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Depth images’ processing to improve the performance of sows through early detection of lameness and changes in body condition score

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Thesis presented to obtain the degree of Doctor in Science. Area: Agricultural Systems Engineering

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DEDICATORY

To my dear mother, from whom I have always had unconditional love and support, and whose steps I have been following, so that today I could learn to fly;

I dedicate

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To "Fast Family", my crazy family of athletes (some not so much) that, to this day, do not know in which city I live and what is my major, but that always accompany me and vibrate with my achievements;

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To my in-laws, Ana and Claudemir de Oliveira, who allowed me to be part of their family and entrusted me their most precious possession;

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To God, who is always with me, even when I forget it.

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RESUMO

Processamento de imagens em profundidade para melhora do desempenho de matrizes suínas por meio da detecção precoce de claudicação e de alterações no escore de condição corporal

A observação, o controle e a manutenção das condições físicas de matrizes suínas em níveis aceitáveis são fundamentais para manter o bem-estar animal e a produção em padrões adequados. A claudicação causa dor e dificuldade de locomoção e, no entanto, é uma desordem comum em matrizes suínas que, além do impacto negativo no bem-estar, gera, também, grandes impactos na produção, uma vez que os animais que demonstram esse problema, apresentam um menor número de leitões nascidos vivos, menor número de partos por ano e são removidas do rebanho a uma idade mais jovem do que a ideal. Sabe-se, ainda, que, durante a gestação, cada matriz deve receber uma quantidade de ração diferenciada de acordo com sua condição corporal. Animais abaixo do peso apresentam deficiência nutricional e menor número de leitões nascidos por ninhada. Já as matrizes com excesso de peso apresentam um desenvolvimento anormal das glândulas mamárias, reduzindo a quantidade de leite produzida durante a lactação, acarretando em perdas econômicas. Tanto a detecção da claudicação quanto a classificação da condição corporal são feitos por meios subjetivos e dependentes da opinião pessoal do tratador, o que pode gerar divergências entre as classificações dadas por cada indivíduo. Destaca-se, portanto, a importância do reconhecimento precoce de animais que apresentam condições físicas fora dos padrões exigidos, visando a prevenção de perdas produtivas causadas tanto pelo agravamento das condições apresentadas quanto pelo grande impacto no bem-estar dos animais. Tendo-se isso em vista, o presente trabalho visou obter três características (escore de condição corporal, massa corporal e espessura de toucinho) por meio de imagens em profundidade, que se mostraram eficazes na obtenção dessas características em outros animais (suínos machos não-castrados e vacas leiteiras). Além disso, buscou-se desenvolver um método para a detecção precoce de claudicação em matrizes suínas, utilizando-se a abordagem da cinemática dos animais, que vem dando bons resultados e cujas dificuldades têm potencial para serem sanadas por meio do uso de imagens em profundidade em vez do método de marcadores reflexivos utilizado atualmente. Para predizer a condição corporal, uma regressão linear múltipla foi obtida usando o menor eixo da elipse ajustada ao redor do corpo da matriz suína, a largura dos ombros e o ângulo da curvatura da última costela. Para predizer a espessura de toucinho, foi realizada uma regressão linear múltipla usando a altura curvatura da última da costela, o perímetro do corpo da matriz, o maior eixo da elipse ajustada, o comprimento do focinho à cauda e o escore predito da condição corporal. Foi possível obter a massa corporal com uma regressão linear simples usando o volume projetado do corpo das matrizes. Para detecção de claudicação, três modelos apresentaram a melhor precisão (76,9%): análise discriminante linear, 1 vizinho mais próximo e 10 vizinhos mais próximos. As variáveis de entrada utilizadas nos modelos foram obtidas a partir de vídeos em profundidade (número, tempo e comprimento de passos para cada uma das quatro regiões analisadas-ombros esquerdo e direito e quadris esquerdo e direito; tempo total de caminhada e número de máximos locais para a região da cabeça). Como resultado desses estudos, observou-se que câmeras em profundidade podem ser utilizadas na automação de medidas de peso, condição corporal, espessura de toucinho e claudicação de matrizes suínas.

