PREDICTION OF PSE-LIKE ZONES, ULTIMATE PH AND COOKING YIELD BY COMPUTER IMAGE ANALYSIS OF DEBONNED HAMS

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Abstract – Due to strong variations in the quality of pork meat, the sorting of meat cuts in slaughterhouses is essential for high quality processed meat products as "jambon cuit supérieur" cooked ham. Based on the strong relationship existing between color and meat quality, the objective of the project was to design and construct a vision system, and to develop calibrations for the prediction of the quality of deboned hams (ultimate pH, PSE-like zone presence/absence, cooking yield). After image signal conversion from RGB to L*a*b* data, the system allows an accurate prediction of the PSE-like zones, with 5% of false classification. It can also be used to qualify the meat quality of deboned hams, with a satisfying prediction of ultimate pH and cooking yield mean (r=0.79, and r=0.66).

Key Words – pork meat quality, pse-like zone, vision system, image analysis

I. INTRODUCTION

The "jambon cuit supérieur" remains a major product in the sector of pork processed meat with 21.4% of the French market share. Regarding the meat quality of raw ham, the industry needs are well known: an optimal ultimate pH level (from 5.6 to 6.0) and no PSE-like zones. Until now, boned-in ham was selected in slaughterhouses according to the ultimate pH level of *Semimembranosus.* The ultimate pH value is a good indicator of the cooking yield and also of the PSE-like zones risk level [1]. Deboned, defatted and trimmed hams are becoming the standard in the raw ham trade between slaughterhouses and meat processing companies. With deboned hams, measuring the ultimate pH become more difficult, but a lot of new muscles areas are available to perform meat quality measurements and most of all, the PSE-like zones are observable. Vision systems (using cameras) are more and more popular in the meat industry, and since 2013 the carcass grading in France is performed with a computer-assisted vision system [2]. This technology allows the measurement of multiple areas of the meat and can potentially be more robust than any operator based technique. Vision systems are based on remote measurement and non-contact acquisitions are one of the slaughterhouse's requirements when talking about online sorting system design. The objective of the present project is to design, to build and calibrate a vision system dedicated to the prediction of the meat quality of deboned, defatted and trimmed hams. The system design has to be consistent with online measurement and meat quality parameters selected to develop prediction algorithms for PSE-like zones, ultimate pH, cooking yield and slicing defects.

II. MATERIALS AND METHODS

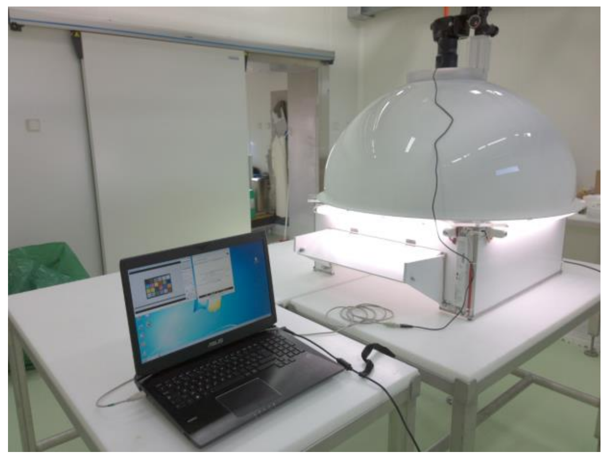
The vision system consists of 3 parts: a 70 cm square lighting box with two doors for online integration, a light collector and a camera (figure 1). The light sources are composed of 4 fluorescent tubes simulating D50 illuminant (Color Proof T18, Osram, Munchen germany). They are positioned at the outside of the lighting box to produce indirect lighting of the meat when reflecting on the light collector. An adjustable camera stand is fixed to the top of the light collector, a PVC 95 cm half sphere. Images were taken with a Nikon 7100D camera mounted with a Nikon 24-70/2.8 AF-S lens (Nikon,Tokyo, Japan). The Nikon Capture Control Pro2 software was used to fix the acquisition parameters: 5.6 aperture, 640 iso sensitivity, 1:125 shutter speed. White balance was set on the neutral white background before starting each picture series.

The first step of the image analysis was to convert the RGB images in the L*a*b color space. To that end, a colorchecker digital SG chart was used (140 color and grey tiles, Xrite, Grand Rapids, USA). The full picture collection was linearized with the ImageJ software to avoid effects of inhomogeneous lighting on colorimetric data, (https://imagej.nih.gov/ij/). Linearization consists of dividing meat images by a white background image. Then, the signal was reset to a suitable level by multiplying by the maximal level of the white background signal. The linearization was performed for each RGB channel independently. Conversion coefficients from RGB were determined by polynomial regression to get final L*a*b* images with the help of PROC REG procedure from SAS 9.4 software (Sas Institute, Cary, USA). Six polynomial regressions were tested and the best fitting model (lower ΔE) was then selected for the L*A*B conversion. Color space conversion and image analysis was performed with ImageJ software. Image analysis consisted in defining and measuring L*a*b average values on four distinctive regions of interest (ROI): roi_2_sm and roi_15_sm (2cm and 15cm wide circles from the inside surface of the *Semimembranosus* muscle), roi_2_bf and roi_10_bf (2cm and 10cm wide circles from the inside surface of the *Biceps Femoris* muscle). Average L*a*b* data from those ROIs were successively used to predict PSE-like zone grading (absence (1+2 class) vs presence (3+4 class)) [1], ultimate pH, cooking yield and slicing defects (rate of slices without defect, slices with cohesion defect, slices with paste-like defect).

