University of São Paulo
“Luiz de Queiroz” College of Agriculture

Automatic assess of growing-finishing pigs’ weight through depth image analysis

Isabella Cardoso Ferreira da Silva Condotta

Dissertation presented to obtain the degree of Master in Science. Area: Agricultural Systems Engineering

Piracicaba
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versão revisada de acordo com a resolução CoPGr 6018 de 2011

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1. Zootecnia de precisão 2. Sensor Kinect® 3. Pesagem I. Título

DEDICATORY

To my dear mother, from whom I have always obtained unconditional love, companionship and support and whose steps I follow so that one day I can 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 God, who is always with me, even when I forget it.

Thank you very much!

EPIGRAPH

Imagination is more important than knowledge.

-Albert Einstein

Cogito ergo sum.

-René Descartes

SUMMARY

RESUMO

Obtenção automática da massa de suínos em crescimento e terminação por meio da análise de imagens em profundidade

Um método de monitoramento contínuo da massa corporal de suínos auxiliaria os produtores, assegurando que todos os animais estão ganhando massa e aumentando a sua precisão de comercialização, reduzindo-se perdas. Obter eletronicamente a massa corporal sem mover os animais para a balança eliminaria uma fonte geradora de estresse. Portanto, o desenvolvimento de métodos para monitorar as condições físicas dos animais à distância se mostra necessário para a obtenção de dados com maior qualidade. Na produção de suínos, a pesagem dos animais é uma prática que representa um papel importante no controle dos fatores que afetam o desempenho do rebanho e o monitoramento da produção. Portanto, esta pesquisa teve como objetivo extrair, automaticamente, dados de massa de suínos por meio de imagens em profundidade. Foi feita, primeiramente, uma validação de 5 sensores de profundidade Kinect® para compreender seu comportamento. Além disso, foram geradas equações para corrigir os dados de dimensões (comprimento, área e volume) fornecidos por estes sensores para qualquer distância entre o sensor e os animais. Foram obtidas imagens de profundidade e massas corporais de suínos e crescimento e terminação (fêmeas e machos castrados) de três linhagens comerciais (Landrace, Duroc e Yorkshire). Em seguida, as imagens foram analisadas com o software MATLAB (2016a). Os animais nas imagens foram selecionados por diferenças de profundidade e seus volumes foram calculados e depois ajustados utilizando a equação de correção desenvolvida. Foram coletadas, ainda, dimensões dos animais para atualização de dados existentes. Curvas de massa versus volumes corrigidos e de dimensões corrigidas versus massa, foram ajustadas. Equações para predição de massa a partir do volume foram ajustadas para os dois sexos e para as três linhagens comerciais. Uma equação reduzida, sem considerar as diferenças entre sexos e linhagens, também foi ajustada e comparada com as equações individuais utilizando o algoritmo de Efroymson. O resultado mostrou que não houve diferença significativa entre a equação reduzida e as equações individuais tanto para sexo ($p < 0,05$), quanto para linhagens ($p < 0,05$). A equação global pode predizer massas a partir do volume obtido com o sensor, com um R^2 de 0,9905. Portanto, os resultados deste estudo mostram que o sensor de profundidade é uma abordagem razoável para monitorar as massas dos animais.

Palavras-chave: Zootecnia de precisão; Sensor Kinect®; Pesagem

ABSTRACT

Automatic assess of growing-finishing pigs' weight through depth image analysis

A method of continuously monitoring weight would aid producers by ensuring all pigs are gaining weight and increasing the precision of marketing pigs thus saving money. Electronically monitoring weight without moving the pigs to the scale would eliminate a stress-generating source. Therefore, the development of methods for monitoring the physical conditions of animals from a distance appears as a necessity for obtaining data with higher quality. In pigs' production, animals' weighing is a practice that represents an important role in the control of the factors that affect the performance of the herd and it is an important factor on the production's monitoring. Therefore, this research aimed to extract weight data of pigs through depth images. First, a validation of 5 Kinect® depth sensors was completed to understand the accuracy of the depth sensors. In addition, equations were generated to correct the dimensions' data (length, area and volume) provided by these sensors for any distance between the sensor and the animals. Depth images and weights of finishing pigs (gilts and barrows) of three commercial lines (Landrace, Duroc and Yorkshire based) were acquired. Then, the images were analyzed with the MATLAB software (2016a). The pigs on the images were selected by depth differences and their volumes were calculated and then adjusted using the correction equation developed. Also, pigs' dimensions were acquired for updating existing data. Curves of weight versus corrected volumes and corrected dimensions versus weight were adjusted. Equations for weight predictions through volume were adjusted for gilts and barrows and for each of the three commercial lines used. A reduced equation for all the data, without considering differences between sexes and genetic lines was also adjusted and compared with the individual equations using the Efroymson's algorithm. The result showed that there was no significant difference between the reduced equation and the individual equations for barrows and gilts ($p<0.05$), and the global equation was also no different than individual equations for each of the three sire lines ($p<0.05$). The global equation can predict weights from a depth sensor with an R^2 of 0,9905. Therefore, the results of this study show that the depth sensor would be a reasonable approach to continuously monitor weights.

Keywords: Precision livestock farming; Kinect® sensor; Weighing

1 INTRODUCTION

The development of methods for automatic monitoring the physical conditions of animals is indispensable for faster and less invasive of data acquisition, eliminating stress-generating source and reducing losses in production.

The animals' dimensions' acquisition is an important factor both in construction projects and for obtaining the weight of animals. For equipment and construction's projects, the animals' dimensioning is necessary to specify the required space, being need to know how the animals' dimensions vary over time.

Weighing is a practice that has an important role in the control of the factors that affect the performance of the herd, including available space per animal and quantity of daily provided food. The knowledge of daily weight gain can allow producers improve the nutritional management, predict and control the weights of boarding and help in monitoring the health of the herd, since this information can be used in the monitoring of disease outbreaks.

However, currently, this practice is long (3 to 5 minutes per animal) and stressful for both the animal and the manager. Thus, it is necessary to develop faster and less invasive techniques of weight acquisition.

An automated system to determine the animals' weight has the potential to assist producers to classify animals to market, and minimize the number of pigs marketed out of specification. An alternative would be to acquire the volume of animals through images and correlate it with the weight of the animals.

One way to obtain this value is through depth images provided by Microsoft® Kinect® sensor. This approach was proposed initially in 2014 for use with boars. The volume of the animal showed a better correlation with weight than its area, as had been proposed so far by other authors. However, the technique of analysis proposed looks very similar to what it is done for colored digital images, not using the full potential of depth data provided by this sensor, and there is still space for improvement.

The use of this sensor makes it necessary to know whether there are differences between the depth data provided by different Kinect® sensors used, analyzing the need for calibration between them. In addition, knowledge about the characteristics of the sensor with the change of its position relatively to the object is also necessary, and if there are differences, it is important to analyze how that data compare with each other.

Thus, the present work was divided into three parts. The first is dedicated to analyze the characteristics of the Kinect® sensor. The second part involves the development and

evaluation of a method for obtaining pigs' dimensions through depth images and correlate these dimensions with the weight of the animals. Finally, the third part aimed to develop a method of predicting weight of pigs from volume obtained with depth images provided by a Kinect® sensor.

2 LITERATURE REVIEW

2.1 Pigs' production in Brazil and in the world

Currently, Brazil is the fourth largest producer of pork. According to the USDA (United States Department of agriculture), Brazilian production in 2016 was 3,710,000 t.

The three largest producers of pork in the world are China, with 51,850,000 t in 2016, the European Union, with 23,350,000 t, and the United States, with 11,310,000 t.

As for the international market, the largest exporter of pork in 2016 is the European Union, with 3,300,000 t shipped, followed by the United States, with 2,350,000 t and Canada (1,350,000 t). Brazil occupied fourth place, totaling 900,000 t shipped in 2016, according to the USDA.

In relation to consumption, China (54,070,000 t), the European Union (20,060,000 t) and the United States (9,450,000 t) lead the world ranking in 2016, followed by Russia (3,160,000 t) and Brazil (2,810,000 t).

When compared with other proteins, pork is the most consumed worldwide, with a total of 108,000,00 t, followed by chicken meat (87,640,000 t) and beef (58,730,000 t).

In Brazil, this world trend does not apply, since the most consumed meat is chicken (9,500,000 t), followed by beef (7,500,000 t) and pork (LIVESTOCK, USDA; 2016). To stimulate consumption in Brazil, the production chain has been mobilized in the modernization of trade of pork, as well as on consumer awareness.

2.2 Weighing on pigs' production

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. As an example, the meat industry pays more to producers for animals with weight, composition and conformation well-defined and within an acceptable range. (FROST et al., 1997)

The inability of the producer in obtaining with precision and control the variables that affect the conformation and fat levels of animals can cause the non-meeting of the market's demands. As soon as the farms have increased in size, even small changes in production practices can have a major impact on the global income (KASHIHA et al.; 2014).

The knowledge of the daily variation of animals' weight in real time, is a practice that would allow producers to improve the yield of production. It would be possible to use this information to optimize the space provided by animal, to improve nutritional management practices, predict and control the weights for the slaughter and, potentially, control the herd's

health, since this information can serve as monitoring of disease outbreaks (BRANDL & JORGESEN, 1996; KASHIHA et al; 2014).

Usually, weighing is done manually, in a process that often requires two managers and can take three to five minutes per animal. This practice can be stressful for both animals and managers, in addition to representing an ergonomic risk (BRANDL & JORGESEN, 1996).

Therefore, an automated system to determine the animals' weight has the potential to assist producers to classify them to market, and minimize the number of pigs marketed out of specification, improving the yield of production. To this end, many attempts have been made to find an alternative to the manual process of weighing.

Essentially, two approaches have been studied (1) electronic and automatic weighing systems combined with automatic identification equipment and (2) indirect determination of weight through the animals' dimensions.

2.2.1 Electronic and automatic weighing systems

Initially, studies using semi-automatic scales were carried out (SMITH & TURNER, 1974; TURNER & SMITH, 1975) to reduce the time of pigs' weighing as well as faster identification of animals outside a specified body weight.

This system consists of a scale that identifies animals with weight above a selected value by marking with spray (manual) or by opening automatic gates and can weight 100 animals/h (36 s/animal) without assistance, with potential to double that number if another manager help in driving the animals between the scale and the pen.

This solution, although it has shown significant improvement in the time of weighing, still requires that the animals are removed from their pens and driven up the scale. This process resembles the manual weighing process itself and do not bring great improvement from the animals' point of view. In addition, from the manager's point of view , for large herds, this process continues to be exhaustive, and weighing speed can be reduced over time.

Subsequently, studies were carried out involving the use of radio frequency transponders for animals' identification. First, this system was used with an electronic feeder (SLADER & GREGORY, 1988), which allowed the entry of the animals according to their identification, being possible to obtain the actual weight of the animals. In addition, the identification transponder was positioned inside an ear tag instead of being injected in animals, which reduces the invasive aspect of this method.

This system is efficient on animals' identification, reducing the work of the managers in the weighing process, in addition to allowing the animals remain inside the pen during the procedure.

One problem that arises with this approach is the cleanup of the weighing platforms, which often doesn't indicate the correct weight of animals due to the presence of waste. Therefore, the control of the cleanliness of these platforms by a manager would be required, which, still, is not ideal. With that, these systems are much more efficient to control the amount of food and water ingested by animals than its weight in fact.

Something similar was done by other authors (RAMAEKERS et al., 1995), who developed a method to estimate the individual body weight of group-housed growing-finishing pigs, using a front leg weighting system located below the feeders. This system proved effective in predicting the weight of animals with a 5% error.

This system, when compared to the entire animal weighing system, requires less space in the pen, but is subject to errors associated with the prediction equation used to estimate the body weight. In addition to the problem with the presence of waste on the platform already discussed, there is also the need of the animal to remain in the feeder for at least two minutes so the standard deviation of the measures is less than 1 kg. This is not always the case, as soon as in a collective pen animals are in constant competition for space near the feeder.

Other problems that can arise with automatic measurement platforms are related to the presence of more than one animal on the platform and the animals' excessive movement, which can lead to errors on data acquisition.

Some researchers (SCHOFIELD et al., .2002) sought to verify the relationship between the animals' weight obtained by conventional scales and obtained by electronic weighing platforms, developing a correlation equation. In addition, the researchers evaluated the feasibility of using weight measurements of 14 consecutive days to predict animals' initial and final weights. This method proved to be effective in predicting weight only for the final weight. In addition, it was shown that animals' weight suffers a great variation over the course of 14 days, which would not be noticed in the manual process of weighing, that is done less frequently. This shows the importance daily measurement of weight.

2.2.2 Weight's indirect determination through animals' dimensions:

As an alternative to the direct methods of automatic weighing, many researchers noted a significant correlation between the weight and the dimensions of the pigs, causing them to

study the possibility of estimating body weight by indirect methods, which involve obtaining dimensions of pigs.

These methods eliminate the problems with the error in measurements caused by presence of waste, animal movements, time in the weighing platform and the presence of more than one animal on the platform. However, other problems arise, mainly related to efficient correlation between weight and dimensions and a faster and non-invasive way of dimensions' acquisition.

Some of these methods, such as the use of tapes and calipers, have been widely used by pigs' producers. These methods are faster than the manual weighing, but still require the pig's immobilization, making the procedure as stressful as the weighing process itself, in addition to not provide the animal's weight with a great accuracy.

It was conducted a study (ZARAGOZA, 2009) of methods for obtaining the dimensions of pigs with the objective of predicting the animals' weight. Two methods for obtaining dimensions were studied; a direct method, using tape measure and calipers, and an indirect method, through image analysis.

With this study, it became clear that, although there is a good correlation between the dimensions of the animals and its weight, the direct method is impractical on an industrial scale.

As for the indirect method, despite having a worse correlation with the animal's weight, it has advantages in relation to other methods that must be taken into consideration, such as, for example, the speed of measurement and the stress reduction for both animals and managers during the acquisition process.

These qualities had been noted by researchers (SCHOFIELD,1990; SCHOFIELD, 1999; WHITTEMORE & SCHOFIELD, 2000), which addressed the subject in different ways.

First, it was investigated (SCHOFIELD, 1990) the possibility to calculate the pigs' weight from its areas and specific dimensions obtained through digital image analysis. The results showed that the analysis can be used to measure the area of an animal when seen straight from above, and that this can be used to determine its weight with 95% of accuracy.

