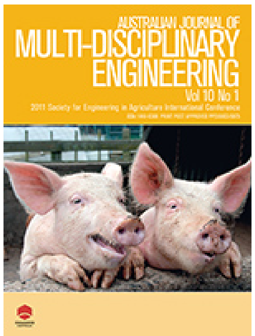

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Review of methods to determine weight and size of livestock from images*

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ABSTRACT: *In this article, the technologies which can determine the weight and growth of livestock are reviewed. Limitations of the weighing task by these different methods are defined. Comparisons between the different techniques highlight the superiority of the non-contact vision-based method. Modelling techniques for weight estimation, size and composition are reviewed along with image segmentation and recognition methods. Conclusions identify that further work is required in regards to (i) estimating the weight, (ii) estimating the weight deviation of groups of livestock animals, (iii) estimating the weight of individual animals, and (iv) improving the design of livestock weighing methods to function in commercially realistic environments. Future direction also centres on enhancing automation, minimising invasive environmental-control, maximising precision and repeatability during the recovery of body measurements and identifying and controlling the effect of any bias in weight estimation.*

KEYWORDS: Machine vision; weight estimation; precision livestock farming; livestock; size estimation.

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1 INTRODUCTION

In practice the most appropriate measures used to determine the nutritional requirements of livestock are live body weight and age relative to their surrounding environment (Whittemore & Schofield, 2000; National Research Council, 1998). Therefore, to maintain and optimise the physical condition of livestock animals, feeding regimes must be structured based on a continuous assessment of their growth. Due to the promise of increased efficiency and subsequent production savings, mechanisms to facilitate control-loops of this nature have long been sought by livestock producers.

The largest cost involved in the production of pigs is feed cost which contributes to approximately 60-65% of the total production cost and accounts for 75-80% of the variable cost (Gillespie & Flanders, 2009). Consequently the way in which feed is managed can easily dictate the profitability of a farm. It is estimated that up to 10% of feed is wasted on-farms, with the majority of feed waste attributed to under or overfeeding the animals and poor feed management (Carr et al, 2008). Overfeeding causes animals to store the energy from the feed as fat, reducing the quality of the animal's carcass at slaughter and attracting penalties in the sale price. Underfeeding causes the animals to grow slowly, thus contributing to reduced production efficiency (Frost et al, 1997; Korthals, 2001). A common behavioural tendency, which further contributes to over and under feeding, occurs when animals of varying weights are grouped together. In this scenario, smaller animals are more likely to be prevented from eating their appropriate portion by larger ones, which use competitive and sometimes aggressive actions to gain access to feeding spaces. It is, therefore, important to introduce management protocols that reduce the level of

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weight-variance found in groups of intensively housed pigs, as regular weight-based sorting of pigs into weight-classes has proven to contribute to production savings through enhanced feed efficiency and product quality (Banhazi & Black, 2009; Korthals, 2001). Hence, by maintaining appropriate levels of feed for individual animals, savings can be made on feed, time, space, health and welfare.

However, before the correct amount of feed can be allocated to a group of animals, their average weight must be determined. Conventionally, the weights of animals are not regularly recorded on individual and group-average bases. Furthermore, an unknown quantity of feed is generally fed to each animal (adlib feeding) (Banhazi et al, 2011). Although this level of record keeping is suboptimal it is common practice as existing farm facilities, tools and resources are unable to acquire the required growth information in a cost effective manner (Frost et al, 1997; White et al, 2004; Black et al, 2001).

Mechanical and electronic scales can be used to weigh the animals. However, a considerable amount of labour is required to move the animals through the scale, and to document and analyse the weight information recorded. It takes two farm workers approximately three to five minutes to weigh a heavy pig (Brandl & Jørgensen, 1996; Kollis et al, 2007). Safety concerns also arise for the worker and animal during the manual handling process as injuries and stress may occur. Some studies show that up to 6% of reported livestock-related injuries to farm workers resulted from standing in close proximity to an animal (Criddle, 2001).

As a result of these practical limitations, the growth rate of successive batches of animals can only be approximated retrospectively based on the number of animals sent to market and the approximate feed consumed during the entire growth period. At this point it is too late to rectify growth problems experienced during the cycle. Hence, automating the growth measurement can help overcome these imitations.

During industrial processes objects are commonly inspected using a range of equipment and techniques in order to classify objects into different groups and to maintain certain standards such as those related to quality, safety and productivity. Often inspection processes are performed manually, and therefore rely on the intuition of skilled workers to manage the task or manage the machine undertaking the task. Long durations of concentration and interaction with a process can result in fatigue and drift from the task at hand. Subsequently errors in judgement can result. Therefore, automating tasks of this nature can improve quality and productivity, as a machine can be managed to operate continuously and maintain a specific standard and reliable measurements.

