

Prediction of primal and retail cut weights of youthful cattle carcasses using whole carcass camera (HCC); a computer vision system (CVS)

J. Segura, N. Prieto, S. Zawadski, H. Scott, J. L. Aalhus and Ó. López-Campos*

Lacombe Research and Development Centre, Agriculture and Agri-Food Canada, 6000 C&E Trail,
Lacombe, AB, T4L 1W1, Canada

*E-mail: oscar.lopezcampos@agr.gc.ca

Introduction

Carcass evaluation and classification are important to determine carcass market value (Aalhus et al., 2014). The implementation of new technologies to assess carcass composition is increasingly desired to enhance both consistency and accuracy (Leighton et al., 2021). In this sense, whole-side carcass image analysis, also known as hot carcass camera (HCC) systems, should be taken into consideration. Such systems were designed to work autonomously integrated into the slaughter chain and entail a colour camera and a lighting system including structured (striped) light to take conventional images of a split carcass. These images are then processed using a software to obtain data such as linear measurements, volumes, angles, curvatures, and colours to predict the conformation and fat class of a beef carcass (López-Campos et al., 2019). Camera Vision Systems (CVS), and particularly HCC, have been used for the estimation of live weight and average daily gain in beef cattle (Cominotte et al., 2020), to predict beef carcass merit (Connolly, Cromie, Sleator, & Berry, 2019) and segregate beef carcasses based on their meat cut attributes (Pabiou, Fikse, Amer, et al., 2011) as well as for meat quality assessments (Rahman, Iqbal, Hashem, & Adedeji, 2020). However, the ability of HCC to estimate beef carcass performance based on primal and retail cut yields is still unknown, particularly in youthful beef where carcass fabrication is customized to meet specifications of the diverse markets. The present study aimed to evaluate the feasibility of HCC to estimate beef primal and retail cut weights of youthful beef using partial least squares regression (PLSR).

Material and Methods

A total of 634 animals (531 steers and 103 heifers) were used in this study. In order to create carcass variation, steers were raised under two production systems (239 spring/calf-fed and 292 fall/yearling-fed), two implant regimens (without or with 200 mg progesterone and 20 mg estradiol benzoate, with 29 mg of tylosin tartrate, Elanco Animal Health, a Division of Eli Lilly Canada Inc., Guelph, ON) and fed with a high-concentrate diets (78% rolled and 22% barley silage) for 100 to 180 days. In turn, heifers were also finished with diets typical for Western Canada (i.e. containing 80-90% barley grain on a dry matter basis) to be representative of North America commercial cattle (CanFax, 2021). All the animals were cared for according to the Canadian Council on Animal Care Guidelines (2009).

Following slaughter at AAFC-Lacombe RDC federally inspected abattoir, carcasses were dressed, split, and weighed (hot carcass weight, HCW, kg). After a final carcass pasteurizing shower, pictures of each carcass side were taken using an HCC (whole-side system): VBS 2000 (e+v Technology GmbH, Oranienburg, Germany). Raw output data of the images comprised of 165 HCC variables describing linear measurements of carcass dimensions, carcass conformation, and colour (Segura, Aalhus, Prieto, Larsen, Juárez et al., 2021). The carcasses were then chilled at 2°C for 72 h and left carcass sides were fabricated into primal and retail cuts with carcass breakpoints identified following the Institutional Meat Purchase Specifications (IMPS) for Fresh Beef Products, Series 100 (USDA, 2014) and NAMI (2022).

All the statistical analyses were carried out using SAS v.9.4 (SAS Institute Inc., 2014). The primal and retail cut weights were included as variables in a PLSR used to generate prediction equations. The number of latent variables (LV) that minimise the predicted residual error sum of squares (PRESS) was reported for the calibrated PLSR models (López-Campos et al., 2018).

Results and Discussion

In the present study, animal carcass weights were within the range of the North American commercial beef carcasses (CanFax, 2021) in terms of dressed HCW (225.0 – 556.6 kg), REA (64.0 – 135.0 cm²), grade fat (3.0 – 45.0 mm), retail cut yield (39.8 – 56.0%), lean meat yield (31.6 – 64.8%), and marbling score (290 – 820). Primal and retail cut percentages were within the range of those previously published by this research group (López-Campos et al., 2018) and similar to the current market averages reported in North America (Cattlemen's Beef Board, 2018).

The coefficients of prediction for the primal cut weight estimations ranged between 0.60 for Rib to 0.92 for Round (Table 1). Pabiou, Fikse, Cromie, et al. (2011), using variables from the HCC system and CCW, reported higher R² values than the present study in the prediction of weights for four commercial value cut groups, namely lower (R² = 0.92), medium (0.86), high (0.93) and very high (0.84).

In lambs, Rius-Vilarrasa, Bungler, Maltin, Matthews, and Roehe (2009) reported R² values of 0.97 for leg, 0.94 for chump, 0.91 for loin, 0.88 for breast and 0.96 for shoulder. In turn, Lorenzo, Guedes, Zdolec, et al. (2018) described stepwise k-fold-R² values of 0.56, 0.89, 0.53 and 0.76 respectively for lower, medium, high and very high value cuts of foal carcasses.