It was pointed out that the correlation between the animal area and its body weight is greater when the animal's head and tail are not considered to calculate the area, since these tend have varying areas depending on its position when the picture is taken.

Later, the possibility of automating the process of images acquisition began to be studied (SCHOFIELD .1999). To do this, an automatic system of images acquisition and

analysis assigned to record the areas and correlate them to the pigs' weight was described and evaluated. This system successfully registered growth rates of three groups of pigs from three different genetic lines (Landrace, Large White and Meishan)., with 95% of accuracy.

In addition, it was shown that different lines require different algorithms to correlate the area with the animals' weight, as demonstrated by the various linear regression coefficients obtained for each line studied.

Other authors (Kashiha et al., 2014) also investigated the viability of an automated method to estimate pigs weight using image processing. It was applied an ellipse algorithm to find pigs in the images and then the area that the animal occupies within the ellipse was calculated. Finally, the animals' weight was estimated using dynamic modeling. The weight could be estimated with an accuracy of 97.5% at group level (0.82 kg) and 96.2% individually (1.23 kg).

Problems with image acquisition method for obtaining the animal's area and, subsequently, its body weight, are related to the need to keep the animal steady to obtain a good picture.

As a solution, it was done a study (WANG et al, 2008) that developed a walk-through system for collecting images without needing movement restriction to obtain a stationary image. A protocol was developed for selecting and automatically show captured images, using the artificial neural network technique to correlate physical characteristics extracted from images to improve the accuracy of the weight value obtained. The results showed that the system's average relative error was about 3%.

The difficulty with the determination of weight through digital images is that, in order to extract the dimensions of the pig, its color must be different from the color of the environment. Dark skinned pigs, stained or dirty make this approach very difficult to automate. In addition to the color of the animal, the presence of adequate light is critical for this application. It was found (KASHIHA et al.., 2014) great lighting values within the range of 40 to 150 lux.

To solve this problem, it was developed (WU et al., 2004) an image capture system with six high resolution cameras (3032 x 2028 pixels) and three flash units to obtain the 3D shapes of live pigs. This system uses the simultaneous capture of three views and later triangulation of the data. The problem with this approach is the excess of equipment necessary, in addition to the high costs involved; what make the use of this type of image capture impossible on an industrial scale to obtain the pigs' weight.

Finally, to reduce the problem with costs and excess of apparatus, it was presented (Kongsro, 2014) a prototype for weighing pigs, using a Microsoft® Kinect® sensor to obtain depth (3D) images. With this, the volume of the animal obtained through this image was correlated with the weight of Landrace and Duroc boars.

This system estimated the weight of pigs with an error of 4 to 5%. Depth images require less concern with calibration and lighting and provide an additional data of height. Difficulties with this approach are related to the fact that the sensor does not capture images in overly lit regions, which can make it difficult to use in facilities that allow the entry of bright sunlight.

2.3 Acquisition of pigs' dimensions

The space distribution is one of the main points to be considered in construction and equipment projects for farm animals. To this end, the ability to specify the space required for animals is necessary (PETHERICK, 1983) and, therefore, is need to know how the animals' dimensions vary over time.

In 1968, ASABE published dimensions' curves varying with the weight of farm animals (dairy, cattle, swine, sheep, horses and poultry), which are used as standard. The changes in the production process over the years, such as nutrition and the use of different genetic lines and facilities, make it necessary to update these curves to dimensions of modern production.

In addition to monitoring the variation in size of animals for space dimensioning, various authors (SCHOFIELD .1990; FROST et al. .1997; SCHOFIELD, 1999; KASHIHA et al., 2014; WU et al., 2004; KONGSRO, 2014) are using this information to predict the weight of the animals. This fact points to the need to develop an ideal method for obtaining this data, not only from a production, but also from a scientific standpoint.

It must also be pointed the fact that the presence of human beings in the management of farm animals, in addition to increasing the costs of the proceedings, is a stress generating source for the animals. Therefore, the development of methods of monitoring the physical conditions of animals from a distance appears as a need to obtain data with higher quality.

The accuracy of three methods for obtaining the dimensions of pigs was studied by Philips & Dawson (1936): (a) using calipers and tape measures; (b) by a livestock scale instrument, proposed by Kelly (1933) and (c) through images. The authors pointed to the fact that the convenience, along with the accuracy of the method to be used, should be considered. As a result, the first method was the most effective, but the need of restriction of animals to

obtain data is considered a point against and, when it comes to predicting weight, can be equivalent to the weighing process itself. The use of images to obtain the dimensions of the pigs would be, according to the authors, useful, when animals are not used to being handled.

Zaragoza (2009) assessed the accuracy of two methods for obtaining the dimensions of pigs for weight prediction of animals: (a) directly, using tape measure and calipers, and (b) by image analysis, using a ruler as a dimensional reference to the transformation of pixels in centimeters. The author obtained the first method as being the most accurate prediction of weight, but pointed to the fact that the need for restriction of animal movements makes it impractical on an industrial scale. The use of images, according to the author, would be interesting from a scientific point of view due to their non-invasive approach.

The potential of using images for acquiring dimensions was noticed by other authors (SCHOFIELD .1990; SCHOFIELD, 1999; WANG et al., 2008; WU et al., 2004; KASHIHA et al., 2014), that correlated the animal area, obtained through images, with their weight, developing prediction equations.

In General, the authors point to the fact that, in order to extract the dimensions of the pig, its color must be different from the color of the environment. Dark skinned pigs, spotted or dirty make this approach difficult to automate. In addition to the color of the animal, the presence of adequate light is critical for this application.

Wu et al. (2004), then, developed a system of capturing images with six high resolution cameras (3032 x 2028 pixels) and three flash units to obtain the 3D shapes of live pigs, however, excess of equipment, in addition to the costs involved, make this type of image capture difficult to use on an industrial scale.

Another approach was proposed by Kongsro (2014), which presented a prototype for weighing pigs, using a Microsoft® Kinect® sensor to obtain depth images. This technique minimizes the problems of lighting and color differentiation of animals and was, therefore, considered in the present study, as a potential for the monitoring, not only the area of the animals but also other dimensions, such as height and depth.

2.4 The Kinect® sensor

The Microsoft® Kinect® sensor (FREEDMAN et al., 2010) has been used as an alternative to expensive laser scanners (KHOSHELHAM & ELBERINK, 2012) in various areas, such as mapping and 3D reconstruction (IZADI et al., 2011, JIA et al., 2012), indoor robotics (GARAGE, 2011; Correa et al.., 2012; GANGANATH & LEUNG, 2012; BENAVIDEZ & JAMSHIDI, 2011), objects' detection and recognition (HERNÁNDEZ-

LÓPEZ et al., 2012) and gesture recognition (CHANG et al., 2011 (a); CHANG et al., 2011 (b), HOSSEIN et al., 2012), and stands out for its low cost, reliability and speed of measurement (SMISEK et al., 2015).

This sensor consists of an RGB camera, an infrared (IR) emitter, an infrared depth sensor, multi-array microphones, a three-axis accelerometer and tilt motor (MICROSOFT). Figure 1 shows the sensor, as well as their components.

Three outputs are provided by Kinect: digital color RGB image (640 X 480 pixels), IR image (640 X 480 pixels) and depth image (640 X 480 pixels). In addition to the depth image, a map is generated, containing the main raw data provided by the sensor with the distances, in mm, between the camera and each pixel of the image. Figure 2 illustrates the three outputs provided.

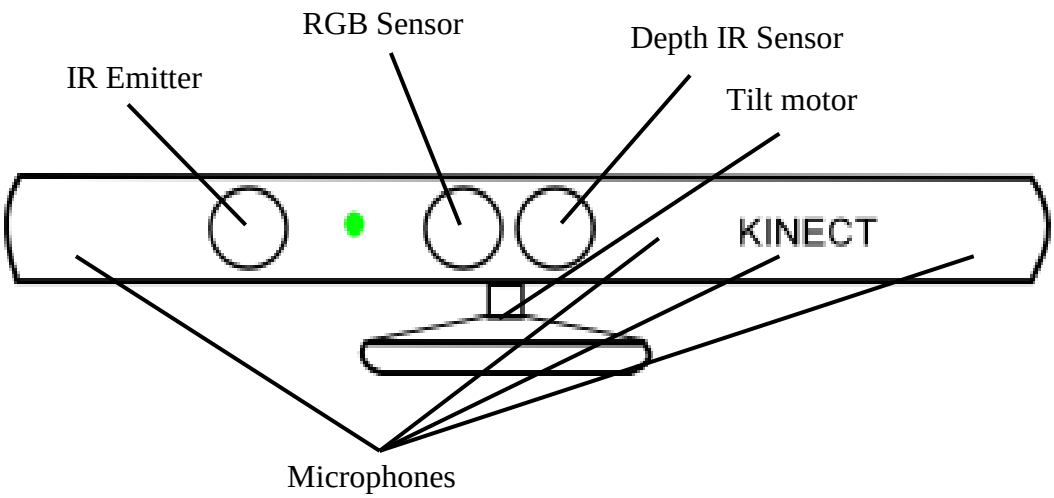

Figure 1 - Components of the Kinect® sensor for Windows®.

To form the depth image, the IR emitter projects on the object a light beam that is reflected and divided into multiple beams, forming a pattern of points which are then captured by the IR sensor (Figure 2 (b)). This pattern is compared with a reference with a predetermined distance from the sensor. The distance from each pixel to the sensor is calculated by triangulation between the projector and the IR depth sensor, and then is used to form the depth image (Figure 2 (c)).

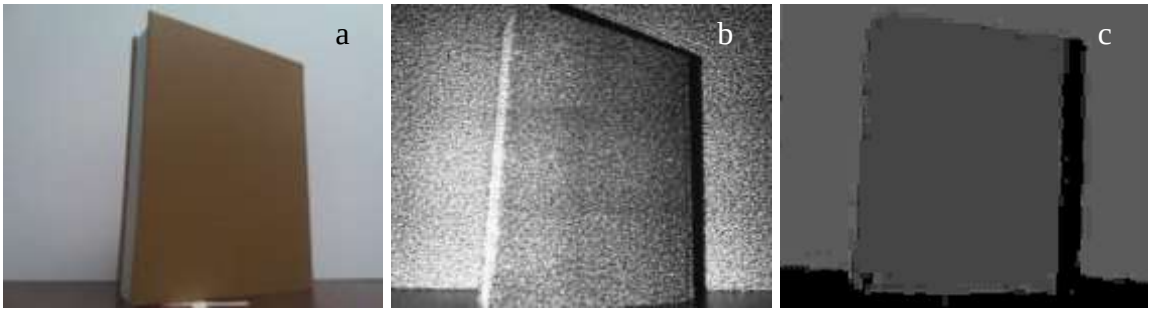

Figure 2 - Images examples generated by the Kinect® sensor: (a) color digital RGB (b) infrared and (c) depth images.

Since the sensor has two different cameras, with slight difference between their focal lengths and not perfectly parallel optical axis, the images provided by them are not necessarily aligned (GOTTFRIED et al., 2011), becoming necessary, for the applications that use simultaneously the RGB and depth images, make a prior calibration of equipment as suggested by several authors (KHOSHELHAM & ELBERINK , 2012; SMISEK .2011; STARANOWICZ & MARIOTTINI, 2012; KHOSHELHAM & ELBERINK, 2012; GOTTFRIED et al., 2011).

In addition, the knowledge of Kinect® behavior provides basis for the development of research involving its use. It is known (MICROSOFT®) that this sensor has two operating depth ranges: the standard range and the proximity range. Figure 3 shows the depth operating ranges of the sensor, in meters.

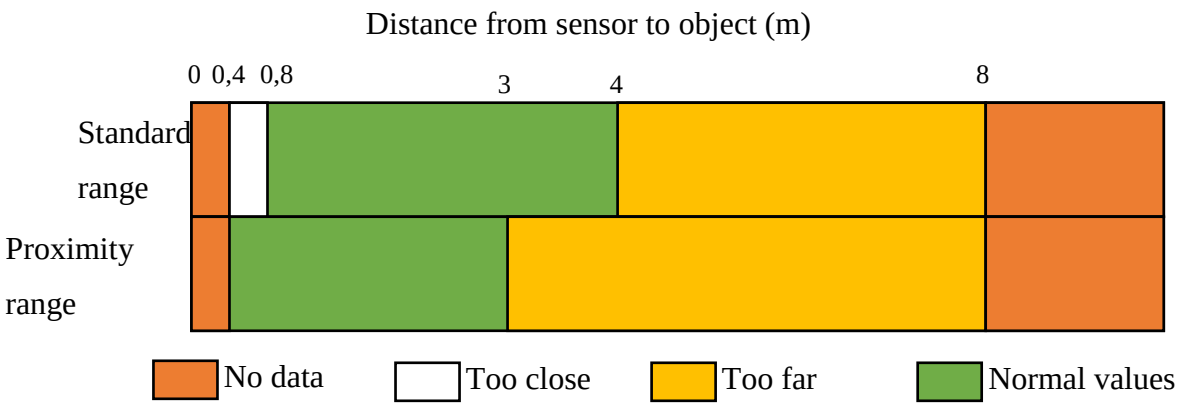

Figure 3 – Distances' ranges allowed between the Kinect® sensor and the object for data acquisition. Adapted from MICROSOFT®.

Khoshelham & Elberink (2012) have examined the accuracy and precision of the depth data, revealing that the random error of measurements increases with increasing distance between sensor and object and fluctuates between a few millimeters up to 4 cm. The

authors also showed that the errors present in the provided distance data can be originated from three main sources:

a) sensor: caused mainly by calibration errors;

b) the configuration of the measuring area, having two main sources:

b.1) inadequate lighting (too intense, for example), generating low contrast in infrared image and, therefore, gaps on the depth image, and;

b.2) image geometry, related to distance from the object to the sensor (greater or smaller than the operating range) and orientation of the object surface (providing areas where the emiter does not iluminate or areas where the sensor does not capture information);

c) the surface of the object: too bright and smooth surfaces are very reflective and prevent measurement.

According to Gottfried et al. (2011), the sensor limitation is the fact that the depth data tend to be unusable or inaccurate on the object edges because, in these areas, the depth map is obtained through discrete projections of the reflected infrared light.

Dutta (2011) has shown that the standard deviation of the distance data, for the three axes of the Cartesian plane, increased with increasing distance between sensor and object and, moreover, this deviation was largest on the corners of the image.