The ultimate pH was measured on the *Semimembranosus* muscle with a pH-meter (Syleps, Lorient, France) equipped with a Lot406 electrode (Mettler Toledo, Columbus, USA). The color (L*a*b*) of the inside surface of the *Semimembranosus* was measured with a CR-400 colorimeter (Konica Minolta, Tokyo, Japan). The “Jambon cuit supérieur” cooking yields were determined after individual processing by our industrial meat processing partner, according to the same protocol than described by Vautier et al. [3].

The meat sample collection was divided in two populations of deboned hams. The first population (n=59), dedicated to the ultimate pH, cooking yield and slicing defect rate prediction, was selected according to the *Semimembranosus* ultimate pH level (uniform pH distribution target, 1:6 ratio per class: <5.5; 5.5 to 5.6; 5.6 to 5.8; 5.8 to 6.0; 6.0 to 6.2; >6.2). The second population (n=110) was selected according to the PSE-like zone class after deboning (1:4 ratio per class: 1, 2, 3, 4). The PROC LOGISTIC procedure from SAS 9.4 software was used to calibrate the vision system by logistic regression for the PSE-like zone prediction. The prediction of ultimate pH, cooking yield and slicing defect rates were determined with the help of the PROC REG procedure from SAS 9.4.

Figure 1: vision system



III. RESULTS AND DISCUSSION

Overall meat quality results of the sampling were satisfying (table 1). The pH distribution of the first sample collection fit quite well with the objective: 7% <5.5; 20% 5.5 to 5.6; 29% 5.6 to 5.8; 25% 5.8 to 6.0; 14% 6.0 to 6.2; 5%>6.2. The r=0.80 correlation level between the cooking yield and the ultimate pH (table 2) corresponds with previous studies using the same protocol [3][4]. The PSE-like zone frequency of the second sample collection is slightly lower than expected (absence=66%; presence=44%).

Table 1: general meat quality results for the calibration data set

	pH 24	L*	a*	b*	cooking yield (%)	slices ok (%)	paste-like slices (%)	cohesion defect slices (%)
n=	110				59			
m	5.69	60	11	11	86.0	41.6	22.2	42.6
sd	0.21	6.2	2.6	2.5	5.2	37.8	20.7	40.5

Table 2: correlation between meat quality parameters and processing yields

	pH 24	L*	a*	b*	Cooking yield	slices ok	paste-like slices
pH24	1	-0.78	-0.45	-0.67	0.80	0.82	-0.78
L*		1	0.48	0.76	-0.63	0.62	0.61
a*			1	0.86	-0.52	0.79	-0.80
b*				1	-0.62	-0.57	0.54
Cook. yield					1	0.79	-0.80

The best fitting model for the conversion RGB to L*a*b* conversion is based on a 3x11 polynomial matrix (table 3). For the model showing the lower validation ΔE, a 2.8 ΔE value is obtained within the calibration data set, what is not far from the minimum ΔE distinguishable by the human eye (2.2) [5]. These results are in agreement with Hong et al. [6].

The prediction of the presence/absence of PSE-like zones from images analysis was better when focusing on roi_2_sm (figure 3) data, with only 5% of overall false classification after logistic regression calibration (table 4). These results are consistent with the fact that the color of the inside surface of the *Semimembranosus* is one of the main criteria used for subjective classification of PSE-like zone defect. Thresholding on the L* value of roi_2_sm is not as efficient as logistic regression treatment: if no PSE-like zone is found for L* value higher than 65.5, the sorting puts aside 30% of hams without defect (figure 2).

Table 3: model performance for RGB to L*a*b* conversion by various polynomial regressions

Matrices/model	ΔE cal.	ΔE val.
3x3 [r g b]	8.4	8.1
3x5 [r g b rgb 1]	4.8	8.6
3x8 [r g b rgb rg rb gb 1]	3.8	7.7
3x8 [r g b rgb r^2 g^2 b^2 1]	4.2	8.0
3x11 [r g b rgb rg rb gb r^2 g^2 b^2 1]	2.8	7.0
3x14 [r g b rgb rg rb gb r^2 g^2 b^2 r^3 g^3 b^3 1]	2.5	7.6

Figure 2: distribution of the subjective grading of PSE-like zones for calibration data set according to ROI_2_SM L* obtained with the camera (n=110)

