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Review

Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation

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ABSTRACT

There has been an increasing demand for animal protein due to several factors such as global population growth, rising incomes, etc. However, farming productivity is stagnating due to a mix of traditional practice, climate change, socio-economic, and environmental phenomena. Precision livestock farming, with intelligent perception tools at its core, and vast amounts of data being acquired from different sensors or platforms, has the ability to analyse individual animal for improved management, and the potential to dramatically enhance farm productivity. In order to facilitate research and promote the development of related areas, this review summarises and analyses the main existing techniques used in precision cattle farming, focusing on those related to identification, body condition score evaluation, and live weight estimation. More than 100 relevant papers have been discussed in a cohesive manner. From this review and extensive discussions of recent trends, we anticipate that intelligent perception for precision cattle farming will develop through non-contact, high precision, automated technologies, combined with emerging 3D model reconstruction and deep learning technologies. Existing challenges and future research opportunities will also be highlighted and discussed.

1. Introduction

Livestock produce is a major source of food for human, ranking the second after agricultural products. Moreover, there has been an increasing demand in animal protein due to population growth and rising incomes, particularly in developing countries (Rowe et al., 2019; Tullo et al., 2019). As a result, the global livestock industry is tasked to meet this pressing demand, with severely limited environmental and skilled labour resources (Fournel et al., 2017).

Within this challenging context, the ability of animal producers to monitor the productivity and welfare of their animals plays an important role in the whole production pipeline (Fournel et al., 2017). In addition, increasing awareness of production methods and changing socio-economic factors are leading to greater public scrutiny of meat quality and a serious need for animal welfare monitoring (Van Hertem et al., 2017). However, continuous manual cattle monitoring is time-consuming and subjective.

The concept of intelligent perception for animal monitoring is proposed by Kendrick (1998). In broad terms, intelligent perception for cattle monitoring relates to perceptive animal body information in complex environments using multi-senor data, and the ability to apply adaptive learning to analyse animal welfare and health status (King, 2017). In recent years, intelligent perception tools, including varieties of equipment (e.g. smart collars (Clark et al., 2015; Molfino et al., 2017), 3D image sensors (Salau et al., 2017; Gardenier et al., 2018), and data analysis technologies (Jones et al., 2017), have become available for monitoring each individual animal in real time. Qiao et al. (2019) proposed deep learning based individual cattle segmentation approach for animal monitoring. Based on intelligent perception, key body indicators with high precision obtained for individual animals can help farmers evaluate animal welfare, health, and productivity throughout their life cycle, and design management strategies efficiently. Continuous monitoring of the varying needs of each individual animal is a core of Precision Livestock Farming (PLF) (Berckmans, 2014; King, 2017; Rowe et al., 2019).

The goal of PLF is to optimize the individual contribution of animals

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and achieve high efficiency of livestock farming with low cost and environmental footprint, while ensuring the quality and safety of livestock products (Rosell-Polo et al., 2015). Through a "per animal" approach, the farmer can achieve quantitative and qualitative results in livestock farming (Bahlo et al., 2019). There is no doubt that PLF is a potential solution to support farmers and other stakeholders in meeting the increasing consumer demands for livestock produce whilst balancing environmental sustainability and animal welfare considerations.

In this paper, we focus on intelligent perception techniques for precision cattle farming, although some parts of discussions might also be relevant for other types of animals. A general illustration of an intelligent perception process for cattle monitoring is shown in Fig. 1. Critical to this process is the identification of individual animals with relevant measured variables, and the Decision Support System (DSS) to utilize the former information to create objective and measurable Key Performance Indicators (KPIs) and management protocols (Berckmans, 2014; He et al., 2016; Qiao et al., 2019).

Intelligent perception for precision cattle farming involves various perception and management tasks (Bahlo et al., 2019). Due to space limitations, this review focuses on intelligent perception and analysis technologies relevant for the following three main tasks: 1) individual cattle identification; 2) cattle body condition score evaluation; 3) live weight estimation. In this work, we summarize and analyse recent works in the above areas, and discuss future research and development opportunities and challenges. We are preparing another overview which is dedicated to the literature of health (lameness detection, etc) and behavior monitoring and analysis of cattle.

2. Cattle identification

Cattle identification enables individual animal level management. The ability to identify and recognize individual animals is a prerequisite for per-animal based PLF, allowing the association and tracking of relevant features for an individual over time (Awad, 2016). Various tools and methods have been proposed for identifying individual cattle from manual to automated methods, as summarised in Fig. 2 and Table 1.

2.1. Ear-tag based approaches

Visible ear tagging and Radio Frequency Identification (RFID) devices are commonly used to identify cattle (Ruiz-Garcia and Lunadei, 2011). The visible ear tagging method uses a plastic label with a number which is attached to the ear of breeds by puncture. As it has been discussed in (Awad, 2016), visible ear tags can have problems with retention.

Recently, RFID devices have been widely used in livestock farming for individual identification, milk and meat traceability (Ruiz-Garcia and Lunadei, 2011). The entire RFID system consists of RFID tags, communication channel, tag reader, RFID network, and the RFID backend. These systems use radio waves (usually is 134 kHz) to transmit animal information wirelessly in the form of a unique electronic code (e.g. sequence of numbers and/or letters). However, the management or instillation of RFID system need skilled personnel. In addition, the data security issues such as tag-content changes, a high possibility of system spoofing have also restricted the applications of RFID.

A common problem with conventional ear-tag based cattle identification systems is the cost and requirement to manually attach the devices to animals. Moreover, its reliability in monitoring large numbers of animals in challenging environments can be poor (Awad, 2016).

