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## Application note

# Estimation of pig weight using a Microsoft Kinect prototype imaging system



## Jørgen Kongsro

Norsvin, P.O. Box 504, N-2304 Hamar, Norway

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#### ABSTRACT

The weight or mass of a pig is of great importance for farmers and stockmen to monitor performance, health and market weight of animals. The paper presents a prototype for pig weighing based on the Microsoft Kinect camera technology, utilizing the infrared depth map images. The system successfully estimated the weight of two different purebred breeds, landrace and duroc with an error estimate of 4–5% of mean weight. The depth map images require less calibration, are less prone to background (i.e. floor) noise compared to visible light camera systems and seem to be more robust between breeds due to additional information from height (depth map) of animals.

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## 1. Introduction

The weight or mass of a pig is of great importance for pig breeding and management, as it serves as an indicator for animal growth, health and readiness for market (Wang et al., 2008). The weight of a pig is usually obtained by manual or automatic scales. Manual weighing of pigs is a laborious operation, and may be stressful both for the animals and the stockman. Automatic scales are usually costly devices, often integrated with feeding stations, in which may occupy valuable pen space in farm environments. The use of imaging or vision systems to predict or measure pig weight has been presented in several papers during the last 30 years (Parsons et al., 2007; Wu et al., 2004; Schofield et al., 1999; Frost et al., 1997). Vision systems based on visible light is often affected by variation in ambient lighting, and must be calibrated accordingly. Differences in animal color and subtraction of background is often a difficult task. Consumer depth sensors based on a structured infrared-light (IR) system, such as the Microsoft Kinect, provide 3D data at low cost and has opened new possibilities for acquiring depth information (Dellen and Rojas, 2013; Choppin et al., 2013). The use of IR depth sensors to measure pig weight, eliminates the errors related to animal color and variation in ambient lighting which is related to visible light vision system. The sensors provide depth information which may be utilized to measure i.e. height of an animal in addition to area, which in turn may give more accurate estimates of weight or mass. This paper aims to

present the potential of a prototype based on the Microsoft Kinect IR depth sensor to measure the weight of pigs.

## 2. Materials and methods

#### 2.1. Animals

37 Duroc and 34 Landrace boars were selected randomly and measured once in different pens at the Norsvin Delta boar test station. The pens contained animals which were similar in weight, and different pens were selected to get a uniform spread of weights. The pigs weight ranged from 29 to 139 kg and the weights were uniformly distributed within both breeds as closely as practically possible. The pigs were weighed and measured with the Kinect prototype in the FIRE® feeding stations manufactured by Osborne.

## 2.2. Microsoft Kinect prototype

The Kinect prototype was set up with a standard Kinect camera from Microsoft. The IR depth sensor was used as input sensor. The camera was fixed to an aluminum rod with telescopic adjustment (Fig. 1) and connected to a Windows PC installed with the Kinect for Windows Software Development Kit (SDK).

## 2.3. Image acquisition

The images were acquired from the Kinect camera using MAT-LAB (MATLAB, 2013) with the Image Acquisition Toolbox (IAT). The depth map channel was chosen in the Image Acquisition Tool-

box. The images (depth maps) were grabbed from the Kinect camera in real-time creating a loop of 50 frames per acquisition using the function *getsnapshot*. A loop of 50 was chosen to ensure that some good images could be acquired during a measurement. For each image in the loop, connected components (objects) that have fewer than 100 pixels were removed using the function *bwareaopen*. The distance information in the pixels were inverted to display the pig as a convex surface rather than a concave which is displayed by default from the depth image (the closer a pixel is to the camera, the larger the pixel value). The larger the height, the larger pixel value. The images were stored on the local disc, and that closed the measurement session for a particular animal, and a new animal was herded into the measurement space in the feeding station.

The image acquisition software was compiled into an executable file (.exe) and run on a laptop running on Windows 7. This was done for bio-security reasons, and the laptop never left the boar testing station or had any contact with other animals outside the station.

### 2.4. Image selection

In order to ensure good quality of images, image selection was performed on all images from each pig. This quality control was done manually by looping through all 50 images from each pig. The single best image from each pig was selected for further analysis, rejecting the remaining 49 images in the loop of 50 images. The result from the single image represented a single observation for each pig with respect to weight. The main criteria was that the image covered the entire pig, and that the pig was in eating position with its head slightly lowered. This position was considered to be the best position due to the uniformity of the pigs shape and reduced movement of the body during eating or drinking.

## 2.5. Image analysis

The images were analyzed and processed using the Image Processing Toolbox (IPT). A binary mask was constructed to cover the distance area of the pig, removing floor background. The largest object, being the pig, was selected using the function *bwareaopen*. The head, ears and tail of the pig was removed using erode and dilation with a disk structure element of radius 40 pixels. This was sufficient to remove the head, ears and tail sufficiently. This was done to improve accuracy in live weight estimation in addition

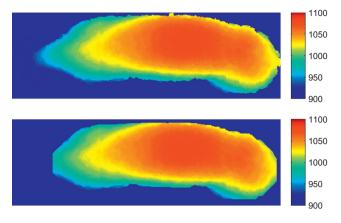


Fig. 2. Depth image and before (top) and after morphological filtering (bottom). Distance is in millimeters.

to remove tiny background interference (Wang et al., 2008). Fig. 2 show the raw image (top) versus the morphological filtered image (bottom). An algorithm using the sum of pixel values of the segmented pig by the MATLAB function *sum*, excluding background, was made in order to sample a volume measurement of the pig:

$$v = sum(X)$$

$$V = sum(v)$$

where v is a row vector with the sum over each column of the image matrix X. V is a scalar of the sum of the row vector v representing the volume measurement of the pig. This volume measurement was used to make a simple statistical relationship with the weight recorded by the FIRE system.

