# Late-finishing pig body weight estimation using extrapolation from side surface point clouds

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## Abstract

The estimation of live body weight (BW) of late finishing pigs from a ridge regression model using biometrics collected from an extrapolated 3-dimensional pig model is evaluated in this study. This work compares the predicted BW of 64 pigs with the ground truth BWs manually determined from a scale. Data consisted of partial point clouds acquired from the side view of the pigs using a mobile camera system. The objective of this study was to evaluate the accuracy of finishing pig BW estimation using extracted biometrics (i.e., girth, length, width, height, and flank) from a pig surface extrapolated from a partial point cloud. These biometrics were used as independent variables in a machine learning formula for predicting BW. The root mean squared error (RMSE) was found to be 5.31 kg for the 64 BWs estimated using the extrapolated technique, with an $R^2$ of 0.79. The extrapolation technique was compared to the manual technique by creating a subset of both datasets, which consisted of fifty pigs. Two BW estimation models were created using the subsetted dataset, using the manually collected and extrapolated biometrics. The two BW estimation models found similar RMSE of 4.17 kg and 5.72 kg for the manual and extrapolated datasets. Overall, the process of extrapolating the surface of a pig from a partial point cloud is promising due to the ability to extract any biometrics from only a single partial point cloud, which avoids the disadvantages of manual BW estimation.

**Keywords:** Blender, camera, machine vision, precision livestock farming, swine

## Introduction

In modern swine production, accurate information on the live body weight (BW) of pigs is an important biological parameter that affects the producer's profitability. In-barn BW estimation is often performed manually using direct measurement using a scale or subjective estimation using a visual inspector. Direct measurement requires multiple people and can take up to 5 minutes per pig (Brandl and Jorgensen, 1996), which does not scale well with large commercial facilities. Leading pigs on and off a scale is stressful to humans and animals, with an increased risk of injury to both. Body weight estimates from visual inspectors are highly subjective, lack repeatability, and are dependent on the years of experience an inspector has (Cabezon et al., 2016).

Three-dimensional data as a noninvasive and objective alternative can be used extract biologically significant features. Several studies show correlations between BW and biometric measurements, including height, length, width, flank, and girth (Yeo and Smith, 1977; Schofield et al., 1989; Walugembe et al., 2014; Pezzuolo et al., 2018). These biometrics are implemented as independent variables in regression models to predict BW, yet many studies indicate that these variables are still collected manually.

Deep learning studies featuring convoluted neural networks have found high performance (Suwannakhun and Daungmala, 2018; Cang et al., 2019), but the major drawback is that the exacted features are unknown. Recent studies using 3-dimensional data in the form of point clouds or RGB-Depth imaging can extract these biometrics to estimate BW with relatively high precision (Kashiha et al., 2014; Kongsro et al., 2014; Wongsriworaphon et al., 2015; Condotta et al., 2018; Pezzuolo et al., 2018; Fernandes et al., 2019) but observed that a major limitation is the viewing angle of the camera. Therefore, to create the most effective prediction model, an extrapolation technique from a partial point cloud is proposed to create a complete pig in which all biometrics can be reliably obtained to create the most robust model for estimating BW.

## Materials and methods

### Data collection

Partial point cloud data were generated from late-finishing pigs with a body weight (BW) range between 111.1 and 131.5 kg housed at: (1) Central Crops Research Station (Clayton, NC); (2) NCSU Swine Educational/Nutrition Unit (Raleigh, NC); and (3) a commercial swine research farm. Three measurements were performed on 72 finishing pigs: heart girth, body width, and body length. Heart girth was measured using a plastic tube following the protocol of Knauer and Wiegert (2017) and body width and length were measured using a standard cloth measuring tape (Anh et al., 2022). Experimental protocols were approved by the North Caroline State University (NCSU) Institutional Animal Care and Use Committee (#19-079-A).

Each finishing pig was moved from their pen on to a calibrated scale for individual BW measurement. After weighing, pigs were directed to a space where videos of each pig were recorded using a camera (D435i; Intel RealSense, Santa Clara, CA, USA) that simultaneously recorded depth and RGB data. Calibration was performed following the manufacturer's procedure. Images were collected by aiming the camera at an individual pig, slightly above the waist at a distance of 2 m and within the camera's field of view. After recording for 10 to 20 s, individual pigs were directed back to a pen. This procedure was repeated for all pigs (Anh et al., 2022).

