Tracking agonistic behaviors in pigs

by

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Abstract

Modern day animal production is intensively increasing to meet global demand for animal products. Producers must balance the increased demand for animal product and instill trust in consumers. Pigs raised in intensive production system display more fighting and unresolved conflict than wildtype pigs. This conflict is called “agonistic interactions”. These undesired behaviors occur mainly at the finishing stage of pigs when resources (water, food, space etc.) becomes limited or when animals meet unfamiliar pen mates. Chronic stress from unresolved conflict is an indication of poor animal welfare and may lead to reduced product quality. The first step in reducing the conflict is finding an efficient system to detect and track pigs at the individual level. Precision animal management is the incorporation of information technology into animal production to monitor animals online, which are supported with artificial intelligence to collect and analyze data that will help to sustainably improve livestock farming. While many systems exist, visual tracking has a great potential for commercial application because it is the least invasive. These systems will, therefore, be useful to producers by providing an early detection of agonistic behaviors in herd, provide timely intervention to compromised animals thereby increasing economic gains.

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Dedication

I dedicate this work to Almighty Allah, the source of my wisdom, knowledge and understanding.

Again, I dedicate this to my mother and beloved late father (Mr. Muntari Shaib) whose memories and training continue to regulate my life. My parents taught me the essence of sacrifice, hard work, persistence, and hope.

Introduction

Similarly, to Precision Agriculture technologies, Precision Animal Management (PAM) technologies have the potential to reduce worldwide food insecurity. The definition of food insecurity is conceptualized on three pillars: availability, access, and utilization and they are hierarchical (Food insecurity, 2020; FAO, 2021). Adequate availability food does not necessarily mean that there is sufficient access to a safe and nutritious food; utilization emphasizes on the consumption of nutritionally essential food. By the end of 2019, an estimated 820 million people around the world will experience food insecurity (FAO, 2005; 2019). Food insecurity is associated with physical and psychological symptoms on vulnerable people. Anxiety, depression, post-traumatic and psychological stress have been reported to be some of the symptoms of people affected (Tribble et al., 2020). By 2050, the global population has been projected to increase to more than 9 billion and the demand for meat will increase. Pork, beef, and chicken constitute 90% of the global meat production (Arulmozhi et al., 2021) and per capita consumption of animal protein sources will increase due to the change in income level and population growth (Lutz and KC, 2010). Some countries anticipate increased demands and food insecurity and with intensification of animal production. In the U.S. many intensive production systems require confining animals and increasing their stocking density (Fraser, 2008a; Palmer, 2008; Godfray et al., 2010).

Without any external pressures, stocking density in growing, fattening swine is a challenge for producers. Many individual animals do not fall into a social hierarchy, and the amount of fighting increases with less space and resources. When there are unexpected bottlenecks in the production systems, then this challenge is catalyzed. For example, the pandemic disrupted the food agricultural sector of many countries like Germany, Canada, Brazil, UK, and USA (Van der Zee et al., 2020). As of September 11, 2020, there were reports of about 186 worker deaths in 50 plants across 27 states in the USA. Processing facilities either closed or working under limited capacities with increasing workloads likely to effect worker welfare. By the end of April 2020, U.S. swine processing operations were operating at an estimated 56% of normal capacity. This backlog caused pigs in the late growing phase to be fed at farms for a longer period, and be switched to restricted feed to slow growth, before a non-local open packing plant could be opened (USDA, 2020; Grandin, 2021).

Pigs will naturally have fighting in a normal intensive or extensive production system. A common practice in both extensive and intensive systems of commercial production is the regrouping of pigs. Pigs are mixed at different stages in commercial production to reduce and balance the weight differences between pigs within the pens and to make the most out of available space. Mixing or commingling increases undesired behaviors such as tail and ear biting, belly-nosing, and mounting (Otten et al., 1997; Marekova et al., 2008; Ison et al., 2017). These combative behaviors are called agonistic interactions. Agonistic interactions are energy intensive and are meant to be used in a group for short bouts to establish dominance hierarchy. Isolating growing pigs is not a good solution because social interactions positively impact animal welfare. For example, social nosing and social play are indicators of growth and good rearing environment (Held and Špinka, 2011; Camerlink and Turner, 2013). Acute conflict may only cause blemishes and wounds that heal, but unresolved, chronic conflict, changes the chemistry of meat, thus lowering meat quality (Fernandez and Tornberg, 1991; Terlouw et al., 2005; 2008; D'Eath et al., 2010) and the risk of mortality among pigs that have chronic agonistic interactions is reported to be 6% (Camerlink et al., 2020). Low quality meat such as a dark cut meat, have low economic gains because consumers perceive it to have undesirable flavor and short shelf-life (Ponnampalam et al., 2017).

Covid-challenges aside, intensive pig production systems have a labor turnover rate (20% - 35%) of animal caretakers. In addition, one caretaker oversees 250-500 sows and her babies (12-24 piglets per sow), and even less caretakers are required for growing pigs (National Hog Farmer, 2001; Boessen et al., 2018; Black and Arruda, 2021). For this reason, the industry cannot depend on human observation alone to provide individual animal care. Technologies for monitoring animals are called Precision Animal Management systems. These new systems may provide a solution to the increasing the level of care in intensive systems (Grandin, 2020; Schillings et al., 2021). A system that is considered precision animal management uses multiple remote sensors, data storage and data analytics to monitor and analyze the behavior of animals daily in group or individually (Berckmans, 2017). The potential for PAM to allow for every animal to be observed at the individual level is great, and there is potential for PAM to detect and track agonistic interactions.

Food Insecurity

Food insecurity is defined as the lack of physical, economic, and social access to sufficient food to meet the dietary requirements (FAO, 2008; Hendriks, 2015; Saint Ville et al., 2019). The United Nation’s 2030 agenda for Sustainable Development Goals (SDG) aims at protecting the planet and alleviating poverty, the subject of food security plays a key central role (UN, 2019). The term, food insecurity, emphasizes more on the quantity of food rather than quality; the term, nutrition security emphasizes on the quality of food which often goes together (Hendriks, 2015; Farrell et al., 2018;) and in most cases, the two goes together. Food insecurity is a global crisis and is worsening with the growing global population. Data from 2019 were used to estimate that more than 820 million people would be food insecure globally (FAO, 2019). By 2050, researchers estimate that global food demand for the growing population will be between 50-70% and approximately 60% of the demand will be from developing countries due to the rapid population growth and low income within those regions (Valin et al., 2014; Bajželj et al., 2014; Global Agriculture towards 2050). Plant-based food products that is supposed to be easily accessible has the challenge of needing to spend a lot more time being processed and developed, which does not make it as accessible to people in underdeveloped countries as it does in wealthy countries (OECD, FAO., 2021; Alexandratos and Bruinsma, 2012).

