Image and sound analysis for poultry health and welfare indicators

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Abstract

Guaranteeing consumers that poultry farming respects animal welfare is the heart of the poultry farmer, but civil society is demanding greater transparency in farming practices. Meeting society's expectations must go hand in hand with the competitiveness of poultry meat production, which is globalised and highly competitive. The notion of animal health and welfare can be assessed using a variety of methods, and new technologies offer an opportunity to take continuous measurements in real time, without disturbing the animals in their living environment. Image and sound processing enables finer and more frequent analyses than those carried out by humans. These new technologies are helping to improve monitoring and responsiveness to health problems or changes in animal behaviour through predictive analysis. The EBroilerTrack project led by ITAVI has produced promising proofs of concept in imaging and acoustics under controlled broiler rearing conditions. In the field of imaging, image analysis algorithms have been developed to monitor individual broiler chickens on the farm, with the aim of identifying welfare and health indicators for each animal observed. The performance of these algorithms is presented in this article. In the field of acoustics, the work carried out has demonstrated the benefits of using acoustic analysis to monitor the health and well-being of broilers, in the specific case of infectious bronchitis.

Keywords: welfare, health, poultry, image analysis, acoustics

1. Introduction

Growing public awareness of the way in which animals are reared is prompting the poultry industry to introduce ways of reporting on the welfare and health of poultry. Methods exist for assessing animal welfare on farms. They involve the application of welfare measurement protocols, based on occasional observation of the animals by trained personnel. Many researchers are interested in the possibility of using new technologies to assess and report on animal welfare on farms. The advantage of these tools is that they enable data to be collected more regularly, without causing stress to the animals, more objectively, sometimes more accurately (on an individual scale) and less time-consumingly than the methods traditionally used by a human observer (Créach *et al.,* 2019). The farmer can then take corrective action if necessary during the flock. Using image or sound analysis would also make it possible to identify a problem (health or welfare) at an earlier stage so that action can be taken more quickly to limit the spread of the pathology to the entire flock of poultry and thus reduce the associated direct and indirect costs (e.g. limiting the use of antibiotics, reduced growth and animal mortality).

According to Rowe *et al.* (2019), a majority of papers related to precision farming use image analysis to measure welfare in poultry farming (42% out of a total of 264 publications). The use of microphones seems to be less widespread in poultry farming (14%, according to Rowe *et al.,* 2019). However, sound signals play an important role in animal communication, and certain signals can reflect the state of well-being and health of the animals. They are used to alert conspecifics, or to communicate with each other with the aim, for example, of maintaining contact or attracting conspecifics (Manteuffel *et al*, 2004). Certain vocalisations can easily be perceived as indicators of the animal's state of well-being (distress, comfort or fear vocalisations, for example - Dawkins, 1998; Michaud *et al.,* 2019). These vocalisations, which may even be emitted a few hours before hatching, are quite distinct from singing, which appears later in the life of the bird (Wood-Gush, 1971). Other types of sound can be emitted by poultry in the event of pathology and thus directly reflect the state of health of the animal, such as rales and sneezes. These respiratory symptoms can be heard and recognised by the human ear, but only when the disease is already well established. Pathogens affecting the respiratory system of chickens can be viruses (e.g. Newcastle disease, Infectious Bronchitis: IBV, avian coronavirus), bacteria (e.g. *Mycoplasma* spp., *Bordetella* spp.) or fungi (e.g. *Aspergillus* spp.) (*Dal Pozzo*, 2019).

It is already possible to use image analysis to monitor changes in poultry activity and their distribution in the building, at group or individual level. A first approach is based on the percentage of pixels whose colour changes over successive images of a video. This is used to assess the activity of a group of chickens (Fraess *et al.,* 2016; Dawkins *et al.,* 2021). The data generated has, for example, been correlated with chickens' carriage of *Campylobacter* bacteria (Colles *et al.,* 2016), the occurrence of pododermatitis and tarsal burns (Dawkins et al., 2017; Peña Fernández *et al.,*2018) and chickens' gait scores (Silvera *et al.,*2017). This list of articles is far from exhaustive. One company has marketed the EyeNamic solution, based on this approach (De Montis *et al.,* 2013). The disadvantage of this method is that it is based on the analysis of pixel colour change and not on the direct analysis of animal behaviour. A second approach to image analysis involves tracking individual birds. Some researchers, such as Collins in 2008, have monitored individual birds in groups of 20 for a limited period (10 minutes). A French company has recently launched a solution based on this approach (Copeeks), but no publication is available on the methodology used or the performance of the proposed solution. The videos available are only of very short duration (30 seconds). The approach involving animals wearing RFID (*Radio Frequency Identification*) chips (Siegford *et al.,* 2016; Sales *et al.,*2015; Feiyang *et al.,*2016; Li *et al.,*2020; Oliveira *et al.,* 2019) makes it possible *to* collect individual animal activity, like visual *tracking* (speed, acceleration, time spent near specific equipment, etc.). Although the reliability of this solution is interesting for assessing welfare, it is not feasible to use it in commercial farming. Removing the device requires handling the RFID-chipped animals, which is time-consuming and laborious for farmers. Developments in image analysis to assess poultry activity show that the tools developed can still be perfected and are still at the prototype stage. Although systems are being developed, there is currently no system adapted to commercial stocking densities that can collect individual data to calculate welfare indicators for chickens.

