

Table of contents

CHAPTER 1	1
1. Introduction	2
1.1. Current livestock production.....	2
1.2. Modern farming challenges	5
1.3. Precision Livestock Farming (PLF): principles and objectives	7
1.4. References.....	10
CHAPTER 2	13
2. Labelling procedure.....	14
2.1. Sound analysis	14
2.2. Image analysis.....	17
2.3. Objectives	21
2.4. Overview of the chapters	22
2.5. References.....	24
CHAPTER 3	25
3. Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments.....	26
3.1. Introduction.....	28
3.2. Material and methods.....	30
3.3. Results.....	36

Table of contents

3.4.	Discussion	38
3.5.	Conclusions	39
3.6.	References	41
CHAPTER 4		49
4.	Vocalisation sound pattern identification in young broiler chickens ..	50
4.1.	Implications	52
4.2.	Introduction	52
4.3.	Material and methods	55
4.4.	Results and Discussion	61
4.5.	Conclusions	68
4.6.	References	69
CHAPTER 5		73
5.	An innovative approach to predict the growth in intensive poultry farming.....	74
5.1.	Introduction	77
5.2.	Material and methods	79
5.3.	Results and discussion.....	85
5.4.	Conclusion.....	91
5.5.	References	93
CHAPTER 6		97
6.	Discerning pig screams in production environments	98

6.1.	Introduction.....	100
6.2.	Material and Methods	102
6.3.	Results.....	114
6.4.	Discussion.....	117
6.5.	Conclusion	122
6.6.	References.....	124
CHAPTER 7		129
7.	General discussion and conclusion.....	130
List of publication		134
1.	Publication in peer reviewed international journal publications.....	134
2.	Publication in international conference proceedings	135
Acknowledgements		137

CHAPTER 1

1. Introduction

1.1. Current livestock production

The constantly growing yearly demand for meat, dairy products and eggs has important implications for agricultural production methods (Tullo et al., 2013).

The global human population has increased during the last 70 years and after the Second World War, during the 1950s, nearly about 2.6 billion people populated our planet. After 50 years, at the beginning of this century, the number of people reached 6 billion units, while nowadays is estimated to be of the order of 7.5 billion people (FAO 2015).

Moreover, the world population is expected to grow throughout the rest of the century and will reach 9.6 billion people in 2050 and 11 billion people by the year 2100 (Mountford and Rapoport, 2015) and, as a consequence, the world's food scenario is rapidly changing.

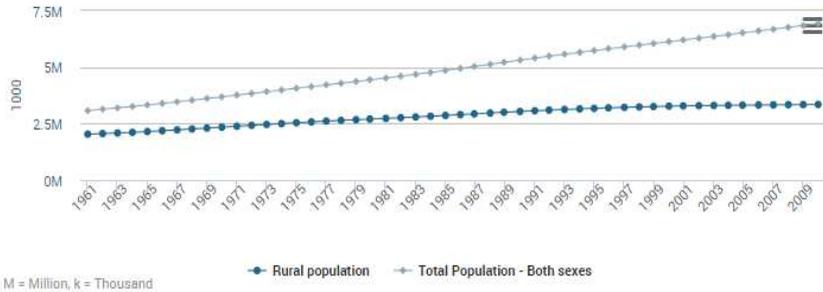


Fig. 1 Global population dynamics 1961 - 2010 (FAOSTAT 2015)

As reported in Fig 1, during the last decades, there has been an enormous growth in livestock production, driven by population growth, growing economies and changes in dietary preferences associated mainly with

increasing wealth and urbanisation, which led to the increasing demand and consumption of animal products (Tullo et al., 2013) (Fig 2 and 3).



Fig. 2 Meat production quantities by country (1993 - 2013) (FAOSTAT 2015)

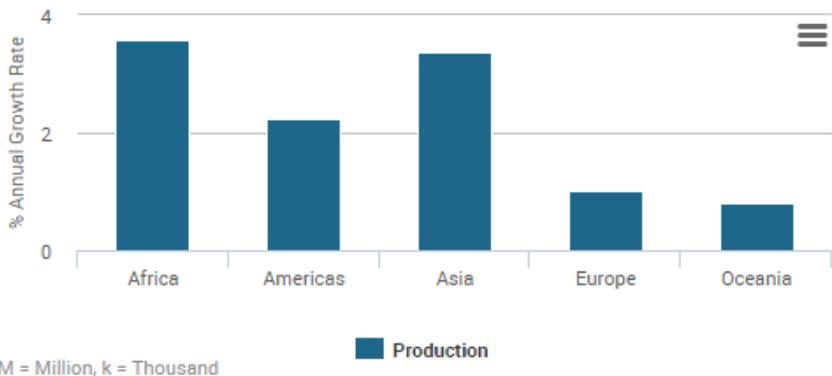


Fig. 3 Meat production growth rates by regions 2000 - 2013. Africa 3.6%, Americas 2.2%, Asia 3.4%, Europe 1%, Oceania 0.8%

Meat consumption is projected to rise nearly 70% by 2050 and dairy consumption will grow 58% over current levels.

Chapter 1

The current global meat demand is growing and meat production will need to increase from the current 300 million tons to 480 million tons by 2050, depending on the changing diets worldwide. This demand for meat is growing rapidly especially in the five major emerging economies of Brazil, Russia, India, China and South Africa (BRICS countries). In the BRICS countries, which combined represent the 40% of the global population, the meat consumption rose by 6.3% annually between 2003 and 2014, with a further 2.5% yearly increase forecasted for the 2015-2022 period. This means that approximately 80% of the world's meat sector demand by 2022 will occur in developing countries (FAO, 2015).

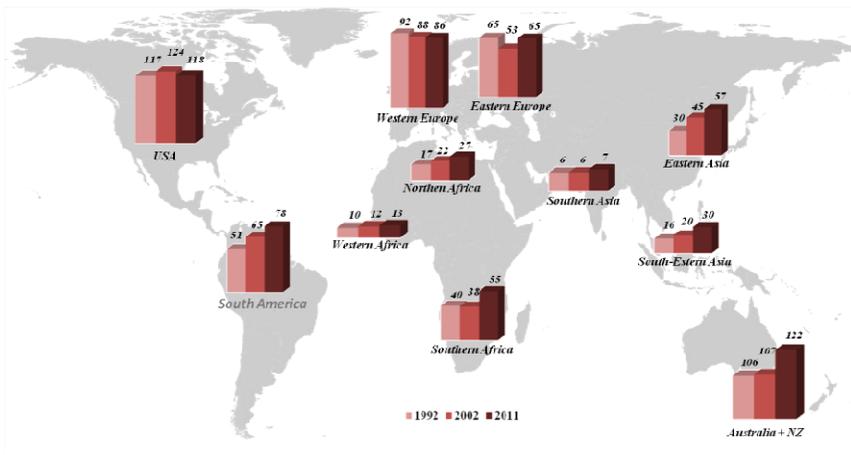


Fig. 4 Meat Consumption (Kg per capita/year) referred to the years 1992, 2002 and 2011

In particular, poultry has shown the highest increasing trend concerning meat demand and consumption (Fig. 4). It is one of the lowest cost sources of animal protein in the world, and poultry meat demand is growing every year all over the world (Fontana et al., 2015). Poultry production has increased during the

last decades due to the low price of the final product but, most of all, because poultry meat consumption is not affected by religious issues.

1.2. Modern farming challenges

The increasing demand for meat, dairy products and eggs has important implications for agricultural production methods; in fact livestock/crop production is becoming increasingly industrialised worldwide, shifting from extensive, small-scale, subsistence production systems towards more intensive, large-scale, geographically-concentrated, specialised and commercially oriented ones (Tullo et al., 2013).

Currently, intensive and big farms with higher number of animals involved have largely overtaken small-scale family activities.

The shift in livestock farming methods from extensive to intensive poses a number of significant challenges for animal welfare, environmental sustainability and food security (Tilman et al., 2002).

Intensive or confined livestock production involves thousands of animals of similar genotypes which are raised for one purpose (such as pigs, laying hens, broiler chickens, ducks, turkeys) with a rapid population turnover and under highly controlled conditions, often in constrained housing without adequate space and fed with industrial feeds instead of natural forages (Tullo et al., 2013).

In the past, livestock management was based on the farmer's experience and simple animal observation. Today, the farmer has to play a completely different, more entrepreneurial, role which forces him to spend most of the day in the office, losing contact with the animals reared (Guarino, 2005).

The increasing number of animals reared per farm also leads to a higher probability to develop pandemics of zoonotic origin, with several diseases such as Avian Flu (2003) and H1N1 Flu (2009) outbreaks, occurred globally during the last recent years.

It is important to control the spread of these diseases and the use of medication is becoming very important to avoid their transfer from animals to humans. This is especially true in livestock and poultry, where antimicrobials are used to prevent diseases and to treat infections. This over-use of antibiotics leads to the development of antibiotic resistance, which has several negative aspects both in human and animals, such as the increased in morbidity and mortality due to inappropriate therapies and the increase in costs for medical treatment (Acar, 1997).

In order to arrest the current global increase in antibiotic resistance and to reduce costs related to diseases and veterinary interventions, methodology might include the exclusion of unnecessary use of medication through the introduction of disease surveillance strategies and by promoting research and development into new approaches to the control and prevention of pathologies.

One potential method of achieving better control of the food production chain is to develop reliable automatic monitoring systems in order to increase food safety, animal health and welfare (Tullo et al., 2013).

1.3. Precision Livestock Farming (PLF): principles and objectives

One of the main objectives of Precision Livestock Farming (PLF) is the development of automatic on-line monitoring tools (Guarino et al., 2008) to monitor animals' behaviour and their biological responses to external stimuli, such as changes in house environment conditions, or the occurrence of disease (Tefera, 2012).

PLF involves the application of the principles and techniques of process engineering to livestock farming to monitor, model and manage animal production.

The PLF approach has potential to be applied at different scales, from the individual animal, to the entire flock/herd, and to assess environmental and animal health, welfare and management both in intensive and extensive farms without imposing additional stress to animals (Wathes et al., 2009).

PLF relies on four essential elements (represented in Fig. 1):

1. The continuous sensing of the process responses at an appropriate frequency and scale with a continuous exchange of information with the process controller;
2. A compact mathematical model, which predicts the dynamic responses of each process output to variation of the inputs and can be – and is best – estimated online in real time;
3. A target value and/or trajectory for each process output, e.g. a behavioural pattern, pollutant emission.
4. Actuators and a model-based predictive controller for the process inputs.

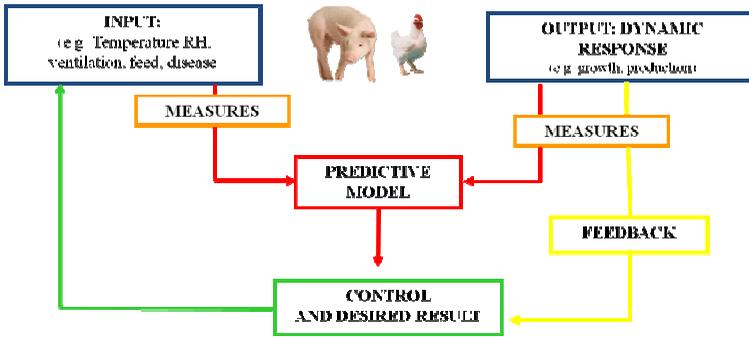


Fig. 1 Schematic representation of the PLF application to intensive livestock systems.

A potential added value of PLF may be the capability to provide ‘prediction’, such as health and welfare status, production, growth trend. Integrated systems might help the farmer in taking positive action in response to warnings. Monitoring equipment (cameras, microphone, feed and water monitors, environment monitors) associated with predictive algorithms could be part of a management tool used by the producer to detect and improve health and welfare issues.

PLF technology is based on the use of cameras, microphones and sensors to monitor continuously the animals as the most important part of the biological process.

The development of an accurate algorithm is preceded by the definition of specific Key Indicators (KIs) and Gold Standard (Fig. 2).