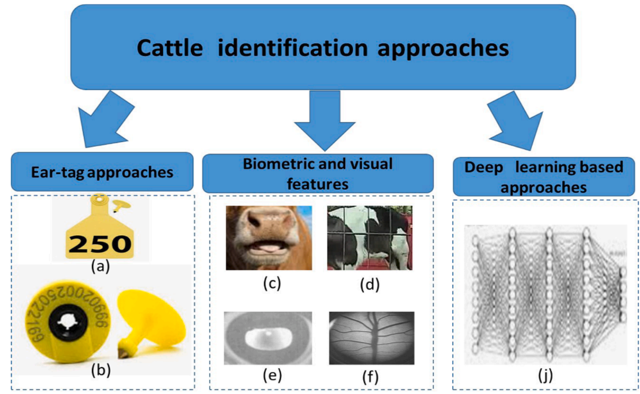


Fig. 2. Cattle identification approaches. The (a), (b) are plastic and RFID ear-tag respectively, (c) is cattle muzzle image, (d) is cattle coat pattern, (e) is cattle iris image from (Lindu, 2011), (f) is the cattle retinal image from (Allen et al., 2008), while (j) is a sketch of deep learning network.

2.2. Biometric and visual feature-based approaches

As each animal has unique external characteristics such as muzzle

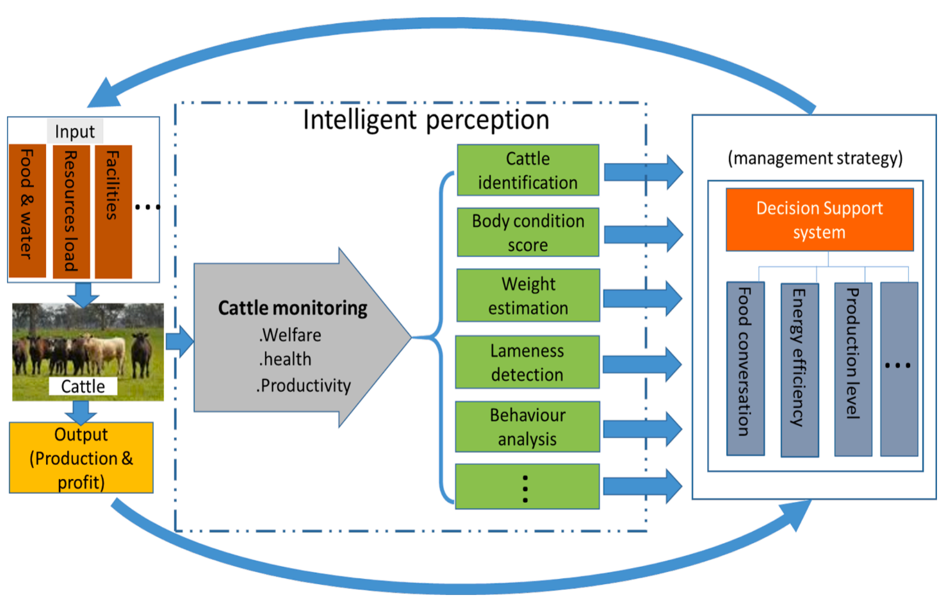


Fig. 1. The framework for intelligent perception for precision livestock farming.

Table 1
Main research work of cattle identification.

Work	Breed	Dataset size (images)	Data type	Feature used	Method	Accuracy
Barry et al. (2007)	N/A	290 (29 herd)	muzzle image	image pattern	Euclidean distance	98.85%
Allen et al. (2008)	Bovine	2266 (869 herd)	retinal image	Retinal vascular patterns	visual comparison	98.30%
Sun et al. (2013)	Bovine	90 (18 herd)	iris images	SIFT and bag-of-features	histogram distance	98.15%
Cai and Li (2013)	N/A	3000 (30 herd)	face image	local binary pattern descriptor	weighted Chi square distance	92.80%
Tharwat et al. (2014)	N/A	217 (31 herd)	muzzle print image	Gabor features	support vector machine	99.50%
Lu et al. (2014)	N/A	60 (6 herd)	greyscale iris images	2D-CWT coefficients	Hamming distance	98.33%
Kumar et al. (2015)	N/A	1200 (120 herd)	face images	SURF and Local Binary Patterns	weighted sum rule fusion	92.50%
Zhao and He (2015)	Holstein Friesian	81730 (30 herd)	side view images	deep learning features	convolutional neural network	93.33%
Andrew et al. (2016)	Holstein Friesian	86000 (40 herd)	side view images	local ASIFT coat descriptors	support vector machine	97.00%
Kumar et al. (2017)	Balinese, Hybrid Ongole, Friesian and Crossbreed	5000 (500 herd)	face images	salient sets of features	support vector machine	95.62%
Andrew et al. (2017)	Holstein	160 videos (23 herd)	back view videos	deep learning features	LRCN	98.13%
Kusakunniran et al. (2018)	N/A	217 (31 herd)	muzzle images	Gabor feature Local Binary Pattern	support vector machine	100.00%
Kumar et al. (2018)	N/A	523 sequences (16 herd)	muzzle point images	deep learning features	CNN	98.99%
Zin et al. (2018)	N/A	22 days' video (45 herd)	back view videos	deep learning features	CNN	97.01%
Okura et al. (2019)	Holstein	523 sequences (16 herd)	back view sequences	gait and texture	score-level fusion	84.20%
Andrew et al. (2020)	Holstein Friesian	18 videos (6 herd)	back view videos	deep learning features	LRCN	100.00%
Hu et al. (2020)	Holstein–Friesian	4353 (93 herd)	side-view images	deep cow-part features	support vector machine	98.36%
Qiao et al. (2020)	N/A	363 videos (50 herd)	rear-view videos	spatial–temporal features	BiLSTM	91.00%
de Lima Weber et al. (2020)	Pantanal cattle	27,849 (50 herd)	side-view images	deep learning features	DenseNet201	99.86%
Shen et al. (2020)	N/A	523 sequences (16 herd)	cow back image sequence	deep learning features	AlexNet	96.65%

patterns, retinal vascular patterns, and coat patterns (Andrew et al., 2016; Arslan et al., 2014), biometric and visual feature based approaches through computer vision and data analysis, can offer a rapid and secure solution for identification of animals or species (Andrew et al., 2017). Existing approaches, according to their adopted features, can be classified into three categories: cattle muzzle, retinal and iris, facial and coat pattern.

