Chapter 19

The use of 3D imaging technology in animal management, with a special emphasis on ruminant production

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Abstract

An important aspect of livestock management consists of carefully observing the animals, which, depending on the species and type of farming operation, can be extremely time-consuming for farmers. To assist in these activities, researchers have begun investigating the use of 3D imaging. Among its many advantages, the most beneficial is that it enables easy and safe measurement of traits of interest, both those that have historically been used as well as new traits that until now have not been obtainable from living animals. With recent developments, image-based approaches are becoming increasingly accessible to farms, regardless of scale or method of production (e.g. conventional or organic). This article reviews the principles of this technology and its current applications, mainly in dairy farms, but also presents some promising future perspectives. Imaging technology can already provide access to rapid and repeated measurements of body condition score, surface area, volume, and morphological traits from a large number of individuals. However, further development is needed to improve the efficiency of data processing and interpretation, particularly with respect to automation and image analysis. To date, applications of imaging data have been limited by constraints on the frequency of monitoring. In the future, the use of machine learning will probably help to identify new body areas or traits of interest. However, even if most technical and technological obstacles have been removed (or will soon be removed), improvements are still needed with respect to data transfer and storage capacity, the type of information stored, and analysis and communication of reliable and usable information in real time. The application of high-throughput monitoring to these indicators opens new possibilities which thus far remain largely unknown. Finally, much work remains on determining the best use of these data, the advice to give to breeders, and the training needed by farmers.

Keywords: 3D imaging; dairy cows; new phenotype; high-flow data

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19.1 Introduction

The management of livestock is defined by daily tasks that cannot be delayed and for which a farmer must be continually on-call, such as milking, feeding, and monitoring animal health and reproduction. An essential part of this monitoring consists of direct observations of animals to evaluate the feeding strategy, to detect if animals are sick or if reproductive females are in heat, to determine if animals are losing body condition, or to confirm their growth patterns are normal. Even if monitoring involves only visual observation, this still represents a significant amount of time-consuming work. To alleviate this burden, technologies have been developed that allow farmers to delegate certain tasks related to monitoring and visual observation. Most approaches have been devoted to a single task. However, recent developments, such as 3D imaging approaches, open new opportunities to improve efficiency by managing several tasks at once. In order for such technology to be useful to farmers, though, it must record phenotypic information in such a way as to facilitate dynamic monitoring of animal performance, in order to enable farmers to adapt management practices in real time. In many cases, a number of questions arise: Is it possible to delegate part of this monitoring/surveillance to new technologies? Can the technological eye really help the human eye to carry out these activities?

Image-based technologies are evolving very quickly and offer multiple advantages to livestock farming operations, regardless of their size or method of production (e.g. conventional or organic). Imaging technologies can monitor continuously and observe several animals with a single eye, either collectively or individually. They can carry out measurements that would otherwise be difficult to perform. In particular, imaging technologies enable the collection of data without any physical interaction between the farmer and the animal, and thus avoid the hazards associated with handling or restraining animals that are large or not used to being handled by humans. Two- and three-dimensional imaging technology not only facilitates easy and safe access to traits of interest that are already used on-farm, but it also provides access to new traits that are difficult to measure on living animals, such as surface areas or volumes of a whole animal or specific parts (Le Cozler *et al.*, 2019b).

The application of imaging technology to agriculture is not new, but the pace of technological development, in particular that of image analysis, has increased rapidly in recent years (see, for example, Vázquez-Arellano *et al.*, 2016 or O'Mahony *et al.*, 2019, for reviews). The development of technologies that are accurate, automatic, high-throughput, and not dependent on human operators – which for many years was considered a bottleneck in biology, particularly for large, live, and mobile animals such as dairy cows (Chéné *et al.*, 2013) – has generated progress in addressing the issues described above. A quick search using the keywords 'computer vision' OR '3D imaging' AND 'animal production' reveals that the number of published articles on this tropic has increased significantly over the last several years, with, as of early 2021, 72 articles in the Web of Sciences Core Edition and 181 in Medline. The first exhaustive review was conducted by Stuyft *et al.* (1991) and considerable progress has been made since then, as described by Wurtz *et al.* (2019), with significant developments in both image acquisition technologies and image processing. The areas of interest/study are also changing; more numerous and diverse aspects of animals' biology are being studied, from morphological traits to behavioural characteristics.

Certain methods focus only on animals' exterior surfaces, while others, such as ultrasound technologies, enable precise and advanced analyses inside an animal's body, which is useful in following gestation or studying fat deposition, for example.

Finally, approaches based on optical detection present interesting alternatives to manual measurements or to currently existing devices that enable visualisation of the internal composition of animals, but also are expensive and require animals to be anaesthetised (tomography) or restrained (ultrasounds) (Pezzuolo *et al.*, 2018). External imaging technologies (i.e. optical imaging) have also been developed to detect events or to measure indicators that are visible from the exterior of the animal, such as lameness in cows (Van Hertem *et al.*, 2014; Zhao *et al.*, 2018) or body condition score (Fischer *et al.*, 2015; Halachmi *et al.*, 2008; Sploliansky *et al.*, 2016).

The present paper aims to introduce the principles of imaging technology, focussing mainly on 3D imaging, and the applications to ruminant production. It also discusses the initial performance of such approaches and addresses future trends and challenges for new developments.

19.2 Principles of 3D imaging technology

Many phenotyping goals can be accomplished using either 2D or 3D imaging approaches, although the underlying technology is different in each case. In general, imaging technologies have had to overcome several technological challenges, including the costs of equipment and of expertise, hostile environmental conditions arising from dust, gases, and light interference, and processing challenges such as image distortion, reconstruction, and the automation of treatment. From the original image to the final processed dataset, several steps need to be considered (Figure 19.1) and are discussed in the following section (see also Vasquez-Arellano *et al.*, 2016).

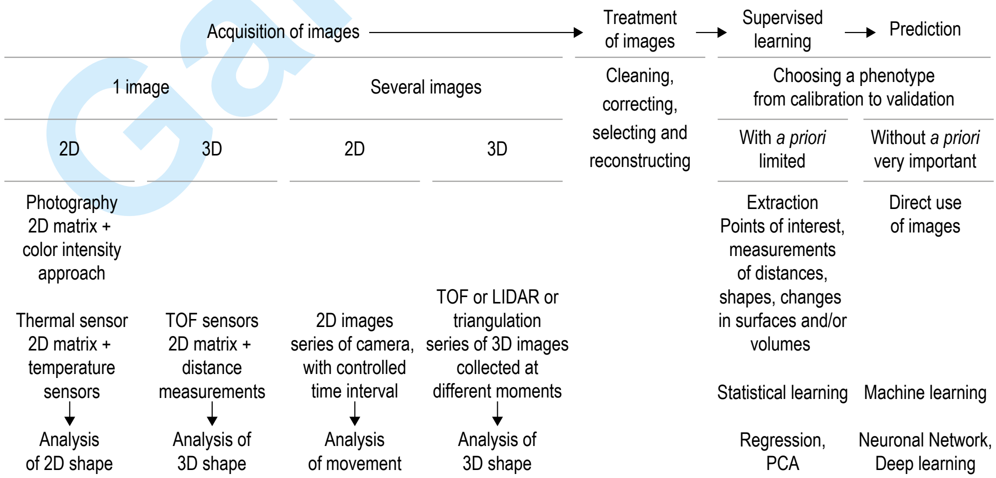

Figure 19.1. From image acquisition to information (prediction) in the 3D imaging process.

19.2.1 Definition and processing of 3D imaging

Many imaging technologies have been used to characterise different phenotypes (Table 19.1). The first use of video cameras on farms was intended to monitor animals' overall behaviour (e.g. heat or calving events). Then, new approaches based on 3D imaging enabled the extension of this technology to the monitoring of phenotypes such as body condition, weight, and lameness.

2D versus 3D imaging: a question of choice?

At the most basic level, a two-dimensional (flat) image depicts only the length and width of an object. To our knowledge, two-dimensional imaging was first applied in livestock to estimate the body weight of pigs (Brandt and Jorgensen, 1996). Later, the addition of a temporal dimension to 2D images (i.e. a succession of images) enabled the detection and analysis of normal animal behaviours (e.g. time spent lying down or walking), abnormal behaviour such as stereotypies (tongue movements in beef production for example), foot lesions (Orman and Endres, 2016), and animal identification (Zin *et al.*, 2018). However, the effectiveness of the 2D imaging process is limited by the lack of a third dimension, distortion problems, and the calibration procedures required. In addition, for practical reasons, 2D imaging requires lenses with short focal lengths, which may result in significant image distortions in terms of metric conservation, especially if the position of the animal varies from the centre of the lens and if the distance between animal and sensor is high. A principal limitation of 2D imaging is the complexity of obtaining information about surfaces that are not flat, which makes it difficult to determine morphological traits or animal characteristics such as body weight, body condition, and bone and muscle development. It is possible to accomplish these goals using 2D-image photogrammetry, but this requires capturing several shots of a fixed object from different places, which is difficult to carry out with living animals. Following pioneering developments in 2D imaging, recent technological advances have occurred in the field of three-dimensional imaging. The first and most commonly used applications were the determination of body weight in pigs (Brandt and Jorgensen, 1996) and cattle (Arias *et al.*, 2004), and the analysis of animal behaviour, mainly for animals reared indoors (Wurtz *et al.*, 2019). These behavioural analyses, carried out at the scale of the group, also resulted in the development of commercial tools associated with feeding or ventilation systems that can respond in real time to abnormal behaviour.

