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Research Paper

Evaluation of a depth sensor for mass estimation of growing and finishing pigs

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A method of continuously monitoring animal mass would aid producers by ensuring all pigs are gaining mass and would increase the precision of marketing pigs. Therefore, the development of methods for monitoring the physical conditions of animals would improve animal well-being and maximise the profitability of swine production. The objective of this research was to validate the use of depth images in predicting live animal mass. Seven hundred and seventy-two depth images and mass measurements were collected from a population of grow–finish pigs (equally divided between barrows and gilts). Three commercial sire lines (Landrace, Duroc, and Yorkshire) were equally represented. The pigs' volumes were calculated from the depth image. Linear equations were developed to predict mass from volume. Independent equations were developed for both gilts and barrows, each of the three commercial sire lines used, and a global equation for all combined data. Efroymson's algorithm was used to test for differences between the global equation and the two equations for the gilts and barrows and between the three commercial sire lines. The results showed that there was no significant difference between the global equation and the individual equations for barrows and gilts ($p < 0.05$), and the global equation was also no different from individual equations for each of the three sire lines ($p < 0.05$). The global equation was developed to predict mass from a depth sensor with an R^2 of 0.9905. In conclusion, it appears that the depth sensor would be a reasonable approach to continuously monitor pig mass.

1. Introduction

The main objective of most animal production companies is to provide a product that meets the demands of the customer at a price that allows profit. These demands, however, are becoming more well-defined: e.g. the meat industry pays more to producers for animals within a specified range of mass and composition. Another example is the dairy industry, which pays more or less to milk producers according to the quality and composition of the product (Frost et al., 1997).

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The inability of the producer to obtain, with precision and control, the variables that affect the conformation and fat levels of animals can cause the failure to meet the market's demands. Taking into consideration that farms have increased in size, even small changes in production practices can have a major impact on the global income (Kashiha et al., 2014).

Knowledge of the daily variation of the animals' mass in real time would allow producers to improve the animal well-being and production. It would be possible to use this information to improve nutritional management practices, predict and control the mass at slaughter and, potentially, serve as a monitor for disease outbreaks (Brandl & Jorgesen, 1996; Kashiha et al., 2014).

Weighing animals is typically done manually, a process that often requires two workers and can take three to five minutes per animal. This practice can be stressful for both animals and workers, time consuming, and represents an ergonomic risk (Brandl & Jorgesen, 1996).

Therefore, an automated system to determine the animals' mass has the potential to assist producers to classify them to market and minimise the number of pigs marketed outside specification, improving the yield of production. Many attempts have been made to find an alternative to manual weighing.

Essentially, two approaches have been studied: automated weighing systems combined with individual animal identification equipment and indirect determination of mass using the animals' dimensions.

In general, the automatic weighing systems involve direct contact with the animal. They can be used in the form of semi-automatic scales (Smith & Turner, 1974), significantly reducing the time of weighing, in the form of automatic feeders with automatic scale (Ramaekers et al., 1995; Schofield, Whittemore, Green, & Pascual, 2002; Slader & Gregory, 1988), and can be successfully used for individual monitoring of pigs in a herd, reducing the time spent on the process. Problems with this approach involve the presence of more than one animal or other material on the scale during weighing, and material under the feeder, which could generate measures that cannot always be trusted.

The significant correlation between mass and pigs' dimensions has led many authors to study the possibility of estimating body mass using such a relationship (Brandl & Jørgensen, 1996). Some methods of indirect measurement of mass, through pigs' dimensions, using tapes and callipers have been widely used by producers. Although these are faster methods than manual weighing, they still require that the pig is immobilised and they do not provide mass with great accuracy. Alternatively, several authors (Frost et al., 1997; Kashiha et al., 2014; Schofield, 1990; Schofield, Marchant, White, Brand, & Wilson, 1999; Wang, Yang, Winter, & Walker, 2008; Whittemore & Schofield, 2000) have developed techniques for obtaining animals' dimensions from digital images, and this has been shown to be an efficient non-invasive method.

