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Review

A review of three-dimensional computer vision used in precision livestock farming for cattle growth management

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ABSTRACT

Within precision livestock farming, three-dimensional computer vision can improve growth monitoring in cattle management. To investigate the implementation of three-dimensional computer vision in cattle growth management, this systematic review, adhering to the PRISMA 2020 statement guideline, collected 47 eligible studies from the Web of Science database. Studies were analysed separately based on the incrementally encoded titles, and their outcomes were extracted and recorded in a pre-designed form. The survey of outcomes was conducted by using pivot analysis. The results showed that the body measurements assessment task contributed to other kinds of three-dimensional cattle growth tasks. Using Kinect sensors fixed at nadirs to obtain dorsal features was the most frequently applied approach in three-dimensional data acquisition. For three-dimensional data pre-processing, while empty scene subtraction was the most effective approach to removing background from point clouds, clustering and conditional filters were the most adopted functions to eliminate noise. In the discussion, this review provides actual insights into the knowledge of three-dimensional computer vision in cattle growth management, synthesises common considerations within data acquisition, forms a general procedure of data pre-processing, considers the potential of building an automatic and successive three-dimensional multi-task cattle growth monitoring management system, and discusses factors affecting the performance of models for cattle growth management. This review inspires the practice of future three-dimensional computer vision research in cattle growth management and could be extended to other livestock or wild animals.

1. Introduction

For cattle growth management, the key is regular and adequate monitoring of body health indices, such as body measurements, body weight (BW), body condition score (BCS), and lameness. Body measurements, also named morphological traits or zoometric measurements, are essential to support cattle management decisions on a herd's breeding, nutrition status or daily weight gain. For example, hip height related to age is used to assess beef cattle's maturity type (Walmsley et al., 2010). BW is one of the most important parameters for monitoring cattle health. For example, it can detect or predict disease outbreaks by monitoring unexpected changes; based on detection or prediction, farmers or herders can take necessary actions (Kashiha et al., 2014). BCS assess cattle's energy reserve or nutritional status by using a five-point scale ranging from the minimum for a thin animal to the maximum for a fat animal in increments of 0.25 or 0.5 (Hansen et al., 2018; Zin et al., 2020). BCS informs feeding strategy and provides an opportunity to fine-tune nutrition (Zin et al., 2020), improving cattle's health. Lameness is reflected as impaired locomotion in cattle legs (Schlageter-Tello et al., 2018), and it is one of the most critical health and welfare issues (Bruijnis et al., 2012). Detection of lameness guides an appropriate treatment strategy. While the trend of herd sizes per farm is increasing (Schlageter-Tello et al., 2018), attention must be paid to individuals accurately, efficiently, and humanely.

In modern intensive farming, the traditional cattle growth management way is defective. Humans conventionally do it with direct-contact tools or in-situ observations, but humans' observations have limitations. First, the practices of the traditional way are stressful for both the animals and the people themselves. For example, the presence of humans often affects the cow's behaviour (Jabbar et al., 2017) because cattle can

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suffer stress and welfare issues from disturbance, while during manual operations, people face the risk of injury (Guo et al., 2017). Second, the results are affected by the assessors. When humans manually carry out cattle management, experienced operators tend to decide with high-quality results (Wilkins et al., 2015), but their observations are not quantified, and they are poor at detecting small or subtle changes (Hansen et al., 2018; O'Leary et al., 2020). However, these changes are more informative and helpful for individuals, such as in the early detection of lameness. Last, other specific disadvantages of the conventional methods can be identified. For body measurements, cattle are measured manually by trained operators using a variety of instruments such as the Aparicio measuring stick (Gaudioso et al., 2014), Lydtin stick (Ruchay et al., 2020), tape measure, or hipometer (Martins et al., 2020; Kamchen et al., 2021). These measurements require temperamental cattle to be stillstand through cattle crushes or containment boxes, which is against animal welfare. For BW, cattle are scaled using industrial scales placed in designated locations. The scales need a large budget to purchase, a high cost to maintain in the harsh condition covered with manure and urine (Dickinson et al., 2013), and skilled labourers to operate. For BCS, assessors evaluate cattle following a qualitative manual body condition scoring protocol. The assessors must be familiar with skeletal structures and fat reserves to support them in visually assessing cow body shape and palpitating defined anatomical regions (O'Leary et al., 2020; Zin et al., 2020). For lameness, observers visualise cattle using locomotion scoring (Flower and Weary, 2006). The visualisation procedure combines several gaits and posture characteristics such as back arch, gait asymmetry, and weight-bearing into one overall locomotion score (LS) (Van Hertem et al., 2016; Schlageter-Tello et al., 2018). In summary, traditional manual methods are labour-intensive, labour-limited, time-consuming, and subjective (Wilkins et al., 2015), which means that limited attention can be paid to individuals.

For the innovation in traditional methods, computer vision (CV) in precision livestock farming (PLF) contributes significantly. It refers to continuous directly, remote, and non-invasive monitoring or observation of identified individuals' health and welfare in real-time for farmers by providing meaningful and understandable information (Harrison et al., 2007; Berckmans, 2017; Neethirajan, 2017). The information concerns refined data, mainly created from sensors and analysed by models. CV is innovative in combining sensors and models. It shapes a non-contact way of minimising humans' intervention to conduct cattle management (Viazzi et al., 2014; Van Hertem et al., 2016; Ruchay et al., 2020) because sensors can replace the observations of human eyes. CV includes two-dimensional (2D) and three-dimensional (3D) vision systems (Song et al., 2019). 2D CV has already contributed to improving cattle management practices in PLF. For example, it has been explored to measure morphological characteristics to estimate live BW (Tasdemir et al., 2011). However, 2D CV has inherited limitations on anatomical landmark identification and cattle segmentation. Anatomical landmarks scatter on the surface of a cow's body and determine morphological traits, which are critical for cattle growth management. Some landmarks are hard to identify by 2D CV because they distribute on bodies three-dimensionally, and changes in perspective and distance can influence the capture of landmarks. Typically, 2D CV approaches need to segment individual cattle's data before landmark identification, but the segmentation is impeded by different light conditions, backgrounds, and other factors (Salau et al., 2015) where the data are images. In the last decade, 3D CV has increasingly contributed to cattle management in PLF. For example, Cominotte et al. (2020) used a 3D CV system to predict BW in beef cattle. Inexpensive 3D cameras are referred to as alternative tools for the 2D's as 3D CV provides the extra valuable third dimension, "the depth", which is the distance between sensors and the targets and is represented mainly in the form of point clouds. It overcomes the problems mentioned in the 2D CV.

Several reviews and basic research on 3D CV in cattle or livestock management have recently been published; still, they are not enough to describe and summarize the knowledge of conducting 3D cattle growth management. Nasirahmadi et al. (2017) reviewed image processing techniques based on 2D and 3D CV for automated monitoring of cattle' and pigs' characteristics and behaviours in specific classified applications. This study illustrates that with accurate information from 3D CV systems, there are further possibilities for improvement for these applications, but acquiring accurate 3D information is undiscussed. Wang et al. (2021) compared machine learning applications based on CV for livestock BW prediction. This shows the possibility of fully automating BW prediction from digital images when introducing the machine and deep learning. However, other methods such as linear models are also used, whose performance could also be compared. Salau et al. (2016a) implemented an elaborate extrinsic calibration through an additional 3D calibration object for six-Microsoft Kinect v1 camera frameworks. This primary step of acquiring raw data fundamentally influenced later research on collecting data. For example, Salau et al. (2020) determined the body parts of cows, including the head, rump, back, legs, and udder; Salau et al. (2017) recognised the udder and rear leg of cows and calculated morphological characteristics. Salau et al. (2017) subtly performed raw data pre-processing for 3D object recognition through concise and ingenious specifying thresholds and background subtraction, simplifying the extraction of target point clouds. However, these two studies only choose one specific data acquisition issue and pre-processing for research. To our knowledge, there has been no attempt to systematically expound on the general data acquisition and pre-processing procedure for 3D CV cattle growth management.

The purpose of this review was (1) to map out the current knowledge regarding 3D CV to support cattle growth management, (2) to describe thorough considerations and general procedures of three-dimensional data acquisition and pre-processing, (3) to analyse cattle growth management tasks among categories, and (4) to generalise common issues to improve the performance of cattle growth management models. The results of this review will help to understand the research gaps in 3D cattle growth management, and the insights in the discussion could guide future research in this field.

Because of the large number of abbreviations used in the relative scientific works, the abbreviations and cattle term explanations appearing in this work have been listed in supplementary 0 (https://doi.org/10.5281/zenodo.7406521).

2. Material and methods

To review the literature on 3D CV for cattle management in PLF, we applied the guideline developed in the PRISMA 2020 statement (Page et al., 2021). This systematic review approach analysed the bibliography in three phases: (a) collecting relevant papers, (b) performing a detailed review, and (c) analysing the studies (Fig. 1). This section describes the essential implementations in the following paragraphs, and details for explanation can be found in Supplementary 5.

