doi：10.12133/j.smartag.SA202204004

Pig Sound Analysis: A Measure of Welfare

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Abstract: Pig welfare is closely related to the economical production of pig farms. With regard to pig welfare assessment, pig sounds are significant indicators, which can reflect the quality of the barn environment, the physical condition and the health of pigs. Therefore, pig sound analysis is of high priority and necessary. In this review, the relationship between pig sound and welfare was analyzed. Three kinds of pig sounds are closely related to pig welfare, including coughs, screams, and grunts. Subsequently, both wearable and non-contact sensors were briefly described in two aspects of advantages and disadvantages. Based on the advantages and feasibility of microphone sensors in contactless way, the existing techniques for processing pig sounds were elaborated and evaluated for further in-depth research from three aspects: sound recording and labeling, feature extraction, and sound classification. Finally, the challenges and opportunities of pig sound research were discussed for the ultimate purpose of precision livestock farming (PLF) in four ways: concerning sound monitoring technologies, individual pig welfare monitoring, commercial applications and pig farmers. In summary, it was found that most of the current researches on pig sound recognition tasks focused on the selection of classifiers and algorithm improvement, while fewer research was conducted on sound labeling and feature extraction. Meanwhile, pig sound recognition faces some challenging problems, involving the difficulty in obtaining the audio data from different pig growth stages and verifying the developed algorithms in a variety of pig farms. Overall, it is suggested that technologies involved in the automatic identification process should be explored in depth. In the future, strengthen cooperation among cross-disciplinary experts to promote the development and application of PLF is also nessary.

Key words: pig sound classification; animal welfare; sound analysis; feature extraction; precision livestock farming; sound monitering

CLC number：S-1; S828 **Documents code**：A **Article ID**：SA202204004

Citation：JI Nan, YIN Yanling, SHEN Weizheng, KOU Shengli, DAI Baisheng, WANG Guowei. Pig sound analysis: A measure of welfare[J]. Smart Agriculture, 2022, 4(2): 19-35. (in English with Chinese abstract)
纪楠, 尹艳玲, 沈维政, 寇胜利, 戴百生, 王国维. 叫声在生猪福利监测中的研究进展与挑战[J]. 智慧农业(中英文), 2022, 4(2): 19-35.

1 Introduction

Pork consumption holds a stable increase in the worldwide. As an example, pork is the most consumed meat in China. In 2021, pork production reached 52.96 million tonnes, accounting for more

Received date: 2022-04-24

Foundation items: The National Natural Science Foundation of China (32172784, 31902210); The National Key Research and Development Program of China (2019YFE0125600); China Agriculture Research System of MOF and MARA (CARS-36, CARS-35); The University Nursing Program for Young Scholars with Creative Talents in Heilongjiang Province (UNPYSCT-2020092); the Academic Backbone Project of Northeast Agricultural University

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than half of the total output of pork, beef, mutton, and poultry[1,2]. The huge demand for pork has led to a growing trend toward of modern pig production. Production intensification and specialization are two typical characteristics of modern pig farming[3] which contribute to increased productivity of pigs, leading to the economic efficiency of production. Simultaneously, animal welfare is being a concern with the farm mode transformation in pig herds.

In general, animal welfare includes three parts, i.e., natural living, affective states, and basic health and functioning[4] in different behaviors and various conditions. Monitoring animal body conditions is beneficial for both animals and farmers. First of all, animal health could be improved, which decrease usage of veterinary drugs and reduced mortality. Meanwhile, better animal health contributes to better animal emotion[5]. Secondly, less cost in veterinary bills leads to direct financial benefits for farmer and improved quality of pork[6]. Most importantly, animal health may directly affect human health. It can reduce the risk of zoonoses to monitoring the physical conditions of animals. It is becoming even more crucial to investigate the relationships between good welfare, good health, and disease resistance with enormous commercial and social benefits in setting higher standards.

Precision livestock farming (PLF) is to assist farmers in making appropriate management decisions to avoid certain risks by using real-time monitoring technologies. Some reviews related to pig welfare and relevant technologies have been reported recently. Mahfuz et al.[7] provided a general overview and instruction on smart tools and applications in modern pig farming. Both non-invasive and invasive methods were involved and discussed. Tzanidakis et al.[8] summarized three main categories of non-intrusive technologies, including camera-based, microphone, and communication information technology (CIT) sensors, and attempted to predict technological developments in potential ways. Schillings et al.[9] affirmed the impact of sensor applications on animal welfare from two aspects of health and emotion. Meanwhile, both benefits and underlying risks of PLF were explored and discussed. Furthermore, Racewicz et al.[10]analyzed different technologies to achieve effective monitoring of pig health. They emphasized that pig health and welfare measures should be integrated with the data obtained to establish reliable monitoring systems for pig production assessment. As a diverse range of smart sensors emerged from technology development, their commercial generation possibilities and contributions to welfare were also investigated and evaluated[4].