In general, the difficulty with the determination of mass through images is that, to extract the dimensions of the pig, its colour must be different from the colour of the environment. Dark skinned, stained, or dirty pigs make this approach very difficult to automate. In addition to the colour of the animal, the presence of adequate light is critical for this application. Kashiha et al. (2014) found good illumination values within the range of 40–150 lux. Wu et al. (2004) sought to solve this problem by developing a system for capturing images with six high-resolution cameras (3032 × 2028 pixels) and three flash units to obtain the 3D shapes of live pigs. One problem with this approach was the large amount of equipment and the high costs involved, which makes this type of image capture difficult on an industrial scale.

Finally, Kongsro (2014) proposed the use of a Microsoft® Kinect® sensor to obtain depth images. The Kinect® is a sensor that serves as a 3D measurement device and it has been receiving the attention of several authors due to its low cost, reliability and speed of measurement (Smisek, Jancosek, & Pajdla, 2013, pp. 3–25). The Kinect® sensor is a compound device consisting of a digital colour RGB camera, an infrared (IR) emitter, an infrared depth sensor, four microphones, a three-axis accelerometer and a tilt motor (Microsoft®). The sensor provides three images: infrared, colour and depth. The benefit of using a depth sensor instead of a digital camera is that depth sensors are not as prone to effects of lighting or shadows. Kongsro (2014) showed that the volume of the animal obtained through these images was correlated with the mass of Landrace and Duroc boars. This system could estimate the mass of the boars with an error between 4 and 5%. This work leaves the question, would there be a different correlation for barrow or gilts and is there a significant difference between sire-lines?

The objective of this study was to extract pigs' mass data from depth images, using a low-cost depth sensor and test for the effect of commercial sire lines (Duroc, Landrace, and Yorkshire) and sexes (gilts and barrows).

2. Material and methods

The experiment was conducted in a grow-finish building of the U.S. Meat Animal Research Center, from the Agriculture Research Service-ARS of United States Department of Agriculture – USDA (−98.13°W, 40.52°N). Animal mass and digital and depth images were collected from a population of grow-finish pigs at four distinct time points through the grow-finish period. All animal procedures were performed in compliance with federal and institutional regulations regarding proper animal care practices (FASS, 2010).

2.1. Animal specifics

Two hundred and thirty-four grow–finish pigs (equally divided between barrows and gilts) were sampled at each of four approximate ages: 8-, 12-, 16- and 21-weeks old. The pigs represented three commercial lines sire lines (Landrace, Duroc and Yorkshire). The maternal line was a mix of Landrace × Yorkshire; each of the sire lines were equally represented in the sample. Pigs were housed in standard grow-finish type arrangement, with 39 pigs pen^{-1} (0.93 m^2 pig^{-1}), and had *ad libitum* access to feed and water through the growing period.

2.2. Image acquisition

An image acquisition program was developed in MATLAB software, version R2015b to acquire data from a Kinect®

sensor (Version 1) and deployed to a laptop for data collection. The Kinect® sensor was mounted on the wall above the animal scale (Fig. 1). Both digital colour images (Fig. 2a) and depth images (Fig. 2b) were acquired from the Kinect® sensors at approximately 1-sec intervals. The digital RGB colour image was saved in a png (portable network graphics) format; the values from the depth image were saved in a space-delimited text file (txt). Digital colour RGB images were used for animal identification. As the pigs walked on to the scale, their number was written on a small white board and held in front of the camera to ensure each image could be identified. The depth image was used for acquiring the animals' volumes.

Fig. 1 – Mass and images were captured on individual pigs using a standard pig weighing scale and Kinect® sensor, version 1. The Kinect® sensor was mounted on the wall directly above the centre of the scale.