In some cases, food insecure households maybe consuming sufficient calories but nutritionally unbalanced and the stress of not knowing when the next meal will occur may cause them to include low quality food in their meal (Kendall et al., 1996; Coates et al., 2006). Hadley et al., 2012, conducted a study to understand how the increasing food price affects the food consumption of vulnerable people in East Africa (Ethiopia). Researchers concluded that, food insecurity increases stress and affects the mental and physical health of vulnerable people. Other researchers concluded that anxiety, depression, post-traumatic stress, and psychosocial stress are the symptoms associated with affected people from the North American region (Hoisington et al., 2002; Tribble et al., 2020).

The global food insecurity crises worsened when the Corona virus-2019 disease became a pandemic in Spring 2020. This was due to the deaths, sickness, unemployment, health crises which subsequently slowed down food supply chains (Aday and Aday, 2020; Hobbs, 2020). In some parts of the world, farmers had to feed their harvested crop produces to animals because they were not able to transport them to the markets (Mardone et al., 2020). All these affected the availability of animal-based products to consumers was impacted. For example, in the USA and

Europe, processing plants were constrained, reducing the amount of meat to supermarkets and restaurants were closed (Nepveux, 2020).

Given the current global protein-energy malnutrition around the world and a limited range of plant-derived food, more attention is given to animal protein production for economic stability and good source of 'complete' diet. Also, with the rapid increase in the global population, food insecurity is one of the major challenges to overcome in the foreseeable future, therefore it is necessary to discover alternatives to animal source proteins and more efficient utilization of plant-based proteins to meet the needs of the growing population (Asgar et al., 2010; Aiking, 2011).

The pork industry forms an integral part of the global meat industry and the global food security since pork accounts for more than one-fourth of total protein consumed globally (Bruinsma, 2017). As the global population has increased to about 146% from 1961 to 2013, the global per capita meat consumption has increased to about 100% (Winders and Ransom, 2019), thus, there is the need to produce more meat to meet the demand of the growing population and to reduce the incidence of food and nutrition insecurity.

Impact of COVID-19 on the Pork Industry

The COVID-19 pandemic has affected many industries; however, the focus of this report is on the pork industry. In the pork industry, vertical integration — the single ownership of different stages of production by a company — is very common due to the intensive nature of the industrialized world aimed at increasing production and decreasing cost (Saitone and Sexton, 2017). Therefore, any backlog on any part of the supply chain will most likely have effect on other parts of the supply chain.

The 2017 Census of Agriculture indicated there were 8,386 operations with production contracts and slaughter for about 130 million head of pigs (USDA-NASS, 2019). When the pandemic started spreading, major pork processing regions with plants accounting for 56% of the annual slaughter volumes in the USA had a spike in COVID-19 cases which resulted in a 40% weekly decline in slaughter compared to the rates of 2019 (USDA-NASS, 2020; Hayes et al., 2021) at a time when there was a heightened demand for animal products such as meat, eggs, and dairy as the lockdown was announced (Weersink et al., 2020). The report from the Federal Reserve Bank of Kansas City indicated that by April to June of 2020, more than 80% of the pork and beef packing plants reported confirmed cases of COVID-19 among their workforce (Cowbey, 2020). This resulted in a high rate of worker distrust, and many did not return to work after the closure or temporary closure of slaughter and processing plants (McCarthy and Danley, 2020). The few that temporarily closed, upon reopening, had a challenge of slow operations and slaughter for rest of the year matched the 2019 levels due to worker unavailability and physical distancing among workers which slowed line speed (Grandin, 2021; Padilla et al., 2021).

The swine industry has a fixed and coordinated timeline of events throughout the production year such that, market-ready hogs are sent out to the processing plant and replaced with feeder pigs from the nursery barn (Vincent and McCullough, 2020; Hashem et al., 2020). However, pigs were not able to be sent out to processing plants and this created a backlog on farms (IHS Markit, 2020). Thousands of animals were euthanized, auctioned, or given away because producers kept pigs for longer than expected and they needed to make space for finishers coupled with the difficulty of slowing down the growth of market-ready hogs compared with ruminants (Grandin, 2021). Some farms had to transport animals over long distances to be processed, exposing them to transport stress due to the closure or limited operation capacity of processing plants (Marchant-Forde and Boyle, 2020). Many pigs outgrew their housing and decreased spaced likely caused increased fighting. Media outlets reported that during the months of April to July, 350,000 pigs were euthanized instead of being harvested for meat (The Pig Site, 2020; Cima, 2020).

The pandemic has affected the availability and flow of animals between different countries. In the case of Canada and the United State of America, the pandemic caused a short fall in the number of live animals exported to the USA. Canada mainly exports 4.4 million feeder pigs and 802,871 market hogs to the USA for slaughter (Canadian Pork Council, 2021), however, the drop in USA slaughter capacity has caused the Canadian export of live feeder pigs to reduce by 21% in May 2020. Another concern during the pandemic was a suspicion that the COVID-19 virus could be viable and transmitted to animals, and back into the food products. This caused China to place a temporary ban on the importation of pork from Canada until more data could be collected (Hashem et al., 2020).

The effects of Covid magnified the challenge of food accessibility and wastage. The United Nations reported that 931 million tons of food is wastage annually and 64% of this happens at the consumer level of the food production chain and one of the solutions is through intensive and efficient animal production (Karwowska and Szczepański, 2021). Inevitably, intensive housing of animal makes it easier for the incorporation of innovative farming technologies that improves efficiency compared to the extensive production systems. Incorporating automation into the production of animals increases consumer trust in the food supply chain by producing food with welfare attributes that are well-labeled by internationally recognized and traceable monitoring system (Berckmans, 2017; Hashem et al., 2020; Schillings et al., 2021).