The above reviews briefly described the relevant technologies applied in pig farms, demonstrating the potential and value of PLF technology explicitly. Moreover, it is worth remarking that previous studies have acknowledged sound as a potentially useful indicator for inferring animal welfare. Sound analysis techniques and sensors have been developed rapidly in recent years, which provide the opportunities to achieve automated monitoring pigs and improve their welfare. The main purpose of this paper is to focus on the relationship between pig sounds and welfare based on microphone monitoring. The existing pig sound processing technologies were summarized and discussed in detail. Shortcomings and outlooks in terms of the related technologies were also elaborated. Finally, the challenges and perspectives of sound monitoring with PLF in modern pig farms were proposed.

2 Pig sound and welfare

Sound carries emotional, physiological and individual information[11,12]. It could be considered as potentially valuable indicators for discerning animal welfare. Table 1 illustrates different welfare indicators related to pig sounds. It can be seen that studies on pig sounds were mainly devoted to coughs, screams, and grunts. In these articles, cough sounds can reflect air quality in pigsties and become crucial indicators for health monitoring. Regarding screams and grunts, they provided the reactions to the physical conditions, which are beneficial to improve the pig welfare.

2.1 Pig sound and environment

In an intensive pig farm, air quality and heat stress are two influential factors associated with the living environment, directly affecting pig welfare and product quality. Ferrari et al. [13] assessed heat stress by analyzing continuous pig screams and grunts. It was reported that a peak frequency value higher than 750 Hz of both sounds was considered as an indicator of heat stress[13]. Amaral et al.[14] demonstrated the relationship between the sound pressure levels (SPL) produced by piglet and the thermal environment of the pig nursery. A range of 56.3~60.3 dB was regarded as a good indicator to assess thermal comfort. Meanwhile, cough sound was regarded as an objective and non-invasive biomarker for the respiratory state in studies of exposure to air pollutants[15,16]. Also, the results indicated that cough sound analysis could provide valuable and qualitative information about the air quality conditions in commercial livestock farming, with 1737 Hz on average peak frequency of pig cough (472 Hz higher than the control group) under better indoor air quality[16]. Pessoa et al.[17] assessed a baseline of cough free of respiratory disease and investigated the relationship between environmental conditions and cough frequency of pigs. It revealed a positive correlation between ammonia (NH_3) concentration changes and continuous coughing of pig.

2.2 Pig sound and physical condition

Sound analysis has been applied to evaluate pig physical condition such as body temperature changes, pain, hunger and thirst. Moi et al.[18] identified the differences in swine vocalization patterns according to different stress conditions (thirst (no access to water), hunger (no access to food), and heat stress). Pig was found to be thirsty when sound intensity ranged from 73.87 dB to 80.18 dB. With a value higher than 80.18 dB, it indicated that the pigs were hungry or under heat stress. For further confirming the pig's status, pitch frequency presented a difference, with the hunger of 212.87~276.71 Hz and heat stress of higher than 276.71 Hz[18]. The abnormal conditions by analyzing grunt, frightened screams and feeding howl sounds were also detected[19, 20]. The results showed that the total sound recognition rate could achieve 95.5%[19]. Besides, vocalization is a valuable tool for identifying situations of stress in pigs during the castration procedure[21, 22]. Without local anaesthesia, piglets uttered almost twice screams during the experiment. Also, screams characteristics are significantly different from grunts[23]. Moreover, different acoustic parameters were beneficial for evaluating the level of pain in piglet management. The results showed that the values of pitch, intensity, and maximum amplitude were enhanced from pigs in normal status to castration[24]. Based on the researches of screams characteristics, representative features were focused on and taken into consideration to define pig screams for constructing a more accurate classifier. And pig screams were defined when the pig sound duration was longer than 0.4 s[25]. A simple voting system was constructed to classify the screams with a precision of 83%[25]. With respect to specific emotion analysis of pigs, Riley et al. [26] and Moura et al. [27] proved that phonations increased with fear and distress piglets. Grunting was also found to be highly variable, with the lowest grunting for happy emotion.