2.3. *Image processing*

Pig volumes were found through the processing of the depth images using a program developed in MATLAB software, version R2015b. The depth map was imported to the software using the 'importdata' function (Fig. 2b). The distance from sensor to animal was converted into the animal's height by subtracting the distance between sensor and floor (Zf) from the distance between sensor and animal (Za), (Fig. 3). Then, the values were selected within a limit, covering 50% of the approximate height of the animal (which was found with the sensor), setting pixels outside that limit equal to zero using a logical 'if/else' test (Fig. 2c).

Later, possible noise signals (e. g. parts of the scale) were eliminated, making the values of rows and columns around the animal equal to zero. The resulting matrix was transformed into a binary image ('im2bw') and the object with the largest area on the image was selected using the 'bwareafilt' function (Fig. 2d). Then, the animal was rotated to be in a horizontal position in the image.

The head and tail regions were then eliminated, making their values equal to zero to obtain better correlation with the mass of the animal (Schofield, 1990). The tail and the head were removed automatically by algorithms developed from a subset of 300 images, randomly selected from all for periods of measurements, representing the 3 sire-lines and two sexes of animals (Fig. 4). To remove the tail, the following algorithm

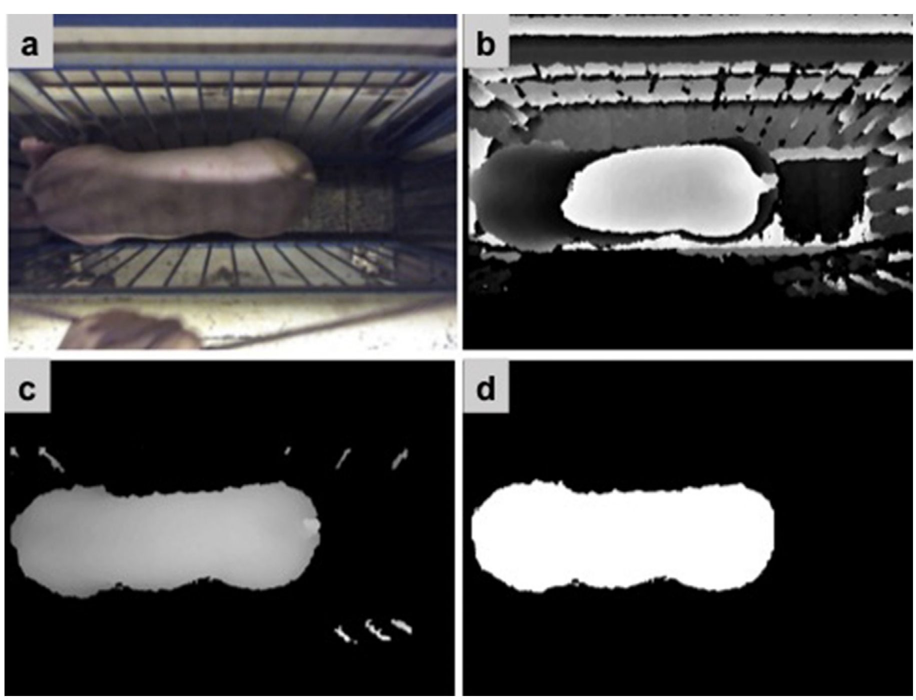

Fig. 2 – Images collected using a Kinect® sensor, version 1, positioned directing above the scale as the animals were being weighed (a) RGB image and (b) depth image processed using Matlab software, version R2015b (c) shows the elimination of areas in the depth image that were outside a pre-established value (range of 20 cm greater or less than the pig's height) (d) indicates the selected pig after eliminating head and tail.

