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On-barn pig weight estimation based on body measurements by a Kinect v1 depth camera

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ABSTRACT

Information on the daily growth rate of pigs enables the stockman to monitor their performance and health and to predict and control their market weight and date. Manual measurements are among the most common ways to get an indication of animal growth. However, this approach is laborious and difficult, and it may be stressful for both the pigs and the stockman. As a consequence, manual measurements can be very time-consuming, induce costs and sometimes cause injuries to the animals and the stockman. The present work proposes the implementation of a Microsoft Kinect v1 depth camera for the fast, non-contact measurement of pig body dimensions such as heart girth, length and height. In the present work, these dimension values were related to animal weight, and two models (linear and non-linear) were developed and applied to the Kinect and manual measurement data. Both models were highly correlated with the direct weight measurements considered as references, as demonstrated by high coefficients of determination ($R^2 > 0.95$). Specifically, in the case of the non-linear model based on non-contact depth camera measurements, the mean absolute error exhibited a reduction of over 40% compared to the same non-linear model based on manual measurements (from 0.82 to 0.48 kg).

1. Introduction

Monitoring pig growth parameters in a frequent and quantitative way is useful to help the maintenance of animal health and to maximize production efficiency (Nilsson et al., 2015; Halachmi and Guarino, 2016). In particular, the live weight of pigs is of great interest for pig breeding and management, as it serves as an index for animal growth (Bracke et al., 2002), health (Stookey and Gonyou, 1994) and readiness for market (Wang et al., 2008).

In the last fifty years, manual measurements have been the most common way to get an indication of animal growth (Pezzuolo et al., 2017). However, this approach is laborious and difficult, and it may be stressful for both the pigs and the stockman. As a consequence, it can be very time consuming, induce costs and cause injuries to the stockman (Marinello et al., 2015).

Alternatively, optical sensing techniques can be implemented in order to overcome limitations arising from manual contact measurements (Dubbini et al., 2017). Several works propose the implementation of classical two-dimensional optical techniques not only to evaluate animal activity (Shao and Xin, 2008; Ahrendt et al., 2011; Nasirahmadi et al., 2015; Stavrakakis et al., 2015; Arcidiacono et al., 2017) and behaviour (Oczak et al., 2014; Costa et al., 2014; Viazzi et al., 2014; Gronskyte et al., 2015; Lao et al., 2016; Nasirahmadi et al., 2016) but also to predict or measure animal growth parameters (Brandl and Jørgensen, 1996; Schofield et al., 1999; Wu et al., 2004; Parsons et al., 2007; Costa et al., 2013; Kashiha et al., 2014; Pallottino et al., 2015; Porto et al., 2015; Mortensen et al., 2016; Oczak et al., 2016; Pezzuolo et al., 2018). Pigs are typically imaged from the top and only seldom imaged from the side by CCD (Charge-Coupled Device) sensors. Images are processed by dedicated software tools in order to correlate the extracted features (e.g., the projected area or profile) to the pig's live weight.

Recently, some commercial systems such as Weight-Detect (PLF-Agritech Europe), eYeScan (Fancom BV, Panningen - The Netherlands), Pigwei (Ymaging, Barcelona – Spain), OptiSCAN (Hölscher + Leuschner GmbH, Emsburen – Germany), Growth Sensor

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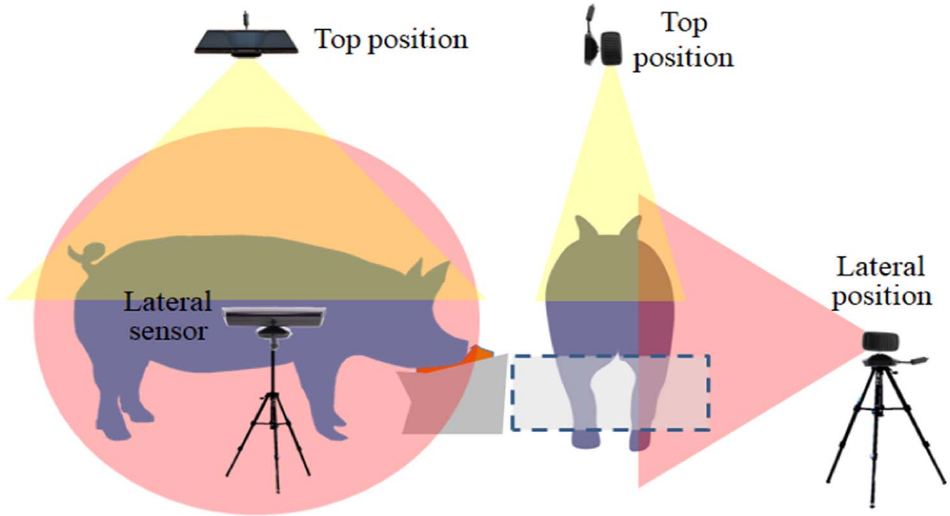

Fig. 1. Depth cameras positioned in the feeding area to obtain lateral and top views of the pigs.

