Precision Agriculture for Farming

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Precision agriculture (PA) is a technology-enabled, data-driven approach to farming management that observes, measures, and analyzes the needs of individual fields and crops. Precision livestock farming (PLF), relying on the automatic monitoring of individual animals, is used for animal growth, milk production, and the detection of diseases as well as to monitor animal behavior and their physical environment, among others.

Keywords: smart farming technologies ; precision agriculture ; precision livestock farming ; trends

1. Introduction

Agriculture has played a key role in the global economy in recent years [1]. Estimates show that current agricultural production must increase 60–100 percent with everything else unchanged to meet the nutritional needs of a future human population of 9–10 billion. In addition, agricultural intensification over the last few decades has had negative environmental impacts [2]. As a result, the pressure on the agricultural system is greater than ever before [1]. In order to minimize these issues, traditional agricultural management methods have been complemented by new sensing and driving technologies and improved information and communication technologies (ICT) [3]. Based on the concept of "produce more with less" [4], precision agriculture, also known as precision farming or smart farming, has the potential to contribute to the wider goal of meeting the increasing demand for food whilst ensuring the sustainability of primary production, based on a more precise and resource-efficient approach to production management [5].

PA technologies are used in the important stages of the crop growth cycle (soil preparation, seeding, crop management, and harvesting). However, it is not just crop and fruit farming that has benefited from precision farming technologies—farmers engaged in livestock rearing are also experiencing the positive benefits derived from precision farming technologies [5]. PA could be divided into two categories: precision crop farming, which consists of the application of precision farming technologies to manage spatial and temporal variability for improving crop performance and environmental quality, and PLF, which is based on the use of advanced technologies to optimize the contribution of each animal. Through this "per animal" approach, the farmer aims to achieve better results in livestock farming [4]. Precision crop farming and PLF are currently being shaped by two major technological trends: big-data and advanced-analytics capabilities on the one hand, and aerial imagery, feeding and milking robots, and intelligent sensors, on the other [6].

2. Precision Livestock Farming

As part of precision farming, managing livestock is one of the current challenges for agriculture [7]. The term 'precision livestock farming' (PLF) appeared in the early 21st century, with the first PLF conference held in 2003 [8] as an innovative production system approach [9], playing a key role in the fourth industrial revolution, also known as Industry 4.0 [10]. PLF is potentially one of the most powerful developments amongst a few interesting new and upcoming technologies that have the potential to revolutionize the livestock farming industries [11].

PLF uses a combination of tools and methods to measure different variables from each animal with high precision, supporting farmers to make decisions concerning the livestock production systems [12]. Decisions are often based on the acquisition, collection, and analysis of quantitative data obtained by continuous real-time from animals and the environment [13][14]. These tools include sensor technology cameras [15], microphones, wireless communication tools, Internet connections, and cloud storage [16], among others. However, the application of the existing tools for PLF can be challenging under extensive livestock management because this occurs on natural pastures that are large, heterogeneous, and highly dynamic environments [12]. Therefore, the main purpose of PLF is to enhance farm profitability, efficiency, and sustainability [15][16] by improving on-farm acquisition, management, and utilization of data management and the utilization of data, in order to enhance the nutritional and other management aspects from distinct species of animals [16]. PLF could also deliver additional food safety, traceability, welfare, and environmental benefits [9][11][16][17]. In addition, PLF aims the management of crop processes to create perfect synergy with livestock feeding [3]. If properly implemented, PLF could (a) promote product segmentation and better marketing of livestock products; (b) reduce illegal trading of livestock products; and (c) improve the economic stability of rural areas [11].

2.1. Animal Monitoring

Successful grazing and pasture management require an understanding of the adjustment mechanisms behind the grazing behavior [18] that enables adaptation to grazing conditions [19] and to facilitate the precise grazing management, the monitoring of animal position, foraging, and other behaviors can bring considerable benefits for animal health and welfare by continuously monitoring each animal in the flock. Deviations from 'normal' behavior (for that individual animal) can be quickly identified and flagged to the farmer [20].

The use of GNSS technology allows for the characterization of grazing behavior including grazing patterns, paths, and favored areas. Grazing activities can also be differentiated based on the speed of movements. The increased knowledge conveyed using GNSS receptors in animal grazing can become a valuable tool to support the decisions that are essential to a more precise pasture management [19].