A need that exists in studies that use more than one Kinect sensor is knowing whether there are differences between the data provided by them analyzing the necessity of calibration between sensors. It is also important to know whether the positioning change of both sensor and object can create differences on the data obtained.

3 MAIN RESULTS AND DISCUSSION

Three articles were developed in this work. The first one involved the study of the Kinect® sensor and its characteristics. Correlation equations were developed between the dimensions of objects on the image (in pixels) and its real dimension (in centimeters) based on the distance between sensor and object, provided by the sensor. These equations were used on the other two articles.

This first study involved two smaller experiments, the first aimed to test the depth data provided by different Kinect® sensors. It was found that data obtained by more than one sensor can be compared, with no need for adjustments. It was also noticed that the standard deviations of the data obtained, increase with increasing distance between sensor and object, which indicates that the ideal is to get measures at distances between 1.0 m and 2.0 m, so that the data is more accurate.

The second experiment of this article aimed to analyze the depth data obtained by the Kinect® sensor when the object is located at different positions in the image (Center, edges, sides and corners), as well as get a relationship between the dimensions of the objects obtained through images and its real dimension, as the distance between the sensor and the object varies.

It was noticed a variation between objects placed in the center of the image in relation to objects placed in the other regions. This distortion is greatest in the vertical direction of the image. Therefore, the ideal is to position the objects always in the same location of the image, avoiding the top and bottom edges.

The main results of this first article are the prediction equations developed, that can predict of the actual dimensions of an object (length, area and volume) from its dimensions in the image, based on the distance between the object and the sensor.

These equations are an advantage from other studies developed so far, because they eliminate the need for an object with pre-determined dimensions on the image. This facilitate the images analysis and the automation of the process.

The second article involved the development of a method for obtaining pigs' dimensions within the image, using the equation developed in the first article. In addition, swine dimensions' curves were updated for modern animals. The study had two main results. The first was the potential use of the Kinect® sensor to acquire pigs' dimensions. One limitation was the location of animals within a scale containing bars, which prevented the dimensions using only depth images, being necessary the use of color digital RGB images, also provided by the sensor.

The second result was the efficiency of the equation developed in the first study to get actual dimensions without needing to touch the animal and without requiring the presence of an object with pre-determined dimensions on the image. The depth sensor data provides the value of distance between the sensor and the animal needed to make the transformation from pixel units to centimeters, making it easier for both researchers and producers to obtain these dimensions.

Finally, the third article aimed to automatic obtain pigs' weights through depth images analysis. For this, animals' weights and Kinect® sensor images were collected. It was written in MATLAB software (2016a) a program to obtain images with the sensor. The depth images were anylised to obtain the pigs' volumes. These volumes were corrected using the equations developed in the first study.

The main discovery of this work was the fact that it is necessary to do to fix the dimensions of the animal to desired units (e. g. cm^2 and cm^3) before correlating that data with the body weight, even when the Kinect® sensor is maintained at a constant distance from the ground. Other studies so far didn't take on to account that higher animals are more close to the camera and, thus, occupy a higher number pixels on the image. This means that, even animals with the same weight, but different heights, due to different body conformation, could have different predicted weight because of a different image area acquire.

Now, with the equation developed, both area and volume can be adjusted so they can be correlated with the animal's weight with less differences between animals with different conformation (e. g. longer legs) but with the same weight.

That's probably why on this study, it was found no difference between equations for different commercial lines and sexes used, being possible to use the same equation for all the animals. Authors that found differences on equations for different lines, did not correct the data for the height of the animal, which may have cause the differences found. Also, the correlation between volume and weight found on this study was higher than the correlation found between area and weight so far by other authors, which indicates this is the best dimension to use for developing prediction equations.

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4 STUDY OF DATA PROVIDED BY KINECT® SENSOR

Abstract

The Microsoft® Kinect® sensor has been used as an alternative to expensive laser scanners in several areas, standing out for its low cost, reliability and speed of measurement. It provides three outputs: digital color image, infrared image and depth image. In addition to the depth image, a map is generated, which is the main raw data provided by the sensor, containing the distances between the sensor and each pixel that makes up the image. For studies that use more than one Kinect® sensor there is a need to know the relative differences between the sensors and the data captured by them. In addition, it is important to understand the differences in the data obtained at different sensor distances and relative positioning of objects within the frame. Thus, the present work aimed to analyze the data provided by the Kinect® sensor by checking the presence of variations that may occur due to the use of different sensors, object sizes, positions and distances from the sensor to the object. In addition, developing correction equations to standardize the measures of length, area and volume with the Kinect® sensor. The work was composed of two major experiments. The first aimed to verify the existence of significant differences between the depth data provided by five sensors. The second experiment aimed to analyze the way parameters (length, area and volume) obtained vary with increasing distance from the sensor to the object, with the change of the position of the object in the picture and change the size of the object. It was concluded that different Kinect® sensors do not provide different depth data. For real values of length, area and volume; there was no significant differences between different sensors. Smaller objects suffer edge effects and do not generate reliable data. To acquire length, there is no significant effect of using different sizes of objects. For different positions of the object on the image, different values of area and length are acquired. This distortion is greatest in the vertical direction of the image. To standardize values of area, length and volume of objects positioned at different distances from the sensor so that they can be compared, it must be used the length ratio (px cm^{-1}) and area ratio (px cm^{-2}) versus the distance, by applying these values to the correction equations proposed in this study.

Keywords: Image analysis; Depth image; Validation

4.1 Introduction

The Microsoft Kinect® sensor (FREEDMAN et al., 2010) has been used as an alternative to expensive laser scanners (KHOSHELHAM & ELBERINK, 2012) in various areas, such as mapping and 3D reconstruction (IZADI et al., 2011, JIA et al., 2012), indoor robotics (GARAGE, 2011; Correa et al.., 2012; GANGANATH & LEUNG, 2012; BENAVIDEZ & JAMSHIDI, 2011), objects' detection and recognition (HERNÁNDEZ-LÓPEZ et al., 2012), and gesture recognition (CHANG et al., 2011 (a); CHANG et al., 2011 (b), HOSSEIN et al., 2012). This sensor stands out for its low cost, reliability and speed of measurement (SMISEK et al., 2015).

The Kinect® sensor is a complex set of sensors, which consists of an RGB camera, an infrared (IR) emitter, an infrared depth sensor, multi-array microphones, a three-axis accelerometer, and tilt motor (MICROSOFT). Figure 1 is a diagram of the sensor including all the different components.

Three different data streams are provided by Kinect®: color digital image (RGB), infrared image (IR), and depth image. In addition to the depth image, a map is generated, containing the main raw data provided by the sensor with the distances, in mm, between the camera and each pixel of the image. This manuscript will focus on only the images.

To form the depth image, the IR emitter projects on the object a light beam that is reflected and divided into multiple beams, forming a pattern of points which are then captured by the IR sensor. This pattern is compared with a reference with a predetermined distance from the sensor. The distance from each pixel to the sensor is calculated by triangulation between the projector and the IR depth sensor, and then is used to form the depth image.

The sensor has two different cameras, with slight difference between their focal lengths and not perfectly parallel optical axis. Applications that use simultaneously the RGB and depth images require calibration of equipment as suggested by several authors (KHOSHELHAM & ELBERINK, 2012; SMISEK, .2011; STARANOWICZ & MARIOTTINI, 2012; KHOSHELHAM & ELBERINK, 2012; GOTTFRIED et al., 2011) to ensure the images are correctly aligned (GOTTFRIED et al., 2011).

In addition, understanding the Kinect sensor behavior provides basis for the development of research involving its use. Khoshelham & Elberink (2012) have examined the accuracy and precision of the depth data, revealing that the random error of measurements increases with increasing distance between sensor and object and fluctuates between a few millimeters up to 4 cm.

The authors also showed that the errors present in the provided distance data can be originated from three main sources. The first source of error is caused mainly by calibration errors. The second source of error is the configuration of the measuring area; both having inadequate lighting (too intense, for example) or image geometry. Lighting, while generally not a problem with Kinect®, can generating low contrast in infrared image and, therefore, gaps on the depth image. The image geometry is related to distance from the object to the sensor (greater or smaller than the operating range) and orientation of the object surface (providing areas where the emitter does not illuminate or areas where the sensor does not capture information). The third and final source of error is related to the surface of the object. Surfaces that are too bright or smooth surfaces are very reflective can prevent measurement.

Although the sensor error is low, it has been noted (DUTTA, 2011) that the standard deviation of the distance data increased with increasing distance between sensor and object, and was largest on the corners of the image. In addition, it has been noted that the depth data tend to be unusable or inaccurate on the object edges because, in these areas, the depth map is obtained through discrete projections of the reflected infrared light (GOTTFRIED et al., 2011).

For studies that use more than one Kinect® sensor there is a need to know the relative differences between the sensors and the data captured by them. In addition, it is important to understand the differences in the data obtained at different sensor distances and relative positioning of objects within the frame.

Thus, the objectives of this manuscript were to evaluate the data provided by the Kinect sensor, looking for variations on the consistency of the data provided that may occur due to the use of different sensors, object sizes, positions in the image and distances from the sensor. In addition, developing correction equations to standardize measures of length, area and volume obtained with the Kinect® sensor.

4.2 Material and methods

The work was composed of two major experiments. The first aimed to determine differences between the depth data provided by different sensors. Six Kinect sensors were compared. Each sensor was used to collected images of a wall at 5 different distances (from 1.0 to 3.0 meters, every 0.5 m). The images were collected using a custom program written in MATLAB software (2016a). One RGB image (using the portable network graphics, png file) and one file from the depth sensor (in a space delimited text file, txt).

Then, using an algorithm written in MATLAB software (2016a), a fixed area of 11 X 11 pixels was selected in the center of the wall and collected the value, the mean and the standard deviation between the values of distance (in mm) obtained for the pixels within that region.

Figure 1 shows the positioning of the sensors and Figure 2 shows images of the region analyzed for the five distances.

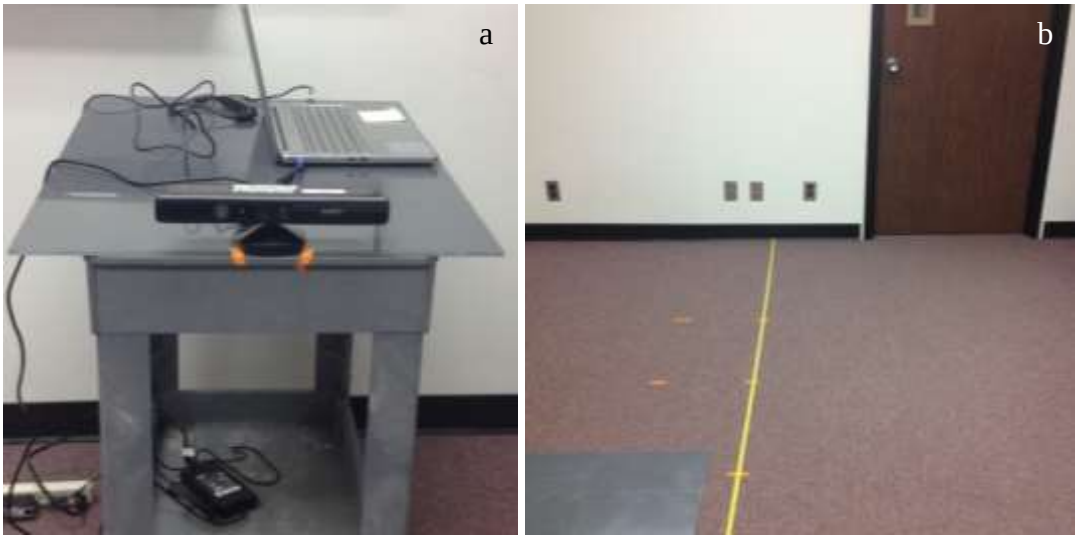

Figure 1 – Positioning of the components of the experiment: (a) table with Kinect® sensor and computer for data acquisition and (b) markings on the floor (0.5 m from each other) to capture images of the wall at different distances (from 0.5m to 3.0 m).

To compare the sensors, a linear regression model was developed in Excel® software, using *dummy* variables (DRAPER & SMITH, 1998), which included the effects of all the sensors in the equation. This model was compared with the reduced model without including the individual effects of each sensor.

This comparison was made by using the Efroymson's algorithm ("stepwise" regression) (EFROYMSON, 1960) for comparing two regression models, with null hypothesis given the reduced model equivalent to the global model and with alternative hypothesis, considering the models non-equivalent. The test statistic is given in eq. 1.

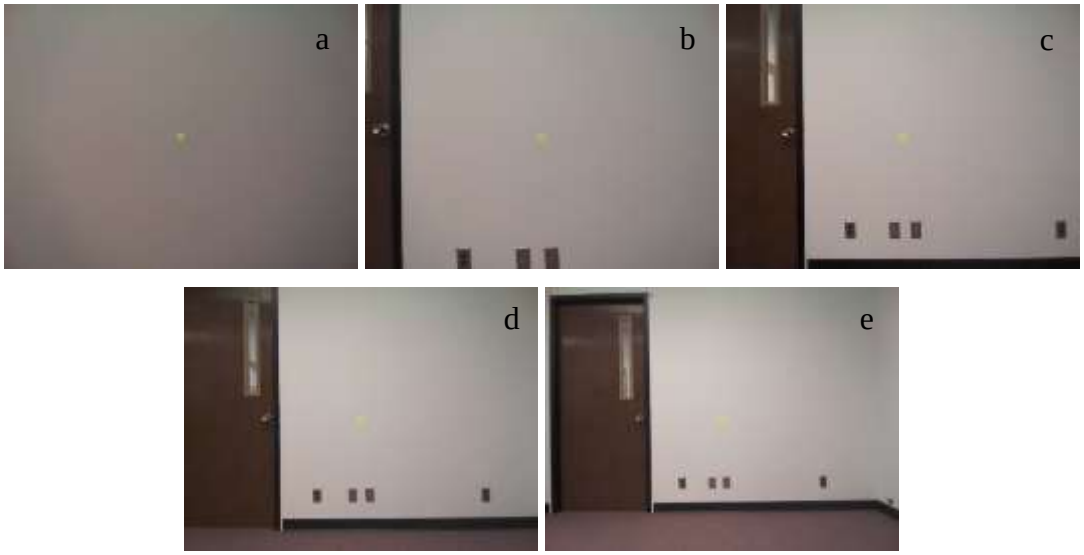

Figure 2 - RGB images captured by Kinect® sensor for 5 distances: (a) 1.0 m; (b) 1.5 m; (c) 2.0 m; (d) 2.5 m; (e) 3.0 m.

$$F(n,d) = \frac{(SS_r - SS_g)/(DF_r - DF_g)}{SS_g/DF_g} \quad (1)$$

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.

