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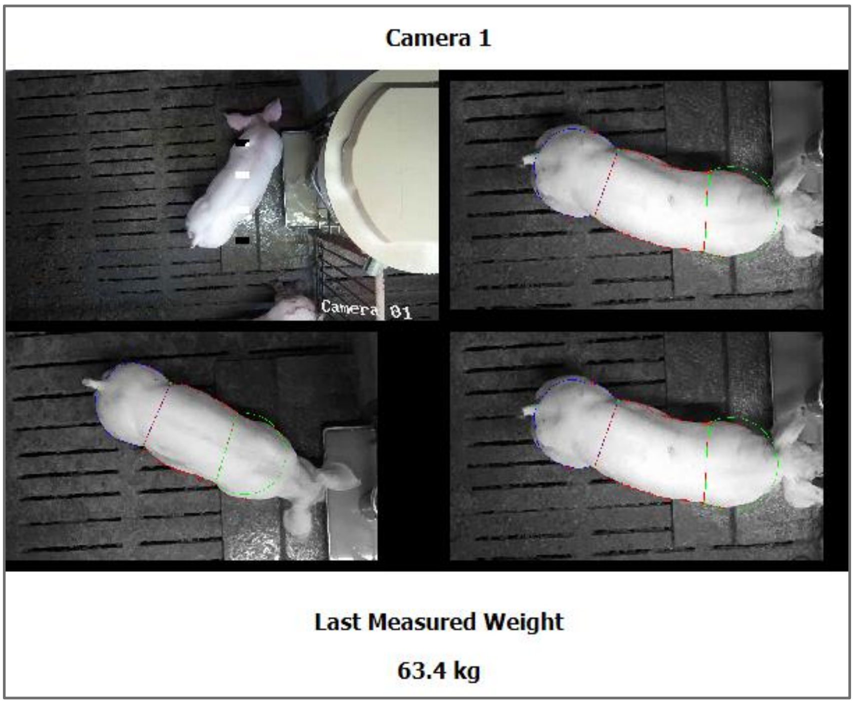

Detecting abnormalities in daily weight gain in finisher pigs using automatic camera weighing

Master's Thesis in Animal Science

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Preface

This thesis is the final work of my Master's degree in Animal Science at Faculty of Health and Medical Science at University of Copenhagen. It was conducted in the time period from February 2018 to December 2018 at the Department of Veterinary and Animal Science, University of Copenhagen. This thesis was conducted as a collaboration between Copenhagen University, SEGES – Danish Pig Research Centre and SKOV A/S. Thus, I will like to thank all involved partners.

Throughout the writing period, many people have been of great help. I would like to thank my main supervisor Anders Ringgaard Kristensen, for constructive criticism, guidance and for helping with the data analysis. I would also like to thank my co-supervisor Dan Børge Jensen, for guidance, reviewing parts of the manuscript and for help with the data analysis. Also, special thanks to my other co-supervisor Julie Krogsdahl Bache for providing invaluable support, guidance and for reviewing large parts of my manuscript.

The study was conducted in collaboration with the Danish company SKOV A/S who provided data for this study. I would especially like to thank Hans Ulrik Jensen, Niels Henrik Lundgaard and Maria M. Bager Sørensen for guidance and for making me feel welcome when I was at the company. I would like to thank Ib Filholm Jensen, for letting me visit the farm where the data analyzed in this study is from and for taking the time showing me the farm.

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Abstract

Knowledge of daily body weight (BW) gain of finisher pigs allows the farm employees to monitor performance and health of the animals. However, weighing pigs has traditionally been a labour intensive and time consuming task, which might have negative implications for the pigs. Thus, an automatic weighing system using camera vision has been suggested as a superior method. However, in order to use the weight observation from automatic camera weighings for a monitoring tool to give an early warning if abnormalities are occurring, it is important that the collected data are processed and analysed. The aim of this thesis was therefor to design a dynamic linear model with Kalman filtering to detect abnormalities in BW gain in a commercial Danish finisher herd based on weighing data generated from the automatic weighing system ProGrow from the company SKOV A/S.

From the literature review, it is clear that BW can be estimated based on body size measurements obtained from camera vision. The best estimates can be found by measuring the body area of the pig. Thus, a top view camera can be enough to obtain measurement. At farm level the cameras can be placed above a passageway or above a feeder. The weighing process can be automated. Thus, frequent BW measurements can be obtained. A DLM with Kalman filter was suggested to analyse BW data. Finally, a tabular cumulative sum chart (Cusum) was described as a method to detect abnormalities in growth. Thus, small shifts in BW gain can be detected.

In the data analysis of this thesis a DLM were used to dynamically filter frequently obtained data from ProGrow. Furthermore, the model was used to construct a monitoring tool based on a Cusum which can detect abnormalities in BW gain and give early warnings as alarms to the farm personnel. The performance of the system was tested on a test data set which was not used to estimate the parameters used in the DLM. Additionally, the performance of the alarm system was displayed using simulated data with a known event of decreased growth rate. The number of alarms from the monitoring system will depend on the reference value and decision interval used as parameters in the Cusum. Thus, these values should be defined based on the choice of the farmer.

Table of contents

1. Introduction

1.1 Background

Trends show that the development in Danish pig production is moving towards fewer farms, but with increased herd size (Christiansen, 2017). Increasing herd size gives the ability to exploit economies of scale and improve the efficiency because of optimized time use and specialization of attributes of the workers. However, increasing herd size also demands more from the farm employees, because they must overview more animals and make smart decisions to insure high production, health, and animal welfare. One way to improve the employees' overview of a herd and improve the decision making is by using integrated monitoring systems (Cornou and Kristensen, 2013; Frost et al., 1997; Wathes et al., 2008). Integrated monitoring systems rely on sensors to generate data which can be analysed to detect abnormalities in a production and give early warnings to the farm employees. In a finisher pig production examples of parameters which could be monitored are; climate, water intake, feed intake, activity, and body weight (BW) (Cornou and Kristensen, 2013). However, if a monitoring system should be integrated in a herd, it is important that it is cost effective and that the early warnings are relevant and without false positives (Dominiak and Kristensen, 2017)

Knowledge of daily weight gain allows the farm employees to monitor performance and health of the animals (Schofield et al., 1999; Shi et al., 2016; Wang et al., 2008). Field studies have shown that large deviations in daily gain can indicate irregularities in production as for example mistakes in feeding (Jessen and Udesen, 2016). Beside its use for early warning of abnormalities, knowledge of daily gain can also be used to optimize production. Thus, it plays an important role in controlling the factors which affect the performance of a finisher herd (Brandl and Jørgensen, 1996; Leen et al., 2017; Parsons et al., 2007). Number of transfers, sorting strategies, group size, floor space allowance, and feeding level are examples of things which the farm employees can change to affect the growth of finisher pigs (Cornou et al., 2005; Flohr et al., 2016). Currently information used as basis for decision making and general monitoring is a combination of the farm employees' observations and typically a monthly or a quarterly report (Cornou and Kristensen, 2013; Madsen and Ruby, 2000). However, real time surveillance of daily weight gain would make it possible to monitor and optimize an ongoing production by detecting irregularities in the production earlier and while change still can be made (Stygar and Kristensen, 2016).

In order to monitor weight gain in a production regular weighing is necessary. Weighing of finisher pigs can be performed in several ways, each with different implications. Manually weighing of pigs is done be either moving a scale into the pen and weighing the pigs individually or by moving the pigs out of the pen and onto a scale in the passageway. Thus, manually weighing is a time-consuming task, as well as a stressor for the pigs (Brandl and Jørgensen, 1996). Weighing pigs manually might also have unwanted implications on the performance of the pigs. Augspurger and Ellis (2002) showed that manually weighing of pigs resulted in a short-term decrease in feed uptake. However, Wolter et al. (2002) found no effect of weighing frequency on growth performance. Although manually weighing is the most accurate method it is doubtful that it will be performed more than once a week, because of the workload and the implications for the pigs. Therefore, it can be argued that manually weighing cannot be used to give early warnings of abnormalities in growth. In that case, an automatic weighing system should be considered.

Present, two kinds of automatic weight systems have been suggested; electronic weigh platforms (Williams et al., 1996), and camera weighing (Kashiha et al., 2013; Kongsro, 2014; Schofield et al., 1999; White et al., 2004; Wu et al., 2004). Electronic weigh platforms theoretically have a high accuracy. However, the pig has to stand in the same position when it is weighed and several pigs can stand on the platform at the same time which will result in wrong weight measurements (Williams et al., 1996). Another alternative could be to use image analysis of the pig, because there has been found a correlation between the area of a pig's image and the weight of the pig (Kollis et al., 2007). Weighing using cameras has been suggested because it causes no stress for the pigs and it can be installed in most farms without modification of the pens. Studies have shown that the live weight of the individually pig can be estimated with 4-6 % deviations using image analysis (Brandl and Jørgensen, 1996; Kollis et al., 2007; Kongsro, 2014; Schofield et al., 1999). Additionally, a recent test has shown that the commercially available system ProGrow (SKOV A/S, Roslev, Denmark) can be used to estimate the group mean of pigs with a deviation in means from manually weighing and image weighing between 0.3- 3.6 % (Udesen and Krogsdahl, 2018).

The level of data generated from an automatic weighing system, depends on the technology availably and the price the farmer is willing to pay for the system. Monitoring of all pigs in a herd would demand a lot of equipment and sophisticated image processing techniques, which could lead to a greater production cost (Kollis et al., 2007). However, these costs could be reduced by only monitor a subset of pigs in a herd. These groups of pigs could serve as a basis for prediction for the remaining pens. (Stygar and Kristensen, 2016; Udesen and Krogsdahl, 2018; White et al., 2004). If, on the other hand, only a subset of the pigs are monitored, the use of the data will be limited, because of the variance of the weight between the pigs and between the pens (Udesen and Krogsdahl, 2018). Currently, there is, to the author’s knowledge, no commercial automatic image weighing system available, which can identify the individual pigs without using additional technology (Artmann, 1999). Thus, the measured BW will be a mean of all pigs in the pen.

In recent years several commercial weighing systems using image analysis have come available (Vranken and Berckmans, 2017). However, in order to use the weight observation as a monitoring tool to give an early warning if abnormalities are occurring, it is important that the collected data are processed and analysed. Thus, this study will investigate how weight measurements can be collected and analysed to detect abnormalities.

1.2 Objective

The aim of this thesis is to design a dynamic linear model with Kalman filtering to detect abnormalities in BW gain in a commercial Danish finisher herd based on weighing data generated from the automatic weighing system ProGrow (SKOV A/S, Roslev, Denmark). The aim is achieved by the following two objectives: 1) a literature review, and 2) a data analysis.

1) The literature review will focus on how the BW can be estimated using camera vison. Furthermore, it will be investigated how dynamic linear models with Kalman filtering can be used to analyse weight data. The following research questions will be answered in the literature review:

- How can BW of finisher pigs be estimated using camera vision?
- How can a camera vison weighing system be used at farm level?
- How can a dynamic linear model using a Kalman filter be used to analyse weigh data?

2) In the data analysis, a DLM to estimate BW gain in pigs will be constructed based on data from two commercial Danish finisher pig herd. The model will be estimated from historical data and will be tested in a dataset which has not been used to estimate the parameters. Additionally, it will be analysed when an abnormality can be detected using simulated data. The following research questions will be answered in the data analysis:

- How can the DLM and the monitoring tool be constructed?
- When can an abnormality be detected with the monitoring tool?
- Which implications could the monitoring tool have on a commercial finisher farm?

1.3 Hypothesis

The main hypothesis of this study is that a dynamic linear model with Kalman filtering can be used to analyse frequent obtained BW data from camera weighing to detect abnormalities in growth of finisher pigs.

1.4 Delimitations

In the data analysis of this study, BW data are generated using the camera technology which is a part of the commercial system ProGrow. The precision of a similar weighing system has been tested in another study (Udesen and Krogsdahl, 2018). The main target of this project is to apply a suitable model to analyse the data and give useful information to the farmer. Hence, no validation of manually weighings is performed.

The system can potentially weigh pigs starting from 7 kg. However, the scope of this thesis is finisher pigs weighing from 30 kg until slaughter marketing.

No information of abnormalities from the farm is available. Thus, the performance of the early warning system will be tested on a simulated dataset where the events are known.

1.5 Structure of this thesis

This thesis consists of a general introduction, a literature review, a manuscript for an article, a general discussion, a general conclusion, and perspectives. The literature review consists of three main chapters. The first chapter reviews how image weighing of the individually pig is performed. The second chapter describes how the image weighing method can be used at a farm level. The third chapter describes how a dynamic linear model can be used to analyse frequent BW estimations.

The literature review is background information relevant for the method used in the data analysis part of this thesis, presented in the article. However, the article can be read alone as, it includes: abstract, introduction, materials and methods, results, discussion, conclusion, and a list of references of its own.

2. Literature review

2.1 Weight estimation using camera vision

The BW of growing pigs is important to know, because the BW is an indicator of performance and health. Additionally, the weight determines if the pigs are ready to be send to slaughter (Kristensen et al., 2012; Schofield et al., 1999). Furthermore, the weight can be used to manage feed change (Whittemore and Schofield, 2000) and floor space allowance (Pastorelli et al., 2006). However, weighing pigs has traditionally been a time consuming and labor-intensive task (Brandl and Jørgensen, 1996). The traditional way of weighing can have negative implication for the pigs, because it has been found, that the pigs have a reduced feed intake on the day of weighing (Augspurger and Ellis, 2002).

An automatic weight system using camera vision has been considered as an alternative to manually weighing pigs. The camera method has the great advantage that it has no implication for the pigs and that the cost and maintenance are minimal because only a camera and a light source are needed in the pen (Schofield et al., 1999).

Many studies have led to the possibility of constructing a weighing system using image analysis. This chapter will review how body dimension of a pigs can be measured and how the dimensions are converted to a BW and lastly, how the process is made automatic.

2.1.1 Correlation between body dimensions and BW

The concept of using the obvious correlation between body dimension and BW is not new. Thus, early studies showed that the body dimensions can be used to estimate the BW of pigs (Petherick, 1983; Phillips and Dawson, 1936).

In order to estimate BW of pigs the first step is to obtain useful parameters of body dimension. Phillips and Dawson (1936), studied three methods to obtain body dimensions to find the most practical method as well as the method with the highest accuracy. The three methods were named method A, B, and C. The dimensions used to estimate BW in method A were obtained directly from the pigs with callipers and a measuring tape. Method B involved a scaling instrument with a sighting device which measured the ratio of one body part compared to another body part. The readings were afterward converted into centimetres using a constant. In method C the pigs were photographed, and the image projected to life-size for measuring. In order to make sure the photograph was projected as life-size the pig was wearing a harness of known size. All methods were used to measure the same 11 pigs. The possible body measurements given the current method was obtained. The study showed that the most accurate method to estimate body dimensions was the manual method A. However, method A was also the most work intensive and included most contact with the pig, so the photograph method, method C, was concluded to be a simpler way to obtain body measurements.

Although, the method using photographs in the study of Phillips and Dawson (1936), was rejected in favour of direct measurements using measuring tape the concept of using photographs has later been revisited. Because, technology advancement has given new possibilities to obtain measurements.

The correlation between body dimension and live weight has caused several authors to investigate the possibility to estimate pigs weight by using direct image analysis of the body area of the pig (Brandl and Jørgensen, 1996; Kollis et al., 2007; Schofield, 1990). However, to apply an image analysis method, the relationship between the dimension parameters which potentially can be obtain from a camera and the estimated BW must be known.

In general, better estimations should be obtained when looking at an area of a pig instead of length or width measurement. Thus, if the volume is calculated by length and width measurements, the error of each measurement is multiplied in order to estimate the volume (Schofield, 1990). Furthermore, the body area will to some extent be able to account for the deviation in body shape between pigs. However, the exact full body area of a pig can be difficult to measure from a 2-dimensional image, due to different compositions of the body. This lead Schofield (1990) to investigate which dimensions of a pig should be taken into account for the best prediction of BW. For this purpose, photographs were used to obtain the body measurements of 15 pigs weekly in the growth period from 30 to 80 kg. These pigs were photographed separately using a side camera. However, both the side view and top view of the pig were obtained. Thus, the image was projected from a mirror above the pig in a 45-degree angle. To compare the correlation, the pigs were immediately weighed manually after the pigs were photographed. From each photograph the height and width of the pig was measured. Additionally, three area measurements of each pig were manually outlined from the top view, and the area extracted. The three area measurements obtained from the top view camera were: 1) the whole body, 2) the body without the head and ears, and 3) the body without the head, ears, and neck. The measured area was afterwards converted into a volume. However, because the full body area was not obtained, the measurements were converted to a volume using a model of a pig constructed using cones and a cylinder. In this study, the density of a pig was assumed to be 1,050 kg/ m^3. The study showed that the highest correlation between dimensional data and the manually weight of the pig was found to be the measurement of the body without head, ears, and neck. This was argued to be due to a larger variation in these parts and due to the visual appearance on a top view image of head and neck changes depending on how the pig was standing. The variation in height found in this study only affected the estimation of BW with a maximum of 0.5 %. Thus, the variation in height of the animals was found to be ± 5 cm.

Although, the study of Schofield (1990) developed a system that was able to weigh pigs, the placement of the camera was not practical. Because, the measurements were very dependent of the distance from the camera to the pig, should be approximately the same in all measurements, due to the ratio of the mirror projection. Furthermore, nothing can be placed between the pig and the scope of the camera. This led to an, investigation of a method placing the camera on top of a pig. Thus, this placement would be more practical under farm conditions (Brandl and Jørgensen, 1996; Van der Stuyft et al., 1991).