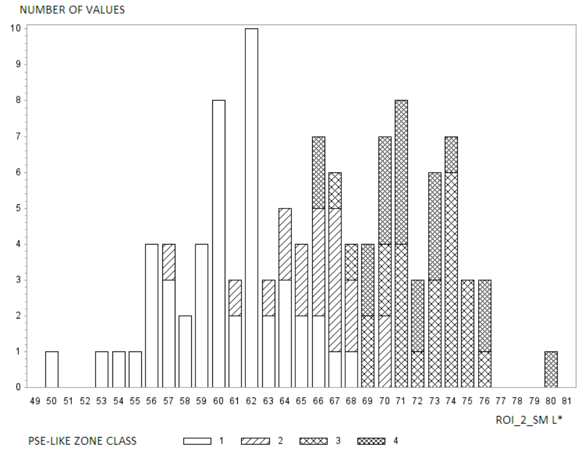


Figure 3: ROI_2_SM, a 2cm wide circle on the internal surface of the *Semimembranosus* muscle

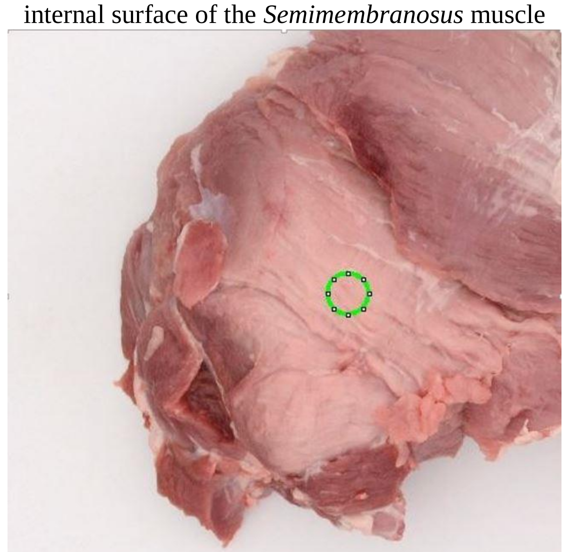


Table 4: PSE-like zone (absence(1+2)/presence(3+4)) prediction results for logistic regression of ROI_2_SM and ROI_2_BF colorimetric data obtained with the camera (n=110)

model	Overall correct classification (%)	Correct classification for 1+2 grade (%)	Correct classification for 3+4 grade (%)
L*a*b*roi_2_sm	95 (104/110)	95 (63/66)	93 (41/44)
L*a*b*roi_2_bf	90 (99/110)	91 (60/66)	89 (39/44)
L*a*b*roi_2_sm +L*a*b*roi_2_bf	93 (102/110)	94 (62/66)	91 (40/44)

Table 5: regression results for the prediction of ultimate pH according to colorimetric data obtained with the camera (n=110)

Ultimate pH prediction model	R²c	rmsec
L*a*b*roi_2_sm	0.56	0.14
L*a*b*roi_15_sm	0.52	0.15
L*a*b*roi_2_bf	0.46	0.16
L*a*b*roi_10_bf	0.41	0.16
L*a*b*roi_2_sm + (L*)² (a*)² (b*)² roi_2_sm	0.63	0.13

Table 7: best regression results for the prediction of the rate of slices without defect, the paste-like defect slices rate, and the cohesion defect slices rate (n=59)

Criterion	model	R²c	rmsec
Slices ok (%)	L*a*b* roi_15_sm	0.48	27.9
Paste-like slices (%)	L*a*b* roi_15_sm	0.24	18.6
Cohesion defect slices (%)	L*a*b* roi_15_sm	0.49	29.6

Regarding their correlation levels, the vision system can predict cooking yield and ultimate pH (r=0.66 and 0.79, respectively, table 6 and 5). These relationships are similar to what can be observed with the L* of Semimembranosus measured with a colorimeter (r=-0.63 and 0.78 respectively, result not shown). Nonetheless, the errors obtained with the vision system are too high for individual prediction. The 4.1 rmsec value for the prediction of the cooking yield is higher than the accuracy we previously obtained with NIRS technology (rmsecv=2.8, [4]). Despite good correlation levels (especially for the rate of slices without defect, and cohesion defect slices, r=0.69 and 0.70, respectively, table 7), the prediction of the slicing defects with the vision system is also not accurate enough. The rmsec levels are high, and the prediction of slicing yields with raw ham image analysis may be useful only for batch characterization.

IV. CONCLUSION

The vision system developed in the present study and its calibrations showed very promising results especially for PSE-like zone prediction (5% of false classification). In this way, it can be considered as a tool to get objective classification of the muscle structure quality, an important criterion for the cooked ham industry. Designed for deboned-hams measurements, the system allows predictions in motion, and does not require operator. Its construction cost is also low. Software design work is still needed to perform automatic ROI detection and calibrations, but pork meat industry expectations are strong on automation of meat quality sorting.

Table 6: regression results for the prediction of cooking yield according to colorimetric data obtained with the camera (n=59)

Cooking yield prediction model	R²c	rmsec
L*a*b* roi_2_sm	0.36	4.3
L*a*b* roi_15_sm	0.43	4.1
L*a*b* roi_2_bf	0.37	4.2
L*a*b* roi_10_bf	0.27	4.6

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