CHEMICAL ENGINEERING TRANSACTIONS
VOL. 58, 2017
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Remigio Berruto, Pietro Catania, Mariangela Vallone

ISBN 978-88-95608-52-5; **ISSN** 2283-9216
DOI: 10.3303/CET1758099

Performance Optimization of Neural-Network Based Colour Measurement Tools for Food Applications

Paolo Barge[a], Lorenzo Comba[b], Paolo Gay[a], Davide Ricauda Aimonino[a], Cristina Tortia*[a], Nahid Aghilinategh[c], Mohammad Jafar Dalvand[c]

[a]DI.S.A.F.A. – Università degli Studi di Torino, 2 Largo Paolo Braccini, 10095 Grugliasco (TO), Italy
[b]DENERG – Politecnico di Torino, 24 Corso Duca degli Abruzzi, 10129 Torino, Italy
[c]D.A.M.E. - University of Tehran, Karaj, Iran
cristina.tortia@unito.it

Colour is the first attribute subject to consumer perception in determining food quality and, in many cases, this is the only possible mean to qualify product at purchase. For this reason, the description of colour by analytical methods is fundamental in food processing control.
Computer vision systems acquire RGB data which are device-dependent and sensitive to the different lightning. Therefore, they are not directly useful for colour evaluation to mimic human vision. On the contrary, traditional colorimeters, which adopt CIELab coordinates, work in human-oriented colour space where euclidean distance between two different colours (ΔE) is well related to the difference perceived by human sight.
Nevertheless, vision systems have many advantages as the capability of acquiring larger areas of the food surface and the easiness of implementation in automated plants at low costs.
Neural networks, trained on a set of selected colour samples, can approximate RGB to L*a*b* relationships to characterise the colour of food samples under test.
The aim of this paper is to present a rapid method based on neural networks for the calibration of a CCD (Charge-Coupled Device) camera colour acquisition system to obtain reliable L*a* b* information. Preliminary results concerning the influence of the composition of the training test and the camera settings (aperture and time of exposure) on the reliability and accuracy of the colour measurement system are also discussed.

1. Introduction

In food processing chains, colour is often checked on production lines to verify the product quality. Traditionally, colour inspection is performed by human eye or by colorimeters, which usually measure the CIELab coordinates with the consequence that the quality control is highly expensive in terms of manpower employed, the colour is affected by subjectivity or, as in the case of colorimeters, a very small area is considered.
The colour acquisition of RGB values by camera sensors has the disadvantage to be dependent on the electronic sensor and on the illuminant. Methods to convert RGB encoded colours in the CIELab colour space have been proposed by different authors (Leon et al., 2006; Valous et al., 2009; Kılıç et Al., 2007; Taghadomi-Saberi et al., 2015). Among these, Artificial Neural Networks gave good results.
This paper aims to investigate the effect of the following factors on the performances of Artificial Neural Networks (ANN) colour calibration:

1) number of hidden neurons in the ANN
2) camera aperture and shutter
3) colours used for training.

The performance was tested separately for different colours using a commercial palette used by photographers for camera calibration.

Please cite this article as: Barge P., Comba L., Gay P., Ricauda D., Tortia C., Aghilinateg N., Dalvand M.J., 2017, Performance optimization of neural-network based colour measurement tools for food applications, Chemical Engineering Transactions, 58, 589-594
DOI: 10.3303/CET1758099

2. Methods

A Nikon D7000 colour DSLR (Digital Single-Lens Reflex) camera with a CMOS (Complementary Metal-Oxyde Semiconductor) image sensor was mounted on a stand and connected with a dome lighting system, which ensured a uniform illumination of food samples. A white plastic hemisphere (350 mm diameter) reflected the light provided by two LEDs circular concentric crowns at the edge of the dome, obtaining a 5500 K colour temperature (Figure 1). The electric power of the lighting system was 8.45 W. The camera and the illumination system were placed into a (500 mm × 600 mm × 900 mm) wooden box internally black-painted to minimise external light and reflection (Valous et al., 2009). This system is a improvement of the equipment used in a previous work (Ricauda et al., 2015).