In a study of Minagawa and Ichikawa (1994) two measurements of the area of pigs obtained from a top view camera was investigated. The two methods were 1) measuring the central area and 2) measuring the orthogonal area. The central area of the pig was specified as the mean projected area of the pig as a simple 2-dimensional measurement. The orthogonal projected area of the pig was the central area of the pig adjusted for the height. Thus, it was an estimate of the actual area of the pig's back. The area of the pig in the image was found using a threshold method where the contrast between the white pig and the dark surroundings was used. A special booth was used in order to test the performance of the two methods. The booth was equipped with a black rubber sheet as floor, a frame around the pig of plywood and additional lighting in order to get the best contrast difference between the pig and the surroundings. In the study, 33 pigs weighing from 7 to 120 kg were measured in order to test the performance of the system. From a video camera placed above the booth, images of pigs were obtained and analysed manually, in order to obtain the projected area of the pig while the pigs were standing. Afterwards, the height of each pig was measured, and each pig was weighed manually, using a scale. In the study, the projected area using both methods was plotted as a function of the BW, found using the scale. It was found that both the central projected area and the orthogonal projected area had high exponential relationship between measured area and the BW of the pig. Thus, the coefficient of determination was 0.999 and 0.998 for the central projected area and the orthogonal area, respectively. The equation to convert the central projected area in cubic centimetres to the BW in kilos of the pig where: $Area = 200 * BW^{0.669}$. The standard deviation between mean central projected area and weight of the pigs was $\pm$ 0.9 kg. The study from Minagawa and Ichikawa (1994) showed, that the measurement of a single pig could be estimated with a high precision using only the central area of the pig using a threshold method if operated under optimal lighting condition. However, this will demand moderation of the pen and would not be feasible in practice on a farm.

In order to investigate the precision of a weight estimation obtained from an image weighing under farm condition, Brandl and Jørgensen (1996) used a recording method, where a pen was video recorded from a camera above the pen. The image was frozen by an operator when a pig was standing under the camera. From the image eight points in the outline of the pig were selected. These points were used as end points for different length and width measurements which were used to estimate the body area of the pig. The aim of the study was to establish the precision of the method and to investigate if the correlation between area and BW depends on breed or feeding methods. The different treatments in the study were breed (different cross breed combinations of Danish Landrace, Danish Large white and Duroc) and feeding methods (ad libitum vs. restricted). In total 416 pigs were used in the study, and each pig was on average weighed 5.5 times. From all observations the weight was estimated with 5-6 % deviation. Furthermore, the study found that different breeds and feeding methods could lead to the need of different algorithms to estimate BW from body measurements.

Measuring method in order to obtain an image of a pig standing in the best position was further investigated in a study of Wang et al., (2006). In this study the image used for estimation was a manually selected still picture from a top view video of approximately one minute of length of each pig. This was done, in order to get a picture of each pig standing. A total of 187 pigs were measured in the weight range of 50 to 150 kg. The images were used to test the correlation between different measured features of the pigs and the BW of the pig which were manually weighed using a scale. In total, 18 features were tested. The best features to correlate to the BW were the area of the pig projected from the top (r = 0.96). Furthermore, the study found great correlation between the BW and the width (r = 0.95). Additionally, five mathematical models were tested to estimate the pigs' weight from the measured rear area of the pig. The five mathematical models were: polynomial, square root, linear, power, and logarithmic. All five models showed a coefficient of variation ranging from 5.68 to 6.42 %, concluding that all five models could be used for the estimation.

The relationship between the plan area and the pig weight was further investigated by Marchant et al., (1999). In the study a full automated algorithm to find the plan view of a pig under farm conditions was found. In the study, 10 female and 10 male pigs were weighed continuously as they grew starting from 30 kg in approximately 60 days. The images of the pigs were captured using a top view camera installed above the feeder. An average of 1,250 images were stored each day. Additionally, the pigs were manually weighed weekly, using a scale. The plan area of the pig was found from each image by dividing the body into three regions as: rump, abdomen and the shoulder region. As seen in Figure I the parameter was found using a "snake" method, where a line follows the boundary as an elastic string. The relationship between body area and the BW was found by plotting the sum of the rump, abdomen and shoulder region (denoted A4) against the manual weighings. Thus, the relationship between the plan area and the BW was well represented as a straight line: $W = -15.56 + 411.3 * A4$ in which W is the predicted weight of the pig and A4 is the plan view area without the head and neck. The study did not find a significant ($P< 0.05$) effect of gender of the pigs. In the study, it was assumed that the pigs were still weighed manually in order to calibrate for variation in shape of the individually pigs. If the pigs were manually weighed weekly, the standard error of the predicted weight compared to the manual weighing were 0.25 kg, 0.17 kg and 0.39 kg for pigs weighing 33kg, 66 kg and 99 kg respectively. However, if the pigs were only weighed every second week, the standard error for the prediction at 33 kg, 66 kg and 99 kg was 0.42 kg, 0.24 kg and 0.58 kg respectively. Lastly, if the pigs were only individually weighed once early in the growth period the BW of the pigs could be estimated with a standard error under 1 kg.

In this study, the weighing method had a relative high precision. However, the relationship found is only valid for the breed of pigs investigated. Furthermore, the method still acquires manual weighings for calibration.

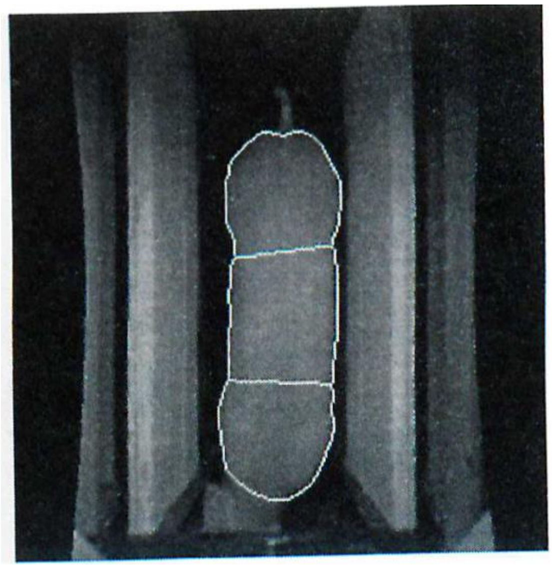

Figure I. Image showing the plan view of a pig dived in three regions as: rump, abdomen and the shoulder region (Marchant et al., 1999)

2.1.2 Automated camera measurements

In the previous section it was established, that pigs' BW can be estimated using camera vision. However, in order to automate the process of capturing usefull images to continuously monitor growth of pigs several steps are necessary.

The first step is to detect when an object is in the scope of the camera's view and an image should be captured. The most commonly described method is using a threshold method, where a change of brightness in the area of the camera would be recognized as a pig (Kollis et al., 2007; Schofield et al., 1999; Tscharke and Banhazi, 2013a). In order for the whole pig to be in the view of the camera before the image is captured, the threshold changes can be compromised to some hotspots which can be placed in the middle of the camera view (Schofield et al., 1999). An alternative method, reviewed by Li et al., (2014), is to use a trigger method where a sensor is activated under the camera when an animal is present. However, this method would demand additional equipment in the pen. Thus, the price of the system would increase.

When an image is captured the body dimensions of the pig should be obtained. In order to get the best estimation of the pig's weight the body area without head and neck should be found (Schofield, 1990; Schofield et al., 1999). Similar, to the detection procedure a threshold method can be used. Thus, the contrast between the white pig and the darker floor could be found

(Schofield et al., 1999; Wang et al., 2006). The outline of the pig can then be detected by using a pre-defined model of a pig which can be scaled in size (Tillett and Marchant, 1990). Alternatively, the outline can be found using a snake method, where the boundary of the pig is followed by a detection line (Marchant and Schofield, 1993; Schofield et al., 1999).

In a study of Kongsro (2014) it was suggested that body measurements of pigs could be obtained, using a Microsoft Kinect prototype imaging system with an infrared-light depth sensor. Thus, from the depth map generated, a pig under the camera would easily be detected, due to a change in depth. Additionally, both the outline of a pig and the height of the pig are visible. In the study 37 Duroc and 34 Landrace boars were selected, ranging in weight from 29 to 139 kg. 50 pictures of each pig were taken. However, the best image of each pig was selected manually afterwards. The best image should be an image containing the whole pig standing with the head slightly lowered. The head, ears and tail of the pig were removed to improve accuracy.
The study showed that the mean weight of the measured pigs was estimated with an error of 4.6-4.9 % for Landrace and Duroc breed, respectively. The advances of using the infrared-light depth sensor are that the weighing is not dependent on visible light to measure the pigs and that darker breeds as the Duroc breed can be measured. Additionally, the height of the pigs can be measured, which might bring new information of the variation. Although, prior studies showed that height only affect the estimation with a maximum of 0.5 % (Schofield, 1990).

Although, images are only obtained when a pig is in the view of the camera, some images can still be unusable if the pig is lying or if two pigs are standing together. These pictures should be removed in order to make a better estimation. One solution was presented in a study of Schofield et al., (1999). Thus, three tests were used to remove unusable images. In the first test, it was tested if the pixels in the area where the pig's shoulder was expected was above 60 % of a predicted value found from a pre-trail. The first test was performed in order to make sure a pig was present, and the lighting of the image was acceptable. The second test was that the whole area of the pig's body should not be less than the predicted minimum value. In the third test the length- to- width ratio was measured and compared with predicted BW value. If an image had passed all three tests the body area of the pig was measured in pixels. In the study 30 pigs were monitored over 47 days during the fattening period from 47 to 90 kg. The pigs were of three breeds (Landrace, Large White and Meishan pigs). The images were captured when the pigs were inside a feeding station. Thus, the pigs were standing and eating at the time the images were captured. The study showed, that the system captured an image on average once every 26 seconds during a 24 hours period.

However, the tests mentioned above removed 32 % of the images. In total 140 weight observations per pig for each day was obtained. The mean weight of the whole group of pigs could be estimated within 5 %. However, if a breed specific algorithm was used the error was reduced to below 2% for both Landrace and Large White pigs and below 3 % for Meishan pigs.

Both image vision weighing systems using 2-dimensional cameras capturing a top view image of a pig and 3-dimensional cameras with depth sensors are commercially available (Pezzuolo et al., 2018; Vranken and Berckmans, 2017). However, the key for an image vision weighing system is that the weighing system should work under farm conditions.

Summary

Direct measuring and manually weighing methods are currently the most accurate due to the fact that the camera cannot obtain the whole-body area of a pig. However, the correlation between body area and BW can be used to give an estimation of the BW. The best correlation between body measurements and the BW is found by measuring the whole-body area of the pig without the head, ears, and neck. Thus, a top view image could potentially be enough. Additionally, it was found that different correlations might be found in different breeds and feeding methods. Therefor, the correlation will have to be recalculated in each system. Furthermore, some manual measurements of height can be necessary in order to get a high precision, even though the height of the pig only seems to deviate a little between pigs.

An automated process of obtaining and analysing images in order to predict BW has been suggested in several studies. The automated process requires some analysing of the image in order only to capture an image when a pig is in the view of the camera and the pig is standing.
Traditionally, the body area of a pig is found by a threshold method by comparing the contrast between a dark background with a white pig. However, this method has some limitations and an alternative method using a 3-dimensional camera with a depth senor has been suggested.

2.2 On farm measurements

In the previously chapter, Chapter 2.1, it was established how estimated BW of pigs from image analysis can be obtained. However, in order for the technology to be useful at a farm, factors as: cost, functionality, practicality, and accuracy should be taking into account (Tscharke and Banhazi, 2013b) In addition it is necessary that the system works in harsh environmental conditions which can be both moisty and dusty (Tscharke and Banhazi, 2013b). Most of the studies of image weighing systems are estimating the weight of the individual pig. However, to detect abnormalities in growth the average weight of the pen can be enough. Thus, most abnormalities will affect more than one individual pig in the pen.

Basically, the vision weighing technology can be used with two purposes in a finisher herd: 1) single measurement or 2) Automatic growth detecting by continuously weighings (Tscharke and Banhazi, 2013a).

Several commercial products using depth images sensors have been developed as hand-held units, which enables the farm employees to walk among the pigs and acquire the weight estimations (Condotta et al., 2018; Wang et al., 2018). Although this approach will enable the farm employees to weigh the individual pig in order to find the pigs that are ready for marketing the system is not as useful as a monitoring system. Hence, to make a useful monitoring system, frequent measurements of each pig are needed.

2.2.1 Walk-trough weighing

One way to use automatic image weighing at a farm would be to use a walk-trough weighing system (Wang et al., 2008). However, a walk-trough weighing system requires the estimation of a pig to be made when the pig is moving. In the study of Wang et al. (2008) pigs were guided individually through a one meter wide passageway to another pen. On top of the passageway a video camera and artificial lighting were installed. 22 pigs with weights from 14 to 123 kg were video recorded as they walked through the passageway. The video was converted into still pictures and both an automatic and a manual method were used in the selection of the pictures. The criteria's set for the manual selection were: the whole body had to be visual inside the area and the pig's body should not have contact with the edges. Additionally, the body and head of the pig had to be in line. The criteria for the automatic selection were: no part of the pig should touch the edges, the ratio between the left and right side should not exceed a certain value, and finally the head had to be within a certain ratio of the body of the pig to ensure that the pig was not looking down. The images were analysed in a similar method as described by Kollis et al. (2007). Additionally, because the pig could move both ways the head was identified by the positions of the ears. The two methods of selecting images manually and automatically showed similar accuracy of the measurements around 3 % compared to direct measuring using a scale. The result indicate that it is possible to use image analysis to estimate the weight of moving pigs. However, this approach will demand moderation of the barn and possibly still some labour in order to make sure all pigs move past the camera.

2.2.2 Pen measurements

A different approach is using the fact that all healthy pigs will be standing in front of the feeding machine or drinker at some point during the day. During feeding, pigs are standing in a relatively stable position for a few minutes several times a day. Therefore, above the feeder has been found to be a good placement of the camera (Banhazi et al., 2011; Pezzuolo et al., 2018). This technic was used by Tscharke and Banhazi (2013a) in a farm trial where the camera was placed above the feeder in a pen with 12 pigs. The weight of the pigs was estimated using a vision system in the growth period between 60 and 120 kg. In this study the average weight estimated as a daily mean of all observations from the pen was obtained and compared to manual weighings using a scale performed seven times during the growth period. Hence, a precision of ± 1 kg error between the estimated and the measured weight on six of the seven days. On the last day, the error was greater due to three pigs jumped over a gate and therefore, the pigs were missing in most observation on that day. The weight deviation of the group was estimated within ± 2 kg error on all days. The study showed that the average weight of pigs can be estimated without any moderation of the pen. However, this method depends on all pigs being measured every day and that the number of pigs in the pen does not changes. Thus, the average pen weight will change if pigs are removed or inserted in the pen if their weight deviates from the mean.

If the weight of the individual pig is important to know, the image-based system can be combined with pattern recognition to identify the pig. In a study by Kashiha et al. (2013) a method was presented to monitor individual weights of pigs full automated. In the study, in a pen with 10 pigs each pig was marked with an individual pattern on the back using a dye marker. These patterns were recognized in 88.7 % of the observations. Thus, the camera weighing could be related to the individual pig. However, the study showed problems with faded colour and dirty pigs which are actual problems under farm condition. Additionally, the paint application would be labour intensive and not convenient for the farmer. Therefore, a more practical method with electronic tags is probably more reliable (Artmann, 1999).

In some studies, the camera used for weighing is placed above a single feeder (Marchant et al., 1999; Schofield et al., 1999; White et al., 2004). A great advantage of using a single feeder is that the pig will be isolated from the other pigs, while the image is captured. One type of single feeder is an electronic feeding machine. The use of an electronic feeding machine could potentially give more information of the individual pig. Thus, if the pig had an ear tag, it could be identified and feeding records could be combined with the weight of the pig (White et al., 2004).

In recent years, several commercial systems to weigh pigs in the pen using camera vision have become available (Vranken and Berckmans, 2017). One of them is ProGrow (SKOV A/S, Roslev, Denmark). ProGrow is a real time monitoring concept where data of water intake, feed intake, and BW are collected (Udesen and Krogsdahl, 2018).

Weight estimation using ProGrow was tested by Udesen and Krogsdahl (2018). In the test ProGrow cameras were placed above the feeder in 12 pens in one section in a commercial finisher farm. The weighing system was tested in two batches of pigs: batch 1) and batch 2). In each pen 16 pigs were inserted. In batch 1 and batch 2, the average insertion weight of the pigs was 29 and 23 kilos, respectively. In the test, weighing data was converted into an average daily gain at pen level. The pigs were weighed in 56 days in batch 1 and 70 days in batch 2 starting one week after insertion. In order to remove outliers, the 25 percent highest and the 25 percent lowest observations per day were removed. Additionally, the pen average growth was estimated as a moving average of three days. The image-based weighings from ProGrow were compared with weekly manually weighings using a scale. In the test, an average of 56 images per day in batch one and 43 images per day in batch two were obtained. The test showed, that the deviation in mean daily gain based on manually weighing and on weighing using ProGrow on average was three percent in batch 1 and seven percent in batch two. However, the test showed, that if the weighings from multiple cameras were collected, the estimate error was improved. Thus, if four cameras were collected, the deviation was in average three percent in batch 1 and five percent in batch 2 and if all 12 pens was collected, the deviation was 0.2 percent in batch 1 and 3.4 in batch 2.

Summary

Vision based weighing systems can be used to analyse the weight of individual pigs or to weigh a group of pigs. However, to have a monitoring system that can give early warnings, frequent measurements are required. Thus, an automated process which can perform under farm conditions is essential.

One implication of an automated weighing system is using a walk-trough method where the pig walks individually through a passageway with a camera above. This method requires that still pictures from video of the pig walking is obtained. This can be done both manually or automatically.