Systems of Livestock Productions

In 2010, researchers reported that there were 17 billion livestock around the world (Herrero et al., 2013). Forty-five percent of this population are raised under the intensive system of production (Thornton and Herrero, 2010). An animal husbandry system is considered an intensive animal production system when 1) confinement 2) small human to animal ratio; 3) intensively monitoring animals. The public typically favors the extensive animal system because extensive system because animals are able to display their natural behavioral repertoire (Harfeld et al., 2016; Beranger, 2017). For a system to be considered extensive the animals need to be raised in a semi to more natural environment with increased space. This of course, requires more labor, and labor shortages are a problem for the swine industry (Villalba, 2016; Temple and Manteca, 2020). Intensive animal systems need less labor, but animals are held in proximity, and consistent monitoring for unresolved fights is a major challenge (Clark et al., 2019; Beranger, 2017). Keeping large animal groups in a small space requires competition for space and resources (Spoolder et al., 1999). Producers need increased technology to track animals' activities, so that undesired behaviors can be better managed (Botreau et al., 2007, Harris et al., 2001, Morris et al., 2012).

Agonistic Behaviors and Social Hierarchy

Agonistic behaviors are natural behaviors, but often are the most undesired behaviors for swine managers. Agonistic behaviors are continuum of social behaviors expressed in conflict situations that entails competition, threats, aggression, and submission (McGlone, 1985; Hayne and Gonyou, 2003). When unfamiliar pigs are put together, they display agonistic behaviors which may include contact such as biting, mounting, and pushing or non-contact such as body postures to threaten their conspecifics (Petherick and Blackshaw, 1987; Marekova et al., 2008; Ison et al., 2017).

These agonistic behaviors are often the animal's toolset for establishing social hierarchy in a new group. In a commercial production facility, the commingling of new pen mates typically occurs at nursey, finishing, and each time sows enter a new parity (Tan et al., 1991; Velarde, 2007). Each time pigs meet an unfamiliar pen mate, dominance needs to be reestablished, therefore agonistic behaviors increase (Ewbank and Bryant, 1972; Algers et al., 1990). When agonistic interaction becomes intense after 24 hours of regroup it can be considered an undesired behavior because it can cause distress and injury, thus reducing production performance, and increasing mortality risk (Meese and Ewbank, 1973; Turner et al., 2006b; Shen et al., 2020). Sows are commingled the most out of all the pigs in a production system, therefore, they also have to rely on memory to determine social hierarchy at each commingling (D'Eath, 2005). Bauer (2005) found that sows could spend an entire farrowing period (28 days) apart from familiar pen mates and display less agonistic interactions than sows mixed with completely unfamiliar sows. Nonetheless, the longer the separation, the more likely increased agonistic interactions are observed.

The type of environment (barren or enriched) can influence the occurrence of agonistic interactions. For example, agonistic behaviors are often observed at the finishing stage especially during cold periods. This is because, during in cold environment, animals increase their feed intake to meet the energy demand needed to increase their body temperature, this largely affects the submissive animal in the social hierarchy because they have limited access to resources (Maes et al., 2004; Oliveira et al., 2009). The notion that barren environmental conditions of animals exacerbate agonistic behaviors has mixed findings in the literature. For example, Morgan et al. (1998) found that straw bedding increased the number of visits to the feeder and subsequently improved growth rate. However agonistic behaviors increased with straw bedding. This result was likely confounded because the feeder only allowed one pig at a time to eat. Bolhuis et al. (2005) reported that straw bedding causes increased oral activities directed at pen mates. Furthermore, other environmental enrichment objects were tested, and these non straw-based enrichment stimulated explorative and foraging behavior of pigs (Van de Weerd, et al., 2003). Floor type also has shown to influence the agonistic behaviors like tail biting (Madsen et al., 1970). Slatted floors are important for hygiene and waste management, but the more floor area with slatted floors, the more likely tail biting occurs in finishing and less incidence of tail biting in the 27% house floors. The tendency of a pig to be involved in a fight contest with a pen mate is largely influenced by their experience of winning or losing a fight than their individual aggressiveness. Therefore, the more a pig wins a fight, it is likely to engaged in more fights subsequently (Oldham et al., 2020).

Large litter size influences aggression between littermates at teat and this could affect the aggression behavior of piglets in the future. Moreover, mortality will likely increase when piglets developed selective teat attachment which can lead to malnutrition of weak piglets. D’Eath and Lawrence (2004) demonstrated how early life aggression experience could affect aggressive behavior later in the life of an individual pigs. They found aggression to be influenced by larger litter size and late individual aggression differences could be traced back to early postnatal aggression. However, Chaloupkova et al. (2007) found something contrary to this. They studied the effect of preweaning social housing system on play and agonistic behavior before and after weaning in 32 litters of domestic pigs. They found that, preweaning play behaviors increased but preconditioning did not have a statistical effect on agonistic behaviors postweaning. The behavior of individual animals can be influenced by the behavior of their sibling or pen mates therefore, to develop strategies to implement and control agonistic interactions among pigs in a group housed system using a computer vision system, it is important to understand the pattern of this behavior to aid the development of the right algorithm for tracking the behavior (Makagon et al., 2012).

Strategies to Reducing Agonistic Behaviors

Sow and boar line companies are interested in reducing agonistic behaviors through selective breeding. In genetics, the goal is to breed against aggression which is a moderately stable temperament trait. The latency to attack or respond aggressively when attacked is known to have a range of moderate heritability (h^2= 0.17-0.43) Løvendahl et al., 2005; Turner et al., 2009). To quantify agonistic interactions, a resident intruder test and lesions scores were measured (Erhard et al., 1997; Turner et al., 2006a). The resident intruder test is conducted by introducing an unfamiliar individual within their home pen and the latency to attack is recorded to determine their aggressiveness. Skin lesions on the frontal parts of animal (head, neck, and shoulders) were used to determine reciprocal engagement. Reciprocal engagement is the tendency of an individual to start or retaliate aggressively when attacked or threatened. The lesions on the back (sides, rump and back) were used to identify the bullied animals and scale the severity of agonistic interactions (Desire et al., 2015). Genetic companies for swine industries use indirect genetic effects (IGEs), which refers to the heritable effects an individual has on social. These IGEs can potentially reduce undesired social behaviors by reducing their heritability (Moore et al., 1997; Camerlink et al., 2013). While genetic companies have the resources to measure and manage agonistic interactions, swine growers do not have the time and labor.