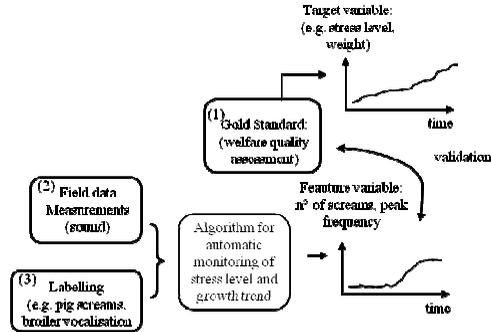


Fig. 2 Process of algorithm development: a schematic overview (Berckmans, 2013)

Key Indicators are defined as parameters giving information on a domain that is relevant for farm management.

Key Indicators related to these different domains, like animal welfare, health, production and environmental load for animal husbandry, which are identified through expert consultation and literature analysis (Tullo et al., 2013).

These indicators provide the basis to identify data coming from sensors such as sounds and images that can be used to develop an algorithm able to predict and manage animal health and/or welfare, or take control actions (climate control, feeding strategies, etc.) on the basis of continuous monitoring.

The further step for the development of an accurate and useful algorithm involves people's expertise in the labelling procedure capable to label the sounds or images based on the Gold Standard provided.

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CHAPTER 2

2. Labelling procedure

Accuracy of data collected is an essential prerequisite for the development of a reliable algorithm able to identify in an automated way health and welfare problems at farm level.

The automated tool should work on any farm in any conditions and data standardisation is strongly dependent on manual labelling. This fundamental step, which is necessary for data analysis and model development, takes an enormous amount of time, manpower and close attention.

The labelling should be very precise and detailed since it plays a crucial role in the development of an accurate algorithm able to detect feature variables at animal level.

2.1. Sound analysis

Sound labelling involves extraction and classification of individual animal sounds on the basis of the amplitude or frequency of the sound signal in audio files recorded in the farm. The labellers identify interesting sounds based on the key indicators and golden standards provided by veterinarians and ethologists (Tullo et al., 2013).

Auditory recognition of sounds coming from a noisy environment such as the farm is a demanding task. On farms, sounds from animals are often overlapped by other sounds (feeders, gates, etc.), the acoustic source is not always at the same distance from the microphones, and reverberation can alter sound propagation.

Due to their discontinuity, it is impossible to filter out all these background noises; audio identification is therefore dependent on the subjectivity of the different labellers as well as their accuracy and interpretation or understanding.

For this reason it is helpful to support listening with visual information about the energy envelope of the noises recorded, using audio editing software such as Adobe® Audition™. This type of software provides a visual representation of sound waves, displaying waveforms to evaluate audio amplitude or the spectrum of the sound, which reveals audio frequency (Fig. 1).



Fig. 1. Screenshot of Adobe® Audition™ CS6. Waveform (upper part) and spectral display (lower part) of an audio file.

The waveform display (Fig. 1, upper part) shows a series of positive and negative peaks. The x-axis (horizontal ruler) measures time while the y-axis (vertical ruler) measures the amplitude that is the loudness of the audio signal (Adobe® Systems Incorporated, 2003).

The spectral display (Fig. 1, lower part) shows a waveform by its frequency components, where the x-axis (horizontal ruler) measures time and the y-axis

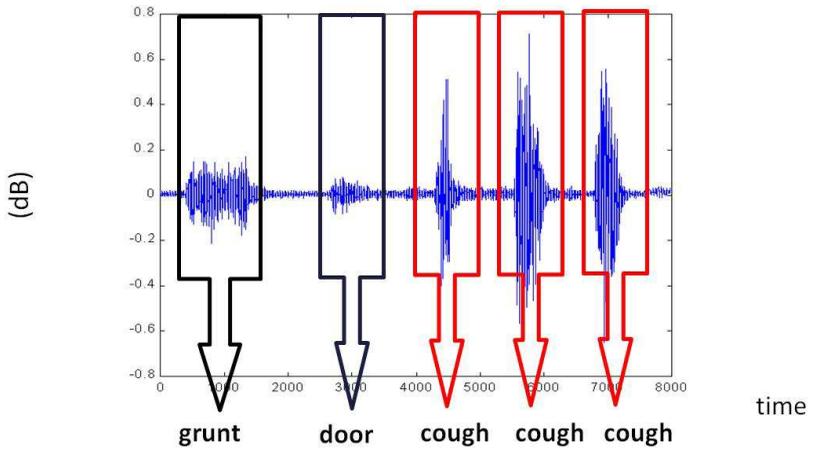


Fig. 3. *Samples of labelled sounds recorded in a pig farm.*

2.2. Image analysis

Video labelling is a precise detection of the occurrence of behaviours performed by animals and it is made by manual extraction and classification of individual frames on a recorded video. This classification is based on key indicators and golden standards provided by veterinarians and ethologists.

Depending on the variables (activity, occupation, behaviours, etc.), the video must be calibrated in order to define zones of interest inside it, where behaviours, activity and occupation can be measured and labelled (Fig. 4).

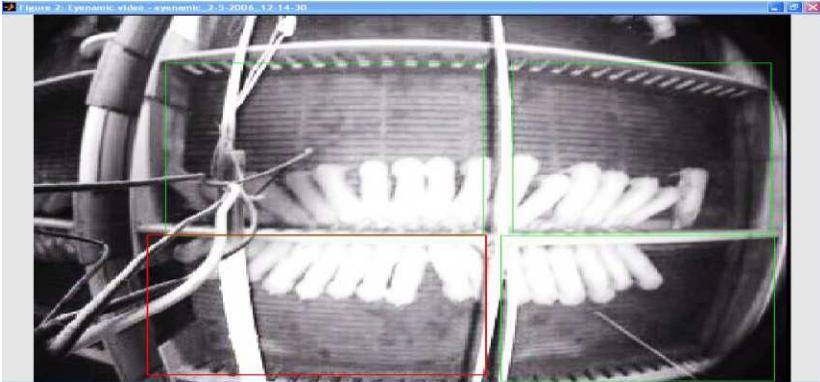


Fig. 4. Definition of zones of interest inside the video where behaviours, activity and occupation can be measured and labelled

Pen floor area must be converted into pixels in the image in order to estimate activity or occupation. Pixel intensity is used to evaluate animal activity.

In order to support and speed up visual labelling, a labelling tool (Fig. 5) was developed in MATLAB[®]. It is based on the principle that relates changes in pixel intensity may affect a good estimation of animal activity (*activity index*, Figure 5b).

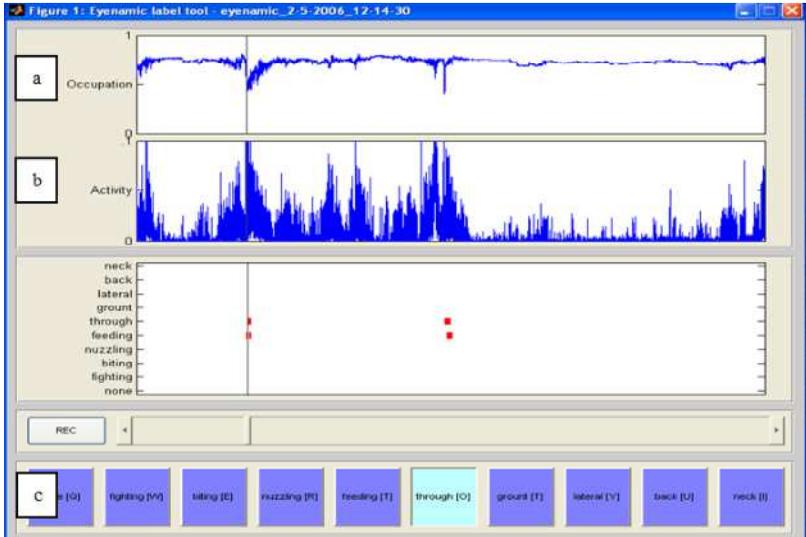


Fig. 5. Screenshot of Labelling Tool. a) Occupation index. b) Activity index. c) Customisable buttons

With this information it is possible to identify parts of video with reduced activity (most of the day) and focus attention only on those sequences which contain movement. Another parameter considered in the Labelling tool is the occupation index (Fig. 5a); it indicates the ratio between the zone occupied by animals and the total pen area. Associating those two parameters, the software creates threshold values for animal activity, making possible to skip periods of the day when animals move out (e.g. feeding, drinking time).

This tool is helpful in detecting periods of increased activity and speeding up to those periods only, the labellers can record all the information about the behaviour detected. The software interface is customisable, so the labeller can name the buttons identifying the chosen behaviours or events of interest (Fig. 5c).

Chapter 2

With this tool the labeller can easily classify behaviours by manual sliding of the video, and when a specific behaviour, or multiple behaviours, is/are observed in the image the matching button/buttons is/are selected. Data collected in this way can be exported in order to create a data set containing all the information that will be useful in developing an algorithm for the automatic detection of behaviours (start/end time, duration, description of the behaviour and animal identification) (Tullo et al., 2013).

2.3. Objectives

This thesis describes a methodology of Precision Livestock Farming, to investigate animal health and welfare, through the monitoring of animal behaviours and vocalisations using image and sounds analysis instead of the visual observation methods.

It wants to investigate whether smart technologies can support the farmer in the management of a large group of animals, using image and sound technologies.

The general objectives of this thesis are:

- Define and realise manual image and audio labelling in order to improve the general knowledge on this topic, for the further development of automatic monitoring systems to control different aspects of the health, welfare, behaviour and production of farming animals.
- Assess the interest of the weaning pigs to the usual environmental enrichments provided.
- Define the vocalisation pattern of young broiler chickens to understand the interaction among co-specifics during the very first two days of life.
- Define and realise manual labelling of broilers sounds as a reference for further studies on this species.
- Investigate the relation between broiler vocalisation and their weight for further development of a tool able to predict the growth trend of the broilers using sound technologies.
- Define a reference for the manual labelling of pigs screams.

- Develop an automated scream detection method based on sound recordings made in pigs barn.

2.4. Overview of the chapters

Concerning the intensive farm, pigs are usually kept in multiple boxes with high density and lack of environmental enrichments. Chapter 3 is dedicated to explore the preference and the duration of interest of weaned pigs for two different types of environmental enrichments using labelling techniques and activity monitoring.

Chapter 4 describes the monitoring of broiler chicken vocalisation under normal farm conditions. The object of this study is the identification and characterisation of vocalisations emitted by chicks, looking for possible connections between specific individuals and social behaviours.

In close relation to chicken broiler production, growth trend is an important indicator to evaluate the body weight of animals; chicken weight provides information about the growth and the feed conversion efficiency of the entire flock.

Nowadays, number of animals within the broiler house is very high and the broilers weight is usually collected by one or two step-on-scales placed on the floor of the house. During the last years, the genetic selection, led to have hybrid genotypes with homogeneous growth rates but, problems can occur such as lameness, lesions and health issues which can affect the uniformity of the flock resulting in less production and troubles for farmers. Moreover, lame and sick birds are reluctant to move and to jump on the scale, for this reason is very difficult to have a total overview of the animals bred during each production cycle.

Chapter 5 deeply describes the relation between peak frequency and weights (already found in chapter 4) in order to monitor birds growth trend for a further development of a non-invasive tool able to monitor the homogeneity of the entire flock.

Pig sounds and vocalisations conveys information about pigs health and welfare status; for instance, pig coughs and sneezes provide information regarding arising pathologies in the barn while pig screams can indicate stressful situation occurring at the piggery.

Several sounds in a pig farm can be detected such as sneezes, coughs, cough attacks, barks, grunts, screams and environmental/background noises. For this reason, when monitoring screams, other sounds can interfere with screams detection.

Chapter 6 describes the process to understand which sound features define a scream and to develop a method to detect screams, based on sound features.

Chapter 7 focuses on the general discussion and conclusion of the previous chapters.

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CHAPTER 3

3. Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments

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Abstract

The aim of this study was to explore the preference and the duration of interest of weaned pigs to two different types of environmental enrichments using labelling techniques and activity monitoring. Two pens each housing 14 Dalland piglets were monitored using a video camera. The videos were labelled during the weaning phase from 30 to 60 days of age. During this time, the video recording software continuously calculated the activity index of the pigs. To detect pig exploratory and playing behaviour, a wooden block and chain enrichment were introduced into each pen for 30 days. Each video frame was manually labelled during the Day 1, 5 and 30 (24 hours a day) for each pen using the Labelling Tool software. To identify the duration and frequency of interactive episodes with environmental enrichments, pig behaviour was labelled as either: no activity, interacting with chain or interacting with the wooden block. The mean duration of interactive episodes for the chain was greater than for the wooden block ($P < 0.001$), while the frequency of interactive episodes was 28.8% higher for the wooden block than for the chain. By day 5, the mean duration of interaction episodes decreased in both pens and by day 30, only a few interaction episodes were observed. The number of interactive episodes were strictly related to the activity index and depended on the time of the day. The peaks of the mean number of interactive episodes calculated for all days of observations corresponded to the peaks of the mean activity index.