The pigs can also be weighed while they are still in the pen. Two methods were suggested: 1) average pen weighing and 2) single feeder measuring. If using a single feeder, the pig is isolated while weighing. Additionally, the feeder can be combined with an identification system and can give more information of the individual pig. However, a single feeder might need moderation of the pen and the pigs might need a training period. In the average pen weighing system, the camera was placed above the feeder. Thus, this was found to be the best placement, due to that the pig is standing in the same position while eating. In this method the ID of the pig can only be recorded using a recognition method. Thus, only the pen average and the deviation in weight is normal recorded. Furthermore, it was found that if data from multiple cameras are combined the precision is increased.

2.3 Growth monitoring using a dynamic linear model

The previous chapters focused on how automatic weighing data can be generated using camera vision. However, to use BW data for monitoring a dynamic production process and to present data in a meaningful way for the farm personnel. The data should by analyzed using a suitable model (Wathes et al., 2008). Additionally, frequent BW observations from automatic camera weighings might need to be filtered (Udesen and Krogsdahl, 2018).

One way of analysing repeated observations is to calculate the moving average, where the average of the observations in a giving time period is calculated. The moving average M at time t of a period of n can be described as: $M_t(n) = (k_{t-n+1} + ... k_{t-1} + k_t)/n$ in which k is a series of observations (Kristensen et al., 2010).

An alternative to the moving average method is the exponentially weighted moving average (EWMA). The EWMA z at time t is defined as: $z_t = \lambda_{kt} + (1 - \lambda)$ (Montgomery, 2005) in which k is a series of observations and λ is a weight factor between 0 and 1 that controls how much weight is put on the recent observation. Thus, if λ is close to zero most weight will be put on all observations up until the recent observation, and if λ is close to 1, most weight will be put on the most recent observation. The choice of λ will results in different shifts shown in the observations (Kristensen et al., 2010).

A different approach is to use a Dynamic linear model (DLM). Thus, a DLM has the benefit that, although it starts with some basic assumptions, it is adaptive to the current situation (Jensen et al., 2017). Furthermore, a DLM can be used for analysing frequent BW observations, as decision support (Kristensen et al., 2012) and to provide meaningful alarms on growth (Stygar et al., 2017; Stygar and Kristensen, 2018). The following section will contain a brief introduction to DLM and Kalman filtering. Moreover, the section will review how DLMs have been used for dynamic growth monitoring in previous studies.

2.3.1 Dynamic linear models

One simple and widely used DLM is the first-order polynomial model (West and Harrison, 1997). The model says, that each observation (Y_t) obtained at time (t) is normally distributed around an unobservable underlying mean (θ_t) (Kristensen et al., 2010). Thus, the observation equation is described by West and Harrison (1997) as:

$$Y_t = \theta_t + v_t,\ v_t \sim N(0, V_t) \quad (2.1)$$

where, v_t is the observational error, which describe the random fluctuation.

The time evolution of the underlying level is modelled as the previously underlying mean and evolution error (w_t). Thus, the system equation allows the model to fluctuate over time as described by West and Harrison (1997):

$$\theta_t = \theta_{t-1} + w_t,\ v_t \sim N(0, W_t) \quad (2.2)$$

Before any observations are made, the prior information set (D_0) of the underlying mean are expressed as a mean m_0 and a variance (C_0) as $(\theta_0|D_0) \sim N(m_0, C_0)$. Thus, to initiate the DLM the prior mean m_0 and variance C_0 are specified. The corresponding conditional distribution at time t, given that all information is available is then $(\theta_t|D_t) \sim N(m_t, C_t)$. Each time a new observation is observed at time t, the DLM is updated. Thus, all prior information is contained in the conditional distribution of θ_t. The variance components V_t and W_t can either be estimated from previously analysed data or the observation variance V_t be unknown (and estimated concurrently) while a discount factor can be used to represent the system variance W_t.

The DLM can also be applied to more general models, where it is possible to model multivariate time series with patterns (Kristensen et al., 2010). In the more general dynamic linear model, both the observation Y_t and the underlying parameter θ_t are vectors with *n* and *m* elements, respectively. In the general DLM the observation equation is an extension of Equation 2.1. However, the observations in the general DLM are multivariate normally distributed around the unobservable underlying mean $\boldsymbol{F}_t'\boldsymbol{\theta}_t$. Described by West and Harrison (1997) as:

$$Y_t = \boldsymbol{F}_t'\boldsymbol{\theta}_t + v_t, \qquad v_t \sim N(\underline{0}, V_t) \quad (2.3)$$

, where, $\boldsymbol{F}_t$ is an $m \times n$ design matrix which relate the observation to the parameter vector θ_t, v_t is an n dimensional random vector, $\underline{0}$ is a vector of zeros, and $\boldsymbol{V}_t$ is an n× n variance-covariance matrix. The system vector $\boldsymbol{\theta}_t$ is similar to Equation 2.2. However, in a multivariate DLM the system equation contains the system matrix $\boldsymbol{G}_t$. Thus the system equation is described by West and Harrison (1997) as:

$$\boldsymbol{\theta}_t = \boldsymbol{G}_t\ \boldsymbol{\theta}_{t-1} + \boldsymbol{w}_t, \qquad w_t \sim N(\underline{0}, W_t) \quad (2.4)$$

, where, $\boldsymbol{G}_t$ is the $m \times m$ system matrix, $w_t$is an m dimensional random vector, $\underline{0}$ is a vector of zeros, and W_t is an $m \times m$ variance-covariance matrix.

All matrices ($\boldsymbol{F}_t$, $\boldsymbol{G}_t$, $\boldsymbol{V}_t$, $\boldsymbol{W}_t$) are assumed to be known at time t, although not necessarily at time from the beginning (Kristensen et al., 2010).

One of the main benefits of using a DLM is that it can be used as a tool for making one-step forecasts, based on prior knowledge by extending the DLM with a Kalman filter (also known as an update equation). Based on all prior information D_t available at time t-1 a Kalman filter provides the prior distribution of $\boldsymbol{\theta}_t$, a one-step forecast distribution for Y_t and the posterior distribution for $\boldsymbol{\theta}_t$. In the following the Kalman filter for a multivariate DLM will be shown. Thus, this model is used in the data analysis part of this study. However, using a similar method a univariate DLM can be extended with a Kalman filter.

The Kalman filter for a multivariate DLM is described by West and Harrison (1997) and formulated in the following equations (Equation 2.5 – 2.10).
The posterior distribution for the underlying level $\boldsymbol{\theta}_t$, at time *t-1* can be described as:

$$(\theta_{t-1}|\boldsymbol{D}_{t-1}) \sim N(m_{t-1}, C_{t-1}) \text{ (2.5)}$$

where m_{t-1} is the mean, and C_{t-1} is the variance matrix.

The prior distribution for θ_t at time t-1 is given as:

$$(\theta_t|\boldsymbol{D}_{t-1}) \sim N(\boldsymbol{a_t}, \boldsymbol{R_t}) \text{ (2.6)}$$

,where $a_t = \boldsymbol{G_t} m_{t-1}$ and $\boldsymbol{R_t} = \boldsymbol{G_t C_{t-1} G'_t} + \boldsymbol{W_t}$.

The one-step forecast for Y_t at time t is then:

$$(Y_t|\boldsymbol{D}_{t-1}) \sim N(f_t, Q_t) \text{ (2.7)}$$

where $f_t = \boldsymbol{F'_t a}_t$ and $Q_t = \boldsymbol{F'_t R_t F_t} + \boldsymbol{V_t}$.

The posterior distribution for θ_t at time t:

$$(\theta_t|\boldsymbol{D}_t) \sim N(\boldsymbol{m_t}, \boldsymbol{C_t}) \text{ (2.8)}$$

With the updating equations: $\boldsymbol{m}_t = \boldsymbol{a_t} + \boldsymbol{A_t} e_t$ and $\boldsymbol{C_t} = \boldsymbol{R_t} - \boldsymbol{A_t Q_t A'_t}$.

The adaptive matrix(A_t) is found as:

$$\boldsymbol{A}_t = \boldsymbol{R_t F_t Q_t^{-1}} \text{ (2.9)}$$

And the forecast errors were calculated as:

$$e_t = Y_t - f_t. \text{ (2.10)}$$

The main point of the Kalman filter is that the posterior mean (Eq. 2.8) is obtained by correcting the prior mean (Eq. 2.6) with a term proportional to the forecast errors (Eq. 2.8). The adaptive coefficient (A_t) scales the correction according to the relative precision (Eq. 2.9). Additionally, the forecast errors can be used in monitoring systems.

Beside its use for dynamic monitoring a DLM can be used to optimize a production by 1) calculating the effect of an intervention, 2) give forecast of future production, and 3) by smoothen data to analyze production, retrospectively.

If a known intervention occurs, as for example a change in feed, and a change in the underlying mean is expected the Kalman filter can be slightly modified by either adding the expected change to the underlying mean if it is known, or by increasing the system variance (Kristensen et al., 2010). Thus, the DLM will be more adaptive to the recent observations. By implementing an intervention, the effect can be compared to the forecast of growth without the intervention. Thus, an intervention can be evaluated.

Another implementation of a DLM is that it can be used to give prognoses for the future production. Thus, one example is the use to forecast when pigs are ready for marketing (Stygar and Kristensen, 2016)

If the parameter vectors are autocorrelated, the DLM can be analysed retrospectively. Thus, the parameter vector will contain information of the true development. A plot of a smoothed DLM can retrospectively be evaluated to analysis a growth pattern for fluctuations. Because, these fluctuations could be avoided by changing routines (Stygar and Kristensen, 2016).

In a study by Stygar and Kristensen (2016) weighing groups of pigs was used to predict the number of pigs ready for marketing at a given future, using a multivariate DLM with Kalman filtering. In the study, a commercial finishing unit with five sections with 14 double pens in each section was used. In each double pen 36 pigs, in average, were inserted, weighing approximately 30 kilos each. In the study, two selected double pens in each section were manually weighed weekly, they should serve as representatives for the whole section. In total nine completed fattening cycles for 9,800 pigs were used. Based on the weighing data, a hierarchical quadratic mixed effects model of pig growth was constructed with fixed effects of intercept, effects of time and square value of time and random effects of intercept, effects of time and squared value of time for each batch and pen. The parameters from the model were used to construct a multivariate DLM for a batch of pigs. In the study, the growth of the pigs was smoothed retrospectively and the effects of events influencing the growth were investigated by comparing irregularities with information from a logbook of particular event such as feed changes or feed mistakes. Additionally, the DLM was used to forecast the number of pigs above a given threshold which could be used to predict optimal slaughter time. Compared to if only the initial weight of all pigs where known, the mean absolute deviation of the observed and predicted number of pigs above 105 kg in a single pen decreased by 1.4 and two pigs in the two batches, respectively, if 15.5 % of pigs in a section were weighed weekly.

In this study the main aim is to use a DLM as a monitoring tool. Thus, this method will be further described.

2.3.2 Dynamic monitoring of BW gain.

Normally, the information available for decision making is the farm personnel's own visual observations together with a monthly or quarterly production report, which provides information of production results from the former batches (Cornou and Kristensen, 2013; Madsen and Ruby, 2000). However, to improve the production process, dynamic production monitoring can be used. One of the main benefits of a dynamic monitoring system is that the information can be analysed to detect abnormalities and provide early warnings of potential problems, while changes still can be made (Dominiak and Kristensen, 2017; Stygar and Kristensen, 2018).

As reviewed by De Vries and Reneau (2010) primarily Shewhart control chart and cumulative sum control (Cusum) charts have been used in animal production to detect changes in production processes. The basic principle of a Shewhart control chart is a plot of the observations over time supplemented with a center line and upper and lower control limits (Kristensen et al., 2010). The center line represents the tendency of the process as a target value. Additionally, if an observation is plotted outside the control limits, it is evidence that the process is out of control (De Vries and Reneau, 2010). Thus, an alarm can be given. The basic assumptions for using a Shewhart control chart is that the error term is mutually independent over time (Kristensen et al., 2010). Shewhart control chart is useful in a process which is likely to be out of control due to the ability to detect large shifts in the monitored parameters (Montgomery, 2005).

Another type of control chart used in monitoring animal production is a Cusum control chart. The Cusum control chart incorporates past observations and is therefore sensitive to small shifts in a process (Montgomery, 2005). The preferred Cusum is the tabular Cusum. Thus, the tabular Cusum monitors the mean of a process. The tabular Cusum works by accumulating derivations from the mean that are either below or above the mean. By applying a DLM with Kalman filter, a forecast error was obtained for each new observation as described in Equation. 2.10. These forecast errors can be used to detect when a process deviates from a given target. Therefore, if the process is in control the forecast errors should fluctuate around a mean of zero. However, if an abnormality occurs the forecast errors would start to drift, as the forecast errors become either mainly positive or negative.

In several studies, a Cusum applied a DLM with Kalman filter is constructed to detect abnormalities in growth (Madsen and Ruby, 2000; Stygar and Kristensen, 2018).

Madsen and Ruby, (2000) developed a method for monitoring productivity in a continuous finisher production without using weighing data. In the study, it was assumed, that the heaviest pig was also the oldest. Thus, if the number of pigs inserted and the number of pigs delivered to slaughter is known, the average time to slaughter can be estimated and converted into an average daily gain each time pigs are delivered. This, average daily gain can be used as an indicator of irregularities. Thus, if something happened in the farm which affects the growth of the animals negatively, the time from insertion to slaughter will become longer. In order to account for the variance in the observations a DLM with a Kalman filter was used to filter the average daily gain. The study showed that the interval from a decrease in productivity until the time it is realised can be shortened. However, the information from the system is still historical.

Frequent BW observations are needed for monitoring an ongoing production. Stygar et al. (2017) developed a precise description of hourly growth. In the study, BW data was collected on a commercial finisher herd with four large common pens with a maximum capacity of 400 pigs in each pen. Each pen was separated in a feeding area and a resting area. Therefore, each time a pig wants to eat it has to pass through a passageway where it is weighed. Consequently, each pig was weighed several times a day. Data from five batches of pigs were used. Thus, a total of 1,710 pigs and 243,160 BW measurements. The data were analysed in order to construct a mixed effects model of pig growth similar to the model used in the study of Stygar and Kristensen (2016), supplemented with fixed effects for the amplitude and frequency of a cosine wave. The cosine wave was used to account for diurnal pattern in daily BW of pigs. Because, it was found, that the pigs were lighter in the morning compared to the evening. In the study the daily variation of the individual pig’s BW was 1.2 kg.

The model parameters obtained in the study of Stygar et al. (2017) was in a study of Stygar and Kristensen (2018) used as a monitoring tool to alert farm personnel if abnormalities in growth occurred. The tool was built as a DLM with Kalman filter where the initial parameters were estimated from historical data. The data analysed in the study were obtained from three batches of finisher pigs from a commercial finisher herd in a large common pen, with a capacity of 400 pigs. The pigs were identified by an electronic ear tag within each weighing. Therefore, a tool for both individually identified and unidentified pigs, was constructed. The DLM with Kalman filter was applied every time a weighing of a pig was observed. Thus, if the growth of the pigs grew as expected the forecast errors should fluctuate around zero. However, if an abnormality occurs the forecast errors start to drift. In order to detect these changes, a standardized tabular Cusum was constructed at batch level for both the unidentified pigs and the identified pigs. Additionally, a similar Cusum was constructed at pig level when each pig was identified. The study showed that the constructed tool was able to detect major abnormalities in growth at both pig and batch level using identified observations and at batch level using unidentified observations. The specificity and the sensitivity of the tool will depend on the parameters set in the Cusum. Thus, if either too few or too many alarms are given, the setting can be changed.

Summary

Frequent BW observations from an automatic weighing system needs to be filtered and analysed in order to obtain useful information. Several methods can be used such as moving average, EWMA or a DLM. The DLM starts with some basic assumptions, but is adaptive to the current situation.

Studies have shown, that a DLM can be used to analyse BW information, to predict time of slaughter and to detect abnormalities in growth.

If only the number of pigs at insertion and slaughter is known, a DLM with Kalman filter can be used to filter data in order to smoothen observations with variance. If the weight at insertion and a subset of pigs is weighed weekly, a DLM can be used to account for the variance between pens. If frequent BW measurements are available, a DLM can be used to give early warnings.

Primarily Shewhart control chart and Cusum charts have been used in animal production to detect changes in production process. Shewhart control chart is mainly used to detect large shifts in the monitored parameters. Whereas, Cusum charts can detect smaller shifts.

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The following manuscript follows the instructions for authors of *Computers and Electronics in Agriculture*

Detecting abnormalities in weight gain in finisher pigs using automatic camera weighing.