Recently, acoustic analysis systems have been developed for the detection of respiratory diseases in pigs (Chedad *et al.,* 2001; Chung *et al.,* 2013) and veal calves (Carpentier *et al.*, 2018; Vandermeulen *et al.,* 2016). In poultry, acoustic analysis for the detection of respiratory symptoms has also been studied (Carroll *et al.,* 2014; Rizwan *et al.,* 2017; Banakar *et al.*, 2016). Apart from Carpentier *et al.* (2019), who worked on a group of 500 chickens but only on the detection of sneezing, the articles previously listed concern trials conducted on small groups of animals or individual birds.

The main objective of this article is to summarise the results obtained within the CASDAR (Compte d'Affectation Spécial Développement Agricole et Rural) Recherche Technologique EBroilerTrack of 2018, led by ITAVI. A first objective of this article is to report on the current performance of a new image-based *tracking* system developed in this project, using artificial intelligence and enabling the individual tracking of broilers in commercial rearing. The three other objectives of this article are 1/ to identify differences between groups infected and uninfected with Infectious Bronchitis (IB) 2/ to characterise the respiratory

symptoms of IB (sneezing and rales) in sick animals from an acoustic point of view and 3/ to develop an algorithm for the automatic detection of these symptoms.

2. Materials and methods

2.1 Algorithms for detecting and *tracking* individual chickens using imagery

2.2.2. General principle and identification of areas of interest

The *tracking* method developed consists of two independent parts. The first involves the individual detection of each chicken in the camera field. A convolutional neural network is used for this detection. It has been trained on a database containing almost 1,000 images, i.e. more than 10,000 chickens. Such a detection model is less sensitive to light conditions and contrast variations and separates crowded chickens more easily, compared with a traditional computer vision detection method (not based on learning) (O'Mahony *et al.,* 2019). At the end of this detection stage, the position and size of each chicken is available (see section 1.1.2). The second step consists of following each detected chicken from one image to the next (*tracking* step). To do this, a unique identifier is assigned to each animal as soon as it enters the camera field. At each moment and based on the past positions of each chicken, the algorithm is then able to predict the position of each animal in the next image. Each chicken detected in this new image is then assigned the identifier of the chicken whose estimated position is closest to it.

Zones of interest are determined in the camera's field of view in order to determine how often each of these zones is used (number and duration of passages in the zone). The feeding zone is defined by a circle around each feeder and the drinking zone by a rectangle around the pipette lines (see Figure 1). The areas of interest are traced manually once. Further development is envisaged to automatically detect feeders and water lines in the field of view. It is also possible to define a zone around an enrichment to find out how often it is used, in the same way as for other zones. A rectangle is automatically drawn around each chicken identified, and the length and width of each rectangle are recorded. The feeding and drinking areas are delimited by 75% of the length of this rectangle above each chicken. Thus, when 75% of the length of the rectangle is included in the zone, the chicken is counted as frequenting the zone of interest.

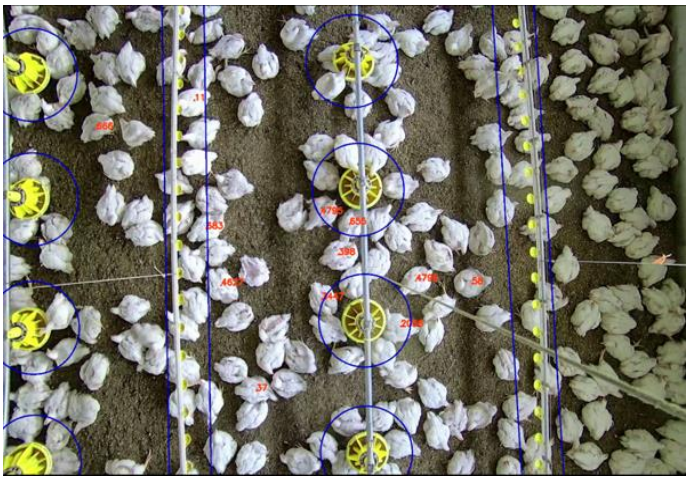

Figure 1: Example of feeder and water line zoning (marked in blue) [photo credit ITAVI].

2.2.3. *Individual data generated by algorithms*

The data generated by these *tracking* algorithms is listed in Table 1 below. The area available per animal corresponds to the area of the Voronoi cells or the maximum area of the polygon in Figure 2, containing a broiler without crossing another cell. An animal that moves or its neighbours modifies its Voronoi cell. There is a small imprecision in the detection, which creates a small permanent movement of the animal. Thus, an animal is considered active above the threshold set for immobile chickens at the 95ème quantile of distances travelled (more imprecision for large chickens). It is considered immobile when its distance is less than the 95ème quantile.

