SPECTROPHOTOMETRIC CHARACTERISATION OF COLOUR CLASSIFICATION SYSTEM OF BEEF MEAT

Albertí P[1]., Sañudo[2] C., Bahamonde[4] A., Olleta[2] J.L., Panea[2] B. Goyache[3] F., Alonso[4] J., Díez[3] J. Fernández[3] I.
[1]Servicio de Investigación Agroalimentaria DGA. Avda. Montañana 930, E-50016 Zaragoza, Spain. palberti@aragob.es
[2] Facultad de Veterinaria. C/ Miguel Servet, 177, E-50013 Zaragoza, Spain
[3] SERIDA-CENSYRA- Somió, C/ Camino de los Claveles 640, E-33208 Gijón, Spain
[4] Centro de Inteligencia Artificial. Universidad de Oviedo in Gijón, Campus de Viesques, E-33271 Gijón, Spain

Background

Meat colour is very important on a commercial level since consumers associate colour and appearance with texture and taste. Colour may be affected by breed type. Specialised beef breeds and light carcasses have pale muscle while rustic breeds and heavy carcasses tend to have red coloured meat.
The spectrophotometer is widely used to objectively measure meat colour, including lightness (L*) redness (a*) yellowness (b*) chroma and hue, all of which define colour. This technique could also help to assess carcass colour classification (Albertí et al., 1993). However, colour is a three-dimensional complex appearance, formed by three attributes: lightness, chroma and hue that may have different rankings, while people define colour using abstract assessments. Therefore, these two measurements may often disagree.
In general, the use of a colour standard improves the prediction of meat colour compared to visual assessment without a standard (Eikelenboom et al., 1992). More recently, the digital camera has also been used in technical imaging applications (Chalmers, 2000; Goyache et al., 2002) including the assessment of meat colour.

Objectives

The aim of this study was to classify, in a few number of groups, meat colour of young bull carcasses commercialised in Spain based on intervals of L*, a*, b*, chroma and hue values. The final goal of the study was the development of a printable colour standard for a meat colour classification system on a Spanish commercial level.

Methods

Eighty light (191 kg) and seventy-six heavy (335 kg) carcasses from young bulls representing seven Spanish beef breeds were used to determine the colour of the *longissimus dorsi* muscle. The carcasses were cut 24 hours after slaughter. At 0 hours (cut time) the colour was measured on three levels on the central part of *longissimus dorsi*-10th rib, into the CIE, L*, a*, b* colour space, by a Minolta CM 2002 spectrophotometer. Samples were stored in a plastic tray wrapped with gas permeable PVC film at 3ºC. The measurement was repeated 24 hours after the first cut (time 24 h).
A representative sample of 23 *longissimus dorsi* was used which included a range from pale to red. A picture was taken of each sample and printed on glossy paper (HP DeskJet colour printer). Fifteen experts make the assessments of colour on these paper prints. The palest rib received 1 point and the most red 23 points. We forced our panel to classify the 23 ribs following this gradient. The mean score was calculated for each sample.
We analysed our scored sample by means of a Machine-Learning algorithm developed by the Artificial Intelligence Centre at the Oviedo University (Díez et al., 2002, unpublished). The description of the algorithm is far of the objective of this study. Briefly, the algorithm learns functions able to assess objects using the information obtained from the comparison of the description a set of objects. Our algorithm tries to find a function that when applied to the colour descriptions (L*a*b) returns a number from 1 to 5 in such a way these value reproduce the human assessments mentioned above. To measure the degree of coincidences between functional and human assessments we consider all possible pair of samples where the first one is paler than the second one. Thus, we analysed a total of 253 (= 23 * 22/2) pair wise descriptions The function obtained by the Machine-Learning algorithm was used to compute a muscle colour classification from the available L*, a*, b* values in the whole population, and the mean and standard error were calculated by group (SAS, 2001).

Results and discussion

The function found by the algorithm can be computed in two steps. In the first one we obtain the number

$$X = 19458.534567\ L + 650053.45616652\ Hue - 648208.89320775,$$

where the hue was calculated from the L*, a*, b* data as Hue= atang (b*/a*). Finally, we found:

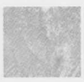
$$\text{Colour sorting} = \text{Round}\,(-0{,}00000000000670195\ X^2 + 0{,}0000115493\ X + 0{,}61378015)$$

This function coincided with human ordering in 70% of the 253 comparisons using the 23 sub-samples. This was a very high degree of coincidence, since the humans only judged printed photos, while the learning algorithm was fed with L*a*b* data.
Lightness L* and hue were the best predictors of colour. Hue is a good predictor of meat colour since hue is a relation between redness and yellowness, which it is related with colour stability (Farouk and Swan, 1998). As the hue angle decreases, colour becomes more stable.
Table 1 summarises the means and standard deviations for five meat colour groups. Redness, yellowness and chroma values overlapped in the five groups. However, lightness and hue angle were well defined between groups. Figure 1 shows why these overlaps occur. Lightness, yellowness and hue decrease steadily from pale to dark red, while redness tends to increase and decreases in a curvilinear manner. Therefore, redness alone is not useful to classify meat colour.
We can conclude that, the muscle colour of carcasses of yearling category, can be classified into one of five groups proposed by measuring L* and hue angle values and applying the function we reported. These results have been calculated for the range of meat colour of yearling bulls commercialised in Spain. Further research will be needed to validate the learning function we reported here by means of visual assessments performed with the help of representative pictures as standards of the 5 meat colour classes