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Key words: Camera weighing, Detecting abnormalities, Dynamic linear model, Finisher pig, Growth, ProGrow

Abstract

Increased sizes of finisher farms sets higher demand for the farm employees. Hence improving the overview of the farm is essential. Frequent information of the daily gain would allow farm employees to monitor performance and health. However, traditionally weighing pigs has been a labour intensive task. Recently, several image weighing systems have been developed to obtain group-weight assessment continuously. The data generated from an automatic weighing system must be filtered and analysed to be useful in a monitoring system. Thus, the objective of the present study was to use a dynamic linear model with Kalman filtering to detect abnormalities in pen-weight data from a commercial finisher pig farm obtained from an image weighing system. For this study, data was obtained as raw data from the commercial available automatic weighing system ProGrow (SKOV A/S, Roslev, Denmark). The data originated from two similar Danish commercial farms (herd 1 and herd 2). A total of 34 pens was used from nine batches. The nine batches were distributed as five batches from herd 1 and four batches from herd 2. Eighteen pigs were inserted in each pen at approximately 30 kg and monitored until time of slaughter. The sections consisted of 16 and 42 pens at herd 1 and herd 2, respectively. However, ProGrow was only installed in four pens at each farm. On average 30,607 body weight (BW) observations from each camera were recorded during the growth period of the pigs. A hierarchical quadratic mixed-effects model was fitted on data from 31 pens (batch 1-8). The last batch from herd 1 was obtained during the study. Thus, it was used to test the system. The final model included fixed effects of intercept, time and square value of time. Furthermore, random effects of intercept and time within batch. Finally, random effects of intercept, time and squared value of time of pen within batch. The random residuals were assumed independent for different batches, pens and time effects. The variance increased over time. Thus, the power of absolute value of variance used to estimate the variance. The parameters and variance components from the mixed-effect model were used to build a dynamic linear model (DLM). The DLM was updated using a Kalman filter at each new observation. The forecast errors obtained from the Kalman filter was standardized and monitored with a one-sized tabular cumulative-sum control chart (Cusum). The constructed tool was tested on data from herd 1 (batch nine) by plotting the filtered growth. The alarm system was tested with different values of the decision interval and reference values. Thus, in future studies the tool constructed in this study should be tested and the decision interval and reference values should be adjusted to the farmers preferences. Because, no information of irregularities in the BW from the herd was available, the tool was tested on simulated BW data with a known event of depressed growth to demonstrate the potential. In this study it is demonstrated how frequent obtained BW data from an automatic weighing system as ProGrow can provide alarms on growth.

Introduction

Danish pig production has evolved rapidly in recent years, as it is moving towards fewer farms with increasing herd size (Christiansen, 2017). However, the increased herd size sets a higher demand for the farm employees. Hence, improving the overview of the farm is essential to ensure high production, health, and animal welfare. The overview of a herd can potentially be improved by using an integrated monitoring system which can detect abnormalities and provide early warnings to the farm employees (Frost et al., 1997).

The growth of finisher pigs is important, as it determines the profitability of the farm (Schofield, 1990). Furthermore, frequent body weight measurements can be used for monitoring health and welfare problems (Cornou and Kristensen, 2013). Currently, the growth information is a combination of the farm employees' observations and typically a monthly or a quarterly report (Cornou and Kristensen, 2013; Madsen and Ruby, 2000; Parsons et al., 2007). Traditionally, weighing pigs has been a labour intensive and time consuming task (Brandl and Jørgensen, 1996) which might have negative implications for the pigs (Augspurger and Ellis, 2002). However, technologies have proven to be able to weigh pigs automatically and none invasively, using weigh platforms (Williams et al., 1996) or camera weighing (Brandl and Jørgensen, 1996; Schofield et al., 1999).

Recently, several commercial image weighing systems have been developed in order to obtain group-weight assessment continuously (Tscharke and Banhazi, 2013b; Vranken and Berckmans, 2017). These systems have the advantages of no equipment needed to be installed within reach of the pigs, where it would be vulnerable (Frost et al., 1997). Additionally, this method overcomes much of the safety risk, labour, and costs associated with the traditional methods (Tscharke and Banhazi, 2013b). However, these systems are not able to identify the individual pig. Furthermore, the system can have a large variability between weight samples collected on the same day. Thus, data analysing and filtering are needed (Tscharke and Banhazi, 2013b).

In order to provide valuable information, the data generated from an automatic weighing system must be analysed. Frequent BW measurements can be analysed using a dynamic linear model (DLM) with a Kalman filter (Stygar et al., 2017; Stygar and Kristensen, 2016). Furthermore, the DLM can be used as a monitoring system, to detect abnormalities in the growth of the pigs (Stygar and Kristensen, 2018).

The objective of the present study was therefore to use a dynamic linear model with Kalman filtering to detect abnormalities in group-weight data from a commercial finisher pig farm obtained with an image weighing system.

Material and methods

Housing and Animals

Weighing data were collected in two Danish commercial finisher herds (herd 1 and herd 2) using the ProGrow system (SKOV A/S, Roslev, Denmark). The two farms were similar because both farms had the same owner and the pigs came from the same sow herd. Thus, the genetic and health status of the pigs were comparable. Additionally, the same manager managed both finisher herds.

Herd 1 consisted of four sections with 16 pens in each section. Each pen measured 6.5 m x 4.5 m. The pens were paired into double pens, with the two pens in each double pen sharing a single dry feeder (TuboMat, Egebjerg). The floor in each pen was composed by 1/3 drained floor and 2/3 slatted floor. The pigs had access to water through two water nipples at the dry feeder and one additional water nipple in the opposite side of the pen. Artificial light was provided for eight hours a day. Furthermore, the sections had windows in the north side. The ventilation was a negative pressure system (SKOV A/S) with diffuse air inlet and three outlets in each section.

Herd 2 consist of one large section of 42 pens. Each pen measured 6.5 m x 4.5 m. The pens were paired into double pens with a single dry feeder (Funki) per double pen. The floor in each pen was composed by 1/3 drained floor and 2/3 slatted floor. The pigs had access to two water nipples at the dry feeder and one additional water nipple in the opposite side of the pen. Artificial light was provided for eight hours a day. Furthermore, the sections had windows in both sides facing east and west. The ventilation was a negative pressure system (SKOV A/S, Roslev, Denmark) with diffuse air inlet and eight outlets.

At both farms all pigs were fed ad libitum during the fattening period. The pigs were during the fattening period fed one of three different feed mixed based on the body weight (BW). The feed was changed when the smallest pig in the section was 45 kg and again at 85 kg based on observed BW estimated from ProGrow. At both farms two woodblocks were provided for each pen to meet the requirement of rooting and enrichment materials.

On both farms 18 pigs with an approximate BW of 30 kilos were inserted in each pen at the start of a batch. The pigs were not sorted by gender or size within the section.
The finisher pigs were a crossbreed, D-LY, the dam of the pigs was a cross breed between Danish Landrace and Danish Yorkshire, and the sire was purebred Duroc.

On both farms any sick pigs were moved to a special sick pen in a separate section. In this study, the number of pigs in the pen were not noted. Thus, it was assumed that the BW of any removed pigs would be equal to the pen average. This was a practical assumption, because the removal of sick pigs would be a rare occurrence, and because the system should be automatic and not need additional registrations from the farm manager. However, if the pig removed from the pen was much larger or smaller than the pen average BW it could potentially affect the observed pen average BW.

The pigs where delivered to the abattoir over a period of three weeks starting 60 days after insertion. The heaviest pigs were delivered first, which would affect the average weight in the pen in a negative direction. Therefore, we only used the first 60 days after insertion to estimate the model parameters for this study.

Image weighing

In this study, the BW is obtained from cameras as part of the commercially available system ProGrow. ProGrow is a management concept where climate data, water intake, feed intake and camera weighing are collected. In this study, however, only the weighing data were used.

The image weighing system (ProGrow) was installed in one section in each of the two herds. In each section where ProGrow was installed, a total of four pens were weighed. Thus, four cameras were installed. The cameras were located on top of the area where the pigs would be standing when eating from the feeder, as seen in Figure 1. The cameras were connected to a CWS controller box (DOL 68, SKOV A/S, Roslev, Denmark) where the images were processed, in order to perform weight estimations.

Figure 1. Image from herd 1 showing the pen and the placement of the camera above the feeder (indicated by a blue arrow).

The image weighing was performed in several steps. In the first step, it was detected if a pig was present in the scope of the camera. The pig was detected by a change in the contrast from darker background to the brighter pig. If a pig was present, one of four "hotspots" in front of the feeder was activated and a still picture was obtained. The hotspots can be seen at Figure 2.

Figure 2. Image showing a pig standing in front of the feeder. At the image the four hotspots can be seen overlayed on top of the pig. Source: (SKOV A/S, Roslev, Denmark)

From the still picture of a pig, several tests are made to validate the picture: The ratio between the length and the width of the pig has to be in a certain interval, the rear end and the front end has to be approximately the same size, and the contrast has to be lighter in the middle of the pig and darker at the boundary of the pig. These boundaries can be changed if either too many pictures are rejected or if to many are accepted. In Figure 3. an accepted picture of a pig can be seen.

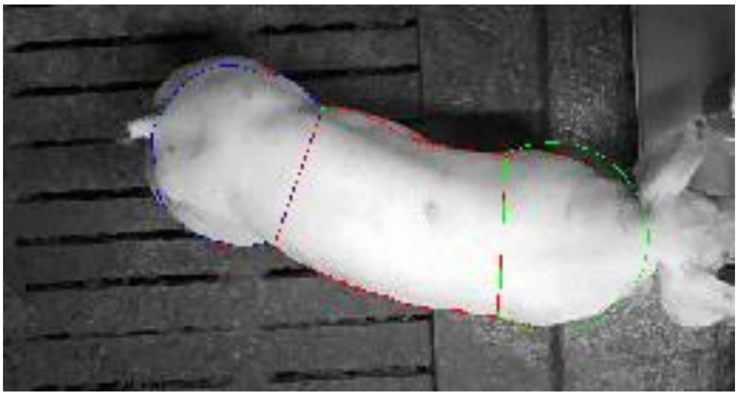


Figure 3. Image showing an accepted picture of a pig, the front and rear end is illustrated with the green and blue boarders. Source: (SKOV A/S, Roslev, Denmark)

If a still picture is taken, and the image is accepted, the perimeter of the pigs without the head and neck is recorded and converted to a measurement of the weight of the pig. The conversion method is not known to the author. The height of the pig is not visible at the top view image. Hence, the height is estimated as a linear coefficient of the body size. A maximum of five pictures of the same pig can be taken at each visit to the feeder. Each measurement was recorded as a weight estimation and a timestamp and send to a computer.

Normally, the weighing data from ProGrow are filtered in the computer system FarmOnline (SKOV A/S, Roslev, Denmark). Thus, measurement noise is removed and a daily section average and deviation from the daily section average is provided. However, in this study, raw unfiltered data were provided from the company.

Explorative analyses

The data used in this study were historical data obtained from two commercial farms. Thus, only little information from the batches were available. Hence, to get an overview of the observations of BW an explorative analysis was done by summarizing the number of observations, and by plotting observed BW as a function of time. Moreover, the number of observations as a function of the hour of the day were plotted. All analysis and data visualizations were done using R, a language and environment for statistical computing (R Core Team, 2018).

In Table 1, both the total number of observations per batch and the number of observations per camera within each batch can be seen. A total of eight batches was used to estimate the parameters for the model. Additionally, a test data set from Herd 1 became available during the writing period of this study. The test data set was used to test the performance of the system developed. Observations from a total of 34 pens were recorded, due to missing observation from camera 2 in batch number 4 and from camera 2 in the test set. Normally, the weighing measurements from ProGrow is combined at section level and an alarm is given if the total number of images from all four cameras is under 100 images per day. However, this approach meant that some of the pens were plagued by missing observations. Thus, in this project, each pen was observed separately. The missing observations could be due to technical errors of the camera or simply that the lens on the camera was dirty.

Table 1. Overview of the data set included in this study. The 8 first batches were used as learning data and the last was used for testing.

				Number of observations per camera			
Batch	Insertion date	Total Number of observations	Herd	No. 1	No. 2	No. 3	No. 4
1	21-06-2017	189,521	1	46,557	46,212	64,691	32,061
2	05-10-2017	154,367	1	26,435	45,832	40,806	41,294
3	28-12-2017	180,914	1	38,041	42,234	61,926	38,713
4	18-04-2018	123,971	1	31,950	-*	53,807	38,214
5	27-07-2017	83,749	2	11,749	14,175	36,504	21,321
6	24-10-2017	116,220	2	24,140	20,920	33,665	37,495
7	01-02-2018	116,749	2	63,809	1,655	15,656	35,629
8	25-04-2018	137,680	2	33,188	14,634	54,214	35,644
Test	18-07-2018	165,974	1	48,758	-*	68,052	49,164

*Data from camera was missing.

The data were corrected as days after insertion using the lubridate packages for R (Spinu et al., 2018). Thus, each timestamp was set as the numeric length from the insertion date. The initial timestamp generated from the ProGrow system was divided in date and time. For example, if a measurement in batch 1 was obtained at 22-06-2017 at 06:01:02, the time after insertion was 1.250718 days after insertion. The raw weight data of each pen from each batch were plotted as a function of the time to get an overview of missing or irregular data. A regular pattern is exemplified in Figure 4A. Moreover, a pen with days missing observations is exemplified in Figure 4B.

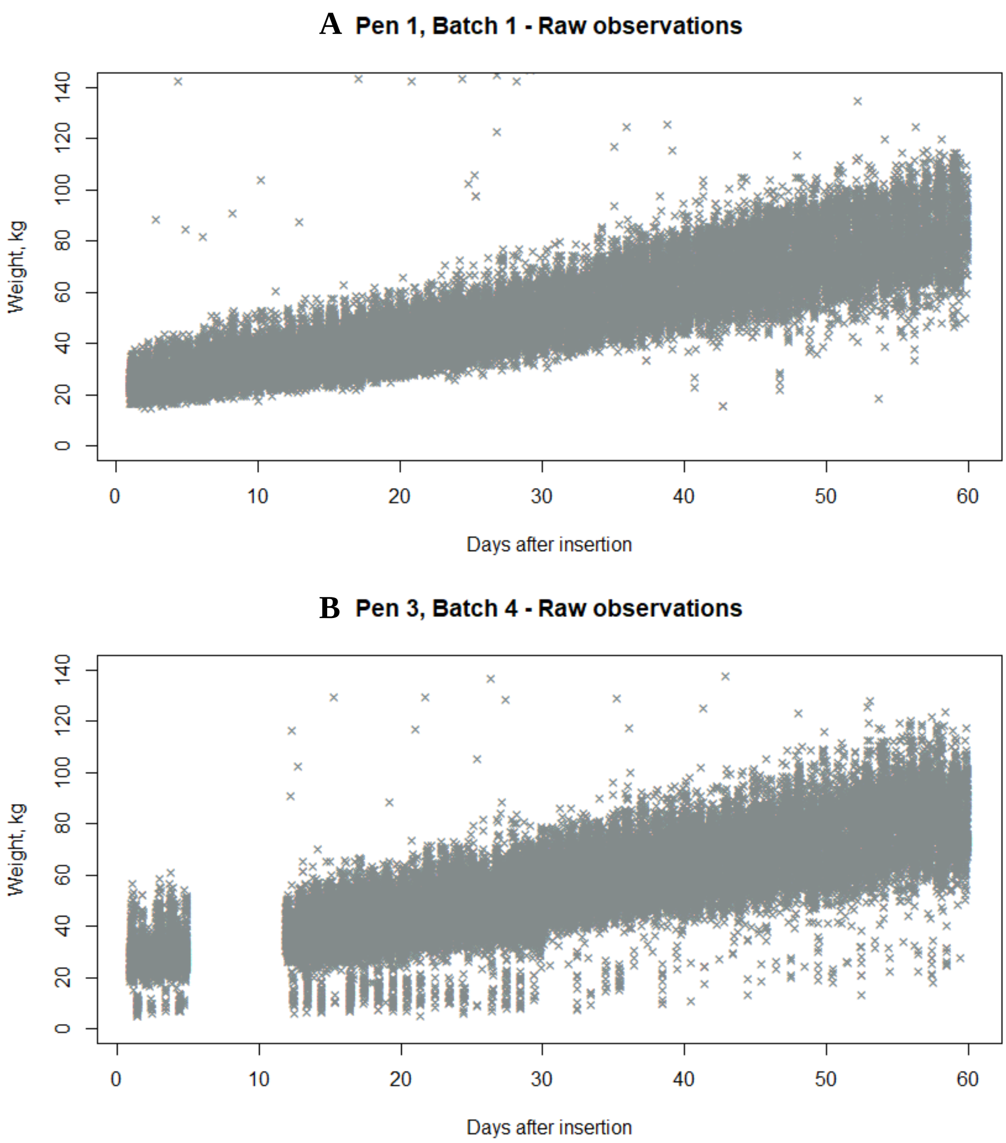


Figure 4. Raw observations of all weight estimations as a function of the number of days after insertion (grey crosses). Examples of A: regular pen (Herd 1, Pen 1, Batch 1) and B: pen with missing observations from day five to day 11 (Herd 1, Pen 3, Batch 4).

The number of observations was plotted as a function of day after insertion as exemplified in Figure 5. The plot shows that the number of observations per day declined during the growth period.