Palavras-chave: Zootecnia de precisão; Bem-estar; Tempo de voo, Dimensões

ABSTRACT

Depth images' processing to improve the performance of sows through early detection of lameness and changes in body condition score

The observation, control and the maintenance of the physical condition of sows in acceptable levels are critical to maintain the animal welfare and production in appropriate standards. Lameness causes pain making locomotion difficult. However, lameness is a common disorder in sows that causes negative impacts in both welfare and production. Since the animals that demonstrate this problem, have a smaller number of born-alive piglets, fewer gestation per year and are removed from the herd at a younger age than the ideal. In addition, it is industry practice to limit feed sows to ensure that they remain at an ideal condition score. It is known that, during gestation, each sow should receive a different amount of food according to its body condition. Underweight animals have nutritional deficiency and lower number of piglets per litter. On the other hand, overweight sows have an abnormal development of mammary glands, reducing the amount of milk produced during lactation, causing economic losses. However, moving sows to group gestation makes it difficult to monitor condition score in gestating sows. Both the detection of lameness and the classification of body condition are currently assessed using subjective methods, which is time consuming and difficult to accurately complete. Therefore, the early recognition of animals that present physical condition outside the standards is important to prevent production losses caused by both the aggravation of the conditions presented and the impact on the animals' welfare. The objective of this project is to obtain three characteristics (body condition score, mass and backfat thickness) through depth images, that proved to be effective on the acquisition of these features in other animals (boars and cows). The second objective is to develop a method for early detection of lameness using the kinematic approach, that has been generating good results and which difficulties have the potential to be reduced by using depth images instead of the method of reflective markers currently used. To predict body condition, a multiple linear regression was obtained using the minor axis of the ellipse fitted around sow's body, the width at shoulders, and the angle, of the last rib's curvature. To predict backfat, a multiple linear regression was performed using the height of last rib's curvature, the perimeter of sow's body, the major axis of the ellipse fitted around sow's body, the length from snout to rump, and the predicted body condition score. It was possible to obtain the body mass with a simple linear regression using the projected volume of the sows' body. For lameness detection, three models presented the best accuracy (76.9%): linear discriminant analysis, fine 1-nearest neighbor, and weighted 10-nearest neighbors. The input variables used on the models were obtained from depth videos (number, time, and length of steps for each of the four regions analyzed - left and right shoulders and left and right hips; total walk time; and number of local maxima for head region). As a result of these studies, it has been demonstrated that a depth camera can be used to automate the weight, condition score, backfat thickness, and lameness acquisition/detection in gestating and lactating sows.

Keywords: Precision livestock farming; Well-being; Time-of-flight; Dimensions

1 INTRODUCTION

The observation, control and maintenance of the physical condition of sows in acceptable levels are critical to maintain the animal welfare and production in appropriate standards. The animal welfare includes its physical and mental state. In December of 1979, it was proposed in the United Kingdom, during the Farm Animal Welfare Council, that the welfare of an animal should be considered in terms of "five freedoms". These freedoms define ideal states rather than acceptable welfare standards (Table 1). Sometimes, a single problem can affect more than one of those freedoms.

Table 1. The five freedoms and their provisions. Adapted from UK Government Web Archive.

Freedom	Provision
Freedom from hunger, thirst and malnutrition	Ready access to fresh water and a diet to maintain full health and vigor
Freedom from discomfort	Appropriate environment including shelter and a comfortable resting area
Freedom from pain, injury or disease	Prevention or rapid diagnosis and treatment
Freedom to express normal behavior	Sufficient space, proper facilities and company of the animal's own kind
Freedom from fear and distress	Conditions and treatment which avoid mental suffering

The animal welfare assessment protocol for pigs, Welfare Quality® (WELFARE QUALITY®, 2009), states that good health, one of the principles of the animal welfare, is composed of three criteria: absence of injury, absence of disease and absence of pain induced by manager (Table 2). It is proposed to evaluate the first criterion on sows by verifying the presence of lameness. This is done visually, rating the animals in three levels: level 0 (normal gait, or the animal with difficulty on walking, but still using all four legs), level 1 (sow severely lame with asymmetric walking) and level 2 (animal cannot support any weight on affected limb, or cannot walk).