The result of the statistics was, then, compared with the F-list using as degrees of freedom in the numerator the value of SS_g/DF_g and as degrees of freedom in the denominator, the value DF_g. F-calculated values greater than the F-list indicate rejection of the null hypothesis.

The second experiment aimed to analyze the way that some parameters vary with: increasing distance between the object and the sensor; the change of position of the object in the figure (center, sides and corners) and the change of the object length. To this end, three Kinect sensors were used for data acquisition of three squares of poster board, with different lengths (10 cm, 20 cm and 30 cm), at five different distances (from 1.0 to 3.0 m; every 0.5 m).

For each of the five distances, images were obtained in four different positions for each square using the same program written in MATLAB software (2016a) for the first. A

tripod was used to place the squares. Figure 3 illustrates the three squares used, and Figure 4 illustrates the four positions.

Figure 3 - Three different sizes of squares used. (a) 10 x 10 cm square, (b) 20 x 20 cm square and (c) 30 x 30 cm square.

The data were analyzed to obtain three different parameters: length, area and volume. The length of the square (in pixels) was obtained through the RGB image, with the 'imtool' function of MATLAB software (2016a).

The square area (in pixels), was obtained through the depth map, by selecting the square with an algorithm written in MATLAB software (2016a). First the depth map was imported through the function ' importdata ' (Figure 5 (a)). Then, the values were selected within a limit, covering 200 mm of the real distance (measure with measuring tape) between sensor and object; making pixels outside that limit equal to zero by through a logical test of type ' if/else ' (Figure 5 (b)). Then, possible noises (e. g. parts of the tripod) was eliminated by making values of rows and columns around the square equal to zero. The resulting array was transformed into a binary image ('im2bw') and the object with the largest area was selected using the 'bwareafilt' function (Figure 5 (c)). The area of the resulting object was finally calculated using the 'bwarea' function.

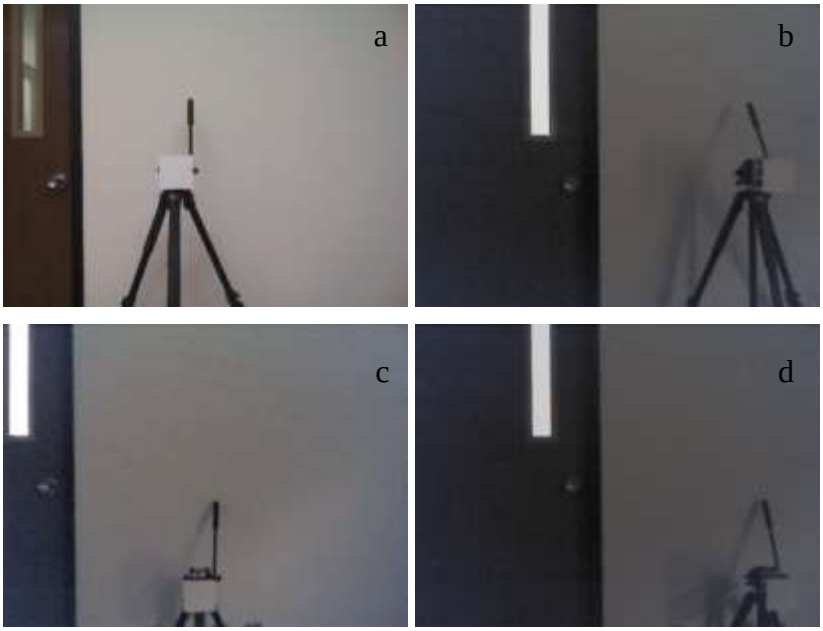

Figure 4 – Positions used for images' acquisition: (a) center, (b) side, (c) central extremity and (d) corner.

To get the volume of the theoretical straight parallelepiped with front face with the same measures of the square being analyzed was used the same algorithm used for the area acquisition and then the following steps were completed.

Figure 5 - Steps taken for the selection of the object in the image: (a) raw depth image generated through the values of the depth map, (b) selection of objects within an expected depth and (c) image after removal of noise and selecting the largest object in the scene.

First, the binary image was used as a mask on the original depth map to select values only the region of interest. Next, the object's volume was calculated by summing of the depths obtained for each pixel of the object between its surface and the surface of theoretical support (in this case, the wall). To find this value, was performed a subtraction between the distance (average) of the sensor to the wall (Zw) and distance (average) of the sensor to the square (Zs), as illustrated by Figure 6.

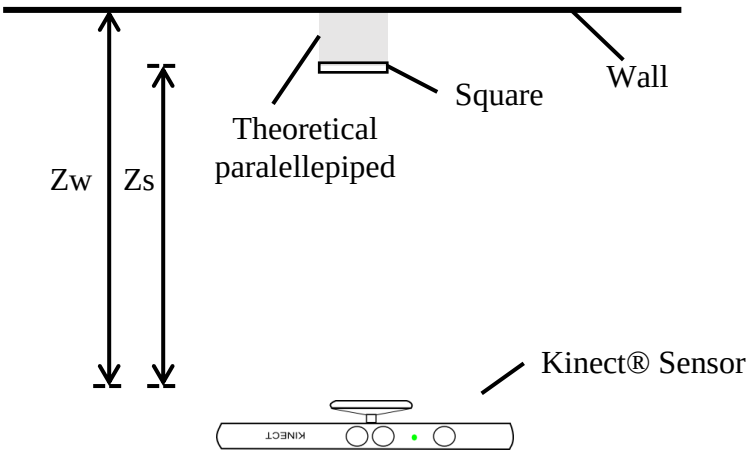

Figure 6 – Diagram of the positioning of the Kinect® sensor and the object being analyzed for the calculation of the theoretical parallelepiped volume with frontal face with the same dimensions of the square being analyzed.

With the length of the square on the image, in pixels, and real, in centimeters, it was calculated the length ratio, in px cm^{-1}. Furthermore, the same was done with the area of the square, calculating the area ratio (px cm^{-2}) between the image and real areas, for each of the distances.

These ratios were analyzed using the General Linear Procedure (proc GLM) of SAS software, testing the effects of the use of different positions of the objects in the image (Center, side, extremity and corner) and different sizes of objects used.

Then, regression models were generated for the length ratio (px cm^{-1}) versus the distance from sensor to object, for the three sizes of square (10 x 10 cm, 20 x 20 cm and 30 x 30 cm), obtaining reduced and global prediction equations, using *dummy* variables (DRAPER & SMITH, 1998). The same was done with the square area ratio (px cm^{-2}).

These equations were compared by the Efroymson's algorithm ("stepwise" regression) (EFROYMSON, 1960), as shown in eqq. 1.

4.3 Results and discussion

The average values of distance obtained for the region of the wall in the picture, as well as their respective standard deviations are shown in Table 1. It can be noticed that there is an increase in the standard deviation with increasing distance from sensor to object, corroborating with the data obtained by Khoshelham & Elberink (2012). The authors proposed a theoretical standard deviation equation for the data provided by the Kinect ® sensor (eq. 2)

$$\sigma_Z = \sigma_d \times \left(\frac{m}{f \times b}\right) \times Z^2 \quad (2)$$

where:

$\sigma_Z =$ theoretical standard deviation;

$\sigma_d =$ measurement error, in pixels;

$m =$ parameter for linear adjustment of disparity of depth data;

$f =$ focal length of infrared camera;

$b =$ distance between the infrared camera and the infrared emitter.

This equation was plotted using the value of the ratio $(m/f \times b)$ as 0.0000285, as proposed by the authors, for two measurement error values (1 and 0.5 pixel) (Figure. 7). Together, it was plotted the standard deviation values shown in Table 1. These values stayed between the two curves, indicating that the measurement error of the sensor is between the values used. This error refers to the possibility of the distance value provided for a given pixel in the image to be, in fact, corresponding to the neighbor pixel. With the increase in distance, both precision and accuracy of the data obtained with the sensors are reduced.

Table 1 - Average depth data obtained by five Kinect® sensors, for the five analyzed distances with their respective standard deviations. "N" is the number of points used in the image to gather each value.

		Distances from sensor to wall (cm)				
Sensor	N	100	150	200	250	300
1	121	98,67 ± 0,14	149,89 ± 0,33	201,97 ± 0,89	254,97 ± 0,99	305,34 ± 1,84
2	121	99,12 ± 0,25	149,81 ± 0,39	202,42 ± 0,93	255,20 ± 0,90	309,12 ± 1,97
3	121	97,67 ± 0,14	149,29 ± 0,51	200,93 ± 0,95	251,74 ± 1,50	304,00 ± 2,03
4	121	98,48 ± 0,13	147,96 ± 0,34	199,47 ± 0,56	249,41 ±0,94	300,11 ± 1,32
5	121	98,10 ± 0,20	148,15 ± 0,38	198,32 ± 0,70	249,68 ± 0,90	299,92 ± 1,76

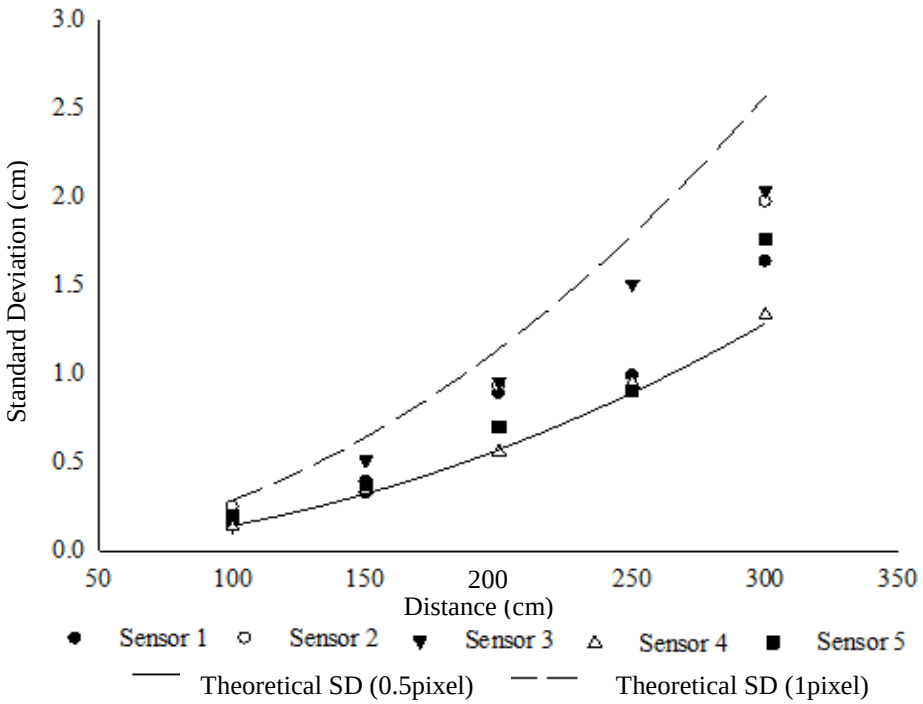

Figure 7 - Curves of standard deviation (SD), with .5 and 1 pixel as errors of measurement and standard deviation obtained for five Kinect sensors ® versus the distance between sensor and object (wall).

The depth data provided by five Kinect® sensors versus the real distance between sensor and object are shown in Figure 8. Visually, the data for the different sensors overlap.

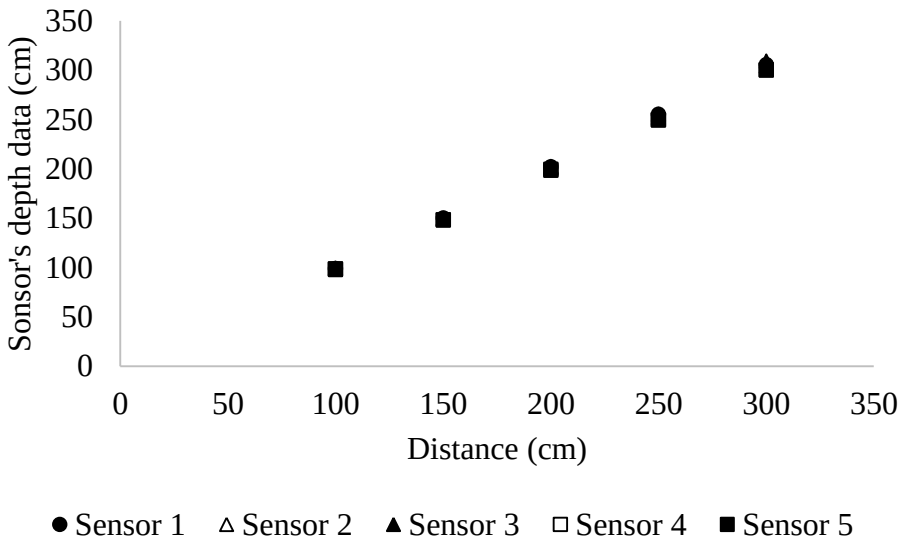

Figure 8 - Adjusted curves for the distances (cm) provided by five Kinect® sensors (numbered 1 to 5) as functions of the real distances (cm) between sensor and object (wall).

The result of the Efroymson's algorithm proved that the behavior of the sensors can, in fact, be considered the same, since the null hypothesis cannot be rejected (P = 0.06).

Figure 9 indicates the length, in pixels, obtained through digital RGB image provided by Kinect® sensor, for the three squares used (10, 20 and 30 cm); varying with the distance, in centimeters, from the sensor to the squares. The variables area (px) and volume (px cm) showed the same behavior as the length, i.e., for each size of object, a different curve is generated, illustrating that it is not possible to extract a prediction equation of these three variables from the distance between sensor and object directly.

To obtain these prediction equations it was used the length ratio of the square on the image (px) and its actual length (cm) and the area ratio of the square on the image (px) and its actual area (cm²).These relationships have resulted in the charts indicated by the Figures 10 and 11. The ratios (px cm^{-1} and px cm^{-2}) on these charts are overlapping, for the three sizes of square, indicating the potential of its use to generate an equation correlating the dimensions of the object with its distance to the sensor.