Table 1: List of indicators generated by individual *tracking of* chickens using imagery

INDICATORS GENERATED	UNIT
Distance travelled	cm/chicken
Travel speed	cm/chicken
Duration of period of activity	s/chicken
Time spent in area of interest	s/chicken
Time spent standing still	s/chicken
Surface area of chickens seen from above (= surface area of the rectangle representing each chicken)	cm² (sq. in.)
Area available per animal (Figure 2)	cm² (sq. in.)

Figure 2: Example of Voronoi cells, one cell containing a broiler chicken [photo credit ITAVI].

2.2.4. *Support for the development of detection and tracking algorithms*

Different recording contexts and different equipment have enabled image analysis algorithms to be developed and trained:

1/ Under experimental conditions at INRAe Nouzilly: Two flocks of ROSS 308 chickens were reared at 2 different densities (10 and 20 chickens per m²) up to 32 days of age. The 2 flocks were in the same room and set up on the same day. Images were captured by 3 x 2 MP (megapixel) cameras per pen, positioned 2.5 m above the pen. The animals were parked strictly under the camera's field of view. These recordings were used to analyse the performance of the detection model at different densities.

2/ Commercial conditions in a ROSS 308 chicken farm: Three 3MP cameras were installed at 3 different heights (2.5 m, representing 8.3 m² of filmed floor area, 3.7 m, representing 28 m² of filmed floor area and 5 m, representing 48 m² of filmed floor area) in a 2,060 m² commercial farm building, with 39,140 chickens reared to 45 days. The animals were not strictly penned under the camera and were kept at a density of 19 chickens/m². These latest recordings were used to analyse the performance of the detection model at different animal resolutions (*i.e.* camera heights and chicken sizes).

2.2.5. *Assessment of detection rate and tracking quality*

The results are analysed firstly in terms of the performance of the detection model and secondly in terms of *tracking* performance. For each particular case (specific camera height, age of chickens, etc.), the analysis is carried out on around ten images taken regularly with a maximum time lag within the same video, lasting from 8 minutes to 1 hour 43 minutes, in which the chickens were active. The analysis therefore covers more than 1,000 chickens. The number of false positives and undetected chickens is recorded manually for each image. The sensitivity and *False* Discovery Rate (FDR) are calculated for each video. The *tracking* analysis is carried out on 100-second videos (i.e. 1,000 images analysed). The measure of *tracking* quality is the number of identification errors (IE). A chicken loses its identifier or swaps it with another. The number of true negatives does not exist (no chicken detected where there is none) in the field of image analysis for chicken detection. It is therefore not possible to assess the specificity of the tests, for example. The aim is to have as few false positives and false negatives as possible, while detecting as many animals as possible. The detection tests are calculated using the following formula:

$$Sensibilité = \frac{VP}{VP + FN} = \frac{\#bonnes\ détections}{\#poulets}$$

$$FDR = \frac{FP}{VP + FP} = \frac{\#fausses\ détections}{\#détections}$$

TP: true positives, FN: false negatives, FP: false positives, #: number

2.2 Automated measurement of sound indicators in poultry, the case of Infectious Bronchitis

2.2.6. *Experimental design and sound recordings*

The trials were carried out at the Unité Expérimentale UE-1277 Plateforme d'Infectiologie expérimentale (PFIE) on Ross 308 chickens reared up to 35 days (Figure 3). Two rooms were set up with 30 chickens per room: a control room (T) with uninfected animals and a room BI with animals inoculated with Infectious Bronchitis. Infectious Bronchitis (IB) is a coronavirus that causes respiratory problems in hens and chickens. It can cause embryonic mortality, deformed shells and a drop in egg-laying in laying hens, and

digestive problems and under-performance in broilers. This is why we chose this pathology in the present study for the inoculation of chickens under experimental conditions. The animals in room BI were inoculated at D28 via the naso-ocular route, either with sterile 1X saline phosphate buffer (control flock) or with 500 µL IBV at 1,105 EID50 (50% *Embryo Infective Dose* = the titre of virus required to produce infection in 50% of inoculated embryos) using a 1 mL syringe (gCoV/chicken/Morocco/I38/ 2014). Both rooms were run in the same way. Viremic monitoring confirmed that the inoculation worked well on all the animals 4 days post-inoculation (D32) and systemically on the tissues. For each room, 4 omnidirectional 1/4" T.bone MM1 microphones were installed 46 cm above the floor, to be as close as possible to the animals without being accessible to them, and evenly distributed in the space above the chickens (Figure 3). The signals were recorded continuously from day 26 to the end of the rearing period using a Scarlett 18i20 Focusrite 8-channel audio interface. Before D26, the birds were kept together before being separated into two groups. Recordings were made at 10-minute intervals in .wav format to limit file size. The signal was broken down using a spectral subtraction algorithm (Ephraim and Malah, 1984; Cappe, 1994), in particular to remove ventilation noise. This required prior recording of this isolated ventilation noise for approximately 10 to 30 seconds. The relative noise level was calculated over the entire rearing period in 10-second increments, in the 2 rooms (day and night) as follows $L = 20\ Log_{10}\ (^{\sigma}/_{p_{ref}})$ with p_{ref} a reference pressure and σ the variance of a 10-second sound sample.