Table 1 Overview of different welfare indicators related to pig sounds

Sounds	Indicators	Welfare	Production phase	Year
Coughs[16]	Air quality	Environment	Weaners	2019
Coughs[15]	Air quality	Environment	Weaners	2004
Coughs, sneezes[17]	Air quality	Environment	Fattening	2022
Coughs[28]	Respiratory disease	Health	Fattening	2001
Coughs[29]	Respiratory disease	Health	Fattening	2008
Coughs[30]	Respiratory disease	Health	Fattening	2008
Coughs[31]	Respiratory disease	Health	Fattening	2008
Coughs[32]	Respiratory disease	Health	Fattening	2008
Coughs[33]	Respiratory disease	Health	Fattening	2008
Coughs[34]	Respiratory disease	Health	Fattening	2008
Coughs[35]	Wasting disease	Health	Fattening	2010
Coughs[36]	Respiratory disease	Health	Fattening	2013
Coughs[37]	Wasting disease	Health	Weaners	2013
Coughs[38]	Wasting disease	Health	Weaners	2016
Coughs[39]	Respiratory disease	Health	/	2020
Coughs[40]	Wasting disease	Health	/	2020
Coughs[41]	Respiratory disease	Health	Fattening	2021
Coughs[42]	Respiratory disease	Health	Fattening	2021
Coughs, screams[43]	Respiratory disease	Health	Farrowing	2016
Coughs, screams[44]	Respiratory disease	Health	Farrowing	2020
Coughs[45]	Respiratory disease	Health	/	2017
Coughs[46]	Respiratory disease	Health	/	2019
Coughs[47]	Respiratory disease	Health	/	2020
Coughs[48]	Respiratory disease	Health	/	2020
Coughs[49]	Respiratory disease	Health	Fattening	2019
Coughs[50]	Respiratory disease	Health	Fattening	2019
Screams[51]	Stress	Health	Piglets	2009
Screams[27]	Stress	Physical condition	Piglets	2008
Screams[21]	Stress	Physical condition	Piglets	2009
Screams[22]	Stress	Physical condition	/	2012
Screams, grunts[13]	Stress	Environment	Piglets	2013
Screams[14]	Stress	Environment	Piglets	2020
Screams[18]	Stress	Physical condition	/	2014
Screams, grunts[23]	Stress	Physical condition	Piglets	2003
Screams[25]	Stress	Physical condition	Fattening	2015
Screams[52]	Distress	Physical condition	Farrowing, nursery, growing, and finishing	2018
Screams[26]	Distress	Physical condition	Piglets	2016
Screams[24]	Stress	Physical condition	Piglets	2018
Grunts, screams, howls[19]	Distress	Physical condition	Farrowing	2020
Coughs, screams, howls[20]	Distress	Physical condition	/	2017

2.3 Pig sound and health

Both screams and coughs could be considered as direct indicators for monitoring pig healthy condition. For instance, the screams of healthy piglets and sick ones (affected by traumatic arthritis) were evaluated by the presence of significant differences[51]. Although artificial neural network was sensitive to more errors in discriminating between healthy and sick pigs, it was meaningful to prove the feasibility by using screams[51]. In existing studies, cough analysis is predominant among all kinds of pig sounds, especially wasting diseases and respiratory diseases.

It could be found that early efforts focusing on pig cough detection in pig herds were undertaken under laboratory conditions from a successive study by Katholieke Universiteit Leuven in Belgium[28, 30, 31, 33, 36]. As demonstrated in the studies, the differences generated by the sound analysis confirmed the variability of sound parameters depending on the health status or disease of the animal. Due to lesions of the respiratory system, infectious cough sounds differed from non-infectious cough sounds. Also, it was proved feasible to complete the pig cough classification from various sounds during a series of trials. And then, the experiments were transferred to a commercial pig farm for further testing[29, 32, 34]. As expected, the most intuitive performance was the decrease in accuracy of cough detection in a complex commercial farm compared to a controlled environment[34]. The main reason was that background noise was the biggest interference factor in sound detection. Although classification performance was much lower, it could still be regarded as an indicator of disease in pig farms. These researches made crucial contributions since the results targeted different frequency ranges of pig sounds and served as a basis for the development of more complicated models.

Based on the large number of basic investigations of pig coughs, Korea University focused on the study of wasting disease. The experiments were performed on a commercial pig farm and aimed at classifying the different porcine wasting diseases, such as Postweaning Multisystemic Wasting Syndrome (PMWS), Porcine Reproductive and Respiratory Syndrome (PRRS) virus, and Mycoplasma Hyopneumoniae (MH) [35, 37, 38, 40]. The research was shown to be robust against noises in pig herds. Moreover, a low-cost sound sensor system was suggested to be applied in small and medium-size farms with limited budgets [40].

Previous researches have contributed significantly to the study of pig cough sounds. While the researches were conducted in the last decade in China. In the early stage, research on sound recognition of predelivery Meishan sow was tried in laboratory conditions[43]. A team of Nanjing Agricultural University transferred the experiment from the laboratory to a pig farm to collect sounds and conduct an in-depth study on the sound of Meishan sows[44]. Meanwhile, Taiyuan University of Technology carried out a series of experiments with machine learning on pig cough characteristics, localization, recognition algorithms, and multi-sensors co-monitoring[45-48]. Based on the ongoing development of technology, Huazhong Agricultural University applied deep learning methods in pig cough recognition and achieved satisfying results[49, 50]. Besides the research teams mentioned above, many researchers in China are focusing on the performance improvement of cough sound recognition by adopting and finetuning various algorithms. Breakthroughs in technologies, including machine learning and deep learning, are boosting the development of PLF.