Over the last two decades, the development and marketing of relatively inexpensive 3D cameras has led to decreased interest in 2D technology in favour of 3D approaches.

What is 3D imaging?

A '3D scanner' is a generic name for devices that are used to analyse real-world objects and produce 3D models of them. Different technologies have been developed for this purpose, including both contact and non-contact scanners. As the name suggests, contact scanners require physical contact between the device and the object to be scanned, and are thus clearly impractical for the applications targeted here. Instead, non-contact scanners rely on light, sound, or other kinds of waves, without physical contact; for our purposes we will focus on those based on light. There are two types of non-contact scanners, active and passive. Active scanners have a light source and detect the reflection of

Table 19.1. Main use of 3D imaging technology in ruminants according to literature review.

Articles	Species	Type of camera	Targeted applications[1]				
			BCS	BW	Lameness	Morpho-logical traits	Others
Abdul Jabbar *et al.*, 2017		ASUS Xtion PRO LIVE			x		
Anglart, 2010		DeLaval Time-of-flight MESA SwissRanger™ SR4000	x	x			
Fischer *et al.*, 2015		ASUS Xtion PRO LIVE	x				
Gardenier *et al.*, 2018		4 Microsoft Kinect-v2			x		
Gomes *et al.*, 2016	beef cattle	Microsoft Kinect					hot carcass weight, empty body fat
Hansen *et al.*, 2018		'Type kinect' Asus Xtion ?	x	x	x		
Huang *et al.*, 2019	beef cattle	LIDAR				x	
Huau *et al.*, 2020	dairy goat	Asus Xtion / Primesense Carmine	x				
Kuzuhara *et al.*, 2015		ASUS Xtion PRO LIVE	x	x			milk yield, fat and protein content
Le Cozler *et al.*, 2019a		5 pairs of monochrome cameras + lasers				x	
Le Cozler *et al.*, 2019b		5 pairs of monochrome cameras + lasers		x			volume, surface area
Lerch *et al.*, 2020	dairy goat	Asus Xtion / Primesense Carmine and 5 pairs of monochrome cameras + lasers (Morpho3D)					body chemical composition
Martins *et al.*, 2020		Microsoft Kinect v2	x	x		x	
Millers *et al.*, 2019	beef cattle	Basler (TOF)		x		x	cold carcass weight, saleable yield, fat and conformation grade
Mullins *et al.*, 2019		DeLaval Body Condition Scoring[2]	x				
Negretti *et al.*, 2008		Nikon Coolpix 800 + lasers	x	x		x	
Nir *et al.*, 2018		Microsoft Kinect v2		x		x	
O'Leary *et al.*, 2020		BodyMat F (Ingenera SA)					
Ruchay *et al.*, 2019a		3 Microsoft Kinect		x		x	
Ruchay *et al.*, 2019b		3 Microsoft Kinect				x	
Salau *et al.*, 2017		Microsoft Kinect v1				x (udder teat, rear leg angle)	
Schlageter-Tello *et al.*, 2018		Microsoft Kinect			x		
Song *et al.*, 2018		Microsoft Kinect-v2		x			
Song *et al.*, 2019		Intel Realsense D415					movement of rumen
Spoliansky *et al.*, 2016		Microsoft Kinect	x				
Van Hertem *et al.*, 2014		Microsoft Kinect			x		
Van Hertem *et al.*, 2016		Microsoft Kinect			x		
Van Hertem *et al.*, 2018		Microsoft Kinect			x		
Viazzi *et al.*, 2014		Microsoft Kinect			x		

[1] BCS = body condition score; BW = body weight.
[2] Commercialised; technology was considered to be commercialised if it is available for use on commercial farms.

the light to obtain information about an object; this category contains different types of technologies, such as those based on time of flight (ToF), laser triangulation, or structured light. Passive scanners rely instead on the ambient reflection of light to analyse an object, without any additional source of light. Examples of this approach are the stereovision scanner (described later), photometric scanner, and the silhouette technique.

19.2.2 Technologies available

The use of cameras for measurement in animal husbandry has become more popular in recent decades. Technological advancements in 3D sensors and data acquisition have increased both the precision and variety of information that can be obtained. The most common devices use one of two main types of technology (Figure 19.2): time of flight cameras or cameras based on triangulation:

Time-of-Flight (TOF) cameras: A TOF camera emits infrared (IR) light in a wave or pulse, which is reflected by an object. The speed of light is then used to estimate the distance between the sensor and the object. This type of camera usually has a range of 0.8 to 5 m, with an accuracy of about 1 cm. It can record up to 54 images per second. Two commercialised models are the Microsoft© Kinect v2 sensor and sensors using LIDAR (light detecting and ranging) technology.

Sensors based on triangulation: Scanners based on triangulation rely on stereovision: the use of two cameras, whose relative position and orientation are known, to capture the same scene (Figure 19.3). When a given point is observed through the two cameras, we can build a triangle with the observed point, and, using the Pythagorean Theorem, calculate the position of the observed point. This approach is called passive stereovision and requires the computation of corresponding points between the two images, which can be a challenge. To address this, several solutions have been developed, such as the addition of a light source that projects a specific pattern, also known as active stereovision, or the replacement of one of the cameras with a laser source or with a video projector that is used as an inverse camera, also known as structured light. The most commonly used commercial products are the Microsoft© Kinect v1 camera (Salau *et al.*, 2016) and the Asus Xtion © Pro camera (Kuzuhara *et al.*, 2015), which are both based on structured light technology.

19.2.3 Image cleaning and reconstruction

Regardless of the type of technology used, 3D cameras return a partial three-dimensional point cloud. For applications requiring a complete shape of the scanned animal to be obtained, it is necessary to use several cameras and therefore to aggregate the different shots taken. The 3D animal reconstruction is often performed thanks to algorithms developed to automatically align the multiple views of 3 D point cloud data of the animal (Figure 19.4).

To move from a point cloud to a final reconstructed shape, an image cleaning and a Poisson surface reconstruction algorithm are often necessary to construct a triangulated mesh and shape smoothing (Kazhdan and Hoppe, 2013). The different stages of the treatment are shown in Figure 19.5.

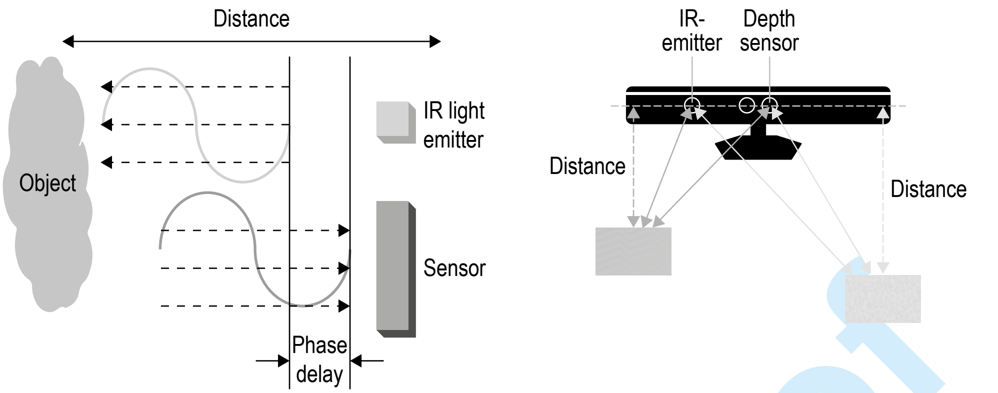

Figure 19.2. Schematic representation of the measuring principles in TOF (left, adapted from He and Chen, 2019) and triangulation (right, from Lun and Zhao, 2015) technologies.

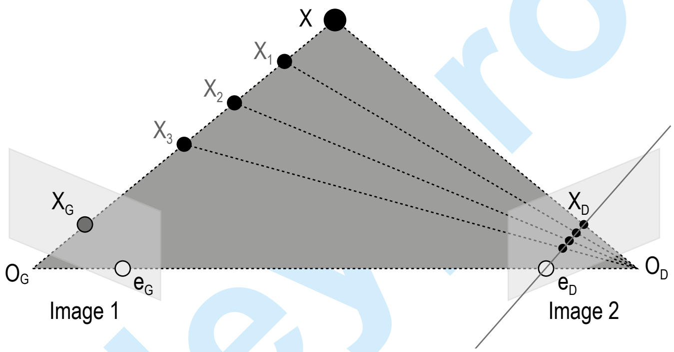

Figure 19.3. Principle of stereovision model.