Tracking location on pasture, through the large dissemination of global positioning system (GPS) sensors have been successfully used to detect static or dynamic unitary behaviors differentiated through changes in path speeds: foraging or grazing, resting, and walking [21]. Likewise, the use of GPS collars for livestock opened the possibility of recording detailed position data for extended periods of time, thus allowing for a more complete understanding of the habits and causes of the spatial distribution of ruminants. The position information can be stored either on collar small flash cards, either transmitted in real-time to a background infrastructure together with substantial amounts of behavior and physiological data [22].

Despite the obvious advantages of satellite tracking technology, these solutions present a common problem, which is related to electrical consumption, and the consequences of this consumption on the autonomy and weight of the devices. In the scope of SheepIT project Guedes et al. [23] developed a RSSI-based mechanism that uses a farm radio infrastructure for tracking animals collars in real-time. The proposed solution presents an accuracy similar to GPS location devices, but highly depends on careful location of the fixed radio nodes.

Animal behavior can also be monitored by means of a collar usually enabled with inertial sensors [18]. Through analysis of rumination rate and the feeding and resting behavior, estrus events can be detected, according to a study by [15]. Similar collars were used, showing that the highest accuracy was achieved with these instruments (>90%) whereas visual human observation was far less accurate [24].

Posture analysis was developed using accelerometers and based on the position of the head: up or down. This information, in combination with GPS-based data, allowed for discrimination between several kinds of feeding related behaviors for grazing animals with high accuracies (>90%). These accuracies were obtained with a brief time window of 5 to 10 s while the data acquisition from the GPS and the accelerometer ran between 4 Hz and 10 Hz [25].

Monitoring cattle movements using accelerometers and using diverse analysis methods, accelerometers recording data at 10 Hz could be used to classify behaviors using a basic statistical method to classify lame and non-lame cows, reaching an average accuracy of 91% [19]. Similarly, in [25], they were classified as multiple behaviors using a machine learning method with accuracies ranging from 29% to 86% with samples windowed for 10 s for all behavior classifications.

As a way to develop a posture control solution, which allows sheep to be used in the animal wave of the viticultural space, Nóbrega et al [18] developed a collar-based mechanism that monitors the postural behavior of sheep during their presence within the vineyard. The monitoring collar contains an ultrasound and inertial sensors and it classifies animal behavior accordingly 5 behavior states (*e.g.* infracting, eating, moving, running and standing) with an accuracy of 91%.

Among the solutions to detect the animal behavior and collect data with a reduced uncertainty [26], image and sound analyses are also promising. However, video recordings require a large amount of time to be analyzed and manually checked, involving potential mismatches in the interpretation of observers. According to Meen et al. [27], there is a correlation between sounds and behavior, as a significant difference emerged between the average maximum frequency of murmurings during the lying and ruminating phase and that of calls during the other phases [24].

In addition, a review carried out by Meunier et al. [28] described machine learning algorithms such as pig-face recognition. Recent advancements in facial recognition have been extended to identify and recognize the patterns of several animal behaviors. Different facial detection and recognition methods such as the VGG-face model, Fisherfaces, and convolutional neural networks can now discern individual animal faces in complex real-time scenarios, in the presence of some shape deformation and even in instances where there is insufficient data. This non-invasive imaging system recognizes the faces of individual pigs in a real farm setting with 96.7% accuracy [29].

2.2. Animal Health and Welfare

Animal health is of key importance in the livestock industry as it impairs production efficiency through growth retardation or even mortality, animal welfare through pain and discomfort, and it can even impair human health through the misuse of antibiotics or zoonosis [30]. In fact, the large density of animals living so close to humans in some countries can transfer a high number of zoonosis diseases to humans [31]. The monitoring of health problems in the early detection of clinical signs of diseases on the farm is one of the key issues from which PLF has arisen [24]. Most diseases are easily treated when detected in an early phase, although prevention is always the priority [30]. Modern technologies such as sensors, big data, artificial intelligence (AI), and machine learning (ML) algorithms enable farmers to react to diseases after they become evident, or pro-actively using vet services, and provide an opportunity to constantly monitor key animal health parameters such as movement, air quality, or consumption of feed and water. By constantly collecting these data and using advanced technology to predict deviations or abnormalities, farmers can identify, predict, and prevent disease outbreaks. Therefore, this technology has a significant cost advantage over older detection methods [29].