Query = Criterion "cattle" AND Criterion "3D vision" NOT Criterion "exclusions" **(1)**

In the first phase, 47 relevant papers were collected. All the papers are either published or available online before February 1st, 2022. They were directly searched in the Web of Science (WoS) database and manually filtered after searching. These eligible papers met all three criteria listed in Table 1 within a record by using WoS search syntax (Equation (1)). The search using Equation (1) on WoS was performed on February 1st, 2022, generating 109 papers; citations retrieved from the literature search were imported to EndNote, including titles and abstracts. After importing citations into EndNote, a manual selection was further performed. The selection pruned the searching results to remove irrelevant papers by reviewing titles and abstracts. The eliminated paper through selection used either a non-3D CV approach or non-oriented cattle growth management. For example, the force plate system was used to measure ground reaction forces for predicting lameness (Dunthorn et al., 2015); the collision between the cattle and the manipulator was predicted by using point clouds (Jo, 2020); hoof growth was

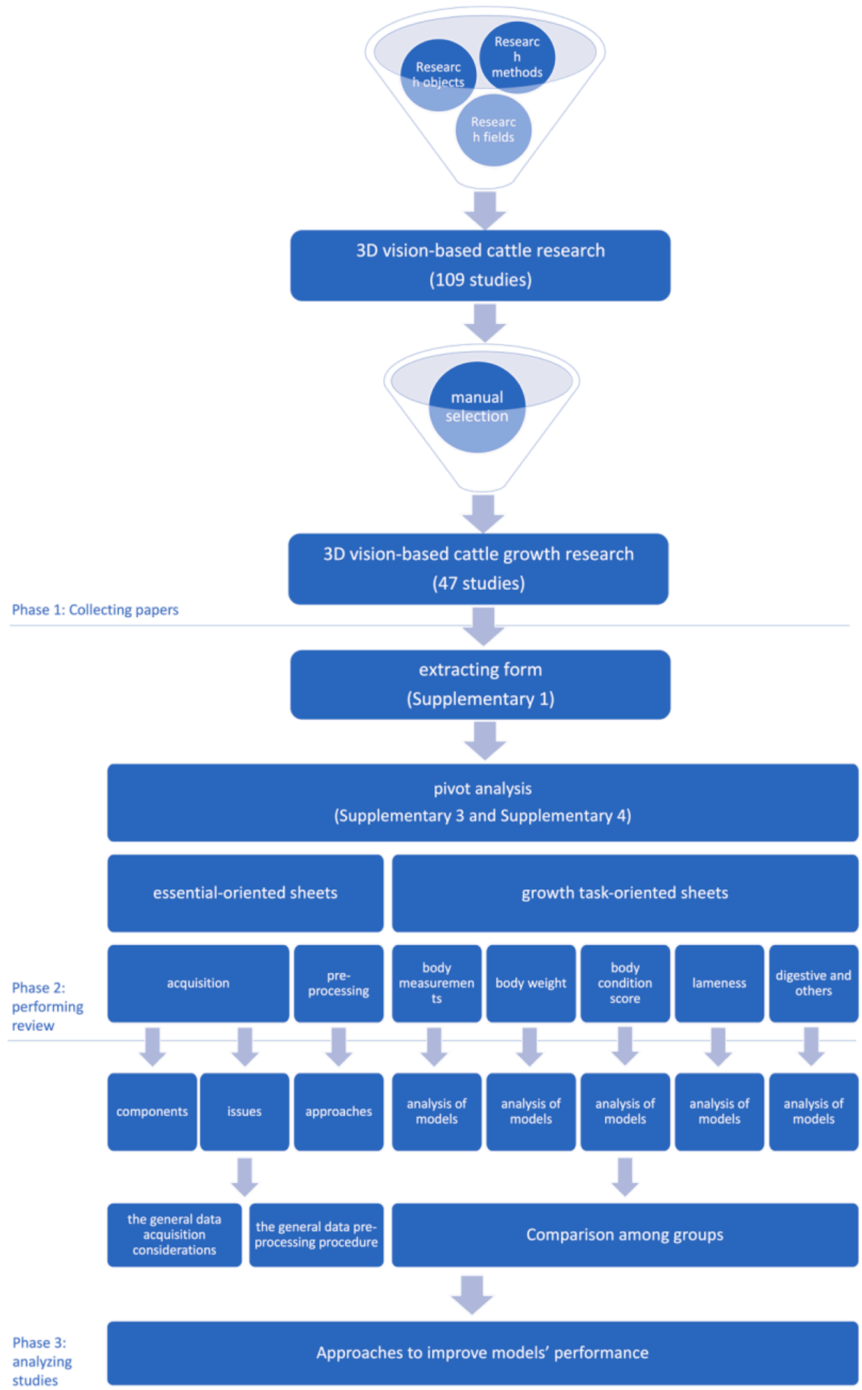

Fig. 1. Flowchart of the methodology used in this systematic review.

researched by using stable isotope analysis (Harrison et al., 2007). Through manual selection, 47 papers remained available for this review, and the full text of all 47 potentially eligible studies was retrieved.

In the second phase, the selected 47 papers were reviewed, and data were extracted for each paper and stored in a systematic datasheet. First, we designed a standardised data extraction form in Supplementary 1, where data on study characteristics were extracted from eligible studies. When the form was designed, the following questions were considered for each paper:

1. What was the research topic, or specifically the studied issue of 3D CV-based cattle management in PLF?
2. What were the tools and scenarios for the data acquisition, and how were the problems solved, including cattle traffic, individual identification, extrinsic calibration, and recording triggering?
3. What were the methods for pre-processing the raw data to maintain proper images for the next step, including selecting images, aligning rigid point clouds, removing background, filtering outliers, segmenting the objective point cloud, and dealing with point clouds with cattle movement?
4. What were the processing and analysis methods for different research purposes, what were the results, and how was the quality of results assessed?

We presented the significant outcomes during review in

Table 1
Overview of criteria used as components of query on WoS. TS: the topic fields, including Title, Abstract, Author, Keywords, and Keywords Plus.

Criterion name	Description	Formula
cattle	Research objects	TS = cattle OR "cows" OR cow
3D vision	Research methods	TS = "point cloud$" OR ("3-dimension*") OR ("three-dimension*") OR ("3D data" OR "3D cow $" OR 3D NEAR/2 vision OR 3D NEAR/2 video* OR 3D NEAR/2 imag*) OR LIDAR OR (RGBD OR RGB-D)
exclusions	Research fields	TS = (glacier OR "ice") OR (canopy OR forage) OR (leather) OR (rock$ OR habitat OR Emission$ OR erosion OR bio$mass OR manure) OR (surgery OR tooth OR patient$ OR cell$ OR gene $ OR protein$ OR bone$ OR gland$ OR needle$ OR larvae OR vitro OR immun* OR x-ray OR dissect OR molecular OR blood) OR (acceler* OR ultras*) OR heat OR children OR sustainability OR "food safety"

Supplementary 1, based on the encoded data in supplementary 2. The encoded data were the titles of all studies that were encoded incrementally from 'cattle No.2′ to 'cattle No.48′. The outcomes were collected and analysed in a few dimensions listed in Supplementary 5. Second, we clustered Supplementary 1′s outcomes into Supplementary 3 and Supplementary 4 using the pivot table analysis. Each sheet of these two files remained homogeneous studies.

In the last phase, we further integrated statistical information and essential operations for 3D cattle growth task-oriented studies within the essential-oriented sheets in Supplementary 3. While statistical information included the statistics of studies and research objects, essential operations included 3D data acquisition and pre-processing. In the 3D data pre-processing, similar steps that included image selection, background and noise filtering, and feature extraction were synthesised. We also compared studies among each cattle growth task in Supplementary 4, where each sheet represents a specific kind of task in cattle growth management. Within each task-oriented sheet, models and features from each study were distinguished. The results of the integration and comparison are shown in the results section. After comparison, we synthesised approaches to improve the models' performance in 3D cattle growth management, and the approaches are described in the discussion section.

3. Results

For synthesising the current knowledge regarding 3D CV to cattle growth management, 47 studies were grouped into three main categories: books, review papers, and task-oriented papers (Fig. 2). The categories of books and review papers belong to the non-growth task. The remaining 44 task-oriented papers contained one non-growth task, which conducted extrinsic calibration for a multi-Kinect camera system (Salau et al., 2016a), and 57 cattle growth management tasks as one study might contain multiple tasks. Among multi-task studies, Martins et al.'s (2020) and Hansen et al.'s (2018) had triple tasks, while seven other studies included double tasks. The research on cattle growth management started in 2014 and reached peaks in 2018 and 2020 ($n = 13$). Among all tasks, body measurements assessment was the most attractive task ($n = 17$), followed by lameness classifications ($n = 9$). BW estimation has become important since 2018 (Supplementary 3).