Inspection tasks in the livestock industry focus on the animals and their activities. Arguably the most important inspection task within these industries is determining weight of the animal. For a number of reasons it is valuable to determine the weight of livestock as they grow. At the core of this reasoning is the livestock system's output; the condition of all of the animals the enterprise cares for. This growth measurement is fundamental as it quantifies all inputs going into the production process. Subsequently the online feedback obtained during the process can be used to control and optimise management procedures (Kristensen, 2003; Parsons et al, 2007). Growth is a prime indicator of animal condition, therefore successive weight measurements are required of both individual and groups of animals for quantification and optimisation to occur. Several suboptimal conditions can be identified and managed from measuring growth, such as: (i) determining whether sorting is appropriate into smaller weight ranges to avoid competitive behaviour; (ii) determining whether the animal is ready for market to maximise returns (and forecast when it is likely) (Korthals, 2001); (iii) forecasting the likely requirements for feed, space (Petherick, 1983; Pastorelli et al, 2006) and transport in the future; (iv) identifying weak or unwell animals by separating animals which exhibit periods of poor growth (Maltz, 2010); and (v) to monitor and analyse the animals' response to different feed and environmental scenarios to optimise and standardise the process (Green & Whittemore, 2005; Frost et al, 1997; Doeschl-Wilson et al, 2005; Whittemore & Schofield, 2000). Considerable value can be gained from refining these management processes (Niemi et al, 2010). There are also additional benefits when monitoring livestock weight continuously. As continuous record keeping and analysis of weight in combination with and size and composition data will assist with enhancing traceability, improving quality control and increasing the frequency of welfare assessment. Due to the importance of these measures from a production and welfare perspective, techniques have been devised to assess the weight of livestock both on an individual and group basis.

Progressively systems that measure the weight of livestock have evolved from inefficient, time-consuming and labour intensive methods to advanced methods designed to facilitate (i) higher levels of automation and sampling frequencies, (ii) increasingly accurate and semantic information, and (iii) a safer working environment. Throughout this evolution several different types of scale have emerged which can be categorised into four different groups based on how they function during weight assessment. Of these four weighing methods the method that is best suited to undertake the weight estimation task is identified and it is determined whether it can be improved and how. These aspects form the basis of the two main sections of this review.

The first section undertakes an in-depth look at the existing scales which can be used to automatically determine the weight of livestock automatically. The design considerations are presented, highlighting the positive and negative aspects of each of the weighing methods. The second section reviews research-based and commercially available machine vision systems that are used to estimate the weight of animals. The body measurements of several different species of animals are shown to have strong correlation to weight. The type and effectiveness of different equations in modelling weight using various body measurements are also determined. Segmentation and recognition techniques that are used to identify animals in images are also reviewed. Conclusions highlight the current limitations of this technology and provide insight into future research to enhance the method.

2 LIVESTOCK WEIGHING METHODS

Essentially, four methods exist that can obtain weight estimates of livestock animals automatically: (i) automated cage scales, (ii) foreleg and platform scales, (iii) vision-based scales, and (iv) walkthrough scales. The following section presents the function and obtainable precision of each of these methods.

An automated cage scale is comprised of a load cell or cells, a cage area and pneumatically, electronically or mechanically controlled gates. Sensors on the gates and inside the cage detect the presence of an animal and coordinate its confinement while weight assessment takes place. After a weight reading is obtained an adjacent set of gates are opened to release the animal. Advanced scales of this type can automatically sort animals by opening alternative release gates to direct an animal into an enclosure containing animals in its weight class (Weight Watcher, Osborne Industries, Inc., Kansas, USA). In this process the weight of the animal is determined using load-cell(s) which are generally accurate to within ±1%. Some scale systems offer finer readings for different weight classes such as ±100 g from 1 to 49 kg and ±500 g from animals 50 to 150 kg. A single automatic cage scale can handle between 500 and 1500 animals depending on pen layout and the number of exit gates on the scale. If the scale can be transported easily it may be moved periodically between pens with the same layout to optimise the use of the scale and cater for additional groups of animals.

A foreleg weigher is alternative type of scale developed to obtain livestock live-weight continuously. A foreleg weigher consists of a small load-cell platform which makes a total weight estimate of the animal based on the weight of the animal's front legs. Foreleg weighers have been reported to estimate pig's weight to within 5% precision with 95% repeatability (Ramaekers et al, 1995). The weight "state" of a pig using a foreleg weigher can be further refined using a Kalman filter (Williams et al, 1996). Foreleg weighers have also been used to weigh cattle (Ramaekers et al, 1995). Platform scales measure the weight of the entire body of pigs using a load-cell device such as the ACCU-ARM Weigh Race (Osborne Industries, Inc., Kansas, USA). A platform scale requires the animal to remain stationary during assessment. Platform type scales have also been used to automatically weigh poultry (Turner et al, 1984; Lott et al, 1982) and cattle.

The weight of an animal can also be estimated based on the animal's body measurements as measured directly from the body of the animal using a flexible measuring tape called a tailors rule. In this weight estimation process a stockperson uses the animal's body measurements as variable inputs into a weight-estimation equation. From this concept steps have been taken to minimise the labour requirement for weight estimation based on the body measurements of the animal. An alternative and superior method based on the same concept is to extract the body measurements of the animals from video frames and use them to estimate the live weight of animals without making physical contact. We term this technique a vision-based scale. This method has proven to estimate the live weight of certain livestock animals to within 5% of their actual weight (Schofield, 1990). The assessment process requires the animal and its body measurements to be identified within the image frame so that the body measurements can be used in a weight-estimation equation to form a weight estimate. Minagawa et al (2003) reported an average mean error of 2.1% for individual pigs and 1.3% for group mean estimates using the pig's height and area as determined from images. Commercial systems for image-based weighing of pigs also exist and some report a maximum deviation of 3% for the group average weights of finishing pigs (Fancom, 2011; Hoelscher & Leuschner, 2011; Innovent Technology, 2010).

Walkthrough scales estimate the animal's body weight while the animal is in motion (dynamically). This type of scale records the unique weight-signal over time which results from the animal's weight distribution across its feet as it moves across the load-cell platform of the scale. This signal-pattern is then used to identify the walking motion of a single animal, after which, an assessment of the relative load-cell reading(s) can take place to determine the weight (Cveticanin, 2003). An example of a walkthrough weigher for dairy cows was provided by Filby et al (1979) and for cattle by Martin et al (1967). An alternative form of walkthrough dynamic scale was presented by Wang et al (2008), who used a machine vision system to determine the live weight of pigs as they walked through a raceway. Several body measurements were extracted from video frames and then used in a weight-estimation equation to make an assessment of the pig's weight.

