P-07-25

Estimation of the tissue composition of bellies by a magnetic induction scanner (#491)

Gerard Daumas[1], Mathieu Monziols[1], Juan Manuel Rodriguez[2], Jacobo Alvarez-Garcia[2], David Causeur[3]

[1] IFIP - Institut du porc, Le Rheu, France; [2] LENZ Instruments SL, Barcelona, Spain; [3] Agrocampus Ouest, Irmar, UMR 6625 CNRS, Rennes, France

Introduction

The objective of the study was to develop models and assess the estimation error of bellies composition using a magnetic induction device.
Magnetic induction, which principle takes advantage of the dielectric properties of tissues, was successfully tested by Swan *et al.* (2001) on bellies, hams and shoulders. Simoncini *et al.* (2012) estimated fat and muscle composition of hams with a more recent device. In the following, we draw conclusions based on experimental data on the extent to which such a device can be used to grade bellies.

Methods

In a meat plant 80 bellies were selected based on a visual evaluation of their fatness level. For each of the four fatness levels (E, 1, 2, 3, from the leanest to the fattest) 20 bellies were selected.
The bellies were analysed by a magnetic induction scanner, called HAM-Inspector II™, which was developed by Lenz Instruments S.L. (Barcelona, Spain). For each belly, the output described the magnetic induction signal along the cut.
The day after, the bellies were weighed and scanned by an X-ray tomograph (CT) used as a reference method for tissue composition. The CT images were segmented according to the procedure developed by Daumas and Monziols (2011) to calculate the weights and proportions of muscle and fat tissues.
For each of these four dependent variables a regression model was fitted based on the cut's weight, some standard geometrical parameters of the magnetic induction signal (maximum amplitude, area under the signal), and shape parameters extracted from a B-spline decomposition of the normalised (same length and maximal amplitude) magnetic induction signals.
In addition, based on the same profile of explanatory variables, a classification model for the fatness level of bellies was developed using a multinomial logistic regression.
Statistical analyses were performed with the R software (R Core Team, 2018).

Results

The means, standard deviations, and extreme values for tissues weights and proportions in bellies are shown in Table 1.

Table 1 – Summary statistics of bellies composition (n = 80)

Dependent Variable	Mean	Standard Deviation	Minimum	Maximum
Muscle weight, g	3816	457	2568	4757
Fat weight, g	2835	815	1263	4584
Muscle content, %	55.6	6.45	42.8	67.0
Fat content, %	39.9	5.79	30.0	51.7

Model selection procedures aiming at the minimization of the Bayesian Information Criterion lead to models including four to six explanatory variables. Among these variables there were one or two shape parameters of the normalised curves (Table 2). The highest adjusted coefficient of determination (Adj. R^2 = 0.94) was achieved for the fat weight. The other adjusted R^2 ranged from 0.76 to 0.80, which was partly due to non-optimal measurement conditions.
Similarly, the model established by Swan *et al.* (2001) accounted for 78% of the variance in muscle weight.

Table 2 – Summary statistics for best fit models for the assessment of bellies composition (n = 80)

Dependent variable	Explanatory variables [a]	Adjusted R^2	Residual Standard Deviation
Muscle weight, g	W, 1/W, P, A, B14, B15	0.78	214
Fat weight, g	W, 1/W, A, B14	0.94	207
Muscle content, %	W, 1/W, P/W, A/W, B14, B15	0.80	2.89
Fat content, %	W, 1/W, A, B14	0.76	2.84

[a] *W: belly weight, P: maximum amplitude, A: area under the signal, B14 and B15: shape factors.*

As an example, the scatterplot of "fitted *vs* observed response values" is shown for the percentage of belly fat in Figure 1.
Bellies classification performance results are summarized in Table 3. The overall rate of well ranking was 88%.

Table 3 – Confusion matrix for the classification model [(a)]

	Estimated class			
Observed class	E	1	2	3
E	95%	5%	0%	0%
1	5%	95%	0%	0%

Notes

2	5%	15%	75%	5%
3	0%	0%	15%	85%

[a] From class E (the leanest) to class 3 (the fattest).

Conclusion

Models for belly composition using a magnetic induction scanner were found to be more accurate for muscle and fat weights than for muscle and fat contents. Shape parameters deduced from a spline approximation of the magnetic induction signals have been found to be insightful explanatory variables.

These first results are promising for further use of magnetic induction devices to grade bellies, and possibly other cuts.

Acknowledgements

Thanks to the French Ministry of agriculture for financial support (HYPER-SCAN project).

References

- Daumas G., Monziols M., 2011. An accurate and simple computed tomography approach for measuring the lean meat percentage of pig cuts. Proc. 57th ICoMST, Ghent, Belgium. Paper 061.
- R Core Team, 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- Simoncini N., Virgili R., Schivazappa C., Pinna A., Rossi A., Alvarez J., Rodríguez J.M., 2012. Assessment of fat and lean content in Italian heavy green hams by means of on-line non-invasive techniques. Proc. 58th ICoMST, Montréal, Canada, ID CARCASSSP-12.

Swan J. E., Parrish F. C., Wiegand B. R., Larsen S. T., Baas T. J., Berg E. P., 2001. Total body electrical conductivity (TOBEC) measurement of compositional differences in hams, loins, and bellies from conjugated linoleic acid (CLA)-fed stress-genotype pigs. J. Anim. Sci., 79, 1475–1482.

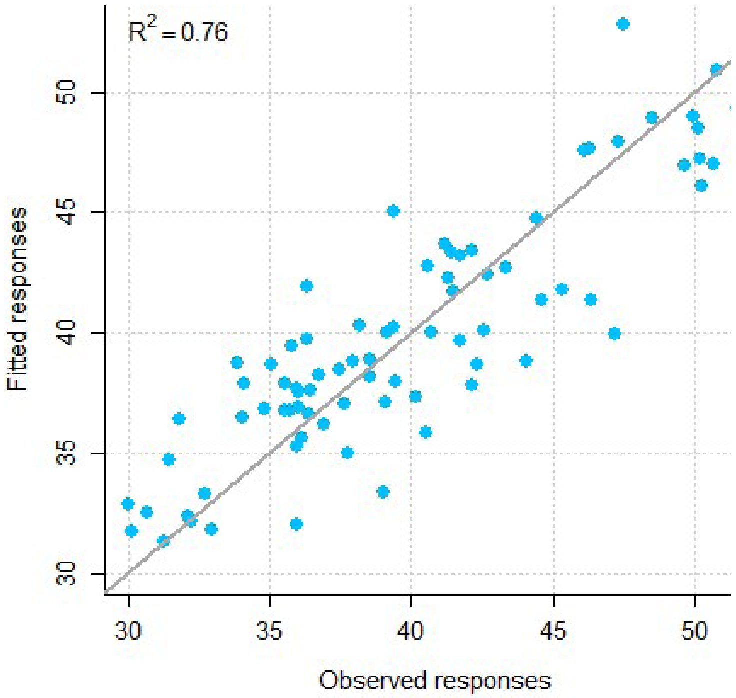

Figure 1. Fat content (in %) in belly: adjusted (magnetic induction) vs observed (X-Ray tomography)

Notes