2.2.1. Cattle muzzle patterns-based approaches

The uniqueness of cattle muzzle patterns has been recognized since 1922 (Petersen, 1922). Muzzle images can be collected using digital cameras (live-captured images), then used for pattern description. In many cases, feature-description algorithms such as Scale-Invariant Feature Transform (SIFT) or Speeded-Up Robust Features (SURF) are employed (Lindeberg, 2012; Kumar et al., 2017). Meanwhile, features such as Local Binary Patterns and Gabor are also used for cattle identification (Kusakunniran et al., 2018), which achieved a very promising performance of the 100% accuracy on 20 cattle when the number of gallery images per cattle is at least four. Barry et al. (2007) used principal component analysis and Euclidean distance classifier to recognize the normalised muzzle pattern, and they achieved 98.85% identification accuracy for 29 cattle. Tharwat et al. (2014) extracted Gabor filter from muzzle print images for cattle identification, which achieved 99.5% accuracy.

2.2.2. Retinal and iris based approaches

Biometric features such as retinal and iris patterns (Allen et al., 2008; Lu et al., 2014) have also been used for cattle identification. Retinal vascular patterns are consistent across time and the iris contains discriminating information (Allen et al., 2008). Hence, based on extracted image features, both vascular and iris patterns are applicable for animal identification (Allen et al., 2008; Sun et al., 2013). Lu et al. (2014) incorporated iris patterns with the 2D Complex Wavelet Transform for cattle identification, which achieved 98.33% accuracy. However, these approaches lack applicability due to the difficulty of capturing retinal and iris images from moving cattle.

2.2.3. Facial and coat pattern based approaches

Machine learning methods have also been adopted to extract facial and/or coat features, which are used further for individual animal identification (Arslan et al., 2014).

Cai and Li (2013) and Kumar et al. (2015) extracted local features from facial images and then fed these into machine learning models for cattle identification. Kumar et al. (2017) used salient features (e.g., pixel intensity) to identify individual cattle, with resultant accuracy of over 85% on 5000 cattle face images. On the other hand, Andrew et al. (2016) utilized local coat descriptors and support vector machine to identify individual cattle. In addition, Okura et al. (2019) proposed a cow identification method based on three-dimensional video analysis using RGB-D cameras. The proposed approach there unified gait and texture features for identification, which achieved 84.2% accuracy.

It should be noted that for the facial and coat pattern based approaches, appropriate feature extraction and selection methods are important for the final cattle identification results. Also, in the above approaches, the used features are manually selected and extracted which are prone to be influenced by illumination or the camera angle.

2.3. Deep learning based approaches

Deep learning approaches with powerful feature extraction and image representation ability have gained popularity in the tasks of visual recognition (Xu et al., 2020), image segmentation (Qiao et al., 2019; Qiao et al., 2020), and automatic visual feature extraction (Jiang et al., 2020). It has more recently been applied for cattle identification purposes without requiring the pre-specification of any features (Kumar et al., 2018; Andrew et al., 2017).

Andrew et al. (2017) used deep neural architectures to exploit coat uniqueness for Holstein Friesian cattle identification, and according to their experiments, using a frame-based approach achieved 86.1% accuracy on 89 cows whilst a video processing pipeline obtained 98.1% accuracy on 23 cows. Zhao and He (2015) proposed a method for detecting a cow's trunk and then used convolutional neural networks (CNN) to identify cow trunk images, and their results showed that 90.55% of the testing frames and 93.33% of the testing videos were recognized correctly, respectively. Kumar et al. (2018) proposed a CNN-based approach for identification of individual cattle by using primary muzzle point images, which achieved 98.99% accuracy. Zin et al. (2018) trained a CNN-based on back images of cows to identify individual cows, and their approach got 97.01% identification accuracy. However, this approach ignored the information of the head and legs which also include useful identification information such as contour and texture features. Shen et al. (2020) used YOLO model to detect the cow object in the side-view image, and then fine-tuned a CNN model to classify each individual cow, achieving an accuracy of 96.65% in cow identification.

Qiao et al. (2019) proposed a beef cattle identification framework using image sequences which unifies the advantages of both CNN and Long Short-Term Memory frameworks, and their proposed approach achieved an accuracy of 88% for 15-frame video length on a dataset with 41 cattle. Lately, Qiao et al. (2020) further developed a Bidirectional Long Short-Term Memory (BiLSTM)-based approach for cattle identification, which achieved 91% accuracy for 50 cattle. More recently, Andrew et al. (2020) proposed an InceptionV3-based biometric Long-term Recurrent Convolutional Network (LRCN) for individual animal identification. de Lima Weber et al. (2020) provided individual recognition for Pantaneira cattle breed using CNN networks, which achieved an accuracy of 99%. Hu et al. (2020) extracted and fused discriminative deep cow-part features for cow identification using side-view images, achieving 98.36% identification accuracy in a dataset containing 93 cows.

However, deep learning approaches are confronted with two challenges. Firstly, the training of deep learning models requires large datasets (Van Hertem et al., 2017; Kamilaris and Prenafeta-Bold, 2018). Although data augmentation techniques can increase the training samples through flipping or rotation, in reality at least several hundreds or even thousands of images are required, depending on the complexity of tasks and accuracy required. Additionally, deep learning-based identification approaches often experience limitations in generalisation to new datasets or other types of animals.

2.4. Summary

Cattle identification has become vital to the PLF for animal welfare monitoring, disease control, vaccination management, production supply, and ownership management (Allen et al., 2008). The traditional cattle identification methods of ear tagging or tattooing are vulnerable to losses, damages, and fading. RFID identification systems provide dramatic advantages and operational improvements over classical methods, but involve many security and privacy challenges that render any such system susceptible to various risks (Awad, 2016).