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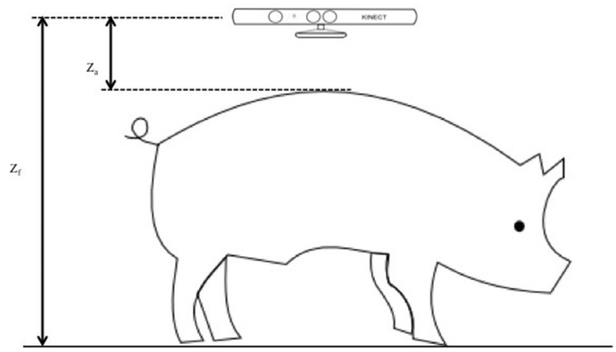

Fig. 3 – Height of the animal was determined by subtracting the distance to the floor (Z_f) and the distance to the animal (Z_a).

was completed. Step 1, the centroid of the animal was found (using 'regionprops' function); Step 2, the hip of the animal was located by finding the widest column between the centroid and edge of the image, found using the 'sum' function; Step 3, the base of the tail was determined by adding 60% of the width of the hip, in pixels, to column number containing the hip; and, Step 4, make all columns after the column containing the base of the tail equal to zero (Fig. 4).

To remove the area of the image that contained the head, the following algorithm was completed. Step 1, the width of the hip, in pixels, was multiplied by 3; Step 2, this number was subtracted from the column number that contained the base of the tail; Step 3, all columns after this number were turned into zeros. The largest area on the image was selected again using the 'bwareafilt' function, to make sure that parts of the ear were eliminated.

The final step in the image process was to apply the binary image as a mask on the original map to select only the region of interest values. The projected volume of the pig (Fig. 5) was determined by summing all the pixels that were under the binary mask. For simplification, this projected volume will be referred to as volume throughout the manuscript. These pixels contain the height of the pig at each point and their sum corresponds to a measurement of the volume of the projection of the pig, without head and tail. This volume value obtained was adjusted for the distance from camera to object, using Eq. (1); to obtain a corrected volume of the projection, in cm^3.

$$V = V_0 \times 6.47774 \times 10^{-6} \times Z^{1.85304} \quad (1)$$

where:

V = corrected volume, in cm^3;
V_0 = Volume, in pixels × cm;
Z = distance between sensor and object, in cm.

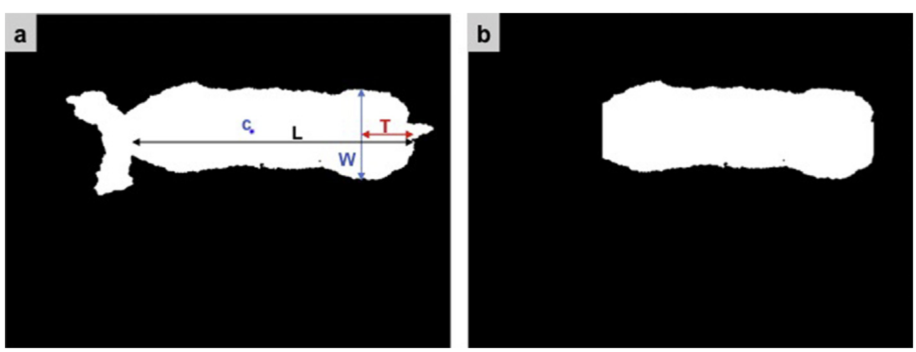

Fig. 4 – Head and tail removal. (a) "c" represents the centroid of the pig, "W" is the width of the hips, found as the column with more number "ones" from the centroid to the edge of the image, "T" is the distance from the hip to the tail of the animal, found as 60% of the width of the hip, and "L" is the length of the animal, measured from the base of the tail to the base of the neck, found as 3 times the width of the hip. (b) shows the resulting image after removal of the columns that are outside the length of the animal from the base of the neck to the base of the tail.