The good feeding, another principle proposed by the Welfare Quality®, is composed of two criteria: absence of prolonged hunger and absence of prolonged thirst. The first criterion must be assessed, in sows, by measuring the body condition of the animals. This is done visually and by touch, classifying the body condition in three levels: level 0 (sow in good condition, with well-developed muscles on the bone), level 1 (thin sow, with bones easily felt; or sow visually obese) and 2 (very thin sow, with the hips and backbone prominent).

For the quantification of these two principles, both the detection of lameness and the classification of body condition are done by subjective methods, dependent on the opinion of the handler, which can generate differences between ratings given by different people. Lameness causes pain and difficulty of locomotion (Anil, Anil, & Deen, 2009) and, however, it is a common disorder in sows that causes negative impacts on both welfare and production, since the animals that demonstrate this problem, have a smaller number of born-alive piglets, fewer gestations per year and are removed from the herd at a younger age than the ideal (Anil et al., 2009).

It is known that, during pregnancy, each sow should receive a different amount of food according to its body condition. Underweight animals present nutritional deficiency, fewer piglets born per litter, and those that are born, can present also nutritional deficiencies and smaller body mass (Eissen, Kanis, & Kemp, 2000). Overweight sows are usually larger than the space provided in the pen, which leads to stress for the animal and may cause death of piglets by crushing. In addition, overweight sows have an abnormal development of mammary glands, reducing the amount of milk produced during lactation. Sows that are obese during pregnancy tend to reduce the amount of food ingested during lactation, which also reduces the amount of milk produced (Eissen et al., 2000).

Table 2. Evaluation of sows Welfare. Adapted from Welfare Quality® (2009).

Welfare Principles	Welfare Criteria		Measurements
Good feeding	1	Absence of prolonged hunger	Body condition score
	2	Absence of prolonged thirst	Water supply
Good housing	3	Comfort around resting	Bursitis, shoulder sores, absence of manure on the body
	4	Thermal comfort	Painting, huddling
	5	Ease of movement	Space allowance, farrowing crates
Good Health	6	Absence of injuries	Lameness, wounds on the body, vulva lesions
	7	Absence of disease	Mortality, coughing, sneezing, pumping, rectal prolapse, scouring, constipation, metritis, mastitis, uterine prolapse, skin condition, ruptures and hernias, local infections
	8	Absence of pain induced by management procedures	Nose ringing and tail docking
Appropriate behavior	9	Expression of social behaviors	Social behavior
	10	Expression of other behaviors	Stereotypies, exploratory behavior
	11	Good human-animal relationship	Fear of humans
	12	Positive emotional state	Qualitative Behavior Assessment (QBA)