Traditionally, animal nutritionists work with producers to mitigate behaviors with diet and feeding delivery. For example, magnesium supplementation was proposed because it is advertised for humans to reduce anxiety. However, the results in using magnesium supplementation are complex. Caine et al., (2000) studied the effect of magnesium aspartate hydrochloride on frequency of aggression behavior on pigs with homozygous-normal and heterozygous carrier genotype for porcine stress syndrome before slaughter. Their data showed that, the magnesium supplementation did not reduce aggression behavior but rather, increased frequency of the behavior before transport to the slaughterhouse. However, D'souza et al., published in the same year, and reported that magnesium supplementation improves meat quality among crossbreds (Large White × Landrace) types of pigs subjected to acute stressor before slaughter. In this project, the incidence of pale, soft and exudative pork, was reduced after supplementing magnesium aspartate for two days at a dose of 1.6 g elemental Mg (D'souza et al., 2000). Pale, soft and exudative pork is often associated with intense acute stress just before slaughter. O'Driscoll et al., (2013) reported less aggression incidence among magnesium supplemented group of piglets. Further research will be useful to determine the right amount of magnesium required to be effective in reducing the agonistic behaviors.

Amino acid formulation in the pig’s diet is another classic nutritional strategy. Tryptophan is an immediate precursor of serotonin which acts as an inhibitory neurotransmitter in the central nervous system (Koopmans et al., 2005; Li et al., 2006). Serotonin is essential for aggression inhibition and regulates appetite, sleep, and mood. Therefore, researchers supplemented diets with tryptophan (0.5%) to increase the synthesis of serotonin (Sève, 1999; Guzik et al., 2006). Researchers reported hypothalamic serotonin concentrations to be greater in pigs than in controls when they had increased tryptophan for 4-5 days. These animals subsequently reduced agonistic interactions and the concentrations of cortisol and norepinephrine (Koopmans et al., 2005; Poletto et al., 2010).

Aside from nutrition, producers have control over the development of their growing pigs. Pigs learn social skills when allowed to co-mingled with pigs from different litters before weaning and that experience helps to reduce agonistic behaviors in later in life and increase growth rate. Pre-weaning socialization can either be by opening piglet doors between adjacent pens (Hessel et al., 2006; Salazar et al., 2018; Ko et al., 2020), by group housing system for lactating sows (Cox and Cooper, 2001) or by having a contact space in a communal piglet area (Parratt et al., 2006). Pre-weaning socialization comes with a little possibility of agonistic behaviors and even when it occurs, it is not severe (Ledergerber et al., 2015).

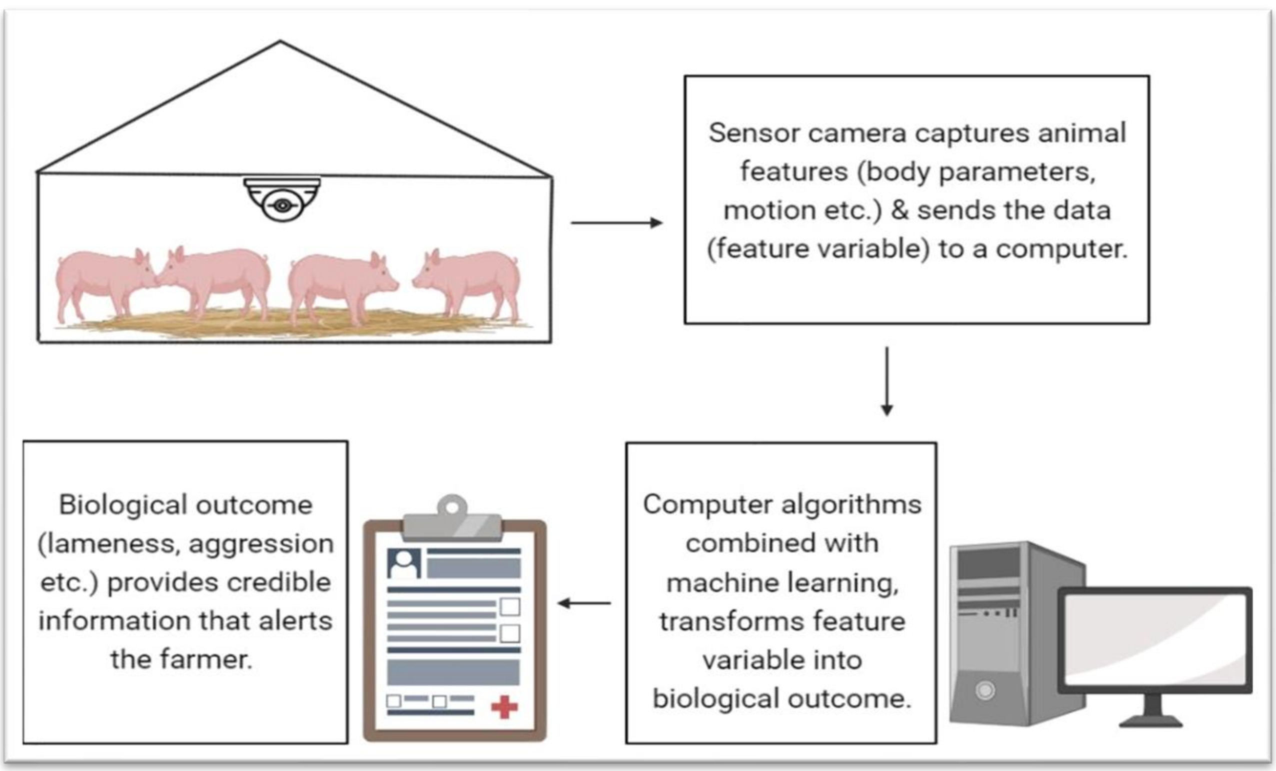
Precision Animal Management

The main challenge in intensive swine production is identifying the individual animals that are causing fights, or that are in distress from bullies. Therefore, the development of precision animal management systems that can monitor and track individual pig activities and report activities to managers may address this challenge (Peden et al., 2018; van der Zande et al., 2021).