Animals can be monitored by methods based on the sound, with the potential to be automated for large-scale farming [28]. A sound-based tool (Pig Cough Monitor™ (PCM), Soundtalks®, and Fancom B.V.) has been developed for automated pig cough detection that is based on a mathematical algorithm that processes all incoming sound and identifies the number of coughs automatically [27]. In addition, Van Hertem et al. [32] evaluated the effect of using a microphone and subsequent advanced methods for labelling in the early detection of cough in calves and highlighted how the adoption of an algorithm with >90% precision allowed reducing the emergence of bovine respiratory disease (BRD). In addition, distress can be vocalized by animals or shown though unusual activity. Vocalization could be measured via microphones, whereas activity could be observed and recorded using staff observations or surveillance cameras, with the interpretation of sounds and images to produce meaningful information [33].

Automated sensors and algorithms can reliably predict and reduce the risk of mastitis in cows. Air sensors in the poultry industry can predict the onset of Coccidiosis by constantly monitoring the concentration of volatile organic compounds in the air increase, as the number of infected birds increases. Air sensors could detect this change much earlier than a farmer or a vet could [29]. In other cases, by carrying out image analysis and calculating model parameters from the image information, it was possible to develop an algorithm for automatic detection of lameness based on animal locomotion [29][34]. In the case of cattle health, a few common diseases can be identified using non-invasive, cheap sensor technologies. More complex sensor platforms exist, for instance, camera systems to detect back posture, and ingestible pills for heart rate determination [35]. Furthermore, the continuous feed and water registration in the farm makes it possible to assess the first freedom from hunger and thirst. Climate control sensors such as temperature sensors, relative humidity probes, and CO_2 sensors will allow the automatic evaluation of thermal discomfort in the house [30].

2.3. Feed and Live Weight Measurement

Based on real-time feedback from sensors [36], precision livestock feeding [17] aims to provide to individuals or a group of animals with the amount of nutrients that maximizes its utilization without loss of performance [17]. Therefore, accurately and automatically measuring the amount of feed used per day per animal or distinct group of animals is extremely important [16], since it can decrease protein intake by 25%, and nitrogen excretion into the environment by 40%, while increasing profitability by nearly 10% [17].

The implementation of automated feeding systems (AFS) can provide a cost-effective alternative to manual regimes. Feeding units have been developed for a variety of animal systems including cattle, sheep, and pigs. These systems can be advantageous by providing an interface that monitors time and date of feeding, the electronic identification of each animal, the weight of the feed consumed, and the duration of feeding [16][37].

Demmers et al. [38] used an automated feeding system to control the amount of feed delivered to pens and the ambient temperature to optimize growth and reduce ammonia emissions [17]. In Canada, a next generation feeding system was recently developed to tailor both the amount and composition of the feed. In the next few years, we might be able to adjust the nutrient intake to match the requirements of individual animals in real-time, based on their state-specific needs, as estimated from the sensor data [35]. We must also emphasize a study by Evangelista et al. [39] that highlights the use of portable near infrared spectroscopy (NIRS) to evaluate the physio-chemical composition of total mixed ration (TMR) and manure in dairy farms. According to the authors, the use on barn NIRS, through appropriate calibrations, is a rapid and accurate analytical technique with high potential benefits.

RGB-D cameras can also help farmers to measure feed intake for individual cows [40]. In addition, several advanced algorithms can help farmers calibrate and optimize feed expenses according to their animals' needs [30]. Finally, mathematical nutrition models can be useful components to correctly estimate the contribution of ruminants to greenhouse gas emissions (GHG) [35].

The measurement of average live weight gain (speed of growth) of a distinct group of animals is one of the most important measurements to be undertaken on livestock farm as the speed of growth will affect both the financial performance of the farming enterprise as well as the final body composition of the animals [16]. Recent systems have appeared on the market (such as the *Osborne Weight-Watcher*™). Weighing systems based on image analysis techniques have been designed to determine the weight of individual or groups of animals (specifically pigs) with acceptable precision by correlating dimensional measurements of the animals to weight. Recent studies [40] demonstrated that those systems can reliably provide a performance record of successive batches of animals in a timely manner.

2.4. Automatic Milking Systems

The milking robot is a classical PLF application [7] with a growing popularity. Automatic milking systems (AMS) have gained widespread acceptance, particularly in western Europe to reduce labor on dairy farms, increase production per cow, and improve the lifestyle of dairy farm families [41]. The first installations were typically associated with 'indoor' systems and nearby grazing fields but can be applied both to indoor and pasture-based feeding systems [42]. As a robot-based, milking process can now be spread over a 24-hour period, allowing the animal to choose when to be milked.