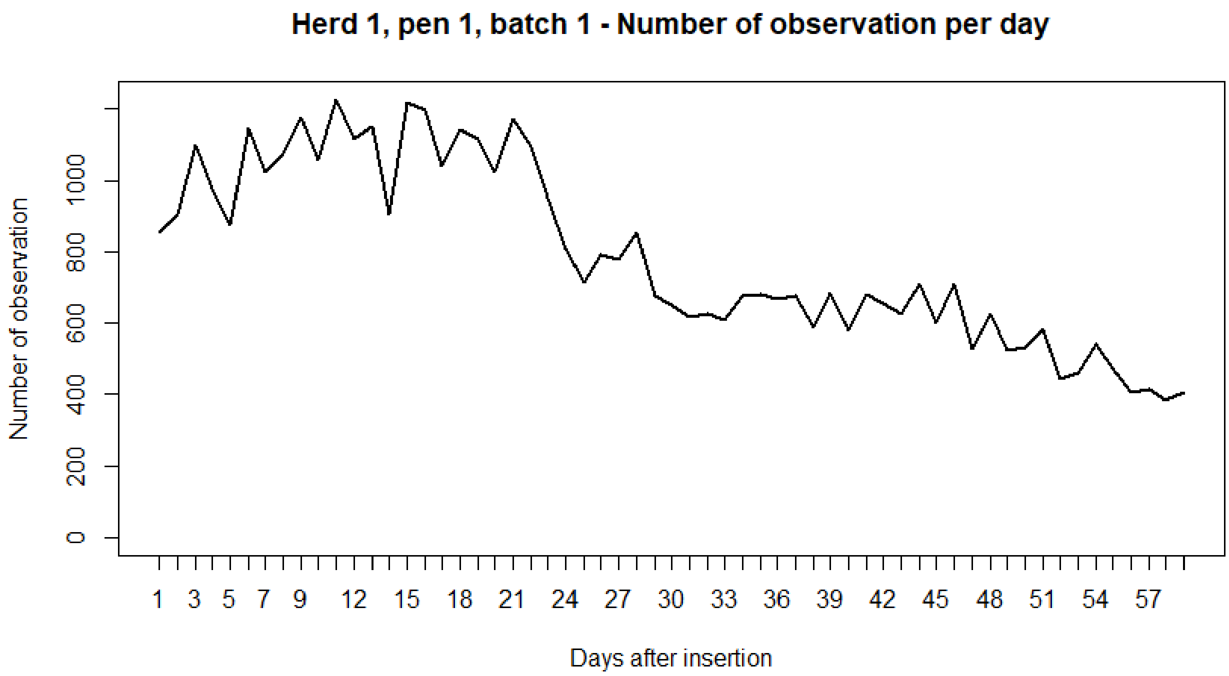
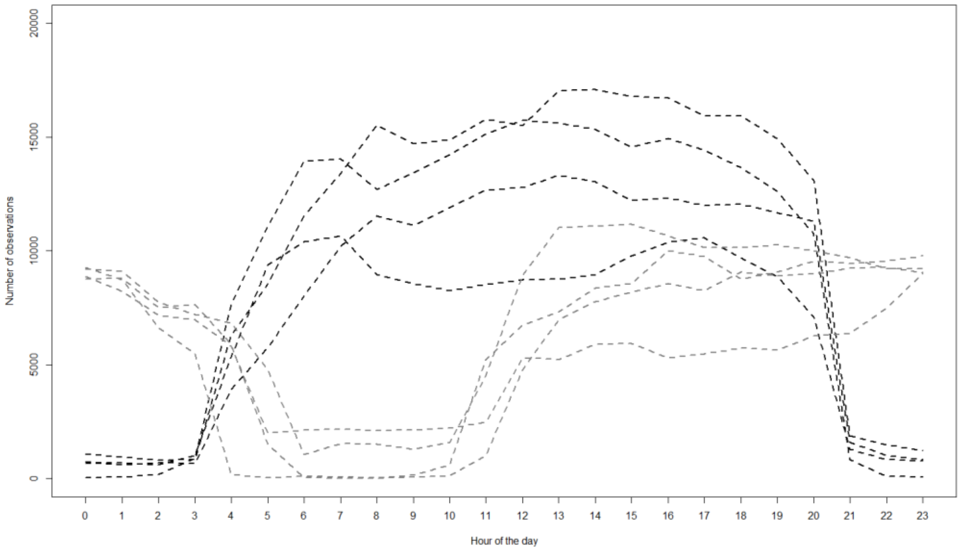


Figure 5. Number of observations as a function of the number of days after insertion (black line) (Herd 1 pen 1 batch 1).

Figure 6 represents the amount of observations as a function of the hour of the day in both herds. It was expected that only a few images were obtained during the night, as the BW observations were obtained by camera vision using a 2D camera and ambient light to detect the perimeter of a pig. Thus, light in the section was important to obtain reliable estimates. Additionally, the activity level of the pigs was expected to be lower during the night. The pattern seen in Figure 6A from herd 1 (black dotted line) match the expectations where very few observations were made between 9 pm and 3 am. It can, however, be seen from Figure 6A that the pattern of herd 2 (grey dotted line) was different with only a few observations between 5am and 10 am. This was most likely due to a wrong setting of the time in herd 2. The time was therefore corrected with plus 17 hours as seen in Figure 6B.

A



B

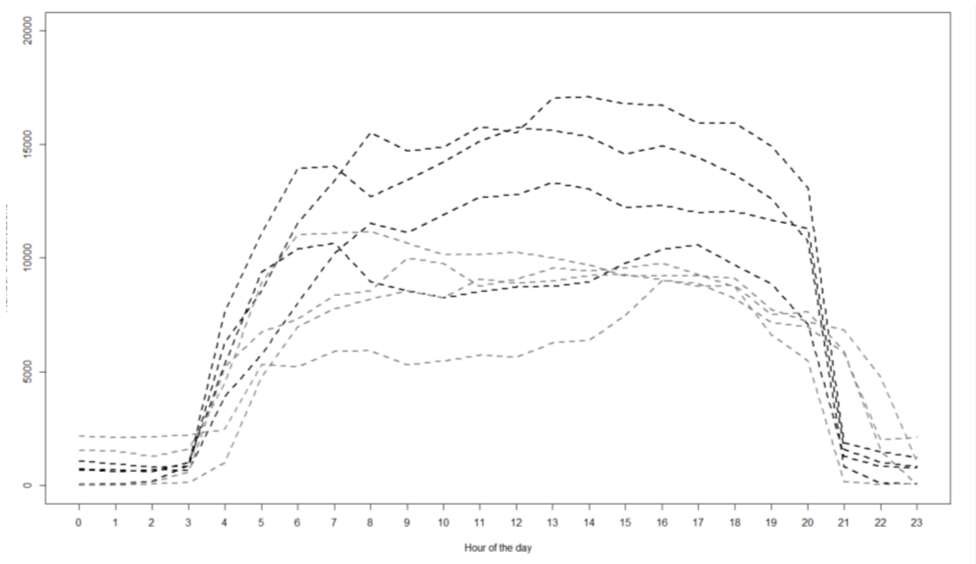


Figure 6. Number of observations as a function of the hour of the day for herd 1 (black dotted line) and herd 2 (grey dotted line). A) Before correction, and B) after correction.

The explorative analysis showed that the weight estimates made during the night period were unrealistically low (outliers) due to the lack of light in the section during the night hours. Normally, this data would be filtered away automatically by the ProGrow system, which removes the lowest 25 percent of the observations per day. For these reasons, only weight estimate data made between 4 am and 10 pm were included in the current study. This removed some outliers. However, the explorative analysis showed, that some pens were still plagued by outliers. These outliers were in this study not removed, thus the DLM should be able to cope with all observations.

Parameter estimation

The explorative data analyses showed difference in initial BW, growth rate and slope of the growth rate between each pen and batch. Furthermore, the variance in observations increased over time. The pens within the batches represented pigs from the same weaning thus batch effects were also expected.

To estimate the parameters and variance components needed to model the mean live weight over time, a static mixed-effects model was mas made using the nlme package in R (Pinheiro et al., 2018). The observed BW(Y_{jkt}) of a pig was described as a function of the pen *j* and batch *k* over time after insertion *t* as:

$$Y_{jkt} = (\beta_0 + B_{0k} + b_{0j,k}) + (\beta_1 + B_{1k} + b_{1j,k})t + (\beta_2 + b_{2j,k})t^2 + \varepsilon_{jkt} \quad (1)$$

,where $\beta_0, \beta_1$and β_2 are the fixed effects of intercept, time, and square value of time. The random effect vector of batch $B_k = \begin{bmatrix} B_{0k} \\ B_{1k} \end{bmatrix}$ and the random effect of pen within batches $b_{j,k} = \begin{bmatrix} b_{0j,k} \\ b_{1j,k} \\ b_{2j,k} \end{bmatrix}$ were assumed to be independent, so that

$$N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{B0}^2 & 0 \\ 0 & \sigma_{B1}^2 \end{bmatrix}\right)$$

and $N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{b0}^2 & 0 & 0 \\ 0 & \sigma_{b1}^2 & 0 \\ 0 & 0 & \sigma_{b2}^2 \end{bmatrix}\right)$

The random residuals $\varepsilon_{jkt\ \sim N(0,\sigma_t^2)}$ are assumed independent for different batch, pen, and time effects.

Variance components

The explorative analysis suggested that the variance of the live weights would increase over time within a given pen. For this reason, three variance models were tested. The three models were: 1) power of the absolute value of variance covariate, 2) an exponential function of covariate and 3) a constant plus power of covariate variance functions. These functions are furtherly described by Pinheiro and Bates (2000). The chosen model was the power of the absolute value of variance model based on the highest adjusted R^2 value (0.7635) corresponding to the variance model:

$$\sigma_t^2 = \sigma^2 |t|^{2\delta} \quad (2)$$

Where σ^2 is the variance for t=1 and δ is a constant.

Autocorrelation

A serial correlation structure was considered, because the data consist of repeated measurements of each pen. An exponential spatial correlation was tested because measurement data are not equidistantly distributed over time. However, it was not possible to estimate a correlation different from zero, as the within-group errors could not be separated from the general errors of estimations.

Model validation

The ANOVA method was used to test significance of the parameters of the model (p<0.05), and parameters for the final model were selected by backwards elimination. The test showed no significant random batch effect for quadratic time (p=0.894). Thus, the final model was without random batch effect for quadratic time. Finally, the parameters used in the model were tested using adjusted R^2 values, in order to avoid overestimating the model.

Model parameters

The final model parameters estimated from the eight batches can be seen in Table 2.

Table 2. Parameters implemented in the DLM.

Parameter	Symbol	Value	Standard error	P-value
Fixed effect for intercept	β_0	26.744719	0.9225273	< 0.01
Fixed effect for time	β_1	0.830208	0.0708756	< 0.01
Fixed effect for quadratic time	β_2	0.004107	0.0005175	< 0.01
Standard deviation in random batch effect for intercept	σ_{B0}	0.08838439		< 0.01
Standard deviation in random batch effect for time	σ_{B1}	0.1720983		< 0.01
Standard deviation in random pen effect within batch effect for intercept	σ_{b0}	5.098993		< 0.01
Standard deviation in random pen effect within batch effect for time	σ_{b1}	0.1994472		< 0.01
Standard deviation in random pen effect within batch effect for quadratic time	σ_{B2}	0.002852625		< 0.01
Residual standard deviation at time t=1	σ	3.598213		
Power of variance	δ	0.3005379		

Modelling

A Dynamic linear model (DLM) is constructed by an observation equation and a system equation. In this study, only a single batch is observed at a time. Thus, the herd effect and batch effect could be combined. However, similar to Stygar and Kristensen, (2018) the generic version was kept in order to be able to extend the model in future research.

In this study, the observation equation describes the observed BW Y_{jkt} at time *t* in the current batch in pen *j* as:

$$Y_{jkt} = \boldsymbol{F}'_{\boldsymbol{jkt}}\boldsymbol{\theta}_{\boldsymbol{t}} + v_t, \qquad v_t \sim N(0, \sigma_t^2) \text{ (3)}$$

Where $\boldsymbol{F}'_{\boldsymbol{t}}$ is the transposed design matrix, $\boldsymbol{\theta}_{\boldsymbol{t}}$ is the parameter vector, and $\boldsymbol{v}_{\boldsymbol{t}}$ is the random observation error.

The parameter vector $\boldsymbol{\theta}_{\boldsymbol{t}}$ was composed of 17 parameters with elements from three subvectors: herd $\begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}$, batch $\begin{bmatrix} B_{0k} \\ B_{1k} \end{bmatrix}$ and a vector of each of the four pens in each batch $\begin{bmatrix} b_{0j,k} \\ b_{1j,k} \\ b_{2j,k} \end{bmatrix}$ as:

$$\boldsymbol{\theta'}_{\boldsymbol{t}} = [\,\beta_0,\ \beta_1,\ \beta_2, B_0, B_1, b_{01}, b_{11}, b_{21}, b_{02}, b_{12}, b_{22}, b_{03}, b_{13}, b_{23}, b_{04}, b_{14}, b_{24}] \text{ (4)}$$

The design matrix $\boldsymbol{F}_{\boldsymbol{jkt}}$ indicates which of the four pens in a section that was observed, i.e. which parameters in the parameter vector $\boldsymbol{\theta}_{\boldsymbol{t}}$ should be used. As an example, the transposed design matrix for pen 2 in a batch at time t would be as follows:

$$F'_{2,t} = [1,\ t, t^2\ ,1\ , t\ ,0\ ,0\ ,0\ ,1\ , t\ , t^2\ ,0\ ,0\ ,0\ ,0\ ,0\ ,0\ ,0] \text{ (5)}$$

The system equation was defined as:

$$\boldsymbol{\theta}_{\boldsymbol{t}} = \boldsymbol{G}_{\boldsymbol{t}}\boldsymbol{\theta}_{\boldsymbol{t-1}} + \boldsymbol{w}_{\boldsymbol{t}}\ , \qquad w_t \sim N\big(\underline{0}, \boldsymbol{W}_{\boldsymbol{t}}\big) \text{ (6)}$$

Where $\boldsymbol{G}_{\boldsymbol{t}}$ is the system matrix, $\underline{0}$ is a zero vector and $\boldsymbol{w}_{\boldsymbol{t}}$ is the variance covariance matrix. However, in this study, the system equation can be reduced as: $\boldsymbol{\theta}_{\boldsymbol{t}} = \boldsymbol{\theta}_{\boldsymbol{t-1}}$. Thus, the system matrix $\boldsymbol{G}_{\boldsymbol{t}}$ will be an identity matrix and the variance covariance matrix $\boldsymbol{W}_{\boldsymbol{t}}$ is a zero matrix, as the parameters are expected to be constant.

Prior to the first observation the belief is that $\boldsymbol{\theta}_{\boldsymbol{0}}$ is distributed as:

$$(\theta_0|D_0) \sim N(m_0, C_0) \text{ (7)}$$

Where D_0 is the prior information, m_0 is the mean vector and $C_0$is a variance-covariance matrix. In this study, the mean vector m_0 is a vector with the length of 17 and consist of estimates for the fixed effects of the herd. The remaining part of the vector is zeros as:

$$\boldsymbol{m'_0} = [\widehat{\beta_0}, \widehat{\beta_1}, \widehat{\beta_2}, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] \quad (8)$$

The variance-covariance matrix $\boldsymbol{C_0}$ was a 17×17 matrix and it was constructed by a 3×3 matrix with the variance and covariance of fixed herd effects and diagonal of the variance of random effects of batch and pen within batch effects as:

$$\boldsymbol{C_0} = \begin{bmatrix} \sigma^2_{\beta_0} & \sigma^2_{\beta_{1,\beta_0}} & \sigma^2_{\beta_{1,\beta_2}} & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \sigma^2_{\beta_{0,\beta_1}} & \sigma^2_{\beta_1} & \sigma^2_{\beta_{1,\beta_2}} & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \sigma^2_{\beta_{0,\beta_2}} & \sigma^2_{\beta_{1,\beta_2}} & \sigma^2_{\beta_2} & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \sigma^2_{B0} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{B1} & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{b01} & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{b11} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{b21} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{b24} \end{bmatrix} \quad (9)$$

<u>Kalman filter</u>

The DLM was updated using a Kalman filter at each new observation, using the notation described by West and Harrison, (1997). The Kalman filter makes a short-term prediction for the next observation based on the prior information (Roush et al., 1992). The difference between the predicted response and the actual observation is the prediction error e_t which can be applied in an alarm system.

<u>Alarm system</u>

In this study a BW estimation was collected very frequently. In order to detect abnormalities in the BW gain of the pigs, a tabular cumulative-sum (Cusum) control chart method was used. If the process is in control, the Cusum should fluctuate stochastically with mean zero. However, if the underlying mean changes, the Cusum will drift. In this study, the tabular Cusum was used. The tabular Cusum is separated into an upper and a lower Cusum. If the accumulated deviation exceeds either the upper or lower decision interval *H* the process is considered to be out of control, and an alarm is given. In this study, only the lower Cusum is of interest, as it can detect persistent negative tendency in the growth.

In order to, apply the Cusum control chart, the standardized forecast errors were obtained similar to the method used of Stygar and Kristensen, (2018) as:

$$u_{tn} = \frac{e_t}{\sqrt{Q_t}} \quad (10)$$

, where e_t is the 1-step forecast errors and Q_t is the variance of the forecast model, which is calculated as part of the Kalman filter.

The lower Cusum value is defined as formulated by (Montgomery, 2005) as:

$$Cusum_t^- = \max[0, (0 - K) - SE_t + Cusum_{t-1}^-] \quad (11)$$

Where 0 is the target value and K is the reference value.

The reference value *K*, and decision interval *H* must be chosen in order to design the tabular Cusum. Generally, the *K* is chosen relative to the size of the shift desired to be detected. The shifts were expresses in standard deviation units. Thus, if K = 1 the aim is to detect two standard deviation units, and if K=0.5 the aim is to detect one standard deviation unit. The decision interval *H* is chosen in order to provide a long average run length performance. The higher the value of H, the more observations are needed before an alarm is giving. Similar to Stygar and Kristensen (2018) forecast errors higher than three standard deviation units was removed in order remove outliers.

<u>Simulated alarms</u>

In this study, no information of irregularities in the BW data from the herd was available. Thus, in order to test the performance of the alarm system a scenario with depressed growth was simulated. In order to make the simulations as close to a real scenario as possible, the timestamps from pen 1 in the test dataset was used to mark when the weight measurements were obtained. Before each simulation an initial mean $\beta_{0_{sim}}$, an effect of time $\beta_{1_{sim}}$, and a quadratic effect of time $\beta_{2_{sim}}$ were found from a normal distribution of the fixed effect at herd level as mean and standard deviations of random pen effect from the parameters estimated in the mixed effects model (shown in Table 2).