2.1 Adding functionality and value to weighing methods

Four different methods of automatic weighing have been presented above. Below is a summary of the advantages, disadvantages and additional practical potential of these methods.

A major benefit of automated cage scales is that they can be used to sort animals into enclosures of different weight ranges. There are several benefits of sorting animals into different weight classes, these include facilitating target diets for specific weight ranges, minimising tail biting and fighting and consequently mortality, identifying the number of market ready animals and adjusting feed accordingly. Therefore, these characteristics of sorting devices can lead to improvements in animal growth, feed management and welfare as well as feed and labour savings. The disadvantages of cage-type scales are that they make direct contact and confine the animals during weighing. This inherently increases the risk of stress and injury to the animals. An alternative function of a platform scale may be to determine whether the force distribution exerted on the weigh platform indicates the animal is protecting an injured leg, while it is stationary on the scale.

Identification of weight from walkthrough scales relies on the identification of unique force-time patterns attributed to the animal walking over the load-cell platform. Correct recognition of a walking-sequence pattern can effectively filter out other patterns such as those attributed to crowding on the scale or when there is only a small time difference between successive animals walking over the scale (Cveticanin, 2003). However notably, finer detail in walking-sequence patterns reveal the characteristic force-time patterns useful in the classification of gait (StepMetrix BouMatic, Madison, Wisconsin, USA). In addition, if points of impact between the animal and the platform can be identified on the horizontal plane then there is potential for multiple animals to be classified and assessed for their weight on larger platforms.

Vision systems also present a range of potential functionality. As the system is appearance-based, additional code can be integrated into the system for the detection of certain behaviours such as fighting (Šustr et al, 2001) or tracking the movement of animals around their enclosure (Lind et al, 2005; McFarlane & Schofield, 1995). Vision-based scales automatically record various body measurements of the animals' bodies as they grow; alternative methods are unable to achieve this. Output from vision-based scales have been used to provide grounds for sorting animals which are similar to the tasks performed by automated cage-type scales (Hoelscher & Leuschner, 2011). The vision-based method also has the greatest future potential to contribute to individual animal identification due to advancements in the techniques for vision-based biometric-identification. The level of detail and semantic information is also likely to improve with the development of 3D vision systems capable of recording accurate reconstruction of the animal's body in 3D space (Wu et al, 2004). It has also been proposed that the identification of gender breed and body composition is attainable using vision-based methods based on the extraction of certain body measurements (White et al, 2004; Doeschl-Wilson et al, 2005; Fisher et al, 2003). An extension is using the system for body condition scoring (Bewley et al, 2008). The use of different vision-based sensors can also introduce additional functionality into the system. Although it is not feasible at this time for commercial applications, thermal imaging has potential to help determine an animal's temperament, thermal comfort and health as well as helping to simplify the segmentation process, all while maintaining the functionally attributed to image sensors that sense in RGB colour except appearance (Stajnko et al, 2008). This is because thermal imagers record the heat radiating from the animal and therefore body temperatures can be determined from cooler backgrounds in the image. The animals' temperature also has potential to be used as an indicator of animal activity and behaviours. For example, elevated temperatures at certain regions on the animals' body may indicate fighting or inflammation. In addition, the spacing between animals and their image-derived temperature can indicate their thermal comfort levels. Two-dimensional (2D) vision systems also have the capability of viewing a large area and may be used to track individual animal movements and social interactions in future.

Determining the measurement equipment that is best suited for automatic weight estimation is governed by factors such as cost, functionality, practicality and accuracy. It is important for the cost of the device to remain low to help persuade farmers to adopt and justify technological advancements. In addition it is also necessary for the sensor to work in harsh environmental conditions where both moisture and dust are often unavoidable. These environmental considerations also provide additional reasoning to keep the equipment inexpensive in case damage occurs and a replacement is required. The sensor must also be accurate enough to ensure that the information gained is practical and comparable to measurements obtained using conventional methods (White et al, 2004).

The characteristics of the current methods used to automatically estimate livestock group-weight are summarised in table 1. The vision-based weighing method is the preferred method given (i) the very low level of contact between the scale, operator and animal, (ii) the very low level of additional infrastructure required for the scale to function, and (iii) the very low safety risk associated with the scales operation.

Level of operator/animal contact refers to the requirement of stockpersons in the process. Notably the manual weigh method requires a very high level of animal handling skill. The walkthrough method would require some animal handling (low) to either

Table 1: Summary of scale selection characteristics.

Weigh method	Level of operator/ animal contact	Level of scale/ animal contact	Level of infrastructure required	Safety risk
Manual	VH	VH	L	VH
Foreleg	VL	ML	L	L
Platform	VL	H	MH	L
Automatic cage	ML	VH	VH	H
Vision	VL	VL	VL	VL
Walkthrough	L	H	H	ML
Walkthrough vision	L	L	MH	L
VL = very low, L = low, ML = medium to low, MH = medium to high, H = high, VH = very high				

train or persuade the animals to move through the raceway. The automated scale has been assigned a medium to low (ML) level due to the additional challenges involved in training the animals' to overcome any fear related to entering a confined area with moving parts.

Level of scale/animal contact refers to the requirement for the scale to make direct contact with the animal. The most extreme cases are the automatic scale and manual method which require some form of confinement of the animal. An automated scale's gates are also often in direct contact with the animals. The raceway in the walkthrough-type scale both encloses the animal and makes contact with the animal.