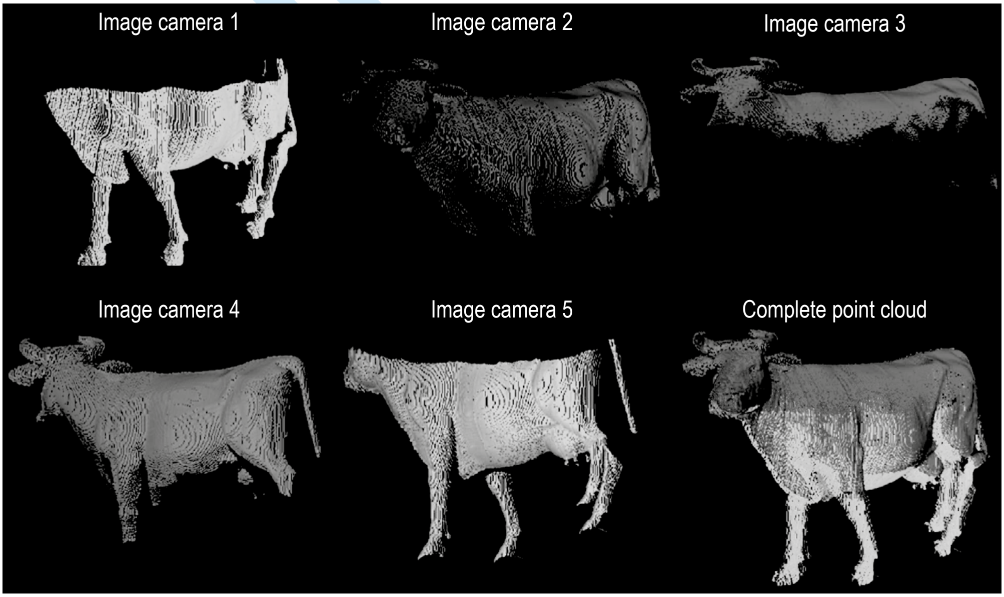

Figure 19.4. An example of points cloud reconstruction.

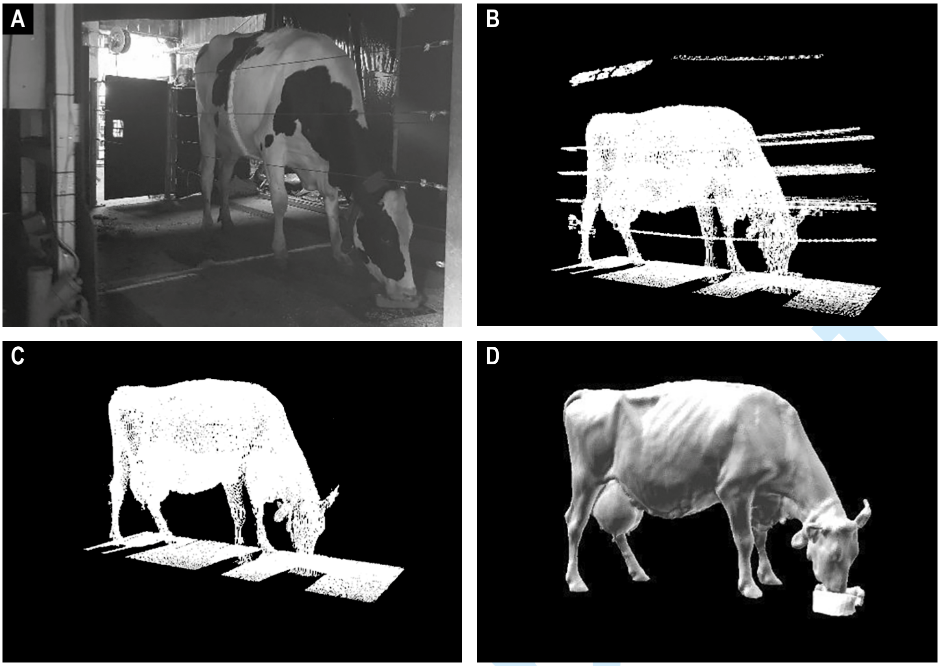

Figure 19.5. From acquisition to final data: (A) data acquisition; (B) raw cloud; (C) cloud after cleaning; (D) final image after normalisation and Poisson reconstruction.

19.3 Barriers and solutions for the use of 3D imaging technologies

Most of the technologies and applications presented previously are not available on the market at the end of 2020 (Table 19.1). Except a few of them (Ingenera BodyMAT, Delaval BCS system or dsp-Agrosoft GmbH CBS), the others were developed for research purposes and were never transferred into commercial offers. This chapter will describe the barriers to the use of 3D technologies and the potential solutions to overcome these main limits, which are animal movements and lighting exposure. Indeed, to obtain useful information from images, the initial quality of an image is as important as the methods used for processing.

19.3.1 Light and dust problems

According to Salau *et al.* (2014) using TOF cameras, the quality of an image can be affected by sunlight, dust, insects, and humidity during the measurement process, as well as by the colour of an animal's fleece. The use of this camera appears promising for several types of applications in livestock farming, although a few techniques require the animal to stay still during the scanning process. This has led to a high animal effect for certain applications, such as the estimation of body condition score (BCS) and back thickness from images (Salau *et al.*, 2014). For the sensors based on triangulation, Salau *et al.* (2016) noticed that white and black fleeces can present problems for the use of the Kinect camera. However, the authors concluded that the Kinect structured-light camera was less sensitive to motion artefacts than the TOF camera, because the former uses the deformation of IR patterns projected on the object, whereas the latter uses calculations from a series of signals to evaluate the distance of the object to the camera.

As described earlier, the main limits on the use of 3D imaging technologies arise from animal movements and lighting exposure. To obtain useful information from images, the initial quality of an image is as important as the methods used for processing.

19.3.2 Animal movement and light: the possibility of using partial 3D images

The effects of animal movements can be limited by using pre-trained animals, special equipment, or capturing only partial images (Fischer *et al.*, 2015). Recently, the Morpho3D scanner project investigated each of these possibilities (Le Cozler *et al.*, 2019a,b). A cow was restrained in the scanner by eight stainless steel cables, four on each side. If necessary, the cow could also be restrained by a self-locking head gate. The cows usually required three to four attempts to get used to the equipment and stand still. At the beginning, a feed fence was used to avoid excessive movements of the head, but this usually excluded the head and neck from the field of view. Algorithms were then developed to estimate the full volume or surface area of animals from the partial 3D data (Figure 19.6). These algorithms were also applied to 3D images that were of poor quality due to head movements during the scanning procedure (Figure 19.6). The authors concluded that, compared to a scanning procedure, a one-shot approach would significantly reduce the time of acquisition and therefore the sensitivity to cow movements.

A second device based on a one-shot approach is therefore under development, and would be better suited to commercial farms. In general, the image quality from one-shot technology is lower, but should be high enough for the level of precision desired for the phenotypes of interest. The prototype consists of a fixed metal frame with three series of five paired sets of a camera and a laser (Asus Xtion Pro cameras). Each series of five camera-lasers is connected to a computer, which is itself connected to a unique terminal. These cameras are only sensitive to direct sunlight and not to movement. The images taken simultaneously by these 15 devices are then combined to reconstruct a 3D image of the entire animal (Figure 19.7).

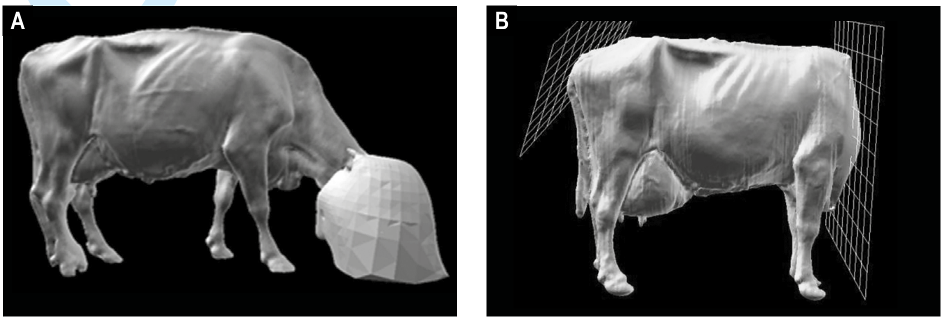

Figure 19.6. (A) Low quality image due to head movement and (B) partial image.

Figure 19.7. From animal to 3D image, using one-shot technology.

19.4 Processing: from image to information

Two types of information can be extracted from imaging data. The first type is purely geometric – e.g. distances between points, curvature, areas, and volumes – while the second type is not directly accessible through geometric measurements but is thought to be highly correlated to the 3D shape (e.g. BCS or weight).

For geometric information, standard mathematical measurements can be computed, such as normals or curvatures. These computations often rely on a search structure to speed up the search for neighbours (e.g. kd-trees, octrees). Many other features can also be calculated, such as normal spherical histograms, point feature histograms, and normal aligned radial feature (NARF) descriptors. Several libraries (e.g. Meshlab, PCL, OpenFlipper) are available to extract these features, and can be chosen according to the surface representations (mesh, point cloud, voxel grid) used for each feature.

For information that is not directly accessible from image data, the targeted variable is estimated from the shape using a model, which is usually computed with a machine learning algorithm. For example, Pezzuolo *et al.* (2018) estimated the weight of pigs from body dimensions such as heart girth, length, and height. Similarly, Song *et al.* (2019) extracted anatomical landmarks and used them to compute a set of features to estimate BCS.

Over the past decade, 3D imaging has been applied to many different purposes. One application has been the identification of animals based on gait and texture analysis, as presented by Okura *et al.* (2019), or based on face recognition (Yeleshetty *et al.*, 2020). In this section, we will discuss this aspect, with a focus on breeding-related traits such as morphological traits, body weight, or feed intake. Body weight, morphological traits, and BCS are regularly recorded on both experimental and commercial farms, whereas measurement of individual feed intake is currently only performed on experimental farms. Thanks to 3D technologies (Shelley *et al.*, 2016), however, such information might soon be available also on commercial farms.