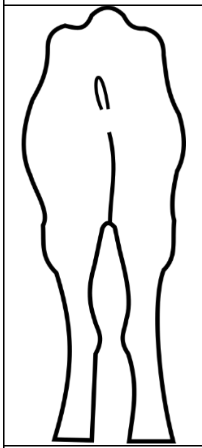
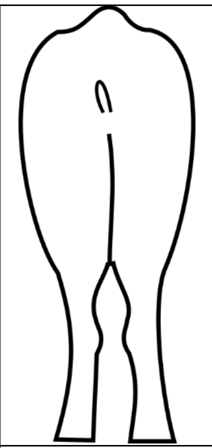
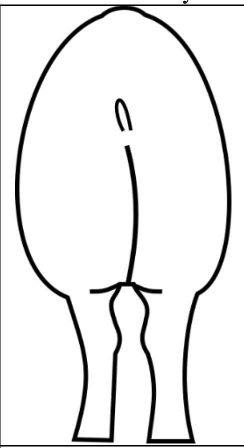
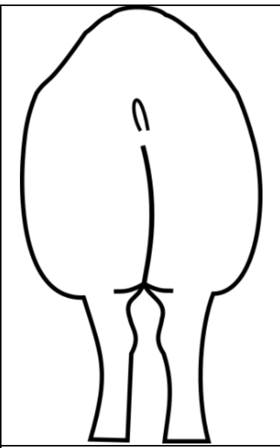
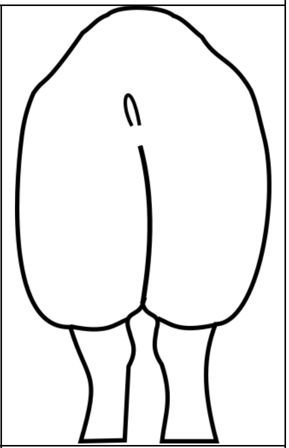
Therefore, the early recognition of animals that present physical condition outside the ideal condition is important to prevent production losses caused by both the aggravation of the conditions presented and the impact on the animals' welfare. Some authors have been using ratings like those proposed by the Welfare Quality® to assess body condition of sows over the years (Charette, Bigras-Poulin, & Martineau, 1996; Esbenshade, Britt, Armstrong, Toelle, & Stanislaw, 1986; M. T. Knauer & Baitinger, 2015; Mark Knauer, Stalder, Baas, Johnson, & Karriker, 2012; Maes, Janssens, Delputte, Lammertyn, & De Kruif, 2004; Salak-Johnson, Niekamp, Rodriguez-Zas, Ellis, & Curtis, 2007) (Patience & Thacker, 1989). In most of the cases, this classification is done using a scale from 1 to 5, ranging from very thin to obese. The classification proposed by Patience & Thacker (1989) is the most used and estimates the fat reserves of the animal through both visual assessment and the pressing of the pelvic girdle of the animal, using the fingers (Table 3).

The most common method to quantify lameness is also the visual score. The scoring systems proposed by Main, Clegg, Spatz, & Green (2000) and by the Welfare Quality® are the most used. That method consists in classifying the gait of the animals on a scale from 0 to 5, ranging from an animal that shows no lameness (score of 0) to an animal that can't stand up (score of 5).

As alternatives to these subjective methods of classification, various methods have been proposed to obtain a more objective measure. For lameness, kinetics and kinematics have been widely used in horses and cows and they began to be used in pigs. The kinetics aims to relate the movement of the bodies with their causes and considers the dynamic forces and acceleration. The footprint was analyzed in many species to study locomotion disorders. One of the possibilities of kinetic is to study simultaneously the positioning of the four legs and quantify parameters that cannot be measured with kinematics, such as slips when walking, trodden angles and the area of limbs in contact with the floor (Nalon, Conte, Maes, Tuyttens, & Devillers, 2013). The use of a hallway with floor covered in clay has been tested for acquiring the footprints of sows (Grégoire, Bergeron, D'Allaire, Meunier-Salaün, & Devillers, 2013), but it has not been possible to establish a relationship between the footprint pattern and the level of lameness, perhaps because of the floor type used.

Kinematic analysis quantifies the characteristics of the animal's gait in the form of measures related with time, distance and angles that describe the movements of the body segments and the joint angles. This analysis is made using reflective markers in predetermined locations on the body of the animal and video recording of the gait. With this technique, several parameters can be analyzed simultaneously by an auto-tracking software, however, some problems have been associated with it, mainly related with the placing of markers and their movement with the walk, the difficulty in finding joints or bones located behind muscle and fat where these markers will be positioned, and repeatability of positioning (Nalon et al., 2013). Despite the problems, this method has been effective showing (Grégoire et al., 2013) that lame sows have lower walking speed, spend less time standing during a period of 24 hours and tend to step more often during the time following the feeding.

Table 3. Body condition score of sows. Adapted from Patience & Thacker (1986).