## 3. Results

The quality control of the images (Fig. 3) show examples of images that were rejected for further processing. The images are scaled with a high pixel window to show the outline of the pigs, so the detailed pixel level shown in Fig. 2 is not shown here. There were a number of deficiencies in the images, i.e. image #1 did not contain the whole pig, and the head was not properly removed. The head was not properly removed in image #2. The pose of the pig was the main reason for this deficiency. The camera was did not measure in the correct distance interval in image #3, leaving a





Fig. 1. Kinect prototype.

"hole" in the pig where the Kinect could not pick up any signal due to the close proximity of the camera.

For the accepted images in Fig. 4, the images show that the entire pig is measured, head and tail are removed, leaving a "cigar"-shaped object which is considered to be optimal for further processing.

In Fig. 5, a scatter plot of the measured FIRE weight vs. the estimated Kinect weight grouped by breed in shown. More detailed estimation results is shown in Table 1, where both breeds were estimated with  $R^2$  of 0.99, and the root mean square error (RMSE) of 3.32 and 3.38 for Duroc and Landrace, and all breeds, respectively.

#### 4. Discussion

The Kinect prototype weighing system proved the ability to estimate the weight of pigs of different sizes and breeds using a simple statistical relationship with the depth map generated from

**Table 1** Estimation results.

Breed	n	$R^2$	RMSE, kg	RMSE, %	
Landrace	34	0.99	3.32	4.6	
Duroc	37	0.99	3.32	4.9	
All	71	0.99	3.38	4.8	

the Kinect system. The landrace and duroc breed are very different in terms of shape; the duroc being more compact compared to the leaner and longer landrace. This shows the potential robustness of the Kinect prototype in terms of accuracy across different breeds. Including breeds with a very different body shape, i.e. Meishan, would be interesting to test with the algorithm presented in this study to see the effect of different shape to weight relationships. The error (RMSE) in percentage show that the accuracy of the Kinect prototype is within previously published results using vision systems (Schofield et al., 1999; Wang et al., 2008). Parsons

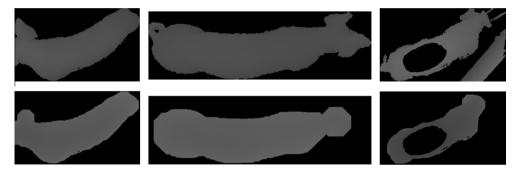


Fig. 3. Quality control of images. Rejected images from 3 pigs. Top images are raw images, and bottom images are processed images. The images are not scaled, but the pixel sizes are identical.

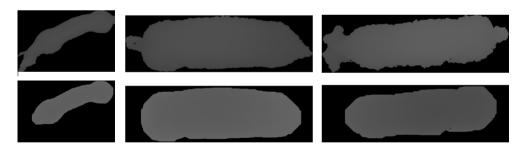


Fig. 4. Quality control of images. Accepted images from 3 pigs. Top images are raw images, and bottom images are processed images. The images are not scaled, but the pixel sizes are identical.

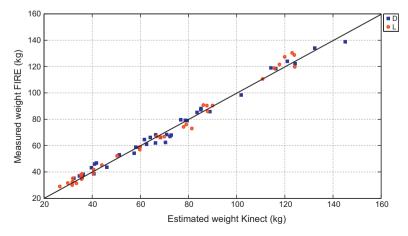


Fig. 5. Scatter plot; measured FIRE weight vs. estimated Kinect weight by breed.

et al. presented a RMSEP after optimization of 4–5 kg for a realtime control system of growing pigs. The pigs in Parsons' study were subject to a growth study where pigs were weighed several times during the growth period, whereas the pigs in this study were only weighed once during their growth period. According to a report from the Osborne FIRE system (Korthals, 2006), the average accuracy of weights from the FIRE stations should be about 1.5% in field conditions. This average error of 1.5% contributes to the RMSE for the model, and a higher accuracy of the reference weights might improve the results. However, it was not practically possible to separate the error from FIRE and from the Kinect system.

The volume estimate was based on the height of the animal (depth) multiplied by the width or area. The main contributor to weight in this study was the estimated volume (the area multiplied by the height of the animal). This might help to bring in new and informative variation, not only of area, but of height of the animal. The camera was in a fixed position for each measurement, so the depth data is considered to be a valid estimator of height.

The images were subject to intervention or subjective quality control, where images or entire sets of images from animals were rejected or accepted based on the posture of the animals. The drinking posture worked best for the morphological operations removing head, ears and tails. This was based on the study of Wang et. al where the accuracy was improved by removing these body parts. Further automation is required to make a more objective selection of image quality in order to apply this in a farm or breeding environment. The aim of this paper was to show the potential of a Kinect prototype to estimate the weight of live pigs, and the result clearly show its potential.

The advantage of the Kinect prototype is the use of depth maps instead of visible light images, which are more prone to noise in ambient light and require a more complex calibration setup with respect to lighting and color (Wu et al., 2004). In addition, the duroc breed may be difficult to segment from its background (dark

floor type) using visible light. The Kinect prototype using depth map show that dark colored breeds like the duroc breed is easily segmented from its background using depth map images.

#### 5. Conclusion

The Kinect prototype weighing system proved its potential to estimate the weight of pigs of different sizes and breeds using depth map images. The mean weight of pigs were estimated with an error of 4.6–4.9 for landrace and duroc breed, respectively. The image analysis required some degree of intervention or subjective selection of image quality, and more automation is needed to apply the Kinect prototype in a farm environment.

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