Estimating backfat depth, loin depth, and intramuscular fat percentage from ultrasound images in commercial swine

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Abstract

The objective of this study was to develop an equation-based model for the automation of swine backfat depth (BF), loin eye depth (LED), and intramuscular fat percentage (IMF) estimates obtained from ultrasound images. Commercial pigs (n = 190; Duroc × Large White) were reared in a mechanically ventilated facility in eastern North Carolina. An ExaPad ultrasound machine was used to capture longitudinal images (n = 1168) of the tenth rib at 194 (± 5) days of age. To establish standard measurements for model validation, trained personnel obtained BF and LED measurements manually from the images following standard company procedures. Soxhlet extraction was used to obtain IMF at slaughter. Average BF, LED, and IMF were 14.6 (± 2.6) mm, 63.7 (± 5.5) mm, and 2.0 (± 0.5) percent, respectively. During image processing, the image gradient was used for edge detection to segment ultrasound images into backfat, loin, and rib regions. Segmented images were then used to estimate BF, LED, and IMF. After image quality control and filtering, 1,018 images (190 pigs) were analyzed for trait prediction and linear models were developed. Correlation between measured and predicted values of BF, LED, and IMF were 0.77, 0.76 and 0.51, respectively. Root mean square error of BF, LED, and IMF prediction were 1.65 mm, 3.58 mm, and 0.40%, respectively. Results demonstrate the feasibility of using ultrasound image gradient and an equation-based approach to automate swine backfat depth, loin depth, and intramuscular fat measurements.

Keywords: genetic selection, meat quality, pig

Introduction

Swine backfat and loin muscling are directly associated with the value of swine carcasses and intramuscular fat percentage of the longissimus muscle can add carcass value in niche markets. Ultrasound technology has been used in the evaluation of these traits and carcass composition in live swine since the early 1950s (Houghton and Turlington, 1992). Conventionally, real-time ultrasound scans of the fat layers and longissimus muscle have been made transverse to the long axis of the pig at the 10th rib and been shown to accurately predict backfat and longissimus muscle measurements. Studies have reported a 66 to 89% correlation between live ultrasound and actual backfat depth measurements at the 10th rib (Forrest et al., 1989; Cisneros et al., 1996). However, the capture of these images and manual interpretation of these traits from transverse images can be labor intensive.

More recent research has focused on using computer programs to automate the measurement of intramuscular fat in swine from real-time ultrasound. Seminal programs showed promising prediction estimates with coefficients of determination of 0.3 – 0.4 (Ville et al., 1997; Ragland et al., 1998; Newcom et al., 2002). Lakshmanan et al. (2012) reported a coefficient of determination of 0.76 through the use of spectral ultrasound backscatter analysis. Further improvement in prediction accuracy has been shown with the application of deep learning. Kvam and Kongsro (2017) reported a correlation of $\bar{R}$ = 0.82 with RMSE of 1.2%. However, excluding high intramuscular fat pigs (> 6%) improved the prediction to a $\bar{R}$ = 0.88 with RMSE of 0.99% due to low representation. A commercially available image capturing and interpretation system, BioSoft Toolbox (Biotronics Inc., Ames, IA), was released in 2007 for estimating carcass traits on ultrasound of live swine, with later releases for scanning hot carcasses (BioQScan; Biotronics Inc., Ames, IA). However, we aim to assess the accuracy of a novel method for estimating carcass traits of live swine as a fully automated image processing pipeline with inherent image quality control to reduce variability between end-users.

The goal of this study was to develop an algorithm to quickly and automatically produce accurate and reliable estimates of backfat depth, loin depth, and intramuscular fat percentage in swine breeding stock. Specific objectives were to (1) capture longitudinal ultrasound images from breeding pigs, (2) create a fully automatic image processing algorithm to estimate backfat and loin depth and intramuscular fat percentage, and (3) compare the accuracy of the algorithm to comparative standard measurements. Results can be used to increase genetic improvement, farm profitability, and overall efficiency.