19.4.1 Morphological traits and animal scoring

Apart from live weight (see below), growth-related measurements are still mostly collected manually (e.g. measuring tape, ruler for linear measurements of morphological traits), visually, and/or by palpation (e.g. BCS; Heinrichs and Hardgrove, 1987). These measurements are time-consuming, dangerous, and a source of stress for both animals and farmers; they can also be subjective and prone to operator bias. There is thus significant appeal in the idea of using 3D imaging to quantify morphological traits. In an early study, Buranakarl *et al.* (2012) compared measurements (height at withers, chest circumference, shoulder width) obtained from 3D images to manual measurements of buffalos. The 3D scanner in this case consisted of 16 stereo cameras and 6 video projectors, and was based on the structured light method. The authors placed adhesive paper markers on the animal's skin to identify important measurement points. For all types of measurements, a significant correlation was detected between measurements obtained using this method and manual measurements taken directly from the animals. Similar work was carried out on calves in Italy (Marinello *et al.*, 2015), using a Microsoft Kinect camera in conjunction with an IR laser. Measurements were taken from 20 animals, with a very short scan time (less than 0.20 s). In all cases, a strong correlation (R^2 from 0.966 to 0.986) was observed between manual and 3D measurements. Recently, our group developed and tested a new device called 'Morpho3D', which scans, in 3D, a large animal from the pin bones up to its head (Le Cozler *et al.*, 2019a,b) and thanks to dedicated software, it offers numerous possibilities for obtaining measurements from a 3D image, providing access not only to standard morphological traits usually measured on farms, but also to new ones such as surface areas and volumes (Table 19.2).

An analysis of repeatability and reproducibility indicated that the manual and 3D-estimated morphological measurements were very similar; indeed, average coefficients of variation were lower than 3%, which indicating that both methods are precise and reliable. Differences between the two approaches could be due to the presence of hair, animal movements in response to manual measurement, or even slight variations in the locations of manual measurements. Additional work is probably needed to better understand the source of these differences and their relative importance.

Existing tools on the market

Few tools are or have been marketed to assess the morphological characteristics of farm animals. Among the existing devices, BodyMat V (portable scanner) and X (stationary scanner) devices were developed by Ingenera company (Figure 19.8). These technologies were developed to estimate the measurements of young growing cattle as part of genetic selection. Field test results (unpublished) gave fairly poor correlations with estimates given by trained observers:

Table 19.2. Comparison between manual measurements (gold standard) and those obtained from 3D images using the Morpho3D device on 30 Holstein cows (adapted from Le Cozler *et al.*, 2019a).

Measurement, cm	Manual	Morpho3D	*P*-value
Heart girth (HG)	207.5	221.5	<0.0001
Chest depth (CD)	79.4	83.8	<0.0001
Wither height (WH)	146.9	148.8	<0.003
Hip width (HW)	55.5	54.4	<0.02
Thirl width (TW)	51.9	54.4	<0.008
Ischium width (IW)	17.4	19.6	<0.02

Figure 19.8. BodyMAT V and X from Ingenera company.

R^2<0.4 for hips width, back width, estimation of muscle rounding;

0.4<R^2<0.7 for body length, buttocks width and length;

R^2>0.7 for withers height, hearth girth.

The Ingenera company does not exist anymore and thus, the device is no longer available.

19.4.2 Body weight

Body weight (BW) is one of the most commonly recorded phenotypic traits, and is mainly used to monitor morphological changes in ruminants during both growth and gestation-lactation cycles (Maltz, 1997). Farmers and most animal husbandry advisors (specialists in nutrition or animal health) also use BW dynamics in formulating diets, planning breeding, or managing decisions related to health. Other morphological traits, such as heart girth, hip width, and BCS are also commonly used and can provide information on changes in an animal's status. For example, changes in BCS reflect the mobilisation and accretion of body reserves (Banos *et al.*, 2005; Friggens *et al.*, 2011; Thorup *et al.*, 2012). BW is measured with weighing scale systems or estimated from measurements of heart girth (Heinrichs *et al.*, 1992). For decades, the weighing of animals required the presence of human operators, but the recent development and adoption of electronic identification has made it possible to carry out this operation automatically. Automatic weighing systems have been developed for use with milking robots, but can also be placed in strategic places (e.g. the entrance or exit of the milking parlour) to enable the daily monitoring of weight changes in animals. However, this technology is still expensive and lacks versatility, and is thus not commonly found on farms. Recent developments in 3D imaging should increase the use of this indicator, as 3D imaging can be used to predict BW based on morphological traits, surface areas, or volumes calculated from 3D images (Gomes *et al.*, 2016; Kuzuhara *et al.*, 2015; Le Cozler *et al.*, 2019b; Martins *et al.*, 2020; Miller *et al.*, 2019; Song *et al.*, 2018).

Body weight estimated from morphological traits

Buranakarl *et al.* (2012) established equations to predict the BW of buffalos using morphological traits from 3D images. In their study, the authors developed models that used measurements of heart girth, shoulder width, iliac width, ischial tuberosity width, the length from shoulder to ileac wing, the length from ileal wing to ischial tuberosity, and the length from shoulder to ischial tuberosity. These models of BW prediction achieved a coefficient of determination (R^2) of 0.86 for females, 0.81 for males, and 0.76 for all animals.

Cominotte *et al.* (2020) assessed the predictive quality of an automated computer vision system used to predict BW and average daily gain (ADG) in beef cattle; and compare different predictive approaches, on 234 images of Nellore beef cattle during different phases of growth. Traits originated from 3D images collected from Kinect camera. Despite promising results, they concluded it was still necessary to establish a procedure for segmentation and selection of variables that is fast and automatic, but more measurements in different herds were also needed for validation.

Body weight estimated from surface areas and volumes

Body weight can also be estimated from partial or total volumes and from the surface areas of animals (Le Cozler *et al.*, 2019b). For example, from data on an animal's volume, we were able to accurately estimate the BW of dairy cows, with a prediction error between 15 and 25 kg for animals weighing 550 to 850 kg (Figure 19.9). It is interesting to note that the relationship between volume and BW observed among individual cows was not exactly the same as the relationship within a single cow over the course of its lactation. This difference suggests that volume changes may be due to factors with a high degree of inter-individual variation.

Under commercial conditions, the 'BodyMat V' system previously presented also estimated BW of calves based on surface area (Figure 19.10).

19.4.3 Body condition score

BCS is useful in managing reproduction and nutrition because it reflects the status of a body's reserves, which affects reproductive performance (Roche *et al.*, 2009). BCS can be determined using different scales (Aalseth *et al.*, 1983; Bazin *et al.*, 1984; Earle, 1976; Edmonson *et al.*, 1989;

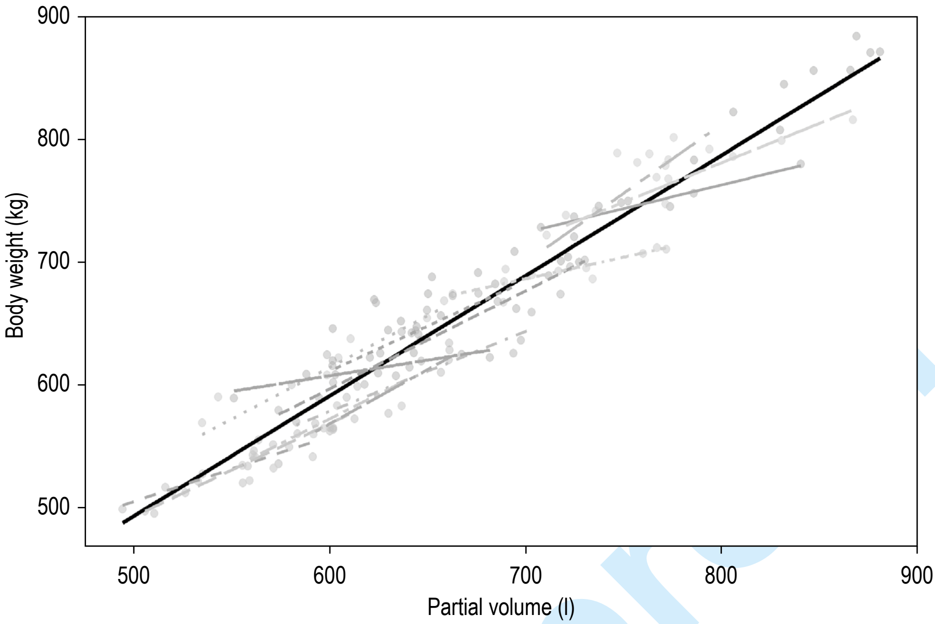

Figure 19.9. Estimation of body weight based on partial volume of cows over 8 months of lactation (in this case, the head volume was not included since animals were restrained with a locking fence). Each colour represents one cow. The black line shows the linear regression across all cows and datapoints, while the coloured lines are fitted for each cow.