Figure 3. Photos of the installation with the chicks [photo credit INRAe].

2.2.7. *Characterisation of infectious symptoms*

A database of 400 sound signals was first labelled by 5 experts (veterinarians and zootechnicians) on the basis of 10-minute audio tapes. In total, 278 signals were labelled as sneezes and 122 as rales. Table 2 shows the list of descriptive acoustic indicators generated from the sound signals labelled as sneezes and rales. The indicators selected for the study are simple, complementary and commonly used to describe acoustic signals (order 0, order 1 and order 2 indicators). The labelled signals were processed using R software to perform a Principal Component Analysis (PCA) incorporating the acoustic indicators listed in Table 2. This analysis was used to describe the two symptoms. The estimation of these indicators was implemented using Python3 software.

Table 2. List of acoustic indicators calculated

INDICATOR	DEFINITION
Maximum amplitude	Most important signal value
Minimum amplitude	Lowest value
Average amplitude	Signal average
Variance	Indicator of the dispersion of amplitudes around the mean
Standard deviation or rms value	Standard deviation of the signal
Crest factor	Measuring signal dynamics
Signal energy	Signal strength

2.2.8. *Development of a model to predict respiratory symptoms*

Creating a database with only the events of interest (sneezing and moaning) is not enough to set up a prediction model. There are a multitude of sound events from chicken farms. For this reason, a second

database was created with the same experts. In addition to sneezing (n = 271) and rale (n = 84), this database also contains the chirping (n = 106) and other classes (n = 66). These data show events of about 1 s. 60% of these data were used for training and the remaining 40% for testing the prediction model.

The sound signals used in this database were transformed. Each signal is represented by the average of its cepstral coefficients of the Mel frequency (Zheng *et al.,* 2001). This frequency (Mel scale) aims to mimic the perception of sound by the human ear and is important in establishing the prediction model based on machine learning. The learning model used in this case is that of a neural network (Multilayer Perceptron MLP). This is an algorithm whose expected result should predict as accurately as possible the 4 classes of interest that we want to model (Sneeze, Rale, Peep and Other) as a function of the sound signals represented by their cepstral coefficients. This network consists of an input layer (cepstral coefficients), three hidden layers and an output layer representing the variable to be predicted (the 4 classes). The hidden layers act as intermediaries to model the output as a function of the input parameters. They are of major interest because they give more flexibility to the model so that it fits the inputs as closely as possible.

3.1 Performance of algorithms for detecting and *tracking* individual chickens using imagery

2.2.9. 3.1.1. Detection performance as a function of age and camera height

The videos taken on commercial farms were used to obtain the following results. Table 3 shows the detection performance for a given age and camera height. With a camera at 2.5 m, sensitivity varied from 96.9% at D12 to 100% at D39. When the camera is positioned at 3.7 m, this percentage varies from 84.2% at D12 to 99.8% at D39. Finally, a camera positioned 5 m away gave sensitivities ranging from 75.9% at D12 to 99.5% at D39. Sensitivity decreased with the height of the camera but increased with the age of the chickens. The number of pixels per chicken (the surface area of the chicken in the image) varies with the height of the camera. of the camera (image resolution) and with the age of the chickens. This surface area varies from around 2,500 pixels/chicken for a camera 5 m high and 12-day-old chickens to 17,500 pixels for 39-day-old chickens and a camera 2.5 m high. The neural network used to detect chickens is sensitive to the surface of each animal in the image. A convolutional neural network works by successively reducing the size of the image analysed. An initial image of 1,000 * 1,000 pixels is reduced to a size of 22 * 22 pixels. For example, a 12-day-old chicken filmed by a 3 MP camera at a height of 5 metres has a surface area of less than 1.5 pixels at the end of the neural network analysis. The smaller the initial surface area of the animal, the lower the probability of it being detected by the neural network. Increasing the height of the camera in order to gain access to a wider field of view then requires an image enlargement transformation to be applied so that each animal is large enough to be detected by the neural network. On the other hand, analysing a larger image increases the computing time required. Increasing the height of the camera by a factor of n not only degrades the image, but also increases its size and the calculation time by a factor of n^2. A compromise must be found between calculation time and the size of the desired camera field in order to film a maximum number of animals and process a maximum length of video in a minimum amount of time. Table 3 shows the sensitivities on enlarged images as a function of initial median area of the chickens (in bold in Table 3value in pixel). There appears to be a limit of between 3,500 and 4,000 pixels per animal, below which the detection rate falls sharply.

Table 3. Detection performance of the algorithm as a function of height at 12 days of age (in bold the surface of a chicken in pixels).