Materials and methods

Experimental data

Image data used for model development were collected from Commercial (Duroc × (Large White × Landrace)); n = 190) pigs born in January 2021 at a farm located in North Carolina. Image data were collected on gilts and boars. Pigs were weighed (mean ± SD; 138 ± 14.5 kg) at 182 ± 12.8 d of age and imaged a mean of 4.6 d prior to slaughter, with no pigs being slaughtered greater than 6 d post-imaging. An ExaPad ultrasound machine (v1.3.26.5; IMV Imaging, Rochester, MN) fitted with 3.5 MHz 14 cm linear-array L3130B transducer with a focus of 8 cm was used for imaging. Pigs' hair was shaved across the 10th to 13th ribs and vegetable oil was used as conducting material between the ultrasound probe and skin. A minimum of four longitudinal images (Table 1) were collected 7 cm off-midline across the shaved region (10th to 13th ribs). Ultrasound images were stored locally as Portable Network Graphics (PNG) files for later interpretation. A single technician was responsible for data collection and image interpretation.

Comparative standard data

A single trained technician used BioSoft Toolbox (v4.0.1.2; Biotronics Inc., Ames, IA) to estimate backfat and loin depth from the images. A mean of 6.1 ± 0.5 images per pig were analysed with a minimum of four images per pig. The BioSoft Toolbox features an auto-selection setting for estimating depth and intramuscular fat. When enabled, the auto-selection outlines the region predicted to contain the backfat layers and ribs as well as boxes in the loin region for intramuscular fat. The technician then manually inspected each image to verify that the outlined regions were correct and made manual adjustments as necessary. Backfat and loin depth were calculated by the software following company protocols then averaged for each pig, resulting in each pig having a single value for backfat and loin depth, respectively.

Following slaughter, a portion of the longissimus muscle from each pig between the 10th and 11th rib was analysed for carcass intramuscular fat using Soxhlet fat extraction as described by the Association of Official Analytical Chemists (2004). The Soxhlet procedure is the conventional method for solvent fat extraction in swine.

Backfat and loin depth estimation and intramuscular fat analysis was conducted on all pigs (n = 190). Backfat and loin depth estimation obtained on-farm as well as intramuscular fat obtained via chemical extraction were used as the comparative standard values for each trait, respectively.

Image processing algorithm and trait estimation

MATLAB (v.R2021a) and the Image Processing Toolbox (MathWorks, 2021a) were used for developing the image processing algorithm, illustrated in Figure 1. Raw grayscale ultrasound images were cropped to 420 × 640 pixels to remove ultrasound software metadata (Figure 1a). Brøndum et al. (1998) recommended the reduction of noise or image haze as the first step of ultrasound image analysis, so image sharpening and zero padding were applied to reduce haze, increase acutance, and improve identification of image gradient (Figure 1b). The MATLAB function imsegfmm (MathWorks, 2021b) was used for binary image segmentation using the fast marching method. Using the computation of weights based on the image gradient, threshold values, and a seed location in the lower left corner, the algorithm segmented images into three separate regions: backfat, loin, and rib.

The lower limit of the three backfat layers was identified using a series of threshold values (Figure 1c). Backfat region depth (pixels) was calculated as the average pixel value across the x-axis of the image within a continuous region starting at the top of the image (Figure 1c). If the average backfat region depth was less than 22.8 pixels, the minimum y-value of the backfat region was used as backfat region depth. The threshold of 22.8 pixels corresponds to the minimum backfat depth (7.62 mm) observed in previous studies of similar genetic lines (unpublished data). The resulting images contained the labelled backfat region (Figure 1d; top).

After removing the backfat region of the image, a second set of threshold values was used to identify the rib line of the loin-rib image (Figure 1e). The five largest white blobs were identified and the image was segmented at the greatest y-value of any of the blobs, signifying the highest point of the rib line. The image loin region depth (pixels) parameter was calculated as the distance from the minimum y-value of the backfat line to the maximum y-value of the rib line. The images were then segmented into the loin (Figure 1f; middle) and rib (Figure 1f; bottom) regions. Within the loin region (Figure 1f; middle), image intramuscular fat was calculated as the mean grey intensity value within the region.