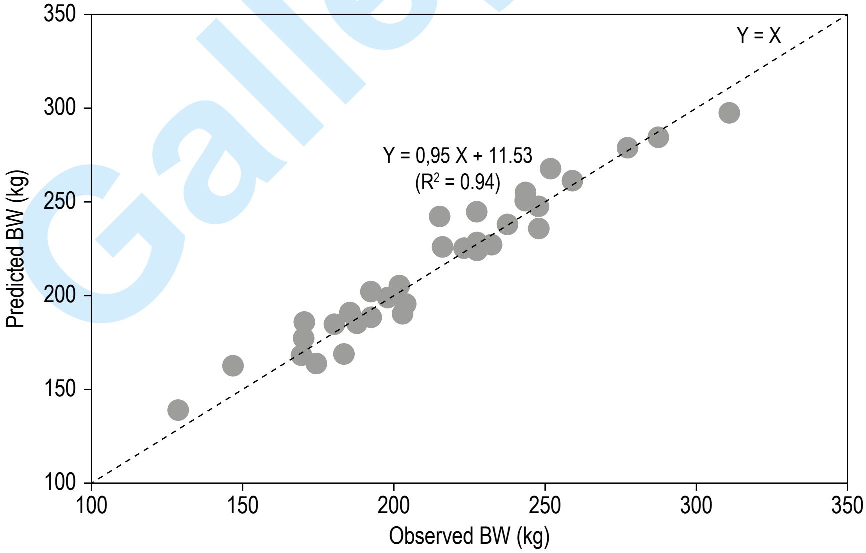

Figure 19.10. Principles of data acquisition and the relationship between predicted bodyweight (BW) and observed BW (calibration data).

Lowman *et al.*, 1976; Macdonald and Roche, 2004), but it is possible to transform all of these into a common scale, as presented by Bedère *et al.* (2018). However, this transformation supposes that BCS is linearly related to body reserve content, a hypothesis that has not yet been experimentally verified; for this reason, transformation should be used with caution. Regardless of the choice of scale, the determination of BCS is prone to operator bias and therefore subjective, and it is difficult to compare values across scoring systems. To address these limitations, efforts have been made to develop less-subjective methods for BCS assessment based on 3D images of ruminants.

Spoliansky *et al.* (2016) used a Kinect camera (Microsoft) with a scan time of 4 s to estimate BCS in dairy cows on a scale of 0 to 5. Their assessments of accuracy estimated a mean absolute error of 0.26 and a median absolute error of 0.19. The results also indicated a high level of repeatability among the 101 cows tested. Similarly, Kuzuhara *et al.* (2015) tested the usefulness of 3D images of the rear posture of cows in estimating BW and BCS using an ASUS Xtion Pro camera coupled with a portable acquisition system and a storage device. Depth detection was performed using an infrared projector. The images were captured by an operator standing behind the cows at a distance of about 1 m, who moved the device about 0.8 m around the cow using a pole. The 3D measurements were then validated through an analysis of the correlation between the observed values and manual measurements. Overall, strong correlations were found (0.74), and the authors concluded that 3D cameras represent an innovative tool for estimating body condition. Fischer *et al.* (2015), using a Xtion Pro Live motion sensor with a capacity of 30 images per second, obtained similar results. BCS values estimated with 3D images were three times more repeatable and reproducible than manually derived scores. Because manual determination of BCS was used as the reference method in this case for the development of 3D-BCS, the prediction error of the latter was naturally similar to that of the former. In dairy goats, using a portable Asus Xtion device and the same PCA methodology as Fischer *et al.* (2015), Huau *et al.* (2020) calibrated 3D image measurements at lumbar and pelvic locations with BCS values recorded at the sternal and lumbar areas by a trained assessor. Overall, a mean absolute error of around 0.25 (on a BCS scale of 0-5) was obtained, suggesting a good predictive capability for BCS; this was confirmed and extended to the prediction of body lipid mass using a separate data set of 20 goats (Lerch *et al.*, 2020). With respect to image quality, the imaging method of Fischer *et al.* (2015) was able to acquire good quality images, recorded within 3 s, but was sensitive to animal movement: nearly 20% of the 2D images were rejected due to poor quality, presumably for this reason. In the study of Spoliansky *et al.* (2016), when images presented 'holes', restoration was performed via extrapolation based on neighbouring pixels. The holes were caused by sunlight, moonlight, and cow movements, which appear to be the main problems when using such technologies.

To conclude, the error of BCS estimation from current 3D imaging technology is typically equivalent to that present in the manual approach. However, in the future, the use of 3D imaging in conjunction with high-throughput monitoring will reduce this error. Such a monitoring scheme will also create opportunities for new applications of BCS in animal husbandry, which until now have not been possible because of the infrequency of measurement. For on-farm applications, some commercially devices are available, such as the fixed system developed by the DeLaval Company ((DeLaval Body Condition Scoring, BCS DeLaval International AB, Tumba, Sweden) or mobile apparatuses such as BodyMat F (BMF, Ingenera SA, Cureglia, Switzerland) (Figure 19.11).

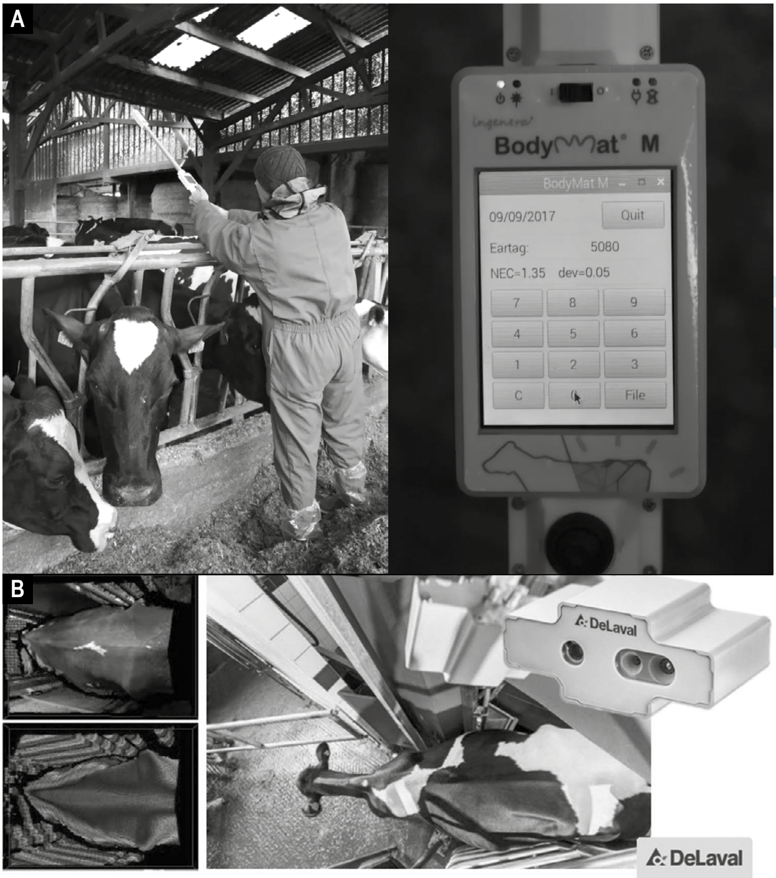

Figure 19.11. Two examples of BCS analysis devices available to commercial farms: (A) BodyMat from Ingenera; and (B) BCS by DeLaval.

Mullins *et al.* (2019) compared the notes given by the BCS DeLaval device to conventional manual scoring. They concluded that automated BCS technology was highly correlated with manual scoring, accurate for a BCS between 3.0 and 3.75, with a lower error rate compared to the standard detection threshold of 0.25 for manual scoring. But the system was found to inaccurate at determining under- and over-conditioned cattle compared to manual scoring. Clouet and Porhiel (2020) noticed similar results in a herd were cows had on average low condition score: the automated BCS technology gave a 1.5 points higher value on average during lactation. Zieltjens (2020) also concluded that the DeLaval system scores BCS on average 0.3 higher in comparison with the manual BCS. The BCS of cows high in condition was scored lower by the automated system in comparison with the BCS measured manually. Similarly, the cows low in condition were scored higher in BCS by the automated system.

Finally, O'Leary *et al.* (2020) used the BodyMat F to automatically determined BCS and compare measurements to manual values. They were lower for extreme values, particularly in over-conditioned cows but the BodyMat F outperformed human assessors in terms of reproducibility.

All these results indicated that these tools are of interest but probably need further developments and as explained earlier, though, the performance and precision of any equipment will need to be carefully studied by users/buyers prior to purchase.

19.4.4 Lameness and behaviour

In recent years, there has also been increased attention paid to the use of 3D cameras for the detection of lameness. Lameness can be detected either through analysis of an animal's posture or analysis of its locomotion (Figure 19.12).

Viazzi *et al.* (2014) compared the use of 2D and 3D cameras in evaluating the back and leg posture of dairy cows, and automatically classified cows as lame or not. Depth values were obtained using an infrared projector that emitted a light pattern on the animal. The IR sensor detected the reflected light pattern, analysed the distortion, and produced an image. The device's main limitation – its known sensitivity to light – was overcome by performing the measurements at night. Images (both 2D and 3D) were trained and tested with respect to a visual score of lameness calculated by a trained scorer (repeatability of 85.6±3, kappa coefficient of 0.64). The 2D algorithm performed slightly better in external validation (1-2% higher accuracy) than the 3D algorithm. However, 2D imaging appeared to be less adaptable to farming conditions than 3D imaging, because the 2D method was more susceptible to possible bias due to, e.g. shadows. The methodology of Van Hertem *et al.* (2014) used 3D imaging at night with the Microsoft Kinect camera to automatically classify cows as lame or not; this approach matched the classifications by expert evaluators 81.2% of the time. For applications in the field, in 2018 the company dsp-Agrosoft (Germany) developed a commercial device called

Figure 19.12. Lameness detection in dairy cows, using (A) analysis of posture (Sprecher *et al.*, 1997; Zinpro, 2021) or (B) analysis of locomotion (Gardenier *et al.*, 2018).