2.4 Summary

In summary, as an indicator of animal welfare, pig sound has been well-tested and some findings have been generated in progress. However, it is evident that the current researches on pig sounds mainly concentrate on coughs, screams and grunts. The meanings of other pig sounds and their relationship with welfare need to be further studied. Meanwhile, it is relatively straightforward that the majority of previous studies were targeted at improving a particular type of pig welfare based on qualitative or quantitative studies. Indeed, a specific sound points to multiple aspects of animal welfare. This situation dramatically increases the soundscape complexity, especially in the commercial pig farm. As a whole, the relationship between pig sound and welfare is a combination of multiple occurrences rather than changes caused by a single factor. This has become a major issue for animal welfare research based on pig sounds. Meanwhile, it deserves to be a significant study. For example, it is possible to distinguish different coughing sounds as further management indicators. Whether the coughing sound is triggered by diseases (pig wasting diseases and respiratory diseases) or air pollutant in the pigsty. Such refinement would have a profound effect on the global improvement of the PLF and positive welfare.

3 Sound analysis

Benefit from the development of sensor technology, animal welfare could be monitored in diverse manners[7]. In general, monitoring sensors available in pig farms could be divided into two types, namely invasive sensors and non-invasive sensors. RFID and accelerometers are two commonly used invasive sensors[53]. The advantage of invasive sensors is that they satisfy the identification and tracking requirements of individual information. In contrast, the disadvantages are also apparent in two aspects. Injury, pain, and stress are brought to pigs when attaching a tag, which goes against animal welfare. Another limitation is that the devices are not easy to maintain. Non-invasive equipment frequently used in pig farming include camera-based sensors, microphones, and infrared thermal cameras[54]. The advantage is relatively easy to check equipment in time and to reduce the pressure on pigs. However, researches are still focused on the group monitoring level. Improving the accuracy of individual monitoring is one of the challenges of non-invasive equipment.

Among the non-invasive equipment, a microphone has been adopted for pig sound recognition and welfare assessment benefitting from its non-invasive and continuous monitoring merits[10]. Statistically, the number of studies based on microphone technology is the fourth highest among the existing smart technologies[4]. Welfare monitoring research are in high demand. Meanwhile, it shows relatively potential for commercial implementation due to its low cost of devices. It is an important component of PLF by combining technological advancements in the management process and animal behavior[55, 8].

In general, the process of sound analysis consists of four steps, namely, sound recording[56], individual sounds labeling[57], sound feature extraction [58] and classification [59], as shown in Fig. 1.

3.1 Sound recording and labeling

The first step is the collection of raw data recorded by microphone. Typically, the microphone was placed around the pen in a pig room. Its position was explored in field conditions in terms of height and the relative position from the walls and disruptive sound sources such as ventilation. Also, the sampling rate could be adjusted. In most cases,

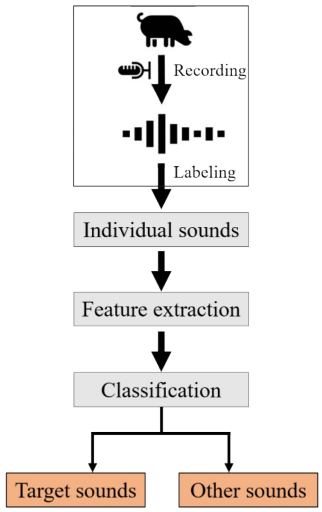


Fig. 1 Flowchart of sound analysis

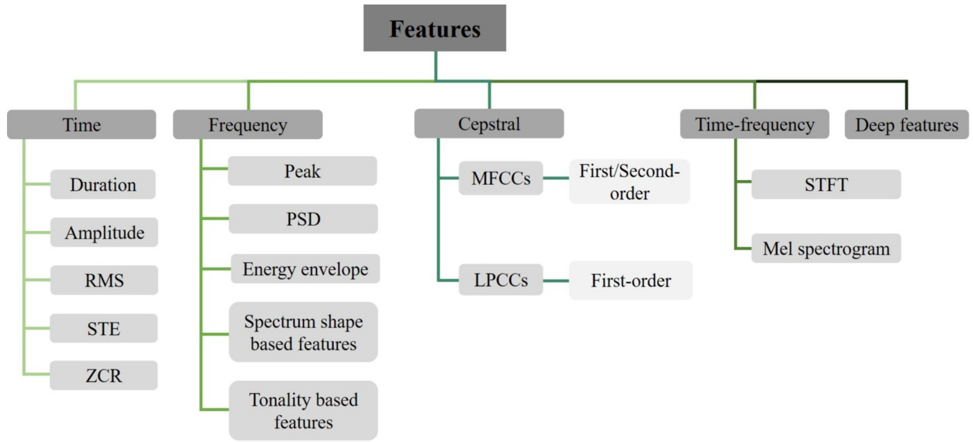
44.100 kHz was used in the field condition. Another factor to consider is the number of microphones. Limited by experimental conditions, one microphone was adopted in most existing studies. Inevitably, the number of microphones could also affect the sound recording quality. Subsequently, the collected sound recordings need to be pre-processed to reduce background noises as much as possible for further processing and analysis. Pre-processing includes filtering, pr-emphasis, framing, and windowing, etc. In order to evaluate the performance of classification algorithms, it is necessary to segment and label the continuous recording data. The segmentation and labeling of individual sounds could be completed automatically or manually. Currently, most of the studies on pig sounds were implemented in a manual labeled way. While few studies were focused on the recording labeling. The double threshold endpoint detection method was frequently used in collecting individual sound segments from recordings[38, 45]. Besides, Li et al.[47] adopted the bi-rectional long short-term memory-connectionist temporal classification (BLSTM-CTC) model to complete the continuous cough sound recognition task, with a total accuracy of 93.77%.