3.1. Objects of task-oriented papers

In cattle growth management tasks, the studied objects were mainly cows. The ratio of tasks on non-cattle objects to cattle-oriented objects was 4:42 (Supplementary 3). Within the four tasks of non-cattle objects, two tasks owned inherited relationships. They used pigs as the research objects to verify the analysis software for body measurements, and the software was intentionally extended by the researchers to measure cattle due to similar body forms remaining between cattle and pigs. The other two tasks researched cattle's feed and cattle's faecal, respectively. For cattle-oriented tasks, 37 of 42 specified the type of cattle (Fig. 3a). The differences among cattle types were listed in Supplementary 3. Of all specific types, cows accounted for slightly above 70%; the other types, including heifers, steers, and calves, were far less used than cows with the numbers 4, 2, and 2, respectively.

For most cattle-oriented tasks, amounts of cattle, also named cattle numbers, were statistically low (Fig. 3b). The range of less than 25 individuals of cattle was the most often used, followed by the range between 50 and 75 individuals. Ranges indicated cattle numbers used by researchers for their experiments, and they were expressed in half-open integer intervals that included the left endpoint, excluded the right endpoint, and the length of each range was 25 except $[200, 250)$ of which the length was 50. The special length was introduced because the cattle numbers used in three tasks fluctuated from 208 to 242. Ranges of medium-scale (≥ 100 *and* < 200) were less used in studies than those of both small-scale (< 100) and large-scale (≥ 200). Moreover, no tasks were known with cattle numbers in the ranges $[125, 150)$ and $[150, 175)$.

Holstein was the most frequently used breed among the breeds of 42

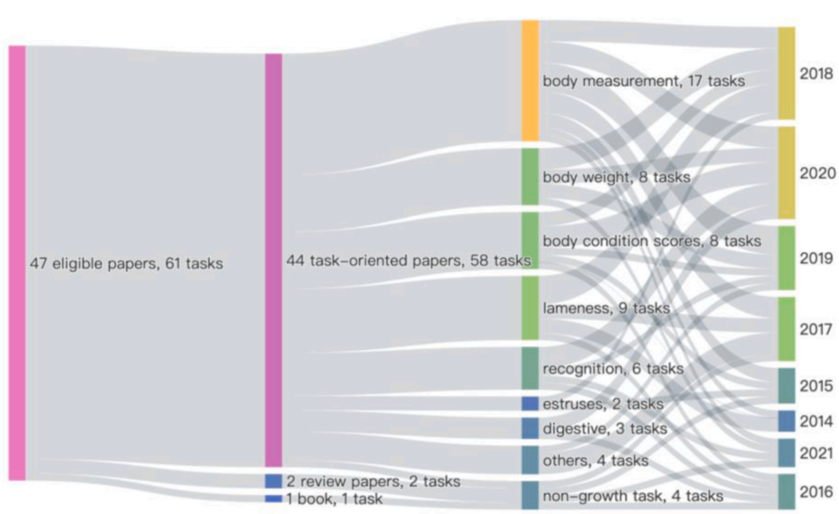

Fig. 2. Overview of the eligible studies' flows starting from paper types, passing task-oriented categories, and ending at groups of years.

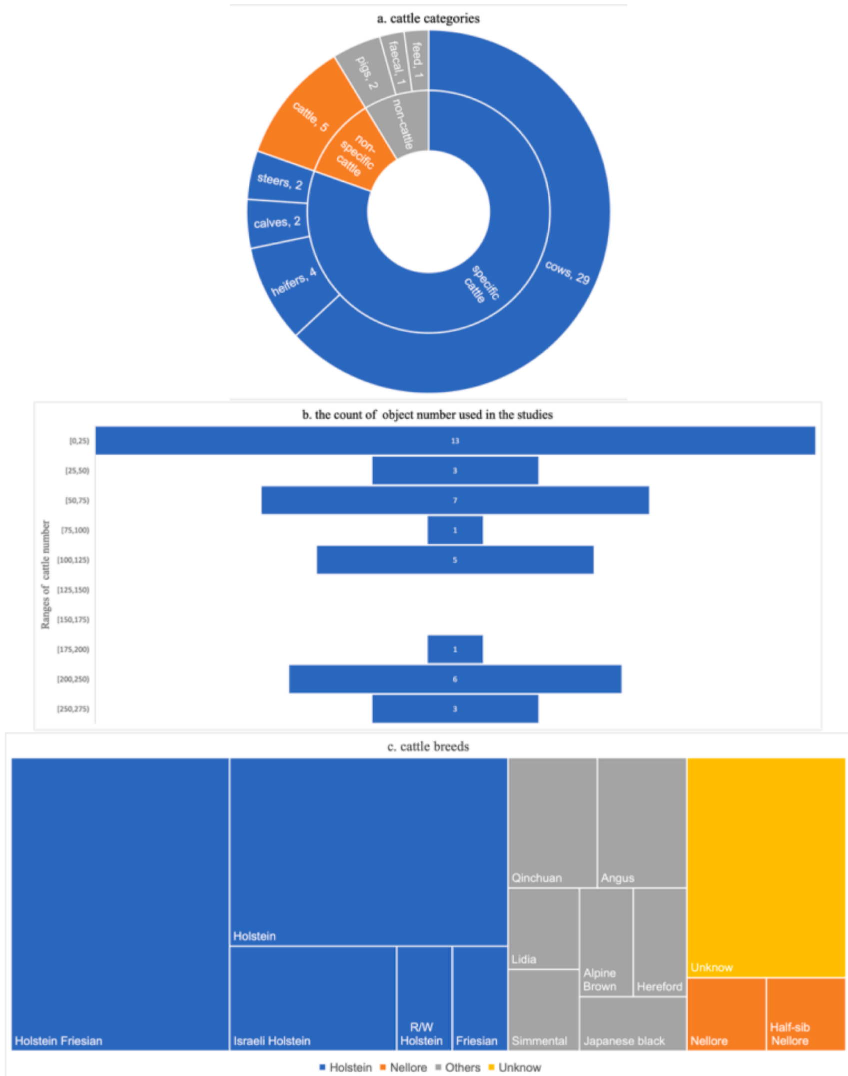

Fig. 3. Investigation of research objects used in the growth task-oriented studies: a) the pie chart for objects' categories; b) the statistics of the studies' count distributed among ranges of cattle's number used in studies; c) the statistics of cattle breeds used in the studies.

cattle-oriented tasks (Fig. 3c). Holstein cattle were used in 25 tasks, and various sub-breeds were investigated, such as Holstein Friesian, Israeli Holstein, and red & white Holstein. The use of breeds was influenced by cattle sex. For females as research objects, which means cows and heifers, the Holstein breed was the most often applied, which resembled the overall trend. For males as research objects, which means steer, breeds used were mainly Angus, (half-sib) Nellore, and Qinchuan.

3.2. Three-dimensional data acquisition

For the 3D data acquisition, two groups of depth cameras were applied. The first group named IR depth camera, used an infrared emitter to project a pattern of laser points whose deformation is detected by the infrared sensor and used to compute depth values (Salau et al., 2016b). Microsoft Kinect V1 was the representative of this kind. Since this kind of sensor was susceptible to sunlight, the experiments were conducted mainly indoors. However, Van Hertem et al. (2014) and Viazzi et al. (2014) deployed their sensors outdoors but carried out the experiments under external artificial light at night. The second group used the time of flight (ToF) principle to calculate the depth. Microsoft Kinect V2 was the representative of ToF cameras.

There were generally two approaches in 3D data acquisition for 3D cattle growth management tasks (Supplementary 3). The popular one was capturing cattle's backs by using one depth camera fixed at the nadir. The nadir was referred to as the position directly below a platform at a relatively high place. For this type of data acquisition, the depth camera was usually attached to a fixed platform that commonly was a frame at the height of between 1.95 m and 3.45 m above the ground. The depth camera opted to acquire data at a frames-per-second of between 15HZ and 30HZ (Supplementary 3). The other approach was capturing from various viewpoints by using multiple cameras that captured cattle bodies and specific parts like the udder (Martins et al., 2020). Data from multiple cameras reconstructed point clouds of cattle, which was a generalisation of triangulation in photogrammetry, and the reconstruction methods differed regarding the types of cameras. The cameras were usually comprised of either identical depth cameras or the same 2D cameras, and they simultaneously captured 3D and 2D data, respectively, at diverse viewpoints with calibration before the acquisition. However, in Le Cozler et al. (2019b), five pairs of 2D cameras and laser projectors were used as data acquisition devices. Morpho3D laser projectors in their studies emitted lights as stripes, generated a vertical plane from the intersection between the lights and the cattle each time, and thus merged point clouds of planes chronically to a point cloud of cattle. In addition, the acquisition was also conducted from multiple viewpoints by moving only one camera. While Pezzuolo et al. (2018) and Martins et al. (2020) placed one 3D camera at different places around the standing cattle, Shao et al. (2020) acquired data that were recorded by the 2D camera equipped on an unmanned aerial vehicle.