### Partial point cloud to mesh reconstruction

After video processing, raw video data were saved as .bag files, the default file format generated by the depth camera. All collected recordings were partitioned into individual frames consisting of 3 to 5 frames per pig. Each frame consisted of RGB (Figure 1a), depth, and point cloud data (X, Y, and Z coordinates)

### Mesh reconstruction

Each partial point cloud of an individual pig was converted into a reconstructed mesh (Figure 1b) using MeshLab (Cignoni et al., 2008) by (1) computing normal surfaces, (2) downsampling of raw point clouds, and (3) reconstructing the surface. Normal surfaces were determined by using 10 neighboring points to create a tangent face at the point of each pointset. This yields an array of the normals for all points that are perpendicular to the tangent face for each point.

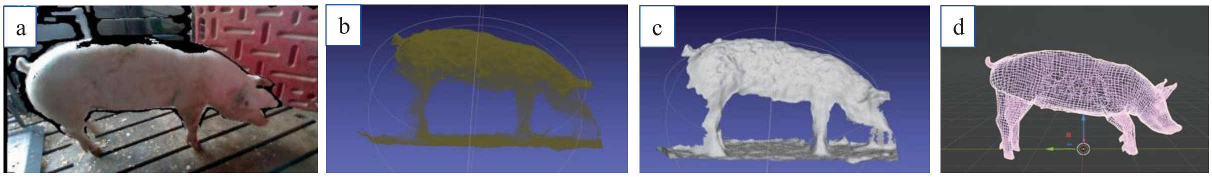

Figure 1: Extrapolation of a pig surface from a partial point cloud derived using mesh reconstruction with (a) visualizing the raw image, (b) importing the point cloud, (c) surface reconstruction, and (d) extrapolation. The head and legs from the model pig were not modified from the shrinkwrap algorithm.

Raw partial point clouds on average consisted of >80,000 points and due to this high density, were downsampled to 10,000 points. Downsampling was performed using the Poisson-Disc sampling algorithm (Mederios et al., 2009). Points arranged in a congested pattern were removed if they were within a specific minimum distance of each other. The downsampled point cloud has minimal points without distorting the original shape.

Surface reconstruction used the Ball-Pivoting algorithm (Bernardini et al., 1999) due to the faster processing speed and high accuracy of the reconstructed surface compared to the Screened Poisson algorithm or the Visualization and Computer Graphics Library (VCG) filter. The radius of the ball was kept at a default value of 20 units. Increasing the radius of the ball resulted in an ambiguous shape while decreasing the radius resulted in a completely flat surface. The output of this function is a reconstructed mesh surface that displays the individual triangles that connect all the points of the point cloud into a unified surface (Figure 1c). Reconstructed mesh point clouds were then re-oriented such that the pig's spine was parallel to the X axis.

Corrupted meshes were removed, which were point clouds with large gaps or holes, missing body parts, or were "hazy" due to air quality. Glare from skin oil was a leading cause of corrupted meshes. Only point clouds that had pigs facing forward were used.

## Extrapolating the surface of a complete model pig

A 3D model pig was used to extrapolate the surface of a complete pig from a reconstructed mesh, derived from a partial point cloud. The model pig was developed by a Blender content creator (Deemsys, 2021) designed for Blender v2.93 and contained 11,101 vertices with 11,574 polygons. This model mesh first required rigging to model various poses of the pig. All reconstructed meshes featured pigs facing forward, but since several faced up or down, which changes the curvature of the spine and therefore, estimates of biometrics could be affected.

The origin (0, 0, 0) was set in the Blender (Community, 2018) workspace to ensure the pig would rotate in all planes. Blender's quadrupedal addon was used to carefully rig the model pig such that the reconstructed mesh of the partial point cloud could be imported into the Blender workspace. The "On the Ground" addon was used to translate the entire object to 0 on the Z axis. This ensured that the height of both mesh models started from the origin. The model pig was rigged to express different poses found in the reconstructed mesh, such as moving the head, body, or spine up, down, or to the side. After rigging the model, the pose mode was saved as the default rest pose.