(GroStat, Newport), and WUGGL One (WUGGL GmbH, Lebring – Österreich) have been introduced (Vranken and Berckmans, 2017). Most of these currently available systems are apparently based on three-dimensional reconstructions produced by either two- or three-dimensional cameras (Vázquez-Arellano et al., 2016); however, they typically operate as black boxes, with no clear information on their principles, procedures or uncertainties.

More detailed information can be retrieved from scientific papers. As noted by Nasirahmadi et al. (2017), machine vision techniques based on two-dimensional or three-dimensional cameras are increasingly applied to monitor cattle or pig feeding, locomotion, and aggressive or reproductive behaviours. Specifically, as discussed by Rosell-Polo et al. (2015), there is an interesting trend in the use of a commercial 3D camera developed as a game interface, the Microsoft Kinect, for agricultural and livestock applications. Spoliansky et al. (2016) reported the quantification of body condition scoring after the application of three-dimensional cameras on cows; Kongsro (2014) reported weight estimation results from two different pig breeds (Landrace and Duroc) in the 20–140 kg interval based on volume information, and Jiao et al. (2016) took advantage of the three-dimensional depth information to enhance the collection of thermal images from pigs. Kulikov et al. (2014) and Lee et al. (2016) reported on the application of the same Kinect camera for tracking pigs and the automatic recognition of aggressive behaviours in commercial pigpens.

The present work proposes the implementation of the same low-cost Kinect v1 depth camera for fast, non-contact measurements of pig body dimensions such as heart girth, length and height. Such body values can be directly related to weight; the estimated data were eventually compared with the results from manual measurements during the weaning period. Then, unlike previous works (Kongsro, 2014), the experimental analysis focused on pigs with a weight lower than 50 kg, which is a particularly critical size typically characterized by relatively high weight estimation uncertainties. The proposed approach takes advantage of non-linear models to exploit the full performance of the Kinect depth camera and eventually reduce the standard error of the estimate.

2. Materials and methods

2.1. Animals and housing

All observations were conducted in a commercial pig weaning farm located in the North of Italy after the placement of pigs in the pens. The pigs had an initial live weight of approximately 6.0 ± 1.0 kg (mean ± s.d.) and an average age of 24 days. Pigs were monitored for a 55-day period (day only), with an average final weight of 46.6 ± 4.1 kg.

The pigs breed was a crossbreed of Large White (50%) and Landrace (50%), and pigs were fed *ad libitum* using feeders with a commercial dry pelleted feed; water was supplied *ad libitum* through bite nipple drinkers.

Each pen in the weaning barn had an average size of 6.75 m wide × 3.10 m long, with a solid floor and straw bedding, and contained 30–35 pigs of mixed gender (males and females). Pens were separated from each other by solid walls to avoid physical contact. The temperature was automatically kept at approximately 24 °C (the temperature was adjusted if the pigs showed adverse behavioural responses), and the lighting was on a 12/12 h light/dark cycle with an average light intensity of 70 l× measured at ground level using a luminance metre (Konica Minolta T10, Inc., Osaka, Japan).

2.2. Experimental design

To verify the suitability of the depth camera for the 3D reconstruction of body shape and extraction of parameters, a measurement campaign was carried out comparing the depth camera results with those obtained from manual measurements. For the scope of the campaign, 78 animals underwent single contact and non-contact measurements that specifically focused on four main parameters, body length, heart girth, front height and back height.

Pigs were randomly picked from 4 pens and imaged by the depth camera at the same time of the day (between 09:30 and 11:30 AM) for the whole weaning period. Before the beginning of the experiment, a two-week observation phase was implemented to define the best measuring conditions in terms of the time of day, placement of the scales and arrangement of the Kinect three-dimensional imaging area.

The eating or drinking position was defined as the best position for the direct camera imaging; indeed, during feeding, pigs remained in a relatively stable position for a few minutes several times a day. During this time, the head of the animals was slightly tilted downward, helping the extrapolation of parameters with relevant points in the proximity of the neck (such as the height or the body length). Thus, two Kinect v1 cameras were positioned in the feeding area, as depicted in Fig. 1, allowing lateral and top imaging of the body. Such positions exploit the performance of the depth camera, which performs best when imaging relatively large surfaces.