Figure 1: Picture of the Computer Vision System

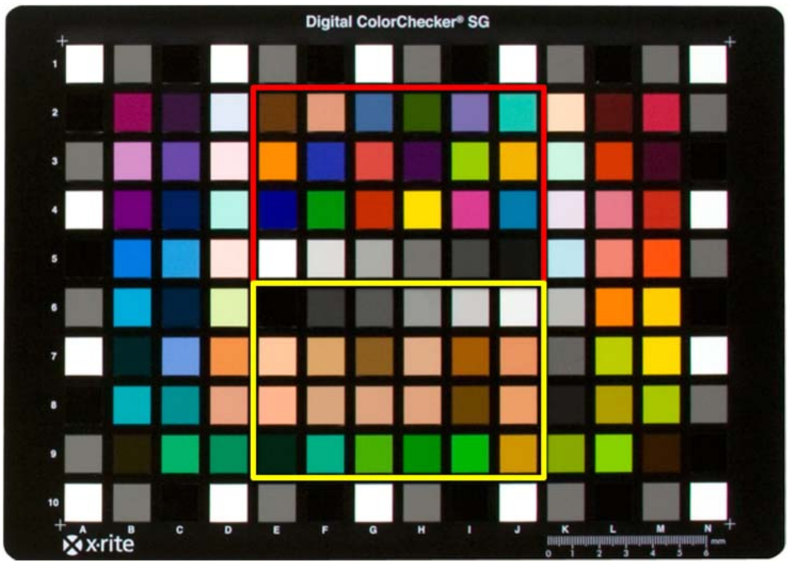

Figure 2: X-rite Digital Colorchecker SG. Zone A and zone B are contoured in red (upper zone) and yellow (lower rectangle) respectively.

The white balance was obtained using a X-rite white balance card. For each colour, 195 pictures of a ColorChecker Color Rendition chart were taken in all combinations of 11 apertures (5.6, 6.3, 7.1, 8, 9, 10, 11 13, 14, 16, 18, 20 and 22) and time of exposure (1/15 s, 1/20 s, 1/25 s, 1/30 s, 1/40 s, 1/50 s, 1/60 s, 1/80 s, 1/100 s, 1/125 s, 1/160 s, 1/200 s, 1/250 s, 1/320 s and 1/400 s). Camera ISO sensitivity was set to 200 and the image resolution at 300 x 300 dpi. Shooting sequence, shutter and aperture were automatically controlled by a PC running the software Digicam Control and a customised Matlab® program.

The ColorChecker Color Rendition chart contains 24 patch of different colours (McCamy et al., 1976) and is widely used in photographic and video sectors for calibration purposes of imaging devices. Another ColorChecker version (Digital SG) was added with other colours (e.g. similar to skin, sky and grass) and more repetitions of grey-scale colours for a total of 140 patches. The manufacturer provides CIE L*a*b* coordinates for illuminant D50 (2 degree obsever) of the various patches for the two different ColorChecker versions as, for toxicity of pigments, in 2014 the firm had to change pigment formulations. Pictures of two zones of the two versions (February 2011 and July 2016) of the Munsell Digital ColorChecker SG (X-rite) were taken separately: a 6x4 patches zone containing the colours of the classic ColorChecker, which is the rectangle defined by the letters E2 (left upper corner) and J5 (right bottom corner) was defined as set A, and a set B, which refers to the zone defined by the E6 (left upper corner) and J9 (right bottom corner) patches (Figure 2).

RGB values were obtained post-processing the acquired images by sampling RGB values in Matlab®. From each colour patch 200 random 10x10 pixel square zones were sampled. Mean RGB values were used to train the neural network, for a total of 4800 RGB data used as input for each photo.

CIE L*a*b* values (2° standard observer, D65 illuminant) were acquired by a Konica Minolta Chroma Meter CR-400 with a CR-A33f glass light-protection tube on Colorchecker. Five repetitions for each measurement were performed.