Cattle biometrics and visual features have emerged as a promising cattle identification mechanism. The three current cattle biometric identifiers are muzzle pattern, retinal/iris patterns, and facial and body coat features. Meanwhile, deep learning approaches with its automatic learning ability makes feature extraction more efficient. Therefore, combing biometric identifiers with deep learning techniques will bring progress in the overall identification accuracy, which also could be a promising trend in the cattle identification domain. In recent years, Unmanned aerial vehicle (UAV) platform with on-board deep learning inference is began to autonomously locates and visually identifies individual cattle in a geo-fenced farm area (Andrew et al., 2019; Andrew et al., 2020).

Although significant progress has been achieved, many issues still exist due to paucity of benchmark datasets and evaluation standards. As each paper uses different datasets, pre-processing techniques, metrics, and models, it is not easy to perform comparisons between existing methods without clear evaluation standards (Bahlo et al., 2019). Benchmark datasets of livestock biometric samples (muzzle print images, iris images, and retinal vascular images) should be created for large-scale evaluations of feature extraction, classification, and feature-matching algorithms. Additionally, comparison standards are sorely needed to test various biometric features and equally compare different algorithms.

3. Body condition score evaluation

3.1. Cattle body condition score

Body Condition Score (BCS) is one of the most important indicators for animal welfare which can reflect the fatness/thinness of cattle (Krukowski, 2009), their productivity, health and longevity (Alvarez et al., 2018). Low values of BCS are generally considered to be an indication of health risks, low productivity level, and impaired pregnancy rate (Bell et al., 2018). As illustrated in Fig. 3, areas of focus for BCS include the loin, rump, pin bones, tuber sacral (hooks) and tail head (Krukowski, 2009). The BCS system usually uses a 5-point scale with 0.25 or 0.5 point increments (with 1 representing emaciated cattle and 5 representing obese cattle).

Traditionally, BCS is usually obtained manually by an experienced farmer using tactile or visual methods (Salau et al., 2014; Halachmi et al., 2013). However, the manual method requires experienced farmers and it is also time consuming. In addition, the results are subjective which are prone to be affected by the exterior environment and the experience. Therefore, there is an urgent demand for objective, accurate and robust BCS measurements.

In modern livestock industry, 2D and 3D based sensors are widely used to obtain cattle body parameter information for BCS evaluation (Bercovich et al., 2013; Anglart, 2014). Vision as a non-intrusive approach is extensively used (Lynn et al., 2017), usually involving two steps. Visual feature extraction of relevant features such as curvature, distance or body contour and the estimation of model construction where collected features are used to construct a regression model either via manual construction or computer programming. In Table 2, the main characteristics and results of existing BCS evaluation works are provided.

3.2. Body condition scoring using 2D sensors

2D camera-based methods are widely used for automated body condition scoring (Tedin et al., 2012; Halachmi et al., 2008). Existing frameworks mainly use rear or top views to get the cattle back area, which makes body parameter measuring or feature extraction convenient (Tedin et al., 2012).

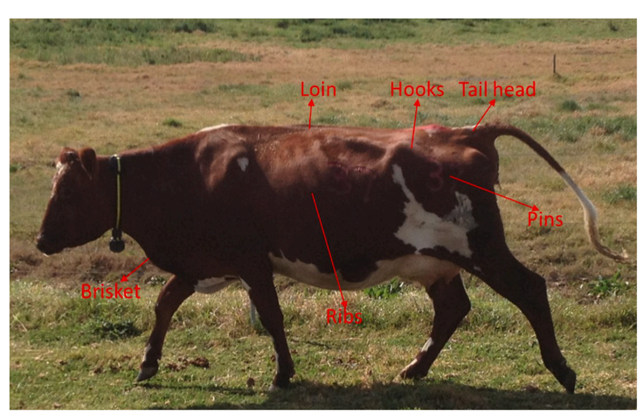


Fig. 3. Areas useful for visually determining BCS in cattle.

Table 2
Main research work of cattle body condition score estimation.

Work	Sensor	Dataset Size (images)	Automation level	Results
2D Sensors				
Bewley et al. (2008)	2D	834	low	92.79% within 0.25 deviation, 100% within 0.5 deviation
Battiato et al. (2010)	2D	286	low	Mean BCS error is 0.31
Azzaro et al. (2011)	2D	286	low	BCS error is 0.31
Halachmi et al. (2013)	2D (Thermal)	172	high	$R = 0.94$
Bercovich et al. (2013)	2D	151	medium	50% within 0.25 deviation, 100% within 0.75 deviation
Li et al. (2019)	2D	2231	low	64.55% within 0 deviation, 94.5% within 0.5 deviation
Huang et al. (2019)	2D	8972	medium	98.46% BCS accuracy
3D Sensors				
Krukowski (2009)	3D (ToF)	471	medium	79% within 0.25 deviation, 100% within 0.5 deviation
Salau et al. (2014)	3D (ToF)	540	high	$R^2 = 0.7$
Hansen et al. (2015)	3D (RGB + depth)	95	high	93.33% BCS accuracy
Anglart (2014)	3D (ToF)	1329	high	$R = 0.84$
Fischer et al. (2015)	3D (RGB + depth)	82	low	Test Set 1: $R = 0.89$, RMSE = 0.31 Test Set 2: $R = 0.96$, RMSE = 0.32
Shelley (2016)	3D (RGB + depth)	18,517	high	71.35% within 0.25, 93.91% within 0.5 deviation
Spoliansky et al. (2016)	3D Kinect	20	high	91% within 0.5 deviation
Kuzuhara et al. (2015)	3D	27	medium	$R^2 = 0.74$
Alvarez et al. (2018)	3D (RGB + depth)	1661	high	78% within 0.25 deviation, 94% within 0.5 deviation
Song et al. (2019)	3D	44	medium	0.72 BCS classification sensitivity
Yukun et al. (2019)	3D	3430	medium	77% within 0.25 deviation, 98% within 0.5 deviation
Rodríguez Alvarez et al. (2019)	3D	1661	medium	82% within 0.25 deviation, 97% within 0.5 deviation
Martins et al. (2020)	3D	53	medium	$R^2 = 0.63$
Liu et al. (2020)	3D Kinect	38	medium	76% within 0.25 deviation; 94% within 0.5 deviation
Zin et al. (2020)	3D (ToF)	52	medium	3.9% mean absolute percentage error

*R is correlation coefficient; R^2 is coefficient of determination.
RMSE (Root Mean Square Error) is the standard deviation of prediction errors.