An average of three pigs per day were picked and sent to a separate feeding area where 3D analysis and subsequent manual measurements

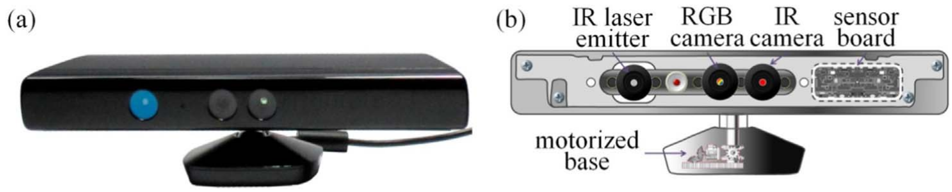

Fig. 2. Actual (a) and schematic view (b) of the Microsoft Kinect v1 depth camera.

were carried out. Three-dimensional data acquisitions were performed at an average distance of approximately 1.0–1.2 m from the animal, in order to allow the entire body length to be captured. Several scans (five to ten on average) were taken for each animal during each feeding session. The best scan was then selected based on the minimum noise principle (Wang et al., 2008) to extract the relevant parameters. The animals underwent no more than one manual measurement in order to avoid excessive stress that negatively affects the natural growth of pigs.

Measurements were carried out by the stockman by means of an electronic scale (Laumas Electronics mod. Bil, accuracy ± 0.05 kg). Additionally, every selected pig underwent length, heart girth, front height and back height manual measurements by means of a flexible measuring tape.

According to EU legislation (Council Directive 86/609/EEC), no procedures requiring approval from the local ethics committee were used.

2.3. Depth camera technology

This work takes advantage of the Microsoft Kinect™ v1 (Fig. 2) three-dimensional sensing instrument.

Three-dimensional reconstruction by the Kinect camera is achieved by combining an infrared laser emission source with an infrared-sensitive camera. The infrared laser beam is split by a diffraction grating into a distributed pattern projected on the scene. Concurrently, the infrared sensor reveals and segments the pattern from the scene and correlates it with the projected one (Han et al., 2013). All detected local pattern shifts are combined to create a disparity plot. Higher displacements occur when the target surface is located at a greater distance from the depth camera, and lower shifts occur when it is closer to the sensor. The reconstruction ability thus depends on the capability of the sensor to recognize the infrared pattern displacements; this capability could be negatively impacted by some conditions, such as the presence of highly absorbing or diffracting surfaces (which is not the case for pig skin) or high intensity infrared radiation from the sun or external lamps. The latter condition seldom occurs during indoor pig 3D measurements, but it could introduce limitations during outdoor analyses.

The Kinect depth cameras were positioned by aluminium rods equipped with telescopic adjustment capabilities, which allowed the working distance to be optimized. Image acquisition was controlled by a PC running the Kinect for Windows Software Development Kit (SDK) version 7.1.

It is worth noting that the simultaneous collection of multiple-view 3D data sets is not possible at present, since two simultaneously operating Kinect devices could interfere with each other. Nevertheless, thanks to a relatively high frame rate (> 10 Hz) and ability to alternatively turn on and off the sensors, such potential interference does not pose limitations on pig shape reconstruction. Therefore, the first Kinect device collected data while the second was temporarily turned off and vice versa.

2.4. System calibration and data analysis

To allow the traceable extrapolation of quantitative data, the instrument was calibrated by taking advantage of substitution method principles, as discussed by Carmignato and Savio (2011). The substitution method relies on the results of a specific calibration task carried out by implementing reference artefacts featuring calibrated geometries that resemble the measured shape, and it has been already been successfully applied for Kinect calibration (Marinello et al., 2018). Specifically, polystyrene hemispheres with diameters ranging from 100 to 400 mm, which resemble the curvatures typical of the body and the back of the studied animals, were implemented.

Calibration of the Kinect depth camera was carried out at increasing distances (ranging from 400 to 1600 mm) from the sensor to the average reference plane where the hemispheres were positioned to reproduce different possibilities of the scanning setup. The calibration procedure eventually allowed the quantification of linear and non-linear calibration coefficients, according to the model proposed and developed by the same author for scanning instruments (Marinello et al., 2009); the results are briefly reported here (1):

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} c_{xx'} & c_{xy'} & c_{xz'} \\ c_{yx'} & c_{yy'} & c_{yz'} \\ c_{zx'} & c_{zy'} & c_{zz'} \end{bmatrix} \cdot \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} + \begin{bmatrix} c_{xx'^2} & c_{xy'^2} & c_{xz'^2} & c_{xx'y'} & c_{xx'z'} & c_{xy'z'} \\ c_{yx'^2} & c_{yy'^2} & c_{yz'^2} & c_{yz'y'} & c_{yz'z'} & c_{yy'z'} \\ c_{zx'^2} & c_{xy'^2} & c_{zz'^2} & c_{zx'y'} & c_{zy'z'} & c_{yy'z'} \end{bmatrix} \cdot \begin{bmatrix} x'^2 \\ y'^2 \\ z'^2 \\ x'y' \\ x'z' \\ y'z' \end{bmatrix} \tag{1}$$

where x', y' and z' represent the coordinates of the points measured by the Kinect device, while x, y and z represent the corrected coordinates. The two c coefficient arrays are the linear and the non-linear calibration coefficient matrices, computed through a comparison of the calibrated radius values and Kinect radius of curvature measurements on the same reference hemispheres.