Body condition Score				
				
1	2	3	4	5
Too thin	Skinny	Ideal	Overweight	Obese
Prominent hip bones and spine	Hip bones and spine easily felt without applying pressure.	Hip bones and spine felt only with palm pressure application.	Hip bones and spine cannot be felt.	Hip bones and spine thickly covered with fat.

At the end of the 90's, it was noted (Charette et al., 1996) the need for evaluation of body condition of sows using not just subjective methods of classification, but also more objective values, as body mass, the thickness of subcutaneous fat and dimensions of the animal, taking into consideration the parity of the animals. This type of classification, covering a larger number of variables, was adopted more recently (Sell-Kubiak, 2015) and expanded, using also the duration of the sow's gestation as a factor to be considered, proposing a classification of the sow's body condition throughout gestation and lactation, and obtaining measures of body mass and backfat thickness at the time of insemination, after birth and after weaning.

To reduce the errors with the body condition scoring, one should try to reduce the variation generated by the classification done by different managers. A way of doing that was proposed by Knauer & Baitinger, 2015, who developed a caliper that quantifies the angularity from the spinous process to the transverse process of a sow's back and concluded that this instrument can be used as a tool to standardize this classification.

Another way to standardize this measurement would be to automate the process by analyzing images generated by depth cameras. This method has already been used for dairy cows (Kuzuhara et al., 2015), obtaining a correlation of 74% between the predicted and actual body condition score. This can indicate the possibility of using this method for sows. In addition to the body condition classification by scores, one can also combine it with data of backfat thickness, body mass, parity and dimensions of sows to obtain a new classification regarding the body condition of these animals as soon as these parameters have been proved to be effective in the body characterization of sows (Charette et al., 1996; Sell-Kubiak, 2015).

The most used method for acquiring the backfat thickness (De Rensis, Gherpelli, Superchi, & Kirkwood, 2005; Kim et al., 2016; M. T. Knauer & Baitinger, 2015; Maes et al., 2004; Magowan & McCann, 2006) is obtaining it through ultrasonic probes. One problem with this approach is the difficulty of applying it on an industrial scale, since this assessment should be manually done for each animal. Noticing this difficulty in the production of dairy cows, Weber et al., 2014 proposed the use of a depth camera for prediction of the animals' backfat, obtaining a correlation of 96% with the fat thickness measured with ultrasonic probes. This indicates the possibility of using this method on sows to predict their backfat.

Weighing is a time consuming and stressful practice for both the animal and the handler. Taking this into account, several authors (Frost et al., 1997; Kashiha et al., 2014; Kongsro, 2014; Schofield, 1990; Schofield, 1999; Wu et al., 2004) have been using pigs' dimensions data for predicting animal's mass. To replace the scale by an indirect method, both the convenience and the accuracy of the method to be used should be considered. Different methods of obtaining pigs' mass have been tested by many authors (Philips & Dawson, 1936; Zagaroza, 2009). The use of calipers and tape is shown to be effective to this end, but the need to restrict the animals to obtain the data, makes this process impracticable on an industrial scale and equivalent to the process of weighing itself. With that, the use of images to obtain pigs' dimensions would be interesting because of its non-invasive approach.

The potential of using images for calculating dimensions was noted by other authors (Kashiha et al., 2014; Schofield, 1990; Schofield, 1999; Wang, Yang, Winter, & Walker, 2008; Wu et al., 2004), which correlated the animals' area obtained through images with their mass and developed prediction equations. In general, these authors point to the fact that to extract the pigs' dimensions, their skin and hair colors must be distinct from the environment color. Dark, stained or dirty animals hinder the automation of this approach. In addition to the color of the animal, the presence of adequate light is critical for this application. Kashiha et al. (2014) found great lighting values within the range of 40 to 150 lux. To avoid this problem, it was developed (Wu et al., 2004) an image capture system with six high-resolution cameras (3032 × 2028 pixels) and three flash units to obtain the 3-D forms of live pigs. However, the excess equipment and the high costs involved make it difficult to use this type of image capturing on an industrial scale.