Once the models pig's default rest pose closely matched the reconstructed mesh's pose, model pig dimensions were verified. A model pig too large will overestimate, while a model pig too small would underestimate biometric dimensions. The model pig had a length (143.7 cm), height (67.6 cm), and width (40.5 cm) similar to the typical size of a late finishing pig in a BW range of 110 to 136 kg (Condotta et al., 2018). These dimensions were adjusted by constraining the model pig's length and height to the reconstructed mesh's length and height to maintain consistency during extrapolation.

The mesh was then bisected using the knife function in Blender to slice the model pig in half longitudinally. The bisected model pig resembled the form of the reconstructed mesh of the pig in the side view. The mesh model was then superimposed on the model pig using the snap function. Points of the model pig were identified if they were near the points in the reconstructed mesh. The model pig was shrinkwrapped to the mesh pig using Blender's shrinkwrap algorithm. Four methods could be used for shrinkwrapping, but the nearest surface point method was found to be most effective. This method selects the nearest point over the target object's surface, effectively translating the vertices of the model pig to the closest vertex of the reconstructed mesh. This resulted in a shrinkwrapped mesh of the model pig, but now, the model pig was modified in a way where the surface of the model pig consisted of the same surface features and details as the reconstructed mesh. This step was repeated to create the best extrapolated surface (Figure 1d). The missing half of the bisected, shrinkwrapped, model pig was completed by applying the mirror function across the Y axis. Since no biometric features from the head or legs were collected in this study, they were not modified from the model pig.

Statistical analysis

Ridge regression is a predictive modeling technique that is used when independent variables show collinearity with each other or the dependent variable (Hoerl and Kennard et al., 1970). All variables were correlated to each other, and generally increased with increasing BW. Prior to ridge regression, all data were normalized so the average value was 0. The ideal lambda value was found by a 10-fold cross validation approach to fit a model with the biometrics as independent variables and BW as the dependent variable. Data were partitioned into 10 random groups, where one group represented the training dataset, and the other nine groups represented the test datasets. A model was created based on the training dataset and a lambda value was determined. This step was repeated 10 times, and the most optimal lambda value was determined. Statistical metrics used to evaluate the ridge regression model were the root mean square error (RMSE) and the coefficient of determination ($R^2$).

## Results and discussion

This study used the biometrics collected from manual measurements and through the extrapolation technique as independent variables to create a predictive model for estimating BW. The original dataset consisted of 771 pigs, but not all pigs contained three complete entries for length, width, and girth. The complete dataset is a subset of the original dataset, and comprised of 72 pigs where length, width, and girth measurements were manually collected. The extrapolation technique collected length, width, girth, flank, and height from 64 suitable partial point clouds of pigs in the complete dataset (now referred to as the "extrapolated dataset"). Only pigs that were common between the completed and extrapolated datasets can be used to compare the results of the ridge regression model. A subset of the complete datasets for the manual and extrapolated technique was created where 50 pigs that were in common between the two datasets were used to compare the manual and extrapolated technique.

Correlations between the manual and extrapolated biometric datasets, and with BW are presented in Table 1. Length was poorly correlated with BW, in both the manual and extrapolated datasets. Width was moderately correlated with BW for the manual and extrapolated datasets. Correlation between BW and girth was like that of width for the manual and extrapolated datasets. In the complete extrapolated dataset, height and flank measurements were obtained. Height was poorly correlated with BW (Table 1). The correlation between flank and BW was moderately low. The average measurements of the extrapolated technique were larger than measurements collected manually.

Table 1: Summary statistics of all collected biometrics in the complete, extrapolated, and subset datasets.

| Biometric | Method | n | Correlation | Correlation with Body Weight |
|---|---|---|---|---|
| Length | Manual | 50 | 0.84 | 0.17 |
| | Extrapolated | 50 | | 0.01 |
| Width | Manual | 50 | 0.37 | 0.45 |
| | Extrapolated | 50 | | 0.41 |
| Girth | Manual | 50 | 0.51 | 0.56 |
| | Extrapolated | 50 | | 0.42 |
| Height | Manual | - | - | - |
| | Extrapolated | 64 | | 0.03 |
| Flank | Manual | - | - | - |
| | Extrapolated | 64 | | 0.26 |