Different body-related parameters were extracted. For the extraction, the depth images produced by the Kinect sensor were processed and analysed with a commercial software (SPIP™, Image Metrology, Inc.). Each three-dimensional dataset underwent a number of processes allowing the extraction and quantification of features. More precisely, each point cloud was opportunely calibrated in order to get metric datasets (Fig. 3A) using a calibration coefficient computed by using the hemisphere reference standards. Next, each 3D data set was processed by using a Gaussian filter with a relative cut-off of 1:5 in order to allow the removal of noise and insignificant features and extract of the overall shape (Fig. 3B).

Each 3D filtered image was processed to extract the pig contour (Fig. 3C), which was usefully implemented to get relevant coordinates and positions of body parts, such as the withers (p1), abdomen (p2), hips (p3) and tail (p4) zones (Fig. 3D). Indeed, such positions have been proven to be among the most important for the characterization of animal body evolution (Sungirai et al., 2014; Shi et al., 2016). A body cross section (i.e., the area resulting from the intersection between the body volume and a vertical plane perpendicular to the body local axis) was extracted at each relevant position, and the parameters were calculated as follows:

- length l, measured as the average distance between section p1 and the most backward position of the pig in p4;
- front height f, measured as the distance between the floor level and

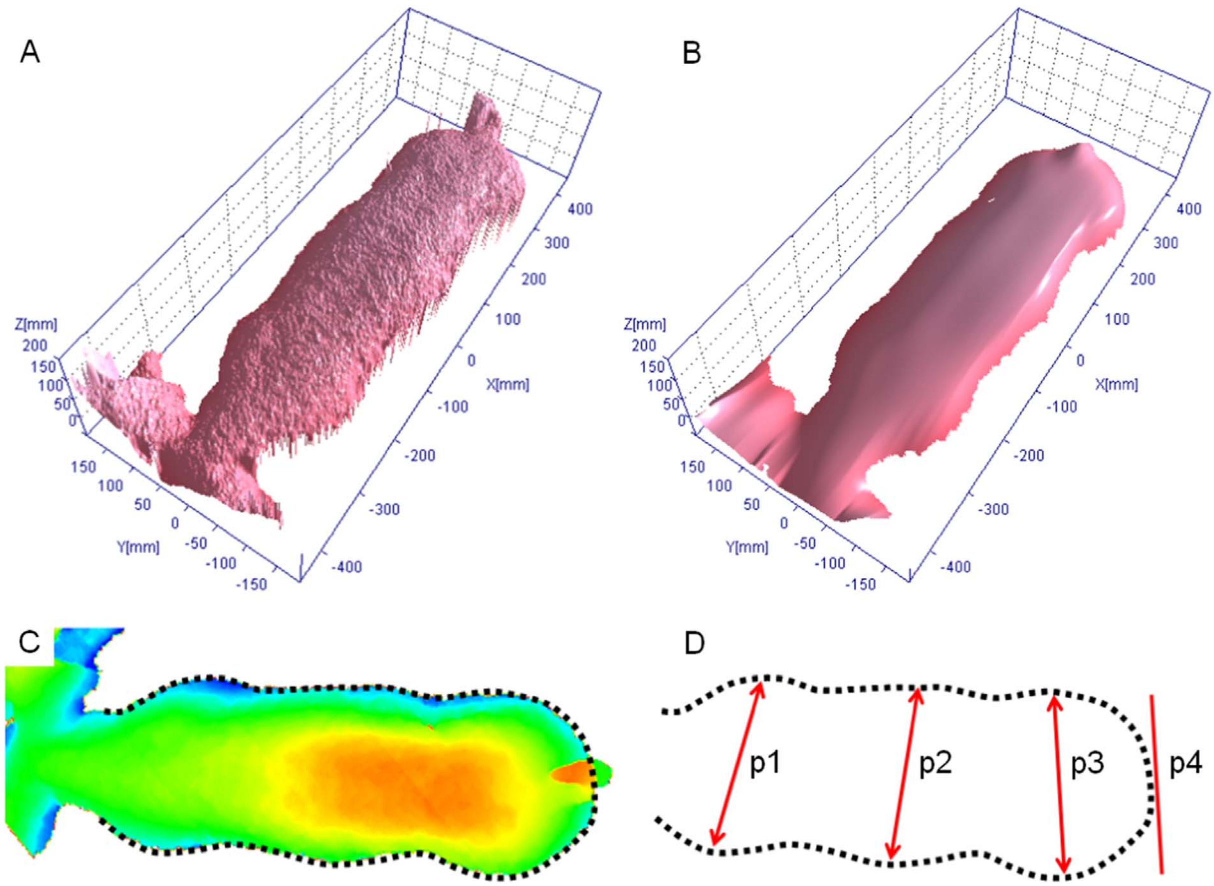

Fig. 3. Example of a portion of the animal back, as revealed by the top sensor before (A) and after (B) Gaussian filtering. Definition of the animal external profile (C) and localization of the reference cross sections (D).

the maximum height position in section p1;

- back height *b*, measured as the distance between the floor level and the maximum height position in section in p3;
- heart girth *c*, measured by the calculation of the average radius of curvature between the top and lateral scans in section p2 and its subsequent multiplication by 2π.