Keywords: *piglets, environmental enrichment, labelling, activity monitoring, camera images*

3.1. Introduction

Numerous scientific studies under farm conditions show that pigs tend to display the same habits and behaviour as wild pigs including foraging, playing and exploring (Wood-Gush and Vestergaard, 1991; Van de Weerd and Day, 2009). Many scientific studies have also shown that modern intensive farms compromise the natural behaviours of pigs resulting in negative social behaviours such as tail and ear biting (Meunier-Salaun et al., 1987; Fraser et al., 1991; Van de Weerd et al., 2006) and aggression towards their penmates (Kelly et al., 2000; Melotti et al., 2011). It is widely accepted that environmental enrichments that facilitate the natural motivated behaviours of pigs improve their welfare (Wood-Gush and Beilharz, 1983; Arey, 1993; Beattie et al., 2000) and more specifically can: reduce aggressive behaviour (Grandin, 1989; Schaefer et al., 1990; Beattie et al., 1996; Melotti et al., 2011; Nowicki and Klocek, 2012); reduce belly nosing (Beattie et al., 1996; Rodarte et al., 2004; Bench and Gonyou, 2006); reduce tail biting (Bøe 1993; Petersen et al., 1995; Van der Weerd et al., 2005; Zonderland et al., 2008); and improve production performance (Beattie et al., 1995; O'Connell and Beattie, 1999; Beattie et al., 2000) and ease of handling (Day et al., 2002) In order to enhance animal welfare on farms the EU Directive 2001/93/EC has provided a minimum standard for the protection of pigs stipulating that: "Pigs must have permanent access to a sufficient quantity of material to enable proper investigation and manipulation activities, such as straw, hay, wood, sawdust, mushroom compost, peat or a mixture of such, which does not compromise the health of the animals." However, some substrates suggested by the Directive 2001/93/EC are impractical for industrial production (Fraser et al., 1991; Van de Weerd et al.,

Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments (2003). For example, large quantities of straw, hay or sawdust in standard pens with partly or fully slatted floors may block the liquid-slurry disposal systems (Van de Weerd and Day, 2009). The effective environmental enrichment provided to the pigs should not only enable the expression of relevant natural behaviours and maintain their interest, but also be practical for the existing farming systems and cost-effective for the farmers. At present, the use of point-source enrichment objects such as chains and wood blocks are a widespread alternative to disposable substrates. Point-source objects are often referred to as 'toys' and generally limited in size. Their use is often restricted to a single location in a pen (Van de Weerd and Day, 2009). Despite many scientific studies on the effect of different types of point-source objects on pigs (e.g. Bracke et al., 2006), it is still not clear which of them is most effective and what type of environmental enrichment is the most attractive to pigs and keeps their interest the longest. The material characteristics of point-source objects play a crucial role in the interest and frequency of pigs' interactions with the object. The objects preferred by weaned and growing pigs have been characterized as 'chewable', 'deformable' and 'destructible' (Grandin, 1989; Feddes and Fraser, 1994; Van de Weerd et al., 2003) which may be linked to engaging in foraging and exploring behaviours. Some authors suggest that the combination of the enrichments are more interesting for pigs (Zonderland et al., 2003; Van de Weerd et al., 2003). It is important that the enrichment provided is able to maintain continuous interest of the animals to minimize the risk of behaviour being redirected towards penmates (e.g. Wood-Gush and Vestergaard, 1991; Fraser et al., 1991; Bolhuis et al., 2005). However, with point-source objects, pigs can become habituated to them within a few days after introduction (Van de Weerd et al., 2003; 2009), indicating that these

enrichments lose novelty and pigs' interest (Nowicki and Klocek, 2012). Understanding how pigs interact with enrichments over time is essential for curbing negative behaviour and promoting positive ones. Using tools to continuously monitor and quantify pig behaviour allows farmers to intervene as suitable. As stated by Cangar et al. (2008), changes in the behaviour of farm animals indicate that human intervention is necessary. The aim of the present study was to evaluate pigs' interest and preference toward two commonly used point-source environmental enrichments (chains and wooden blocks) through monitoring their activity and labelling playing and exploratory behaviours. The methodology to evaluate animal behaviour was developed with an approach of Precision Livestock Farming (PLF). One of the objectives of Precision Livestock Farming (PLF) is to develop on-line tools for monitoring farm animals continuously and automatically during their life. The objective is to measure criteria calculated on-line from collected data without imposing additional stress to the animals. Besides on-line automatic monitoring, PLF also offers possibilities in automatic control for supporting the management of such complex biological production processes (e.g. feeding strategies, growth rate control, activity control) (Morag et al., 2001; Halachmi et al., 2002; Aerts et al., 2003 a, b; Guarino et al., 2004).

3.2. Material and methods

3.2.1. Housing conditions and animals

Experiments were conducted in a swine weaning building located in Pianura Padana, Pavia province, Italy. The building was naturally ventilated, containing six fully-slatted pens (1.90 m × 2.50 m) located in two rows of three on either

Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments

side of an access area 0.80 m wide. Additional lighting over the experimental pens facilitated video recording.

A total of 28 Dalland piglets (14 males and 14 females) aged 30 days and weighing an average of 13 kg were placed as two uniform groups into adjacent pens. The animals were fed ad libitum from a feed trough and water was available from a drinking nipple. No environmental enrichment was provided in the pen before the experiment commenced.

3.2.2. Animal activity monitoring

Pig activity was video recorded continuously using an infrared-sensitive CCD camera (VCB 35721RP, Sanyo Electric Co. Ltd., Osaka, Japan) for 30 days. The camera was mounted to the roof at 3.25 m above the pen's floor. The camera lens was placed directly above the corridor separating the two pens and connected to a PC with built-in frame grabber using the coax connection cable. Images were captured at a resolution of 768 × 586 pixels at a sample rate of 1 Hz. The image analysis software Eyanamic analysed these images simultaneously in real time to create the animals' activity index – a measurement that quantifies the activity of animals in the field conditions inside the barn (Leroy et al., 2006; Bloemen et al., 1997). The activity index is determined by dividing the image of each pen into rectangular zones (Fig. 1) and tallying when pixels change between two consecutive frames within each zone.



Fig. 1: The two observation pens and the division of the images into areas for the activity index calculation

The software acquired a monochrome image $I(x, y, t)$ from the camera and then calculated the difference between its intensity values and of the previous image $I(x, y, t-1)$ taken one second earlier. From this difference image, the binary ‘activity image’ $I_a(x, y, t)$ was calculated by containing the pixels for which the intensity change exceeded a threshold:

$$I_a(x, y, t) = \begin{cases} 1 & \text{if } I(x, y, t) - I(x, y, t-1) > \tau_1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

From the activity image $I_a(x, y, t)$, the activity index $a_i(t)$ for pen (Z_i) was calculated as the fraction of moving pixels with respect to the total number of pixels within the pen Z_i :

$$a_i(t) = \frac{\sum_{(x,y) \in Z_i} I_a(x, y, t)}{\sum_{(x,y) \in Z_i} 1} \quad (2)$$

Labelling the behaviour of piglets and activity monitoring from video as a tool
of assessing interest in different environmental enrichments

The threshold τ_1 accounted for small intensity changes due to noise, such as electrical noise in the coax cabling and image acquisition circuits, and small lighting variations. The lower threshold value was set to 10% of the maximal intensity value as estimated by looking at the intensity variation of an ‘empty’ region outside of the pig pen in the first 60 images (equivalent to one minute of recording).

The upper threshold τ_2 was applied to the activity index $a_i(t)$ to compensate for drastic intensity changes (e.g. when lights were switched on/off). In case of such an event, almost all pixels in the activity image I_a were ‘active’ and the activity index $a_i(t)$ was almost equal to 1 in the two pens. The threshold τ_2 was set to 0.5 of the maximal activity index. If this threshold was exceeded, i.e. more than half of the pen was active, the activity index was set to zero.

The pixel area sums in the nominator and denominator of equation (2) have an accuracy of one pixel which, using the camera calibration factor, was equivalent to an area of 2.9 cm².

3.2.3. Behaviour labelling procedure

On 1st day of video recording the chain and wooden block enrichments, were introduced to the pens at 10:00 AM. The chain was fixed in vertical position at piglet eye level and the wooden block was placed randomly on the pen floor. The environmental enrichments were kept in the pens for 30 days. The videos of Day 1, Day 5 and Day 30 were analysed to determine the level of object-directed behaviour. These days were chosen to test the initial, short and long term interest of the piglets to the selected environmental enrichments.

The recorded videos were analysed by one observer using the software “Labelling Tool” (Viazzi et al., 2011) developed in Matlab (R2009a, The MathWorks Inc., MA).

Chapter 3

The image files were visually checked and manually labelled by observing each frame (one frame per second) when the start of manipulation with the environmental enrichment was detected on the video. The labelling procedure permitted the identification of every playing/exploratory event n during Day 1, Day 5 and the Day 30 of the experiment for 24 hours/day (totaling 144 hours of observations for 2 pens). The observations of video recordings from Day 1 started from the moment when the enrichments were introduced to the pens. On Day 5 and Day 30. The observations started at 08:00 AM in the morning.

The recorded images were calibrated in order to define how many square centimeters in the pen correspond to a pixel. At this stage the camera images were subdivided into two equally-sized observational zones, one per each pen to define zones of interest inside the video. By creating multiple zones it was possible to relate the behaviours to a specific pen. For each zone the activity index was measured from the video and displayed on the Labelling Tool interface in order to speed up the manual labelling process. If the activity was close to zero (the animals were not moving in the particular zone), the observer could leave out these intervals.

For each behaviour pattern the following specific buttons were created: no activity, interacting with chain, interacting with wooden block. Each recorded image (one image per second) was visually checked and manually labelled separately per observation zone according to the chosen behaviours of pigs through playing the video or sliding the images frame by frame. When a specific behaviour was observed in the image the matching button was selected, at the same time the labelled behaviour was displayed on the panel of Labelling Tool containing the list of behaviours. It was possible to press multiple buttons in case different playing/exploratory behaviours occur in the same image. It

Labelling the behaviour of piglets and activity monitoring from video as a tool
of assessing interest in different environmental enrichments
was also possible if the same behaviours take place in consecutive images to
register their start and end by pressing the “record” button.

The labelling procedure facilitated an exact record on the true duration of
exploratory/playing behaviour, frequency and the time at which interactive
episodes with each type of environmental enrichment began and ended.
Interactive episodes were measured as the length of time (sec) from first touch
of environmental enrichment by pig or group of pigs to termination of action
for more than 5 seconds.

3.3. Results

The duration of interaction episodes with both environmental enrichments had a similar trend in both pens. No significant difference in duration was identified; therefore, in this case, both pens were taken as one experimental unit. The mean duration of interaction episodes was significantly greater for the chain than for the wooden block ($P < 0.001$), whereas the frequency of interaction episodes was 28.8% higher for wooden block than for chain (Table 1).

Table 1: Least Square Means of duration (sec), frequency of interaction episodes with two types of environmental enrichments and mean day activity index of weaned piglets.

Enrichment type	Duration		Frequency Interaction		Activity Index
	LSMean \pm SEM				Mean \pm SD
	Chain	Wooden Block	Chain	Wooden Block	
Overall mean	35.45 \pm 6.55 ^A	20.12 \pm 4.93 ^B	241	436.3	0.012 \pm 0.017
Day 1	59.79 \pm 6.45 ^A	36.35 \pm 4.67 ^B	423	663	0.015 \pm 0.019
Day 5	43.06 \pm 6.66 ^a	21.50 \pm 3.85 ^b	298	643	0.013 \pm 0.016
Day 30	3.50 \pm 10	2.50 \pm 4.01	2	3	0.0079 \pm 0.012

(A,B) least means within the same row differ for $P > 0.001$

(a,b) least means within the same row differ for $P > 0.01$

Analysis of the 24-h environmental enrichment use pattern from video records showed that mean duration of interactive episodes with chain as well as with wooden block had already decreased on Day 5 and Day 30, and use had diminished to 2–3 sec with few sporadic interactive episodes (Table 1). A time of day effect was found on interactive episodes (Fig. 2).

Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments

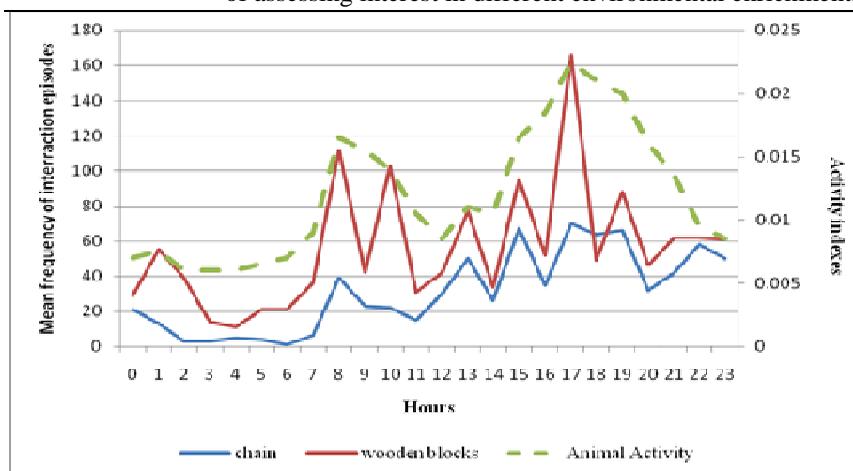


Fig. 2: Effect of time of the day (24 h) on frequency of interaction episodes with different environmental enrichments (chain and wooden block) and animal.

There was a drastic decline of interaction episodes frequency from 02:00 AM. to 07:00 AM, which is expected as the lights were turned off during the night. Activity indexes during this hours showed the lowest values (with a range from 0.005 to 0.008 units). The peaks of activity coincided with the most frequent interactions of piglets with both types of environmental enrichments.

3.4. Discussion

The importance of environmental enrichment material properties is widely shown in literature. According questionnaire done by Bracke *et al.* (2006), the majority of pig welfare scientists believes that a chain is not sufficient enrichment material for pigs. Pigs play with chains but they prefer to play with pliable objects when they are given a choice (Grandin, 1988). However, in this study long interactions with chain were observed, even if they were not as frequent as interactions with wooden block. This could be connected to “flexibility” characteristics of the chain, the position of the chain suspended at eye level. It was found that pigs played more frequently with wooden block but the duration of playing episodes was short. Unfixed environmental enrichments (laying free on the pen floor) were less attractive for the pigs than fixed ones since they become soiled with excreta (Blackshaw *et al.* 1997, Jones *et al.*, 2000, Scott *et al.*, 2009; Nowicki *et al.*, 2007; 2012). However, the destructibility features of wooden block, availability in different locations within the pen and ease to manipulate them could be a reason of increased frequency use. These results suggest that the the material characteristics and the position of the point-source objects are the important factors, influencing on frequency and duration of of pigs’ interactions with them. The combination of the point-sourced environmental enrichments with different characteristics could be an effective solution.

The results of experiment: the duration of interaction episodes with environmental enrichment is remarkably reduced with time is not surprising as it is corresponding with results of other authors (e.g. Van de Weerd *et al.* 2003, Zonderland *et al.* 2003; Trickett *et al.* 2009, Nowicki *et al.*, 2012).

Labelling the behaviour of piglets and activity monitoring from video as a tool of assessing interest in different environmental enrichments

Also the time of the day influenced the frequency of interactions of pigs with environmental enrichments. The activity index showed the hours when the pigs were mostly active during the day and these peaks of activity were corresponding with hours when pigs were interacting most with environmental enrichments. This could be explained by a variety of factors influencing the general distribution of pigs activity during the day such as photoperiod, feed consumption, etc.

3.5. Conclusions

The present experiment was a preliminary study to assess the interest of the pigs to different types of environmental enrichments using the combination of the labelling method and the activity index parameter. This method allowed the specific discrimination of behaviour type and duration in order to accurately quantify the interest pigs show in environmental enrichments.

The results received from this experiment suggest that the chain and the wooden block, often used by the farmers as the low cost enrichments, are not effective for the long term use. In case of short term use it is advisable to combine the point-source enrichment objects with different characteristics to increase the playing time during the day.

In both pens, the number of interaction episodes with environmental enrichments were linked to the activity index, which allowed to determine the diurnal behavioural dynamics of the animals.

Low cost cameras, in combination with image analysis techniques, can be used to quantify animal behaviour (De Wet et al., 2003; Leroy et al., 2004). There is a potential for the development of the algorithm for an automatic control of

Chapter 3

pigs/playing exploration behaviour, basing on the method described in this article.

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Chapter 3

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of assessing interest in different environmental enrichments

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CHAPTER 4

4. Vocalisation sound pattern identification in young broiler chickens

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Abstract

In this study, we describe the monitoring of young broiler chicken vocalisation, with sound recorded and assessed at regular intervals throughout the life of the birds from day 1 to day 38, with a focus on the first week of life. We assess whether there are recognisable, and even predictable, vocalisation patterns based on frequency and sound spectrum analysis, which can be observed in birds at different ages and stages of growth within the relatively short life of the birds in commercial broiler production cycles. The experimental trials were carried out in a farm where the broiler were reared indoor, and audio recording procedures carried out over 38 days. The recordings were made using two microphones connected to a digital recorder, and the sonic data was collected in situations without disturbance of the animals beyond that created by the routine activities of the farmer. Digital files of one hour duration were cut into short files of ten minutes duration, and these sound recordings were analysed and labelled using audio analysis software. Analysis of these short sound files showed that the key vocalisation frequency and patterns changed in relation to increasing age and the weight of the broilers. Statistical analysis showed a significant correlation ($P < 0.001$) between the frequency of vocalisation and the age of the birds. Based on the identification of specific frequencies of the sounds emitted, in relation to age and weight, it is proposed that there is potential for audio monitoring and comparison with 'anticipated' sound patterns to be used to evaluate the status of farmed broiler chicken.

Keywords: acoustic parameters, broiler chicken, welfare assessment, audio labelling, spectrogram

4.1. Implications

The vocalisation sounds in broiler chickens, reared under intensive farm conditions, may have potential to be used as a tool to improve their health and welfare status. Precision Livestock Farming (PLF) develops management tools aimed at continuous automatic monitoring of animal welfare, health, environmental impact and production in real-time. Audio analysis, decision making informed by audio information and prediction and avoidance of health, welfare and disease through use of automated measures in PLF may have the potential to have positive effects on animal health and welfare and consequently on public opinion with regard to maintenance of animal health and welfare in poultry farming systems.

4.2. Introduction

Farming systems for rearing chickens for meat have changed significantly during the last 40 years. Broiler chickens now have a very rapid growth rate, high feed conversion efficiency and high processing yields. Commercial production birds are created through the use of hybrid genotypes (Rizzi et al., 2013); and genetic selection has led to progressively reduced slaughter age and higher final weight (Rauw et al., 1998; Aerts et al., 2003).

The global production of broiler chickens is estimated to be of the order of 61 billion animal slaughtered per year according to FAOSTAT 2015; 70% of world production of broiler chickens is 'industrialised' (Steinfeld et al., 2006; Tefera, 2012), that is, reared in closed housing systems provided with artificial lighting and under a timed lighting programme (Appleby et al., 1992; Weeks and Butterworth, 2004). Chicken health, welfare and growth performance is dependent on human management, environmental management, genetics, nutritional and disease factors (Yahav et al., 2005; Buijs et al., 2009; Kenny et

al., 2012). Progress has been made in the last 10 years to develop indices and potential on-farm measures of animal welfare, for example the AWIN (2015) and Welfare Quality (2009) protocols. It is apparent that no one single measure suffices animal health and welfare and is currently common to use a number of different indicators of health, welfare, and animal experience to provide a holistic assessment of animal welfare (de Jong et al., 2012). Assessment of animal behaviours may be one of the measures used in these multi aspect assessments of welfare. Assessment of behaviours may provide indirect evidence of how an animal 'feels' (Dawkins, 2004). Animals use vocalisations to express different conditions such as: warning, alarm, social contact, territorial, laying, nesting, mating, threat, submissive, distress, fear, contentment, food, dust bathing, perching, battle cries, privacy, dominance and time calls (Manteuffel et al., 2004; Tefera, 2012; Vandermeulen et al., 2015). One of the potential ways to assess an animal's health and welfare status is the analysis of audio and video to identify behaviours, vocal and other sound producing behaviours.

Hearing is an important sense for birds; they are sensitive to a frequency range of about 60 to 11950 Hz (Appleby et al., 1992; Tefera, 2012).

In the wild, chicks which have just hatched are able to identify their mother and their siblings (Appleby et al., 1992; Nakamori et al., 2013); one day old chicks can recognise and discriminate maternal vocalisations from sounds emitted by other conspecifics (Ferrante and Lolli, 2009; Tefera, 2012). Social behaviour is the behaviour displayed by animals in relation to other animals, and social interaction in chicks is likely to be important for group development. The first days of a chick's life are likely to be an important period for the development and the acquisition of a correct behavioural pattern (Ferrante and Lolli, 2009). Vocalisation is strongly dependent on social context in chicks; they vocalise at

the very beginning of their life in the hatchery, and there is evidence that this vocalisation (from within the egg) is linked to acceleration of the physical development of other chicks, in order to synchronise hatching (Ferrante and Lolli, 2009).

Principal objectives of Precision Livestock Farming (PLF) include the development of automatic on-line monitoring tools (Guarino et al., 2008) to monitor animals' behaviours and their biological responses to external stimuli such as changes in house environment conditions, or to occurrence of disease (Tefera, 2012). The analysis of images and sound, can be carried out in comparatively non-invasive ways using PLF methods, and, when compared to direct human visual observation, may be less time consuming (Aydin et al., 2014; Fontana et al., 2014). Camera and microphone systems could result in innovative ways to monitor farm animals, and may eventually become quite low in cost as the trend is for electronic devices to become more cost effective with time. Automated animal monitoring with images or sounds could potentially be used to support farmers in achieving farm production, and animal health and welfare goals (Costa et al., 2013) and have potential for wide application in animal husbandry (Halachmi *et al.*, 2002; Ismayilova et al., 2013). The PLF approach has potential to be applied at different scales, from the individual animal, to the entire flock/herd, and to assess environmental and animal health, welfare and management (Wathes et al., 2009).

A potential added value of PLF may be the capability to provide 'prediction' (such as health and welfare status, production, growth trend); integrated systems might help the farmer in taking positive action in response to warnings. Monitoring equipment (cameras, microphone, feed and water monitors, environment monitors) associated with predictive algorithms could be part of a management tool used by the producer to detect, and improve, health and

welfare issues. In this study, sound analysis techniques are explored as a PLF application, (Manteuffel et al., 2004; De Moura et al., 2008) and are used to measure and analyse animal sounds in order to discriminate and classify specific vocalisation in poultry houses. The objectives of this study were a) the identification and characterisation of vocalisations emitted by chicks during their first five days of life under normal farm conditions; b) examination of the possible connections between specific individual sounds and social behaviours and c) characterisation of possible vocalisation changes in terms of frequency and type of sound emitted with increasing age.

4.3. Material and methods

Two experimental trials were carried out at an indoor reared broiler farm; the first took place in June and July 2013 (trial 1) and the second in August and September 2013 (trial 2). The farm where the experimental trials took place was an indoor broiler farm rearing birds to the UK Red Tractor Farm Assured (ACP) standard. The house dimensions were 61 x 21 m and the total floor area available to the birds was 1130 m². Inside the house 2340 nipple drinkers and 385 feed pans were available to the birds, and 27940 one day old chicks were placed in the house in both trials.