Height	**Sensitivity J12**	**Sensitivity J26**	**Sensitivity J39**
2,5m	96,9 % **4940**	99,2 % **11470**	100 % **17360**

3,7m	84,2 % **3250**	98,6 % **5830**	99,8 % **8240**
5m	75,9 % **2800**	98 % **4090**	99,5 % **5830**

2.2.10. 3.1.2. Detection performance as a function of animal density at the same age (D29)

The videos collected under experimental conditions were used to obtain the following results. Table 4 shows the detection performance of the neural network as a function of 2 different densities, 10 and 20 chickens per m². The percentages of animals detected in the field of vision differed little according to density (+1% of animals detected for the low-density floor compared with the high-density floor). However, the false discovery rate (i.e. the number of times the system detects an animal when there is none) is higher in the low-density floor than in the high-density floor. The higher the concentration of animals, the greater the risk of one animal hiding another. The sensitivity is explained by these occlusions. The variation in the false discovery rate is due to the fact that a false positive can only appear in an area with no chickens. The more animals there are, the fewer empty zones there are, leaving less room for false positives.

Table 4: Detection performance of the algorithm as a function of animal density per m² at D29

	10 ax/m² (1)	*20 ax/m² (1)*
Sensitivity	99,2 %	98,1 %
False discovery rate	6,6 %	4,8 %

2.2.11. 3.1.3. Tracking performance

The videos taken on commercial farms were used to obtain the following results. Animal *tracking* performance was calculated over 1,000 successive images. The number of identification errors is presented per animal per minute (10 images/second, i.e. 600 images per minute analysed). This value reflects the average frequency of occurrence of an identification error per minute. The results are presented both for a capture made with a higher level of activity on 26-day-old chickens and on 39-day-old chickens at rest. At 39 days of age, there was almost no *tracking/animal/minute* error (0.03). At 26 days of age, less than one error per animal per minute was identified (0.67), which is equivalent to one error every 1.5 minutes per animal in the field of vision. *Tracking* performance depends on the model's ability to detect all the animals and the *tracking* algorithm's ability to identify each animal. The greater the animal activity, the more difficult it is to track the animals. Errors in identification (an animal losing its identifier) occur in areas of very high density (mainly resting areas near walls). It is also in these areas that false negatives most often occur.

3.2 Results of monitoring and acoustic analyses carried out on poultry, case of Infectious Bronchitis

A total of 2,238 10-minute audio tapes were collected from the test room (BI) and 4,263 from the control room, i.e. 373 hours of video and 710 hours of video respectively. This difference can be explained by the fact that the recordings in the test room (BI) were not made from the start of the flock but began 2 days before the animals were inoculated (when they were transferred to their respective rooms).

2.2.12. 3.2.1. Monitoring of relative noise levels

An average difference of 3 dB was detected at night in the BI room compared with the control room over the 5 days post-inoculation. This result reflects a noise intensity twice as high in the test room (BI) compared with the control room (Figure 4). This also reflects the higher acoustic activity of the chickens in this room at night. Symptoms of infectious bronchitis were clearly visible and audible to the animal keepers at D+3/D+4, but the study of sound levels showed a clear increase in intensity in the test room (BI) from D+2 (Figure 4). A difference of 2 dB or more is considered significant. This corresponds to a 50% increase in sound intensity (sound intensity equals sound level). According to Figure 4, the noise level in the control room was fairly stable throughout the trial.

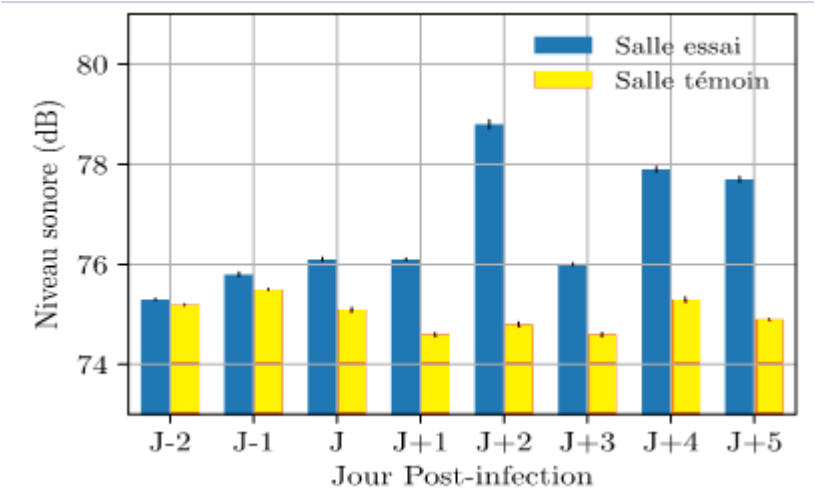

Figure 4: Changes in relative noise levels (in the control room and the trial-BI) at night as a function of the number of days of inoculation.