The ground level was determined as the plane best fitting the floor areas not covered by manure or litter substrates.

Concurrently, the same parameters were collected for all of the animals after measurements with contact rulers; additionally, the weight was measured by using an electronic scale, and the collected values were taken as references for subsequent analyses. Such measurements are very difficult to conduct due to the stress induced by human contact on the animals. For this reason, long measuring times (time to approach the animal and correctly position and read the rulers or wait for the electronic scale to stabilize) had to be considered in order to increase the confidence in the recorded parameters.

3. Results and discussion

3.1. Calibration procedure

The Kinect instruments were calibrated according to the procedures described in the Materials and Methods section. Table 1 reports the main scanning performance parameters in terms of lateral range (i.e., the length and the width of the measured area) and resolution (i.e., the minimum resolvable separation between two pixels), the vertical resolution (i.e., the minimum resolvable depth) and the curvature deviation (i.e., the relative standard deviation of the measured curvatures from the calibrated curvatures).

Table 1
Kinect v1 scanning performance.

Distance [mm]	Lateral range [mm]	Lateral resolution [mm]	Vertical resolution [mm]	Curvature deviation [%]
400	415 × 310	0.65	0.7	1.1
800	625 × 470	0.95	1.6	2.7
1200	833 × 630	1.30	2.4	4.1
1600	1040 × 790	1.60	3.3	5.6

3.2. Daily growth rate

The stockman's aim is to monitor the daily animal growth rate during the weaning period. In general, there is an apparent correlation between the animals age and weight; however, it is not sufficiently robust to allow the definition of a reliable growth model. Indeed, it is well known that weight evolution is influenced by a number of factors with a large variability as a consequence of animal health and well-being (Stookey and Gonyou, 1994; Brandl and Jørgensen, 1996; Bracke et al., 2002).

Accordingly, during the set of experiments carried out in the present work, the weight analyses not only showed a relatively high coefficient of determination ($R^2 = 0.836$) but also showed standard errors as high as 1.3 kg and 4.1 kg for animals at 40 and 80 days, respectively (Fig. 4). Such errors, corresponding to absolute deviations as high as 45% from the reference weight linear model, are unacceptably high for proper animal mass monitoring.

Since animal weight cannot be predicted only on the basis of age, a

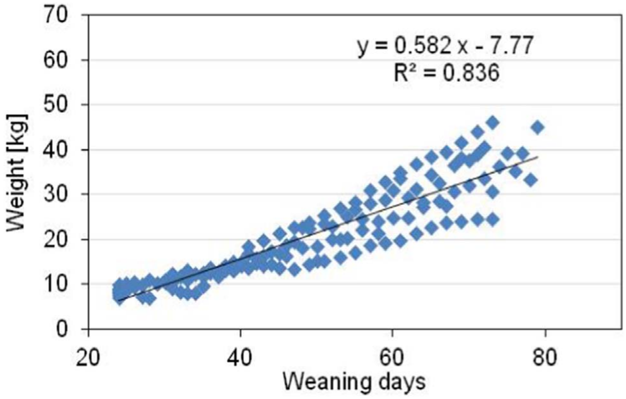

Fig. 4. Daily growth rate recorded during the weaning period.

different approach is needed; therefore, in this study, the weight was modelled on the basis of physical parameters.

3.3. Manual measurement vs non-contact measurements

The main results are reported in Fig. 5. In general, the Kinect data exhibits a slight deviation, quantified by the slope $\alpha < 1$, from the linear regressions. However, this trend is repeatable and can be considered systematic for quantitative measurement purposes. In general, relatively high coefficients of determination highlight a good prediction capability, especially in the case of heart girth ($R^2 = 0.931$) and length ($R^2 = 0.839$). In the case of the front and rear heights, a lower prediction capability was associated with the difficulty in properly defining the paw-floor interface, especially when litter substrates or manure are present.

3.4. Weight estimation models

The animals' physical parameter measurement data allowed the definition of a model that can be implemented to estimate weight. Examples of prediction models in pig husbandry were suggested in the literature, such as the suggestion by Schofield et al. (1999), which considers animal weight, image analysis, growth rate, quality and conformation, feed intake, and monitored feeding behaviour to be inputs for management decision support systems.