The term, precision animal management (PAM) was borrowed from precision farming which is a term used to describe the use of information technology to increase efficiency in the management of agriculture, mainly crops (Blackmore, 1994; Auernhammer, 2001). For example, a precision agriculture technology that is widely used for crop producers is Geographic Information system (GIS) for yield monitoring, variable rate irrigation system, etc. (Koch and Khosla, 2003).

A system is considered a PAM when sensors (e.g., microphones, cameras, accelerometers) collects behavioral data, and the data are automatically processed in semi-real time so that a response to an event can be given by either automation, or the animal caretaker (Figure 1.) (Benjamin and Yik, 2019; Rosa, 2021; Berckmans, 2006; Guarino et al., 2017; Schillings et al., 2021). The main challenge with intensive animal production is delivering care at the individual level, rather than the group or barn level. Individual-level assessments of pain, injury, and disease may be detected with more accuracy and precision than a human management system. The information and application of precision animal management has increased greatly due to the expertise of computer scientists and inexpensive sensors combined with the computer's capability of capturing and processing data (Bos et al., 2018; Benjamin and Yik, 2019; Bahlo et al., 2019).

Figure 1. Schematic diagram summarizing precision livestock farming with computer vision technology**.**



A good tracking system for pigs should have the following characteristics:

- Economical and simple outlook: the integrated parts (hardware and software) of an automated tracking system should be affordable for researchers and farmers to purchase and easily use. Even if researchers do not have the skills to use them, the necessary technical expertise should readily be available to assists (Peden et al., 2019).
- It should be versatile to track in various conditions, environmental landscape, track individual animals of different body sizes, shapes, and behaviors (Chen, 2015).
- It should have a single camera sensor instead of multiple cameras that continuously capture the activities of animals and automatically identify each animal. The side effect of having a multiple camera is that it is hard to synchronize all camera sensors which can easily cause disturbance effects during tracking (Peden et al., 2018).
- The system should have the ability to collect and store large data in real-time instead of using large storage devices which should be accessed in different ways (Berckmans, 2017).

Precision Animal Management and Agonistic Interaction Tracking

There are several potential contenders for PAM technologies that could result in detection and response to agonistic interactions in pigs (Table 2). Many are based on visual tracking (e.g., regular cameras, thermal cameras), but others include wearable devices (e.g., accelerometers), or sound (e.g., microphones). Many technologies in the scientific literature date back more than twenty years and initial reporting is focused on logistics, feasibility, and accuracy, and precision. However, just because a tracking system is accurate, does not necessarily mean it is precise, and just because the system is precise, does not mean accurate (Table 1). Precision is defined as the state where the score obtained in a first event is repeated in the second event (Streiner and Norman, 2006). That is, precision is the index of how close different results can be replicated on different measurements. On the other hand, accuracy is defined as the degree of closeness of different measurements to a standard or real value (Hattori et al., 2008).

Table 1. Definition of precision and accuracy

Precision	Accuracy
Degree of closeness of measurement with each other: • Repeatability & Reproducibility • Sensitivity	Degree of closeness of the measurements to the target value: • True positives/negatives vs. False positives/negative • Specificity

Example: Visual tracking system needs to recognize the pig's nose

Precise but not accurate

Accurate but not precise

Not Precise nor Accurate

Precise and Accurate

Accelerometers were one of the first contenders for PAM, especially in ruminants. The animal has to wear the accelerometer, which functions by the continuous stressing of small crystals to generate voltage inside the device during movement and the size of the voltage is interpreted.

A more recent publication by Ramonet and Bertin, (2018) attached accelerometers on the legs of sows to measured physical activities like lying and standing on 6 group-housed system. The automatic recording showed high specificity of 99.8% and high sensitivity of 98.8%. The advantage of this system is that, if lying and standing can be detected, this technology, when used with other technologies can aid in the easy detection of agonistic postures. On the other hand, the disadvantage is that only few animals were used in this study.

Nonetheless, wearable devices are not preferred technologies for pigs, so visual and audio data collection are primary candidates for PAM (Viazi et al., 2014; Lee et al., 2016). Vocalizations could be tracked using a system that senses sound and then categorizes the vocalizations by frequency, amplitude, and patterns. A recent publication (2022) by Briefer and others, used vocalization tracking to successfully identify and classify features that can be more indicative of emotional state. They used microphones to capture the vocalization of 411 pigs from birth to slaughter and analyzed 7414 emotional calls. They identified high vocal frequency to be associated with more painful context and low vocal frequency to be associated with less pain or playful context and reported a classification accuracy of 91.5%. This system can provide a non-invasive tool to assess the affective state of wide range of age of pigs. However, the disadvantage in this study could be that the application of this technology in commercial system could be challenging due restriction of pig age at different stages of production.

Prior to this publication, many innovators were discouraged with vocalization collection and assessment because of overlapping noise or the insufficient availability microphones can interfere with the quality of detection. Therefore, visual data collection has been more widely studied than audio for PAM (Valletta et al., 2017; Peden et al., 2018).

Chen et al. (2017) used a computer vision technology to detect social and aggressive behaviors in grouped-housed piglets by measuring acceleration from visual data. They captured the activities of aggressive piglets in an experimental setting to extract key frame sequence of their displacement to analyze their acceleration features. To calculate the acceleration, the two piglets in aggression were considered as a rectangular box and the four sides of the rectangle was analyzed to set the threshold of high and medium aggression. High aggression was defined as more damaging behaviors (like body biting, neck biting, ear biting) whereas medium aggression was less damaging behaviors (like head knocking, head to body knocking, parallel pressing, inverse parallel). They reported an accuracy of 97.04% to detect high aggression with a sensitivity and specificity of 92.54% and 97.38% respectively. The accuracy to detect medium agonistic interactions was 95.82% with a sensitivity and specificity of 90.57% and 96.95% respectively. The drawback to this system is that all accelerating pigs were tracked. However, improvements maybe limited to only aggressive