The Artificial Neural Network (ANN) was composed by an input layer (N_i) containing the three RGB coordinates (Figure 3), a hidden layer (N_h) composed by a variable number of n neurons (with $7<n<12$) and an output layer (N_o) which, in turn, contains the calculated values (O) for the CIELab coordinate considered (O=L, a or b). The feedforward Levenberg-Maruardt backpropagation method was used and run in the software Matlab® NN Toolbox (R2015b).

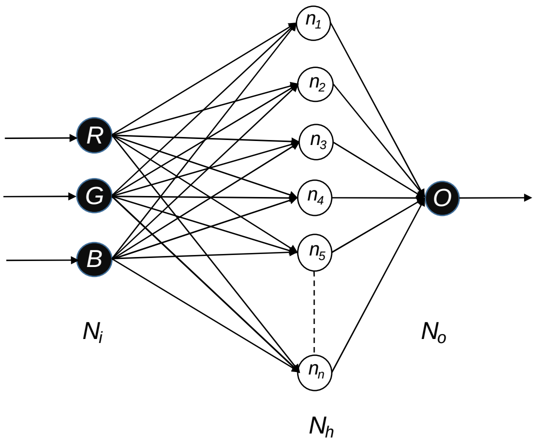

Figure 3: Architecture of the neural network. N_i : input layer, N_h : hidden layer, N_o : output layer.

Initial weights as well as bias values were fixed and taken by a randomly generated matrix in the -0.5÷0.5 range.

Input parameters were the three normalised RGB values while the output were the L* a* b* values. A neural network was obtained for each coordinate. The outputs of the three ANNs were then used to calculate the euclidean distance between the colours acquired by the images and the colorimeter data (indicated by circumflexed letters) following Eq. (1).

$$\Delta E = \sqrt{(L^* - \widehat{L^*})^2 + (a^* - \widehat{a^*})^2 + (b^* - \widehat{b^*})^2} \quad (1)$$

For the ANN training, 58.8% of data were used for training while 23.6% for test, 17.6% for validation. Data acquired by colorimeter were used as target.

A total of three ANNs (one for each of the CIELab coordinate) for each of the 195 pictures containing each 24 colour patches were obtained.

A matrix containing the different factors (shutter time, aperture, number of neurons of the ANN, photo, type of training) was analysed and the euclidean distance was considered as dependant variable.

3. Results

The 2016 Colorchecker zone A colours were used to obtain the first series of ANNs. The ouputs of the ANNs were compared to the Cie L*a*b* values taken on the same zone of the 2011 Colorchecker. Similarly, the training of the network was performed on images of Colorchecker 2016 zone B and tested on the same set of the 2011 Colorchecker.

A colour difference lower than 1.5 among the L*a*b* output of the ANNs and the measurements by colorimeter was considered as a detection threshold of a colour difference difficult to detect by the human eye (Guiné et al., 2015; Pathare et al., 2013).

The analysis was performed on the whole matrix of 56160 cases: 195 images, 24 colours, six type of ANN (7, 8, 9, 10, 11 and 12 neurons) and two colorchecker zone (A and B).

The mean colour difference (Table 1) was quite high but it should be noted that saturated and underexposed images were also considered.

Table 1: Euclidean distance of the ANNs and colorimeter colour values on the two zone of the 2011 Color-Checker. Mean colour difference and number of cases of patch colour at $\Delta E < 1.5$ are reported.

ANN neurons number	Colorchecker zone A		Colorchecker zone B	
	Mean ΔE	% cases ΔE<1.5	Mean ΔE	% cases ΔE<1.5
7	4.67	21.6%	6.25	9.9%
8	4.07	27.1%	5.63	13.2%
9	4.79	29.3%	5.58	14.9%
10	3.71	32.5%	5.68	17.6%
11	3.76	34.4%	5.24	19.7%
12	3.29	35.9%	5.06	20.8%

It was demonstrated that increasing the neurons number from 7 to 12 the ANN efficiency improved. This can be seen both from the mean euclidean distance as well as the rate of cases where differences among colours acquired by colorimeter and those calculated by the ANN have ΔE<1.5 which is considered a colour difference hard to be perceived by human eyes (Pathare et al., 2013).