For example, Tedin et al. (2012) recorded multiple images from the rear of the cows for BCS evaluation. Halachmi et al. (2008) extracted curvature of cattle tailhead contour, after which the BCS score was predicted by calculating the mean absolute error between a fitted polynomial and the cow contour.

The feasibility of utilizing digital images to determine BCS has also been assessed with top view images (Azzaro et al., 2011). Bewley et al. (2008) manually identified anatomical points to the top images, then used the angle features from those points to determine BCS, which achieved 92.79% accuracy. Battiato et al. (2010) employed statistical shape analysis and regression machines to evaluate BCS, and the achieved mean BCS error is 0.31. Huang et al. (2019) proposed Sing Shot multi-box Detector (SSD) method to detect the tail and evaluate the BCS. The experiments showed that the improved SSD method can achieve 98.46% BCS classification accuracy and 89.63% location accuracy on 898 cow images.

Despite the above progress in 2D sensor systems and approaches, it should be noted that 2D vision only offers two dimensional projection of the animal; the lack of the third dimension in vision limits applications utilizing depth information (Spoliansky et al., 2016).

3.3. Body condition scoring using 3D sensors

Recently, 3D sensors, which bring more body surface information than 2D-based or thermal image-based systems, are emerging in the applications of body condition scoring (Spoliansky et al., 2016; Yukun et al., 2019).

Currently, one of the most popular sensors to obtain 3D information is Time of Flight (ToF) camera (Anglart, 2014). The ToF are based on visible or near-infrared (NIR) light, where smart pixel sensors receive the reflected light and measure its return time. In Krukowski (2009) cows were photographed manually with ToF camera, and the features extracted from dorsal and posterior parts were shown to achieve 100% accuracy of the predicted BCS within 0.5 points deviation of actual BCS (regarded 0.5 points variation between the groundtruth score and estimated score is favorable).

More recently, 3D cameras such as Microsoft Kinect cameras are also used in the literature to capture images for automatic BCS evaluation (Spoliansky et al., 2016; Salau et al., 2017). Rodríguez Alvarez et al. (2019) used Kinect v2 camera to capture the images from the top as cows voluntarily walked below it and then adopted SqueezeNet model to estimate BCS, achieving 97% overall accuracy within 0.50 points deviation of actual BCS. Zin et al. (2020) extracted 3D surface roughness parameters for BCS prediction using regression analysis, achieving a mean absolute percentage error of 3.9%, and a mean absolute error of 0.13.

Machine learning techniques have also gained popularity in obtain BCS from sensor data. For example, Alvarez et al. (2018) proposed a SqueezeNet based approach which achieved 94% overall accuracy within 0.5 points deviation of actual BCS. Song et al. (2019) improved automated BCS classification using extracted body condition-related features in 8 body regions. Yukun et al. (2019) developed a deep learning framework to determine BCS using 3 channels data including depth, gray and phase congruency. The framework achieved accuracies of 77% and 98% within 0.25, and 0.5 points deviation, respectively. Although complex machine learning algorithms allowed models to mine useful image features themselves, this kind of approaches require a large number of labelled images to prevent over-fitting, limiting their applications on small and medium-sized farms.

3.4. Summary

The works in body condition scoring based on 2D/3D sensors and related techniques show significant progress. It should also be remarked that although there has been increasing interest for adopting 3D techniques in livestock farming, 3D sensors are more expensive than 2D tools, and 3D data processing and related algorithms are more complex. Therefore, 3D sensors will probably not replace the 2D tools completely in automatic BCS evaluation. It deems crucial to look into a few remaining challenges for further development.

Firstly, it is necessary to have an extended dataset with an equitable data distribution in order to achieve a quality jump in the system accuracy. In general, having a dataset with samples distributed evenly can help the machine learning system to converge faster and generalize well. Therefore, a large dataset is needed to consummate a complete 5-point scale BCS system.

Secondly, a more accurate BCS ground-truth apparatus is needed. As the shapes of cows are easily confused during expert scoring, more objective measurements or veterinary experts should be involved for the scoring work to eliminate subjective errors.

The last is that most BCS evaluation studies only consider a part of cattle body features (e.g. the angles and distances between five anatomical points, curvature of cattle tailhead contour). This leads to the lack of robustness. To address this issue, a combination of global and local features is essential for further improving the BCS evaluation accuracy.

4. Cattle weight estimation

Cattle weight plays an important role in optimizing the growth performance, increasing the farmers' income and monitoring animal welfare (Bercovich et al., 2013). Weight can affect factors such as lactation (Jaurena et al., 2005), growth (Koenen et al., 1999), pregnancy (Koenen et al., 1999), fertility (Swanson, 1967) and Rumen fill (Berry et al., 2002). The measurement of cattle live weight is also used as a management tool for diet calculation, determining insemination date of heifers in PLF. Therefore, an automatic, accurate and non-intrusive cattle weighing method is a desirable tool for cattle farmers. There are many live weight estimation approaches (Fordyce et al., 2013; Tasdemir et al., 2011), and these can be classified into two categories, namely direct or indirect methods.

The most direct method is individual weighing by moving each livestock to ride on the electronic or mechanical scale (Dingwell et al., 2006). Although this method can achieve the most accurate live weight, it is time-consuming and could cause injury and stress to cattle especially when forcing the cattle on the scale (Dickinson et al., 2013; Tuyttens, 2005). What's worse, as a costly and cumbersome device, automatic scales can not easily be installed and used in the pen space or the open farmland.