Concurring with the primal cut estimations, retail cut weight predictions using HCC technology showed, overall, promising results (Table 2). In this sense, the chuck retail cuts R² values of HCC predictions ranged from 0.32 for #114F (Clod tender), to 0.94 for #113C (Semi-boneless chuck), whereas the R² values of the retail cuts fabricated from the rib ranged from 0.27 for #112 (Ribeye roll, denuded ribeye) to 0.91 for #112A (Boneless lip on, 14 up or down, 2x2). Likewise, R² values of the retail cuts from the loin ranged from 0.38 for #189 (Full Tenderloin) to 0.81 for #184 (Top Sirloin butt, boneless, cap on). Regarding the round retail cuts, R² values ranged from 0.45 for #169C to 0.91 for #161 1.

Most of the models developed were satisfactory for most of the retail cut weight predictions. Nevertheless, some specific retail cuts showed low to moderate (R² values from 0.32 to 0.45) accuracies (e.g. Ribeye roll clod tender, full tenderloin, back ribs; Table 2). Predictions using HCC are carried out by means of carcass conformation measurements. Therefore, the low R² values observed for loin retail cuts using HCC may be caused by their low implication on carcass conformation. In fact, Matthews, Pabiou, Evans, Beder, and Daly (2022) showed low R² values for those retail cuts without any pixel involved in the HCC carcass conformation. Similar results were reported by Lorenzo et al. (2018) in foals and by Batista et al. (2021) in light lamb carcasses.

Overall, the present results suggest the feasibility of CVS technologies to accurately predict carcass performance in terms of primal and retail cuts outputs. The implementation of CVS to predict carcass primal and retail performance at early processing stages could benefit beef industry with accurate carcass segregation into the subsequent fabrication lines to meet diverse cut specifications of targeted markets.

Conclusions

Preliminary results of the present study suggest that weights of beef primal cuts from carcasses of youthful animals can be potentially predicted by HCC technologies applying partial least square regression statistical analysis. Furthermore, retail cut weights predictions showed the potential feasibility of using HCC approaches that could benefit the industry by more accurately identifying retail cut performance of the carcasses at earlier fabrication stages.

These results suggest reliable carcass primal and retail cut estimations using HCC variables. These predictions could benefit the beef industry with accurate carcass segregations based on fabrication performance. Further studies should be performed taking into consideration the diverse functional and operational considerations of the beef plants and the different CVS approaches that offer versatility for their potential implementation in beef plants.

References

- Aalhus, J. L., López-Campos, Ó., Prieto, N., Rodas-González, A., Dugan, M. E. R., Uttaro, B., & Juárez, M. (2014). Review: Canadian beef grading – Opportunities to identify carcass and meat quality traits valued by consumers. *Canadian Journal of Animal Science*, *94*(4), 545-556. doi: 10.4141/cjas-2014-038
- Batista, A. C., Santos, V., Afonso, J., Guedes, C., Azevedo, J., Teixeira, A., & Silva, S. (2021). Evaluation of an image analysis approach to predicting primal cuts and lean in light lamb carcasses. *Animals*, *11*(5). doi: 10.3390/ani11051368
- Canadian Council of Animal Care (2009). Guidelines on: The care and use of farm animals in research, teaching and testing. Ottawa, Canada: Canadian Council on Animal Care. (www.ccac.ca/Documents/Standards/Guidelines/Experimental_Animals_Vol1.pdf; www.ccac.ca/Documents/Standards/Guidelines/Farm_Animals.pdf)
- Canfax 2021. Annual Report. Canfax/Canfax Research Services, Calgary, AB. (Retrieved January, 2021 from www.canfax.ca)
- Cominotte, A., Fernandes, A. F. A., Dorea, J. R. R., Rosa, G. J. M., Ladeira, M. M., van Cleef, E. H. C. B., Pereira, G. L., Baldassini, W. A., & Machado Neto, O. R. (2020). Automated computer vision system to predict body weight and average daily gain in beef cattle during growing and finishing phases.. *Livestock Science*, *232*, 103904. doi: 10.1016/j.livsci.2019.103904
- Connolly, S. M., Cromie, A. R., Sleator, R. D., & Berry, D. P. (2019). Predicted carcass meat yield and primal cut yields in cattle divergent in genetic merit for a terminal index. *Translational Animal Science*, *3*(1), 1-13. doi: 10.1093/tas/txy129
- Leighton, P. L. A., Segura, J., Lam, S., Marcoux, M., López-Campos, O., Soladoye, P., Dugan, M. E. R., Juárez, M., Prieto, N. (2021). Prediction of carcass composition and meat and fat quality using sensing technologies: A review. *Meat and Muscle Biology*. doi.org/10.22175/mmb.12951
- López-Campos, Ó., Prieto, N., Juárez, M., & Aalhus, J. L. (2019). New technologies available for livestock carcass classification and grading. *CAB Reviews*, *14*(018), 1-10. doi: 10.1079/PAVSNNR201914018
- López-Campos, Ó., Roberts, J. C., Larsen, I. L., Prieto, N., Juárez, M., Dugan, M. E. R., & Aalhus, J. L. (2018). Rapid and non-destructive determination of lean fat and bone content in beef using dual energy X-ray absorptiometry. *Meat Science*, *146*, 140-146. doi: 10.1016/j.meatsci.2018.07.009
- Lorenzo, J. M., Guedes, C. M., Zdolec, N., Sarries, M. V., Franco, D., De Palo, P., Muchenje, V., & Silva, S. R. (2018). Prediction of foal individual primal cuts yield using video image analysis. *South African Journal of Animal Science*, *48*(6), 1057-1065. doi: 10.4314/sajas.v48i6.8
- Matthews, D., Pabiou, T., Evans, R. D., Beder, C., & Daly, A. (2022). Predicting carcass cut yields in cattle from digital images using artificial intelligence. *Meat Science*, *184*, 108671. doi: 10.1016/j.meatsci.2021.108671
- NAMI. The Meat Buyer's Guide from the North American Meat Institute. (2022). Accessed on-line May 26, 2022. <https://www.meatbuyersguide.com/Account/Login.aspx?ReturnUrl=/>
- Pabiou, T., Fikse, W. F., Amer, P. R., Cromie, A. R., Nasholm, A., & Berry, D. P. (2011). Genetic variation in wholesale carcass cuts predicted from digital images in cattle. *Animal*, *5*(11), 1720-1727. doi: 10.1017/s1751731111000917
- Pabiou, T., Fikse, W. F., Cromie, A. R., Keane, M. G., Nasholm, A., & Berry, D. P. (2011). Use of digital images to predict carcass cut yields in cattle. *Livestock Science*, *137*(1-3), 130-140. doi: 10.1016/j.livsci.2010.10.012
- Rahman, F. M., Iqbal, A., Abul Hashem, M., & Adedeji, A. A. (2020). Quality assessment of beef using computer vision technology. *Food Science of Animal Resources*, *40*(6), 896-907. doi: 10.5851/KOSFA.2020.E57