A statistical analysis was therefore carried out with the Statgraphics Centurion™ (StatPoint Technologies, Inc, Warrenton, VA, USA) software to provide a model for the manual measurements and non-contact measurements generated by multiple linear regression, in order to predict pig weight. A backward stepwise regression analysis was then applied to determine the predictors, considering all the collected body parameters, length *l*, heart girth *c*, and mean height *h* (averaged between back and front values).

The models resulting from the stepwise regression are reported in Eqs. (2) and (3):

$$m_{MAN} = 0.268 \cdot c + 0.409 \cdot l + 0.530 \cdot h - 40.29 \tag{2}$$

$$m_{KIN} = 0.280 \cdot c + 0.381 \cdot l + 0.388 \cdot h - 34.19 \tag{3}$$

where m_{MAN} and m_{KIN} are the weights estimated from manual and Kinect measurements, respectively.

Related values are shown in Table 2, where only parameters with statistically significant non-zero correlations at the 95% confidence level (p-values < 0.05) are reported for heart girth, length and mean height.

A graphical representation of the models is reported in Fig. 6. Both models exhibit a high correlation with the manually measured weights considered as references (Table 3), as demonstrated by the high

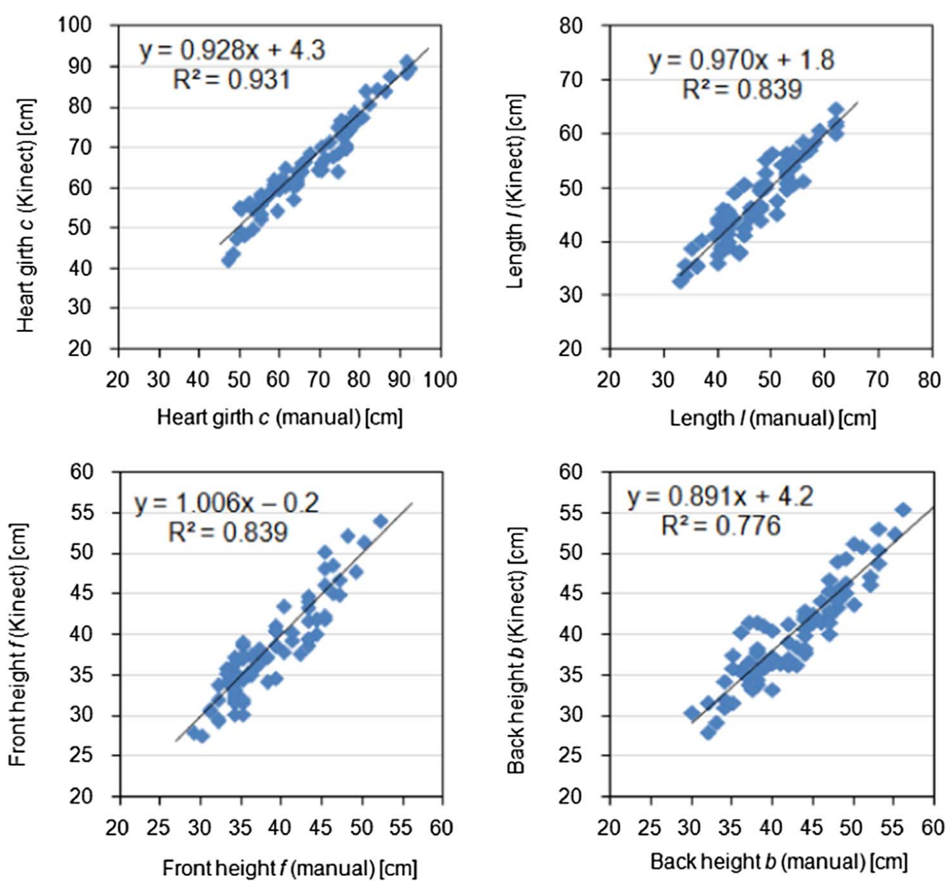

Fig. 5. Kinect measurements vs manual measurements for the four different body parameters: heart girth, length, front and back height.

Table 2
Stepwise regression results.