Animal sounds were recorded for one hour, at intervals of two days, from day 1 to day 38 of the chick's life (from the beginning to the end of the cycle of production), using a handheld solid state audio recorder Marantz PMD 661 MK II (Hampshire, UK). The device was connected to two directional microphones placed at a variable height of between 0.4 and 0.8 m (depending on the height of the animals during growth in order to keep the same distance - ~0.3 m - between the animals and the microphones throughout the data-collection process). Recordings were made with the same positioning of the microphones

in both trials. The Marantz PMD 661 MK II recorder has a large range of potential recording settings. The settings found to give the most sensitivity to bird sounds in the poultry house environment were: Rec. Format: PCM-16, Stereo Sample Rate: 44.1k; Level Control: Manual; Low Cut: Off; High Cut: Off

Microphone 1 (MIC 1) was a supercardioid/lobe microphone Sennheiser K6/ME66, (frequency response: 40 to 20000Hz \pm 2.5 dB; Sennheiser Electronic Corporation, USA) and this was supported on a short tripod microphone stand Quiklok A341 (U.S. Music Corp., Buffalo Grove, US) above the feeder. Microphone 2 (MIC 2) was a more diffusely focussed Sennheiser K6 / ME64; (frequency response: 40 to 20,000Hz \pm 2.5 dB; Sennheiser Electronic Corporation, USA) and was placed on a long tripod arm, Quiklok A492 Heavy-Duty Boom Mic Stand, (U.S. Music Corp., Buffalo Grove, US) directly above the drinkers. Both the microphones were slightly inclined toward the floor in order to capture preferentially the sounds coming from birds in front of the microphone axis. The recordings provided both a localised sound picture (MIC 1) and a more generalised sound including background noise (MIC 2), and this combination of microphones was found to provide the best results in capturing sounds within the broiler house where the chicks tended to cluster "in groups" classified as House Sounds (HS). At the same time as the sound recordings were being made, video recordings were acquired by placing a digital video camera on a low-level tripod focussed on the area where the birds were most active and in the locality of the microphones. After each period of continuous recording, three chicks, chosen at random, were moved into an enclosed 'shielded recording area' (30 cm high box with an area of 0.8 m²), in order to collect individual bird sounds of "isolated" chicks by shielding the microphone from background environmental noise. The chicks were individually placed

into the separation box at times 0 (chick 1), 1 min later (chick 2) and 2 min later (chick 3); 5 minutes of recording box sounds, (BS) were initiated when the first chick was placed in the box. Simultaneously with the BS audio recordings video recordings were made, positioning the video of the chicks inside the box, and also of chicks in the area just outside the box. After five minutes of recording, the barrier was removed and the chicks were returned to the flock. The final sound ‘library’ consisted of 27 h 24 min of sound recordings for trial 1 and 27 h 56 min of sound recordings for trial 2. It was decided to analyse and manually label the vocalisations recorded with MIC 1 (bird focussed) due to the higher quality of the sounds compared to the ones recorded with MIC 2 (background focussed). In this study, the sounds (HS and BS) recorded during Day 1 and Day 5 in both trials have been analysed. Day 1 and Day 5 were chosen in order to provide a time interval appropriate to examine the difference of the sounds emitted within the first week of the birds life.

4.3.1. Sound and image analysis

Sound recordings were manually analysed offline and labelled using sound analysis software: Adobe® Audition™ CS6. Sound labelling involved the extraction and classification of both individual ‘isolated’ animal sounds (BS) and general sounds coming from the whole flock (HS). Analysis examined amplitude and frequency of the sound signals in audio files, each file being manually labelled using a procedure based on acoustic analysis combined with visual spectral analysis, used to extract recognisably distinct and characteristic sound patterns from the entire recording file.

Every hour long digital recording was cut in shorter labelled files of 10 minutes duration in order to facilitate the sound analysis and the labelling procedure.

Chapter 4

The sound analysis was divided into two different phases. Firstly, the file was examined (listened to with high frequency response headphones) in its entirety in order to recognise the regions of the recording with the clearest sounds. During the ‘listen through’, the regions of the recording with the clearest sounds were then digitally marked (flagged) in order to classify different types of sound. The methodology for the labelling procedure and the sound analysis is that described by Marx *et al.* (2001).

The labelling procedure was carried out offline, identifying those sounds that the operator classified as significant vocalisation sounds through the combination of auditive analysis (listening with headphones) and the visual observation of the spectrogram of the sounds corresponding to each sound ‘group’ (Ferrari *et al.*, 2008). Through Adobe® Audition™ CS6, a number of discrete sound ‘groups’ were identified and analysed using time (x-axis) and frequency (y-axis) for further statistical comparisons. A Fast Fourier Transform (FFT) was used to perform the frequency analyses using a Hamming window with a FFT dimension of 256 (Fig. 1).

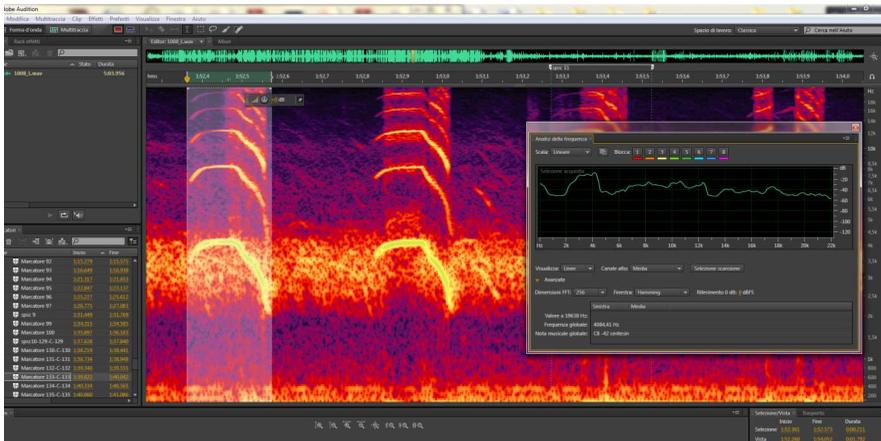


Fig. 1 Screenshot of Adobe® Audition™ CS6 software. Spectrograms and frequency analysis of an extracted sound.

Figure 1 shows the spectrogram of a labelled vocalisation. The time is reported on the x-axis and the frequency on the y-axis. Bright areas indicate sounds with high energy. The small box on the right shows the frequency analysis of the marked sound on the left.

The mean duration, the mean interval and the number of repetitions of each kind of vocalisation were collected. For both HS and BS, the peak frequency (PF = representing the frequency of maximum power) was manually extracted. The frequency range was band pass filtered between 1000 and 13000 Hz. The lower frequency limit was set at 1000 Hz to remove the low frequency background noise and the upper limit was set at 13000 Hz to cut off high frequency noise and also because broilers are sensitive to a frequency range of about 60 to 11950 (Appleby et al., 1992; Tefera, 2012).

Video and sound recordings were synchronised during the labelling procedure in order to link the behaviours to the sounds emitted by the animals.

4.3.2. Statistical analysis

Statistical analysis was performed using statistical software SAS 9.3. The difference in PF of HS and BS recorded during Day 1 and Day 5 were tested using a paired t-test in order to evaluate whether there were statistically significant changes in vocalisation PF related to different days and situations (isolated/in group).

Paired sample t-tests were made to compare the PF of vocalisations emitted by the chicks in six specific situations:

- a) BS collected in Day 1 and in Day 5 (BS1-BS5)
- b) HS collected in Day 1 and in Day 5 (HS1-HS5)
- c) BS and HS collected in Day 1 (BS1-HS1)

- d) BS and HS collected in Day 5 (BS5-HS5)
- e) BS collected in Day 1 and HS collected in Day 5 (BS1-HS5)
- f) BS collected in Day 5 and HS collected in Day 1 (BS5-HS1)

Statistical analysis of sounds was performed using the clearest vocalisations (the loudest, the 'clearest', and with the highest energy) found during the labelling procedure of recordings made on Day 1 and Day 5. The final dataset consisted of 60 BS (isolated chicks) sound files, and 136 sound files from HS.

The correlations between BS and HS were evaluated to identify whether chicks emitted specific sounds on a specific day (1 or 5) or specific sounds during a stress situation (isolated or in group). A further comparison among the different BS sounds was first performed analysing the spectrogram of each sounds (visual analysis) and then using the PDIFF (differences between least squares means) option in the GLM procedure of SAS to verify their similarity/dissimilarity (SAS User's Guide, 2010).

The differences between the PF of the vocalisations emitted by the birds were tested using the proc TTEST (SAS 9.3). The T-test and the PROC LOGISTIC (SAS 9.3) were also used to explore potential associations between the isolation sounds (BS) and the vocal behaviour of the chicks outside the box in response to the vocalisations of chicks within the box. The Contrast statement in PROC LOGISTIC was used to determine which isolation BS sounds had most affect on the response of the chicks outside the box.

Logistic regression was considered an appropriate analysis, because the chicks' response in this study consisted of dichotomous, categorical variables, for example, presence or absence around the box. It should also be noted that logistic regression makes no assumption about the distribution (normal or otherwise) or the equality of variances within each group of independent

variables. The results from the logistic regression are presented as odds ratios (OR) for the predictors. The P - values were calculated based on Wald χ^2 and 95% Wald confidence limits were used.

4.4. Results and Discussion

During the analysis of BS, 12 discrete and frequent types of vocalisations sounds were audio and visually identified and labelled as A, B, C, D, E, F, G, H, I, J, K, L. Sounds were grouped based on the frequency analysis that permitted differentiation between similar sounds. Eight types of BS with markers from A to H (Fig. 2) were found only during the first day of recording (Day 1), whilst four types of BS marked from I to L (Fig. 3) were found only during the fifth day of chicks' life (Day 5).

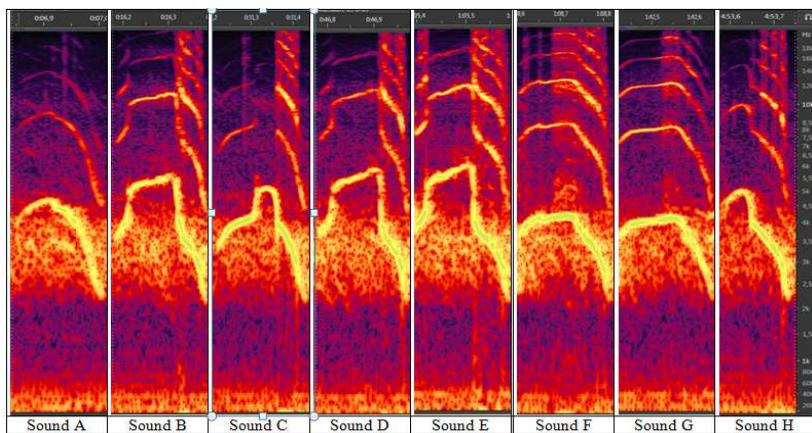


Fig. 2 Screenshot of the Adobe® Audition™. Spectrograms of the eight types of sounds recognised with the manual labelling of sounds collected during Day 1 of recordings.

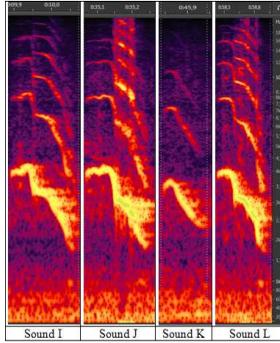


Fig. 3 Screenshot of the Adobe[®] Audition[™]. Spectrograms of the four types of sounds recognised with the manual labelling of sounds collected during Day 5 of recordings.

This led us to consider that the pattern of vocalisations changes with increasing age of the birds. The duration, the number of repetitions and the PF of each kind of BS are reported in Table 1.

Table 1 Mean duration, number of repetitions and peak frequencies (PF) ranges of the 12 different types of vocalisation sounds emitted by isolated broiler chicks collected in Day 1 and Day 5.

Vocalisation ¹	Day of recording	Mean duration (s) ²	N of repetitions	Range of PF (Hz) ³
A	1	00:00.205	14	3445-3962
B	1	00:00.214	31	3101-3618
C	1	00:00.214	9	3445-3962
D	1	00:00.210	31	3445-3618
E	1	00:00.222	26	3445-3790
F	1	00:00.223	7	4134-4307
G	1	00:00.222	11	3962-4134
H	1	00:00.176	8	3273-3790
I	5	00:00.199	78	2929-3273
J	5	00:00.209	7	2929-3273
K	5	00:00.123	7	2756-3273
L	5	00:00.180	6	2929-3273

¹ Type of vocalisation emitted by isolated broiler chicks.