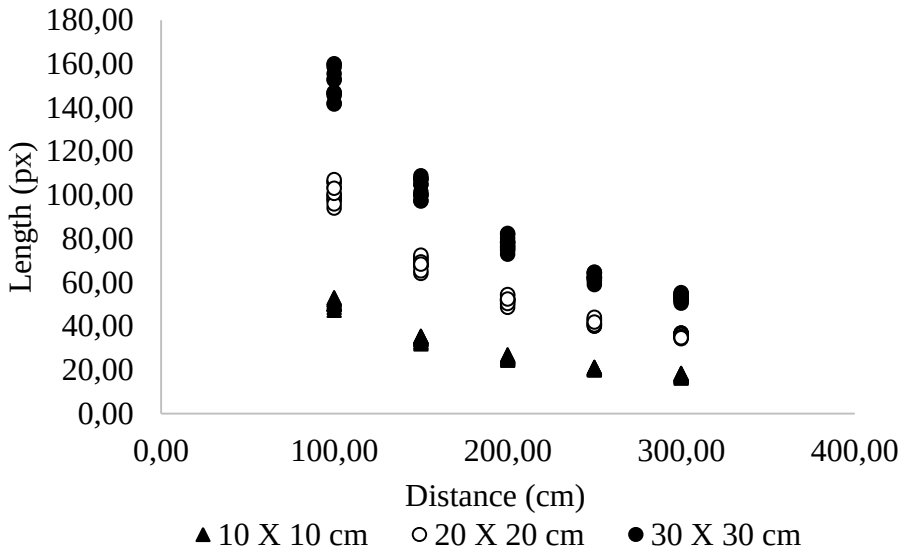

Figure 9 – Length, in pixels, of the squares (10, 20 and 30 cm) on the image obtained with Kinect® sensor versus distance from sensor to square.

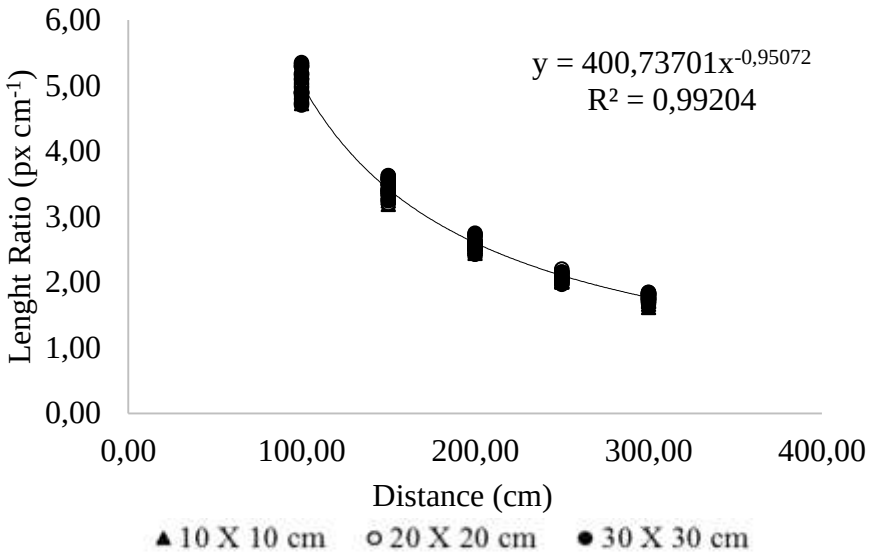

Figure 10 – Global curve adjusted for the length ratio between the length of the square on the image (px cm^{-1}) and the real length of the square (cm).

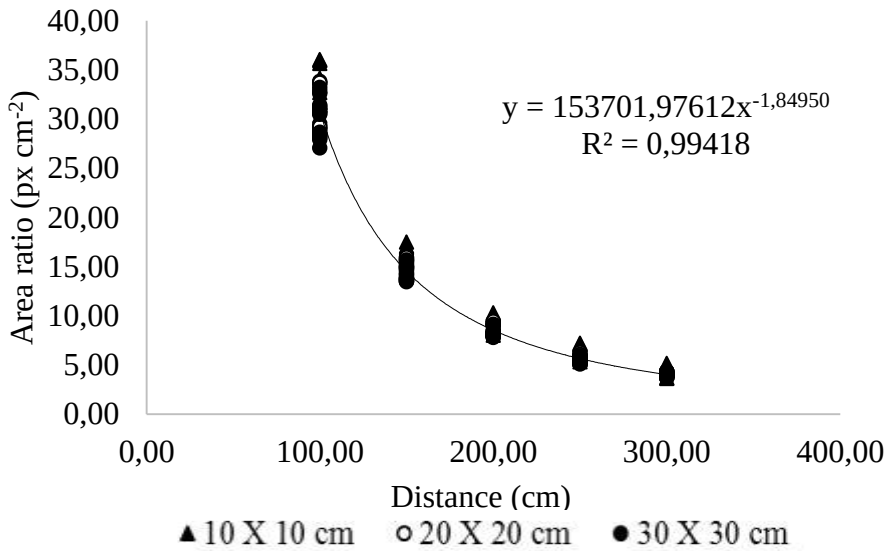

Figure 11 - Global curve adjusted for the area ratio between the area of the square on the image (px cm^{-1}) and the real area of the square (cm).

No significant effect was obtained ($p<0.01$) for using different sensors on the length ratio (px cm^{-1}) ($P = 0.6269$) and on the area ratio (px cm^{-2}) ($P = 0.7015$).

Testing the effects of using different sizes of objects on the length (px cm^{-1}) and area (px cm^{-2}) ratios, there was no significant effect ($p<0.01$) on the length ratio ($P = 0.2584$), however it was obtained (Table 2) difference ($p<0.01$) for the area ratio to the square of 10 cm X 10, indicating that very small objects suffer from the effect of omitting depth values at the edges, as indicated by Gottfried et al. (2011).

Table 2 – Averages and standard deviations obtained for length ratio (px cm^{-1}) and area ratio (px cm^{-2}), for the three sizes of square used

Square Size (cm)	Length Ratio (px cm^{-1})	Area Ratio (px cm^{-2})
10 X 10	3.00 ± 0.01	13.87 ± 0.14[a]
20 X 20	3.02 ± 0.01	12.74 ± 0.14[b]
30 X 30	3.01 ± 0.01	12.37 ± 0.14[b]

[a, b, c] Rows for each column, with different superscripts are significantly different ($p<0.01$).

The test of the effect of the objects' positions in the image (center, side, end and corner) on the length (px cm^{-1}) and area (px cm^{-2}) ratios showed (Table 3) that, for the length ratio (px cm^{-1}), central and lateral positions were equivalent and differed from the central edge and the corner, which also were equivalent between themselves. For the area ratio (px cm^{-2}), the central position differed from the others ($p <0.01$).

The difference of position did not influence significantly the acquirer of the volume of the object ($p<0.01$).

These differences between the positions of the object in the image is support by data obtained by Dutta (2011), that showed that the standard deviation of the distance data increase on the corners of the image. Thus, the ideal for data comparison of length and area acquired a with Kinect® sensors is positioning it at a fixed region of the image, preferably in the center. If offsets need to be made, the ideal is to make them on the horizontal direction of the image, in which the differences are smaller, reducing distortion of values and enabling data comparison.

Table 3 – Average and standard deviation obtained for the length (px cm^{-1}) and area (px cm^{-2}) ratios and for the uncorrected volume (px cm)

Position of the object on image	Length Ratio (px cm^{-1})	Area Ratio (px cm^{-2})	Volume (px cm)
Center	3.10 ± 0.01[a]	14.09 ± 0.16[a]	306871.617 ± 27485.581
Side	3.07 ± 0.01[a]	12.89 ± 0.16[b]	275836.110 ± 27485.581
Central Edge	2.95 ± 0.01[b]	12.49 ± 0.16[b]	233566.240 ± 27485.581
Corner	2.93 ± 0.01[b]	12.52 ± 0.16[b]	219321.7 97± 27485.581

[a, b] Rows for each column, with different superscripts are significantly different ($p<0.01$).

As the square of 10 cm X 10 cm had a different area when compared with the others, it was decided to generate a new regression equation (Figure 12) of the area ratio (px cm^{-2}) versus distance between sensor and object (cm), using only the values of the 20 cm X 20 cm and 30 cm X 30 cm squares, to obtain a more reliable equation.

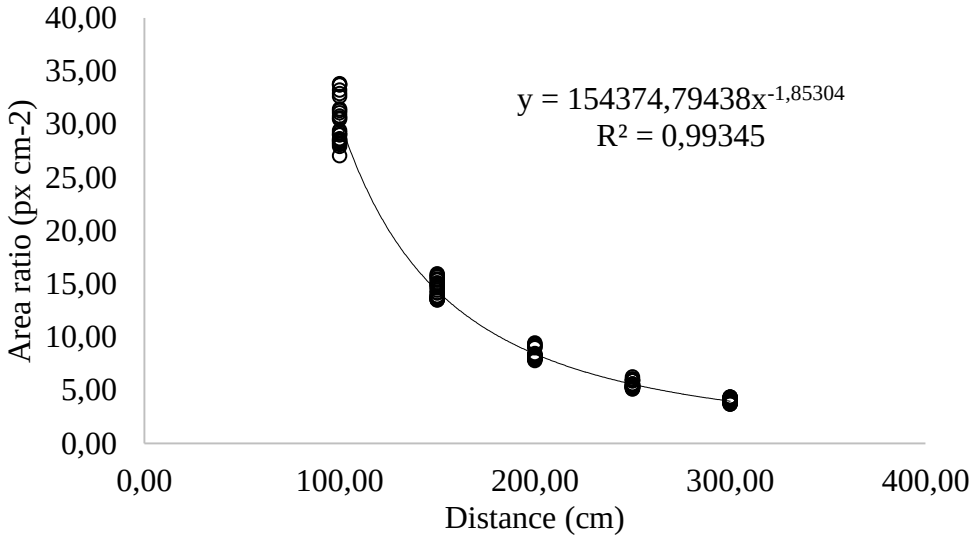

Figure 12 - Global curve adjusted for the area ratio between the area of the square on the image (px cm^{-1}) and the real area of the square (cm) for 20 X 20 cm and 30 X 30 cm squares.

The equations obtained (eq. 3 and eq. 4) by regressions of length and area ratio versus distance can be used to calculate the actual dimensions of objects contained in a digital RGB image generated by the Kinect® sensor. This eliminates the need for the presence of an object with predetermined size to accomplish this calculation, as has been used by several authors (PHILIPS & DAWSON, 1936; ZARAGOZA, 2009).

$$l_{cm} = l_{px} \times 2{,}4954 \times 10^{-3} \times Z^{0{,}95072} \quad (3)$$

where:

l_{cm} = length, in centimeters;

l_{px} = length, in pixels;

Z = distance between sensor and object, in centimeters.

$$S_{cm^2} = S_{px} \times 6{,}47774 \times 10^{-6} \times Z^{1{,}85304} \quad (4)$$

where:

S_{cm} = area, in squared centimeters;

S_{px} = area, in pixels;

Z = distance between sensor and object, in centimeters.

There is also the possibility of using the data provided of the depth map to calculate the volume of objects. This approach also raises the need for conversion of units, since the volume is calculated by the sum of the data of distance from the object to its support surface ('height of the object') for its area in the image. As the distance data provided by Kinect® are in mm (can be transformed easily in cm) and the area of the object is given in number of pixels, the volume is retrieved from an unwanted unit (px cm).

Another problem is the fact that the area of the object in the image varies with its distance from the sensor. This generates the need for correction of the value obtained to perform any comparison between volumes. In other words, for the same object,different values of volumes can be acquired, and the same is true to the length and area of the object, if the distance to the sensor varies.

As what changes to the calculation of the volume is the area of the object and not its depth (distance between the square and the wall), this value can be adjusted using the equation obtained for correcting the area, as indicated by eq. 5.

$$V_{cm^3} = V_{px\ cm} \times 6{,}47774 \times 10^{-6} \times Z^{1{,}85304} \quad (5)$$

where:

V_{cm} = volume, in cubic centimeters;

$V_{px\ cm}$ = volume, in ‘pixels centimeters’;

Z = distance between sensor and object, in centimeters.

4.4 Conclusions

Depth data given by different Kinect® sensors does not differ.

Very small objects suffer edge effects and do not generate reliable data. There is no significant effect of using different sizes of object to acquire its length, using digital RGB images provided by Kinect® sensor.

Different values of area and length can be acquired with the data provided by the Kinect® sensor, for the same object located at different positions in the image. This distortion is greatest in the vertical direction of the image.

As the variation of distances from sensor to object generates different values of length, area and volume to the same object, its necessary to standardize these values so that they can be compared. This can be done using the equations 3, 4 and 5 proposed in this study.

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5 ACQUISITION OF PIGS' DIMENSIONS THROUGH DEPTH IMAGE ANALYSIS

Abstract

The space distribution is one of the main points to be considered in construction and equipment's projects for farm animals. To this end, the ability to specify the space required for animals is necessary and, consequently, there is a need to know how the animals' dimensions vary over time. The changes in the production process over the years, such as nutrition and the use of different genetic lines and facilities, make it necessary to update these dimensions for modern animals. The potential of using images for dimensions' acquisition was noted by several authors. In general, they point to the fact that, to extract the dimensions of the pig, its color must be different from the color of the environment. Dark skinned pigs, stained or dirty make this approach difficult to automate. In addition to the color of the animal, the presence of adequate light is critical for this application. The Kinect® is a sensor that serves as 3D measurement device, which features low cost, reliability and speed of measurement. This device provides three outputs: infrared image, digital color image and depth image. The latter is accompanied by a depth map, which is nothing more than a numerical array that contains the values of the distances between the sensor and each of the pixels of the image. These values can be used for the transformation of the dimensions obtained on the image (in pixels) to the actual dimensions (cm) of the animal. The fact the image consist of distance values allows the selection of the animal in the image using a simple logic test. This indicates the potential of using these data to automate the sizing of the animals. Thus, the present study aimed to: (a) update the data available for dimensions of pigs and (b) assess the potential of the Microsoft® Kinect® sensor as a tool for the automatic data acquisition of pigs' dimensions for use both for producers and for researchers. It was concluded that, with the data obtained was possible to update the dimensions of pigs to growing-finishing phase. There is a great potential for automatic acquisition of pigs' dimensions through depth images generated by the Kinect® sensor.

Keywords: Kinect® sensor; Automation; Precision livestock

5.1 Introduction

The space distribution is one of the main points to be considered in construction and equipment projects for farm animals. Thus, the ability to specify the space required for animals is necessary (PETHERICK, 1983) and, therefore, it is need to know how the animals' dimensions vary over time.