Characterisation of sneezes and rales

Figure 5 shows two spectrograms, (a) of a sneeze and (b) of a rale. This representation is close to human perception because the human ear is capable of analysing the temporal evolution of the frequency of a signal as well as its sound level. The frequencies allow us to assess whether the event is severe or acute as a function of time, and the energy whether the event is perceptible to the ear. The sneeze is short in time, 0.25 s, and its energy is distributed over a frequency band of 200 Hz to 5 kHz. The rale is a weaker event and is confused with noise. Moreover, the energy of the rale is between 100 kHz and 1 kHz. The PCA performed on the 400 labelled sound signals (278 sneezes and 122 rales) revealed 3 separate clusters, 2 relating to sneezes (Clusters 2 and 3 in Figure 6, in red and blue respectively) and 1 relating to rales (Cluster 3 in Figure 4, in green). The sneeze is characterised by the acoustic parameters: skewness, kurtosis, crest factor, mean frequency, frequency spread, maximum amplitude, energy and RMS value of the signal (in blue and red in Figure 6). These last acoustic indicators identified show significantly different averages (at the 5% significance level) and higher averages for the sneeze than for the rale. The rale is characterised by the other acoustic parameters: signal duration, temporal spread, maximum amplitude and mean time (Figure 6). All these parameters have a higher mean for the rale and are significantly different (at the 5% significance level) from the mean for the sneeze (Table 5).

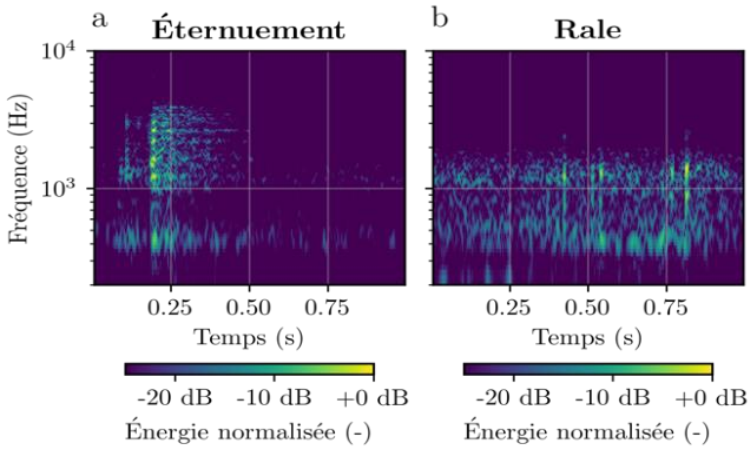

Figure 5. Spectrogram (a) of a sneeze (b) of a rale.

Figure 6. Biplot of the results of the Principal Component Analysis (PCA) applied to the acoustic descriptors

Table 5. Averages of acoustic indicators calculated for moaning and sneezing (in bold the variables that characterise each symptom and are therefore significantly different).

Indicator	Medium rale	Average sneeze
Skewness (without unit)	0,17	**0,38**
Kurtosis (without unit)	15,30	**36,24**
Crest factor (without unit)	11,33	**14.31**
Average frequency (Hz)	1289,48	**1783,79**
Frequency spread (Hz)	1212,04	**1758,82**
Maximum amplitude (V)	0,02	**0,07**
RMS value (V)	0,000026	**0,000038**
Energy (V2)	**0,12**	1,19
Duration (s)	**1,09**	0,69
Time spread (s)	**0,27**	0,08

Minimum amplitude (V)	**-0,01**	-0,06
Average time (s)	**0,56**	0,32

2.2.13. Performance of the algorithm for automatic detection of developed symptoms

The neural network model implemented in this study showed 82% accuracy for the test data. 4 classes were evaluated: Sneezing, Raling, Peeping and Other (Table 6). For the Sneezing class, 104 were correctly identified (True Positives: VP) out of 109 and 20 False Positives (FP), 82 True Negatives (VN) and 5 False Negatives (FN). This gives a sensitivity (VP/(VP+FN)) of 95% and a specificity (VN/(VN+FP)) of 80%. The rale class has a sensitivity of 65% and a specificity of 98%. The peeping class gave a sensitivity of 71% and a specificity of 99%. For the other class, 69% sensitivity and 94% specificity were obtained (Table 6). These results are quite encouraging, particularly for sneezing, since the accuracy of the model for the sneezing class is in line with that obtained by Carpentier *et al,*(2019). The neural network model developed in this study was trained on a fairly small database, especially for rale, chirping and other classes. It would be interesting, at a later stage, to feed the database with more data in order to improve its performance and robustness.

Table 6. Confusion matrix for the prediction model used

	Reference			
Prediction	Other	Sneezing	Chirping	Rale
Other	18	3	5	4
Sneezing	6	104	6	8
Chirping	0	2	30	0
Rale	2	0	1	22

3. Conclusion

The quality of detection depends on a number of parameters: the definition of the camera, the size and age of the animal, the height of the camera, the density and activity of the animals. The quality of monitoring depends very much on the system's ability to detect the animals, but also on their activity. The density of animals per square metre does not seem to hinder animal detection when the animals are evenly distributed, at the densities of 10 and 20 chickens per square metre tested. The detection algorithms developed for monitoring broiler chickens in commercial farms perform very well (> 99% of animals detected from D26 with a 2.5 m camera). However, *tracking* performance is less good in areas of higher density (particularly near walls) and could be improved by enriching the image database in these specific areas. Publications on similar developments do not allow a strict comparison with the results presented in this article, since the trials are only carried out on small groups of birds, where 100% of the birds are detected, and the objectives and methods for evaluating the quality of detection and *tracking are not the* same. The next step is to determine alert thresholds for the early detection of animal health and welfare disorders. Work is also being carried out to predict the expression of specific behaviours, such as exploration and grooming, using activity data from *tracking*.