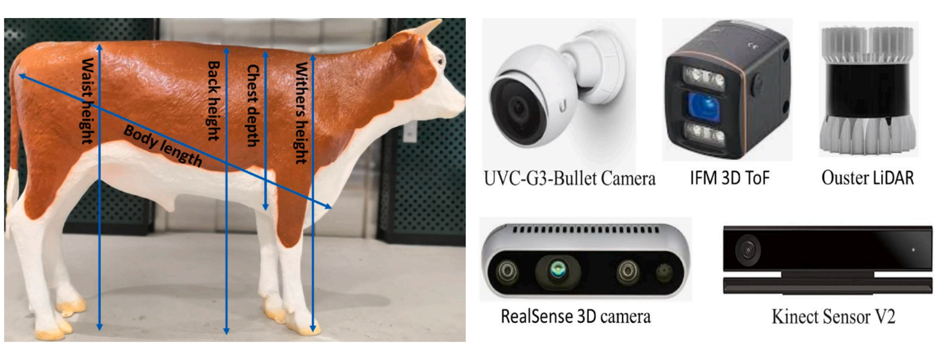
On the other hand, the indirect cattle weight estimation method is done through assessment of cattle morphological traits such as wither height, heart girth, body length and hip width based on 2D or 3D sensors (e.g. RGB, thermal, LiDAR, passive stereo, structured light and TOF) (Kashiha et al., 2014; Hansen et al., 2018; Zhu et al., 2018). Then the relationship between body parameters and weight is constructed based on data analysis. Measurements of heart girth and hip width have the highest correlation with body weight (Enevoldsen and Kristensen, 1997), but body parts such as heart girth, wither height, and body length could also be included when predicting body weight (Schröder and Staufenbiel, 2006). In Fig. 4, some cattle body parameters and sensors used for live weight estimation are displayed. In addition, Table 3 lists some main 2D and 3D sensor-based approaches for cattle weight estimation.

4.1. 2D sensor based cattle weight estimation

Among the existing methods, camera-based approaches, combined with automatic image analysis, are arguably most cost-effective, and efficient (Zhu et al., 2018; Bercovich et al., 2013). In camera-based frameworks, morphological features such as body length, body width and area are extracted firstly. Then based on image analysis and machine learning (Gomes et al., 2016), the models between the features and weight are constructed for estimation purposes.

In terms of 2D camera-based approaches, Stajnko et al. (2008) estimated cattle live weight by measurement of body dimensions based on thermography and thermal image analysis. Moreover, a statistically significant relationship between two heights (wither height and hip height) and live weight was found, whereby Standard Error of the Estimate (SEE) was varying from 21.76 kg to 33.59 kg at day 139. Lukuyu et al. (2016) used heart girth, body length, height at withers for weight estimation based on linear regression, which achieved a root mean-square prediction error of 26 kg (adjusted $R^2 = 0.71$) and predicted live weight of over 95% of crossbred dairy cattle in the range of 100–450 kg. Tasdemir et al. (2011) and Ozkaya (2013) utilized top and side view cameras for cow live weight detection based on multi linear regression and fuzzy rule models. Visual features such as hip height, body length, hip width, and chest depth extracted from images were used in their models. Tasdemir et al. (2011) obtained body measurements (i.e. wither height, hip height, body length, hip width) using digital image analysis and these were used to estimate the live weight of each cow. Yan et al. (2019) extracted withers height, body diagonal length and body side area from images of yaks, and applied these body measurements using multiple linear regression to predict weight, which achieved RMSE values between 7.5 kg and 13.4 kg in three different seasons (i.e. summer, winter, and spring). Gjergji et al. (2020) implemented EfficientNetB1 model for weight estimation, which achieved a Mean Absolute Error (MAE) of 23.19 kg.

Besides, 2D cameras have also been used to estimate carcass weight. Alonso et al. (2013) predicted carcass weights 150 days before the slaughter day using a Support Vector Regression algorithm based on zoometric measurements (i.e. withers height, loin length, rump length, chest girth, thighs width, and round profile). The method achieved an average absolute error of almost 11 kg (4.27% of the ground-truth). Data from a total of 134 cattle were presented in Lee et al. (2019), where 20



(a) Cattle body parameters (b) Sensor examples

Fig. 4. Some key body measurements and widely used sensors for cattle weight estimation.

Table 3
Main research work of cattle weight estimation.

Work	Sensor	Cattle number	Traits	Model	Automation level	Results
2D approach						
Lukuyu et al. (2016)	2D	452	heart girth, body length, height at withers	linear regression	medium	Adjusted $R^2 = 0.71$
Alonso et al. (2013)	2D	144	zoometric measurements	support vector regression	medium	Relative error is 11 kg
Tasdemir et al. (2011)	2D	115	body measurements	regression analysis	medium	Correlation coefficient is 0.98
Tebug et al. (2018)	2D	459	heart girth and height at the withers	stepwise regression	medium	Adjusted $R^2 = 0.85$; RMSE = 34.25 kg
Kashoma et al. (2011)	2D	300	heart girth	regression analysis	medium	$R^2 = 0.88$
Odadi (2018)	2D	160	morphological measurements	linear regression model	medium	$R^2 = 0.90$; Residual standard error is 12 kg
Jakaria et al. (2019)	2D	68	body measurements	regression analysis	medium	$R^2 = 0.79$; RMSE = 18.1 kg
Lee et al. (2019)	2D	134	20 variables	regression; neural network	medium	Relative errors is within 4%
Yan et al. (2019)	2D	146	body diagonal length, body side area, withers height	linear regression model	medium	RMSE is between 7.5 kg and 13.4 kg in different seasons
Weber et al. (2020a)	2D	34	morphological measurements	stepwise regression	medium	$R^2 = 0.7$; RMSE = 42.52 kg
Weber et al. (2020b)	2D	110	dorsal area	regression trees bagging	medium	MAE = 13.44 kg
Gjergji et al. (2020)	2D	20	dorsal area	EfficientNetB1	high	MAE = 23.19 kg
3D approach						
Yamashita et al. (2017)	3D	48	cattle trunk	3D successive cylindrical model	low	an average percentage error of 21.46% (around 20 kg)
Song et al. (2018)	3D	30	morphological traits	multiple linear regression model	high	RMSE = 41.2 kg; 5.2% mean percentage error
Hansen et al. (2018)	3D	185	back volume	regression analysis	high	average error 78.18 kg (11% mean percentage error)
Sousa et al. (2018)	3D LiDAR	107	rump height and back area	linear regression	medium	$R^2 = 0.85$; RMSE = 8.93 kg
Cominotte et al. (2020)	3D	62	biometric body measurements	artificial neutral networks	medium	RMSE $\leqslant$15 kg
Martins et al. (2020)	3D LiDAR	55	morphological traits	statistical analysis	medium	$R^2 = 0.89$ (RMSE = 49.20 kg) for lateral perspective; $R^2 = 0.96$ (RMSE = 26.89 kg) for dorsal perspectives
Nir et al. (2018)	3D Kinect	107	biometric body measurements	artificial neutral networks	medium	Root mean squared error percentage is 42.6%
Kuzuhara et al. (2015)	3D	8	six geodesic line lengths	linear regression	medium	$R^2 = 0.80$; RMSE = 42.65 kg
Miller et al. (2019)	3D	674	biometric body measurements	artificial neutral networks	medium	$R^2 = 0.7$, RMSE = 42 kg
Anglart (2014)	3D	70	biometric body measurements	artificial neutral networks	medium	$R = 0.87$
Nishide et al. (2018)	3D	184	cattle trunk	3D contiguous cylindrical model	medium	Mean absolute percentage error is 6.39%