In 1968, ASABE published dimensions` curves for farm animals (cattle, dairy, pigs, sheep, horses and poultry), which are still used as standard. The changes in the production process over the years, such as nutrition and the use of different genetic lines and facilities, make it necessary to update these curves for modern animals.

In addition to monitoring the variation in size of animals for space sizing, various authors (SCHOFIELD, 1990; FROST et al.,1997; SCHOFIELD, 1999; KASHIHA et al.,

2014; WU et al., 2004; KONGSRO, 2014) are using this information to predict the weight of animals. This shows the need for development of an ideal method for the acquisition of dimensions' data, not only from the production point of view, but also from a scientific point of view.

Besides that, the presence of human beings on the farm activities, is a stress generating source for the animals. Therefore, the development of methods for monitoring the physical conditions of animals from a distance appears as a necessity for obtaining data with higher quality.

Philips & Dawson (1936) pointed to the fact that the convenience, along with the accuracy of the method to be used for obtaining the dimensions of pigs, should be considered. The use of images to obtain the dimensions of the pigs would be, according to the authors, useful when animals are not used to being handled.

The potential of using images for acquisition of dimensions was noted by several authors (SCHOFIELD, 1990; SCHOFIELD, 1999; WANG et al., 2008; WU et al., 2004; KASHIHA et al., 2014) that correlated the animal area, obtained through pictures, with its weight, developing prediction equations.

In general, the authors point to the fact that, in order to extract the dimensions of the pig, its color must be different from the color of the environment. Dark skinned, stained or dirty pigs make this approach difficult to automate. In addition to the color of the animal, the presence of adequate light is critical for this application.

It was proposed a new method (Kongsro, 2014) to fix these problems using a Microsoft® Kinect® sensor to obtain the volume of animals through depth image analysis. This method minimizes the problems with lighting and color differentiation of animals in the image.

With this, this sensor was considered in this study as a potential for the monitoring of other dimensions of animals, such as area, height, and depth.

The Kinect® is a sensor that serves as 3D measurement device, which features low cost, reliability and speed of measurement (SMISEK, 2013). It is a composite device consisting of a digital color RGB camera, an infrared (IR) emitter, an infrared depth sensor, four microphones, a three-axis accelerometer and a tilt motor (MICROSOFT®). The infrared depth sensor and the projector are used to triangulate points in space. The RGB camera can be then used to texture the 3D points or to recognize the contents of the image. The device provides, therefore, three exits: infrared image, digital color RGB image and a depth image.

The depth image is accompanied by a depth map, which is nothing more than a numerical array that contains the values of the distance between the sensor and each of the pixels of the image. These values can be used for the transformation of the dimensions obtained in the image (in pixels) to the actual dimensions (cm) of the animal. With that, there is no need to use objects with known dimensions in the image, which can potentially improve the accuracy of the data obtained.

In addition, the fact that the image is composed of distance values allows the selection of the animal in the image through a simple logic test. This shows the potential of using these data to automate the sizing of the animals.

The present study aimed to: (a) update the data available for dimensions of pigs and (b) assess the potential of the Microsoft® Kinect® sensor as a tool for automatic pigs' dimension's acquisition for use both for producers and for researchers.

5.2 Material and methods

The experiment was accomplished at the growing-finish building of the Meat Animal Research Center-MARC, from the Agriculture Research Service-ARS of United States Department of Agriculture –USDA.

A hundred and twenty growing-finishing pigs were used, 40 (20 males and 20 females) from each of the three commercial lines used: Yorkshire and Landrace, Duroc.

The data were collected in four periods (pigs with 8, 12, 16 and 21 weeks old on average) using two Microsoft® Kinect® sensors, positioned above (Figure 1(a)) and on the side (Figure 1(b)) of the pigs. This was made during the weighing of animals. Weight of the animals, colored digital images and depth images were acquired.

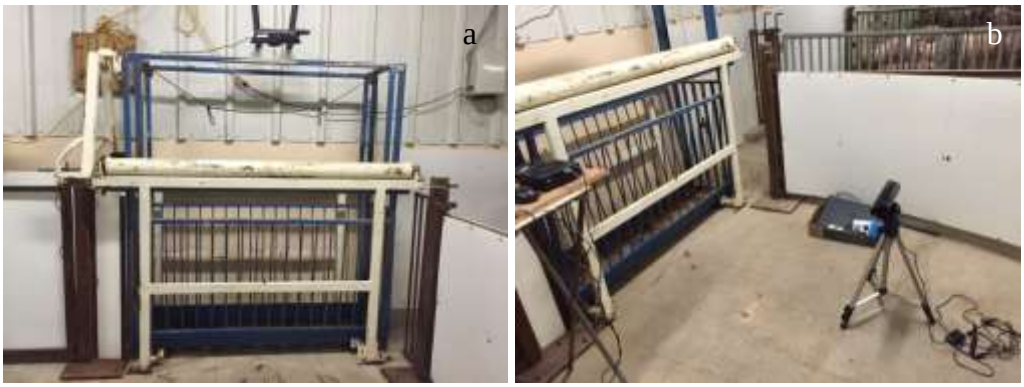

Figure 1-Positioning of Kinect® sensors: (a) at the top and (b)on the side of the scale.

The images were collected using a program developed in MATLAB software (2016a), which, every second, recorded on a laptop computer, a digital color RGB image in png

(portable network graphics) format and the values from the depth image in space-delimited text file, txt.

For the analysis of the images, two dimensions' collection methods were used: (a) automatic, through the depth map provided by the sensor, and (b) manual, through the color image. Automatic acquisition was made with the data captured by the sensor positioned above the animal. It was possible to select the region of interest in the image and write an algorithm for the acquisition of the dimensions.

The data provided by the sensor located on the side of the animal didn't allow the automatic acquisition of dimensions due to the presence of the bars of the scale in front of the animal.

The dimensions obtained for each animal are displayed in Figure 2. The width (W) of the animal and the average height were obtained through the automatic method. The height of the front legs (FL) was calculated by the difference between H (height) and D (depth). The remaining dimensions were all obtained by the manual method.

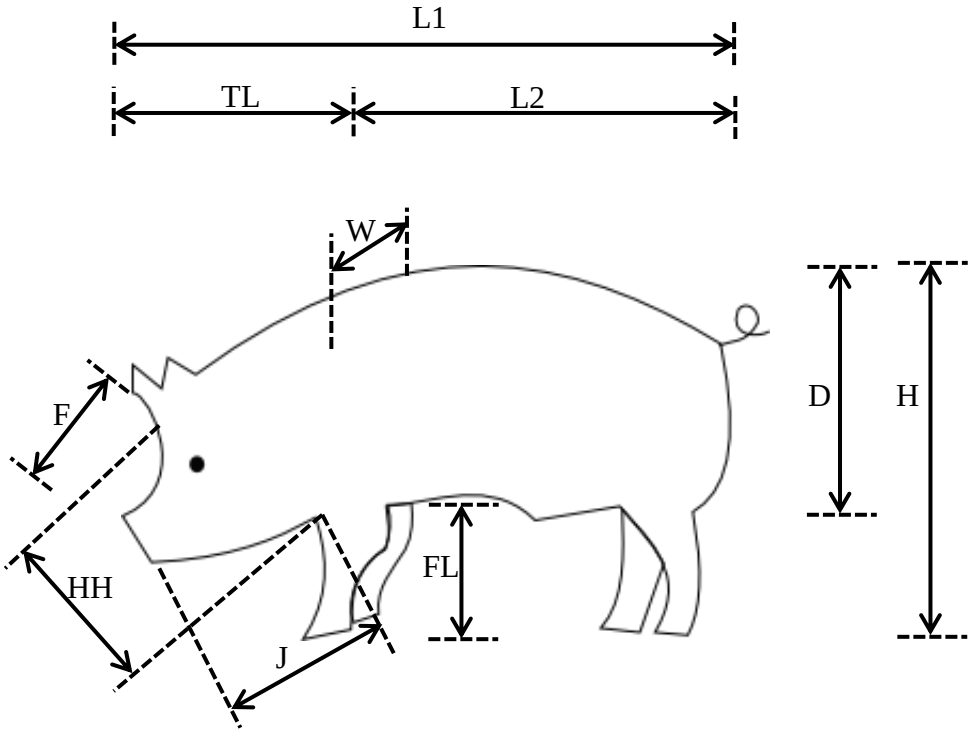

Figure 2-Pigs'dimensions, where: L1 = total length; L2 = length from shoulders to tail; TL = taper length; W = width of the shoulders; F = length of the face, from nose to ears; HH = head height, measured from a point in front of the front legs to the top of the head between the ears; J= jaw; FL = height of front legs; D = depth, lowest point on the belly to the top of the back; H = height.

It was written an algorithm in MATLAB software (2016a) for automatic acquisition of dimensions. First, the depth map was imported to the software using the 'importdata' function (Figure 3 (b)), then the distance from sensor to animal was converted on the animal's height, which was made by subtracting the distance between sensor and floor (Zf) from the distance between sensor and animal (Za), according to Figure 4. Then, the values were selected within a limit, covering 500 mm from the approximate height of the animal; making pixels outside that limit equal to zero using a logical 'if/else' test (Figure 3 (c)).

Later, possible noises (e. g. parts of the scale) were eliminated, making the values of rows and columns around the animal equal to zero. The resulting array was transformed into a binary image ('im2bw') and the object with the largest area on the image was selected using the ‘bwareafilt’ function (Figure 3 (d)). 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 facilitate the location of the animal's shoulders. Then, the binary image was applied as a mask on the original map to select only the region of interest values.

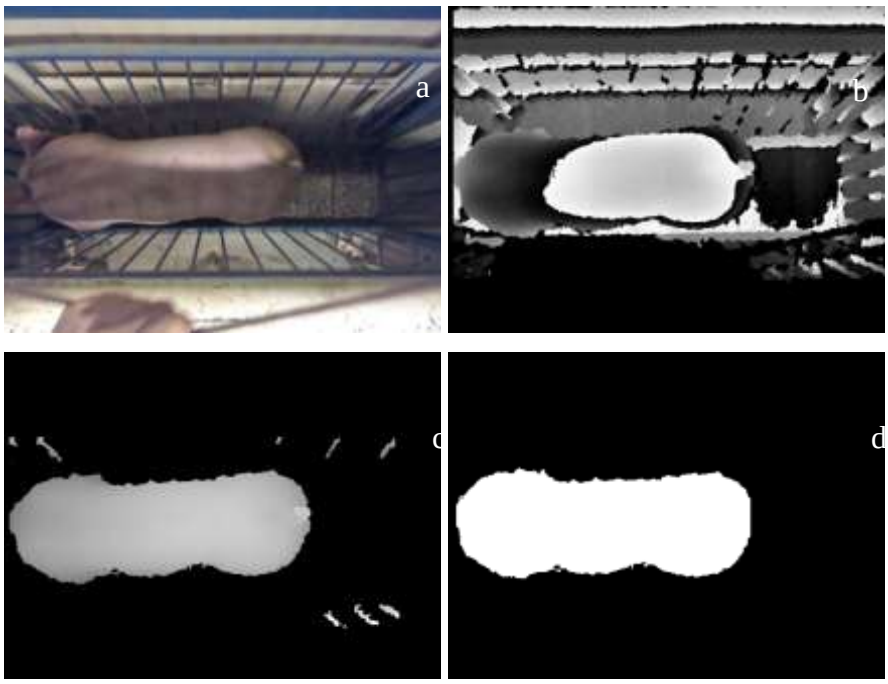

Figure 3 - (a)RGB image and (b) depth image obtained with the Kinect® sensor located above the animal. (c) shows the elimination of areas in the depth image that were out of a pre-established value. (d) indicates the selected pig after eliminating head and tail.

Finally, the value of the width (in pixels) of the pig (sum of the largest column of elements equal to '1 on the front half of the animal) was acquired through the 'sum' function.

In addition, the value of the distance between the sensor and the animal was obtained by the difference between the distance from the sensor to the floor and the average height of the animal, for further transformation of dimensions in pixels to cm.

For the manual acquisition of dimensions, the MATLAB 'imtool' function was used, which makes it possible to measure the image in pixels. For this, it was used the digital color image obtained through the sensor located on the side of the scale (Figure 5). In addition, the depth image (Figure 5 (b)) was used to obtain the distance between the sensor and the animal. Figure 6 illustrates the manually (a) and automatically (b) measured regions.

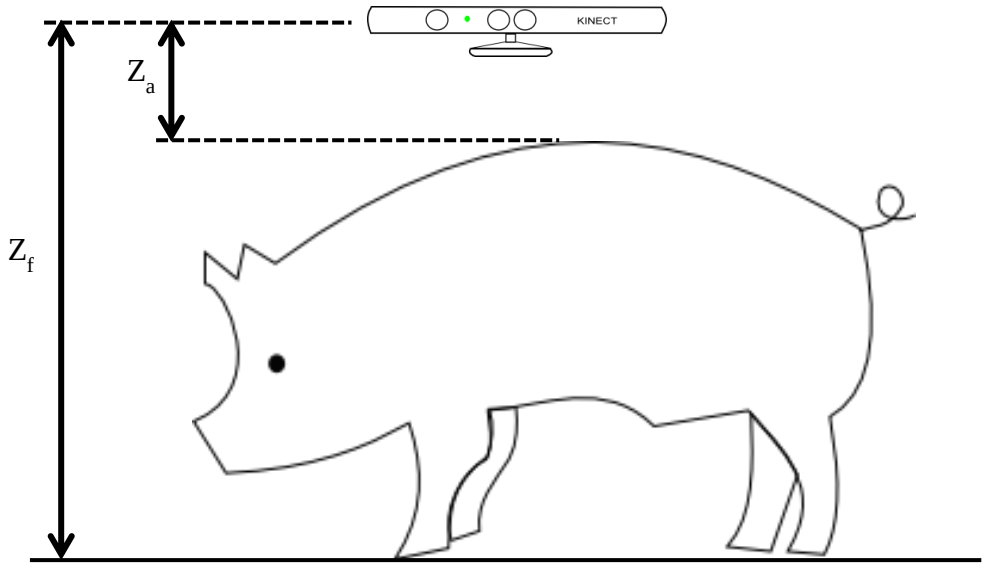

Figure 4 – Height of the animal (Zf-Za).

Figure 5 - (a) RGB image and (b) depth image obtained with the Kinect® sensor located on the side of the animal.