The colour difference was greater when the net was trained in zone B. This may be due to the fact that the colour palette was much more uniform.

Some colours were poorly identified by the ANN, as shown in Figure 4. In many factors combinations, the ANN has reached the target to correctly recognise the colour (at < 1.5 ΔE) for colour present in both of two zones of the Color-Checker (Figure 4 and 5).

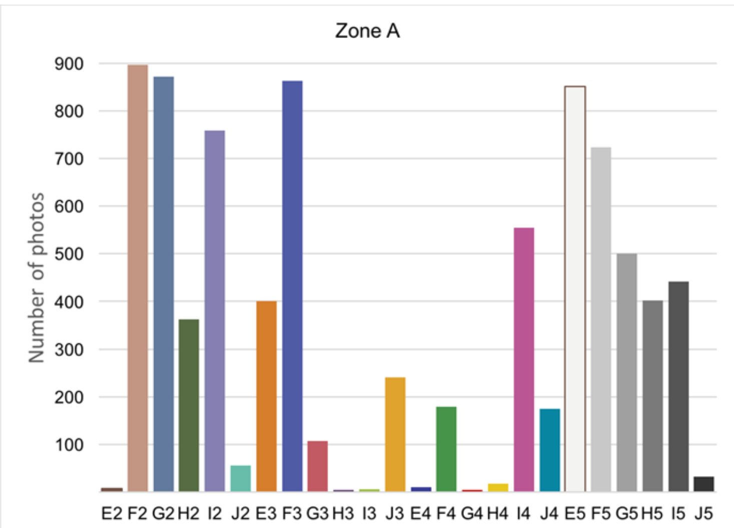

Figure 4: Comparison of the ability of the ANN (12 neurons) to distinguish the different colours for both the zone of the 2011 Color-Checker. The number of photos by which colours are distinguished at euclidean distance above 1.5 are reported for each colour (Zone A colours).

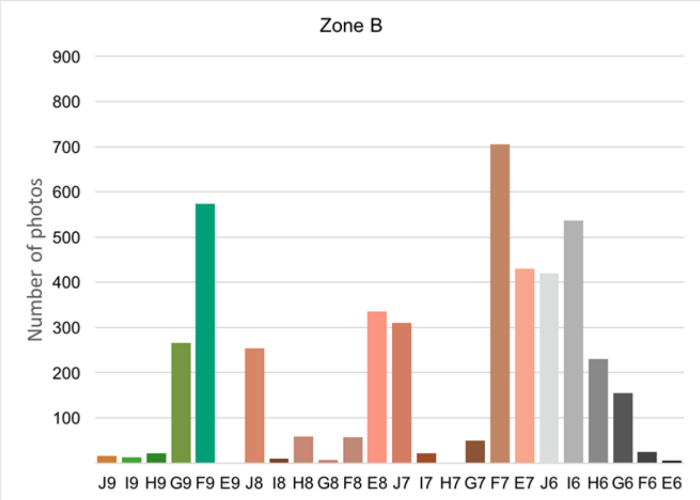

Figure 5: Comparison of the ability of the ANN (12 neurons) to distinguish the different colours for both the zone of the 2011 Color-Checker. The number of photos by which colours are distinguished at euclidean distance above 1.5 are reported for each colour (Zone B Colours).

Nevertheless for some colours (E2, J2, H3, I3, E4, G4, H4 in zone A and J9, I9, H9, E9, I8, H8, G8, F8, I7, H7, G7 in zone B) the euclidean distance was very high. Among these, dark grey and black were also poorly discernible.
It was observed that, using this method and choosing the 12 neurons ANN, it was possible to have good results only on maximum of 13 colours per photo, demonstrating that optimal shutter and exposure is different for each of the considered colours.
For a possible use in food quality control the aperture/shutter combination for colour calibration of the ANNs should be chosen targeted to the dominant colour of the sample. In any case, the shooting of more than one image in different shutter/aperture combination could be envisaged.