Level of infrastructure required refers to the level of additional infrastructure in direct contact with the animals which is required for the system to function correctly and obtain growth information. The vision system performs best in this category as it can be fixed to the roof of the building and therefore can make weight assessments without having direct contact with the animal and its environment. Depending on the level of cooperation of the animal, the manual weight assessment method may be achieved without confining the animals, however, in general, some confinement would be necessary to ensure operator safety and to obtain the measurements in a timely manner. Walkthrough weighers and automated scales require fencing to channel the animals through the scale area, adding to system cost and complexity.

Safety Risk refers to a combination of the risk of stress or injury on the operator or the animals during the weigh process. Essentially this measure is based on the level of operator/animal contact, level of scale/animal contact and level of infrastructure required.

3 MACHINE VISION SYSTEMS FOR WEIGHT ESTIMATION

The following section covers the image analysis techniques and systems used in agricultural applications for weight estimation. In such a system a camera is responsible for acquiring images of the animal and the software on a computer is responsible for controlling acquisition, storage and analysis of image frames using a routine set of instructions. These instructions automatically recognise the animal within the image and extract one or more of the animal's body measurements to use as a predictor of weight in a weight-estimation equation.

3.1 Livestock body measurements and their correlation to weight

The information gained from studies of vision-based and manual-based weight estimation methods (using a tailors rule) exemplify the underlying correlation between weight estimation and physical linear body measurements of animals. These physical body measurements have been obtained using four different methods to approximate the weight of several species of livestock. These body-measurement methods include manual measurements taken directly from the animal and measurements obtained indirectly by machine vision systems in either 2D (Schofield, 1990; Schofield et al, 1999), 3D perspective (Kmet et al, 2000) or 3D stereo configurations (Wu et al, 2004).

The body measurements have been extracted from images by either: (i) using a printout image containing a reference object of known body measurements on the animal and taking the measurements manually (Phillips & Dawson, 1936); (ii) implementing an operator controlled process where instructions are imposed on a computer to control the identification of the animal's body and detect and extract the respective body measurements (Arias et al, 2004; Minagawa et al, 2003); and finally (iii) a machine controlled process where instructions are automatically imposed on a computer to control the identification of the animal's body and detect and extract the respective body measurements to estimate the growth of animals (Schofield et al, 1999; Parsons et al, 2007; Green et al, 2003). These three extraction methods represent manual, semiautomatic and completely automatic processes.

The concept of using an animal's body measurements to estimate its weight has been applied to several livestock animals including cattle, buffalo, chickens, pigs, sheep, fish, horses and rabbits. The relationship extends to wildlife such as elephants (Hile et al, 1997).

In cattle and buffalo these extracted body measurements include heart girth, wither height, hip width, hip height and body length. Other measures include age and condition related information such as the parity of the animal. In a study based on the direct manual-extraction of body measurements of Holstein heifers, Heinrichs et al (1992) determined that the highest coefficient of determination was between the heart girth and weight. Heart girth, wither height, hip width and body length also demonstrated high correlation $R^2 > 0.95$. Similarly a study of Holstein calves found that heart girth was also the highest correlating body measurement to weight. However, correlations were less pronounced between the different age groups studied R^2 0.72-0.77 (Wilson et al, 1997). Dairy cows have been assessed for their weight based on their body measurements and parity with R^2 in the range of 0.80 to 0.89 (Enevoldsen & Kristensen, 1997). A coefficient of determination of 0.94 was found for Simmental heifers using the heart girth (Willeke & Dursch, 2002). There have also been several attempts to extract livestock body measurements using an indirect vision-based approach from different perspective views of the animal. Kmet et al (2000) used three views (top side and end) of Simmental cattle to determine the shoulder width, lumbar protuberance in the body width, rear thy area and the top-view body area. The R^2 relationship between weight and the various body measurements obtained was from 0.94-0.80. Different age classes of Simmental cattle have also been assessed for their wither height and hip height using thermal imaging techniques. Hip height (R^2 0.46-0.74) performed slightly better than wither height (R^2 0.43-0.66) across the growth period (Stajnko et al, 2008). Minagawa (1994) used a stereo imaging method to recover the side surface of the Japanese shorthorn cattle to estimate their weight. Correlation coefficients for the five animals studied were $r = 0.88, 0.81, 0.89$ for weight estimates based on surface area, volume and projected area respectively. External body measurements have been used to determine the weight of buffalo (Manik et al, 1981; del Pilar et al, 2002). The side-view surface area of Mediterranean buffalos have also proven to correlate well to weight with $r = 0.90$ using a light projection method and an image processing technique (Negretti et al, 2007a). A vision system is also in development to determine the live weight and condition scoring of buffalo (Negretti et al, 2008). Measured and modelled parameters include the animals wither height, rump height, body height, trunk, rump length and surface areas of the lateral profile (side view), of the profile of the hindquarters (end view) and of the lateral iliac tuberosity. The best performing parameters in respect to weight were the side view R^2 0.94 and end view R^2 0.92. Using these two parameters in a multiple regression equation obtained slightly better coefficient of determination R^2 0.96 (Negretti et al, 2008).

Image analysis has also been used to determine the daily growth rate of broiler chickens. De Wet et al (2003) estimated the weights of chickens using their perimeter and area as weight-predictors (as viewed and extracted from above). The perimeter and area predictors estimated the chickens' weights to 15% and 10% of their body weight (standard deviation of the residuals), respectively (de Wet et al, 2003). Similarly, other studies report errors in the weight estimates of broilers between 0.04% and 16.47% up to 35 days of age using image-based techniques for the estimation (Mollah et al, 2010).