CBS-system to determine lameness and BCS in cows (Figure 19.13). As stated above regarding BCS, though, the performance and precision of such equipment need to be carefully evaluated prior to purchase.

19.4.5 Carcass composition

In the 3D imaging of live animals, more attention has been paid to dairy cattle than to beef cattle. In the limited amount of research that has been conducted in beef cattle, efforts have tended to focus on applications of 3D imaging technologies to the estimation of carcass traits. For example, Gomes *et al.* (2016) investigated the correlations between measurements taken by a Microsoft Kinect camera and yield-related traits. The camera was held in a fixed position 2.95 m from the floor, and 20-s videos were taken of the top of a cattle chute. Recordings were made of 25 Black Angus bulls and 15 Nellore bulls at night, with no artificial light in order to avoid problems with lighting and shadow (see above). Images of the back of animals were manually selected directly from the video and used to measure morphological traits related to BW, hot carcass weight, carcass chemical composition, and empty body chemical composition. Overall, good relationships were found between the traits characterised in the images and actual BW or hot carcass weight, with R^2 values of 0.84 and 0.83, and root mean square errors (RMSE) of 19.4 and 15.4 kg, respectively. However, the correlation between the morphological traits and the proportion of empty body fat was weak (R^2=0.43-0.45). Similarly, Miller *et al.* (2019) estimated BW, cold carcass weight, and saleable meat yield using 3D imaging focussed on the area between the pins and the shoulders. Data from a large and diverse set of finishing beef cattle were split into two subsets (calibration: 70% of observations; validation: 30%) and analysed with an artificial neural network (R^2 of 0.70, 0.88, and 0.72, and RMSE of 42 kg, 14 kg, and 14%, respectively). Images were taken both during the day and at night, but problems with image quality were noted during the day due to strong and direct sunlight. Images were subjected to automatic analyses that extracted measurements, ratios, areas, and volumes. Carcass conformation and fat classes were also estimated from morphological traits, but there were numerous cases of misattribution between classes.

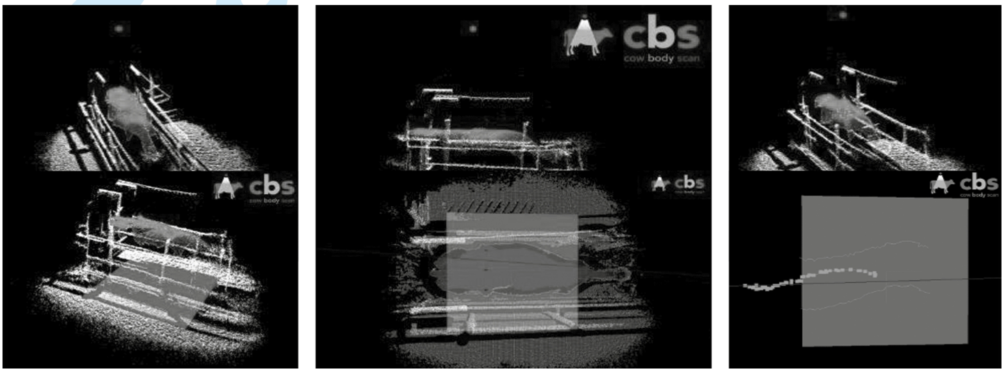

Figure 19.13. Example of images obtained from the cow body scan (CBS) device developed by dsp-Agrosoft GmbH. Top pictures: determination of BCS and bottom pictures: detection of lameness.

Recently, an attempt was made to use the Morpho3D device to estimate the empty body chemical composition of dairy goats (Lerch *et al.*, 2020). Unfortunately, whole body surface area and volume measurements recorded by 3D imaging failed to accurately estimate the body chemical composition of goats (R^2 values were all below 0.43). This low performance may have been due to the relative size of the 3D scanning equipment compared to the target animals; the apparatus was originally built for adult cows, and was not adapted for use on small ruminants. Those results highlighted the importance of ensuring that the 3D scanner is appropriately sized with respect to the targeted animal. An ongoing project aims to perform similar body and carcass estimates on crossbred heifers, bulls, and steers (Xavier *et al.*, unpublished data). The novelty of this work is that whole body 3D images of live, growing cattle are being acquired not only for estimates of chemical and anatomical empty body and carcass compositions, but also for the dynamic estimation of growth and its effect on these parameters. Currently, these types of measurements are obtained using calibration against reference body composition as measured after slaughter (dissection, grinding, and chemical analyses; Figure 19.14).

Figure 19.14. The use of 3D technology to estimate carcass composition (photo credits: Agroscope).

19.5 New and promising applications of 3D imaging

19.5.1 Surface of entire animals

An animal's volume can be used to determine its body weight, but using surface area for this purpose is of less interest (Le Cozler *et al.*, 2019b). But measurements of surface area are commonly used to determine maintenance requirements based on body weight; the equations used for these calculations have been relatively unchanged for almost a century and are similar to those published by Elting (1926). However, it must be noted that bodyweight, because it is the sum of several components, is not an exact representation of an animal's size and/or fattening status. Measurements of surface area can also be useful in considering issues related to heat dissipation. For instance, the ratio between surface area and volume is known to be a good predictor of the capacity to dissipate heat. This ratio usually decreases as weight increases, almost linearly in adult cows (Figure 19.15), but not in growing heifers. One might thus expect that the heaviest or higher-parity cows would be the most sensitive to heat stress, and indeed, Bernabucci *et al.* (2014) reported that higher-parity Holstein cows were more susceptible to heat stress than primiparous cows. The Holstein breed is known to have low genetic diversity and may thus be especially susceptible to stress. The use of 3D imaging to calculate surface areas could be used to tackle the issue of heat stress resistance in dairy cows.

In practice, it is almost impossible to accurately measure the surface area of living animals, but it can be estimated using a measuring tape and indirect approaches (Cutullic and Flury, 2011). Such indirect methods are less precise, time consuming, and also dangerous, because they require the handling of animals. The use of 3D imaging for this purpose has already yielded insights into bovine growth that run counter to commonly held assumptions. For example, in the formulation of most nutrition recommendations for cows (INRA, 2018; NRC, 2001), full adult size is thought to be achieved at the end of the first lactation. However, the use of 3D imaging technologies has revealed that this assumption may be inappropriate, as we observed that surface area and other morphological

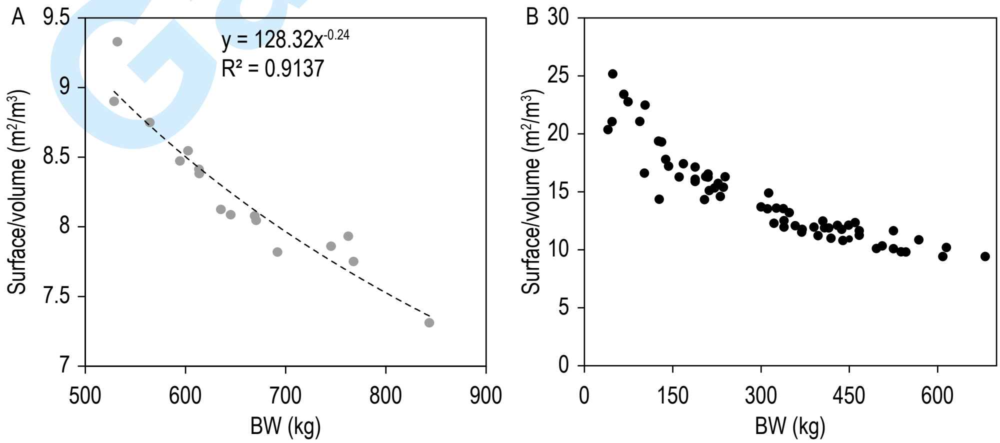

Figure 19.15. Relationship between the surface-to-volume ratio and body weight in (A) 16 lactating adult Holstein cows and (B) 5 growing Holstein heifers (preliminary results, unpublished).

traits continued to increase for cows in their third (or higher) lactation (Figure 19.16; Xavier *et al.*, 2022). With more-precise information on both the development of surface area and growth traits, it will be possible to improve estimations of individual maintenance and growth requirements and therefore to more precisely adapt feed allowances to individual requirements.

In the future, improvements in the measuring process could also facilitate the use of surface area for estimations of co-products such as wool and leather from living animals.

19.5.2 Volume of animals

Recently, Lebreton *et al.* (2020) explored how 3D imaging technologies could be used to estimate changes in volume of a dairy cow's rumen (Figure 19.17). When combined with the ability of such technologies to also estimate individual feed intake (see Section 19.5.3), this could provide a new way to characterise and select for feed efficiency in cows (see Deffilait project results at http://www.deffilait.fr/). Indeed, this study highlighted that rumen volume and feed intake may be key indicators in characterising feed efficiency.

19.5.3 Feed intake

Three-dimensional imaging can also be used to estimate feed intake, and more particularly, individual feed intake (Bezen *et al.*, 2020; Shelley *et al.*, 2016). Feed is the most significant cost on dairy farms, which explains why improving feed efficiency is an important target for both researchers and farmers.