Gan et al. (2021b) investigated the ability of a novel automated detection system to individually track and detect the social behaviors of pre-weaned piglets in a commercial system. The study detected the social behaviors (such as social nosing, social playing, and aggressive behavior) of pre-weaned piglets. These social behaviors are useful for the management of the welfare, health, and productivity of pigs (McFarlane and Schofield, 1995). The system used spaciotemporal features to allow the distinction of behaviors that are similar, like play and aggressive behaviors, by tracking specific activities like snout-to-snout contact and nosing the tail. Spaciotemporal refers the occurrence of behavioral activities in a certain location and time. They collected short video clips and long videos clips (8 h long) to determine the resolution of temporal data needed to represent continuous observation. They reported a precision of 0.9309 for short video clips and 0.9187 for long video clips. The good feature with this system is that it is capable of distinguishing aggressive and play behaviors which is not common in many systems that have previously been reported. However, the limitation of this system is its inability to sustainably track long-term individual behaviors of piglets.

In tracking agonistic behaviors of pigs, keeping track of the of individual identification numbers of pigs is important. Kashiha et al., (2013) used a computer vision technology using an image processing to identify marked pigs in a commingling study. They mixed 10 pigs each in four pens and captured the video of their activities for 156 h. Each pig had a painted mark inscription on their back as ID other than the conventional ear tags. The videos were recorded at a frame rate of 25 frames per second. Their system was able to automatically detect the painted marked IDs with an accuracy rate of 88.7%. They attributed their detection errors (low accuracy) to camera visibility which was not able to capture the faded painted marks on the backs of some pigs.

In Viazzi et al., (2014), a method to detect aggression in pigs by image processing was developed using weaned piglets housed in a pen with a slatted floor. They mixed 24 piglets from four different litters were mixed in two pens and video recording was captured for 60 hours. Through manual annotation of video frames, they first identified 378 episodes of social interactions. They scored 228 interactions as agonistic and 150 interactions as not aggressive interactions. Then, 150 of the positive interactions were randomly selected and all the non-aggressive interactions were selected to process in what the researchers called the Motion History Image Algorithm. Motion History Image is an image that shows how objects move by the intensity of their motion (Bobick and Davis, 1996). The Motion History Image technology had an accuracy of 89.0% with a sensitivity of 88.7%, and a specificity of 89.3%. The potential benefit of this research is that the method used in this study provided valuable information because not all behavioral activities could be included. However, more development can be made to improve the detection of aggression by using the pattern of motion during interaction rather than the intensity of motion.

Lao et al., 2016 used a computer vision-based system to automatically detect the behaviors of sows in farrowing crates. The algorithm they used in this study analyzed images of the sow from the pen and classified behaviors such as standing, sitting, kneeling, drinking, lying, feeding, and transition between behaviors. A camera was installed above the floor of the crates to capture depth images of pigs. The accuracy was evaluated by tracking the individual animal's horizontal and vertical distribution attributes and further extracting these features for analysis and detection. The behavior that was most accurately detected was lying (99.9%) and the least accurate behavior was kneeling (78.1%). The least accuracy recorded for kneeling was attributed to the misclassification when the head of sow is lowered during sitting or standing. The benefit of knowing lying time in a farrowing crate is that it helps to determine what time sows are more active to engage in damaging behaviors.

In Oczak et al. (2014), they classified aggression behaviors into high and medium aggressiveness. They mixed and captured the behavioral activities of 11 intact boars with camera and each pig was identified with a marker on their backs. The pigs were provided ad libitum feed with a feeder that feeds only two pigs at a time. Image analysis technique was used for the segmentation and quantification of behaviors. An algorithm known as multilayer feed forward neutral network was used to classified aggression events based on the image analysis regardless of the contrasting background. High and medium aggression were determined based on the level of damage caused by animal during the aggression interaction. Medium aggression involved behaviors like head-to-head, head-to-body knocking, parallel pressing, inverse parallel pressing (i.e., pressing shoulders against each other while facing opposite directions), and flee. High aggression behaviors involve behaviors like neck biting, body biting, and ear biting. The automated images were first identified as true agonistic interactions by a manual labeler. Their study reported high aggression events with a precision and accuracy of 96.1%, and 99.8% respectively. On the other hand, medium aggression event was classified with a precision and accuracy of 86.8%, and 99.2% respectively. The advantage of this system is that it has the potential for objective measurement of aggressive behavior regardless in different environmental setting. This allows aggressive measurement to be compared between different farm conditions. The limitation is that detection of aggression has a possibility to delay between a range of 3 to 120 secs which could affect real-time detection.

The feasibility of using precision management technology to detect aggressive behavior among weaning pigs in an intensive commercial pig pen containing 22 pigs has been validated by Lee et al., 2016. Their system extracts animal activity features from the pen by capturing depth images to detect aggression behavior. The proposed method is cost-effective and with a detection accuracy of 95.7%. The good thing with this system is that it is robust in overcoming the problem of shadows during tracking in an intensive commercial system. On the other hand, to improve the accuracy of aggression detection in this system, perhaps using the velocity of fighting pigs will be a better candidate for detection instead of using only the activity features of pigs.

Mounting is when a pig place it’s front legs and chest over any part of the body of its opponent and it can pose as a threat. By using an image processing technique, Nasirahmadi et al. (2016)

detected mounting behavior after mixing pigs together and video images of them were captured from the top view for 24 hours. The 24-hour video recorded video was manually labelled to select mounting behaviors and the images from the video were prepared for image processing. The system uses the distances between the tail and head, sides and head to automatically detect mounting. Their system could detect mounting event with a precision of 94.5% and accuracy of 92.7%. Automatically detecting mounting behaviors will be helpful since this behavior increases the risk of stress, lameness, and skin lesions therefore, alerting the farmer to make necessary intervention.

Automated tracking of motion can add to the visual data collection system's ability to track postural changes. Zhang et al. (2020) reported to use the motion information of pigs to detect various behaviors including mounting, and scratching. They collected the video recordings of pigs in the finishing phase of production for 80 days. The videos were edited to contain episodes of the five behaviors (like feeding, lying, walking, mounting, and scratching) and then filtered to remove blurred videos. The spaciotemporal (describes an activity at a certain location and time) features of each behavior was extracted from the videoclips and recognition of the behaviors were done with 98.99% recognition average. Using both the posture and motion of animals can be used to detect agonistic behaviors like mounting and scratching. The advantage with this system is that, unlike other systems, detection is not affected by contrast between pig and the complex background. The system can also identify different behaviors that pre-inform the welfare condition of pigs at the same time.