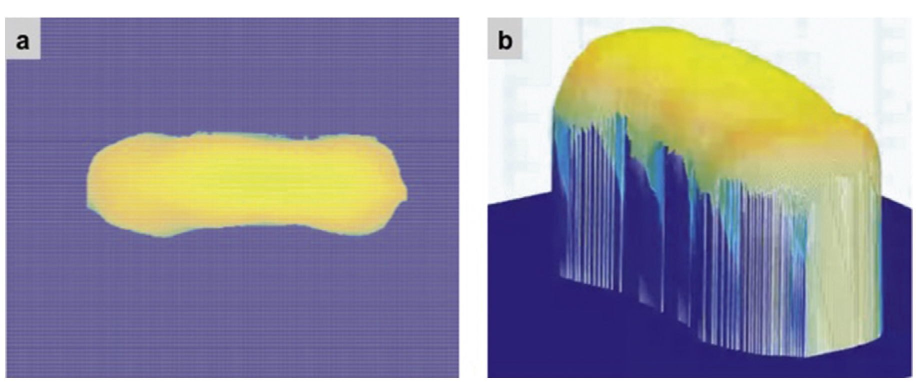

Fig. 5 – (a) Top image of the pig. (b) volume of the projection of the pig. Each pixel on the top image has the height from the back of the pig to the floor. The values of each pixel are summed to obtain a volume measure.

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2.4. Statistics

Linear equations were developed for each sire-line and one global equation by using regression procedure in SAS. The general linear model procedure in SAS was used to test the effects of pig volume, sire-line and the interaction of pig volume and sire-line on the mass of the pigs. Similarly, linear equations were developed and tested with general linear model for barrows and gilts.

To test the error associated with the model, a multiple linear regression equation was developed using the software Microsoft® Excel® 2016 to describe the effects of volume (cm^3) on the mass of the pigs (kg). A 60% random sample of the data was used in the initial development of the equations and the remaining 40% was used for testing the accuracy of the model.

Efroymson's algorithm (stepwise regression; Efroymson, 1960), was used to test the level of significance of sex and sire line in the multiple linear regression equation. The null hypothesis considered the reduced model equivalent to the global model and the alternative hypothesis considered the global model different from the reduced model. The global model was developed in Microsoft® Excel® 2016 software and considered the effects of the sexes and the commercial sire lines used, using *dummy* variables (Draper & Smith, 1998). The test statistic is given in Eq. (2).

$$F(n,d) = \frac{\left(SQ_r - SQ_g\right)\Big/\left(DF_r - DF_g\right)}{SQ_g\Big/DF_g} \tag{2}$$

where:

SS_r = sum of the squares of the residue of the reduced model;
SS_g = sum of the squares of the residue of the global model;
DF_r = degrees of freedom of the residue of the global model;
DF_g = degrees of freedom of the residue of the reduced model.

Then, the chosen model was evaluated by Pearson's correlation I and determination (R^2) coefficients. In addition, to assess the accuracy of the model, the model was tested on the remaining 40% of the data to compare estimated mass and actual mass. The generated equation was used in these data, comparing the predicted mass with the estimated mass, and then, the Willmott's concordance index (d; Willmott, 1981) and the refined Willmott's index (dr (Willmott, Robeson, & Matsuura, 2012); were calculated, according to Eqs. (3) and (4), respectively.

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2} \tag{3}$$

where:

d = Willmott's concordance index;
P_i = i-th predicted variable;
O_i = i-th observed variable;
$\overline{O}$ = Observed variables average.

$$d_r = \begin{cases} 1 - \dfrac{\sum_{i=1}^{n}\left|P_i - O_i\right|}{2 \times \sum_{i=1}^{n}\left|P_i - \overline{O}\right|}, \textit{when } \sum_{i=1}^{n}\left|P_i - O_i\right| \le 2 \times \sum_{i=1}^{n}\left|P_i - \overline{O}\right| \\ 1 - \dfrac{2 \times \sum_{i=1}^{n}\left|P_i - \overline{O}\right|}{\sum_{i=1}^{n}\left|P_i - O_i\right|}, \textit{when } \sum_{i=1}^{n}\left|P_i - O_i\right| > 2 \times \sum_{i=1}^{n}\left|P_i - \overline{O}\right| \end{cases} \tag{4}$$

where:

d_r = refined Willmott's index;
P_i = i-th predicted variable;
O_i = i-th observed variable;
$\overline{O}$ = Observed variables average.