Obviously, researches on labeling and extraction of pig sound segments are lacking. Most studies remained at the manual-labeled stage. This is partly because the research requires the involvement of experts in animal research to give certain criteria, but there is no unified standard yet. Another reason is that an open-source database of pig sounds is scarce. Due to the different characteristics of pig growth, it is necessary to capture information of breed, age, weight, as well as the environment and location where these sounds are produced. All these information would enrich the diversity and comprehensiveness of pig sounds. A sufficient number of sound samples are needed to extract valuable information and to eliminate distracting sounds. Also, it is a key step to achieve high accuracy in the following sound analysis.

3.2 Sound features extraction

After labeling individual sounds from continuous recordings, the crucial step is to extract valuable information from sound signals, which is termed as audio feature extraction[60]. In existing studies, various features were extracted from five domains, including time, frequency, cepstral coefficients, time-frequency, and deep features, as shown in Fig. 2.

Time-domain features are fundamental features which represent signal variation regarding time. Among them, duration and amplitude are often chosen to explore the basic information and properties contained in sound itself. Duration is a kind of rhythm-based feature, which represents a regular recurrence of patterns over time. It was proved that the average duration for infectious and healthy coughs were 0.67 s and 0.43 s in the length of a single cough, representatively[31]. While the maximum amplitude refers to the maximum amplitude of the sound wave, which was used to estimate



Note：Root mean square (RMS)；short-time energy (STE)；zero crossing rate (ZCR)；power spectral density (PSD)；Mel frequency cepstrum coefficients (MFCCs)；linear prediction cepstral coefficient (LPCCs)；short-time Fourier transform (STFT)

Fig. 2 Audio features used in analysis of pig sound

the level of pain of piglets[24]. The results showed that maximum amplitude was growing from pain-free to castration, with the value ranging from 0.2683 Pa to 1 Pa [24]. Root mean square (RMS) is an energy based features that can be used to measure the sound loudness. The RMS value of non-infectious pig coughs has been proved to be higher than that of infectious pig coughs[31]. Another energy based feature called short-time energy (STE) is commonly combined with zero crossing rate (ZCR) to detect voice activity. It was found that the STE of piglets grunts was highly variable in distress[26].

Features extracted from the frequency domain are effective ways in conducting signal processing of pig sound. Simply, a peak is an index of the maximum power of a signal. The average peak frequencies of infected and healthy pig coughs were calculated of 618 Hz and 1603 Hz[24], which means it can be used to effectively distinguish the coughs of infected and healthy pig. Tonality based features in terms of fundamental frequency and pitch were utilized to monitor pig vocalization, especially for detecting whether the pigs were in normal. When the average value of formants was lower than 2671.99 Hz and duration of the signal was lower than 0.28 s, the piglets were proven to be in normal condition[61]. Otherwise, pigs could be considered in an abnormal state. Moreover, the pitch could help identifying sex, age, and distress[52]. It indicated that the pitch value of female pigs (218.2 Hz) was higher than male pigs (194.5 Hz) when all the pigs were in the same conditions[52]. Also, the pigs in nursery and growing stage held higher pitch, followed by the finishing stage[52]. Spectrum shape based features were also used in recognizing various sounds suffered from different diseases, including spectral flux, spectral spread and spectral centroid[62, 63]. In addition to the features mentioned above, power spectral density (PSD) and energy envelope were another two common representative features in the frequency domain, which were often used to distinguish pig coughs and non-cough sounds.

The cepstrum is obtained by applying a Fourier inverse transform to the logarithm of the signal spectrum. Developed by Davis and Mermelstein, Mel frequency cepstrum coefficients (MFCCs) are commonly utilized in human speech and animal sound recognition[64]. Both the original coefficients and their first-order or second-order coefficients are added and combined as the acoustic features in the process of feature extraction. For instance, the first 20 coefficients were extracted as a whole feature vector for discriminating infectious coughs in pigs[65]. To reflect both static and dynamic characteristics, 12-dimensional original and 12-dimensional first-order delta coefficients were calculated from each cough sound sample[16]. Furthermore, 39-dimension MFCCs, combining 13-dimensional MFCC and first-order as well as second-order differential coefficients, were obtained for continuous pig cough sound recognition[39]. In addition, linear prediction cepstral coefficient (LPCC) and its first-order differences were also utilized in detecting abnormal status of dry and wet cough sounds[45].