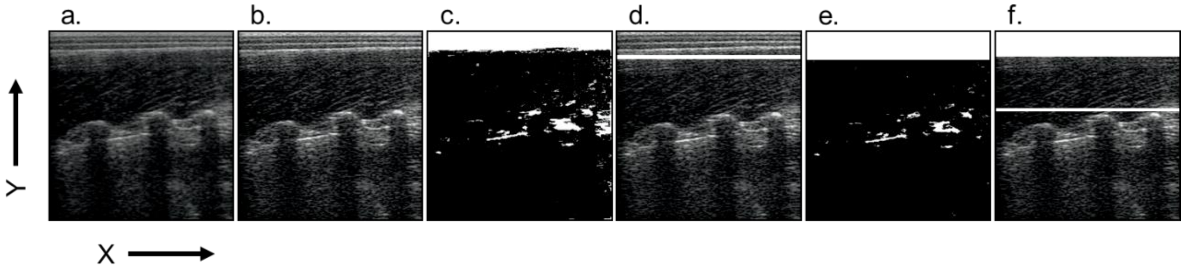

Figure 1: Image processing algorithm.

Quality control

Following image processing, segmentation, and image parameter estimation a quality control step was implemented using the interquartile range to identify possible outliers for each of the three traits. Interquartile ranges were calculated using all initial pixel output values for all images and each trait respectively. Values outside 1.5 times the interquartile range for backfat and loin depth were excluded. In addition, if image backfat or loin depth was considered unacceptable, image intramuscular fat was also excluded for that image.

Trait prediction and validation

Image parameter estimates (backfat pixel depth, loin pixel depth, and average pixel value of loin region) were averaged by each pig as recommended by Hassen et al. (1999). Breed, weight, sex, and age were included as covariates in prediction model development for each comparative standard trait. Linear regressions were performed in R (v.4.1.1). Non-significant ($P > 0.05$) covariates were removed for each trait independently.

For each linear regression, coefficient estimates for significant covariates were used to convert the image parameter estimates (pixels or average pixel intensity) to a predicted value (mm for backfat and loin depth and percent for intramuscular fat). The accuracy of model predictions was evaluated against the comparative standard data using the coefficient of determination, Pearson product-movement correlation, RMSE, the percent RMSE (RMSE/mean of comparative standard data), and ratio of performance to deviation (RPD).

Results

Image processing

All Commercial pigs had at least one image per pig that met algorithm quality standards for all traits analyzed. Image inclusion rate for backfat depth, loin depth, and intramuscular fat percentage was 97%, 89%, and 88%, respectively. On average the algorithm processed 2.07 images per second (Dell Precision 3560, 4 cores, 11th Gen Intel® Core™ i7-1185G7 3.00GHz 1.80 GHz).

Backfat depth

The mean comparative standard backfat depth was 14.6 mm with values ranging from 7.9 to 21.8 mm for Commercial pigs. The final model used to predict backfat depth included image backfat depth, loin depth, and intramuscular fat, and sex (Equation 1). The coefficient of determination, RMSE, percent RMSE, and RPD of the linear model were 0.58, 1.65 mm, and 11.3%, and 1.56 respectively.

$$Backfat\ depth\ (mm) = -0.240 + 0.009M_{06;} + 0.0017M_{P;} + 0.0044M_{:Q6} + 0.34Sex \qquad (1)$$

Where M_{BFD} = mean image backfat depth (pixel) by pig; M_{LD} = mean image loin depth (pixel) by pig; M_{IMF} = mean image grayscale intensity value by pig; Sex = 0 for gilt, 1 for boar. The correlation between predicted backfat depth and the comparative standard is 0.77.