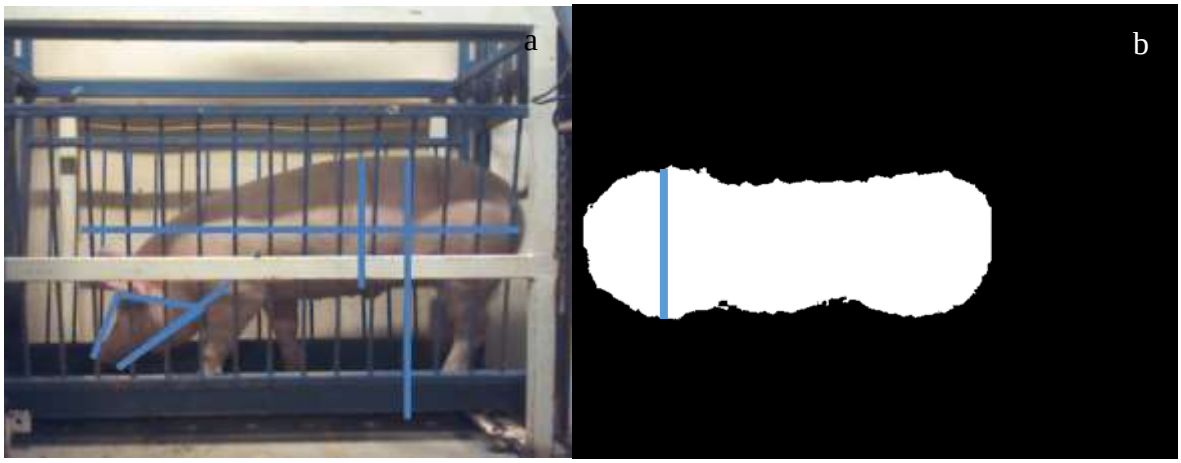

Figure 6 - Manually (a) and automatically (b) measured regions.

For the transformation of the dimensions in pixels to cm eq. 1 was used. Then curves were plotted of dimensions varying with the weight of the pigs using Excel® software and regression equations were generated.

$$l_{cm} = l_{px} \times 2{,}4954 \times 10^{-3} \times Z^{0{,}95072} \quad (1)$$

where:

l_{cm} = length, in centimeters;

l_{px} = length, in pixels;

Z = distance from sensor to animal, in centimeters.

5.3 Results and discussion

Figure 8 shows the graph of the dimensions (cm) obtained. Comparing this graph with the dimensions' graph obtained by ASABE in 1968, there was a relative increase of the taper length (TL), jaw (J) and head height (HH); as well as relative reduction of the length of the face (F).

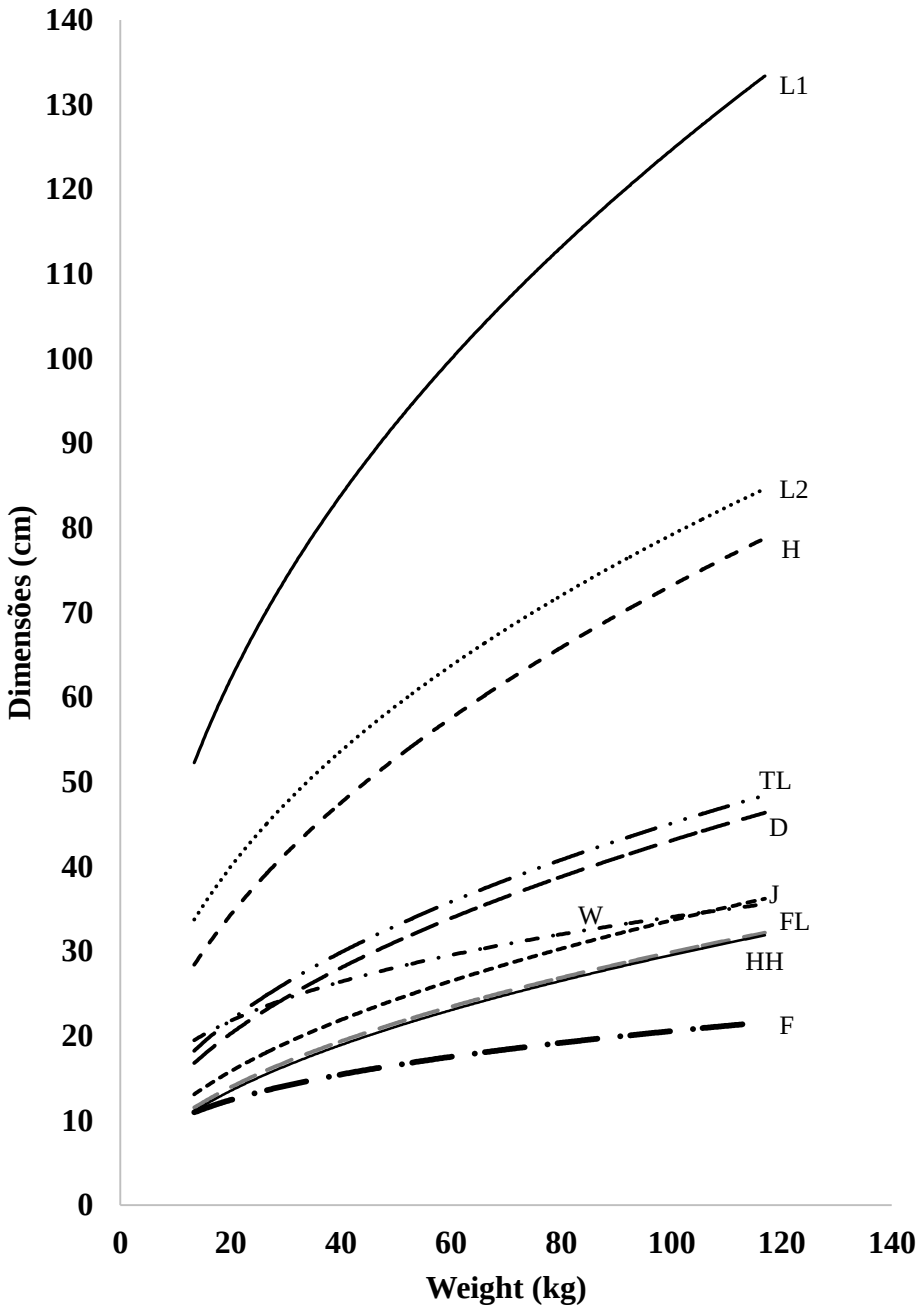

Figure 8 – Graph of dimensions (cm) versus weight (kg) of pigs, where: L1 = total length; L2 = length from shoulders to tail; TL = taper length; W = width of the shoulders; F = length of the face, from nose to ears; HH = head height, measured from a point in front of the front legs to the top of the head between the ears; J= jaw; FL = height of front legs; D = depth, lowest point on the belly to the top of the back; H = height.

The pigs' dimensions' acquisition through image analysis proved to be efficient, indicating the potential use of the Kinect® sensor to obtain these data.

Table 1 contains the coefficients of the generated equations for each of the curves, as well as their respective coefficients of determination (R^2).

Table 1 – Generated equations for dimensions (Di, in centimeters) from body weight (WT, in kg), where: L1 = total length; L2 = length from shoulders to tail; TL= taper lenght; W = width of the shoulders; F = length of the face; HH = head height, J = jaw; FL = front legs' height; D = depth; H = height.

Equation: $Di = aWT^b$ (power)

Dimension	a	b	R^2
L1	16.986	0.4328	0.9236
L2	11.187	0.4249	0.9029
H	8.3635	0.4710	0.9309
TL	5.6642	0.4506	0.7811
D	4.9715	0.4689	0.9526
W	9.4745	0.2778	0.9388
J	3.8764	0.4693	0.7261
FL	3.3709	0.4739	0.7994
HH	3.1442	0.4865	0.7480
F	4.8686	0.3129	0.6706

The dimension data related with the head of the animals (jaw, head height, face and taper length) feature a smaller coefficient of determination. This indicates that, in addition to the mass of animals, there is one or more other factors influencing on these dimensions. The height of the legs showed the same behavior, which could mean that factors, such as the commercial line, for example, influence also in this dimension.

As for the other dimensions acquired, the coefficient of determination was above 0.9; which indicates that the weight is greatly correlated with those variables, and may be used for the estimation of the same.

An improvement that can be made to the method of obtaining the dimensions presented in this study is the acquisition of data in an area free of objects between the sensor and the animal to automate the process. The correction equation (from pixels to cm) used proved to be efficient and avoided other types of tools for calibration of the image, as used by other authors (PHILIPS & DAWSON, 1936 and ZARAGOZA, 2009).

5.4 Conclusions

With the data obtained it was possible to update the growing-finishing pigs' dimensions.

The Microsoft® Kinect® sensor have potential for automatic acquisition of pigs' dimensions through the depth image provided. For that, there is a need for acquiring images without visual interference between sensor and animal.

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6 EVALUATION OF A DEPTH SENSOR FOR GROWING AND FINISHING PIGS` WEIGHTS ESTIMATION

Abstract

A method of continuously monitoring weight would aid producers by ensuring all pigs are gaining weight and increasing the precision of marketing pigs thus saving money. Electronically monitoring weight without moving the pigs to the scale would eliminate a stress-generating source. Therefore, the development of methods for monitoring the physical conditions of animals from a distance appears as a necessity for obtaining data with higher quality. In pigs' production, animals' weighing is a practice that represents an important role in the control of the factors that affect the performance of the herd and it is an important factor on the production's monitoring. Therefore, this research aimed to extract weight data of pigs through depth images. Prior to completing this work, a validation of 5 depth sensors was completed to understand the accuracy of the depth sensors. In addition, equations were generated to correct the volume data (cm* pixels) provided by these sensors for any distance between the sensor and the animals. Depth images and weights of finishing pigs (gilts and barrows) of three commercial lines (Landrace, Duroc and Yorkshire based) were acquired. Then, the images were analyzed with the MATLAB software (2016a). The pigs on the images were selected by depth differences and their volumes were calculated and then adjusted using the correction equation developed. Curves of weight and corrected volumes were adjusted. Equations for weight predictions through volume were adjusted for gilts and barrows and for each of the three commercial lines used. A reduced equation for all the data, without considering differences between sexes and genetic lines was also adjusted and compared with the individual equations using the F ratio test. The result showed that there was no significant difference between the reduced equation and the individual equations for barrows and gilts ($p<0.05$), and the global equation was also no different than individual equations for each of the three sire lines ($p<0.05$). The global equation can predict weights from a depth sensor with an R^2 of 0,9905. Therefore, the results of this study show that the depth sensor would be a reasonable approach to continuously monitor weights.

Keywords: Precision livestock; Kinect® sensor, Image analysis

6.1 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, that pays more to producers for animals within a specified range of weight 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)

The inability of the producer in obtaining with precision and control the variables that affect the conformation and fat levels of animals can cause the non-meeting of market's demands. Taking into consideration that the farms have increased in size, even small changes

in production practices can have a major impact on the global income (KASHIHA et al.; 2014).

The knowledge of the daily variation of the animals' weight in real time, is a practice that would allow producers to improve the yield of production. It would be possible to use this information to optimize the space provided by animal, improve nutritional management practices, predict and control the weights for the slaughter and, potentially, control the herd's health, since this information can serve as disease outbreaks' monitor (BRANDL & JORGESEN, 1996; KASHIHA et al; 2014).

Usually, weighing is done manually, a process that often requires two managers and can take three to five minutes per animal. This practice can be stressful for both animals and managers, and it represent an ergonomic risk (BRANDL & JORGESEN, 1996).

Therefore, an automated system to determine the animals' weight has the potential to assist producers to classify them to market and minimize the number of pigs marketed out of specification, improving the yield of production. To this, many attempts have been made to find an alternative to the manual process of weighing.

Essentially, two ways of approach have been studied: automatic and electronic weighing systems combined with automatic identification equipment and indirect determination through the animals' dimensions.

In general, the electronic and automatic weighing systems involve direct contact with the animal with electronic boards. 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 (SLADER & GREGORY, 1988; RAMAEKERS et al. .1995; SCHOFIELD et al., 2002), 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 in the scale during weighing, and presence of other animals or other material on the scale; generating measures which cannot always be trusted.

The significant correlation between weight and pigs' dimensions has led many authors to study the possibility of estimating body weight using this relationship (BRANDL & JORGENSEN, 1996).

Some methods of indirect measurement of weight, through pigs' dimensions, as tapes and calipers have been widely used by producers. Although those are faster methods than manual weighing, they still require that the pig is immobilized and not provide weight with great accuracy, currently required for maximum payment.

Alternatively, several authors (SCHOFIELD, 1990; FROST ET AL., 1997; SCHOFIELD, 1999; WHITTEMORE & SCHOFIELD, 2000; WANG et al., 2008; KASHIHA et al., 2014) developed techniques for obtaining the animals' dimensions through digital images that have been shown to be a non-invasive, efficient method.

In general, the difficulty with the determination of weight through images is that, to extract the dimensions of the pig, its color must be different from the color of the environment. Dark skinned pigs, stained or dirty make this approach very difficult to automate. In addition to the color of the animal, the presence of adequate light is critical for this application. Kashiha et al. (2014) found great illumination values within the range of 40 to 150 lux.

Authors (WU et al., 2004) sought to solve this problem by developing a system for capturing images with six high resolution cameras (3032 x 2028 pixels) and three flash units to obtain the 3D shapes of live pigs. One problem with this approach was the excess equipment and the high costs involved, what make the use of this type capturing really hard on an industrial scale.

Finally, it was proposed (KONGSRO, 2014) the use of a Microsoft® Kinect® sensor obtain depth images. The volume of the animal obtained through these images was correlated with the weight of Landrace and Duroc boars. The system could acquire the weight of the pigs with an error of 4 to 5%. These images require less concern with calibration, and lighting, as well as provide a given additional time.

The Kinect® is a sensor that serves as 3D measurement device and it's been receiving the attention of several authors due to its low cost, reliability and speed of measurement (SMISEK, 2013).

It is a compound device consisting of a digital color RGB camera, an infrared (IR) emitter, an infrared depth sensor, four microphones, a three-axis accelerometer and a tilt motor (MICROSOFT®). Three images are provided by the sensor: infrared, color and depth.

The present study used the Kinect® sensor as a mechanism for weight prediction of growing-finishing pigs, aiming to provide with this approach an alternative to problems of automation and animal selection on the image, as well as to the problem with the cost and size of the equipment involved.

Thus, the study aims to extract pigs' weight data from depth images, using a low-cost depth sensor, for three commercial lines (Duroc, Landrace and Yorkshire) and for gilts and barrows.