For time-frequency features, one-dimensional audio signals are frequently transformed into two-dimensional time frequency representations. Among them, short-time Fourier transform (STFT) and Mel-STFT spectrograms are frequently used in pig sound recognition in two ways. One is that spectrograms are combined with deep learning models. In this way, the process of hand-crafted features is not required. For instance, STFT spectrograms were applied to Alexnet and MnasNet deep architectures, respectively[40, 41]. While Mel spectrograms were adopted to convolutional block attention module with convolutional neural networks (CNN) for recognizing abnormal pigs sounds[66]. The other way is extracting deep features based on deep learning models, which are regarded as feature extractors. Lee et al.[67] extracted deep features from a 6-layers CNN and put into muti-layer perception for pig wasting diseases classification[67]. A MFCC-CNN feature was extracted from a one-layer CNN and put into a support vector machine (SVM) classifier for pig cough recognition in Shen et al.[42]

Up to now, most studies aimed at the time or frequency domain features of pig sounds. Fewer studies have been conducted on time-frequency domain as well as deep features. Besides, other features could be considered in the pig sound analysis. For instance, harmonicity is utilized to distinguish tonal and noises, which have been used in bird sound classification[68,69]. Spectrum shape based features have been used in music and animal sound classification, including spectral centroid, spectral roll off, spectral flatness, spectral bandwidth[70-72]. Moreover, other time-frequency representations could be investigated in time-frequency features and deep features, in terms of MFCC[73], mel-scaled spectrograms[74], constant-Q transform (CQT)[75].

3.3 Sound classification

In previous researches, mathematical modeling of analyzing and classifying pig sounds can be divided into three main categories: statistical analysis, machine learning and deep learning.

Statistical analysis was used to complete fundamental research on the pig sound characteristics. For instance, one-way analysis of variance (ANOVA) was one of the most frequently used statistical analyses[76]. It was shown that healthy coughs had much higher peak frequencies (750~1800 Hz) than infectious coughs (200~1100 Hz)[34]. Also, a significant difference ($P<0.001$) was observed between non-infectious coughs (a mean duration of 0.43 s) and infectious coughs (mean duration from 0.53 s to 0.67 s)[34]. Thus, single cough duration could be regarded as an indicator to classify different kinds of cough sounds[77]. Subsequently, ANOVA has been further used to distinguish pig wasting disease[37]. The results indicated that no differences in cough durations between normal coughs and coughs with diseases[37]. In addition, there is a significant difference between porcine circo virus type 2 (PCV2) and other coughs (normal, porcine reproductive and respiratory syndrome (PRRS) and Mycoplasma hyopneumoniae (MH) cough sounds) in pitch, intensity, and formants 1, 2, 3, and 4[37]. Not only cough sounds but also grunts and screams were analyzed using the statistical analysis to assess heat stress and evaluate the level of pain on pig farms[13,24]. The results showed the differences in pig grunts and screams, which was beneficial for pig production management in a good welfare way[13,24].

Machine learning has demonstrated superior performance in many fields[78]. Fuzzy c-means clustering was used to form two clusters: cough and non-cough sounds [79], including in laboratory installation with nebulization of citric acid[33] and pathologic disease and under aerial pollutant control design with ammonia, dust, and temperature[15]. The overall performance of identified sounds (chemically induced coughs, sick coughs, and other sounds) achieved 85.5%[33]. Moreover, average cough classification achieved 94% in different experiment designs with various aerial pollutants[15]. SVM is suitable for classification in both linear and nonlinear ways[80] and was used in a variety of fields among pig sounds, especially in pig cough recognition. It was shown that the average detection accuracy of wasting disease approached 98.4%[81]. Subsequently, Wang et al.[16] provided an average recognition rate of 95% for cough sounds in different air qualities. Shen et al. [42] achieved a cough recognition of 97.72%. A decision tree was built for classifying diverse conditions in different status, such as thirst, hunger, and thermal stress[18], cold and pain[61], as well as distress conditions[52].

Deep learning is a popular tool in recent years, contributing to its strong ability in pattern recognition[82-84]. Some deep learning models have been fine-tuned to be applied in pig sound recognition in terms of CNN and recurrent neural networks (RNN). For CNN models, Yin et al. [41] finetuned Alexnet model to recognize the pig coughs, with an accuracy of 96.8%. Although CNN was proved to be effective in recognizing spectrograms, but CNN inevitably generated various redundant information during the process. For this reason, an attention mechanism named convolutional block attention module (CBAM) was introduced for optimizing CNN[66]. The study provided a satisfying recognition rate of abnormal pig sounds with 94.46%[66]. Since deep neural networks require greater computational capacity and higher hardware requirements, these conditions become one of the factors limiting pig sounds research into practical applications. To address this issue, researchers introduced lightweight models to pig sound classification. A lightweight model based on MnasNet and MobileNetV2 was used to classify pig sounds with different pig diseases, and got an F1-score of 94.7%[40] and a total accuracy of 97.3%[19]. For RNN models, not only RNN but also its variant models including long short-term memory (LSTM), BLSTM, CTC and gate recurrent unit (GRU) were applied in pig cough recognition[49, 50, 85]. The results proved that RNNs were able to be feasible and stable models for completing the classification task[85].