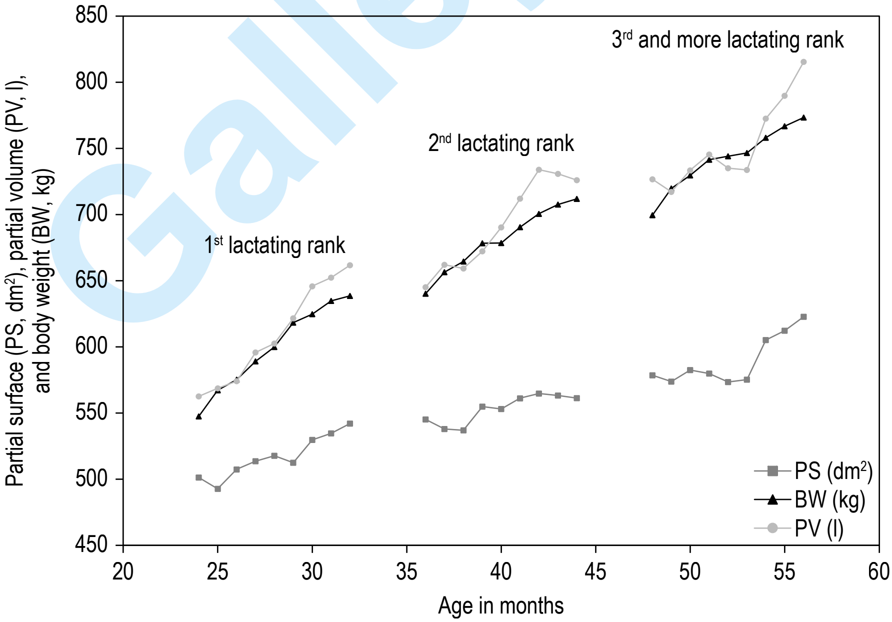

Figure 19.16. Changes in surface area, volume, and live weight of dairy cows, according to age and lactation rank (Xavier *et al.*, 2022).

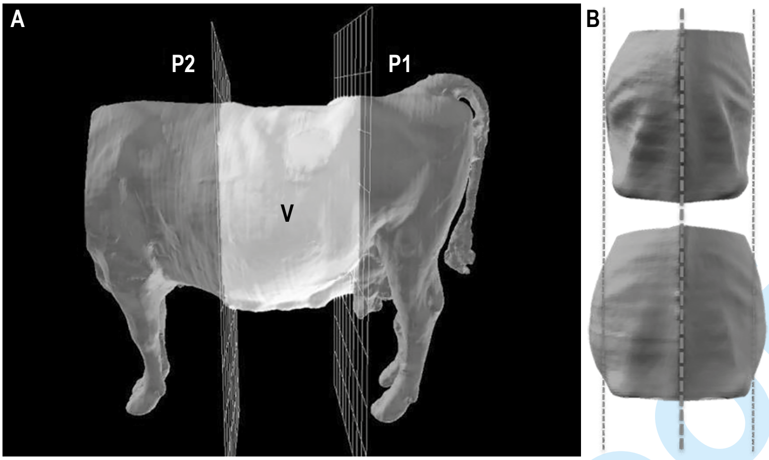

Figure 19.17. The use of 3D imaging technology to study changes in rumen volume: (A) definition of abdominal volume (highlighted in light grey; according to Depuille, 2018) as the volume between 2 orthogonal planes (P1 and P2); (B) abdominal volume before (left) and after drenching (right; according to Lebreton *et al.*, 2020).

Ruminants are usually fed in groups, but more and more attention is being paid to individual feed intake (Halachmi *et al.*, 2016; Holtenius *et al.*, 2018), which, in combination with milk production, milk composition, and body weight, can be used to estimate individual feed efficiency. Automatic monitoring of individual feed intake requires expensive facilities and can be time-consuming; this approach is therefore only available in some research facilities. For on-farm use, instead, computer vision systems have been developed to measure feed intake (Bloch *et al.*, 2019; Shelley, 2013; Shelley *et al.*, 2016), most of which are based on a linear correlation between image features, e.g. the volume of a feed heap, and the heap's actual weight. As for BCS, however, the interference of sunlight with the cameras' infrared sensor can impede the system's functioning (Borchersen *et al.*, 2018; Shelley *et al.*, 2016). It should be noted that the estimation of individual feed intake also requires the individual identification of animals, with, for example, video facial recognition or the installation of RFID antennas at the feeding area, which are too expensive for many farmers. For example, Bezen *et al.* (2020) developed a machine vision system that performed both tasks: monitoring individual feed intake and identifying individual cows. Further refinements are necessary, as only 93.6% of cows were correctly identified in the feeding lane, but the system serves as a proof of concept for the use of reliable, low-cost cameras in the measurement of individual feed intake on dairy farms, in open cowshed conditions. Although a similar tool is not yet commercially available, initial results confirm the potential of 3D imaging technology used together with electronic identification.

19.5.4 Continuous recording and analysis

Applications related to BCS

Depending on the intended use of BCS data, different aspects of a BCS recording system may be prioritised. For the purposes of genetic analysis or selection, accuracy is crucial. Instead, in the context of monitoring BCS to prevent metabolic or fertility issues, the focus is on repeatability and speed, i.e. automation. To this end, several technologies have been developed to estimate BCS quickly and repeatedly (Table 19.1). Most of these devices have been developed under specific housing conditions and for certain breeds, and therefore must be validated under farm conditions before their potential deployment. Daily or more frequent BCS recording might be possible on some cows using BodyMat technology, but the DeLaval system probably requires extensive calibration for most breeds and farming systems (unless the device is able to use machine learning technology to perform the process; see above). Recently, Faverdin *et al.* (unpublished data) adapted 'one shot' camera technology (similar to Asus Xtion Pro camera) to avoid low-quality images (in most cases, fuzzy images caused by animal movement); this represented an improvement of the device developed by Fischer *et al.* (2015), which required a scanning process. In this new prototype, the camera was mounted on a rotary milking system. As in Fischer *et al.* (2015), they focussed on the rump of cows. The 3D Three-dimensional images were taken twice a day, at each milking. Although the overall image quality of the 'one shot' system was lower than that of the scanning process, this could be offset by the potential for high-throughput monitoring of BCS.

To date, BCS has been used on commercial farms as an indicator in determining dry-off period, calving condition, and time of insemination. Indeed, farmers and advisors often use specific target values for BCS at different times of an animal's career to prevent health or reproductive issues. In general, guidelines about when and how often an animal should be scored have been largely determined by the logistical limitations of the process (time, cost); currently, scoring can be performed once or twice a month, but rarely occurs more than a few times in total for any given animal. The use of 3D imaging to estimate BCS opens the door to high-throughput BCS monitoring and therefore enables new applications, particularly in the fields of animal nutrition, metabolic diseases, and reproduction. As mentioned earlier, a change in body reserves plays an important role in fertility performance, health issues (such as ketosis or lameness), and growth. One possible application of 3D imaging could be the monitoring of energy balance, and more particularly changes in energy balance, which can be used to predict changes in body reserves. For example, through the use of high-throughput monitoring, the device developed by Faverdin *et al.* (unpublished data) estimates BCS in dairy cattle accurately enough to enable investigations of the relationship between BCS and net energy balance (Figure 19.18).

Because of the close relationship between changes in cumulative energy balance and changes in BCS, high-throughput/continuous monitoring of BCS is of great interest, and a significant amount of research is currently focussed on how to make this type of system more accessible. As an example, new algorithms are being developed for continuous analysis of BCS, which could be used, for example, as a tool to rapidly correct and adapt feeding strategies (Figure 19.19).

A promising example of one-shot technology on a full animal

To ensure their flexibility and overall utility, future systems must be able to fulfil multiple, diverse objectives, with little maintenance. For example, an automated system placed in an area through which all animals must pass daily (e.g. entrance of the milking parlour or a corridor) would be able to measure, frequently and automatically, multiple phenotypes (BW, surface areas, volumes, BCS, meat content of carcasses), to detect and/or predict disturbances (e.g. lameness, weight variations), or even to perform new diagnosis (e.g. gestation). Imaging based on a one-shot approach appears

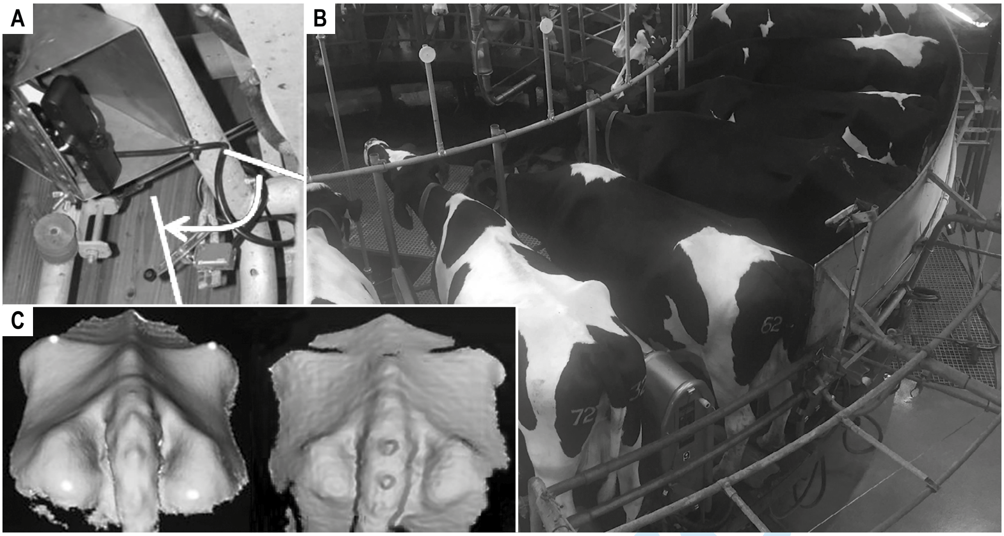

Figure 19.18. Two technologies developed on experimental farms to monitor BCS: (A) an Xtion PRO Live motion sensor with scanning process (Fischer *et al.*, 2015) and (B) Asus Xtion Pro sensor that captures one-shot 3D images. On the bottom (C)t, the associated 3D images (Credit INRAE).