3. Results and discussion

A total of 772 digital and depth images, each from a unique animal and/or time point, were captured and analysed in this project. A number of images were not analysed, as they were not of sufficient quality. The pigs weighed 17.6 ± 2.87, 44.7 ± 4.84, 72.0 ± 7.48 and 100.6 ± 9.75 kg at each of the four time points, respectively. The algorithm, developed using MATLAB software, version R2015b, calculated the volume of the pigs using only a top view image. The volumes and mass were manually matched for this project.

It was found that the mass of growing-finishing pigs varied with the volume obtained through depth image analysis (Fig. 6). Visually, the animals' mass varies linearly with the volume obtained by image analysis, which is proved by Pearson's correlation coefficient (0.9952; Table 1). The result of the Efroymson's algorithm ($p = 0.8237$) showed that the effects of sex and commercial line do not need to be considered in the prediction equation, indicating that the reduced equation is sufficient for mass prediction of the three commercial lines used for both gilts and barrows.

It was found that mass was significantly affected by the pig volume ($p < 0.0001$). No significant effects of sire line ($p = 0.3405$), sex ($p = 0.1852$), volume by sire line ($p = 0.4622$) or

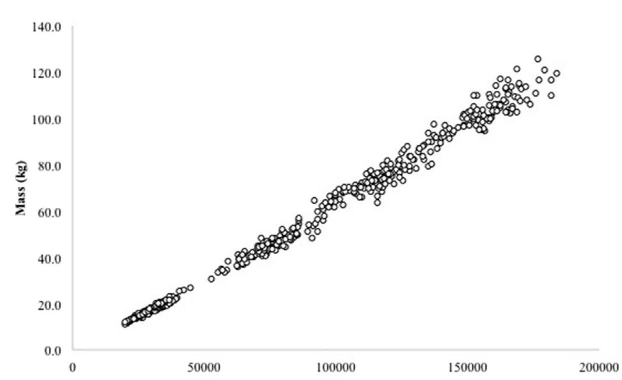

Fig. 6 – The relationship of grow-finish pigs' volume as obtained through depth analysis provided by a Kinect® sensor, and the mass of the pigs obtained through a conventional scale.

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Table 1 – Linear regression model's coefficients (W = a + bV), where: W = estimated weight (kg) V = volume of the animal obtained through image analysis (cm^3), b and a = estimated coefficients; N: number of data pairs used to fit the model; R^2: coefficient of determination.

	Intercept a	Coefficient b	N	R^2
Global	−3.75 ± 0.24	(673.6 ± 2.4) × 10^{-6}	772	0.9907
Sire-lines				
Duroc	−4.42 ± 0.44	(678.7 ± 4.2) × 10^{-6}	244	0.9909
Landrace	−3.52 ± 0.42	(672.4 ± 4.3) × 10^{-6}	251	0.9898
Yorkshire	−3.46 ± 0.39	(670.0 ± 3.8) × 10^{-6}	277	0.9912
Sex				
Barrows	−4.18 ± 0.36	(678.2 ± 3.4) × 10^{-6}	423	0.9895
Gilts	−3.29 ± 0.31	(667.0 ± 3.2) × 10^{-6}	349	0.9921

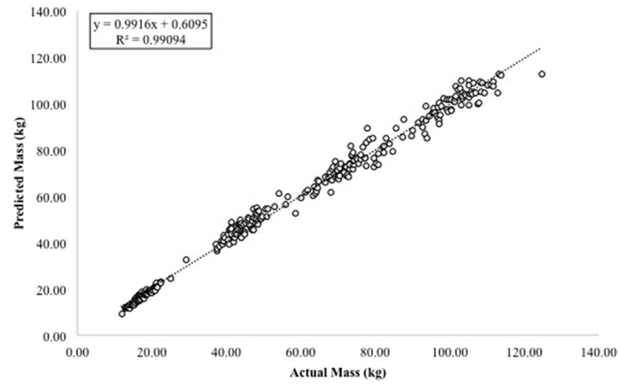

Fig. 7 – Actual versus estimated mass (in kg) of growing and finishing pigs to three sire lines (Landrace, Duroc and Yorkshire); R^2 is 0.9909 and the standard error is 3.0121 kg.

volume by sex (p = 0.0635) were found. The coefficients obtained are shown in Table 1.