The results of the ridge regression model are displayed in Table 2. The complete dataset for the manual data consisted of 72 pigs with a $R^2$ of 0.84 with an RMSE of 1.63 kg. The subset of the complete manual data consisted of 50 pigs with a similar $R^2$ of 0.82. The RMSE was found to be 4.17 kg. The complete dataset for the extrapolated data consisted of 64 pigs with an $R^2$ of 0.79 and an RMSE of 5.31 kg. The subset of the extrapolated data consisted of the same 50 pigs as the subset of the complete manual dataset and obtained a model $R^2$ of 0.75. The RMSE was found to be 5.72 kg. The relationship between the extrapolated and ground truth BWs is displayed in Figure 2. The final ridge regression model using the complete dataset with extrapolated biometrics of length (L), girth (G), width (W), height (H), and flank (F) was BW = 17.03 + 3.9(L) + 1.73(W) + 4.1(G) + -0.07(H) + 0.59(F).

Table 2: Statistical metrics and coefficients of the ridge regression model to estimate body weight in the manual, extrapolated, and subset datasets. L = Length; W = Width; G = Girth; H = Height; and F = Flank.

| | | | | | Coefficients | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | n | $R^2$ | RMSE (kg) | λ | Intercept | L | W | G | H | F |
| Manual (Subset) | 50 | 0.82 | 4.17 | 0.52 | 30.01 | 1.56 | 2.27 | 3.73 | - | - |
| Extrapolated (Subset) | 50 | 0.75 | 5.72 | 1.02 | 192.83 | -1.09 | 1.186 | 2.19 | - | - |
| Manual (Complete) | 72 | 0.84 | 1.63 | 1.13 | -100.99 | -1.98 | 1.75 | 6.36 | - | - |
| Extrapolated (Complete) | 64 | 0.79 | 5.31 | 0.76 | -17.03 | 3.9 | 1.73 | 4.1 | -0.07 | 0.59 |

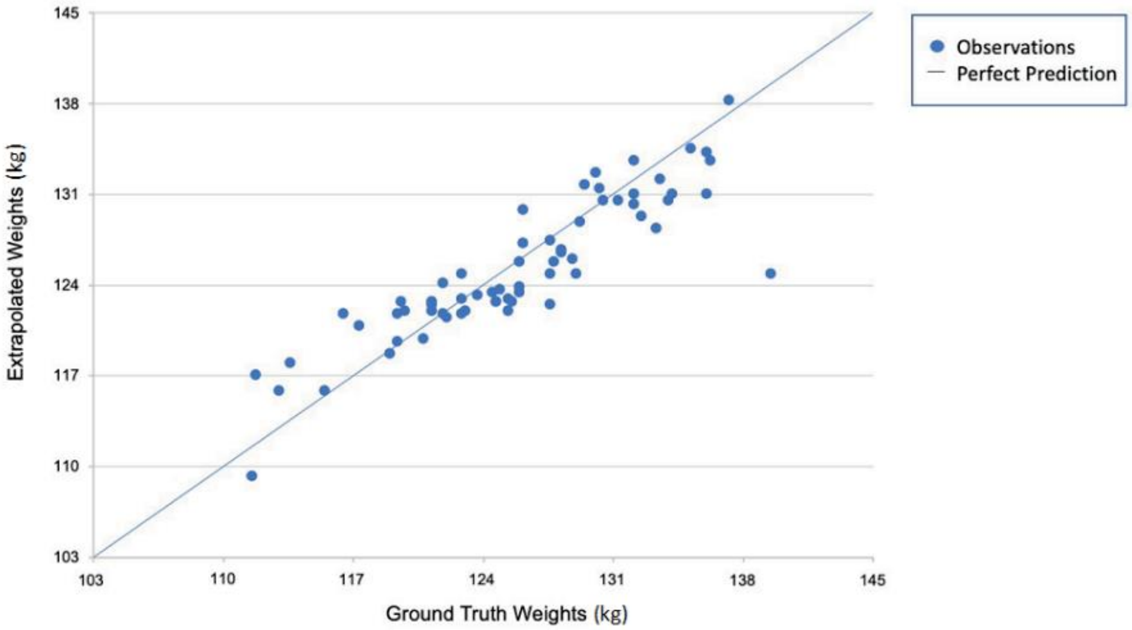


Figure 2: Scatterplot displaying the relationship between the ground truth and extrapolated body weights of the 64 pigs in the complete dataset. The blue line represents the line of perfect fit ($R^2$ = 1).