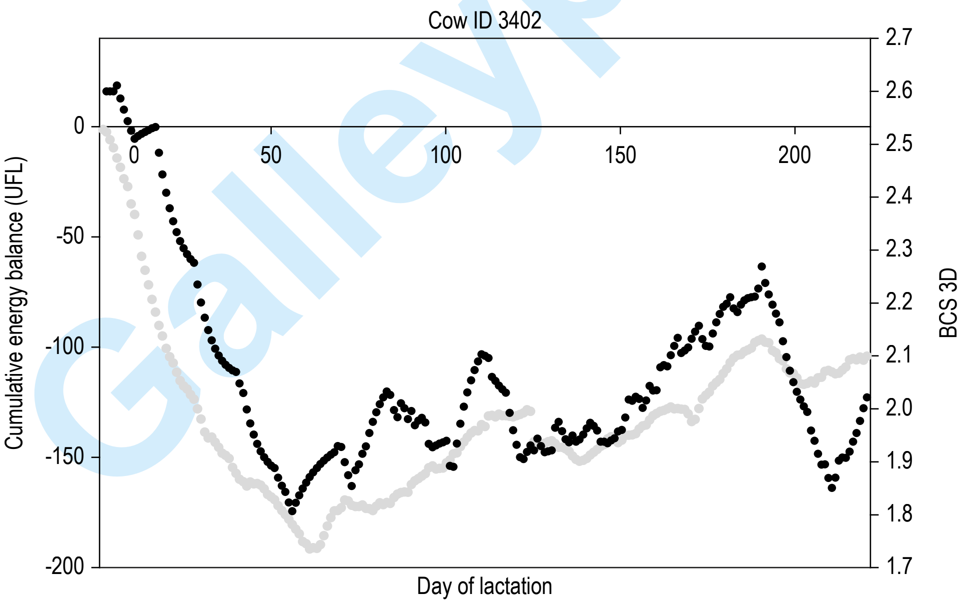

Figure 19.19. Change in body condition score (BCS) (black circles; 0-5 scale) and in cumulative energy balance (grey circles) for an individual dairy cow.

to be a promising tool for such purposes and could be used in the near future on commercial farms.

Compared to 3D scanners, such as Morpho3D, the one-shot approach is less sensitive to light and distortions caused by animal movement, and is able to acquire many images in a shorter amount of time. Generally speaking, image quality is not as good as with scanners, but is typically high enough to reach the required resolution. A comparison of images taken of a plastic model cow by the original Morpho3D scanner and the one-shot device indicated only minor differences, even before the one-shot device was optimised (Table 19.3).

From this complete 3D image, which is obtained instantaneously, it will soon be possible to investigate the acquisition of only certain parts of the body (partial 3D images), which could then be used as proxies for other analyses.

Automation of extraction and analysis

Regardless of the type of information desired (Section 19.4), the first step is to extract geometric features from the data. This can be accomplished automatically or manually, with features that are pre-defined or not. The nature of the targeted application – in the field or for research purposes – will also influence the expected degree of automation. If a large-enough database of labelled data

Table 19.3. Preliminary comparison of several morphological traits calculated for a plastic model cow with two 3D imaging technologies that deliver whole-body 3D images of live animals: a technology based on a scanning device (Morpho3D) and a technology based on a one-shot approach (Deffilait).[1]

Device		Morpho 3D	Deffilait
			
Hip width	Average, mm	394.6	391.3
	SD, mm	3.5	8.5
	CV, %	0.9	2.2
Wither height	Average, mm	1,272	1,238
	SD, mm	3.2	8.2
	CV, %	0.3	0.7
Volume	Average, m^3	0.521	0.539
	SD, m^3	0.043	0.048
	CV, %	0.8	0.1
Surface	Average, m^2	5.62	5.94
	SD, m^2	0.16	0.11
	CV, %	2.9	0.2

[1] SD = standard deviation; CV = coefficient of variation.

is available, automatic extraction can rely on a robust geometric algorithm in addition to machine learning techniques. However, pre-defined feature extraction can be avoided by transforming the shape directly into the desired variable. In 2D imaging approaches, this can be achieved with a convolutional neural network (CNN; see below), as in, for example, the identification of cows based on their skin patterns (Zin, 2018). A dataset that includes both the image and its associated target variable is used to train the neural network. If the training is successful, the network can be used to create measurements from new data. The network defines its own features, which are by definition unknown to users, although. It is possible to check *a posteriori* which features were selected in the optimisation process.

In recent years, computer vision and deep learning (a subset of machine learning) methods have undergone considerable development and are increasingly widespread in the field of agricultural data analysis (Espejo-Garcia *et al.*, 2019; Kamilaris and Prenafeta-Boldu, 2018) and livestock production (Bezen *et al.*, 2020). In particular, CNNs have become increasingly common in detection, classification, recognition, and tracing, thanks to improvements in the computational capabilities of graphics processing units (Tsai *et al.*, 2018) and to the increasing amounts of data available (Zhang *et al.*, 2018). Indeed, CNNs are able to learn a huge number of parameters, but require large amounts of data. CNNs follow the biological principle of replicating patterns in order to identify them in different locations (see Rawat and Wang, 2017 for details). However, according to these authors, the use of CNNs can easily lead to overfitting, regardless of the size of the training set used, which can affect the model's ability to generalise on new data. The easiest and most common method to reduce overfitting is data augmentation (cross-validation). To check the robustness of this approach, it is not uncommon to introduce voluntary errors.

When it comes to 3D methods, the learning process will depend on the type of data: CNNs can still be used on depth maps, for example, but are unsuited for unordered point clouds (although networks for point clouds are emerging, e.g. (PointNet). Another approach is to provide the learning algorithm a normalised representation of the 3D data. In an experiment by Fischer *et al.* (2015), body condition scores calculated by three experts were compared using principal component analysis (PCA) to BCS values generated from 3D images. Specifically, each 3D image was projected onto a new reference plot, whose axes were defined as the principal components of the PCA. The coordinates on this PCA-reference were then used in a linear regression to predict the BCS. An analysis of the reproducibility and repeatability of the method revealed that the 3D-BCS was three times more repeatable than the manually derived BCS.

19.6 Conclusions

The interest in and use of 3D imaging technology in livestock production is steadily increasing, especially for large animals such as dairy and beef cattle. These technologies decrease the occurrence of stressful situations that would affect the 'normal' behaviour of the animal and can provide access to physical measurements that can be repeatedly obtained from a large number of individuals without any safety risk to the human operator. The sensors required are gradually becoming less expensive, more resistant to extreme conditions on-farm (e.g. temperature, humidity, dust, direct light), and do not require regular calibration. The information that can be gained from such technology is no doubt of interest for most ruminant farms, regardless of the size or mode of production. However, more work is still needed to automate the treatment and analysis of images. Three-dimensional imaging is also of interest for other species, with ongoing tests in ewes and horses.

It is too early to tell what the possible consequences of the information gained from this technology might be in terms of labour conditions, the mental load of farmers, or benefits to animal husbandry. The number of indicators that will be available for use in livestock production systems (e.g. BCS, body weight, ingestion capacity) will surely increase, along with the frequency of data collection. Indeed, up to now, many indicators have been used in only a limited way because of the logistical challenges of data collection. The availability of high-throughput monitoring these phenotypes opens new applications for research and in the field, many of which remain to be discovered. In particular, important work remains to be done with respect to reflection on the use of these data, the advice to give to breeders, and the training of farmers.

19.7 From science to practice: perspectives

The practical implementation of 3D imaging technologies on commercial farms will probably require some barn adaptations and investments, which would be similar to the adaptations required to install a milking robot. Dedicated areas may be necessary, in particular for full-body 3D images, due to potential minimum distance requirements between the object and the camera. In some cases, it is possible that images of a single part of the animal may be able to serve as an informative proxy for full-body data. For example, the volume or surface area of an animal can be estimated with high precision from a truncated image, such as that obtained from an animal whose head is restrained (Le Cozler *et al.*, 2019b). The use of machine learning will probably help to identify new body areas or new traits of interest. However, even if most technical and technological obstacles have been removed (or will soon be removed), the use of this technology is still hindered by limitations associated with data transfer and storage capacity, the kind of information stored, data analysis, and the ability to generate relevant feedback in real time. Large-scale deployment of this technology will also necessitate training for farmers and consultants who lack computer skills. The real challenge for the future will lie in our ability to combine all of the data generated on a farm by all available sensors in a useful and informative way.

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