Although the focus of this report is agonistic interactions, the PAM used at packing plants have potential to improve detection of compromised pigs. A non-ambulatory pig is one that is unable to move or keep up with the movement of his group. Packing plants deal with 0.3 % to 0.4% of non-ambulatory pigs (Ritter et al., 2005). The major animal welfare concern is that these pigs can get trampled by the other pigs, or potentially dragged to a location to euthanize them. Dragging non-ambulatory pigs at the packing plant is forbidden, so early detection (before the pig goes down) would greatly help reduce the risk of a pig being dragged. Gronskyte et al. (2016) reported using a technology called Optical Flow. This PAM tracks the movement of image objects between two frames (with a frame rate collection of 30 frames per second). Healthy pigs move at a steady pace in a group, and potential non-ambulatory pigs lag behind. Pigs were video recorded immediately after unloading from the truck. The movement of the pigs was determined to identify the specific walking pattern of the herd as opposed to individual movement. This method was successfully used to identify stationary pigs which could be an indicator of non-ambulatory pigs. The group or individual assessment has potential to track agonistic interactions back at the farm because often time, agonistic interaction results in the injury of animals. Therefore, when abnormalities are identified, it will spark the need for addition inspection on the farms. Another good thing about this system is that it has the potential to help in detecting agonistic behavior by identifying sudden changes in the movement of pigs as a result of aggressive encounter among pigs. However, using few frames to detect abnormal movement of pigs can result to false alarms, therefore, the method needs to ensure abnormality is estimated consistently by increasing the number of frames.

Table 2: Sampled literature on some precision technologies used for monitoring animals

Type of PAM technology	Topic	Reference
Computer vision system	Agonistic interaction	Viazzi et al., 2014; Oczak et al., 2014; Lee et al., 2016; Nasirahmadi et al., 2016; Chen et al., 2017; Ju et al., 2018; Zhang et al., 2020
	Weight estimation	Schofield, 1990; Brandl and Jørgensen, 1996; Kollis et al., 2007; Wang et al., 2008; Kashiha et al., 2013; Kongsro, 2014; Kashiha et al., 2014a; Wongsriworaphon et al., 2015; Shi et al., 2016; Pezzuolo et al., 2018; Jun et al., 2018; Fernandes et al., 2019;
	Mobility and Posture	Wu et al., 2004; Ferre et al., 2009; Kashiha et al., 2014b; Stavrakakis et al., 2015; Nilsson et al., 2015; Nasirahmadi et al., 2015; Gronskyte et al., 2016; Stavrakakis et al., 2015; Lao et al., 2016; Kim et al., 2017; Nasirahmadi et al., 2017; Zhu et al., 2017; Gan et al., 2021a; Gan et al., 2021b
Accelerometers	Activity	Marchioro et al., 2011; Escalante et al., 2013; Pastell et al., 2016; Ramonet and Bertin, 2018;
	Posture	Mainau et al., 2009; Thompson et al., 2016; Oczak et al., 2016b;
Microphones	Agonistic bout	Schon et al., 2004; Vandermeulen et al., 2015; Cordeiro et al., 2018
	Sickness	Exadaktylos et al., 2008; Guarino et al., 2008; Ferrari et al., 2008; Moura et al., 2008; Chung et al., 2013

Benefits and Pitfalls of Precision Animal Management to Detecting Agonistic interactions in Pigs

The shape of the swine industry is being changed by the technological advancements across the world. Precision animal management has provided a variety of technologies for measuring the behavior, physiology, and production variables on individual pigs in a group house system. These technologies are gradually changing from wearable devices to more image-based systems. The goal of precision animal management is to help producers make daily management decisions without being much dependence on human labor.

Early detection of agonistic behaviors helps to better identify and manage pigs. A pig that is identified as an overly aggressive pig could be managed at the individual level by culling them out of the group to be given any of the interventions mentioned above to mitigate their aggression level. A pig that is constantly fleeing aggression could be better managed either by destabilizing their social hierarchy or separating them out of the group for special treatment. This toolset could help animal caretakers make more uniform decisions, and clear protocols for treatment (Naas, 2002). Automated tracking allows for the early detection of animals with subclinical conditions which often, could be challenging to be identified by human observation since humans needs obvious symptoms to make intervention (Radostits et al., 2006).

Tracking agonistic behavior of pigs has a good potential to aid in the coherent assessment and improvement of the welfare conditions of farm animals. Animal welfare audits are a thorough benchmarking system that ensure and assess the minimum husbandry standards for raising animals are met. The purpose of welfare auditing is to assure consumers that the welfare of food animals is met, and to improve the welfare status of animals (Duncan, 2005). Generally, assessment of animal welfare is done in four different ways, that is, animal-based assessment, prohibited practices, resource based, and standards of documentation. The most recommended of all is the animal-based measure because it considers the number of animals that have lesions, emaciated, lameness which gives indications of poor animal management practice, bad housing design or animal abuse (Whay et al., 2007). The prohibited measure considers the application of practices that can deter the welfare of animal such as, throwing, kicking, dragging, which is prohibited by the slaughter standards of the OIE (OIE, 2009). Furthermore, resource-based standards specify the space requirements, and the effective of equipment used to perform procedures. Animal-based measures can be used to detect some of the problems with ineffective equipment. For example, Ineffective captive-bolt stunning can be an indication of agitated animals, the percentage of animal vocalization could be an indication of undue pressure on the animal by the restraint device, and percentage of animals falling in slaughter area can be associated to agitated animal caused by use of excessive electric prod or slippery floor (Gregory and Grandin, 2007). Lastly, standardize documentation considers audits to observe standard documentation to ensure it corresponds to the animal base measurement because some facilities may falsify documents (Grandin, 2020).