Because the true mean of the simulated observations ($Ysim$) at time t was assumed to be:

$$Ysim_t = \beta_{0_{sim}} + \beta_{1_{sim}} t + \beta_{2_{sim}} t^2 + \varepsilon_t \quad (12)$$

the daily gain was found as the differentiated function:

$$Y'sim(t) = \beta_{1_{sim}} + 2\beta_{0_{sim}} (13)$$

The simulated observation was then finally found as a random number from a normal distribution with $\beta_{0_{sim}}$ as mean and the variance function (eq. 2) as standard deviation. At each new day, the mean was updated by adding the daily gain $Y'sim_t$.

The abnormality was then constructed by decreasing the daily gain function $Y'sim_t$ at the days of the event. In this study, the abnormality was constructed as: - 20 %, -60% and -80 % in daily gain at day 20, 21 and day 22-25 after insertion, respectively.

Results and discussion

Model performance

The DLM was used to estimate the filtered mean from the three pens in the test data set. Thus, this data set were new information, which had not been used to define the model. To get an overview of the performance of the model in the three pens (data from pen 2 was missing due to a failure) the raw observation, the calculated daily mean, and the filtered mean is plotted for pen 1, pen 3 and pen 4 in Figure 7A, Figure 7B, and Figure 7C respectively.

As it can be seen on the plots, the DLM uses the first day to adjust to the individual pen. Thus, the blue line indicating the filtered mean is fluctuating unusually. This is caused by the pigs being inserted in the pens with different start weight. One approach to avoid this would be to manually weigh each pen or batch in order to derive the initial BW of the pigs, which could be used as a parameter in the DLM. On one hand, this would be an extra workload, which do not seem necessary. Because, the DLM seems to be stabilizing during the first day. However, on the other hand, most farmers already weigh their pigs when they are moved from one section to another. In that case, the extra workload of typing the weight into the system would be minor and the advantages greater. Thus, knowledge of the BW gain the first day after insertion can be of great interest for the farmer. Because, the pigs are vulnerable just after a move.

After the first day, the DLM seems to adjust to the current pen as the filtered mean is following the calculated daily mean until the time of the first delivery. However, as is seen on the plots, some of the calculated daily means are fluctuating, especially in the end of the growth period, due to fewer images per day. In order to present reliable information to the farm personnel, these fluctuations should be avoided. Thus, if the estimated BW is fluctuating, the user might lose trust

in the system. However, the filtered means estimated using the DLM seems in all three pens to be growing steadily. Thus, this mean can be reported to the farmer.
The model parameters (Table 2) were, only estimated on data from the first 60 days after insertion, due to first deliveries of pig at that point. Nevertheless, as seen in Figure 7 the filtering procedure seems to be able to continue after 60 days. However, in all tree pens a major negative dive in the calculated mean weight is realized around day 62 and again at day 76 after insertion. These dives are most likely due to the farmer sending the heaviest pigs to slaughter. Thus, removing the heaviest pigs will affect the pen mean in a negative direction. However, the filtered mean of the DLM applied in this study, does not seem to be affected by the drop in the mean. This is most likely due to the few measurements obtained in the end of the period. If the farmer was interested in the growth rate after deliveries, the systematic variance component of the DLM could be increased on the day when pigs are removed from the pen, thus making the DLM temporarily more adaptable to new observations.

In the explorative analysis of data, it was seen that the variance was increasing over time. Similar results have been found in other studies of frequent BW measurements where a scale was used (Stygar et al., 2017; Stygar and Kristensen, 2018, 2016). Thus, the increase is most likely due to the within-group variance of the pigs increasing, rather than an increase in variance of the BW estimations from the vision-based weighing system.

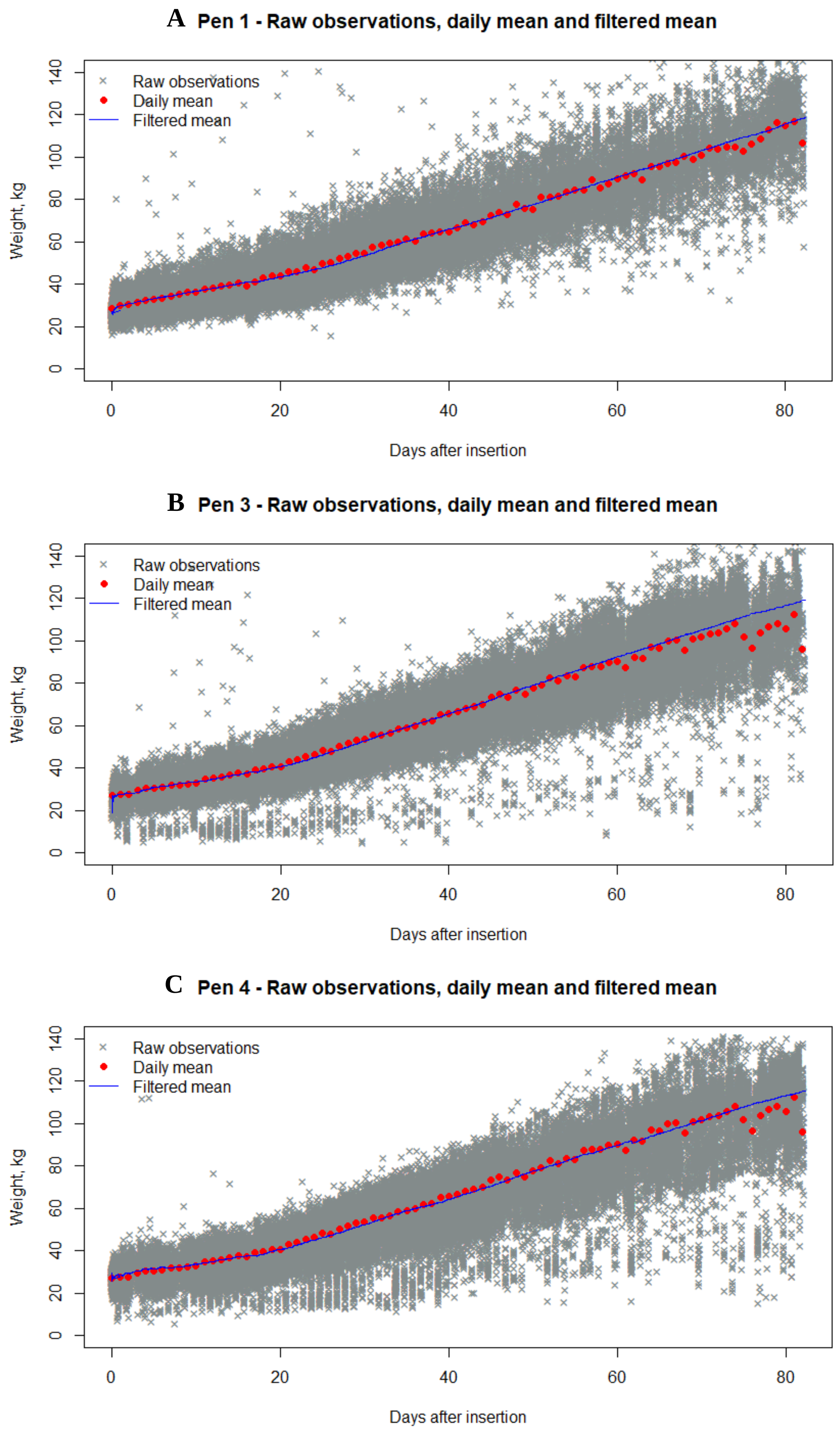


Figure 7. Growth of pigs - Raw observations, daily calculated mean and filtered mean from the test dataset (herd 1). A) Pen 1, B) Pen 3, and C) Pen 4.

Missing observations

The explorative analysis showed, that BW data were missing on some days. Because, the cameras are placed inside a harsh environment in a barn with dust, water, and flies, days with missing data cannot be avoided. As described by Jensen et al. (2018), however, a DLM can be designed to handle missing data; the DLM provides forecast values which are automatically adjusted over time based on the observations. When no observations are available, the DLM will continue to make its forecasts. When data again become available, the DLM will use the new observations to update its parameters according to the Bayesian framework described under Materials and Methods. In Figure 8, one of the pens with missing observations can be seen together with the raw observations, the calculated daily mean and the filtered mean. It can be seen, that in the period of the missing data, the filtered mean of the DLM still follows the trajectory described by its parameter vector. Thus, when observations are available again, the filtered mean still matches the calculated daily means.

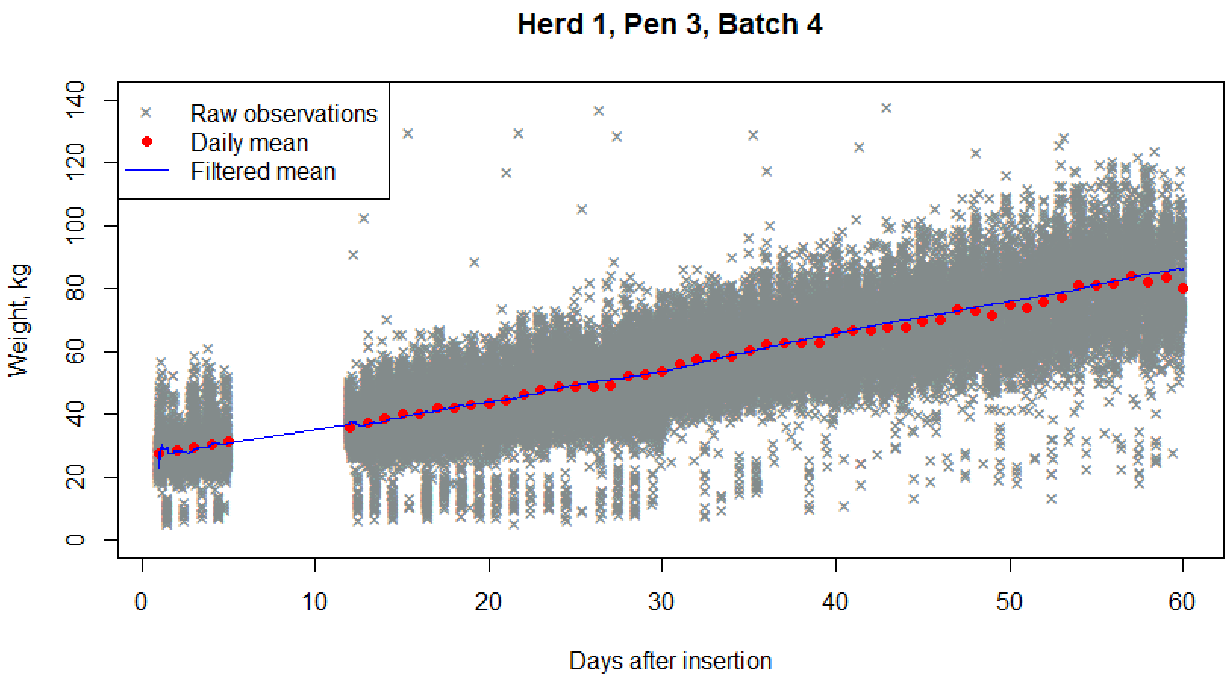


Figure 8. Example of missing observation - Raw observations, daily calculated mean and filtered mean.

Filtered means at batch level.

In Figure 9, the filtered mean curves of all four pens from the test dataset are plotted. As seen in the plot, the filtered mean of pen 2 is estimated, even though no observations were available. The parameter vector used in the DLM was designed so that effects of both batch and pen level were used. This implementation meant, that the observations from one pen also affected the estimated parameters of the other pens in the same batch. Thus, if image data were missing from one pen, the part of the parameter vector relating to that pen could still be updated based on information from the other pens. However, as seen in Figure 9, the growth of pen 2 is deviating from the growth of the other pens after approximately 30 days after insertion. This, is most likely due to the random effect of quadratic time, only was estimated as a pen effect within batch effect and not at batch level. Thus, each pen would find a individually quadratic time effect independent of the other pens.

In figure 9 it can be seen, that the filtered growth curves of pen 1 is above the filtered growth curves of the other pens indicating a higher mean weight in the pen. However, after day 40 after insertion, the filtered mean of pen 3 is above the other pens. These retrospective observations could potentially be used as a learning tool to optimize management in each pen if knowledge of events in the pens is known (Stygar and Kristensen, 2016). One example of events which could be investigated retrospectively is effect of shortage of feed placed in the pen. Thus, this could affect the largest pigs first. However, in order to detect this, data from more than one batch is needed (Stygar and Kristensen, 2016).

In this study, the DLM was applied at pen level, in order to analyse the effect in each pen separately. However, a different approach could be to estimate the growth at section level. This could be done by combining BW data from the four cameras in each batch. Because, as Udesen and Krogsdahl (2018) showed, the estimated weight using more than one camera at a time gives a better estimation for the whole section. In this study, an exponential spatial correlation, which was used in similar studies (Stygar et al., 2017) could not be estimated. However, if instead the DLM was applied at section level, a correlation between pens could most likely be found. Therefor, if a pen was above the batch average in one time observation, it would probably also be above in the next observation.

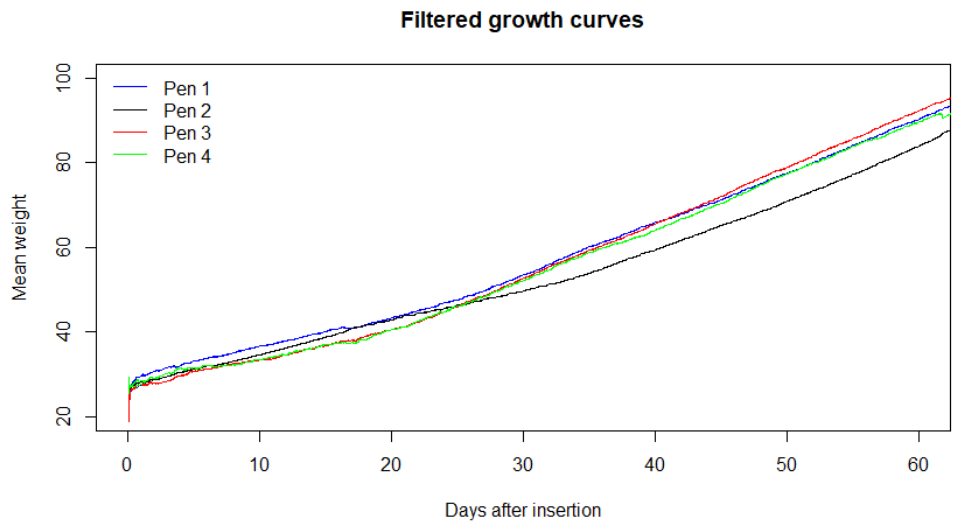


Figure 9. Filtered growth curves of the four pens (Pen 1-4) in the test dataset (herd 1).

<u>Diurnal pattern</u>

In this study, a diurnal pattern in growth at pen level was investigated, using similar methods as used in Stygar et al. (2017). However, the diurnal pattern in growth did not improve the model significantly, based on the adjusted R^2 value (0.76452 and 0.76450 without and with the diurnal component, respectively). In a study of Stygar et al. (2017) a diurnal amplitude for pig growth varied between 0.9 to 1.4 kg during a day during 5 batches. In their study, the BW observations were found using automatic scale measurements. However, in this study, the BW is found from camera weighing. To the authors knowledge, no other studies have investigated diurnal pattern in pigs growth from camera weighing, thus a comparison cannot be made. However, it is intuitive to think that the cause of the pigs being heavier in the evening than in the morning is due to the feed uptake during the day. These changes are likely too small to be detected using a camera. Another reason could be, that in this study it is not identified which pig is weighed. Thus, the smaller pigs might eat on different times than the larger pigs in the pen.

<u>Alarm system</u>

In this study an alarm system using a Cusum chart was implemented on data from the test data set using the method described by (Montgomery, 2005). In Figure 10, examples of alarms are plotted as red vertical lines at the time of the alarm. In this, study, no actual recordings of undesired events were available. Thus, different decision interval and references value were tested in order to give alarms to illustrate the effect. However, if the DLM-Cusum alarm system had been implemented at the farm, it was not known to the author whether any alarms should actually have been given.

The number of alarms will depend on the reference value K and decision interval H used as parameters in the Cusum. Thus, the sensitivity of the system can be adjusted. On Figure 10 B,C it can be seen, that increasing the decision interval from 10 to 15 results in fewer alarms from four (K=1, H=10) to two (K=1, H=15). Additionally, it can be seen on Figure 10A, that if the reference value K is decreased to 0.5 the number of alarms is increased to seven (K=0.5, H=15). These effect are further exemplified in Figure 11, where the corresponding lower Cusum charts for a reference value of 0.5 and 1 are shown for the same pen as used in Figure 10. On Figur 11 it can be seen, that if reference value is lowered, the lower Cusum values are higher. Consequently, the Cusum value reach the threshold more often. The same pattern was found in Stygar and Kristensen (2018) for both identified and unidentified pigs. The final parameters could be defined based on the choice of the farmer.

A general challenge is if an alarm system produces too many alarms because false alarms reduces the reliability of the system (Dominiak and Kristensen, 2017). In a study by Dominiak et al. (2018) an alarm system to detect systematic changes in water consumption using a standardized two sided Cusum was constructed. In the study, the optimal parameters used in the Cusum was found using an area under the ROC curve. However, this approach would demand that the alarms are verified, and correct and false alarms are noticed. Even though it seems easy, this could be a difficult task. It is the author's belief, that events such as feeding mistakes can be verified. However, illnesses without clinical sign would be more difficult (Weber et al., 2015). Thus, some correct alarms could potentially be verified as false positive. Additionally, it can be discussed that, because BW gain is one of the direct parameters of interest for the farmer, any sign of lowered growth should be reported. Even if no events occur in the farm, the growth is still lowered, and this could potentially give the farmer new knowledge to optimize from.

In this study, similar to other studies (Stygar and Kristensen, 2018, 2016), a quadratic growth term was included in the model. On one hand, the quadratic effect was significant and improved the model fit. Thus, the growth of the pigs was not a simple linear line. However, on the other hand, Madsen and Kristensen (2005) argued that a DLM used for monitoring for detection of abnormalities should not adapt to sudden changes. Thus, it is the deviation between observed data and the model predictions that is of interest. The quadratic effect makes the DLM more adaptable to shifts in BW gain, which could delay the time of an alarm.