variables related to carcass weight and body measurements were extracted to estimate the cold carcass weight of Hanwoo cattle. The R^2 values from testing the developed models by multiple regression, partial least square regression, and an artificial neural network with seven significant variables were 0.91, 0.91, and 0.92, respectively (relative errors were within 4%). Weber et al. (2020b) measured cattle dorsal area from 2D Image and then predicted cattle body weight using active contour models and regression trees Bagging, which achieved Mean Absolute Error of 13.44 kg.

Despite the above progress in 2D camera-based systems and approaches, it should be remarked that features extracted from 2D cameras are prone to be influenced by camera viewpoints or the changes posture of cattle's movement.

4.2. 3D sensor based cattle weight estimation

Unlike 2D sensors, 3D sensors (e.g. 3D camera, LiDAR) can give depth information on the body surface, which can significantly improve the weight estimation accuracy. Additionally, certain morphological traits quantified using 3D sensors are more accurate compared with stereo (Song et al., 2018).

In terms of 3D camera-based works, Yamashita et al. (2017) proposed a body weight estimation method by modeling the shape of calf using three-dimensional information extracted from the stereo images. The method achieved an error of 21.46% (around 20 kg) by averaging the multiple volumes of the slide division method considering adjoining circle. Gomes et al. (2016) conducted body measurements using the Kinect camera, and heart girth was found to have a high correlation coefficient ($R^2 = 0.967$) with body weight. Similarly, Song et al. (2018) automatically measured morphological traits (e.g. hip height, hip width and rump length) from 3D vision, and investigated the influence of various data sources on body weight prediction. In their studies, the best multiple linear regression model using hip height, days in milk, age, and parity information achieved 41.2 kg root mean square error and 5.2% mean absolute percentage error. Cominotte et al. (2020) developed an automated 3D computer vision system used to predict body weight and average daily gain in beef cattle by using biometric body measurements of each animal, such as body volume, area, length, and others. Martins et al. (2020) used Microsoft Kinect 3D camera from lateral and dorsal perspectives to determine body weight respectively, which achieved an R^2 of 0.89 (RMSE = 49.20 kg) and 0.96 (RMSE = 26.89 kg) for lateral and dorsal perspectives, respectively.

Apart from the above-mentioned works, 3D cameras have also been shown to achieve good performance in carcass weight estimation (Miller et al., 2019). Greiner et al. (2003) predicted weight and percentage of beef carcass retail product using ultrasound and live animal measurements (measurement of rump fat and body wall thickness). Miller et al. (2019) predicted live weight and carcass characteristics of live animals using 3D imaging technology and machine learning algorithms (artificial neural networks). In their work, sixty morphological traits (e.g. lengths, heights, widths, areas, volumes, and ratios) were used to develop predictive models, the prediction for live and carcass weights achieved RMSE of 42 kg ($R^2 = 0.7$) and 14 kg ($R^2 = 0.88$), respectively.

More recently, 3D LiDAR technology has also been used for remote sensing of cattle 3D information in precision cattle farming (Huang et al., 2019). Huang et al. (2019) explored automatic cattle measurements with transfer learning from LiDAR sensing. Based on cattle point cloud datasets (PCD) sensed by LiDAR, cattle silhouettes was extracted for body measurement. Their experimental results showed that the comprehensive error of body dimensions was close to 2%. Sousa et al. (2018) developed a LiDAR sensor platform to estimate cattle live weight in feedlot. Based on LiDAR scanning data, cattle rump height and the area of the back view were computed and then fed to a artificial neural network based-model for weight estimation. By comparing the estimated and measured cattle weight, the proposed approach achieved an R^2 of 0.85 and RMSE of 8.93 kg.

4.3. Summary

Numerous studies investigating the use of body linear measurements to estimate weight have focused on morphological traits such as body width, length, and so on. One should note that changes in body weight, whether measured directly or indirectly, reflect not only changes in amounts of tissue but also changes in body water, protein, gastrointestinal content, and so on (Schoder and Staunfenbiel, 2006). However, the understanding of how live weight is related to these factors and traits such as height, body condition, genetic parameters, and genotype is still not very clear in cattle management (Fordyce et al., 2013). Therefore, further research is needed to better assess the accuracy and implications of live weight estimation in commercial or research situations.