A different approach has been used (I.C.F.S. Condotta, Brown-Brandl, Silva-Miranda, & Stinn, 2018; Kongsro, 2014; Pezzuolo, Guarino, Sartori, González, & Marinello, 2018), applying depth cameras to obtain pigs' mass (grow-finish pigs). This information is obtained from the correlation between the body volume generated from the depth images and the mass of the animal. This approach reduces concerns about calibration and lighting, in addition to providing the animal's height.

These depth cameras have been used in many areas, such as 3D mapping and reconstruction (Izadi et al., 2011, Jia et al., 2012), indoor robotics (Correa et al., 2012; Ganganath & Leung, 2012; Benavidez & Jamshidi, 2011), object detection and recognition (Hernández-López et al., 2012) and recognition of gestures (Chang et al., 2011 (a); Chang et al., 2011 (b), Hondori et al., 2012). A commercial sensor that is being used (I.C.F.S. Condotta et al., 2018;

Kongsro, 2014; Kulikov et al., 2014; Lao et al., 2016; Lee, Kim, Lim, & Ahn, 2016; Pezzuolo et al., 2018; Stavrakakis et al., 2015; Zhu, Ren, Barclay, McCormack, & Thomson, 2015), as an alternative to expensive laser scanners (Khoshelham & Elberink, 2012) and stands out for its low cost, reliability and measurement speed (Smisek et al., 2015) is the Microsoft Kinect sensor. The version 1 (Figure 1) of this sensor uses structured light technology, which is the process of projecting a known pattern into a scene or object and obtaining depth values according to its reflection pattern. For that, the emitter projects a beam of light in the near infrared region and the infrared camera is triggered to obtain the infrared image, which contains the pattern of dots of reflected light in the scene. Another commercial sensor that also uses the structured light technology and is being applied (H. Guo et al., 2017; Y. Guo, Zhu, Jiao, & Chen, 2014; Kuzuhara et al., 2015) in the animal area is the Xtion® Pro, from Asus (Figure 2).

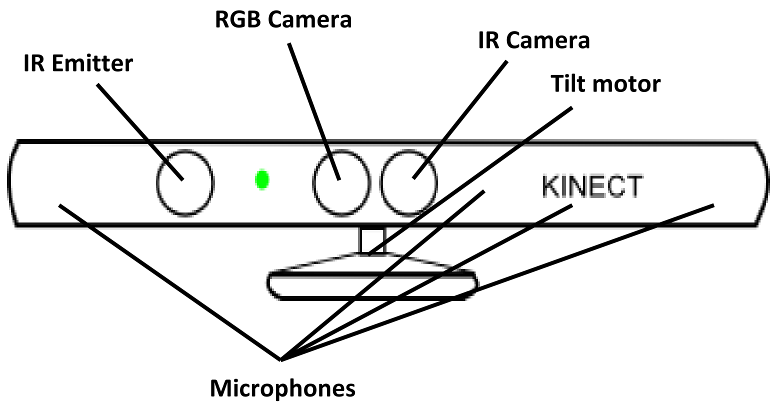


Figure 1. Microsoft Kinect sensor v.1 components.

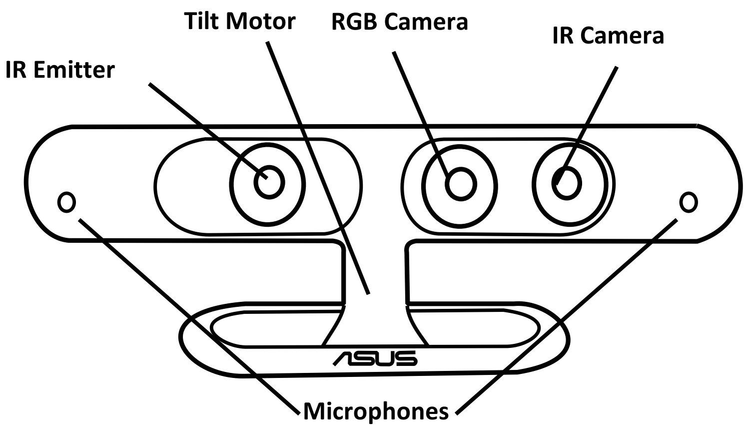


Figure 2. Asus Xtion® Pro sensor components.