3.4 Summary

Over the years, many bioacoustics models have been developed to analyze and recognize pig sounds. Statistical analysis is the scientific methods of collecting, exploring, and presenting large amounts of data to discover underlying patterns and trends[86], and it is a classical method for calculating variations among variables. A limitation of empirical methods is that their applicability is often constrained to the conditions during experimental testing. When conditions exceed the scope of the investigation, they may not be applicable. For instance, one-way ANOVA requires that the dependent variable is normally distributed in each group and that the within-group variability is similar across groups. However, it is better to ignore assuming the distribution of the data and employ it directly for prediction in solving practical sound classification problems[87]. For comparison, machine learning (ML) provides complementary data modeling techniques and has become a more desirable approach to handling complex data sets. An advantage of ML is the flexibility, which means it contains a number of adjustable parameters. However, it also introduces certain complexity in the selection of parameters for better fitting the model. Meanwhile, the predictive results are relevant to the selected features, which becomes one of the factors sensitive to the choice of ML algorithm. To this end, deep learning models dominate great potential in addressing the problem of automatic extraction of abundant features from original data. However, deep learning relies on training and modification of the model by a large amount of data, leading to more complex simulation and computation. Therefore, machine learning is still a useful and continuously researched approach. By studying the existing literature, it can be found that the selection of a classifier is still subject to a certain degree of randomness. The most suitable classifier should be further validated on running time for achieving the trade-off between accuracy and processing speed.

4 Challenges and perspectives

4.1 Sound monitoring

It could be found that a specific production phase was commonly targeted in pig sound analysis in Table 1. Specifically, fattening pigs hold the highest percentage, followed by sows and piglets, which is consistent with Gómez et al[4]. Measurement and further validation of pig production stages are reasonably necessary and still lacking. On one hand, the diversity of pig sounds is present at all growth stages. In other words, monitoring typical sounds, such as coughs and screams, is required at each growth stage. Therefore, sound monitoring can be enhanced by expanding the range of study stages. On the other hand, due to the outbreak of African swine fever virus (ASFV), stricter management is conducted in big commercial pig farms and researchers are temporarily curtailed. As a result, it leads to intermittent experiments in pig farms. This situation will be improved as the epidemic eases. Meanwhile, continuing experiments can be considered from small and medium-sized pig farms in the future.

In addition, with regard to pig sound localization, it is an important topic to be investigated in the future. On one hand, it locates the pig with healthy problems, which is better to enhance the management of pig herds. On the other hand, the relevant studies are fewer and still stand in the early exploratory stage in the field. Currently, time difference of arrival (TDOA) between different microphones was applied in pig cough localization[30, 47, 88]. Although the current positioning results are proved to be feasible in pig houses (mean error less than 1 m), a challenging issue also comes to the surface, namely the trade-off between the number of microphones and their cost. These results are instructive and meaningful during the experimental phase for further studies and the number of tested microphones is acceptable. However, when considered for application in a commercial context, the cost associated with each additional microphone is undoubtedly expensive. This also motivates researchers to deepen the cough positioning research and continuously optimize the experiments. The aim is to achieve an optimal balance between the number of microphones, positioning accuracy and cost. Another problem is how to locate and track sick pigs in real-time, since the pig is a moving target. In addition, it is worthwhile to study how to solve the problem of multi-targeting localization when the number of targets with abnormal conditions is large. By far, sound recognition is also relatively difficult to locate from group recognition to individual recognition. Given that sound localization studies are still scarce, pig sound analysis is suggested to be developed for sound localization in the future.

In general, the current researches were based on a laboratory or a specific pig farm with great differences in size, environment, and individual pig conditions. Despite modern technologies have been implemented to analyze the collected sounds from the barn, expected results are still not available at this stage. This is because the combination of the pig housing environment and the individual body condition affects the variability of the pig's vocalizations. Therefore, the current methods are insufficient for the complex interaction between pigs and their complex environment. This has become a major factor that makes it difficult to popularize PLF at present[89]. To address this issue, it is suggested that attention could be focused on interactions between multiple monitoring modules rather than concentrating on individual processes in the future. It is possible for us to find the most appropriate interface between multiple modules by interpreting multiple sets of inputs from a variety of biological responses. Moreover, it could be a better way to handle the whole PLF process.

Cough based identification monitoring technology is still at a highly technology dependent stage of development. No integration of animal welfare has been considered to date. This could be due to a lack of well-developed rating system between the welfare indicators and the pig sounds. Hence, it is essential and extremely significant for applying to pig production. To address the weakness, the participation and cooperation of researchers in different disciplines should be strengthen in the future. The latest study by Silva et al.[90] focused on generating technical monitoring indicators by monitoring the frequency of coughs in the pig house and the corresponding disease diagnosis. Their preliminary findings validated those dry and non-productive coughs indicated the presence of Mycoplasma hyopneumoniae. Although these researches are essential and significant, they have not yet been carried out in China. It is recommended to refine the details of experiments in pig farms by combining sound analysis and pig diseases in the future.