Loin depth

The mean comparative standard loin depth was 63.7 mm with values ranging from 46.5 to 79.1 mm for Commercial pigs. The final model used to predict loin depth included image backfat depth, loin depth, and intramuscular fat, weight, and sex (Equation 2). The coefficient of determination, RMSE, percent RMSE, and RPD of the linear model were 0.57, 3.58 mm, 5.6%, and 1.54, respectively.

$$Loin\ depth\ (mm) = 0.56 + 0.0065M_{06;} + 0.008M_{P;} - 0.003M_{:Q6} + 0.0018k - 0.059Sex \qquad (2)$$

Where, M_{BFD} = mean image backfat depth (pixel) by pig; M_{LD} = mean image loin depth (pixel) by pig; M_{IMF} = mean image grayscale intensity value by pig; k = pig body weight at image capture; Sex = 0 for gilt, 1 for boar. The correlation between predicted loin depth and the comparative standard is 0.76.

Intramuscular fat

The mean comparative standard intramuscular fat percentage was 2.0% with values ranging from 1.13 to 3.48%. However, 80% of the pigs fell between 1.4 and 2.6% intramuscular fat and 95% of the pigs were between 1.2 and 3.0% intramuscular fat. The final prediction model for intramuscular fat percentage included the comparative standard for intramuscular fat (Equation 3). The coefficient of determination, RMSE, percent RMSE, RPD of the linear model were 0.25, 0.40%, 20.2%, and 1.52, respectively.

$$Intramuscular\ fat\ (\%) = 0.85 + 0.03M_{:Q6} \qquad (3)$$

Where, M_{IMF} = mean image grayscale intensity value by pig. The correlation between predicted intramuscular fat percentage and the comparative standard is 0.51.

Discussion

Model prediction accuracy was lower for intramuscular fat percentage when compared to backfat and loin depth prediction. This difference in accuracy could be attributed to image deformations, particularly of those within the loin region of the ultrasound images. Brøndum et al. (1998) described the low ratio of signal to noise as being one of the main disadvantages of ultrasound technology. Two of the most common types of noise in ultrasound data are double reflections and scattering. Double reflections occur at high-intensity echoes such as the backfat region. After reaching the transducer, the sound wave from the backfat region is reflected and echoed back a second time resulting in a reflection or image haze directly below the backfat line. Ultrasound scatter occurs from the reflection of small objects such as intramuscular fat. This reflection is typically referred to as a "salt" noise in ultrasound images. If it is not properly taken into account during analysis, salt noise can impact the amount of intramuscular fat measured in the loin region of ultrasound images through false signals.

During data collection images were taken consecutively with minimal probe repositioning, thus reducing variance between images from a single pig and increasing the likelihood of multiple low-quality images occurring for a single pig. The anatomical location of ultrasound scans can also be a limiting factor in obtaining accurate predictions; however, with standardization of location the reliability of trait estimates can be improved. Sandelin et al. (1999) reported multiple sampling locations across the loin to be highly related ($P < 0.0001$) to the intramuscular fat content of the entire longissimus dorsi through proximate analyses; however, fat content differed between different regions, thus emphasizing the importance of imaging the same anatomical location within a research trial or genetic selection.

Prediction results showed that the novel image processing algorithm performs acceptably across a wide range of backfat depth, loin depth, and intramuscular fat percentage values. However, predictive models tended to overestimate lower values and underestimate higher values with respect to comparative standards. Newcom et al. (2002) also reported an overprediction of pigs with low intramuscular fat (< 2%) and an underprediction of pigs with greater intramuscular fat (> 5%). Moeller and Christian (1998) found similar trends for backfat depth and loin eye area, a comparable trait to loin depth.

Conversely, Kvam and Kongsro (2017) reported model prediction accuracy tends to decline only in pigs with a higher value intramuscular fat content. Although the mean intramuscular fat percentage in the present study (2.0%) was lower than that which was present in Newcom et al. (3.76%; 2002) and Kvam and Kongsro (4.25%; 2017), both the present study and Newcom et al. (2002) report a normal distribution in measured intramuscular fat percentage. The skewed residuals observed in Kvam and Kongsro (2017) may be due to an insufficient number of pigs with higher intramuscular fat content or poor representation of high intramuscular fat images in the training data.