Recordings of depth cameras were often triggered automatically by signals from other devices or sensors. The most frequently used one was the radio frequency identification (RFID) reader that was used to identify each cow by reading the cow's electronic ID tag. Successful identification triggered the start of a new data recording as well as the stop of an old recording that was also stopped when the recording time was exhausted. Other simple triggers of recordings were a proximity sensor activated when the cattle approached it (Shigeta et al., 2018), a passive infrared motion detector that was placed ahead of the cameras (Spoliansky et al., 2016), or singles of the changing status of a door (Fischer et al., 2015). One combination of two sensors fixed on both sides of the passage was applied by Wilkins et al. (2015) as triggers for recording; when the animal moved past the sensors, while one activated the recording, the other deactivated the recording. An advanced trigger was introduced by Okura et al. (2019). They took advantage of the depth sensor and used real-time foreground extraction to detect approaching cattle and decide the start of image capturing.

For high-quality recordings of 3D data acquisition, cattle were treated in two divergent approaches. First, cattle were constrained to stand still, especially in live BW estimation. The methods included feeding cattle(Le Cozler et al., 2019a,b) , calming them (Huang et al., 2018; Huang et al., 2019a), or habituating them ahead (Guesgen and Bench, 2018; Le Cozler et al., 2019a). In the other approach, cattle walked following designed paths. During walking, cattle traffic could be controlled to ensure the quality of captured data (Van Hertem et al., 2018) by introducing physical facilities or using existing facilities. Van Hertem et al. (2014) and Viazzi et al. (2014) handled the cattle traffic through their designed corridors. Their studies made use of an after-milking sorting gate followed by a 90° turn corridor that provided the necessary time delay between successive cows to obtain smooth cattle traffic; the gate was the only place on the farm where all cows passed after milking in a side-by-side milking parlour. Van Hertem et al. (2018) built a walk-through acquiring system at the exit of a rotary milking parlour where a single cow was released each time.

3.3. Ground truth acquisition

Ground truth (GT), also known as reference data for training and validation purposes, refers to data provided by direct observation, manual scoring, and manual measuring. During 3D cattle growth management systems, the acquisition procedure of GT was the same as the mentioned conventional approaches. While tools such as tapes and sticks were used for body measurements assessment tasks, industrial scales were applied for BW estimation tasks.

For BCS, GT was acquired by 2 or 3 assessors who independently assessed cattle following a manual body condition scoring protocol. GT's values were usually the mean of the results given by assessors, and the range of GT's values reflected the growth condition of the cattle herd. To qualify for the results of the manual assessment, the inter-assessor agreement was introduced, and three studies implemented this step in their work. Song et al. (2019) used Cohen's kappa (κ) and the scoring correlation coefficient Spearman's rho (ρ) to express the agreement of inter-assessor, while the other two used Lin's Concordance of Correlation Coefficient (O'Leary et al., 2020) and correlation (Martins et al., 2020) to express the agreement of only inter-assessor. The quality was also validated by intra-assessor agreement, which was done by measuring the pairwise agreement of each assessor across two days (Song et al., 2019). Besides, the ranges of GT's values were clarified in most reviewed studies (Supplementary 4). The GT's values of each study were distributed within a BCS 5-scale subset that centered at 3, and the mean width of the range of these subsets was 2.4, which was less than half of the width of the 5-score scoring protocol.

In the lameness detection tasks, GT presented cattle's lameness, which was digitised to LS. LS followed one of three sorts of score levels. First, a discrete five-point (1–5) numerical score derived either from Sprecher et al.'s (1997) or from Flower & Weary's (2006) work, where cows scored at level 1 was healthy and cows scored at level 5 had a severely lame. Second, a binary classification considered LS scores of 1 and 2 as non-lame; on the other hand, LS scores ≥ 3 as lame. Last, a four-point numerical score grouped LS 4 and LS 5 as one level, and it was used only in Van Hertem et al. (2016). Like the BCS estimation, the reference was also assessed by the observers, but the observers in lameness detection were quite divergent. The divergence was first shown according to the number of observers. While using only one observer was adopted to assess cattle in four studies, two observers did the same work in the other three studies. In Van Hertem et al.'s (2016) and Van Hertem et al.'s (2018) research, there were two trained and experienced observers, but they scored LS alternatively. The second divergence was proficiency. The observers were usually well trained, but two without previous standard training were employed in Schlageter-Tello et al. (2018).

3.4. Three-dimensional data pre-processing

Three-dimensional data pre-processing for cattle management systems is a critical procedure between 3D data acquisition and 3D model training. It conversed raw data from 3D data acquisition to point clouds and extracted features from these point clouds for models of 3D cattle growth management tasks. In Supplementary 3, all collected studies for 3D cattle growth management tasks were analysed, and then the general procedure (Fig. 4) was synthesised from the analysis. In Fig. 4, each blue box's content contains the functional item's name and the function's presented count in all explored studies. The synthesised general procedure comprised four essential components and one optional component.

The data selection was the first essential component. It was used to select available data from raw data acquired in 3D data acquisition. The selection discarded data with poor quality or data without cattle and sieved the remaining data to meet requirements such as disconnection to the border of scenes (Cominotte et al., 2020).

After data selection, 3D construction was the optional component. It constructed 3D data from multi-view 2D images using structure from motion (SfM) when the selected data were optical images. This construction operation was seen in three studies (Gaudioso et al., 2014; Lomillos and Alonso, 2020; Shao et al., 2020).

The second essential component of 3D data pre-processing consisted of the selection and utilisation of filters. It segmented point clouds of cattle from selected data in three steps. The steps started with removing the background. Background removal was mainly conducted by subtracting empty scene point clouds and/or applying a conditional filter with experimentally determined thresholds. It was done by selecting the largest point clouds after clustering (Huang et al., 2018). The second step was to filter outliers as noises. Noises were sieved through filters that included a clustering filter, conditional filter, statistical filter, and convolutional filter. The clustering filter was the most frequently applied in all noise removal filters and was presented ten times (Fig. 4). The second important one was the conditional filter. The third step was to use filters to fulfil specific tasks. For example, the voxel filter down-sampled point clouds by compressing a partition into a voxel (Foley et al., 1996).

The third essential component processed point clouds to fit models. The treatments comprised the body parts exclusion, point clouds alignment, normalisation, point clouds smoothness, and point clouds restoration. Of all treatments, point clouds normalisation was the most critical one because it adjusted the position and orientation of the point cloud to make the point clouds suitable for models.

The last essential component of 3D data pre-processing is extracting features from point clouds for models' input. Before feature extraction, anatomical landmarks of cattle on the point clouds could be identified, which could benefit feature extraction.