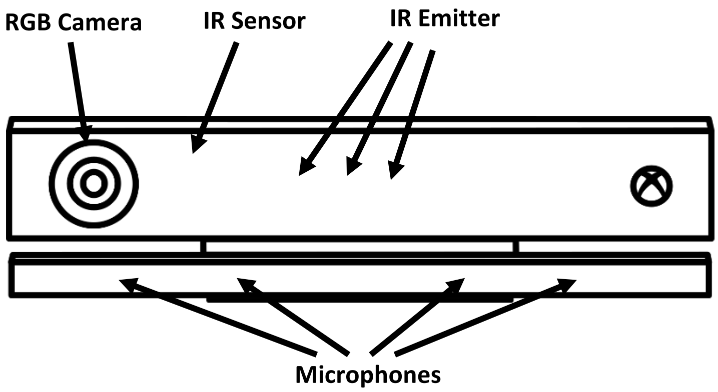


Figure 3. Microsoft Kinect sensor v.2 components.

According to the technical specifications provided by Microsoft, the version 2 of the Kinect sensor (Figure 3) is composed by an RGB camera, three infrared (IR) emitters, an infrared depth sensor and four multi-array microphones, and presents less problems with capturing images in widely lit environments when compared to the first version of the sensor. Three image outputs are provided by Kinect: (1) RGB image with 1920 x 1080 pixels, (2) IR image with 512 x 424 pixels, and (3) depth image with 512 x 424 pixels, in addition to the possibility of audio capture. Parallel to the depth image, a numerical map is generated, which is the main raw data provided by the sensor, containing the distances, in mm, between the sensor and each pixel that makes up the image. For generating the depth image, this second version of the sensor uses the time-of-flight technology, which is based on the principle that, "knowing the speed of light, the distance to be measured is proportional to the time required by the active lighting source to travel from the emitter to the target"(Lachat, Macher, Mittet, Landes, & Grussenmeyer, 2015).

The present work aimed to obtain three characteristics (body condition score, body mass and backfat thickness) of sows using a commercially available depth camera, that proved to be effective in obtaining these characteristics in other animals (dairy cows). In addition, with the same sensor, a method for early detection of lameness in sows was developed, using the kinematic of animal's approach, that has been giving good results and which difficulties have the potential to be overcame using a depth camera instead of the method of reflective markers currently used.

This thesis was divided into three papers that will be sent for publication this year. The first paper will be sent for publication on the Computers and Electronics in Agriculture journal and covers a study of the current available depth sensing technologies and evaluate its use on precision animal management applications. The second and third papers will be both send for publication on the Biosystems Engineering journal. The second paper covers the body condition characterization of sows through depth images, and the third paper covers the detection of lameness on sows also through depth images.

On the first paper unit transformation equations were developed. These equations make it possible to determine the actual dimensions of an object (length, area and volume), in metric units, from its dimensions in the image, in pixels, based on the distance between the object and the sensor, that can be easily obtained with depth cameras. These equations are an advantage on animal applications that use computer vison because they eliminate the need for the presence of an object with pre-determined dimensions on the image. This facilitate the images analysis and the automation of the process.

These equations developed were used on the third chapter of this thesis to obtain dimensions of animals in metric units. Also, one of the conclusions of this first paper was that the time-of-flight technology is the best to be used for indoor applications and the combination of stereo vision with structured light is the best for outdoor applications. With that in mind, Kinect v.2 camera was selected to be used on both the second and third papers, as it is a low-cost depth camera that uses the time-of-flight technology.

On the second paper, body condition, backfat and weight were assessed using a depth camera. For that, a multiple linear regression was obtained using the minor axis of the ellipse fitted around sow's body, the width at shoulders, and the angle, of the last rib's curvature to predict body condition. To predict backfat, a multiple linear regression was performed using the height of last rib's curvature, the perimeter of sow's body, the major axis of the ellipse fitted around sow's body, the length from snout to rump, and the predicted body condition score. It was possible to obtain the body mass with a simple linear regression using the projected volume of the sows' body.