The global equation presents an R^2 of 0.9907; indicating that 99.07% of the variability of the mass of the animals can be explained by volume obtained through the data provided by the Kinect® sensor. This value is greater than that obtained by Kashiha et al. (2014) for both a linear (R^2 = 0.871) and a SISO TF model (R^2 = 0.975), by Brandl and Jørgensen (1996); (R^2 = 0.98) and by Slader and Gregory (1988) (R^2 = 0.98), on the prediction of mass of pigs through its area (acquired with images). In addition, this is also equal to the value obtained (R^2 = 0.99) by Kongsro (2014) for boars.

The Pearson's correlation coefficient obtained (0.9952) indicates that there is a strong positive linear correlation between the volume and the mass of the animal. This value is greater than the one found (r = 0.97) by Schofield (1990) for correlation between pigs' mass and its area on a digital colour image.

The standard error of the estimate for the global equation was 3.13 kg, when compared to the 60% of data that was used to develop the equation. This value is smaller than the obtained by Kashiha et al. (2014), for a linear model (SE = 4.52 kg), but greater than the SE obtained by the same authors for predicting pigs' mass from its body area using a non-linear model (SE = 2.68 kg) and a SISO TF model (0.82 kg). This shows that the current method has the potential to present smaller errors if other models are used to analyse the data. Brandl and Jørgensen (1996) found standard errors ranging from approximately 2.3 to 8.5 kg, using spline functions to predict body mass from body area; the errors were dependent on the weight range of the animals; heavier pigs (around 95 kg) had bigger errors than lighter pigs (25 kg).

When the global equation is compared to the test data (40% of the data), plotting the actual weight of the animals versus the predicted weight (Fig. 7), the standard error found was 3.01 kg. Kongsro (2014), who also used a Kinect® sensor to predict weight through pigs' volume, found a slightly larger error (3.38 kg) for a linear regression that represented the actual weight plotted against the predicted weight. The higher error found by Kongsro (2014) could be explained by the lack of correction of the volume measure for the distance from the sensor to the animal.

Using the test data set (40% of the data), the global equation predicted mass using calculated volumes with an average absolute residual of 4.6% or 2.2 kg. This value was not consistent among all mass ranges. The smallest mass range (10–39 kg) had an average absolute residual of 5.6% or 0.97 kg. The mass range of 39.1–68 kg had an average absolute residual of 5.4% or 2.55 kg. The next mass range (68.1–96 kg) had an average absolute residual of 2.7% or 2.9 kg, and the largest pigs or a mass range of 96.1–125 kg had the smallest percent absolute residual of 2.8% but a large absolute residual (2.9 kg). Some of these values are smaller and some are greater than the value (3.07%) found by Wang et al. (2008) for a walk-through image system, using neural network that correlated the area of the pig in the image with its mass. It has to be taken into consideration that these authors used the average of several areas obtained for the same pig while it was walking through an alleyway; this possibly reduced the error of the system, as already pointed by Schofield (1990), who found errors of 6.2% (for pigs weighing around 75 kg), 8.5% (for pigs weighing around 52 kg) and 15.4% (for pigs weighing around 30 kg) if a single image was used to predict the mass of the pig from its area on the image, but found that if the average area of 6 images were used, this errors dropped to 2.5, 3.6 and 6.3%, respectively. Schofield et al. (1999) found errors of 5.3–7.3% (for pigs weighing around 45 kg) and of 1.3–3% (for pigs weighing around 60–90 kg), depending on the sire line analysed (Landrace, Large White or Meishan), using the correlation between the area of the pig in the image and its mass. Brandl and Jørgensen (1996) found an error of 10% for the correlation of pigs' area with its mass. Kashiha et al. (2014) obtained an error of 10.04% (or 4.52 kg) for the mass estimation using area if a linear model was used and an error of 1.82% (or 0.82 kg) when a SISO TF model was used. Kongsro (2014) found an error of 4.6–4.9% (or 3.2–3.8 kg) for boars' mass prediction using volume obtained with a Kinect® sensor. These values are greater than the ones found in this study.