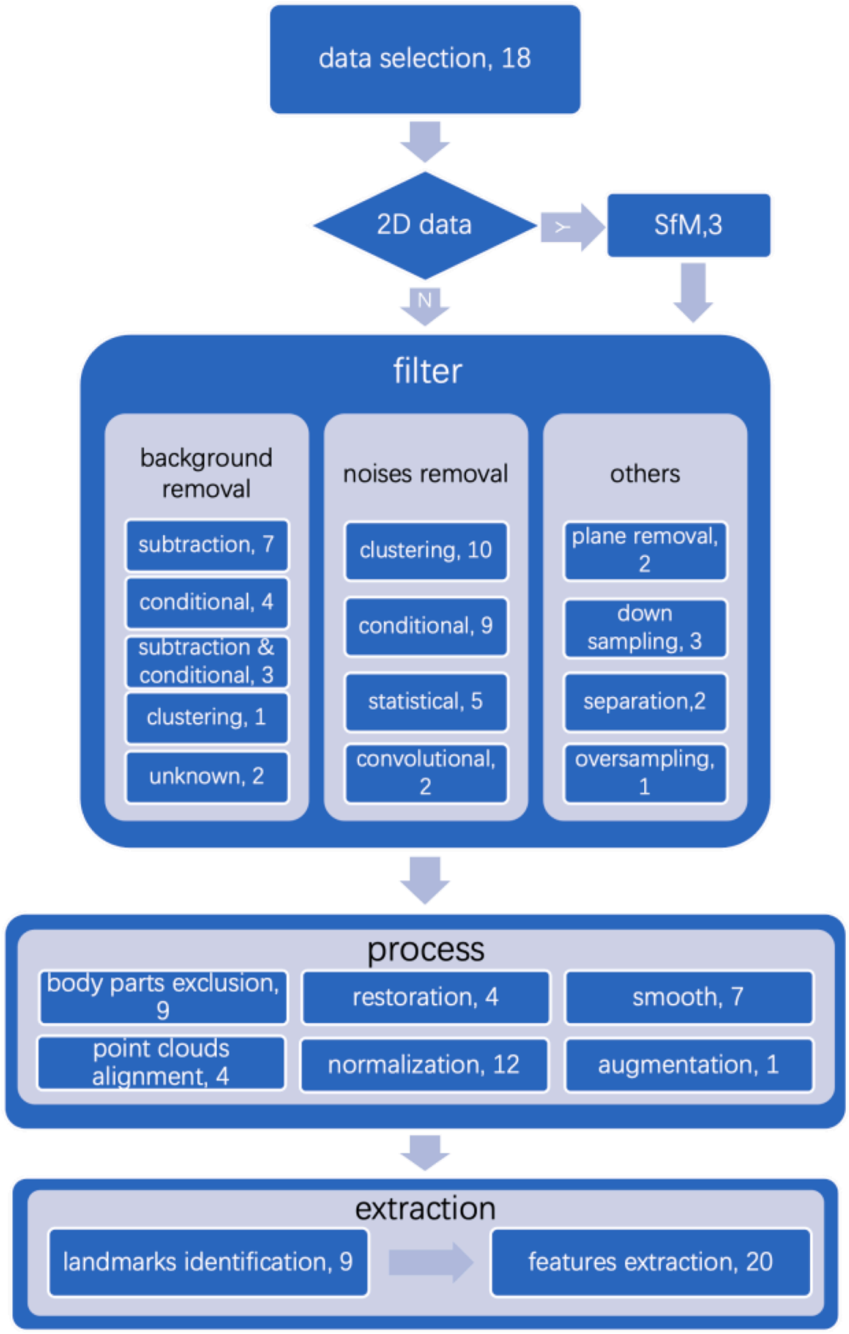

Fig. 4. Flowchart of a general pre-processing procedure derived from pre-processing steps identified in the selected studies. Each blue box's content contains the functional item's name and the function's presented count in all selected studies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.5. Body measurements assessment

A total of 17 3D body measurements assessment tasks were grouped into four categories (Supplementary 4). In four categories, direct 3D measurements amounted to the most significant role, with a count of 13. The other three, including morphometric characterisation, body area & volume, and the effects of fur, were rarely investigated. Forty-four types of 3D body measurements were used in 17 assessment tasks. The top 10 are shown in Fig. 5a, and they all belong to direct 3D measurements.

A large range of acquisition procedures could be identified in the 3D acquisition approach for direct 3D measurements. Many studies measured them from cattle's backs by fixing the sensor at a nadir that resembled what we concluded in the data acquisition section. For example, Kamchen et al. (2021) and Nir et al. (2018) applied one 3D camera indoors at 2.5 m and 2.8 m above the ground, respectively. Compared with nadir views, Huang et al. (2018) and Huang et al. (2019b) used a LiDAR sensor from a lateral view of Qinchuan beef cattle. Besides, the multi-views acquisition was conducted to acquire direct 3D measurements. For example, Ruchay et al. (2020) acquired data from multiple views by locating three RGB-D cameras on the left, right, and top of a passage and synchronised the data collection process. Pezzuolo et al. (2018) and Martins et al. (2020) obtained multiple view data by moving one camera around cattle. While the former acquisition scanned cattle in four different positions: left, right, top, and front, the latter took the dorsal and lateral images from the top and side. Moreover, direct 3D measurements were implemented by photogrammetry. Gaudioso et al.

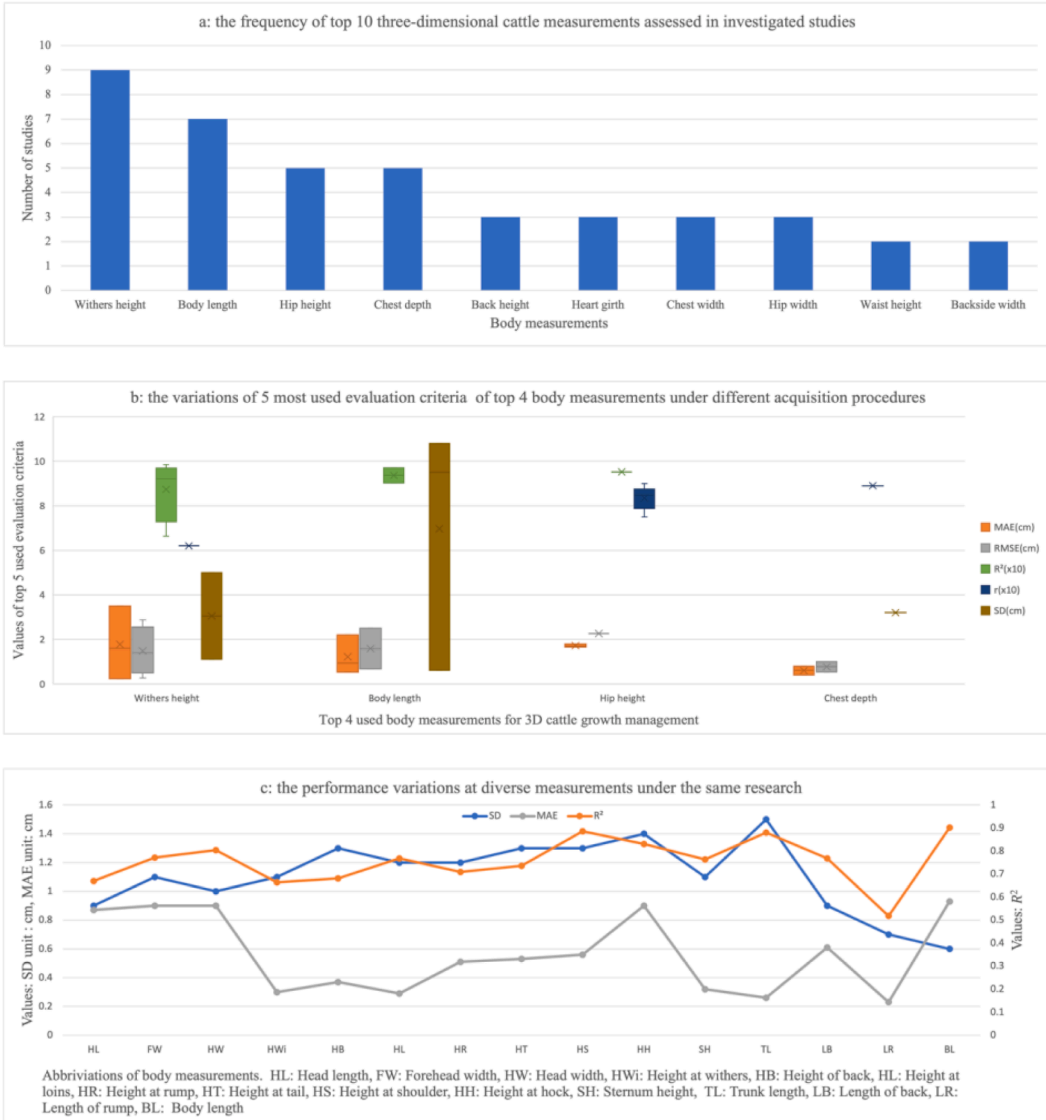

Fig. 5. The body measurements used in the bibliography and the performance of the results. a) the bar chart shows the top 10 of mostly used body measurements in researched 3D cattle growth management; b) the chart shows the effect of different acquisition procedures in 3D cattle growth management by comparing the value ranges of the five most used evaluation criteria of the top four used body measurements; c) the line chart shows the effect of body measurements by visualizing the fluctuations of body measurements' values under the same criterion and acquisition procedure.

(2014) and Lomillos and Alonso (2020) measured animals in their natural environment at 10 to 15 m distance using a portable instrument incorporating two synchronised 2D cameras.

The diversity of 3D data acquisition procedures affects the results' quality of direct 3D measurements. The results for the 5 most used evaluation criteria of the top 4 used direct body measurements under different acquisition procedures were visualised in Fig. 5.b. The visualisation of evaluation criteria on withers height and body length frequently showed huge ranges of values. The evaluation criteria "standard deviation (SD)" for body length illustrated the maximum gap of 10.2 cm, which was introduced by Lomillos and Alonso (2020) with a SD of 10.8 cm on assessing body length through using photogrammetry. The trend that, along with the decrease in task number, the evaluation results decreased was explained by the deeply dropping in the number of applying the corresponding evaluation criterion, which did not mean that the effect was eliminated.

Apart from the diversity of 3D data acquisitions, the results' quality of direct 3D measurements was also influenced by other factors. The first factor was the body measurements used in the research. Fig. 5c shows the SD, R2, and MAE fluctuations of 15 measurements implemented under the same condition in Gaudioso et al.'s (2014) work. The second factor was the cattle's sex. Lomillos and Alonso (2020) verified the differences with 20 body measurements and six morphological indexes on Lidia cattle by sex. Cattle's category (Fig. 1. a) also affected the performance of results. McPhee (2017) evinced that the measuring performance of hip height for cows and steers varied. In addition, Salau et al. (2015) proved that fur, fur colour, and moving velocity affect the measuring accuracy.