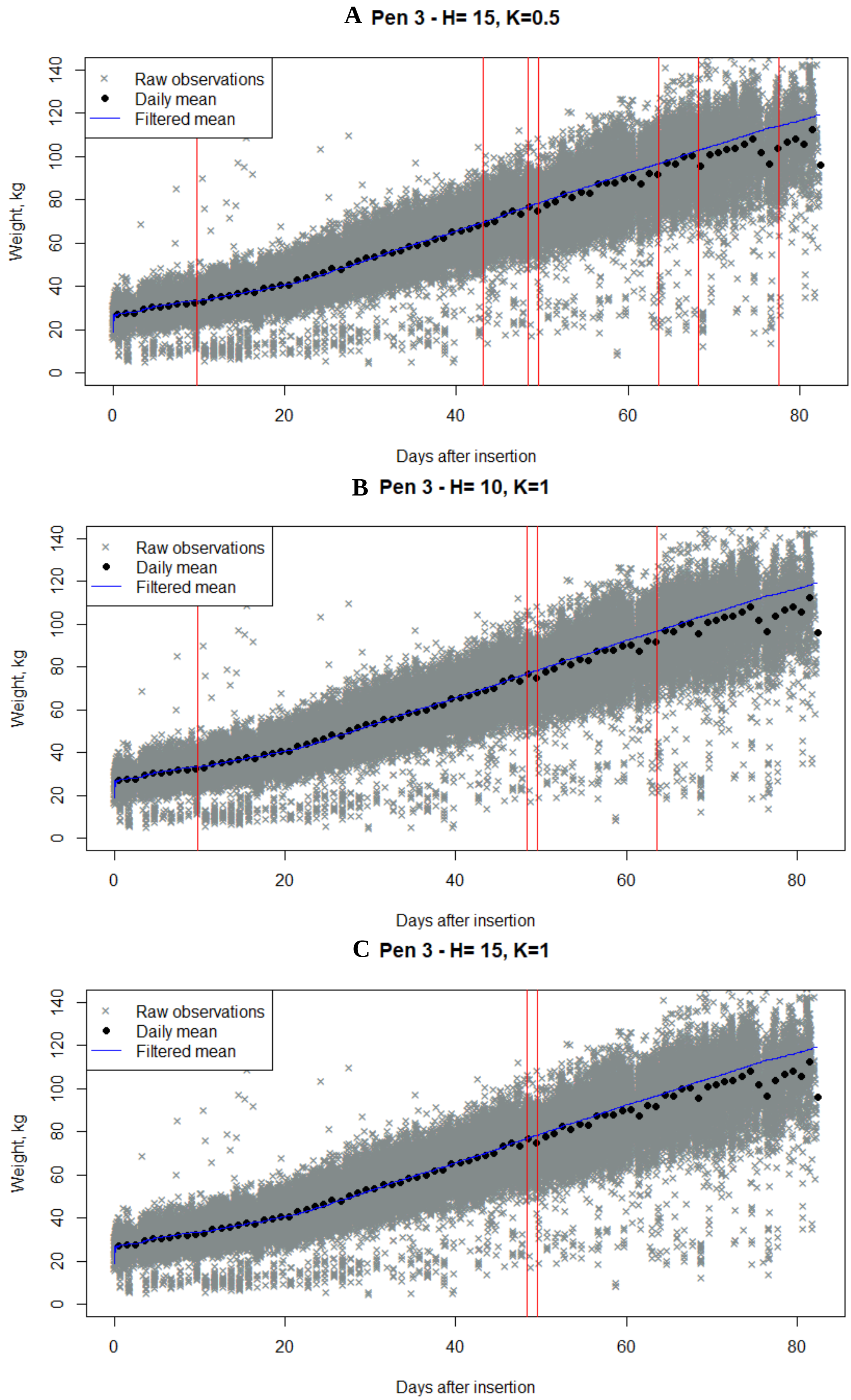


Figure 10. Pen alarms (red vertical lines) for different decision (H) and reference values (K)

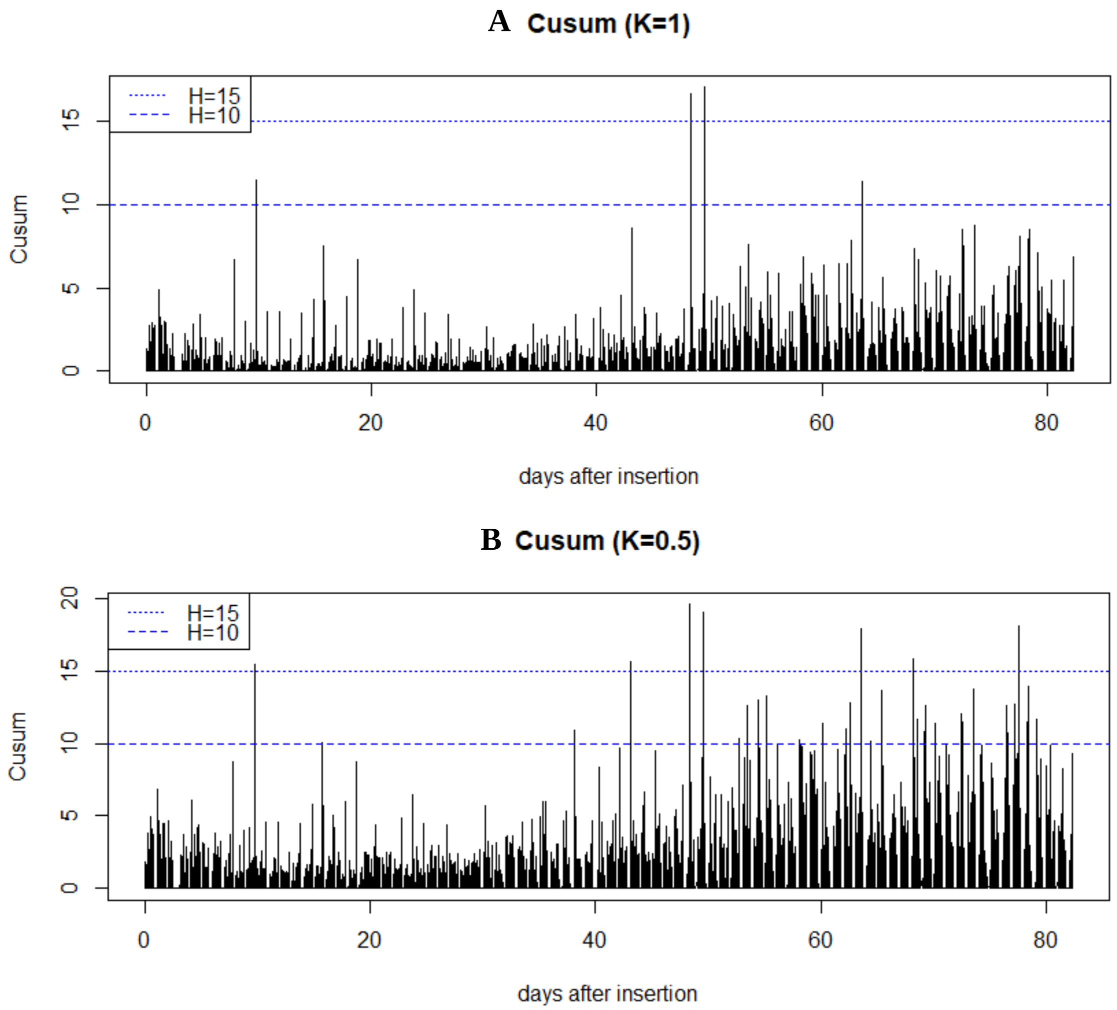


Figure 11. Lower Cusum charts for different reference values (K) and decision interval (H) showed at 15 and 10 (blue horizontal dotted lines) at both A), and B).

<u>Simulated alarm</u>

Because no information of undesired events was available from the herd data set, a scenario with simulated data was constructed in order to show the performance of the alarm system. In figure 12 the simulated dataset can be seen. The vertical dashed lines indicate the start and stop in the decreased growth. In this simulation alarms were given 22 and 24 days after insertion, as indicated by the red vertical lines (H=15, K=0.25). In Figure 12A it can be seen, that the shift in weight was small. Thus, it is difficult to see in the Figure 12A. However, at Figure 12B only day 10 to day 40 is shown. In this figure, it can be seen that after the first dotted line (start of event at day 20) the filtered mean was slightly above the calculated daily mean. Thus, the predicted mean was above the calculated daily mean. Consequently, the prediction errors started to shift, and alarms were given. After the event, (day 26) the DLM was adapted to the lowered growth. Thus, the following days the growth was underestimated.

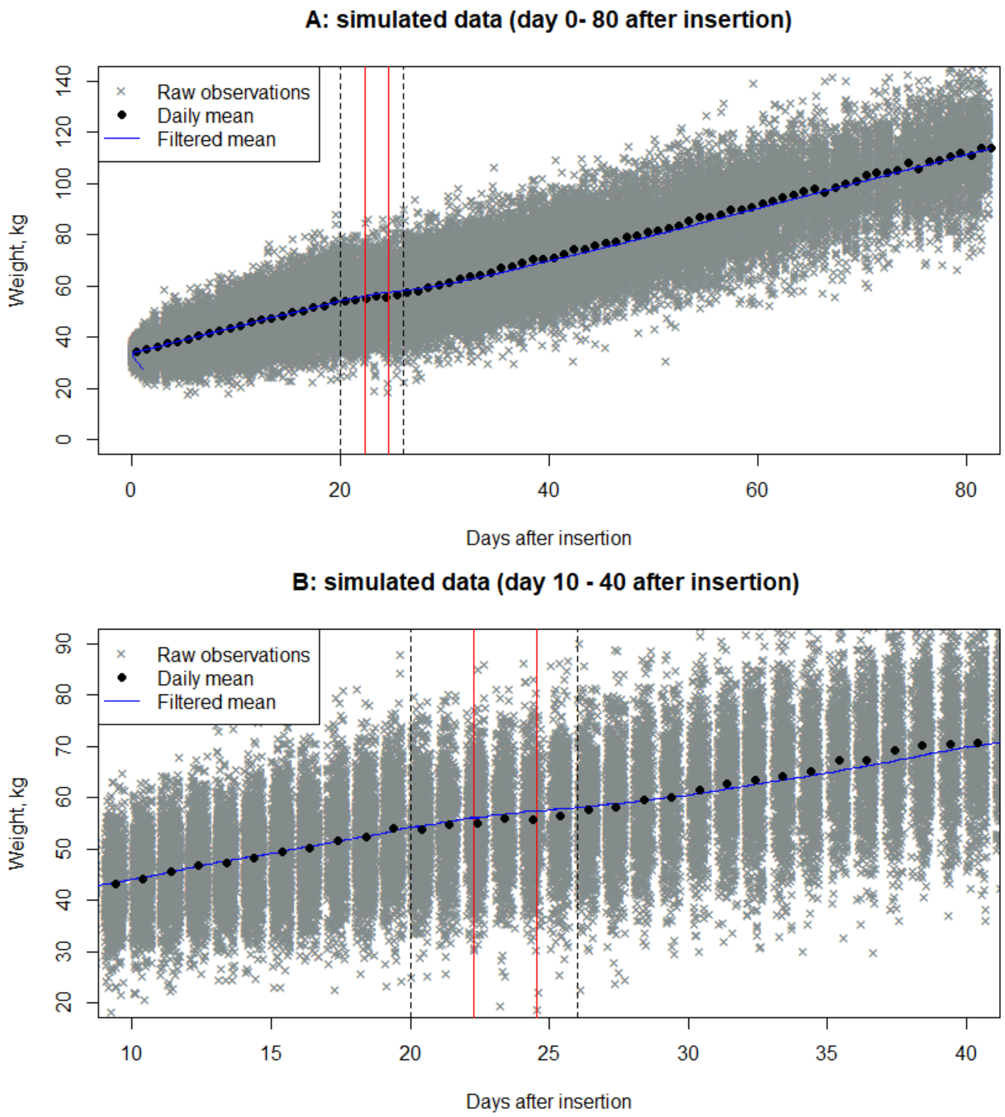


Figure 12. Pen alarms (red vertical lines) in the simulated data set with event of decreased growth between day 20 and day 26(dotted vertical lines). Simulation values: $\beta_{0_{sim}} = 30.7, \beta_{1_{sim}} = 1.00,\ \beta_{2_{sim}} = 0.003$. Decision interval (H) 15 and reference value 0.25.

In order to test the repeatability, the simulation was repeated 1,000 times. The number of alarms can be seen in Figure 13. The total number of alarms was 2,634 with 1,622 being in the interval between day 20 and 25. Thus, 61 % of the alarms were correct. The system gave at least one correct alarm 746 times of the 1,000 simulations or approximately ¾ of the times.

In Figure 13 it is seen that most alarms are given between day 22 and day 25 after insertion (grey). It is expected, that the Cusum will react a bit delayed from an event. Thus, the Cusum needs to reach the threshold value before the first alarm is given. On one hand, if the decision interval was lowered, the alarm would be given earlier. However, on the other hand more alarms (both false and correct) would be given.

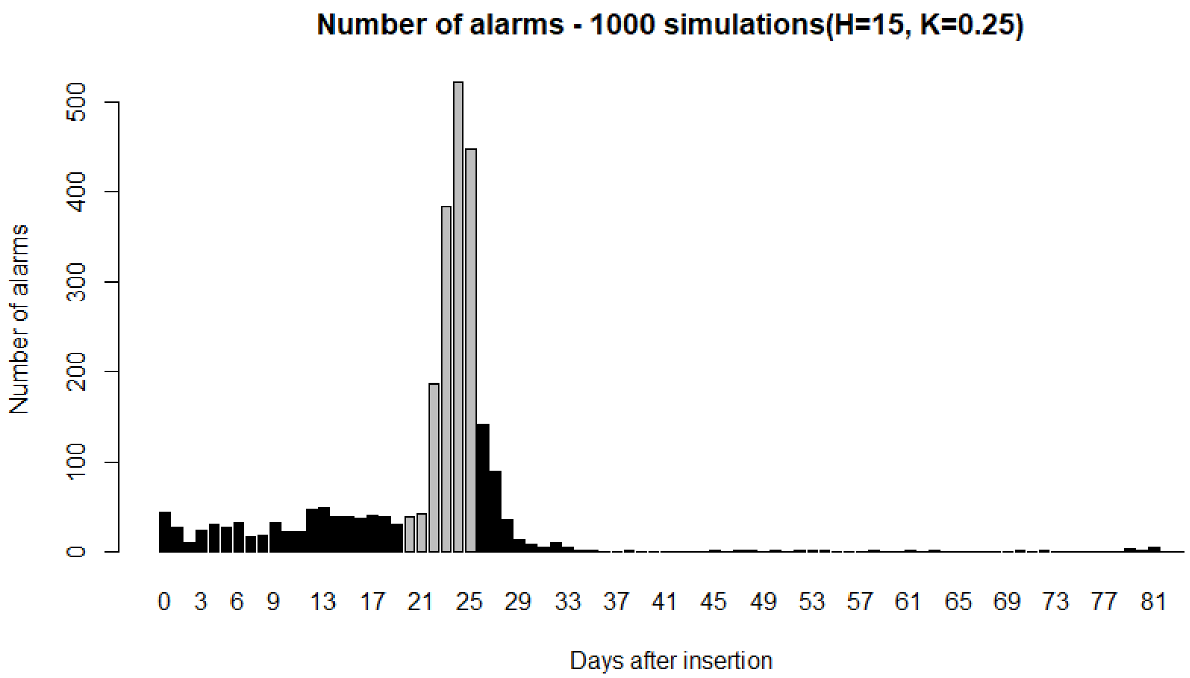


Figure 13. Frequency of alarms per day, when a simulated event occurs after 20 days. Alarms at the time of the simulated event (grey), alarms outside the time periode of the effent (black)

Future studies

In this study, a DLM was applied to frequent BW estimations obtained from the image weighing system which is a part of ProGrow. However, water consumption and feed conversion are also a part of the system. Thus, an alarm system combining the sensors could be implemented using a multivariate DLM, as implemented by (Jensen et al., 2017).

The performance of ProGrow cameras was recently tested by Udesen and Krogsdahl (2018). However, this test showed, that the variance from the estimated BW and the manually weighed BW was 0.2 % and 3.4 % in batch 1 and batch 2, respectively, which indicates fluctuation in the performance. This also indicates that further testing and development should be performed in order to increase the certainty of each measurement. Thus, a systematic error might influence the conclusion from an alarm system as the one presented in this study.

In this study, only limited data were available, due to that the ProGrow system is a relatively new system. However, as production continues, more data are collected. Thus, the parameters could be recalculated with a higher precision and adding additional effects, such as a seasonal pattern, to increase the performance.

The model parameters described in this study were estimated on data available from two similar herds. If the model should be used in another farm, the model parameters would most likely have to be recalculated due to differences in farms as: breed, feed, management, genetics, initial weight etc. Jensen et al. (2018) however, found no effect from whether or not a farm-specific version of a DLM was used in a study of dynamic milk yield monitoring in dairy cows. Thus, a future study could determine if the DLM estimated in this study could be used on another farm.

The DLM constructed in this study could, beside its use to detect abnormalities, be used as a forecast model to forecast when the weight of the pigs would reach a certain threshold. These forecasts could potentially be used for a decision support tool for optimal marketing of finisher pigs (Kristensen et al., 2012). Thus, it could potentially increase the farmers revenue and consequently the farmers willingness to pay for the system.