Moreover, although 2D and 3D sensor-based approaches constitute a non-invasive system to estimate the weight, non-contact testing of live animals is still restricted by many factors such as harsh environment and poor light condition. A realistic weight estimation system for use in farm environment would need to accommodate for challenges including variant lighting conditions and cattle motion to be able to extract useful features reliably.

The realistic weight estimation system should accommodate the farm environment and run stably for a long period. The image analysis algorithm should adapt to uneven illumination environment to get cattle contour. In addition, how to establish the method to extract features from motion videos of cattle, adapt to uneven illumination environment to get cattle contour, and maximizing precision and repeatability should be considered as well.

5. Discussion of current challenges and future research opportunities

In this paper, although we focus on the technologies of cattle farming, the same or similar technologies can be also implemented in the farming of other livestock animals such as pig, sheep and poultry (Rowe et al., 2019). Based on the literature review and cattle farming research work, some main challenges and future research opportunities of precision livestock farming are summarized in this section.

5.1. Main challenges

(1) Lack of high-quality public data and uniform data standards. In the machine or deep learning based approaches, training models using large-scale data is significantly important. Qiao et al. (2020) proposed data augmentation approach uses random image cropping and patching to expand the number of training images and their corresponding labels. However, due to various issues such as ownership and confidentiality reasons, farms and other commercial entities seldom release their collected data to the public domain (Jones et al., 2017). On the other hand, due to lack of uniform data standards (i.e. low spatial resolution, complex data format or restricted farm scale), the value of available public datasets is also very limited.

(2) Demand for Decision Support Systems (DSS). The ultimate goal of precision farming applications is decision support. With the technological improvements, increasing data availability for livestock producers, industry and consumers, this has become more viable than before. However, assessing the non-economic value of information from emerging technologies remains a challenge (Rojo-Gimeno et al., 2019). DSS for grazing systems and livestock are becoming available to assist farm level decision makers, but there is a lack of such systems for broader geographic contexts. The future DSS should adapt to uncertainty and dynamic factors, enrich decision supports for the whole life cycle of the animal, simplify GUIs to enhance the accessibility of DSS, and perform analysis on historical information (Zhai et al., 2020).

(3) Objective assessment of on-farm sensor techniques and systems. Sensors and precision technologies are available to monitor cattle in real-time. However, the bigger question is how to objectively assess their contributions in farm level sustainability (i.e. production efficiency, health monitoring, welfare assessment and environmental impact).

5.2. Promising directions and opportunities

With the development of smart sensors, big data and deep learning, precision livestock farming will continue to develop in the direction of contactless, automated, real-time and continuous detection with fully consideration of cattle living conditions and actual production needs. Based on the above literature review, the following promising directions and opportunities of future research are anticipated:

(1) Improving livestock farming data fusion ability: each individual sensor data has its own advantages, and fusion of various sensing modalities can improve the final performance. Fusing all variables of cattle body or growth together can make the management systems and DSS more reliable and efficient. With rapid developments in big data and deep learning, data or information fusion could be utilized further for large scale evaluation and monitoring systems.

(2) Real-time 3D shape and model construction: most of the current research uses 2D sensors to obtain the cattle body size parameters or shape features (Bercovich et al., 2013). However, for moving cattle, 2D senors such as cameras cannot measure the body or shape size due to viewpoints, angle problems. Using 3D sensors such as Kinect, Intel RealSense or Velodyne LiDAR to realize the cattle 3D model reconstruction and shape extraction will be helpful in the cattle body or growth monitoring. Moreover, using multi-spectral cameras with an animal 3D shape model could have the capability of evaluating the muscle quality from aspects of nutrition, muscle contains, and energy. In addition, based on cattle 3D models, explicit segmentation of animal body regions such as head, neck, torso, limbs can be obtained, which will be meaningful for the cattle posture or behavior recognition.

(3) Objective and automatic body condition estimation: scoring rules are widely used in grading lameness detection and body condition. The scoring criteria are often not robust and has limited ability to reflect the nature of animal movement and body condition changes (He et al., 2016). Therefore, it is necessary to develop a universal animal state (motion or muscle thickness) parameter that does not rely on subjective scoring results, and is objective and measurable. The ultimate goal

should be the development of an objective and automatic estimation criteria.

(4) Socio-economic analysis of animal intelligent perception systems: the ultimate goal of intelligent perception equipment is to serve livestock production, so it is especially important to study the economic benefits of equipment use. Based on the invest and profit information (e.g. animal quantity, annual income, target income, number of employees, etc.), combined with the animal information that new technologies can provide, future research is needed to establish a production and cost prediction model, and conduct economic benefit assessment.

6. Conclusions

Intelligent perception technologies are increasingly improving cost efficiency, safety, and sustainability of the large scale livestock industry through the acquisition, processing, analysis and application of information about individual cattle's welfare, and productivity. In this paper, we conducted a survey of intelligent perception for cattle monitoring in the precision livestock domain. More than 100 relevant papers were investigated, and the research status about the cattle identification, body condition score evaluation, and live weight evaluation were thoroughly examined. Based on the literature review, we conclude that contactless, automated, real-time and continuous cattle detection will play an important role. We have also discussed the existing challenges, potential future research trends and opportunities. Our hope is that this survey will facilitate researchers in studying the field of precision livestock farming, especially, monitoring cattle welfare and productivity.

CRediT authorship contribution statement

Y.Q.: investigation, formal analysis and writing-original draft. H.K.: writing-review and editing. C.C: funding acquisition and paper revising. S.L: resources and paper improvement. D.S. and S.E.: writing-review and editing. S.S.: resources, funding acquisition.

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.

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Appendix A

Some used abbreviations are listed.

Abbreviation	Description
BCS	Body Condition Score
CNN	Convolutional Neural Networks
BiLSTM	Bidirectional Long Short-Term Memory
LRCN	Long-term Recurrent Convolutional Network
SIFT	Scale-Invariant Feature Transform
SURF	Speeded-Up Robust Features
MAE	Mean Absolute Error
RMSE	Root-Mean-Square Error
PLF	Precision Livestock Farming

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