3.6. Body weight estimation

Eight BW estimation tasks were conducted between 2018 and 2021 (Supplementary 4). The estimation models used features extracted from 3D data acquisition and pre-processing as the explanatory variable, including 3D body measurements, and parameters calculated on 3D body measurements. Additional age-related information was also applied as an explanatory variable by the models. In BW estimation studies, a combination of different kinds of explanatory variables was more often used than a single explanatory variable. Over half of the studies used the parameter of calculated area or volume. Multiple variables linear regression was the most frequently applied model, and the artificial neural network acquired the highest correlation between live weights estimated from models and weights obtained from scales with an R^2 of 0.995.

For acquiring the most popular parameter, volume, from point clouds, the methods were not identical. An essential method for calculating the volume applied calculus. The implementation in Le Cozler et al. (2019b) applied Mirtich's (1996) theory that used both the divergence theorem and Green's theorem, where the Green's theorem calculated the area of 3D mesh and the divergence theorem calculated the volume based on the area. The 3D mesh was built from the point cloud that was cut off at shoulder level to remove the distortion of head movement. Cominotte et al. (2020) used a simplified implementation to acquire the volume by integrating volumes of divisions of the cattle's dorsal part from the shoulder to the hip, where a division was treated as a cuboid. Another way of getting volume was arbitrarily the summation of heights between each point on the curvature of the back's point cloud and its projections on one plane (Hansen et al., 2018; Nir et al., 2018). The above studies expressed the volume using cubic pixels. In Kamchen et al. (2021), the volume value was corrected by transforming cubic pixels to cubic meters, reducing the error caused by the distance variation between the animal and the sensor.

3.7. Body condition score evaluation

Eight BCS evaluation tasks were scrutinised. Their implementations complied with the principle of comparing outputs with GT using either linear regression or machine learning classification models.

3D CV systems commonly assessed body conditions through analysing 3D images of cattle' backs taken from nadir. Features extracted from these images, named dorsal traits, were typically used as models' inputs. Three studies (Spoliansky et al., 2016; Martins et al., 2020; Zin et al., 2020) extracted directly acquired dorsal traits such as dorsal length and directly calculated dorsal traits such as dorsal area and convex hull volume to estimate BCS. Two studies extracted indirect dorsal traits after identifying anatomical landmarks on backs. Song et al. (2019) automatically identified the vertebral column, sacral ligament, hook bone, and pin bone. Around these physical landmarks, they measured the bony prominence or the body surface depression and defined them as model features. Fischer et al. (2015) manually identified four anatomical landmarks: top of the left hook bone, top of the right hook bone, and 2 points at the base of the sacrum to define a space centered on the cow's rear before standardising cows' 3D surfaces (the visualisation of them is shown in Supplementary 0). The features were summarised from the normalised 3D shape by performing the principal component analysis (PCA). From cattle's backs, one study extracted the indirect angularity score. Angularity scores were quantified by operating the rolling ball algorithm globally across the surface. Dorsal traits were also combined with other non-back traits. Song et al. (2019) applied multiple 3D cameras positioned at the top, rare, and side to mimic human assessors evaluating different body regions of a cow from different views, thereby improving BCS classification.

Two types of models were used to estimate BCS. The first type was linear regression models comprising stepwise, LASSO, and simple linear regression. The stepwise regression was used most often (3 times). Before training the stepwise model, Spoliansky et al. (2016) normalised all features extracted through 3D data acquisition and pre-processing to values between 0 and 1 to obtain the same scale. Using a stepwise model, Fischer et al. (2015) attained the highest performance, and the model explained all of BCS variability with an R^2 of 1 on the training dataset, but the performance on the test dataset was lower, especially on the dataset with cattle unseen ($r = 0.89$). Using LASSO, Martins et al. (2020) concluded that the model using lateral traits as input performed better than using dorsal traits in predicting BCS. A simple linear regression model expressed the relation between the dorsal trait, indirect angularity score, and the BCS score by Hansen et al. (2018) with a relatively high MAE of 0.21 among all studies. The second approach, machine learning classification models, was applied in two studies. Song et al. (2019) used a nearest-neighbour algorithm to train a model on 88 samples, and the model achieved an overall sensitivity of 0.72 for all BCS classes. Shigeta et al. (2018) introduced a convolutional neural network with a 0.777 F-score on the enormous dataset of 8650 samples in all studies, but the input was 2D 460 $\times$ 310 pixels grayscale images that were converted from point clouds.

3.8. Lameness detection

During the nine lameness studies, several considerable hypotheses were tested. Viazzi et al. (2014) proved that the back arch trait derived from top-view 3D CV attained comparable performance in lameness detection compared to a side-view 2D CV system. It also confirmed that the 3D CV overcame the segmentation limitations such as shadows and dynamic backgrounds of the 2D approach by automatically extracting the back arch trait in real-time. Schlageter-Tello et al. (2018) concluded that the 3D CV automatic LS system based on the measurement of back curvature, overall, performed worse than human observers with similar sensitivity but lower specificity. Van Hertem et al. (2016) proved that the video-based system was suitable for the lameness detection system. Hansen et al (2018) demonstrated that arching of the cow's spine derived from previously extracted 3D region of interest (ROI) was suitable to detect lameness by fitting a second-order polynomial curve. Van Hertem et al. (2018) verified that the two fair 3D lameness classifiers were curvature angle of back around hip joints Characteristics Curve and back posture measurement.

Moreover, lameness detection in the early stage supported curing the animal early so that reduce their suffering from lesions or infection, which benefited animal welfare and to economic for farmers (Van Hertem et al., 2016). Jabbar et al. (2017) explored early lameness detection. They used a support vector machines model to detect the lameness trend by feeding in the dynamic gait symmetry measure that tracked the movements of the spine and hind limbs. The gait asymmetry was reflected by the height variations in the hip joint during walking and was attained from non-intrusive 3D video data. The model achieved high performance with accuracy = 95.7% on 23 samples when considering LS $\geq$ 2 as lame on a 1–5 scoring system.

3.9. Other growth management tasks

Other 3D cattle growth management tasks were also synthesised. First, the recognition task was explored, ranging from the detection of cattle (Salau et al., 2016b; Shao et al., 2020) to body parts analysis (Salau et al., 2020) and individual identification (Okura et al., 2019; Bezen et al., 2020). For recognition tasks, neural networks were the most applied methods to handle visual digital data. Second, oestrus detection was explored by detecting standing to be mounted (Homer et al., 2015) and micro-behavioural changes related to ovulation (Guesgen and Bench, 2018) three-dimensionally. Third, digestive tasks, including feed intake monitoring and faeces consistency assessment (Atkinson et al., 2020). Shelley et al. (2016) estimated feed intake in a laboratory where feed was filled in a designed plastic feed bin, and intake was measured by the difference in estimated weight before and after feeding. In contrast, Bezen (2020) did it in an open cowshed where the intake was measured by evaluating the difference in depth images of the feed pile before and after feeding. Last, reconstruction tasks that aimed to build a point cloud of a cattle's whole body were implemented by two studies. The constructed point clouds hereafter were used for extracting morphological traits (Le Cozler et al., 2019a) and for allocating body parts' temperature (Kawasue et al., 2017), respectively.

4. Discussion

In total, 47 studies were included in this dedicated literature review. These studies were published in a wide variety of scientific journals ranging in publication from the years 2014 to 2021 (Supplementary 2), and they include recent research in 3D data acquisition and analysis for cattle growth management, including morphological measurements, live BW estimation, BCS evaluation, lameness detection, and other types of tasks for PLF. Our review focused on investigating the differences within each kind of task and extracting the common steps among diverse tasks. While the differences are shown in the following session named cattle growth management tasks, the common steps, including data acquisition, automation, and models' performance, are discussed in other sections.

4.1. Data acquisition

3D cattle growth management applications were based on 3D data acquisition, and the acquisition was highly related to the camera. Cameras using infrared (IR) light have been widely applied (Supplementary 3) for a low cost. However, IR depth cameras' disadvantages must be overcome during data acquisition. First, the IR cameras should avoid interference caused by directly natural sunlight on the surface of experimental objects (Van Hertem et al., 2014; Viazzi et al., 2014; McPhee, 2017). Second, the IR cameras should be appropriately placed to adapt narrow measurement range. While for Microsoft Kinect V1, it's within 2.05 m, for Microsoft Kinect V2, it's between 0.5 and 4.5 m (Song et al., 2018). As the distance between the camera and objects increases, the field of view (FOV) increases, and an appropriate FOV supports cattle management tasks better. Jabbar et al. (2017) settled an IR camera named ASUS Xtion PRO Live at the height of 3.69 m above the ground, resulting in a pixel resolution of 3.6 mm $\times$ 3.6 mm and an around 6 m horizontal FOV. While the resolution did not cause heavy distortions in the depth data, the FOV allowed the capture of at least two full gait cycles for their study. Third, the IR cameras should acquire enough frames within a short period because the resolution of IR cameras is low. For the Microsoft Kinect V1 cameras with 640 $\times$ 480 pixels, the point cloud density is low within each captured frame, and it is necessary to fuse multiple frames of point clouds into one high density point cloud. Huang et al. (2018; 2019a) applied IFM O3D303 with the resolution of 176 $\times$ 132 pixels, and they merged five consecutive frames into one file to meet the body shape computation of sufficient density. Last, the IR cameras should prevent inter-camera interference. This occurs when the fields of IR cameras overlap (Salau et al., 2017; Pezzuolo et al., 2018), and the cameras record synchronically. It can be prevented by placing lateral cameras directly facing their counterpart and occluding by the animals when a cow passes between cameras (Salau et al., 2016a; Salau et al., 2016b; Salau et al., 2017; 2021). It can also be prevented by recording intermittently. Huang et al. (2018) and Song et al. (2019) recorded an image from one camera at 2 HZ at a time and sequentially switched to another camera after five consecutive recordings. Ideally, the solution for inter-camera interference should be like the one mentioned by Huang et al. (2018) and Song et al. (2019), and it is, in future studies, to use new types of 3-D cameras without inter-camera interference. Finally, as Martins et al. (2020) did, future research is advised to regularly clean the lens of cameras to remove the accumulation of dust, especially for those cameras placed at the lateral position.