The body measurements of fish have also been used to estimate their mass. Beddow & Ross (1996) estimated the mass of salmon to within ±2% error using manual measuring techniques. Image-based estimation methods have been applied to blue-fin tuna in commercial pens (Costa et al, 2009). The total number of fish was estimated using a dual camera technique to 2.2% and their mass was found to be within 50.6% of the actual total weight which was an improvement on the estimates provided by divers during the same study and conventional methods which had 353.9% error in estimates. Lines et al (2001) found that the linear body measurements of salmon could be used to estimate their mass with a mean error of less than 0.5% and these linear body measurements could be extracted automatically from stereo images with a mean error of less than 10%. The mean mass measurement error was 18% based on an offline analysis of 60 images of 17 fish.

A large amount of work has been undertaken to estimate the live weight of pigs based on their body measurements. One of the first studies undertaken to determine the live weight of pigs from images involved a comparison between manually extracted body measurements and those obtained from images. An object of known dimensions was placed on the pigs back so that the image coordinates could be scaled to the real dimensions of the pig. The body measurements extracted from the images in the study were found to be very close to those extracted manually, with eight of the 11 measurements manually taken from the images measuring less than or equal to 1 cm from the measure obtained from the surface of the animal (Phillips & Dawson, 1936). Similar findings between image-based and physically taken measurements on different species of livestock were presented by Negretti & Bianconi (2004), Yeo & Smith (1977) and Pope & Moore (2002), who used a girth measurement as a parameter to estimate the weight of sows to regulate their feed consumption. Vision-based systems have also been developed to obtain the body measurements of pigs non-invasively. Building on earlier research, Schofield (1990) demonstrated that the live weight of pigs could be estimated from 2D images using the aid of a computer. This dramatically increased the efficiency of the method. The weight of three pigs weighing 75, 52 and 30 kg were estimated using single images of each animal. The relative error in weight estimation was between 6.2% and 15.4%. These errors were minimised by averaging the estimates of several frames of each animal, resulting in a reduction in the relative error to between 2.5% and 6.3%. On average it was stated that, when using image analysis the weight of pigs could be estimated to within 5%. Later Minagawa & Ichikawa (1994) reported the correlation between the weight of two different breeds of pigs and several of their 2D image-extracted body measurements. The weights of 33 pigs weighing between 7 and 120 kg were estimated based on the average body measurements derived from five images of the animal as viewed from above. An image was only included in the analysis if the animal was standing with its body straight and its head was facing forward. The highest correlating body measurement was the central projected area with a coefficient of determination of $R^2 = 0.999$ and standard error of ±0.9 kg followed by the orthogonal area $R^2 = 0.998$ (±1.7 kg), length $R^2 = 0.998$ (±4.4 kg) and mean width $R^2 = 0.988$ (±4.0 kg). A study involving a larger group of pigs was undertaken by Brandl & Jørgensen (1996), which manually recorded the body measurements of 416 pigs (25 to 100 kg) of six different cross breeds from 2D images to determine their correlation to the weight of the animal. The study findings indicated that the body surface area as viewed from above was the strongest predictor of body weight (with $R^2 = 0.98$). Notably compared to Minagawa & Ichikawa's study there was a difference in the way in which the area measurement was derived as pilot testing had indicated that the head of the pig introduced errors into the area measurement from its motion. Consequently a trim above the front shoulder was performed and the total area was derived from a manual trace of the pig's body as thresholding proved to be sensitive to image disturbances (Brandl & Jørgensen, 1996). These studies proved that the body measurements of a pig (as perceived in images) could be manually and in some cases semi automatically extracted to form a basis of weight estimation. However, for practical purposes software and hardware developments were required to facilitate the automatic extraction and weight-analysis of these body measurements from streaming video (Brandl and Jørgensen, 1996; Minagawa & Ichikawa, 1994; Schofield, 1990). In effect these developments would generate a system which could perform online and continuous weight assessment without the need for physical contact with the animal and any manual labour determining the body measurements. Additional work was required to facilitate this level of automation which was further limited by the technology of the day. Later Schofield et al (1999) reported the development of a system at the Silsoe Research Institute (Wrest Park, Silsoe, Bedford, UK) which was able to provide group-weight assessment continuously and without operator involvement. The system monitored the growth of three genetic strains of pigs to within 5% of their body weight for a total of 47 days as they grew from 47 to 90 kg. Further information on the system's performance in determining growth was presented by Marchant et al (1999) and White et al (2003). More recently Yang & Teng (2008) determined the live weight of pigs to 3.2% (mean relative error) using the side and top view of pigs from 2D images, although the level of automation is not explained clearly. More recent investigation into manually obtained measurements (taken physically and from 2D images) was presented by Zaragoza (2009). Preliminarily studies have also been undertaken to assess sheep for their live weight using vision-based methods (Burke et al, 2004; Schofield et al, 2005) and the live weight of lambs (Lambe et al, 2008b). The concept has also been extended to rabbits and horses (Negretti et al, 2007b).