The Willmott's indexes are close to 1.0000 (0.9910 and 0.9731). As this index is given by a mathematical approximation that evaluates the accuracy, the dispersion and the distance of the predicted values compared to observed, it can be concluded that the method of prediction used can estimate pigs' mass in a very similar way to the scale. This is illustrated in Fig. 7, where actual mass (measured on the scale) and estimated mass (by volume) have a high R^2 ($R^2 = 0.9909$) when plotted against each other.

Overall, the proposed method showed a satisfactory performance in the estimation of the mass of grow-finishing pigs. The responses obtained are as good or better than those obtained by other authors who correlated the mass of animals with dimensions obtained from images. The method proved to be fast and efficient. The Kinect® sensor cannot obtain reliable depth data in excessively lit environments, however this is generally not a problem in swine facilities. To develop a system that can be implemented within a commercial swine facility, carefully choice of the area in which to collect images would be necessary. Placing the sensor over the drinker area would offer the advantage of having the pig's head in a somewhat consistent orientation and generally having only one pig in the image. Additional processing would be necessary to eliminate images with more than one pig, especially if the pigs were touching each other.

Currently, there is commercial interest in quickly and accurately acquiring pig mass estimates. There are several commercial products that are currently being developed using depth images. Most of these current commercial products are being developed as hand-held units, which require personnel to walk among the pigs and acquire the mass. Some of the units are using a different algorithm for each different breed of pigs. No details on the image analysis are available for any of these products.

4. Conclusions

A validation of the use of depth images in predicting live animal mass was done in this study. It was possible to obtain grow and finishing pigs' mass from three sire lines (Landrace, Yorkshire and Duroc) and two sexes (gilts and barrows) using volume obtained from depth images acquired with a Microsoft® Kinect® sensor.

For the volume acquisition, an algorithm was developed in MATLAB® software, version R2015b. The algorithm selects the pigs in the image by height difference, deletes head and tail by a relationship with the width of the hip and the length of the animal, then acquires the volume of the pig by summing its pixels. This volume was then corrected for unit transformation and, correlated with the pig's mass by linear regression. A multiple linear regression considering sex and sire line effects was compared against a simple linear regression that did not consider these effects. The test showed that both regressions could be considered as equal in their prediction of mass using volume data. Results showed that the mass can be predicted with an average error of 4.6%, or 2.2 kg. It is believed that this can be improved using other modelling methods including multi-linear regression, or artificial neural network. These methods should be evaluated to find the correct parameters and the modelling methods to reduce the average error.

The method developed and used to obtain volumes of pigs using depth images in this study has the potential to be automated, using both the program and the equation developed.

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Mention of trade names or commercial products in this article is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the U.S. Department of Agriculture. The USDA is an equal opportunity provider and employer. The authors would like to thank John Holman, Dale Janssen, and Hannah Speer for their help in collecting data, and Donna Griess for her help in preparing this document for publication. This research was funded in part by USDA, Agricultural Research Service; by Fundação de Amparo à Pesquisa do Estado de São Paulo - FAPESP (Grant No. 2015/07254-3) and by Conselho Nacional de Desenvolvimento Científico e Tecnológico CNPq (Grant No. 131182/2016-1), Brazil.

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