When using 3D cameras, we also need to consider using multiple sensors because they can better mimic human assessors evaluating different body regions of cattle from different views than a single camera (Song et al., 2019). While a single camera views fewer body regions than those assessed by manual scoring, the fusion of information from cameras located at different viewpoints provides more reliable performance (Ruchay et al., 2020). Before the recording, the calibration of cameras is necessary, which, for example, can eliminate the influence of variation in ambient lighting on 3D cameras based on visible light (Guo et al., 2017).

Suitable platforms are necessary where cameras can be optimally positioned during the acquisition. The most frequently applied platform was a fixed frame around a passage (Supplementary 3), which was easy to be embedded into the existing facilities and was suitable for various research purposes, including BCS estimation (Zin et al., 2020), lameness detection (Hansen et al., 2018), and even BW prediction (Song et al., 2018). The tripod was the most flexible platform that could be moved easily and placed nearby the cattle by the actors, and was suitable for body measurements. However, the tripod is not recommended in future research because it introduces high intervention to cattle and an increased risk of damage to attached cameras when cattle touch the tripod. Ruchay et al. (2020) placed two tripods on the right- and left-sides in front of the animal passage that was headed to the hall with the feeding system. The tripods were in the hall at approximately 2.0 m from cattle when they walked out of the passage, so no obstacle existed between the tripods and the animal if they approached the tripods. Moreover, Shao et al. (2020) used a UAV equipped with 2D cameras to record the data of a wide area above actively. Compared to using the frame and tripod for indoor applications, in the future, using the UAV as a platform could be convenient for conducting outdoor research if the 3D camera is undisturbed by the sunlight and is dense enough; the potential problem is the noise of the flying UAV.

During the acquisition, research objects should be well-known. This review concentrates on cattle's growth management based on 3D CV. A cattle's body is relatively large compared with other livestock like sheep and pigs. It has a complex 3D shape (Pezzuolo et al., 2018), which is unfavourable when using proximal 3D cameras. However, because of the large body shape, anatomical landmarks are prominent, and landmarks' trajectories are apparent when cattle move naturally. These are benefits to 3D cattle growth management. For example, anatomical landmarks like hook bone, spine, and hip bones scattering on the back and the rear were measured for further research like live BW estimation; the walking gaits of cattle were used for lameness detection (Schlageter-Tello et al., 2018). Besides, two additional factors need to be considered when we conduct a future 3D CV-based cattle growth management. The first is the diversity of morphometric traits among cattle breeds, life cycles, and sexes. For instance, the biometry of the horns is a representative morphometric particularity for the Lidia breed (Lomillos and Alonso, 2020); dairy-type traits such as udder, hoof, and rump characteristics, are significant predictors of productivity, fertility, and health for cows (Martins et al., 2020). The second factor is attachments on the cattle's bodies. On the one hand, the exterior mud or debris on the surface of the cattle and hair clumps lying orthogonal to the surface tangent on the coat could be reflected on the final fused point cloud, thereby affecting the curvature estimation. On the other hand, fur, fur colors, and coat texture also affect the sensitivity of cameras, which was proved in Salau et al. (2015). In Huang et al. (2019a), short-haired cattle were their ideal targets. As animals, cattle are constantly moving (Ruchay et al., 2020); during movement, their body shape changes, their body parts are incidentally hidden, and their body portions are sometimes overlapping. Even though small relative movements of the animal could be ignored by compensating for misalignments during the preprocessing phase (Pezzuolo et al., 2018), it is impossible to accept the movement caused by possible heavily cattle moving during the long recording time for one cattle (approximately one minute). To eliminate the effect of cattle movement, animals were confined still for a short while by restricting them in cramped spaces or captured during controlled cattle traffic. However, Ruchay et al. (2020) aligned point clouds containing movement. As movement is the nature of animals, we strongly suggest that future research should pay more attention to the alignment of non-rigid cattle point clouds where 3D shapes of point clouds are slightly different.

4.2. Automation

A cattle growth management system is welcome based on the prerequisites that it offers the least possible interference in the routine of the herd and achieves maximum accuracy with minimal human involvement (Jabbar et al., 2017). To mitigate human intervention in cattle, 3D CV cattle management systems should be automated. We observed no standard approaches or methods yet for automated 3D cattle growth management. There is a need to develop a traceable procedure to conduct 3D vision systems in this kind of study. We recommend that future publications focus more on a detailed description of the automated process.

Automated data acquisition should be built with the capacity of acquiring high-quality images at an affordable price and not too sensitive to environmental changes. When data are obtained, controlled cattle traffic is necessary for the optimal performance of systems (Van Hertem et al., 2018). The controlled cattle traffic could be implemented by changing facilities; a 90° turn in the corridor compelled successive cows to form smooth traffic (Van Hertem et al., 2014; Viazzi et al., 2014). However, changes in facilities were seldom suitable for farms because of the significant variations of structures on farms. A potential solution to handle cattle traffic is using software-controlled gates. When the data are acquired, matching an individual's digital recording with its identity is a remarkable issue. RFID readers are still the prevailing method. However, compared with these RFID readers, non-invasive automated identification of individuals from the collected data should become more acceptable. Automated identification is also much more complied with animal welfare because vision-based identification is non-invasive compared with using RFID tags that hurt the ears of cattle. When data are acquired, the triggers of cameras to record data improve the efficiency of recordings and the ratio of valid data that includes animals. The most common method in the selected studies is triggering the recording when the RFID reader successfully read the RFID tag of an individual. An advanced approach was the real-time foreground extraction that detected approaching cattle from depth images, and decided the start of image capture on the results of the detection (Okura et al., 2019). In this way, it did not need extra tools, which is convenient method of triggering the recording of cameras in future research. Moreover, to monitor the growth trend of each individual cattle, it is necessary in the first place to identify individuals automatically. As the CV approach of identification using neural networks can reach high accuracy without intervention, promoting animal welfare, we recommend that future research uses this method to identify individuals.

4.3. Cattle growth management tasks

Assessing body measurements was fundamental research for 3D cattle management tasks, such as BW estimation, BCS estimation, and lameness detection. Body measurements were heavily used as the features fed into other growth management tasks' models. They were measured using photogrammetry that determines anatomical landmarks of objects on digitally captured data and measures them (Tasdemir and Ozkan, 2019). The landmarks are quantified from bony ridges and depressions on the body surface (Song et al., 2019), and their positions may change even when the animal stands naturally twice but puts weight on different legs. Ruchay et al. (2020) identified anatomical landmarks by pointing with white paint. To acquire precise and accurate body measurements, we recommend using the mean of results from different frames in future research. The second limitation in using anatomical landmarks is that they may be not prominent. Hip positions were found difficult to identify in the case of young cattle by Pezzuolo et al. (2018). Gaudioso et al. (2014) found that their method was difficult to recognise points from data collected from dark animals or without appropriate lighting. They also claimed that the landmarks could be unclear when the BCS is high, which means that too many fats cover the landmarks. One more limitation to using anatomical landmarks is that no visual anatomical landmarks could be available. For instance, the rump length was measured from palpation or exploration of the animal (Gaudioso et al., 2014). To overcome these limitations, we suppose to explore alternative body measurements from a precise 3D body point cloud for 3D models in future research. For example, Jabbar et al. (2017) analysed the animal's gait asymmetry from the height variations in the hip joint during walking instead of traditional limb movements to detect lameness.

Live BW estimation has attained high accuracy. However, the accuracy of reviewed implementations (Supplementary 4) was based on the homogeneous distribution of a relatively small dataset, and the generalisation of these implementations was not verified. Moreover, no breed differences were introduced as features. We infer that breed differences in live weight estimation will gradually emerge in future publications.