3.2 Modelling techniques to estimate the weight of animals

Modelling methods used to estimate body weight include linear, power, quadratic, cubic, spline and artificial neural networks (ANNs). These methods are based on either single independent or multiple variables. Heinrichs et al (1992) used several regression methods including linear quadratic and cubic effects on single independent variables. When considering multiple traits as independent variables the correlation between estimated and actual weights increased. Adding a second body measurement to the highest correlating measurement (heart girth of Holstein heifers) increased the linear, quadratic, and cubic effects from $R^2 > 0.95$ to $R^2 > 0.99$. Similar findings were found when multiple regression modelling was applied to Holstein Calves (Wilson et al, 1997) and dairy cows (Enevoldsen & Kristensen, 1997). Minagawa (1994) found the projected area, surface area and volume were best related to the side view of Japanese short horn cattle using a power function. Non-linear modelling methods such as ANNs have been used to estimate the weight of blue-fin tuna (Costa et al, 2009), pigs (Wang et al, 2008) and cattle (Arias et al, 2004). To further refine models, certain growth periods have been generalised by their own estimation equations. For example, Stajnko et al (2008) created two separate linear models for weight estimation to accommodate two different age categories.

3.3 Body composition, scoring and classification

The conventional method for determining the carcass composition of livestock is using ultrasound. McLaren et al (1989) gave an account of the ability to forecast the carcass composition of pigs using ultrasonic measurement of back fat and loin eye area, to improve genetic selection or optimise selections for market. Correlations have been discovered between different body measurements and the fat and muscle content of the animal (composition). Ermias & Rege (2003) used various tail-based measures to determine the body fat of flat-tailed sheep for genetic selection. Vision-based techniques have also been used in a similar manner to determine the carcass characteristics of lambs (Lambe et al, 2008a; 2009). The degree of fattening in buffalo has been estimated from body measurements extracted from images with a coefficient of determination of $R^2 = 0.85$ (Negretti et al, 2008). An estimation of the value of various slaughter characteristics has also been achieved using vision-based methods on Simmental bulls (Kmet et al, 2000). Cold carcass weight, live body weight, weight of meat in carcass and weight of meat in valuable cuts have obtained R^2 values of 0.7, 0.75, 0.65 and 0.64 respectively for the best performing body measurements extracted from images of the bulls (Kmet et al, 2000). Doeschl-Wilson et al (2005, p. 229) found that the measurements obtained from images of pigs "were useful in the estimation of muscle size, carcass conformation and composition". Wu et al (2004), Tillett et al (2004) and McFarlane et al (2007) used a stereoscopic vision system consisting of three pairs of cameras to recover the surface representation of a pig's body and determine any morphological body changes in respect to different diets. There is also potential to use the measurements obtained from vision-based techniques for body condition scoring (Bewley et al, 2008), classification between different species (Dunn et al, 2003) and classification between genders and breeds of livestock (White et al, 2004).

This research demonstrates the potential that machine vision systems have when used as an online condition assessment tool for livestock, as the body measurements they extract can be used to give an indication of an animal's value, body composition and health through growth variations and morphological changes in their body.

4 IDENTIFYING ANIMALS IN IMAGES

To identify an animal within an image, a method is required to determine image pixel values which represent the animal's appearance.

4.1 Segmentation techniques

Essentially the segmentation method used can be categorised into a scene-, shape-, appearance- or motion-based technique. These techniques may also relate information between frames in a temporal manner. The following section presents the various techniques that have been used to separate the animal from the rest of the image within these categories.

Scene-based segmentation can be an efficient and effective way of segmenting the target object from the background. Scene-based techniques work on the principal that a background image is constantly maintained to maximise the difference between the background and any animal-object. This technique works under the assumption that if the animal-object is not part of the background then removing the background should only leave the animal-object in the image.

Scene-based techniques can be broken into subcategories of background representation, classification, background updating and background initialisation (Moeslund et al, 2006).

Background representation is a method where the image intensity, spatial properties and often temporal information are used to derive a representative template of the background (Elgammal et al, 2002). An example of a basic background representation is chroma-keying which involves manipulation of the image scene environment (lighting and homogeneous background) such that the animal-object can be easily segmented due to the enhanced contrast between it and the known background colour. Dunn et al (2003) used a chroma-keying technique to segment different species of animals from a blue background. An image can also be transformed into an alternate colour space to retain representation of different background features in the image such as shadows (Cucchiara et al, 2001; Schreer et al, 2002). Background classification involves the grouping of the data after segmentation takes place to eliminate the occurrence of false positives. False positives can occur during the subtraction process and are caused by a number of different factors such as large light changes (shadows), non-target objects or changes to the cameras field of view or scene. In a background initialisation method the background model is learned during an initialisation phase and can be considered static in that it does not change once initialised.

Background updating includes the background data in subsequent frames as a weighted combination of various measures. The simplest updating method is to store a template image of the background (updating the background) when no target object is present and then subtract this template image from future frames which contain the animal-object, leaving the animal-object as the difference. Kollis et al (2007) use a similar updating method to determine an adaptive threshold value.

Mixture of Gaussians or Gaussian mixture models are reported as a robust and reliable technique used to segment a target object from the background in outdoor scenes without requiring any physical alteration to the scene or objects within the scene. In this segmentation technique every pixel has its feature information recorded across an image sequence (temporal information of each pixel is maintained). The various changes in the pixels are stored as one of *K* different features related to a pixel. Each *K* feature is represented by its own distribution and cluster (the modes of the background scene). The feature distributions are continuously updated online in an adaptive mixture model. The distributions are used to determine whether a pixel belongs to the background (or not) based on the incident pixels value in relation to the feature distributions. For example, the feature distribution is updated if a pixel is within 2.5 deviations from the distribution mean. If the pixel is not within the range of any of the distributions in the adaptive mixture model then the least significant distribution is overridden with the new distribution. Only two parameters were used in the process, alpha (α) a learning constant and T, which is the assumed proportion of the data related to the background (Stauffer & Grimson, 1999). Zivkovic (2004) improved the Gaussian mixture model by creating an algorithm that automatically determines the number of distributions required to represent each pixel which results in a time saving and improved segmentation.