The animal-based assessment protocols by auditors includes a subjective scale for scoring body conditions, lameness and tail biting lesions which can be subjective, yet a major decision (pass or failure) is made (Pittman, 2016). The upspring of many agonistic tracking algorithms, precision animal management offers a good potential to lessen the burden of animal welfare auditors by offering a consistent animal-based assessment protocol and a faster method for the detection of adverse events in a slaughter or animal production facility (Berckmans, 2014).

By carrying out real-time measurements and developing semi real-time, automated models, animal welfare auditors can predict the expected variation in the future by comparing the relationship between the information obtained from the last few days on each animal. In addition, tracking and monitoring the agonistic behaviors of pigs through computer vision technologies affords auditors the ability to access the environmental conditions of animals such as ventilation, animal crowding since inappropriate environment conditions can be detrimental and lead to the death of animals (Michiels et al., 2015). Improving the welfare condition of farm animals is very important because improving the welfare of animals comes with a cost to a producer, and more importantly, considerations should rather be on what it is worth and if the benefits exceed the cost (McInerney, 2004).

The cost of not improving the welfare of farm animals have been described to come with a greater risk of owners losing their right to own animals for their commercial purposes due to increasing concern on animal welfare (Hampton et al., 2020) and this could result in a potential loss of an estimated USD 3.0 billion by 2030 as against the potential gains of productivity resulting in USD 0.17 billion (Red Meat Advisory Council, 2015). The cost involved in improving the welfare of farm animals may either be one-time associated cost of changing infrastructure or ongoing operational costs. For example, the Australia pork industry spent an estimated amount of USD 38-73 million for changing infrastructure out of sow stalls to group housing (The Sydney Morning Herald).

Data from precision animal management technologies can provide imperative information of a group of animals, and potential information that leads to individualized care, regardless of the intensity of the system. This makes precision animal management a more useful tool at processing and analyzing a large set of data to provide accurate estimates at a faster rate without the immediate intervention of humans (Puri et al., 2016).

Automatically annotating behaviors generates a huge amount of behavioral data that is consistently defined and resolved which will help ethologists and biologists to quantitatively understand the sequences and fundamental principles of behavior (van Dam et al., 2013). Trajectory information (i.e., data collected) of each animal together with their pose information — such as contour shape, head position — will enable ethologist to do behavioral analysis to determine a walking, stationary, or immune-compromised animal.

Extracting knowledge from complex datasets can be daunting for animal behavior researchers, however, machine learning provides a modeling technique where more useful information can be extracted from different dataset. A machine model learns patterns from a data to enhance its prediction. Machine learning has successfully been deployed in different areas including automatic classification of behaviors, collective activities flock (Gronskyte et al., 2016) and to compute individual time budget activities without constant human observation.

Regardless of the outgrowing numbers of PAM technologies, acceptance of these technologies on commercial farms have been slow (Peden, 2019). The reasons have been attributed to a cost-benefit ratio that is not favorable. Investment decisions on these technologies should include in-depth analysis of profitability. 2) insufficient research to validate PAM technologies under commercial production facilities, 3) lack of farmer expertise to interpret data generated (Kamphius et al., 2015). On the other hand, the gradual on-farm adoption of these technologies is motivated by the producer's aim to maximizing profit, unbalanced worker to animal ratios, high cost of labor, control of disease outbreak, performance of individual animals, meeting consumer expectations and compliance with market laws on livestock data record keeping and management (Nash et al., 2011; Yazdanbakhsh et al., 2017).

Another challenge is that video-base tracking is much easier in a laboratory setting with a simple environmental landscape than a more field-like or commercial setting. It becomes much difficult in a commercial swine production system with many pigs in a complex environmental landscape. One of the challenges of tracking the agonistic behaviors of pigs at the individual level is that interactions often happen faster, and the multiple involvement of other pen mates lead to obstruction due to the stochastic behavior of animals which causes identity errors. It becomes labor intensive when such errors are to be corrected manually. Obstruction during tracking of individual animal is a problem that can be overcome when prior information about the body shape of the animal is known (Strandburg-Peshkin et al., 2013). Furthermore, tracking agonistic behaviors in a group of animals within a natural environment is more challenging due to the differences in the body and shape of animals. Varying body size and shape is helpful in tracking individual animal (Pérez-Escudero et al., 2013) therefore many tracking systems with prior information about the individual body size and shape will aid image segmentation and analysis to enhance tracking (Ohayon et al., 2013).

Additionally, tracking the agonistic behaviors of animals in their natural setting is a primary constraint. Natural environments are embedded with drivers — such as temperature, space, wind, and light — which could influence the behavior of animals significantly. Also, distinguishing individual animals from the background in the natural setting is another challenge for many tracking systems. The solution to this challenge is the use of tracking systems that can distinguish or provide sharp contrast between the animal and the environment. Another alternative is to merge image-based tracking systems with other tracking devices such as bio-logging to detect and track individual animals within a complex environment (Weissbrod et al., 2013).

Conclusions

In the resolve to meet the future demand of animal products to the growing global population, product quality might be achieved through precision animal management technologies. These technologies potentially increase the ability to monitor and care for animals and which could reduce the need for a large labor force. Agonistic behaviors are important to detect because identifying aggressive behaviors of pigs early, helps the stockmen to provide specific intervention to enhance effective treatment, lower negative impact on animal welfare, and enhance sustainable pig production (Holyoake at al., 1995).

Additionally, individual identification of pigs allows for the provision of specialized treatment to individual pigs thereby improving productivity and enhancing traceability of products in the supply chain (Naas, 2002). The integration of traceability with livestock management has offered the livestock industry a great potential. Ideally, information that is generated from precision animal management technologies can be processed and stored at a central database and be accessible to the farmer and policy makers. For tracking of agonistic behaviors to thrive, the commercialization tracking technologies may require offering services to farmers where relevant data can be interpreted in simple languages to farmers, and broken sensors be repaired. One of the opportunities this technology provides, is the opportunity for the development of service companies to offer services to the monitoring technologies. Furthermore, as the welfare of confined animals is becoming a major concern to the public, tracking agonistic behaviors provides a good data to the conversation as a prove to the welfare of these animals and to increase consumer trust in the food production chain. Lastly, achieving a better coordination between farmers, veterinarians and researchers is necessary to enhance the effective integration of these technologies into livestock production.

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