6.2 Material and methods

The experiment was accomplished at the growing-finish building of the Meat Animal Research Center-MARC, from the Agriculture Research Service-ARS of United States Department of Agriculture –USDA.

Approximately 230 growing-finishing pigs were used, of three different commercial lines: Landrace, Yorkshire and Duroc. The animals were weighed with 8, 12, 16 and 21 weeks old (on average). The values of weight and number of each animal were stored in a space-delimited text file on a portable computer.

While weighing, a Kinect® sensor ® set up above the scale (Figure 1) was used to acquire digital color image (Figure 2 (a)) and depth image (Figure 2 (b)).

Figure 1 - Scale and Kinect® sensor used for image and weight acquisition.

The images were collected using a program developed in MATLAB software (2016a), which, every second, recorded on a laptop computer, a digital RGB color image in png (portable network graphics) format and the values from the image in depth in space-delimited text file, txt.

Digital color RGB images were used only for the identification of animals' numbers. The depth image was used for acquiring the animals' volumes.

An algorithm was written in MATLAB software (2016a) for automatic acquisition of dimensions. First, the depth map was imported to the software using the 'importdata' function (Figure 2 (b)), then the distance from sensor to animal was converted on the animal's height, which was made by subtracting the distance between sensor and floor (Zf) from the distance between sensor and animal (Za), according to Figure 3. Then, the values were selected within

a limit, covering 500 mm from the approximate height of the animal; making pixels outside that limit equal to zero using a logical 'if/else' test (Figure 2 (c)).

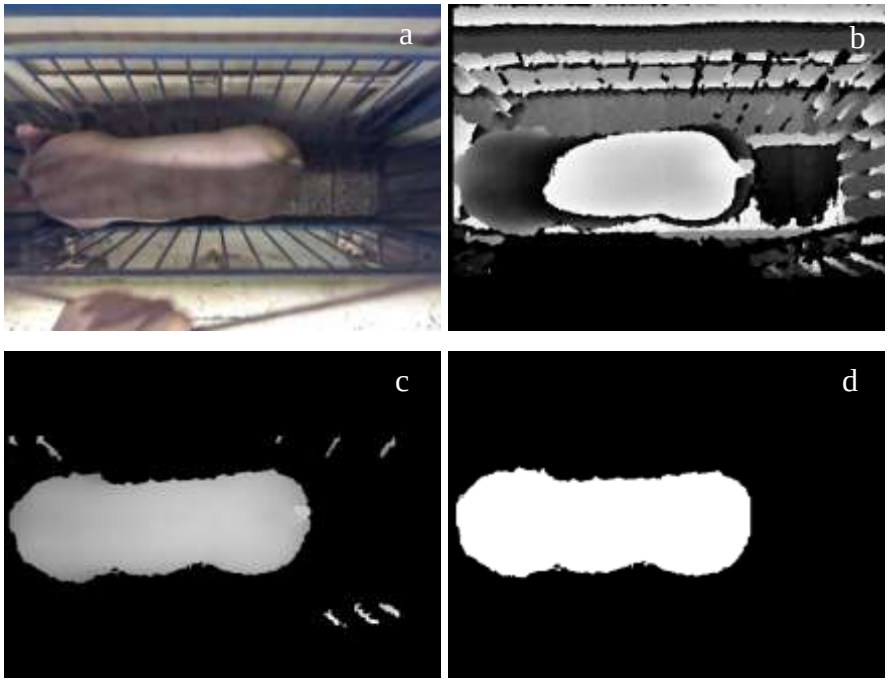

Figure 2 - (a) RGB image and (b) depth image obtained with the Kinect® sensor located above the animal. (c) shows the elimination of areas in the depth image that were out of a pre-established value. (d) indicates the selected pig after eliminating head and tail.

Later, possible noises (e. g. parts of the scale) were eliminated, making the values of rows and columns around the animal equal to zero. The resulting array was transformed into a binary image ('im2bw') and the object with the largest area on the image was selected using the ‘bwareafilt’ function (Figure 2 (d)). 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 facilitate the location of the animal's shoulders. Then, the binary image was applied as a mask on the original map to select only the region of interest values.

Finally, the value of the width (in pixels) of the pig (sum of the largest column of elements equal to '1 on the front half of the animal) was acquired through the 'sum' function.

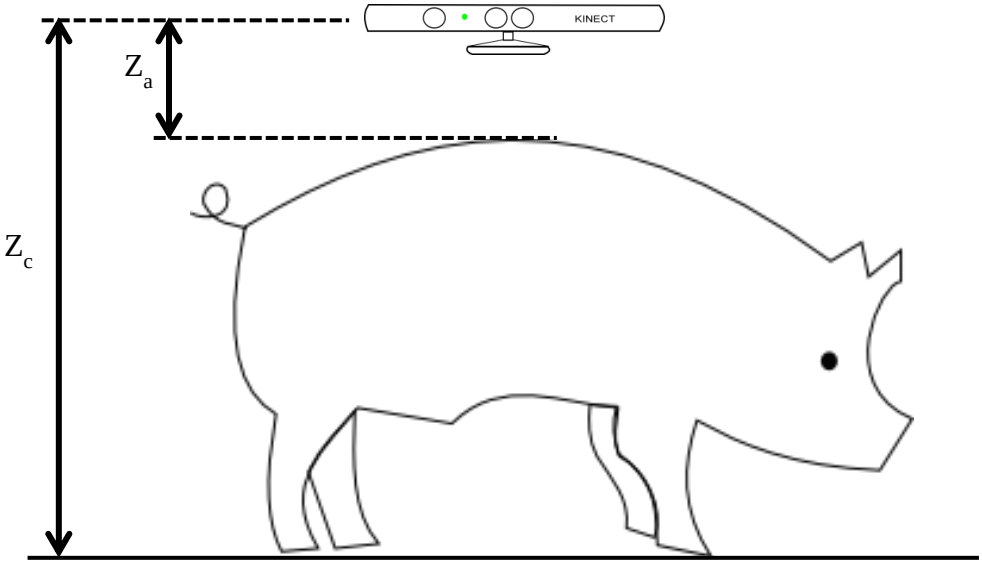

Figure 3 - Height of the animal (Zf-Za).

The volume value obtained (in "px cm") was adjusted, using eq. 1; to obtain the volume of the animal in cm³.

$$V_{cm^3} = V_{px\ cm} \times 6{,}47774 \times 10^{-6} \times Z^{1{,}85304} \quad (1)$$

where:

$V_{cm} =$ volume, in cubic centimeters;

$V_{px\ cm} =$ volume, in 'pixels centimeters';

$Z =$ distance between sensor and object, in centimeters.

The effects of the sex of the animal and of the commercial line used were tested using the Efroymson's algorithm (stepwise regression) (EFROYMSON, 1960) for comparing two regression models (using 60% of the collected data): a global one, including the effects of sex and lineage, through *dummy* variables (DRAPER & SMITH, 1998); and a reduced model without including these effects with null hypothesis given the reduced model equivalent to the global model and with alternative hypothesis, considering different models. The test statistic is given in eq. 2.

$$F(n,d) = \frac{(SQ_r - SQ_g)/(GL_r - GL_g)}{SQ_g/GL_g} \quad (2)$$

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.

The statistics' result was, then, compared with the F-list using as degrees of freedom in the numerator the value of $SS_g/DF_g$and as degrees of freedom in the denominator, the value DF_g. F-calculated values greater than the F-list indicate rejection of the null hypothesis.

Then, the chosen equation was evaluated by Pearson's correlation (r) and determination (R^2) coefficients. In addition, to assess the equivalence between estimated weight and actual weight, a new data series, consisting of 40% of the collected data was used. The generated equation was used in these data, comparing the predicted weight with the estimated weight, and then, the Willmott's concordance index(d) (WILLMOTT, 1981) and the refined Willmott's index (dr) (WILLMOTT et al., 2012) were calculated, according to eq. 3 and 4, respectively.

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

where:

d= Willmott's concordance index;

P_i= i-th predicted variable;

O_i= i-th observed variable;

$\bar{O}$= Observed variables average.

$$d_r = \begin{cases} 1 - \dfrac{\sum_{i=1}^{n}|P_i - O_i|}{2 \times \sum_{i=1}^{n}|P_i - \bar{O}|}, when \displaystyle\sum_{i=1}^{n}|P_i - O_i| \leq 2 \times \sum_{i=1}^{n}|P_i - \bar{O}| \\ 1 - \dfrac{2 \times \sum_{i=1}^{n}|P_i - \bar{O}|}{\sum_{i=1}^{n}|P_i - O_i|}, when \displaystyle\sum_{i=1}^{n}|P_i - O_i| > 2 \times \sum_{i=1}^{n}|P_i - \bar{O}| \end{cases} \tag{4}$$

where:

d_r= refined Willmott's index;

P_i= i-th predicted variable;

O_i= i-th observed variable;

$\bar{O}$= Observed variables average.

6.3 Results and discussion

Figure 4 shows the weight of growing-finishing pigs, varying with the volume obtained through depth images analysis. Visually, the animals' weight varies linearly with the volume obtained by image analysis, which is proved by Pearson's correlation coefficient (0.9952), showed on 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 considered in the prediction equation, indicating that the reduced equation is sufficient for weight prediction of the three commercial lines used for both gilts and barrows.

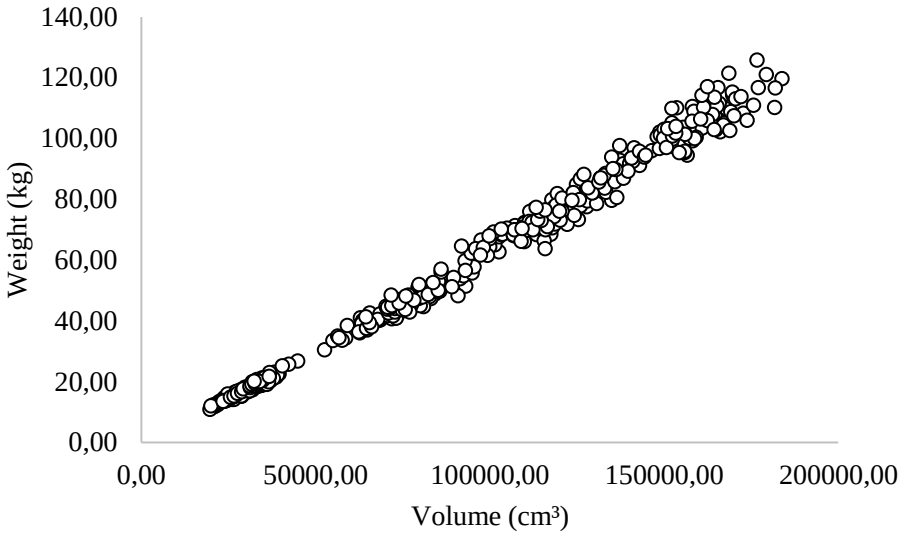

Figure 4 – Ground in grow-finish pigs vary with the volume of animals obtained through in-depth analysis provided by a Kinect sensor ®.

The equation's coefficients obtained are shown in Table 1, as well as the values of the Pearson's correlation coefficient(r), the determination's coefficient (R^2) and the Willmott's indexes (d and dr).

The global equation presents an R^2 of 0.9905; indicating that 99.05% of the variability of the weight of the animals, can be explained by volume obtained through the data provided

by the Kinect® sensor. This value is greater than the obtained (R^2 of 0.92) by Kashiha et al. (2014). 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 weight of the animal. This value is greater than the one found (r = 0.97) by Schofield (1990) for correlation between pigs' weights and its area on a digital color image.

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: Pearson's correlation coefficient; R^2: coefficient of determination; d: Willmott's concordance index; dr = refined Willmott's index.

Intercept	Coefficient	N	r	R^2	d	dr
b	a					
-3.7488 ±0.3160	0.0007 ±3.1 x 10^{-6}	463	0.9952	0.9905	0.9991	0.9731

Using the test data set (40% of the data), the global equation predicted weights using calculated volumes with an average error of 4.6% or 2.2 kg.

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 estimated pigs' weights in a very similar way to the scale. This is illustrated in Figure 5, where actual weight (measured on the scale) and estimated (by volume) exhibit very similar behavior when plotted versus the volume of animals.

Overall, the proposed method showed a satisfactory performance in the estimation of the weight of growing-finishing pigs. The responses obtained are as good or better than those obtained by other authors that correlated the mass of animals with dimensions obtained by images. The method proved to be fast and efficient. The biggest problem with this approach is the difficulty in obtaining reliable depth data in excessively lit environments.

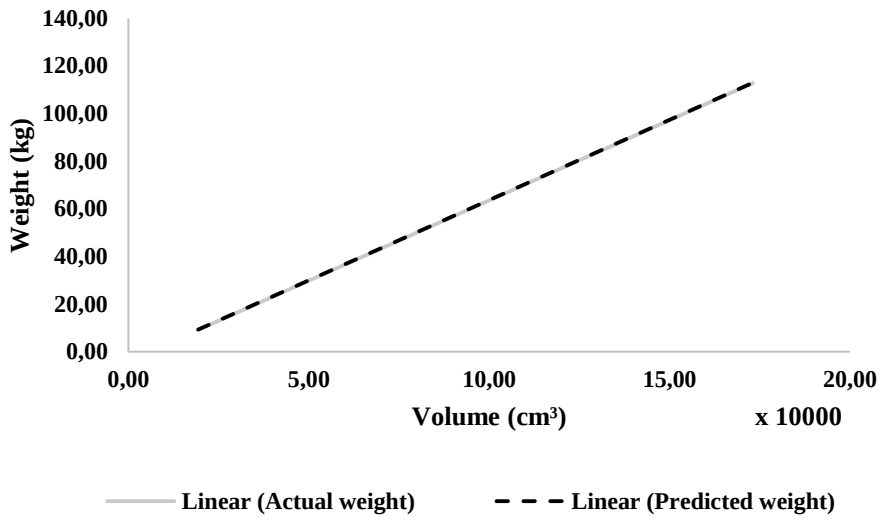

Figure 5 – actual and estimated mass data (in kg) versus the body volume of growing and finishing pigs to three business lines (Landrace, Duroc and Yorkshire).

6.4 Conclusions

It was possible to obtain growing-finishing pigs' weight from three commercial lines (gilts and barrows) through volume obtained with depth images obtained with a Microsoft® Kinect® sensor, using program and algorithms developed with MATLAB software (2016a).

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

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