Limited published research has investigated the prediction of backfat and loin depth in live swine from ultrasound images. Many studies use actual backfat and loin depth or loin eye area for the prediction of carcass composition; however, few have developed prediction models for backfat and loin depth. Moeller (1994) used real-time ultrasonic measurements of backfat depth and loin muscle area for predicting carcass traits in swine. The dataset contained barrows and gilts representing 8 major U.S. purebreds of swine. The overall standard error of prediction of backfat depth and loin muscle area was 3.46 mm and 4.04 cm^2, respectively. Although RMSE was not reported, the formula for standard error of prediction is similar to that of RMSE but with an additional term for bias. Pomar et al. (2001) reported that loin eye area can accurately be predicted by its depth when measurement is performed on digitalized images ($R^2 > 0.86$). This indicates a strong relationship between loin eye area and loin depth.

While few studies have investigated backfat and loin depth prediction from ultrasound images in live swine, a number of studies have analysed the prediction of intramuscular fat percentage. Newcom et al. (2002)

reported coefficients of determination and RMSE for prediction to be 0.32 and 1.02%, respectively, similar to those found by Villé et al. (1997). In a more recent study, Lakshmanan et al. (2012) reported a coefficient of determination and RMSE of 0.76 and 0.34%, respectively. The above studies used images obtained at different stages of production, from live pigs (Ville et al., 1997; Newcom et al., 2002) to carcass (Lakshmanan et al., 2012). Moreover, the mean intramuscular fat percentage of Lakshmanan et al. (1.53 ± 0.69%; 2012) and the current study (2.0 ± 0.47%) is much lower than that of other studies which could contribute to the lower prediction error.

In the field of spectroscopy the RPD, the ratio between the standard deviation of a variable and the standard error of prediction of that variable by a model, has been used as a universal measure to describe the usefulness of an estimation or prediction model. A greater RPD indicates a greater degree of predictive capacity. Data presented by Newcom et al. (2002) and Kvam and Kongsro (2017) have calculated RPD values of 1.19 and 1.3, respectively for intramuscular fat prediction. The current study reported RPD values of 1.56, 1.54, and 1.52 for backfat depth, loin depth, and intramuscular fat percentage, respectively. Self-reported data presented by Biotronics Inc. has a calculated RPD of 1.81 on model validation testing for their commercially available software. Collectively, the current Biotronics software provides more accurate estimates of intramuscular fat compared to the current study (RPD = 1.81 vs 1.52, RMSE = 0.63% vs 0.56%). However, the present study provides a novel mathematical approach to estimating carcass traits and reduces skilled labor requirements as it can automatically analyze 2 images per second without the need for human adjustments.

The developed image processing algorithm demonstrates the feasibility of estimating BF, LED, and intramuscular fat percentage from longitudinal ultrasound images. Overall, results support the use of image gradient to identify and segment backfat and loin regions of longitudinal ultrasound scans and application of linear models to produce predictions of carcass traits in a fast and acceptably accurate manner. Reliability of results is improved when multiple longitudinal images are captured on a single pig in order to increase the probability of obtaining an image of appropriate quality. Greater prediction accuracy was observed in estimation of BF and LED when compared to intramuscular fat percentage (11.3% and 5.6% RMSE vs 20.2% RMSE, respectively).

Conclusions

Fully automatic, accurate, and reliable estimates of swine backfat depth, loin depth, and intramuscular fat percentage are beneficial for the swine industry. Although there is commercially available software to estimate backfat depth, loin depth, and intramuscular fat percentage, an increase in published research in this area could prove beneficial by expanding awareness and continually improving estimation of these traits for specific genetic lines. The ability to automatically identify and measure these traits allows the identification of superior breeding animals for genetic selection programs. The results of the current study included a coefficient of determination and RMSE of 0.58 and 1.65 mm, 0.57 and 3.58 mm, and 0.25 and 0.40% for BF, LED, and IMF percentage, respectively. Future algorithms for prediction of backfat depth, loin depth, and intramuscular fat percentage should include a robust dataset with a wide range of loin intramuscular fat percentage and highly standardized image collection procedures to further improve performance.

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