4.2 Individual welfare

Although microphone sensor-based sound localization techniques are constantly being upgraded, they are only capable of narrowing the range of sound monitoring as much as possible. It is still difficult to be precise about the individual pigs in this way. However, individual identification of pigs is necessary. As an example, when coughs are monitored to occur in a certain pen, it is important to identify and separate the coughs pig from the herd. Therefore, it is promising to aggregate different sensors together to promote individual pig welfare in the future. For instance, it could be attempted to identify unhealthy pigs by using a facial recognition system based on camera-based technologies to overcome the limitations of sound monitoring. In addition, computer vision can provide information on behavioral interactions between individuals, including the detection of aggressive events and mood elevating behaviors. Another promising approach is the application of remote video monitoring technology. Individual pig behaviors can be monitored visually in this way, including body condition, lameness, feed intake, and oestrus [8].

4.3 Commercial applications

Currently, most of the researches on pig vocalization monitoring are still in the developing stage, with few advanced commercial products in terms of SoundTalks[91] and STREMODO system[92]. SoundTalks is a cough monitoring developed by a Belgian company, which is used to measure cough sounds in an automated and continuous way. The STREMODO system proposed by Germany company records and assesses stress vocalization in pig group. Besides, Yingzi Technology established in China is a promising and new technology company[93], which strives to create a multifaceted platform for data-driven agriculture and to facilitate pig farms development involving livestock management and biosecurity. The microphone-based method requires extensive consideration of various factors such as variability and diversity in the barn environment of pig herds. However, it is not easy to meet the demand for accuracy within technical reliability and low cost within equipment maintenance.

4.4 Farmer concerns

The goal of PLF will lead researchers to upgrade the technology into productization eventually. However, in addition to concentrating on technology, concerns from pig practitioners should also be taken into account. After all, the practitioners are the key to implement PLF in pig farming. Concerns from farmers are raised in a few aspects, such as internal constraints in pig farms, technical costs, and technician support. Specifically, the application feasibility is also being tested by whether the hardware conditions in the farm meet the requirements. With suitable farm conditions, it is another concern whether the emerging technology can match the expected results. In addition, the cost of application and maintenance is also worth considering. Moreover, complex new knowledge may reduce motivation to learn and prevent farmers from embracing new technology.

Regarding these concerns, the following suggestions to consider in the future are proposed. First, further validation between PLF techniques and research into positive welfare indicators should be encouraged to enhance the confidence and trust of pig practitioners. Secondly, equipment should be designed and optimized from the view of farmers to provide convenience and reduce product costs. Finally, the awareness of farmers should be raised by strengthening training and communications. Although PLF has not yet reached an industry consensus, it is highly topical. Moreover, pig practitioners are expecting PLF to assist in pig farming.

Contactless sound analysis is a promising way to assess pig welfare. It is a key element of PLF and it has been proved to be a feasible way to promote the PLF. Apparently, it is ongoing progress in pig production and key technology. Overall, considering the demand for farm intensification and better animal welfare, PLF could be a trend for livestock managers to boost their productivity and animal comfort.

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叫声在生猪福利监测中的研究进展与挑战

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摘　要：叫声是评估生猪福利水平的重要方式之一。本文首先分析了生猪叫声与福利之间的相互关系。其中，与生猪福利密切相关的三种生猪叫声包括咳嗽声、尖叫声和呼噜声。基于这三种声音进一步分析声音与环境，声音与身体状况，以及声音与健康之间的关系。随后，对当下的生猪福利监测所采用的传感器，包括穿戴式与非接触式两大类进行分析，并简述不同方式的优劣势。基于非接触式的优势及麦克风传感器技术的可行性，从声音的获取和标记、特征提取以及声音分类三个方面对现有的生猪声音处理技术进行了阐述和评估。最后，从声音监测技术、生猪个体福利监测、商业应用以及养猪从业者四个角度讨论了叫声在生猪福利监测中面临的研究困境以及发展趋势。研究发现，目前关于生猪声音分析的研究大多集中在分类器的选择和识别算法的改进上，而对端点检测和特征选择的研究较少。同时，当下面临的主要挑战还包括不同生长阶段的音频数据获取难度较高，缺乏公共的猪舍内音频数据库以及缺少完善的声音指标与动物福利监测评价体系。总体来说，建议进一步对声音识别过程中涉及的各部分技术进行深入探索，同时加强跨学科专家之间的合作，共同推动声音监测在生猪实际生产中的应用，从而加快精准畜牧业的实现。

关键词：生猪声音识别；动物福利；声音分析；特征提取；精准畜牧业；声音监测