*Finding 1: An extrapolation technique to determine biometrics in finishing pigs was found to agree with manually derived measurements for length and girth.*

As seen in Table 1, length was found to be highly correlated between the manual and extrapolated pig surfaces. Girth measurements were found to generally be higher in the extrapolated dataset than in the manual dataset, which is likely due to overestimation of the girth edge loop. Furthermore, in many cases, the underside of the belly was not completely captured in the point cloud. This resulted in minor imperfections that overestimated girth and flank during the extrapolation process. The width was found to have a different range of values in the extrapolated dataset than in the manual dataset. This is due to the width being measured in a different technique than was done manually. This study found the average difference between the manual and extrapolated dataset for length, width, and girth to be 0.91 cm, 8.69 cm, and 7.34 cm, respectively. Li et al. (2022) compared manually derived measurements with those extracted from back surface point clouds. Their study found high agreement across all traits found, where the difference between the average of the biometrics obtained from manual measurements and extracted measurements from 50 pigs was around 0.03 cm. The study in this paper did not achieve a similar agreement between the manual and extrapolated techniques. However, there were no indications of repeated measurements when collecting manual biometrics and at least three people were collecting manual measurements. These observations suggest that improving the repeatability of the manual measurement procedure can improve the correlation between the manual and extrapolated biometrics.

*Finding 2: An extrapolation technique to determine biometrics in finishing pigs was found to agree with manually derived measurements for length and girth.*

Body weight estimates from a ridge regression model using biometrics from the extrapolated technique were correlated with ground truth BWs. As displayed in Table 2 and Figure 2, the equation developed to estimate BW using the extrapolated dataset found an $R^2$ of 0.79. Many studies have used biometrics extracted from point clouds or RGB depth images to estimate BW or mass, similar to this study. Kongsro (2014) created a BW estimation model from biometrics derived from a Microsoft Kinect that could estimate BW with an $R^2$ of 0.99 when using 71 boars. Condotta et al. (2018) found that by using RGB depth imaging with volume as an independent variable, a prediction formula can estimate BW with $R^2$= 0.9907 in a dataset of 772 depth images. Furthermore, this study evaluated this model with different breeds and genders of pigs and found an $R^2$ = 0.9909, 0.9898, 0.9912 for Duroc, Landrace, and Yorkshire pigs, respectively 0.9895 and 0.9921 for barrows and gilts, respectively. The large sample sizes in that study indicate that the model used in this study can be improved with larger sample sizes. However, the major limitation in this study was the lack of quality point clouds due to a non-neutral pose or holes in the point cloud due to glare from the oily skin of the pig.

*Finding 3: The RMSE of the predictive model for body weight using the manually collected measurements was similar to the RMSE from using the extrapolated technique, and both performed better than visual appraisal*.

The RMSE of the subset datasets (n = 50) for the manually derived measurements and extrapolated technique were 4.17 kg and 5.72 kg, respectively. According to Cheng et al. (2018), prices of pig carcass weights start to discount at intervals of 3.18 kg. Thus, estimates from both models would result in BWs that could fall into the same discount interval, suggesting that the economic loss of using either model would be similar. Both models achieved better results than BW estimates using visual appraisal, where according to Cabezon et al. (2016), the largest error rate reported for estimating BW through visual appraisal was found to be 8%, which is potentially an error of 9.07 kg for a 113.4 kg pig.

## Conclusions

This study advanced the procedure for BW estimation by using an extrapolation technique to extract multiple body biometrics of a finishing pig quickly and objectively, without the disadvantages of manual measurements or subjectivity from visual appraisal. Three major findings indicate that the extrapolation technique can be used to predict BW in finishing pigs: (1) Length and girth measurements from the extrapolated technique were similar to those collected manually; (2) BWs of finishing pigs that were predicted using the extrapolation technique were correlated with ground truth weights; and (3) The RMSE from the BW estimation model for both the manual and extrapolation techniques were similar, and both performed better than visual appraisal.

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