This study shows that sneezing is a short sound (0.25 s) that is clearly distinguishable by ear. The rale, on the other hand, is a longer (1.09 s), less frequent event that can be confused with background noise. The prediction model was developed for events with a duration of 1 second. It gives better results for automatic detection of sneezes: 95% sensitivity, compared with 65% for rales. The database used will soon be populated with more labelled signals to improve the model's detection performance. The noise level emitted by the animals during the nocturnal phase seems to be an interesting indicator for the early detection of a pathology associated with the expression of symptoms, in this case respiratory symptoms for BI. These preliminary results under experimental conditions are promising for future trials. This trial will have to be repeated under the same experimental conditions to check whether the 3 decibel difference between the 2 rooms is systematic and therefore linked to inoculation.

Ethics
The authors declare that the experiments were carried out in compliance with the applicable national regulations.

Declaration on the availability of data and models
The data supporting the results presented in this article are available on request from the author of the article.

Declaration on Generative Artificial Intelligence and Artificial Intelligence Assisted Technologies in the Drafting Process.
The authors used artificial intelligence in the translation process from French to English.

Authors' contributions
- Pauline Créach: EBroilerTrack project leader for ITAVI, coordinating all the work carried out on the project.
- BRUNET Henry: PhD student developing image analysis algorithms for individual monitoring of chickens on farms
- CONCORDET Didier supervised the work of PhD student BRUNET Henry
- PAJUSCO Nicolas analysed the noise intensity results
- RIOU Mickaël: setting up the protocol and monitoring within the PFIE EU
- EL JABRI Mohammed carried out the data analysis
- DOUTART Elodie supervised IDELE's work on the EBroilerTrack project.
- BOUVAREL Isabelle supervised the ITAVI's work on the EBroilerTrack project.

Declaration of interest
The authors declare that they do not work for, advise, own shares in, or receive funds from any organisation that could benefit from this article, and declare no affiliation other than those listed at the beginning of the article.

Acknowledgements
This study was conducted as part of the 2019 EBroilerTrack Technological Case Dar project (n°18ART1832), led by ITAVI in partnership with INRAe and the Institut de l'élevage. It received financial support from the French Ministry of Agriculture. The authors would like to thank the PFIE EU (INRAe Nouzilly), the breeders who took part in the study and the project partners for their involvement.

Declaration of financial support
ITAVI also received financial support for this study from the broiler industry (CIPC).

References :

Banakar A., Sadeghi M., Shushtari A., 2016. An intelligent device for diagnosing avian diseases:Newcastle, infectious bronchitis, avian influenza. Comput. Electron. Agric. 127, 744-753.

Cappe O., 1994. Elimination of the musical noise phenomenon with the Ephraim and Malah noise suppressor; 1994. IEEE Transactions on Speech and Audio Processing, 2(2), p.345-349.

Carpentier L., Berckmans D., Youssef A., Berckmans D., Van Waterschoot T., Johnston D., Ferguson N., Earley B., Fontana I., Tullo E., Guarino M., Vranken E., Norton T., 2018. Automatic cough detection for bovine respiratory disease in a calf house. Biosyst. Eng. 173.

Carpentier L., Berckmans D., Vranken E., Paeshuyse J., 2019. Development of sound-based poultry health monitoring tool for sneeze detection. Computers and Electronics in Agriculture 162, 573-581.

Carroll B-T., Anderson D-V, Daley W., Harbert S., Britton D-F., Jackwood M-W., 2014 Detecting symptoms of diseases in poultry through audio signal processing. IEEE Glob Conf. Signal Inf. Process Glob. 1132-1135.

Chedad A., Moshou D., Aerts J-M., Van Hirtum A., Ramon H., Berckmans D., 2001. Recognition system for pig cough based on prohabilistic neural networks. J. Agric. Eng. Res. 79, 449-457.

Chung Y., Oh S., Lee J., Park D., Chang H-H, Kim S., 2013. Automatic detection and recognition of pig wasting diseases using sound data in audio surveillance systems. Sensors (Switzerland) 13, 12929-12942.

Colles F.M., Cain R.J., Nickson T., Smith A.L., Roberts S.J., Maiden M.C., Lunn D., Dawkins M.S., 2016. Monitoring Chicken Flock Behaviour Provides Early Warning of Infection by Human Pathogen Campylobacter. Proceedings. Biological Sciences 283 (1822): 20152323.

Collins L.M., 2008. Non-intrusive tracking of commercial broiler chickens in situ at different stocking densities. Applied Animal Behaviour Science 112, 1-2, 94-105.

Créach P., Travel A., Bouvarel I., 2019. Image and sound to automate the recording of poultry welfare and health indicators. Revue TeMa n°51.