	Manual measurements				Kinect measurements			
	Coeff.	S.E.	t	p-value	Value	S.E.	t	p-value
Intercept	40.291	1.254	−32.16	0%	−34.187	1.532	−22.35	0%
Heart girth *c*	0.268	0.057	4.70	0%	0.280	0.121	2.31	2.38%
Length *l*	0.409	0.077	5.28	0%	0.381	0.161	2.37	2.04%
Mean height *h*	0.530	0.097	5.48	0%	0.388	0.160	2.42	1.80%

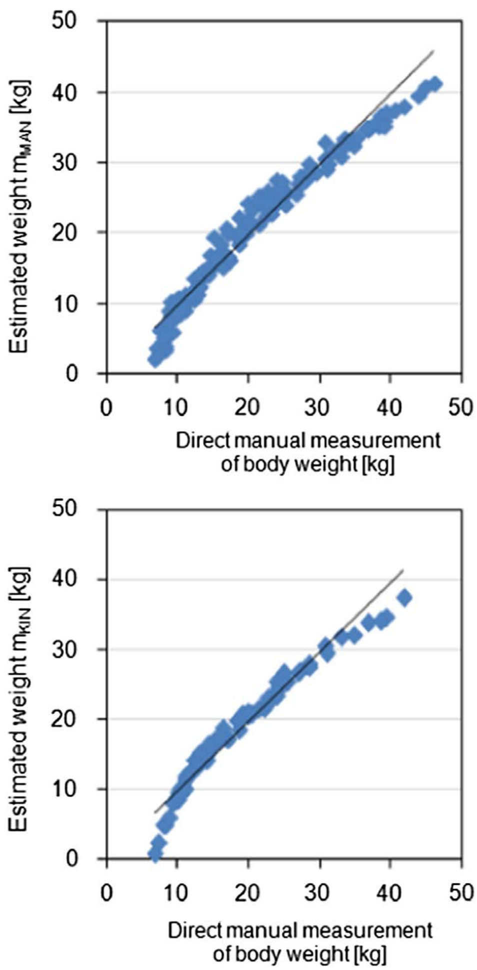

Fig. 6. Weight estimated through the linear regression models (2) and (3) reported as a function of direct measurements.

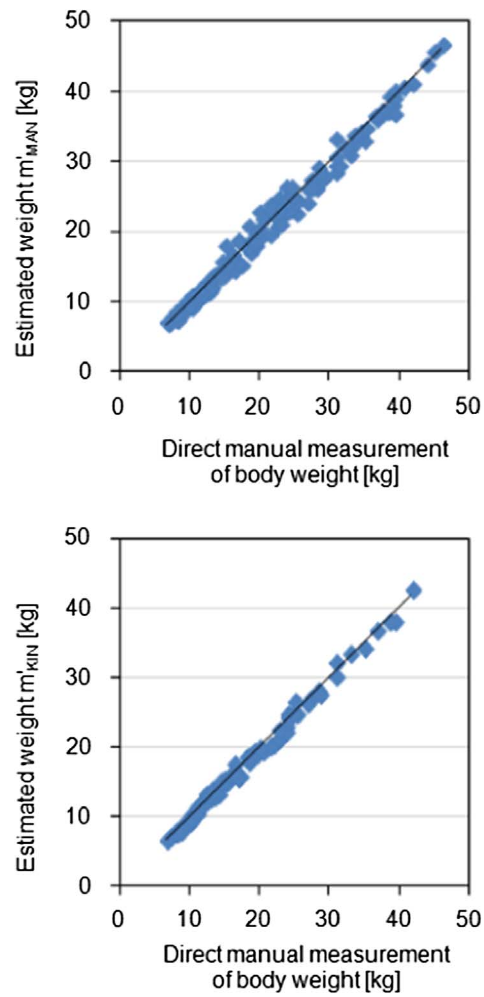

Fig. 7. Weights estimated through the second-degree regression models (3) and (4) reported as a function of direct measurements.

Table 3
Linear and non-linear regression results, where R^2 adj. is R-squared adjusted for the degrees of freedom, SEE is the standard error of the estimate, and MAE is the mean absolute error.

	Linear regression		Non-linear regression	
	Manual measurements	Kinect measurements	Manual measurements	Kinect measurements
R^2	0.9609	0.9543	0.9885	0.9942
R^2 adj	0.9600	0.9524	0.9877	0.9934
SEE	2.04	1.83	1.13	0.68
MAE	1.57	1.33	0.82	0.48

coefficients of determination ($R^2 > 0.95$). Specifically, in the case of the non-contact model derived from measurements from the Kinect depth camera, errors were 10% lower than those from the model based on contact measurements (from MAE = 1.57 kg to MAE = 1.33 kg, as shown in Table 3).

However, a non-linear behaviour of residuals can be recognized, especially in the case of non-contact measurements. As a general statement, linear models are recommended for their simplicity; however, in this study, a second degree regression was also tested in order to verify the potential improvement arising from a more complex model.