While mixtures of Gaussians are effective at maintaining appropriate segmentation in slowly changing scenes they have been known to have difficulty in identifying textures related to backgrounds that frequently change within the image scene. In order to minimise the effect of these characteristic variances during segmentation, various spatial-temporal techniques have been investigated. Zhong & Sclaroff (2003) devised a technique to segment objects away from dynamic textures or backgrounds which have repetitive patterns; a ship in waves for example. In their proposed system Kalman filter estimates the appearance of the dynamic texture and the foreground objects region and an autoregressive moving average model is used to segment the time varying background iteratively.

One well-known motion-based technique in the area of image processing is optical flow. This temporal technique determines the velocity of any movement between two or more images as a result of changes in the images' light patterns. The motion can be caused by a moving object or by movement of the camera itself. Different objects can be segmented based on their motion characteristics, as the rate of change of the objects direction, position and speed help with the identification of the object or its location within an image (Horn & Schunck, 1981). Several different optical flow methods have been developed, a quantitative comparison of nine techniques was presented by Barron et al (1994). One of the major benefits of using optical flow as a basis for segmenting and identifying objects is that small movements which might be hard to perceive in two dimensions can be identified; such as a ball rotating about its axis. In addition the objects motion and its motion history can help with identification and tracking if the object becomes partially occluded by another object. However, the exact shape of the object may be hard to extract using this technique as the entire body may not always be in motion.

An active contour is a shape-based technique (also known as a snake) which involves morphologically displacing a contour (enclosed collection of points) overtime to follow a 2D shape contour in an image. The contour is active in the sense that it moves as it converges to the minimum energy, created by the magnitude of surrounding external and internal edge gradients located within the image search space that form the contour. Although active contours in their most basic form can successfully derive the correct shape of a deformable object and track it between successive frames they have the limitation of not knowing whether their location is correct or how they are deforming is correct as they have no inbuilt intelligence. They can easily drift and produce errors as a result. To prevent drift from occurring, information is required to validate the contour as the target shape. Point distribution models (PDM) and finite element models have been used individually and collectively to obtain more reliable information to form a basis for the active contours next move (Cootes & Taylor, 1995). PDMs determine the correct location of a point on a contour using a statistical-based approach on a network of surrounding pixels. The PDM is trained in an offline process. During training points are applied in close proximity along target shapes over a large number of images. For example, if the model was being trained to detect people's hands for sign language recognition the points in the training set would surround the fingers and palm. The shape data located on and between adjacent points is required to be defined for a given hand signal such that it can describe any persons hand performing the action (Heap & Hogg, 1996). Processes that utilise this technique are often referred to as active shape models (ASMs) (Cootes et al, 1995). Examples of tracking and recognition using ASMs and PDMs were presented by Baumberg & Hogg (1994), Tillett et al (2000), Sumpter et al (1997), Marchant (1993), Onyango et al (1995) and Tillett (1991).

A threshold is commonly applied to the spatial appearance of an image to divide (classify) the image into two colour regions by allocating all pixel intensities above one intensity value (the threshold value) white (1) and all equal to or below the threshold value black (0) . The function of the threshold value is to divide the image into two regions such that the background image is represented by one colour and the foreground image containing the target object is another colour; effectively segmenting the target object. However, the segmentation of the object from the image depends greatly on the environment. If the environment such as the lighting and background is not controlled to suit the vision system's processes then is inevitable that the threshold value will begin to incorrectly divide the image when changes in lighting occur. To overcome this dependence, thresholding algorithms have been developed to automatically determine the threshold value using the information of the intensity within the image regions or the entire image globally. A good comparison of these thresholding methods was presented by Wu & Amin (2003). A simple and manual thresholding technique was used by Minagawa (1994) and Wang et al (2006) to derive the area of the pig from the image. Previously, Yang & Teng (2008) used an adaptive thresholding technique based on the minimum found in a histogram of the image between the light (pig) and dark (background) regions in the image. De Wet et al (2003) and Kollis et al (2007) used adaptive thresholding and erosion and dilation filtering to minimise noise and redundant artefacts present in the background during and after binarisation. Another appearance-based segmentation technique is active appearance models (AAM) which is an extension of ASMs. AAMs are a statistically-based modelling method to match both the shape and appearance of a target object in a new image. Similar to ASM, an AAM first requires offline training using a large number of sample images. During the training procedure landmark locations (coordinate points) are defined on the target object. These points are strategically chosen to adequately represent the spatial variance of the objects characteristics which are to be investigated, as a result the distribution of a set of shapes is found describing the objects shape and appearance at the landmark locations (Cootes et al, 1992). This training data represents a PDM based on the derived principal components. The trained model is then applied within close proximity (good estimate) of the target object within the test images. Convergence to the shape and appearance of the target object occurs after a number of iterations during which the trained model moves according to the residual difference between the trained model and the image containing the target object (Cootes et al, 1998).