As for the third paper, lameness was assessed on sows using one of the three models: linear discriminant analysis, fine 1-nearest neighbor, and weighted 10-nearest neighbors; and input variables obtained from depth videos (number, time, and length of steps for each of the four regions analyzed - left and right shoulders and left and right hips; total walk time; and number of local maxima for head region).

For both papers that assessed the physical conditions of sows, the errors obtained were in acceptable levels (7.7% for body condition scoring, 16.1% for backfat, 3.8% for weight, and 33.1% for lameness classification) when compared with the literature. These works indicate that automation through image processing could be possible. The next steps would be to try to reduce the errors found. One problem with this is the difficulty in correctly identifying subjectively score data as a standard to be used as a comparison. An alternative would be to develop a completely new physical condition classification system based on image processing, that would take into consideration the way that dimensions and behavior of individual animals change over time, rather than try to predict the current indicators of good physical condition (e.g. body condition score, backfat, weight , and lameness presence). This could aid producers to take better and faster management decisions, with a reduced stress level for both workers and animals, improving animal well-being and maximizing the profitability of swine production.

2 CONCLUSIONS

Low-cost depth-cameras use one or a combination of three technologies: structured light, time-of-flight (ToF), and stereo vision. Five different cameras were tested for their suitability to be used in agriculture applications. Significant camera to camera differences were found for all the cameras ($P<0.05$), except for ToF cameras (Microsoft Kinect v.2 and CamBoard Pico Flexx). Increases in standard deviation in measurements were found with all camera as the distance between camera and object in-creased; however, Intel® RealSense™ camera had a much larger increase. Time-of-flight cameras had the smallest error between different sizes of objects. All cameras showed some distortion at the edges of the images; however, the ToF cameras had non-readable zones on the corners of the images. Different values of area and length can be acquired with the data provided by depth cameras, for the same object located at different positions in the image. This distortion is greatest in the horizontal axis of the image for the ToF cameras and in the vertical axis for the structured light cameras. The stereo vision-only camera (ZED) did not show any differences between the different positions for dimensions' acquisition. Cameras that use stereo vision technology can be used for outdoors applications. Cameras that use ToF technology, although provide some data on outside environments, should be used outside only if necessary and in a close range (up to 1.0 - 2.0 m). As the variation of distances from sensor to object generates different values of length, area and volume to the same object, it's necessary to standardize these values so that they can be compared. This can be done using the equations 2 and 3, with coefficients provided on tables 3 and 4 proposed in this study. Considering both the shapes provided and the depth information, the cameras that use ToF technology would be more advisable to be used on animal phenotyping, followed by cameras that use structured light technology.

Regression models were performed to obtain body condition score, backfat, and body mass from variables obtained with a commercially available depth camera. A multiple linear regression was obtained using the minor axis of the ellipse fitted around sow's body, the width at shoulders, and the angle, of the last rib's curvature to predict BCS. To predict backfat, a multiple linear regression was performed using the height of last rib's curvature, the perimeter of sow's body, the major axis of the ellipse fitted around sow's body, the length from snout to rump, and the predicted body condition score. It was possible to obtain the body mass with a simple linear regression using the projected volume of the sows' body. With these three characteristics it could be possible to have better insights on the physical condition of sows and aid on better and faster management decisions.

A method for early detection of lameness in sows was proposed by using commercially available depth cameras and one of the three models: linear discriminant analysis, fine 1-nearest neighbor, and weighted 10-nearest neighbors. The input variables to the models were number, time, and length of steps for each of the four regions analyzed (left and right shoulders and left and right hips); total walk time; and number of local maxima for head region. The lameness can be classified with a good accuracy (76.9%). Future steps of this research should use more animals per level in order to improve the model. With the automation of lameness detection, it could be possible to have better insights on the physical condition of sows and aid on better and faster management decisions.

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