There are numerous offers for automatic milking systems (AMSs) in the market. Recent technological advances have included the integration of more modern sensors/vision systems, the addition of animal monitoring features, and the integration of robots in rotary milking parlors. Time of flight (ToF) depth sensing cameras have been used in many recent developments in AMSs. Acceptable accuracy (teat location detection within 5 mm) has been achieved when the search space is limited to a region of interest 150 mm wide by 80 mm deep [43]. Teat detection and tracking using algorithmic solutions from depth images and point-cloud data were also achieved according to a study by Rodenburg et al. [44]. Other vision technologies have also been investigated using a Kinect structured light camera and a Haar Cascade classifier [45] or using a combination of thermal imaging and stereovision techniques [46]. The task of attaching the milking clusters to the cows' teats is a challenging one as the shape of the udder is variable between cows and between distinct stages of lactation [43].

Cycle time of the milking operation must also be minimal so that both the cow and farmer can be more productive with their time. Therefore, an intelligent control of the robot is required using visual feedback to navigate the cluster onto the cow accurately, safely, and quickly. A system that can milk cows with unusually shaped udders or that do not take to a robot milker, which would otherwise have to be culled as is the case with some existing AMSs, would also be a considerable advantage [43].

Table 1. Overview of PLF technology and applications.

Reference	Application	Involved Methods/Technologies	Main Objective/Function
[47]	Animal behavior	GPS sensors	Tracking location
[21]	Animal behavior	A neck collar with series of sensors	Detection of estrus events through analysis of rumination rate, and the feeding and resting behavior
[25]	Animal behavior	Accelerometers in combination with GPS-based data	Discrimination between several kinds of feeding related behaviors for grazing animals Classification of multiple cattle behaviors

[48]	Animal behavior	A machine learning method	Pig cough detection-processing all incoming sounds and automatically identifying the number of coughs
[27]	Animal behavior	Cameras and microphones Sound tool based on an algorithm	Find a correlation between vocalization and behavior
[29]	Animal behavior	A non-invasive imaging system such as VGG-face model, Fisherfaces, and convolutional neural networks	Pig-face recognition
[32]	Animal health and welfare	Microphones for cough sounds	Detect bovine respiratory disease
[28]	Animal health and welfare	Air sensors	Prediction the onset of Coccidiosis by monitoring the concentration of volatile organic compounds in the air
[34]	Animal health and welfare	Algorithm developed through image analysis	Automatic detection of lameness in dairy cows individually
[38]	Feed management	An automated feeding system	Control the amount of feed provided, and the ambient temperature to optimize animal growth and reduce ammonia emission
[15]	Feed management	A feed sensor	Measure and control the amount of feed delivered to individual feeders
	Feed management	A next-generation feeding system	Provide feed with a variety of nutrient specifications to tailor both the amount and composition of the feed
[37]	Feed management	A computer vision based system CNN models using a low-cost RGB-D camera	Measures cow individual feed intake
[39]	Feed management	NIRS technology	Evaluation of physio-chemical composition of TMR and manure in dairy farms
[40]	Weight management	Weighing system based on image analysis	Determine the weight of individual or group of animals (specifically pigs)

[43][44][45][46]	Automatic milking systems	Time of flight (ToF) depth sensing cameras Algorithmic solutions from depth images and point-cloud data Machine learning based vision for smart MAS Combination of thermal imaging and stereovision techniques	Teat Detection Teat detection and tracking Capability for faster and accurate teat detection Teat sensing

3. Risks and Concerns

It is essential to understand how farmers interpret technology value in their farms context. On one hand, farmers look at value to their farming business in the adoption of the usage of new technologies to solve future problems [31]. On the other hand, many producers perceive that adopting high productive management systems involves increased risk [11]. The perceived risks involve the risk of financial failure because of unforeseen environmental or market circumstances, damage to the farm infrastructure such as soils and pasture, compromises to animal health and welfare, and the risk of increased stress on them from managing an intensified system [11][13].

Another risk that precision farming shares with other technologies is the further consolidation of farms as far as wealthier participants in a sector can benefit the most from recent technologies [49]. There is also the concern about some instances where technology cannot be used effectively. In some cases, farmers are either reluctant or may not be able to use the latest technology on their farms. The selling of pre-mature technology to farmers by companies without sufficient trials or evidence could result in costly losses for the farmers, namely, when it comes to predicting epidemic diseases in large scale animal farms. Furthermore, use of the data is itself a problem. Vast amounts of data from the technology products and services get stored in remote cloud servers. This is often monetized for commercial benefits. Big corporations can now collect, use, and even sell data from farmers. The rising tension between corporations and farmers over data misuse is a considerable threat [29].

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