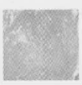
Table 1 Colour standard sorting of muscle *longissimus dorsi* from bulls of seven Spanish beef breeds

	Colour classes					
	1. Pale	2. Pink	3. Pale red	4. Red	5. Dark Red	Sig.
n	131	79	63	28	11	312
L* lightness	$40,1^{a}$±2.24	$37,2^{b}$±2.88	$35,2^{c}$±3.23	$32,3^{d}$± 4.85	$29,9^{e}$± 7,73	0,0001
a* redness	$14,6^{b}$±2.41	$15,6^{ab}$± 3.10	$14,1^{b}$± 3.48	$14,9^{ab}$± 5.21	$16,7^{a}$± 8.32	0,002
b* yellowness	$11,7^{a}$± 2.53	$7,7^{b}$± 2.90	$4,7^{c}$± 3.25	$3,6^{cd}$± 4.87	$2,8^{d}$± 7.77	0,0001
Chroma	$18,8^{a}$± 2.95	$17,5^{ab}$± 3.80	$14,8^{c}$± 4.26	$15,4^{bc}$± 6.39	$17,0^{abc}$± 10.19	0,0001
Hue angle	$38,2^{a}$± 0.46	$25,8^{b}$± 0.60	$18,0^{c}$± 0.67	$13,3^{d}$± 1.01	$9,5^{e}$± 1.60	0,0001

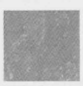
Means in the same row that do not have a common letter in their superscript differ (P<0.01)



1. Pale



2. Pink



3. Pale red

4 Red

5. Dark red

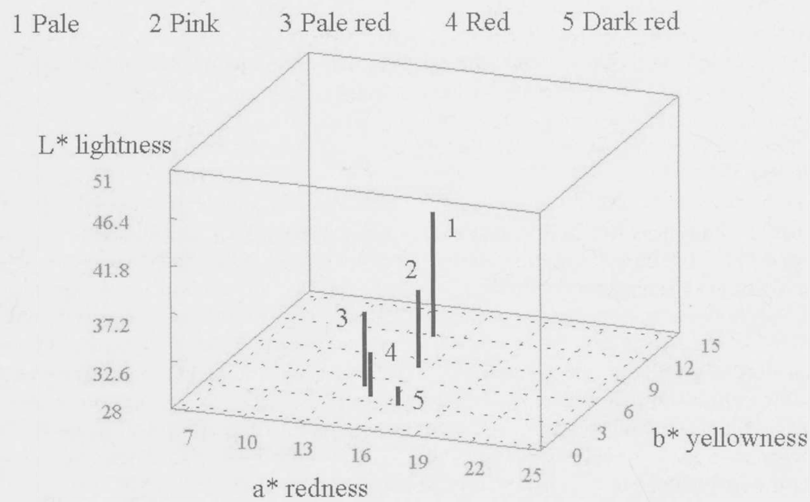


Figure 1. Representation on CIE space of 5 classes of beef muscle colour standard

Acknowledgements: Research financed by MCyT-INIA research project RTA01-106-C2-1 and MCyT and Feder TIC2001-3579.

Pertinent literature

Albertí P., Sañudo C., Santolaria P., Negueruela I., Consigli R., Sierra I., Alcalde M.J. (1991). Representación en tres dimensiones del color de la carne y grasa de bovino y su relación con otras carnes. ITEA Vol Extra 12, 643-645.

Chalmers A. N. (2000). Performance assessment criteria for digital colour cameras. Image vision computing NZ Congress. http//www.manakau.ac.nz/EE/research/staff/chalmers.pdf

Eikelenboom G., Hoving-Bolink A.H., Hulsegge B. (1992). Evaluation on invasive instruments for assessment of veal colour at time of classification. Meat Science 31, 343-349.

Farouk M.M., Swan J.E. (1998). Effect of muscle condition before freezing and simulated chemical changes during frozen storage on the pH and colour of beef. Meat Science 50, 245-256.

Goyache, F., Bahamonde, A. Alonso, J., López, S., Alonso, J., del Coz J.J., Quevedo, J.R., Ranilla, J., Luaces, O., Alvarez, I., Royo, L., Díez J. (2002). The usefulness of Artificial Intelligence techniques to assess subjective quality of products in the food industry. Trend in Food Science and Technology, in press

SAS. 2001. User's guide: Statistics (Version 8 Ed.) SAS Inst. Inc. Cary, NC.