- Rius-Vilarrasa, E., Bunger, L., Maltin, C., Matthews, K. R., & Roehe, R. (2009). Evaluation of Video Image Analysis (VIA) technology to predict meat yield of sheep carcasses on-line under UK abattoir conditions. *Meat Science*, 82(1), 94-100. doi: 10.1016/j.meatsci.2008.12.009
- Segura, J., Aalhus, J. L., Prieto, N., Larsen, I. L., Juárez, M., & López-Campos, Ó. (2021). Carcass and primal composition predictions using camera vision systems (CVS) and dual-energy x-ray absorptiometry (DXA) technologies on mature cows. *Foods*, 10(5). doi: 10.3390/foods10051118

Table 1. Partial least square regression models estimating the weight of primal cuts from whole-side computer vision system values. Coefficient of determination (R^2), number of latent variables (LV) and mean square prediction error (MSPE) are presented for each model.

	n	LV	R^2	MSPE
Chuck	588	7	0.90	6.239
Rib	585	8	0.60	5.658
Loin	587	9	0.85	2.356
Round	494	9	0.92	2.640

Table 2. Partial least square regression models estimating the weight of retail cuts from whole-side computer vision system values. Coefficient of determination (R^2), number of latent variables (LV) and mean square prediction error (MSPE) are presented for each model.

		Retail cut description and specification	n	LV	R^2	MSPE
CHUCK	114D	Top blade (Flat Iron), fat removed	322	5	0.70	0.0365
	NAMI 114E	Clod Heart (Arm roast)	410	9	0.78	0.0957
	114F	Clod Tender	249	2	0.32	0.0058
	113C	Semi-Boneless Chuck	161	6	0.94	5.953
	CAN 114E	Shoulder Clod Arm Roast, blade muscle removed	89	2	0.51	0.9560
RIB	112A	Boneless Lip On, 14 up or down, 2×2	249	10	0.91	0.1143
	112	Ribeye roll (Denuded Ribeye)	266	3	0.27	0.7887
	109E PS03	Steak Style Rib, 2×2	73	1	0.70	0.4262
	124	Back Ribs	249	2	0.45	0.0210
	107	Oven Ready Ribs	160	5	0.81	0.5090
LOIN	174	Short Loin, 1×0	248	6	0.80	0.2724
	184	Top Sirloin Butt, Boneless, Cap On	337	5	0.81	0.1931
	185B	Bottom Sirloin Butt, Ball Tips	321	10	0.52	0.0266
	189	Full Tenderloin	89	1	0.38	0.2513
	180 PS02	Striploin, 1×0	73	2	0.73	0.1545
ROUND	171	Bottom (Gooseneck) Round, (¼ inch trimmed)	73	4	0.87	0.3044
	167A	Sirloin Tip Peeled (Knuckle), Peeled	483	5	0.77	0.1349
	168	Top (Inside), Round, Untrimmed 1 inch	399	7	0.82	0.3547
	161 1	Shank off, Boneless Round	160	6	0.91	1.731

169C

Top (Inside), Round Side Muscle (*pectineus*)

114

3

0.45

0.0047