Conclusion

In this study it is shown that a DLM updated with a Kalman filter can be used to dynamically filter frequently obtained BW data from an automatic weighing system such as ProGrow. Because, multiple cameras are placed in the same section, both batch and pen effects were estimated. Additionally, the prediction errors from the Kalman filter were used to construct a warning system, using a tabular Cusum. The warning system can be used to give warnings about consistent negative BW growth. With this study it was demonstrated how the sensitiveness of the system can be set according to the farmers preferences. Furthermore, the warning system was tested on simulated data with a known event of decreased growth. The DLM and the warning system constructed in this study should be implemented in different farms to furtherly evaluate the performance.

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4. General discussion

The aim of this thesis was to design a DLM with Kalman filtering to detect abnormalities in BW gain in a commercial Danish finisher herd based on weighing data generated from the automatic weighing system ProGrow from the company SKOV A/S. This was done by reviewing how measurements of a pig's weight can be performed using vision-based systems and how the systems can be implemented on a farm. Additionally, methods of analysing the data and constructing a monitoring tool to monitor BW gain was reviewed. Finally, a data analysis was conducted to test the hypothesis, that a DLM with a Kalman filter can be used to detect abnormalities in BW data obtained from a commercially available image weighing system.

In the literature review of this study it was established how pigs can be weighed using camera vision. Additionally, it was found, that an effective method to obtain BW measurements at farm level was to place the camera above the feeder. Furthermore, it was described that a DLM with Kalman filtering would be useful to monitor weight gain in pigs. These findings were used as basis for the data analysis part of this study. Thus, in the data analysis a monitoring tool build on a DLM with Kalman filter was constructed based on parameters estimated from a hierarchical mixed-effect model. Missing data was realised in the explorative analysis of data. Therefore, the DLM was constructed with both effects of batch and pen. The monitoring tool showed that the DLM smoothed the mean of the observations. Additionally, the warning system showed warnings of consistent negative BW growth. The sensitiveness of the system can be set according to the farmers preference. In the previous chapter the result of the data analysis was discussed. The following chapter will include a discussion of the literature review and a more general discussion of the results from the data analysis.

4.1.1 Correlation between body dimensions and BW

In the literature review of this study it was found, that body size measurements of pigs can be used to estimate their BW. However, a general correlation between the measured parameters of body dimension and the estimated body weight is difficult to estimate across different studies. Thus, pigs of different breed and fed with different feeding methods might need different algorithms to estimate the BW (Brandl and Jørgensen, 1996; Marchant et al., 1999). Additionally, different methods of obtaining the body dimensions has been used. Thus, a calibration of each system prior to measurements can be needed.

In most studies, this calibration is performed by comparing the relationship between the obtained body dimensions with manually weighings using a scale. However, this measurement can have some inaccuracies due to the uncertainty of the scale and the time from a manual measurement until the image is obtained. Thus, as shown by Stygar et al. (2017) the BW of pigs are fluctuating during the day. However, manual weighings is a common practise in animal production which indicate that the method is reliable enough to be used. Additionally, the pigs can be weighed approximately at the same time as the image is obtained. Thus, the daily fluctuation in BW becomes irrelevant.

Different regression models to describe the relationship between body area and BW has been used in different studies. Primarily, linear (Marchant et al., 1999) and exponential relationship (Minagawa and Ichikawa, 1994). The use of regression models to describe the relationship between body area and BW was investigated by Wang et al. (2006). In the study it was found, that five common models all could be used to estimate the BW based on the body area. Thus, the average coefficient of variation was approximately the same. Therefore, a simple linear relationship was sufficient. Similar results has been shown in other studies (Marchant et al., 1999; Schofield et al., 1999). However, Brandl and Jørgensen (1996) showed that using a spline function might improve the relationship.

Using most technics of image-based weighing systems the height of the pigs cannot be obtained. Thus, manual measurements could be necessary. Which would be a time-consuming task. In the study of Schofield (1990) it is argued that the correlation between height and BW only varies a little among pigs. Thus, it only affects the estimation a little. Additional it was found by Minagawa and Ichikawa (1994) that the central area of the pigs without correction for the height gave the best estimates for BW. However, as argued by Marchant et al. (1999) the variation in correlation in height of the animals will, if not accounted for, be automatically included in the relationship between body area and BW which can cause inaccuracy in measurements. Thus, measuring the height of the animals may improve the accuracy. Consequently, when implementing a weighing system using image vision it should be considered how accurate the system needs to be.

4.1.2 Automated camera measurements

In order to obtain measurements of body dimensions, it is necessary to be able to separate the pigs from their surroundings. In literature review, three methods were reviewed as: 1) manually detecting (Brandl and Jørgensen, 1996), 2) threshold method using contrast difference (Marchant et al., 1999; Minagawa and Ichikawa, 1994; Schofield et al., 1999) ,and 3) threshold method using depth sensors to detect differences in height of pigs (Kongsro, 2014).

The use of the manual detecting is very limited. Because, an operator needs to spend time to outline the pigs (Brandl and Jørgensen, 1996). Consequently, the manual method might have some use in herd management as weighing pigs for marketing. However, the method is not useful to monitor pigs.

The threshold method using contrast difference between the white pig and the darker background is the most common used method in the literature reviewed. Additionally, it is the method used by ProGrow. This method can be used to automate the process of obtaining measurements (Minagawa and Ichikawa, 1994). However, the limitation of the threshold method is that it is normally performed with clean white pigs without darker spots. However, in a herd there will also exist a small number of non-white or spotted pigs and some breeds, as the brown Duroc pigs, would need a different threshold. Additionally, the method is very dependent on the right light conditions in the section. Thus, shadow at the back of the pig could give wrong measurements (Tscharke and Banhazi, 2013a).

The challenges with light and pigs with dark skin has caused several authors to investigate the use of 3-dimensional cameras with infrared sensors, as an alternative to the contrast threshold method (Condotta et al., 2018; Kongsro, 2014; Pezzuolo et al., 2018). Thus, this method would not depend on the pigs colour or the lighting condition. However, these systems are not yet commercial available.

4.1.3 Precision of weight estimations

One of the main concerns when applying an automatic weighing system using camera vision is the precision of the estimated BW. In the data analysis, no control measurements were available. However, a similar system was tested in a study by Udesen and Krogsdahl (2018). In the test it was found, that the deviation in mean daily gain between manual weighings using a scale and automatic weighings using ProGrow were 0.3 % and 3.6 % after filtration in batch 1 and 2, respectively. This study is not a peer reviewed article. However, similar precision has been found in other studies as Schofield et al. (1999) which found that a group mean could be estimated with 5 % deviation. Another studie of Tscharke and Banhazi (2013a) found a precision of ±1 kg between the vision based and scale measurements of BW. The precision in the study of Tscharke and Banhazi (2013a) was better than the second batch in the study of Udesen and Krogsdahl (2018). However, in the study of Tscharke and Banhazi (2013a) fewer days of observations was obtained.

In the study of Udesen and Krogsdahl (2018) an ongoing production was observed. Thus, factors as natural light, dust, flies and moisture can affect the estimate because of lower visibility of the camera. In the study, especially moisture at the camera lens and natural light was observed to affect the cameras. In the data analysis in this study, the explorative analysis showed missing observations on some days. Additionally, outliers were observed on some days. These problems could potentially be due to some of the problems as reported by Udesen and Krogsdahl (2018). To the author’s best knowledge, no studies have addressed the problem of how the cameras should be maintained over time. However, this would be a technical issue which should be incorporated in the on-farm implementation. One of the benefits of the DLM applied in the data analyse of this thesis is that a batch effect was used in the parameter vector in the DLM. Thus, observations from one camera was missing, the prediction was still affected by the batch effect of the other cameras in the section.

4.1.4 On farm measurements

Despite that several studies addressed the possibility to weigh pigs using an image-based system only a few studies concern the implementation in farm conditions. As argued by (Tscharke and Banhazi, 2013b) a weighing system should be evaluated based on factors as: cost, functionality, practicality and accuracy.

Two methods of automatic camera weighings were suggested as 1) Walk-trough weighing (Wang et al., 2008) and 2) pen measurements (Kashiha et al., 2014; Schofield et al., 1999; Tscharke and Banhazi, 2013a; Udesen and Krogsdahl, 2018). One of the main advantages of using a walk-trough weighing system, is that the farm personnel decide which pigs should be weighed. Thus, each pig could be weighed individual to get information of the individually pig. However, the walk-trough weighing system still requires some manual labour and the pigs have to be moved which can have negative consequences for the pigs (Augspurger and Ellis, 2002). Because the method is labour intensive, it is unlikely that it would be performed frequently enough to detect abnormalities in growth while changes still can be made.

Another method of obtaining frequent BW estimations of pigs is to place a camera in all or a subset of the pens in a section above the feeder. In this study, two kinds of feeders are reviewed as 1) a single or electronic feeder (Marchant et al., 1999; Schofield et al., 1999; White et al., 2004), and 2) a pen feeder (Tscharke and Banhazi, 2013a).

By using a single feeder or electronic feeder, the pig is isolated from the other pigs while the image is captured. Thus, the precision of the image weighing is improved. Because, only the weight of a single pig is obtained while the pig is standing in the wanted position. Furthermore, an electronic feeder gives the possibility to combine the image weighing system with other sensors, as for example a sensor to detect feed consumption which can give more information to the farmer. However, the use of an electronic feeding machine might be costly. Additionally, getting the pigs to walk into the feeder would demand a training period (Stygar et al., 2017) and could potentially lead to increased labour (Tscharke and Banhazi, 2013a).

Implementing a camera above a pen feeder is a practical method to obtain body measurements. Thus, the camera is out of reach for the pigs and does not interfere with the farm personnel and does therefore not require any additional infrastructure in the pen (Tscharke and Banhazi, 2013b). This placement is also the one used in the data analysis part of this study. Thus, only unidentified measurements were available.

4.1.5 Growth monitoring using a dynamic linear model

In order to analyse frequent BW data, several methods can be used. In this study the methods described were 1) the moving average, 2) EWMA and 3) a DLM.

Both the moving average method as used by Udesen and Krogsdahl (2018) and the EWMA can be used to analyse frequent BW data. However, the disadvantages using the moving average method is that all observations are given equal weight. Additionally, the moving average will be affected by the observation excluded from the calculation. Thus, if a high observation is excluded, a negative trend can be seen (Kristensen et al., 2010). The EWMA cope with some of the disadvantages of the moving average method. Because, most weight is put on the most recent observations. Additionally, it is a weighted average of all observation until the recent and prediction errors can be estimated. Thus, the EWMA method can be used to filter and monitor BW data. The EWMA method is described in Kristensen et al. (2010) as rough because the model is rather simple and cannot deal with effects on both batch and pen level. Therefore, a more sophisticated method as DLM was implemented in the data analysis.

4.1.6 Alarm system

In the literature review, a Shewart control chart and a tabular Cusum was suggested as methods for monitoring BW of pigs to detect abnormalities. Thus, these methods have primarily been used in animal production to detect changes (De Vries and Reneau, 2010). The Shewart control chart has the advantage that it quickly can detect large shift (Montgomery, 2005). However, in this study the aim is to detect consistent abnormalities in growth. Because of the physical property of the pigs it is unlikely that pigs will lose a lot of weight quickly. Thus, it is expected that the growth only will decrease a little. A Cusum method can detect small shifts in growth(Kristensen et al., 2010). Therfore, the Cusum was expected to be able to analyse growth data, as also demonstrated by Stygar and Kristensen, (2018) Thus, it was the investigated method in the data analysis of this thesis.

According to several studies (Brandl and Jørgensen, 1996; Parsons et al., 2007; White et al., 2004), a monitoring system for automatic weighing can potentially improve disease surveillance. Weber et al. (2015) found, that pigs can have diarrhoea even though the farm personnel assessed them as healthy, which indicate there is a need of an alarm system. However, as shown by the simulated event in the data analysis of this study, the most alarms were realised after more than two days after the event. Thus, a skilled farm manager will be able to detect it and possibly treat before the alarm is given by the alarm system. Other alarm parameters, as for example water consumption, have been shown to be a good indicator of disease outbreaks like diarrhea (Dominiak et al., 2018). Because, an early warning can be realized before the time of the event. However, a monitoring system on growth can potential provide alarms on factors which do not affect the water consumptions, as for example mistakes in feed formulation, not optimal feed changes or management mistakes (Jessen and Udesen, 2016).

4.1.7 Improved weighing system

Several things can be done to optimize the BW estimation performed by the vision-based weighing system (Minagawa and Ichikawa, 1994; Tscharke and Banhazi, 2013b). However, it is important to keep in mind, that cost and durability are important factors for the farmer. Thus, the final weighing system is a compromise of the cost of the system, the durability and the amount of information which can be derived from the system.

In the data analysis in this thesis, data obtained from a section with four cameras above a pen feeder was analysed. Udesen and Krogsdahl (2018) showed, that if more pens were weighed the estimation of the whole section mean became more accurate. Thus, if the monitoring system should be used to accurately estimate the mean weight of all pigs in a section, more pens should be monitored.

One parameter which could be of interest for the farmer would be the deviation in weight within pen. Thus, the heaviest pig in the pen should be the one which should determine the day of the first delivery to the abattoir. Additional, in an all-inn/ all-out system the lightest pig would give information of when the section should be emptied. A camera weighing system with a good accuracy of the estimated BW should theoretically be able to give these estimates. However, higher accuracy might need some moderation of the pen (Minagawa and Ichikawa, 1994) or additional measurements (Marchant et al., 1999).

In the data analysis of this study, only the pen average BW was estimated. Because, the pigs are not individually identified. However, identification of the individual pigs could have multiple implication. One of the benefits would be, that if a pig is removed from the pen, the DLM can adjust to the missing pig (Stygar and Kristensen, 2018). Another implication would be that individual alarms of abnormalities could be giving. Thus, if the growth of a single pig is decreased an alarm can be giving and give the farm personnel a change to react. The individual growth of pigs would also be a valuable information in order to forecast the number of animals ready for marketing.

A DLM has been used in several studies to analyse BW growth of pigs (Madsen and Ruby, 2000; Stygar et al., 2017; Stygar and Kristensen, 2016). However, the method has not been widely used at commercial farms. Wathes et al. (2008) argues, that precision livestock farming tools like growth monitoring must be demonstrated at a commercial scale for the farmers to have confidence in the product. In this study, the DLM is implemented using data from an already commercial available system (ProGrow). Thus, the implementation of a DLM would upgrade an already existing system and would not have to be marketed as a product on its own.

5. Conclusion

Body weight of finisher pigs can be estimated based on body size measurements which can be obtained from an image. The most practical placement of the camera is above the pig. From a top view image, the whole-body area of the pig without the head, ears, and neck should be obtained. Different breeds have shown to have different correlation between measured body area and BW. The process of obtaining useful images and extract body measurements should be automated to get frequent BW measurements. The automation process contains methods of detecting when a pig is present in the scope of the camera, detecting the outline of the pig, segmentation of the pig's parameter to obtain measurement, and finally a quality control of the process. In most studies, the body area of a pig is found by a threshold method by comparing the contrast between a dark background with a white pig. At farm level the camera to weigh the pigs can be placed above a passageway to obtain the BW while the pigs are moving past, or it can be placed above the feeder. Implementing a camera above the feeder in a pen is a practical method to obtain body measurements. Thus, it does not interfere with the farm personnel and does not require additional equipment in the pen. Frequent BW observations from an automatic weighing system needs to be filtered and analysed in order to obtain useful information. A DLM with Kalman filter can be used to filter BW data from both identified and unidentified pigs. Additionally, the forecast errors from the Kalman filter can be used to monitor growth in finisher pigs using a Cusum control chart.

Based on the findings in the data analysis, it can be concluded that a DLM with Kalman filtering can be used to dynamically filter frequently obtained data from an automatic weighing system such as ProGrow. The estimates from the model was validated using data from a dataset which was not used to estimate the model parameters. Furthermore, a monitoring tool based on the prediction errors from the Kalman filter was designed to detect consistent negative growth. Thus, it can be used as an alarm system. The sensitiveness of the system can be set according to the farmer's preferences. Because no information of undesired events was available from the herd data set, a scenario with simulated data was constructed to show the performance of the system. The warning system should be implemented in different farms to evaluate the performance further.

Image weighing systems as the one used in the data analysis of this thesis, can be improved with higher accuracy or additional information. However, the cost and the durability of a system are important factors for the farmer. Therefore, the monitoring tool constructed in the data analysis of this thesis is constructed as an upgrade to an already proven system.

6. Perspectives

In this thesis a DLM was modelled and a monitoring tool constructed. However, further studies should concern the implementation of the tool in commercial farms. Thus, the parameters used in the Cusum should be chosen based on the farmers preferences of number of alarms.

The scope of this thesis was to detect abnormalities in growth of pigs. However, a DLM as the one constructed in the data analysis of this study, could also be applied with a forecast function. Thus, the day where the average pen weight reaches a certain threshold could be forecasted. This function could for example be used by the farm personnel to plan when a feed change should be made, a vaccination should be performed, or it could be used to forecast when the pigs are ready for marketing. Additionally, the forecast could be of great interest for the abattoir. Because, knowledge of the number of pigs which are ready for marketing in a certain time period could improve their ability to plan the number of pigs they could sell.

Only BW data from finisher pigs was analysed in this study. However, if frequent obtained BW data is obtained, the methods could most likely also be used on BW data from weaning to 30 kg. However, the modelled parameters and variance components would have to be recalculated.

Information of economic value of monitoring systems are scares. However, in this study the monitored trait is the BW gain which is the main product in meat production. Therefore, it would be possibly to estimate a cost of abnormalities using retrospectively analysis. Thus, if the system described in this study was implemented at multiples farms, the average cost of different mistakes could be known, and the economic value of the system could be estimated.

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