² Mean duration (s) of each kind of vocalisation.

³ Range of frequency associated to the highest level of energy of each sound.

Vocalisation sound pattern identification in young broiler chickens

The frequency of sounds emitted during Day 1 was higher than the ones emitted by five day old chicks.

Table 2 Mean, standard deviation, minimum and maximum value of the Peak Frequency (Hz) of vocalisations emitted by broiler chicks.

Sounds	N	Mean (Hz)	s.d. ⁵ (Hz)	Minimum (Hz)	Maximum (Hz)
BS1 ¹	40	3717	336	3187	4393
BS5 ²	20	3075	188	2670	3531
HS1 ³	68	3613	415	2670	5426
HS5 ⁴	68	3162	395	2498	4393

¹BS1: Sounds emitted by the isolated broiler chicks on Day 1

²BS5: Sounds emitted by the isolated broiler chicks on Day 5

³HS1: Sounds emitted by the broiler chicks in the house on Day 1

⁴HS5: Sounds emitted by the broiler chicks in the house on Day 5

⁵Standard deviation

The PF of the sounds emitted by the birds decrease by about 500 Hz in five days (Table 2) showing a significant difference ($P < 0.001$) among sounds emitted by the animals during Day 1 and Day 5 (Table 3), while no significant differences were found between PF recorded during the same day.

Table 3 Statistical difference in Peak Frequency (Hz), among sounds emitted by broiler chicks, in both isolated and in group situations.

Comparison ¹	Mean	s.d. ⁴	95% CI		t-value	d.f.	P-value
			lower	upper			
BS ² 1-BS5	525.4	332.9	369.6	681.2	7.0	19	<0.001
HS ³ 1-HS5	450.9	584.8	309.4	592.5	6.3	67	<0.001
BS1-HS1	81.8	562.6	-98.1	261.8	0.9	39	0.363
BS5-HS5	60.2	322.4	-90.5	211.2	0.8	19	0.413
BS1-HS5	620.2	536.0	448.7	791.6	7.3	39	<0.001
BS5-HS1	534.0	538.7	281.9	786.1	4.4	19	<0.01

95% CI = 95% confidence interval; BS1 = sounds emitted by the isolated broiler chicks on Day 1; BS5 = sounds emitted by the isolated broiler chicks on Day 5; HS1 = sounds emitted by the broiler chicks in the house on Day 1; HS5 = sounds emitted by the broiler chicks in the house on Day 5.

¹ Paired sample t-tests were made to compare the peak frequency of vocalisations emitted by the chicks in six specific situations.

² Sounds emitted by isolated chicks inside the box; 1 and 5 are referred to the day of recordings.

³ Sounds emitted by chicks in group; 1 and 5 are referred to the day of recordings.

⁴ Standard deviation.

The correlations between BS and HS (table not shown) were evaluated to verify if the chicks create specific sounds (A to L) on a specific day (1 or 5) or during a stress situation (isolated or 'in a group'). A significant positive correlation was found between sounds emitted during the same day (Day 1 and Day 5) of recordings (BS1-HS1; average $r > 0.75$; $P < 0.001$; BS5-HS5; average $r > 0.70$; $P < 0.001$), while sounds collected during different days of recordings had low correlation (BS1-BS5; average $r < 0.50$; $P < 0.001$; HS1-HS5; $r < 0.50$; $P < 0.001$). The low correlations within BS and HS collected on different days of recording (Day 1 and Day 5), may also explain the reduced correlation between BS1 and HS5 and BS5 and HS1 ($P < 0.001$). Video analysis showed that, during the recording procedure of BS1, there were a large number of chicks around the box responding to the vocalisations emitted by the animals inside. The same video recording procedure was adopted during Day 5; in this case, chicks outside the box did not respond in such a clear and apparently coordinated way to the vocalisations emitted by the animals inside the box (BS5).

As soon as the first chick was moved into the enclosed box, the vocalisations immediately increased in repetition rate, both inside and outside the box, showing that social isolation in chicks led to an increase in rate of vocalisation. Indeed, when other chicks were introduced into the box, the vocalisation sounds were less frequently emitted by the animals. These findings are consistent with studies on social-separation stress effects on vocalisation (Montevecchi et al., 1973; Marx et al., 2001; Feltenstein et al., 2002). These authors classified these particular vocalisations as sounds induced by stress situations such as social isolation, and they defined them as distress calls.

As reported by Marx et al. (2001) the occurrence of distress calls is higher when a group of isolated chicks is smaller than three animals. The presence of

chicks around the box during Day 1 led to surmise that BS emitted by one-day-old chick were more likely to be classifiable as calling sounds towards conspecifics. Whereas, BS emitted by five days old chicks were more likely to be classified as distress calls resulting from social isolation.

This proposed classification of calling and distress vocalisation may also be supported by the low correlation obtained within BS and HS recorded in different days (Day 1 and Day 5). The 0.70 and 0.75 correlation coefficients obtained for sounds emitted during the same day (Day 1 and Day 5, respectively) indicate that, the sounds had a typical PF in relation to the age of the birds. Moreover, isolation from the flock strongly affected the nature of vocalisations emitted by chicks inside the box; these findings support those made by Montevicchi et al. (1973) and Feltenstein et al. (2002). By analysing the correlation table and the spectrogram of each sounds it was seen that, based on the frequency level, some sounds were more similar than others. For this reason, 12 types of vocalisations sounds were compared using PDIFF option to verify their similarity and dissimilarity. No significant frequency pattern difference was found between sounds B and D, B and E, A and H, J and I, I and L (data not shown) confirming what emerged from the spectral analysis and correlations.

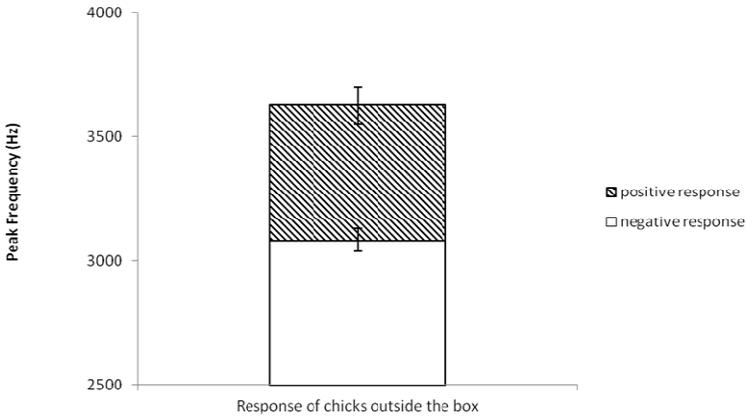


Fig. 4 Stacked histogram of the response of the chicks outside the box in relation to Peak Frequency of vocalisations emitted by isolated chicks ($P < 0.01$). The positive response is represented by the dotted part. Error bars represent s.e.

The histogram shown in Figure 4 indicates the difference in the response of the chicks outside the box in relation to the PF level of vocalisations emitted by isolated chicks. The y-axis (Fig. 4) indicates the PF of the vocalisation (Hz) emitted by isolated chicks. The white area represents the absence of chicks around the box while the isolated chicks were vocalising (negative response). The positive response (dotted area), represents the presence of chicks outside the box when the isolated chicks were vocalising. Both responses were a function of PF of the vocalisation emitted, and it is noted that chicks outside the box reacted more to high frequency vocalisations emitted by isolated chicks during Day 1 than during Day 5. This response is probably linked to the combination of two different key factors: 1) the frequency of the sounds and 2) the specific ‘meaning’ of the vocalisations created.

Vocalisation sound pattern identification in young broiler chickens

Table 4 Results from the logistic regression on the risk of a positive response of chicks outside the box, in relation to Peak Frequency (Hz) of vocalisation emitted by isolated chicks.

Variable	<i>b</i>	s.e. ²	Wald χ^2	OR	Wald 95% CI
Intercept	-39.415	10.519	14.041		
PF ¹	0.012	0.003	14.103	1.012	1.006-1.019

¹ Peak Frequency of the sounds emitted by the broiler chicks

² Standard error.

Indeed, chicks appear to have been more likely to respond to "calling sounds" of the type typically emitted by very young isolated chicks (OR = 1.012; Wald CL 95% = 1.006 to 1.019) reinforcing the proposition that this kind of vocalisation acts in social interaction signalling (Marx et al., 2001). Furthermore, the reduced response to BS at Day 5 (when the group structure has been already established) led us to classify these sounds as "distress sounds", as reported by (Marx et al., 2001; Feltenstein et al., 2002) (Table 4).

Table 5 Results from the logistic regression on the risk of a positive response of chicks outside the box, in relation to changes in Peak Frequency (Hz) of vocalisation emitted by isolated chicks.

Peak Frequency (Hz)	Estimate	SE ¹	95% CI		wald χ^2	P-value
			Lower	Upper		
3000	0.037	0.036	0.005	0.221	10.17	<0.001
3200	0.298	0.120	0.120	0.567	2.22	ns
3400	0.825	0.095	0.563	0.945	5.51	<0.05
3600	0.981	0.021	0.841	0.998	11.49	<0.001
3800	0.998	0.003	0.948	0.999	13.01	<0.001
4000	1.000	0.001	0.983	1.000	13.54	<0.001
4200	1.000	0.001	0.994	1.000	13.77	<0.001

¹ Standard deviation

95% CI = 95 % confidence interval

According to the results reported in Table 5 the probability of a positive behavioural response of the chicks outside the box is 0.037 when the PF is 3000 Hz but it rises to 0.82 when the PF reaches 3400 Hz (P<0.001). When the PF is

3600 Hz the probability of a positive response of the chicks outside the box is higher than 0.98 ($P < 0.001$). These findings are consistent with the findings of Montecchi et al. (1973), Marx et al. (2002) and Feltenstein et al., 2002 in which the important effect of social isolation on vocalisation emitted by chicks is described.

4.5. Conclusions

The behaviour of chicks around the isolation box, apparently responding to the sounds of isolated chicks is more readily identified in younger chicks and less in older birds. The presence of the birds around the enclosed box leads us to surmise that the sounds emitted by one-day-old chicks isolated from the group were mostly classifiable as “calling sounds” directed towards their conspecifics; whereas sounds emitted by five day old chicks might be better classified as “distress calls” due to social (and physical) isolation. The results of the present study led us to conclude that "calling sounds" are vocalisations emitted by very young chicks during the imprinting phase (first two days of life), when birds usually learn fundamental behaviours related to social interaction and vocal communication.

The results also shown that the peak frequency of the sounds emitted by the birds is inversely proportional to the age and the weight of the broilers; specifically, the more they grew, the lower the frequency of the sounds emitted by the animals.

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CHAPTER 5

5. An innovative approach to predict the growth in intensive poultry farming

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Abstract

Chicken weight provides information about growth and feed conversion of the flock in order to identify deviations from the expected homogeneous growth trend of the birds. This paper proposes a novel method to automatically measure the growth rate of broiler chickens by sound analysis.

Through the application of process engineering, Precision Livestock Farming (PLF) can combine audio and video information into on-line automated tools that can be used to control, monitor and model the behaviour, health and production of animals and their biological response.

The aim of this study was to record and analyse broiler vocalisations under normal farm conditions, to identify the relation between animal sounds and their weight. Recordings were made at regular intervals, during the entire life of birds, in order to evaluate the variation of frequency and bandwidth of the sounds emitted by the animals.

Two experimental trials were carried out in an indoor reared broiler farm; the audio recording procedures lasted for 38 days. The recordings were made, in an automated, non-invasive and non-intrusive way and without disturbing the animals in to the broiler house. Once a week, 50 birds were selected at random and their weight recorded in order to follow the growth trend in the birds.

Sound recordings were manually analysed and labelled using the Adobe® Audition™ CS6 software.

Analysing the sounds recorded, it was possible to find a significant correlation ($P < 0.001$) between the frequencies of the vocalisations recorded and the weight of the broilers.

The results explained how the frequency of the sounds emitted by the animals was inversely proportional to the age and to the weight of the broilers; the more they grow, the lower the frequency of the sounds emitted by the animals.

This preliminary study, conducted in an indoor reared broiler farm, shows how this method based on the identification of specific frequencies of the sounds, linked to the age and to the weight of the birds, might be used as an early warning method/system to evaluate the health and welfare status of the animals at farm level. This is the basis for a further development of an automated growth monitoring tool.