We observed that the performance of BCS estimation strongly depends on the reference accuracy of the human assessors' observation and the BCS variations of the required dataset. The agreements of intra-assessors and inter-assessors were used to assess the quality of the observation, and the mean of various assessors' results reduced the reference bias. BCS tasks that calculated the agreements in their work account for 37.5% of all BCS tasks; the percentage of tasks that explicitly set the mean score as the GT is 75% among all tasks calculating agreements (Supplementary 4). While the level of agreement between observers is a limitation in BCS estimation, another limitation mentioned by the analysed papers is the BCS range of samples. We found that all the research did not contain samples of extreme values, which needed extra attention during cattle management (Song et al., 2019), and the distribution of the samples' scores followed a normal distribution with the mean at the center of the BCS range (Supplementary 4). As a result, the distribution of the dataset could cause the accuracy at the center of the BCS range to be higher than the accuracy on both sides of the BCS range. More specifically, BCS classification models' sensitivity can be biased for underrepresented BCS classes (i.e., <2.0 units or >4.0 units) (Song et al., 2019). When the distribution of the dataset is a reliable expression of the herd's body conditions on farms, we suggest that a high BCS variability in herds should be used to train and test models. We also recommend that synthetic point clouds should be used to extend the samples for extreme values for 3D CV classification models.

Accurate lameness detection could reduce animal suffering and minimise losses, especially when intervention was made at an early stage of lameness (Van Hertem et al., 2016; Jabbar et al., 2017). Early lameness was mildly lame that was often undiagnosed and rarely treated until it became severe (Viazzi et al., 2014). We propose successive observations to reduce misdetection at an early stage. Lameness severity was assessed by distances between hoof prints and back arch (Van Hertem et al., 2016; Schlageter-Tello et al., 2018). However, when using the back arch as the indicator, we should realise that the back arch could be unreliable. Poursaberi et al. (2011) mentioned that some lame cows did not present an arched back, but some healthy cows do show an arched back.

4.4. Model performance

Whether a cattle growth management system can be popularised is determined by the performance of the applied model. In general, a model's performance can be influenced by many factors ranging from the raw data to the model itself. For models of 3D cattle growth management, we noticed that no research systematically explored these factors. We suggest that future research could take the utmost to consider the factors discussed below.

The first factor is the GT. GT was compared with the models' output to evaluate cattle management systems' performance. The effect of GT was proved by Wilkins et al. (2015). They compared the correlation of hip height between estimated height and human visual observation with that between estimated height and human tape-based measuring. The result showed that the estimated result was better correlated with visual reference than tape measurements. On the other hand, GT's reliability was seldom reported in 3D cattle growth management systems. Generally, when manual reference data are considered as GT, errors or deviations exist inevitably due to influence factors such as different acquisition methods (Wilkins et al., 2015), slightly changed stances of cattle (Gaudioso et al., 2014), and subjectivity of humans (Salau et al., 2017). To mitigate the adverse effects, repeatability is a solution because it could force manual measuring to approach the real values by estimating an indicator several times from the same sample using the same method in the same environment in a short period (Le Cozler et al., 2019a). The quality of GT should be quantified. Wilkins et al. (2015) calculated the intra-assessor and inter-assessor agreement of two experienced operators to quantify the performance of human measuring. Similarly, Schlageter-Tello et al. (2018) acquired an inter-assessor agreement for BCS estimation. They also calculated the agreement of models against two observers respectively; the model's performance was compared with humans' performance to prove the model's feasibility. Future researchers should consider this kind of comparison, especially when their GT is not persuasive enough.

Datasets refer to the input fed into the model. Apart from the discussed data issues, including the data range, cattle's sex, age, breed, and data selection, the dataset size should be appropriate. It is difficult to increase the dataset's size in real life (Ruchay et al., 2020). A small dataset weakens the generalisation because the model overfits the dataset, which means the model's performance could be way worse on other datasets than the fitted dataset. To enlarge the size of the dataset, data augmentation can be applied. The augmentation was based on the existing data source, augmented the dataset with features orthogonal to the current features, and increased the number of samples (Nir et al., 2018). Huang et al. (2019a) enriched the point cloud dataset of the cattle body silhouette using an affine transformation that rotated existing point clouds by mirroring them in horizontal and vertical directions. To enlarge the size of the dataset, an alternative way is to share the raw data publicly. Benchmark datasets for 3D cattle growth management tasks could greatly facilitate future research, so we appeal to researchers to contribute. Besides, parameters in each item of the dataset should be relatively independent. Multicollinearity and linear or nonlinear relationships of parameters need to be eliminated.

To improve datasets utilisation efficiency and simplify the data acquisition procedure, it is an efficient way to synchronically implement multiple cattle growth management tasks under the same data acquisition procedure because traits can be shared between or among tasks. For instance, hip height is a mutual feature for body measurement, BW, and BCS. BW and BCS are two approaches from different perspectives to monitoring growth rate or growth changes. The accurate hip height as one body measurement supports the decisions of both BW and BCS. Some studies have already introduced multiple tasks of a 3D cattle growth management system in their work. A typical study is the one done by Martins et al. (2020); they implemented triple tasks related to animal conditions, including BW estimation, BCS evaluation, and lameness detection, by concurrently using a 3D Kinect-like depth camera. In summary, further research is advised to consider multiple tasks in a 3D cattle growth management system before their experimental design.

A model should be validated to confirm its feasibility that is estimated with the criteria of repeatability and reproducibility. Repeatability assesses the robustness of the model by repeating several times on the same kind of dataset. Reproducibility assesses the model's generalizability by executing the model under variable datasets. The repeatability of a cattle growth management model was verified on validation or test dataset that was built ahead. In contrast, the dataset is constructed posteriorly for testing the reproducibility of a cattle growth management model. The dataset could be created from the same animal later (O'Leary et al., 2020), different samples at the same herd (Fischer et al., 2015), or a new dairy farm with a different herd (Nir et al., 2018).

A good model should estimate its uncertainty as well. The uncertainty derived from GT has been discussed, which could be mitigated by measuring repeatedly. This kind of uncertainty is caused by tapes' resolution and calibration, Abbe error (due to the misalignment between the measuring tool and the cow body), the positions of anatomical landmarks, animal's hair, or change of cattle's posture (Pezzuolo et al., 2018; Ruchay et al., 2020). 3D sensors could cause another kind of uncertainty. For example, within the valid range, the depth measurement accuracy of Kinect cameras decreases with increasing distance from sensors to the animal (Salau et al., 2016b; Kamchen et al., 2021). Due to a non-linearity of Kinect cameras' accuracy variation along with distance variation, distortion is introduced that influences results, especially at large depths (Pezzuolo et al., 2018), which means that calibration is ahead of the acquisition is essential.

In addition, successive observations benefit model performance in monitoring the growth of individual cattle. The growth changes over time are recorded, and historical data could be added to the models' analysis, which has been proved better than separate observations by Hansen et al. (2018). For future researchers, we suggest that they collect data at regular intervals.

5. Conclusion

This systematic literature review has analysed and synthesised 47 3D cattle management studies. Among various growth management tasks, body measurements assessment is fundamental in addition to other tasks, including BW estimation, BCS evaluation, and lameness detection. While the digestive task monitors cattle's heath in an alternative way, the recognition task is an essential knot of automated individual monitoring. To accomplish 3D cattle growth management tasks, 3D data acquisition and pre-processing are prerequisites. According to the statistics in 3D data acquisition in this review, 3D cattle growth management tasks prefer to acquire 3D raw data by using the Kinect sensors at the nadir of a fixed platform, Holstein cows are the most popular research objects, and cattle fewer than 25 individuals are most often used for the research. This review also synthesised a general procedure to pre-process acquired raw data, which is committed to clarifying and normalising 3D cattle growth management research in the 3D data pre-processing stage; still, it needs to be verified in future work. Moreover, this review also discusses the automation of 3D CV for cattle growth management, aiming to reduce human intervention concerning animal welfare effectively. Finally, this review identified factors affecting the performance of models for cattle growth management. To improve the performance, the GT should be credible, the datasets should be appropriate in size, model repeatability and reproducibility should be verifiable, and the uncertainty should be inclusive. In summary, through this systematic review, we aim to support researchers who want to apply 3D CV for cattle growth management by simplifying 3D data acquisition and pre-processing stages. We advise them to consider model performance ahead at the experimental design stage and to implement multiple growth management tasks successively and automatically.

Ethics approval

Ethics approval was not required for this study.

Data and model availability statement

To view supplementary material for this article, please visit https://doi.org/10.5281/zenodo.7406521.

6. Implications

The present study serves as a reference for future research. It reviews collected eligible studies to update the knowledge of using three-dimensional computer vision to conduct cattle growth management. Besides, the investigation of data acquisition, pre-processing, and models' performance facilitated the practice of using three-dimensional computer vision at the early stages.

CRediT authorship contribution statement

Yaowu Wang: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Sander Mücher:** Conceptualization, Writing – review & editing, Supervision. **Wensheng Wang:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration. **Leifeng Guo:** Conceptualization, Writing – review & editing, Supervision. **Lammert Kooistra:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to my data at the Attach File step.

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