4.2 Recognition techniques

A method is required to validate the object before during or after segmentation. One method applied to fish has been used to identify the fish based on the "crescent" or arc-shape created after subtracting two successive frames from one another within the fish enclosure. This arc shape (a result of movement of the fishes head) was found to be a suitable starting point for further validation for all fish within the tank regardless of size. Other reference points on the fishes' bodies were deemed to be inappropriate to use as identification cues as the swimming motion of the fish caused too much variance in these locations. Before the matching took place the entire body measurements of the fish were extracted using a PDM. This model was then cross-referenced to validate incident test-shape data (Lines et al, 2001). Recognition in pigs has predominantly been based on their shape. Pig shapes have been outlined within the image using active contours where a continuous boundary morphologically deforms toward energies created by edges within the image (Marchant, 1993; Marchant & Schofield, 1993; Cootes & Taylor, 1992). In some studies pig presence was identified by the grey level of a central region of the image; as the pigs under observation were brighter in appearance in respect to their surroundings, an increase in intensity in this central image region indicated the presence of a pig. A search of the image recovered a shape using the snake technique. To validate the shape as a pig-shape the total area of the shape was determined along with the shapes width and length. For the shape to pass as a pig, the area, the ratio between the length and width and the ratio between the area of the front and rear section of the body of the animal were required to be within certain known physical limits based on known pig body measurements. If the shape passed this filtering stage the weight was determined based on the shapes area and recorded along with a time stamp. The shape has been validated by other means. For example, Wang et al (2008) used the asymmetry between the left and right side of the pig's body and only frame samples that had left and right side areas within 15% of one another were considered appropriate for weight analysis. Binary pattern classifiers (Chan et al, 1999), chain-code, s-phi curves (Dunn et al, 2003) are other similar techniques used to match shape geometries in recognition processes.

5 DISCUSSION AND RECOMMENDATIONS

Four methods have been presented that continuously and automatically monitor the weight of livestock. The vision-based method had the greatest potential to overcome various practical limitations due to its non-invasiveness, ability to operate to practical accuracy, ability to determine multiple animal weights in parallel, enhanced safety due to no moving parts, manoeuvrability, maintainability and inherent and potential additional functionality.

The ability of the vision-based method to determine the live weight of several different species of livestock animals was established. Majority of the systems demonstrated that they could work within practical accuracy and some proved to be more accurate than conventional methods. However, common trends in the limitations specific to vision-based methods were found in conclusions drawn from many authors. Predominately, more attention in this field is required in the following areas (listed in order of significance):

1. System automation. Only a few vision-based developments have reached the final goal of system capable of continuous and automatic operation. Many reports had the desire to continue their work to facilitate complete automation (Arias et al, 2004; Minagawa et al, 2003; Wang et al, 2006; Brandl & Jørgensen, 1996). Two vision-based

systems are available commercially. Hoelscher and Leuschner (n.d.) developed a hybrid sorting device which constrains a pig and uses an image-based analysis of the pig's body to determine whether it has reached its market weight. Release gates are controlled accordingly to direct the animal to appropriate pens. Vision-based systems which determine the average weight of groups of housed pigs are also available, however, these systems do not cater for individual animals and the large variability between the weight samples collected daily indicate that the filtering of erroneous data may require further development (Fancom, 2011; Innovent Technology, 2010; Stickney, 2009). The average weights of groups of finishing pigs are reported to have a maximum deviation of 3% using this system (Fancom, 2011). Notably if individual weights are precise enough, the weight deviation within the groups of animals should be able to be recorded and used as an alert to inform the farmer when it is appropriate to sort the animals.

2. Repeatability in measurements. Numerous authors highlight the fact that the pose of the animal was likely to have led to fluctuation in the body measurements obtained from the animal, which in retrospect may have introduced error into weight estimates (Zaragoza, 2009). Those authors that did not remove the head and tail from the analysis experienced additional challenges in repeating measurements (Mollah et al, 2010; Minagawa & Ichikawa, 1994; Kollis et al, 2007; Schofield, 1990; de Wet et al, 2003; Wang et al, 2006). An algorithm is required to automatically select the best images for weight estimation (Wang et al, 2006) and generally a steady posture of the animal is required for analysis to take place (Stajnko et al, 2008; Kmet et al, 2000) to avoid variation in body measurements (de Wet et al, 2003). Furthermore it has been argued that the measurements used to construct the weight estimation models may be of more worth than the final weight estimation value, as these measurements can be used to record genetic and composition characteristics among other classifications (Whittemore et al, 2001; White et al, 2004). Therefore precise measurements are of added importance.
3. Environmental control. Although several authors use structured lighting this approach may not always be practical in a commercial setting. It was interesting to note few authors have attempted to exploit the benefits of spectroscopic analysis to identify the characteristic reflectance of light off of the surface of the livestock animals. Notably if appropriate, this reflectance may be useful in determining a suitable optical filter to place over the imaging sensor to suppress background artefacts and assist in segmentation (de Wet et al, 2003). The colour and cleanliness of the animals also pose problems when distinguishing animals based on appearance. Movement of the animal through artificial environments or to a structured area also facilitated additional levels of control (Minagawa & Ichikawa, 1994; Stajnko et al, 2008). However, these arrangements in some cases were probably outside the bounds of commercial reality due to equipment costs and labour cost involved in moving the animals.
4. Bias and fine tuning. The bias in weight measurements toward individuals within groups of animals can be overcome using radio frequency identification. However for many livestock species this is currently not feasible on a per-animal basis. However, there is potential for individual animals to be identified through images and vision-based tracking in future. Additional causes of bias may result as a consequence of the time of day when the livestock are assessed. For example, broilers may be "significantly heavier in the evening than in the morning" (de Wet et al, 2003, p. 530). The process or system layout may also cause bias (Lines et al, 2001). Thus, in-depth validation should be undertaken. Some fine tuning of parameters may also be required to categorise different weight classes or body types into different estimation equations or recognition routines. Other parameters such as age may be required to further refine estimates (Ramaekers et al, 1995; Brandl & Jørgensen, 1996).

A large amount of work spanning the four previously mentioned categories is still required in this research area to realise the full potential of weight estimation using vision-based techniques.

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