Keywords: broiler, vocalisation, PLF, grow trend, frequency analysis

5.1. Introduction

The demand for meat is rapidly growing all over the world (Tullo et al., 2013) and poultry is one of the cheapest sources of animal protein. Currently, more than 50 billion chickens are produced every year by specialised industries according to FAOSTAT (2015).

Broilers are the fastest-growing farmed species and their performance is influenced by adequate environmental conditions such as environmental temperature, relative humidity, air and litter quality, and ventilation speed. Thank to the progress in farming technologies, broiler chickens now mature at a higher rate than in the past, have higher feed conversion efficiency, a reduced slaughter age and a higher final weight (Aerts et al., 2003; Rauw et al., 1998).

Chicken weight provides information about the growth and the feed conversion efficiency of the flock. Nowadays, the weight of the birds is automatically collected by a single solid “step on scale” placed on the floor of the house. The high numbers of animals inside the flock and the insufficient funds of scales make impossible to collect the weight of all flock. Manually measure the weight of a significant number of animals requires manpower and deprives the farmer of useful time. Due to this, it might be useful to automatically collect simultaneously information about the growth trend of all the birds inside the flock to identify deviations from the expected homogeneous growth trend of the birds (Fontana et al., 2014; Mollah et al., 2010), having also details about the health and welfare status of the animals.

Since the animal health strongly depends on good welfare, during the last years many progresses have been made in developing new indices/indexes and procedures to assess animal's health and welfare status (Fontana et al., 2015). Nevertheless, these monitoring procedures are time consuming and require

trained manpower (Aydin et al., 2014). For this reason, one possible way to make animal welfare assessment easier and faster could be the application of audio and video data analysis (Ferrari et al., 2013; Tefera, 2012; Tullo et al., 2013).

Image analysis, in particular, was successfully used to estimate the body weight of the animals (Mollah et al., 2010), while audio analysis have been widely used to better identify specific behaviours and vocalisation patterns in different animals' species (Chan et al., 2011; Vandermeulen et al., 2013).

Animals use vocalisation to express different inner states provoked either by internal or external events, and also to reveal some of their behavioural needs (Aydin et al., 2014; Vandermeulen et al., 2015). For instance, chicken broiler vocalisations have been studied (Feltenstein et al., 2002; Marx et al., 2001; Montevecchi et al., 1973) to better understand the vocal pattern of this species in relation to environmental temperatures and stress situations (e.g. high/low temperatures). Moreover, information technologies have been used to monitor feed intake, body weight and growth trend (Aydin et al., 2014).

The non-invasive nature of the audio and video equipment allows its use in long term monitoring of animals, without disturbing them (Aydin et al., 2013; Fontana et al., 2015).

The combination of audio and video information into automated tools could be used in early warning systems to detect health or welfare problems (Precision Livestock Farming-PLF) (Costa et al., 2013). PLF develops on-line tools to continuously and automatically monitor farm animals (Viazzi et al., 2011) during their life, without imposing additional stress to them. The PLF approach can be applied to different aspects of management, with a focus on the animals and/or on the environment, and at different scales, from the individual to the entire flock/herd (Wathes, 2009). Moreover, PLF may also be used to aid the

An innovative approach to predict the growth in intensive poultry farming management of some complex biological production processes, to measure the growth trend and to monitor the animal activity (Halachmi et al., 2002; Ismayilova et al., 2013; Tullo et al., 2013).

The aim of this study was to record and analyse broiler vocalisations under normal farm conditions, to identify the relation between animal sounds and their weight. The relation between Peak Frequency (PF) of sounds emitted by broiler chickens during the production cycle and their weights (both measured with an automated and a manual scale) were investigated.

5.2. Material and methods

Two experimental trials were carried out in an indoor reared broiler farm located in the UK; the first one took place in June and July 2013 and the second one in August and September 2013.

The farm where the experimental trials took place was an indoor broiler farm rearing birds to the Right to Farm Act (RTFA) Assured Chicken Production (ACP) standard. The house dimensions were 61m x 21m; broilers are kept indoors and the stocking density allowance is less than 38kg/m² for the entire production cycle. Inside the house there were 2,340 nipples drinkers and 385 feed pans available to birds. 27,940 COBB 500 chicks, of one day old, were placed inside the house at day 1 (after hatching) in both trials.

Sound recordings were collected using a professional handheld solid state recorder (Marantz PMD 661 MK II) which was connected to two different directional microphones placed at an intermediate height of between 0.4m and 0.8m (depending on the height/age of the animals in order to keep the same distance among animals and microphones during the entire data-collecting procedure).

Chapter 5

The supercardioid/lobe microphone (Mic. 1) was a Sennheiser K6/ME66" (frequency response: 40-20,000 Hz \pm 2,5 dB) and it was held by a short tripod microphone stand (Quiklok A341) above the feeder.

The (cardioid) microphone (Mic. 2) was a Sennheiser K6/ME64" (frequency response: 40-20,000Hz \pm 2,5 dB) and it was placed on a long tripod (Quiklok A492 Heavy-Duty Boom Mic Stand) directly above the drinkers.

Both the microphones were slightly inclined toward the floor in order to capture preferentially the sounds coming from the birds walking exactly in front of the microphone axis.

The recordings provided a sound image of background noise, and gave a better idea of the overall condition inside the broiler house.

The Marantz PMD 661 MK II recording machine had a large range of potential recording settings. The settings found to give the most sensitivity to bird sounds in the poultry house environment were:

Rec. Format: PCM-16, Stereo Sample Rate: 44.1k

Level Control: Manual Low Cut: Off High Cut: Off

Animal sounds were recorded from day 1 to day 38 of the cycle production during each experimental trial.

Recordings were made for one continuous hour, using two different microphones, at regular intervals every Monday, Wednesday and Friday, with the same position of the equipment along the trial procedures. After the placement of the equipment, the operator used to leave the broiler house in order to not disturb and influence the animals behaviour. The equipment used for the recordings was taken down after each recording session and replaced before the following session. Recordings lasted for one hour in order to have enough audio data to be analysed. The time interval for the recordings was chosen at random in order to increase the variability of the samples collected.

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Once a week, 50 birds were selected at random and they were manually weighted through using a manual scale in order to follow the growth changes in the birds. Throughout the production period from day 1 to day 38 house temperature and humidity levels were recorded.

The entire data collection consisted in 16 days of sound recordings for trial 1, 15 days of sound recordings for trial 2, and 6 weekly weight collections for both trials.

In total 55 h 20 min of recordings were collected and 600 birds were weighted during trial 1 and trial 2; only the audio files recorded in conjunction with the weight collection of the birds were included in the data analysis.

In total 600 sounds (50 sounds per day), chosen at random and selected from 12 days of recordings were manually labelled and analysed in this study.

5.2.1. Sound analysis

Sound recordings were manually analysed and labelled using sound analysis software: Adobe® Audition™ CS6. The first five minutes of recordings were not taken into account during the sound analysis because the behaviour of the animals might have been influenced by the operator during the setup of the equipment used to make the recordings. Every hour-long duration recorded digital file was cut into shorter files of 10 minutes each in order to simplify the sound analysis.

Sound labelling involved the extraction and classification of both individual animal sounds and general sounds coming from the whole flock on the basis of the amplitude and frequency of the sound signal in audio files recorded at farm level (Tullo et al., 2013).

Labelling is a manual procedure based on acoustic analysis combined with visual spectral analysis, which is used to extract fragments of sounds from the

entire recording. The labelling procedure was done offline (after the sound recordings procedure) by selecting and extrapolating those sounds that the operator classified as usefull vocalisation sounds (loud and clear enough to be labelled) *via* auditive analysis and visual observation of the spectrogram (Ferrari et al., 2008).

Through Adobe® Audition™ CS6 each sounds were identified and analysed using time (x-axis) and frequency (y-axis).

The Fast Fourier Transform (FFT) was used to perform the frequency analyses using a Hamming window with a FFT dimension of 256 sampled points (Fig. 1).

For each sound the peak frequency (PF= representing the frequency of maximum power) was manually extracted. The frequency range was band pass filtered between 1,000 Hz to 13,000 Hz. The lower frequency limit was set at 1,000 Hz to remove the low frequency background noise and the upper limit was set at 13,000 Hz to cut off the high frequency noise and also because broilers are sensitive to a frequency range of about 60 - 11,950 (Appleby et al., 1992; Tefera, 2012).

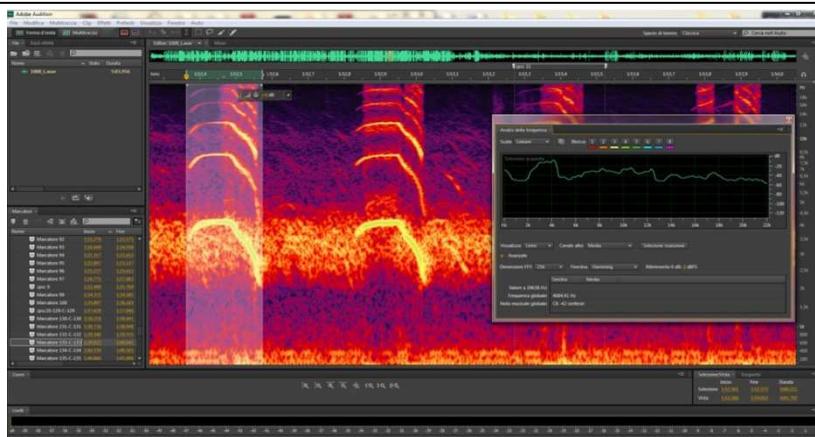


Fig. 1. Screenshot of the Adobe® Audition™ software showing the spectrograms and the frequency analysis window relative to a specific vocalisation. In the main window the time-frequency vocalisation graph is shown, while the inset represents the frequency analysis.

5.2.2. Statistical analysis

The differences among PF extracted from the 600 sounds recorded in the two trials were tested with the PROC TTEST of SAS 9.3 in order to verify the possibility to model the PF of the sound emitted in the two trials as a function of the age of the broilers. A paired t-test was performed to compare PF of sounds recorded at different birds' ages within the same trial. The t-test is commonly used to compare vocalisations in farm animals (Manteuffel et al., 2004), and in this case, the paired t-test was used to compare dependent variables, such as the sounds recorded in two trials of/in the same farm (McDonald, 2009). The correlation among the PF of the sound emitted, the age and the weight of the birds was also investigated with PROC CORR in SAS

9.3. The PROC REG was used to predict variation in the PF according to the change of age of the birds (in weeks).

The estimation of effects influencing the PF was performed with the GLM procedure in SAS 9.3 using a fixed effect (weight*age) divided in 12 classes (Table 1), since in trial 1 the weight of the birds were manually measured during days 1, 8, 15, 22, 29 and 36 while in trial 2 during days 1, 9, 16, 23, 30 and 37.

The division in classes allowed avoiding the nesting effect due to the strict relation between weight and age but taking into account that the weight of birds were collected in different days in the two trials.

Table 6. Description of the fixed effect Weight*age used in the GLM model. The 12 classes, are the result of the interaction (pairing) of the age with the average weight of the birds.

Weight (g)	Age (d)	Trial	Weight*age
40.72	1	1	1
44.56	1	2	2
198.64	8	1	3
231.42	9	2	4
550.30	15	1	5
608.66	16	2	6
1039.46	22	1	7
1092.84	23	2	8
1529.00	29	1	9
1731.60	30	2	10
2104.28	36	1	11
2275.44	37	2	12

5.3. Results and discussion

For each sound the frequency analysis was carried out, in order to extract the peak frequency of each vocalisation. The mean weights collected during both trials agree with the growth trend of this breed found in literature (Aviagen, 2012).

Table 2 shows the means and standard deviations of the peak frequency (PF) of sounds recorded in trial 1 and trial 2.

Table 7. 50 Chicken broilers randomly chosen were weighted during their entire life, both in trial 1 and trial 2. Means and standard deviations (SD) of the peak frequency (PF) of the sounds recorded in both trials.