The following models were therefore found:

$$m'_{MAN} = -0.002\cdot c - 0.020\cdot l + 0.001\cdot h + 0.022\cdot c\cdot l - 0.008\cdot c\cdot h + 0.035\cdot l\cdot h - 0.141\cdot c - 0.695\cdot l - 0.676\cdot h + 25.70 \tag{4}$$

$$m'_{KIN} = 0.043\cdot c + 0.020\cdot l + 0.025\cdot h - 0.056\cdot c\cdot l - 0.063\cdot c\cdot h + 0.064\cdot l\cdot h - 0.301\cdot c - 0.376\cdot l - 0.561\cdot h + 21.91 \tag{5}$$

where m'_{MAN} and m'_{KIN} are the weights estimated using a second-

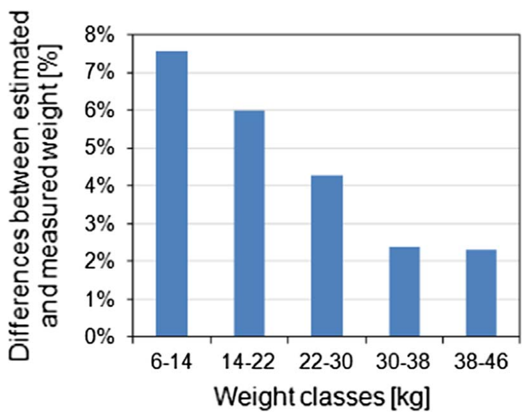

Fig. 8. Average relative absolute deviations between estimated and direct measurement weights for different weight classes.

degree model based on manual and Kinect measurements, respectively.

Both models are graphically reported in Fig. 7. It can be noticed that the second-degree model significantly reduces the residues and almost halves the standard error of the estimate and the mean absolute error, with best performances clearly highlighted in the case of the non-contact measurements (SEE = 0.68 kg; MAE = 0.48 kg).

Results can be compared against a linear regression model, as proposed by Schofield et al. (1999), and a so-called transfer function (TF) model, as developed by Kashiha et al. (2014). The results, which are available in the bibliography, refer to a case study on 240 measurements on pigs with weights in the range of 20–50 kg (Kashiha et al., 2014). The coefficients of determination here reported are comparable with that from the TF model in the bibliography ($R^2 = 0.975$). On the other hand, the current study reports a relevant improvement in the standard error, which is lower than the standard errors for both the linear model (SE = 4.52 kg) and the TF model (SE = 0.82 kg) reported by the literature.

The superior performance of the non-linear regression model based on Kinect measurements (both in terms of the coefficient of determination and standard error) has to be ascribed to the high amount of data arising from its non-contact-derived analysis. Indeed, not only does the Kinect depth camera allow the collection of multiple scans in a few tenths of a second, each scan digitized to 640 × 480 pixels constitutes a robust data set for the extraction of parameters. Conversely, the manual approach is affected in a more significant manner by the variability associated with animal movements and the variability of the measurement procedure in general. The standard error arising from the Kinect-based estimation model (4) is reasonably low for the proper estimation of weights, particularly for larger pigs, as shown in Fig. 8, which reports the average absolute deviations of the estimated values compared to measured values. Deviations are sorted in five weight classes that characterize the weaning phase.

The obtained results show an increasing level of accuracy in the animal weight estimations. Such an increase can be explained by the lateral and vertical performances of the Kinect depth camera, which has an uncertainty typically varying between 4 and 10 mm at the considered working distances. This uncertainty affects measurements, with a higher relative degree of approximation introduced when smaller dimensions must be measured, such as in the case of younger animals with a weight lower than 22 kg. On the other hand, when larger animals are analysed, the sensor uncertainty introduces a lower degree of approximation and thus results in lower mass deviations, as shown in Fig. 8.

The reported results are interesting and promising in terms of the implementation of Kinect-based approaches on a commercial basis. A Kinect-based approach might indeed be applied not only to monitor average weight growth trends but also to recognize anomalies in the growth of individual pigs. To this end, an automatic detection system is necessary, but successful examples of the application of ultra-high frequency radio frequency identification (UHF-RFID) technology to pig recognition have already been reported (Adrion et al., 2015). As discussed, limitations could arise because of intense light conditions, mainly due to radiation from the sun radiation; however, these limitations are seldom found in typical indoor feeding areas.

4. Conclusion

In the present work, a suitable low-cost depth camera (Microsoft Kinect v1) is proposed for the non-contact extraction of pig body dimensions and subsequent estimation of weight based on two possible models (linear and second-degree regression) adapted and applied to Kinect and manual measurements. Both models highly correlate with the reference weights, as confirmed by their high coefficients of determination, which were consistently higher than 0.95, and the standard error of the estimates, which were halved in the case of the non-linear regression model. Furthermore, compared to the manual measurements, the adoption of the Kinect v1 for the quantification of body parameters allows a significant reduction in the absolute error means, with values lower than 0.5 kg for the second degree regression method. Indeed, compared to the use of manual measurements, the non-contact Kinect approach enables the collection of more data in a shorter time and is not affected by difficulties associated with ruler reading or uncertainties related to animal movements that are characteristic of slow manual measurement approaches. The proposed approach can be effectively considered for the estimation of pig body weight during the weaning period, even though the proposed models might need to be adapted and calibrated to the specific breed considered.

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