fusarium head blight: Effect on white salted and yellow alkaline noodle properties. Can. J. Plant Sci. 83:11, 2001.
8. Hatcher, D. W., Anderson, M. J., Edwards, N., and Dexter, J. E. Effects of particle size and starch damage on Oriental noodle quality. Cereal Chem. 79:64, 2002.
9. Hatcher, D. W., Kruger, J. E., and Anderson, M. J. Influence of water absorption on the processing and quality of Oriental noodles. Cereal Chem. 76:566, 1999.
10. Hatcher, D. W., Lukow, O. M., Dexter, J. E., Shahin, M. A., and Edwards, N. M. Recent advances in Canadian research on Asian noodles. In: RACI Nat. Convention—Connect 2005, 55th Cereal Chem. Conf., Sydney, Australia. *In press*.
11. Hatcher, D. W., and Preston, K. R. Investigation of a small-scale asymmetric centrifugal mixer for the evaluation of Asian noodles. Cereal Chem. 81:303, 2004.
12. Hatcher, D. W., and Symons, S. J. Assessment of oriental noodles appearance as a function of flour refinement and noodle type. Cereal Chem. 77:181, 2000.
13. Hatcher, D. W., and Symons, S. J. Influence of sprout damage on oriental noodle appearance by image analysis. Cereal Chem. 77:380, 2000.
14. Hatcher, D. W., Symons, S. J., and Kruger, J. E. Measurement of the time-dependent appearance of discolored spots in alkaline noodles by image analysis. Cereal Chem. 76:189, 1999.
15. Hatcher, D. W., Symons, S. J., and Manivannan, U. Developments in the use of image analysis for the assessment of oriental noodle appearance and colour. J. Food Eng. 61:109, 2004.
16. Izydorczyk, M. S., Lagasse, S. L., Hatcher, D. W., Dexter, J. E., and Rossnagel, B. G. The enrichment of Asian noodles with fiber-rich fractions derived from roller milling of hull-less barley. J. Sci. Food Agric. 2005.
17. Kodaira, K., Nakata, H., and Takamura, M. An apple sorting system using neural network-based image processing. 2nd Neural Network Soc. Meet. Center for Neural Nets Society, Kink's College, London, 1991.
18. Kruger, J. E., Anderson, M. H., and Dexter, J. E. Effect of flour refinement on raw Cantonese noodle color and texture. Cereal Chem. 71:177, 1994.
19. Liu, Z., Cheng, F., Ying, Y., and Rao, X. Identification of rice seed varieties using neural network. J. Zhejiang Univ. Sci. B. 6:1095, 2005.
20. Martin, D. G., and Dexter, J. E. A tandem Buhler laboratory mill. Its development and versatility. AOM Bull. (April), pp. 5855-5864, 1991.
21. Miskelly, D. M. Flour components affecting pasta and noodle colour. J. Sci. Food Agric. 35:463, 1984.
22. Miskelly, D. M. Modern noodle based foods-raw material requirements. Pages 123-142 in: *Pacific People and Their Food*. A. B. Blakeney and L. O'Brien, eds. AACC International, St. Paul, MN, 1998.
23. Miskelly, D. M., and Moss, H. J. Flour quality requirements for alkaline noodle manufacture. J. Cereal Sci. 3:379, 1985.
24. Moss, H. J., Miskelly, D. M., and Moss, R. The effect of alkaline conditions on the properties of wheat flour dough and Cantonese style noodles. J. Cereal Sci. 4:261, 1986.
25. Niblack, W. The QBIC project: Querying images by content using color, texture and shape. Proc. SPIE Conf. Storage Retrieval Image Video Databases 1908:173, 1993.
26. Shahin, M. A., Hatcher, D. W., and Symons, S. J. Automated quality assurance: Noodle-Scanning and TrueGrading at the Canadian Grain Commission. ASABE Resource, January/February, p. 6, 2006.
27. Shahin, M. A., and Symons, S. J. A machine vision system for grading lentils. Can. Biosystems Eng. 43:7.7, 2001.
28. Shahin, M. A., and Symons, S. J. Color calibration of scanners for scanner-independent grain grading. Cereal Chem. 80:285, 2003.
29. Soriano, M., Garcia, L., and Saloma, C. Fluorescent image classification by major color histograms and neural network. Optics Express 8:271, 2001.
30. Stricker, M., and Orengo, M. Similarity of color images. Proc. SPIE Conf. Storage and Retrieval for Image and Video databases III, 2420:381, 1995.