4. Conclusions and perspectives

An Artificial Neural Network model was proposed for colour measurement which could be applied in food quality control. This tool has the advantage to consider a wider area respect to traditional colorimeters and to reduce costs for products colour checking. The method could be used for different food products and eventually paired to other on-line applications for image processing such as defect detection, classification and sorting. The proposed vision system could be adopted by food industries to control products during the processing phase, evaluating in advance possible defects and ensuring standard sensorial characteristics.
Nevertheless, the system has proven to give good results only for some of the considered colours. For this reason, the improvement of the ANN learning is envisaged (e.g. increasing the number of colours in the training phase).

Notation

ANN	Artificial Neural Network
CIE	Commission internationale de l'éclairage
L^*	Luminance or Lightness component of colour in the CIELab colour space calculated by the neural network
a^*	Red and green component of colour in the CIELab colour space calculated by the neural network
b^*	Yellow/blue component of colour in the CIELab colour space calculated by the neural network
$\widehat{L^*}$	Luminance or Lightness component of colour in the CIELab colour space measured by the colorimeter
$\widehat{a^*}$	Red and green component of colour in the CIELab colour space measured by the colorimeter
$\widehat{b^*}$	Yellow/blue component of colour in the CIELab colour space measured by the colorimeter
ΔE	Euclidean distance between two different colours
CCD	Charge-Coupled Device
CMOS	Complementary Metal-Oxyde Semiconductor
RGB	Red Green Blue
DSLR	Digital Single-Lens Reflex

Acknowledgments

This work was partially supported by the grants of the projects FoodVision and ColorEvolution (POR-FESR – Regione Piemonte).

Reference

Guiné R.P.F., Almeida C.F.F., Correia P.M.R., Mendes M., 2015. Modelling the influence of origin, packing and storage on water activity, colour and texture of almonds, hazelnuts and walnuts using Artificial Neural Networks, Food and Bioprocess Technology, 8, 1113-1125, doi 10.1007/s11947-015-1474-3

Kılıç, K., Onal-Ulusoy, B., Yıldırımİsmail, M., Boyacı, H., 2007 Scanner-based color measurement in L*a*b* format with artificial neural networks (ANN), European Food Research & Technology, 226 (1), 121-126.

Leon K., Mery D., Pedreschi F., Leon J., 2006. Color measurement in L*a*b* units from RGB digital images. Food research international, 39, 1084-1091, doi http://dx.doi.org/10.1016/j.foodres.2006.03.006.

McCamy, C.S., Marcus, H., Davidson, J. G., 1976. A Color-Rendition Chart. Journal of Applied Photographic Engineering, 2(3), 95–99.

Pathare, P.B., Opara, U. L., Al-Said F. A. J., 2013. Colour measurement and analysis in fresh and processed food: a review. Food and Bioprocess Technology, 6 (1), 36-60, doi 10.1007/s11947-012-0867-9

Ricauda Aimonino, D., Barge, P., Comba, L., Gay, P., Occelli, A., Tortia, C., 2015, Computer vision for laboratory quality control on frozen fruit, Chemical Engineering Transactions, 44, 175-180, doi:10.3303/CET1544030.

Taghadomi-Saberi, S., Omid, M., Emam-Djomeh, Z., Faraji-Mahyari, K., 2015. Determination of Cherry Color Parameters during Ripening by Artificial Neural Network Assisted Image Processing Technique, J. Agr. Sci. Tech., 17, 589-600.

Valous, N.A., Mendoza F., Sun, D.W., Allen, P., 2009. Colour calibration of a laboratory computer vision system for quality evaluation of pre-sliced hams, Meat Science, 81, 132-141.