Dal Pozzo F., 2019. Pathologies respiratoires chez les poulets, AMCRA Wallonie Elevage, 2019 dossier Sanitaire p64

Dawkins M.S., 1998. Evolution and Animal Welfare. The Quarterly Review of Biology;73(3):305-28.

Dawkins M.S., Roberts S.J., Cain R.J., Nickson T., Donnelly C.A., 2017. Early Warning of Footpad Dermatitis and Hockburn in Broiler Chicken Flocks Using Optical Flow, Bodyweight and Water Consumption. The Veterinary Record 180 (20): 499.

Dawkins M.S., Wang L., Ellwood S.A., Roberts S.J., Gebhardt-Henrich S., 2021. Optical Flow, Behaviour and Broiler Chicken Welfare in the UK and Switzerland. Applied Animal Behaviour Science 234 (January): 105180.

De Montis A., Pinna A., Barra M., Vranken E., 2013. Analysis of poultry eating and drinking behavior by eYeNamic. Journal of agricultural engineering XLIV (s2):e33

Ephraim Y., Malah D., 1984. Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator. IEEE Transactions on Acoustics, Speech, and Signal Processing, 32(6), 1109-1121.

Feiyang, Zhang, Hu Yueming, Chen Liancheng, Guo Lihong, Duan Wenjie, Wang Lu. 2016. Monitoring Behavior of Poultry Based on RFID Radio Frequency Network. International Journal of Agricultural and Biological Engineering 9 (6): 139-47.

Fraess G.A., Bench C.J., Tierney K.B., 2016. Automated Behavioural Response Assessment to a Feeding Event in Two Heritage Chicken Breeds. Applied Animal Behaviour Science 179 (June): 74-81.

Li N., Ren Z., Li D., Zeng L., 2020. Automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming. Animal 14 (3): 617-25.

Manteuffel G., Puppe B., Schön P.C., 2004. Vocalization of farm animals as a measure of welfare. Applied Animal Behaviour Science 88(1), 163-82.

Michaud F., Créach P., Brouard B., Gazengel B., Simon L., Collin A., Métayer-Coustard S., Travel A., 2019. Chick vocalisations: development of a recording and analysis method. Treizièmes Journées de la Recherche Avicole et Palmipèdes à Foie Gras, 20 and 21 March.

Oliveira J.L., Xin H., Wu H., 2019. Impact of Feeder Space on Laying Hen Feeding Behavior and Production Performance in Enriched Colony Housing. Animal 13 (2): 374-83.

O'Mahony N., Campbell S., Carvalho A., Harapanahalli S., Hernandez G. V., Krpalkova L., ... & Walsh J., 2019. Deep learning vs. traditional computer vision. In Science and Information Conference (pp. 128-144). Springer, Cham.

Fernández A.P., Norton T., Tullo E., van Hertem T., Youssef A., Exadaktylos V., Vranken E., Guarino M., Berckmans D., 2018. Real-Time Monitoring of Broiler Flock's Welfare Status Using Camera-Based Technology. Biosystems Engineering, Advances in the Engineering of Sensor-based Monitoring and Management Systems for Precision Livestock Farming, 173 (September): 103-14.

Rizwan M., Carroll B-T., Anderson D.V., Daley W., Harbert S., Britton D.F., Jackwood M.W., 2017. Identifying rale sounds in chickens using audio signals for early disease detection in poultry. In: 2016 IEEE Global Conference on signal and Information processing, GlobalSIP 2016 - Proceedings.

Rowe E., Dawkins MS., Gebhardt-Henrich S., 2019. A systematic Review of precision livestock farming in poultry sector: Is technology focussed on improving welfare? animals 2019, 9, 614, doi:10.3390/ani9090614.

Sales G.T., Green A.R., Gates R.S., Brown-Brandl T.M., Eigenberg R.A., 2015. Quantifying Detection Performance of a Passive Low-Frequency RFID System in an Environmental Preference Chamber for Laying Hens. Computers and Electronics in Agriculture 114 (June): 261-68.

Siegford J.M., Berezowski J., Biswas S.K., Daigle C.L., Gebhardt-Henrich S.G., Hernandez C.E., Thurner S., Toscano M.J., 2016. Assessing Activity and Location of Individual Laying Hens in Large Groups Using Modern Technology. Animals 6 (2): 10.

Silvera A. M., Knowles T.G., Butterworth A., Berckmans D., Vranken E., Blokhuis H.J., 2017. Lameness Assessment with Automatic Monitoring of Activity in Commercial Broiler Flocks. Poultry Science 96 (7): 2013-17.

Vandermeulen J., Bahr C., Johnston D., Earley B., Tullo E., Fontana I., Guarino M.Exadaktylos V., Berckmans D., 2016. Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds. Comput. Electron. Agric. 129, 15-16.

Wood-Gush D.G.M., 1971. The Behaviour of Domestic Fowl. Heineman, London.

Zheng F., Zhang G., Song Z., 2001 Comparison of different implementations of MFCC. J. Computer Science & Technology, 16(6): 582-589.