Week	Trial	Day	Mean weights (g) ±SD	Mean PF (Hz) ±SD
1	1	1	44.56 ± 1.5	3545± 365
2	1	8	198.64 ± 10.1	3059 ±459
3	1	15	550.3 ± 21.7	2618 ±360
4	1	22	1039.5± 68.6	2329 ± 605
5	1	29	1529± 120.5	1943 ± 569
6	1	36	2104.28± 208.5	1506 ±434
1	2	1	40.72 ± 4.9	3621 ±402
2	2	9	231.42 ± 1.1	2953 ± 353
3	2	16	608.66 ± 26.7	2474 ± 384
4	2	23	1092.84± 74.4	1955 ± 520
5	2	30	1731.6± 130.3	1902 ± 585
6	2	37	2275.44± 247.0	1475 ± 493

The comparison shown in Fig. 2 shows how there is no difference (P value = 0.4508) between PF means of the sounds recorded in the two trials.

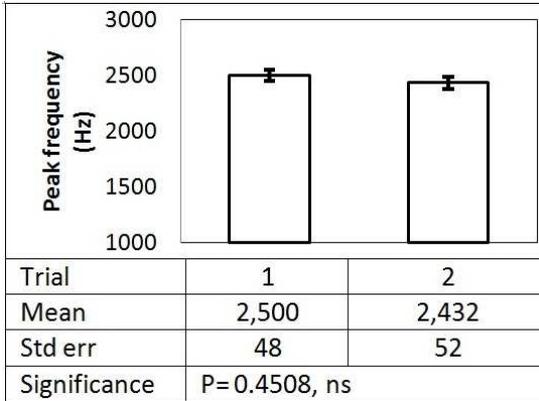


Fig. 2. Comparison between PF means of the sounds recorded in trial 1 and in trial 2

Furthermore, the comparison between PF of sounds collected on the same week of age of birds during the experimental trials (Fig. 3) confirmed that the two trials could be considered as the equivalent. This could be related to the use in poultry farming of fast-growing hybrid broilers with typical and homogeneous growth rate across production cycles.

Indeed all the P values reported in Fig. 3 reveal the non-significant difference between PF means of the sounds emitted by the animals during specific days of both trials.

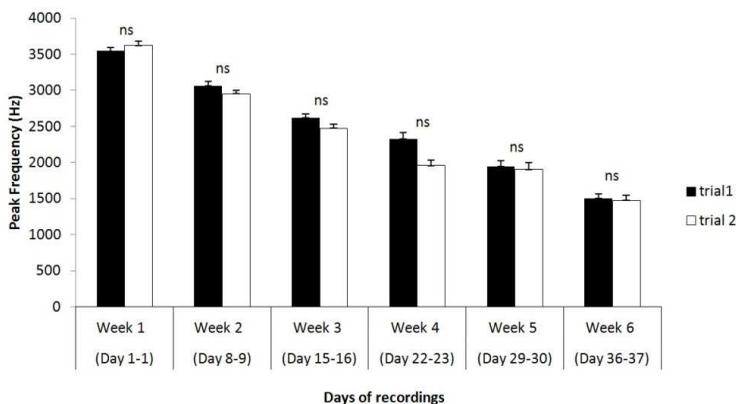


Fig. 3. Comparison between PF means of sounds emitted during days of the same week of age recorded in different trials.

In Table 3 the paired t-test between days of the same trial were tested to verify the difference between the PF means of the vocalisation during the life of the broiler chickens; the difference is resulted significant in both trials.

As it is possible to see in Table 2 and 3 and in Fig. 3 each age is characterised by its own typical peak frequency that decreases with the growth of the birds.

Considering the difference between week 1 and week 6 it is possible to see how the peak frequency decreases of about 2,000 Hz.

In both trials the average frequency reduction was around 350 Hz per week.

The correlation between weight and age of the broilers resulted highly positive (0.97, P-value <0.001) and was also found a high negative correlation (-0.95, P-value <0.001) between the PF of the sounds and the age of the broilers.

Furthermore analysing the PF related to the weight of birds, it was possible to confirm a significant negative correlation (-0.80; P-value <0.001) between the frequencies of the vocalisations recorded and the weight of the broilers, during the different experimental trials.

Table 3. Paired *t*-test between different days to verify the difference between the PF means of the vocalisations during the entire life of the broiler chickens in trial 1 and in trial 2.

Trial 1			Trial 2		
Comparison	Difference Mean (SEM)	P-value	Comparison	Difference Mean (SEM)	P-value
Day 1–Day 8	485.8 (76.7)	***	Day 1–Day 9	668.4 (73.4)	***
Day 1–Day 15	926.8 (66.9)	***	Day 1–Day 16	1,174.3(87.69)	***
Day 1–Day 22	1,216.2(103.8)	***	Day 1–Day 23	1674.1 (121.4)	***
Day 1–Day 29	1602.1 (93.3)	***	Day 1–Day 30	1740.3 (120.7)	***
Day 1–Day 36	2039.6 (94.3)	***	Day 1–Day 37	2146.4 (80.8)	***
Day 8–Day 15	441.0 (72.2)	***	Day 9–Day 16	478.9 (79.4)	***
Day 8–Day 22	730.4 (106.8)	***	Day 9–Day 23	949.7 (96.6)	***
Day 8–Day 29	1,116.3(108.4)	***	Day 9–Day 30	1015.9 (109.0)	***
Day 8–Day 36	1553.8 (85.5)	***	Day 9–Day 37	1478.0 (80.6)	***
Day 15–Day 22	289.4 (91.5)	***	Day 16–Day 23	485.9 (102.2)	***
Day 15–Day 29	675.3 (100.7)	***	Day 16–Day 30	552.1 (107.2)	***
Day 15–Day 36	1112.8 (81.8)	***	Day 16–Day 37	999.1 (97.1)	***
Day 22–Day 29	385.9 (124.8)	**	Day 23–Day 30	366.3 (136.4)	*
Day 22–Day 36	823.4 (101.5)	***	Day 23–Day 37	428.5 (137.0)	**
Day 29–Day 36	437.6 (101.7)	***	Day 30–Day 37	362.2 (130.6)	**

***= P-value < 0.001; **= P-value < 0.01; *= P-value <0.1

As it is shown in Fig. 4 the peak frequency of the vocalisations of the broiler chickens is strictly dependent on the age and on the weight of birds.

The regression model is significant ($F=251.52$, $P < 0.0001$), indicating that the model accounts for a significant portion of variation in the data. The R^2 indicates that the model accounts for 98% of the variation in peak frequency.

The confidence interval (CI_obs_95) of the observed values shows a 95% probability that the true linear regression line of the population will lie within the confidence interval of the regression line calculated from the sample data.

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The confidence interval (CI_exp_95) that includes the expected values of the regression model with a probability of 95% (grey area in Fig 4) indicates the goodness of fit of the regression model.

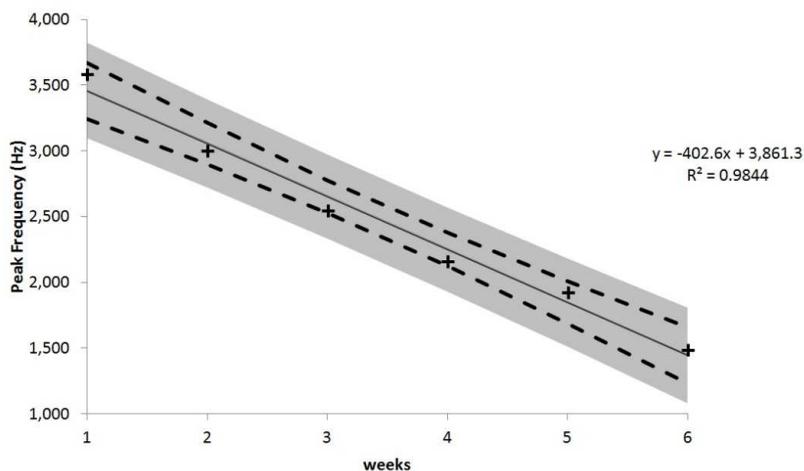


Fig. 4. Linear regression of PF in relation to the age of the animals expressed in weeks. Confidence intervals of the mean are reported in dotted lines. Confidence intervals of the prediction are represented by the grey area.

The results of the GLM were useful to verify the high impact of the weight and the age of the birds on the PF of the vocalisation emitted by the animals during their life. In Fig. 5 are reported the LSMEANS(\pm SEM) of the PF of vocalisations according to the increase of the age and weight of the animals.

There is a decrease of peak frequency in vocalisations according to the age of the broiler chickens.

As reported by Marx et al. (2001) the PF of the vocalisation emitted by one week old chicks ranged from 3,000 to 4,000 Hz, reinforcing the results of the present study that very young chicks vocalise at high frequency under non-stress condition.

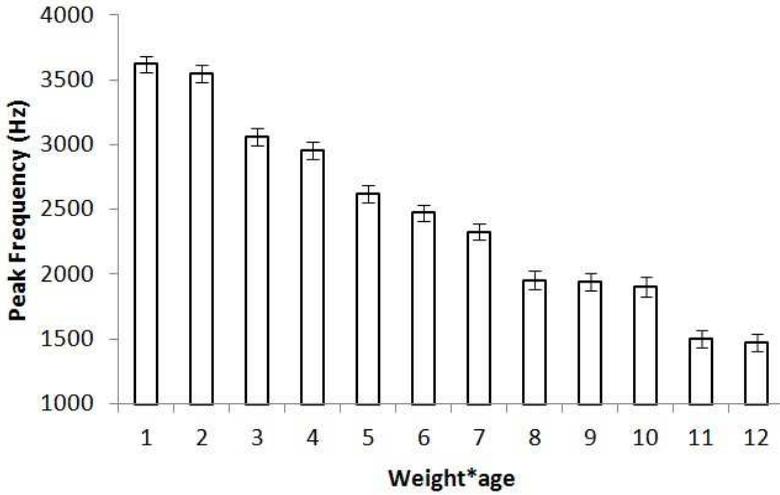


Fig. 5. LSMEANS(\pm SEM) of the peak frequency of vocalisation according to the increase of age and weight. $P < .0001$

5.4. Conclusion

Broiler sounds were recorded with two microphones and 600 sounds chosen randomly were manually labelled and analysed; The PF of each vocalisation was evaluated in order to find a relation with the age and consequently with the weight of the birds.

The results indicate that the peak frequency of the sounds emitted by the animals, is inversely proportional to the age and the weight of the broilers; specifically the more they grew, the lower the frequency of the sounds emitted by the animals.

This preliminary study shows that the methodological approach based on the identification of specific sound frequencies emitted by the animals in an indoor reared broiler farm linked to their age and weight, might be used as an early warning method/system or a continuous monitoring system to evaluate the general status of the animals at farm level. Furthermore, the correlation between weight of the birds and peak frequency of the sounds emitted by the animals might open the scenario to an automated tool based on vocalisation to predict the weight and the growth trend of the birds. This allows the farmer to automatically monitor the growth trend of the birds.

Of course further studies, in different farms, with daily data collection are necessary to improve the knowledge on the relationship between vocalisation and weight of birds in order to create an accurate weight prediction algorithm based on sounds emitted by the animals but, this study proves that audio and video data monitoring might be promising technique for the development of an automated growth-monitoring tool for the farming of broiler chickens.

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CHAPTER 6

6. Discerning pig screams in production environments

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Abstract

Pig vocalisations convey information about their current state of health and welfare. Continuously monitoring these vocalisations can provide useful information for the farmer. For instance, pig screams can indicate stressful situations. When monitoring screams, other sounds can interfere with scream detection. Therefore, identifying screams from other sounds is essential. The objective of this study was to understand which sound features define a scream. Therefore, a method to detect screams based on sound features with physical meaning and explicit rules was developed. To achieve this, 7 hours of labelled data from 24 pigs was used. The developed detection method attained 72% sensitivity, 91% specificity and 83% precision. As a result, the detection method showed that screams contain the following features discerning them from other sounds: a formant structure, adequate power, high frequency content, sufficient variability and duration.

Keywords

Sound analysis, bioacoustics, animal vocalisation, pig scream properties, animal welfare

6.1. Introduction

Animal vocalisations can contain information such as signalling threats [1], choosing mates [2] or alerting infants for suckling [3]. In case of livestock animals, information contained in vocalisations or other animals sounds could serve as valuable information for the farmer. A very good example is the rich vocal repertoire of pigs [4-6]. For instance, high frequency calls of pigs have already been linked to stressful situations [7]. Moreover, animal sounds such as coughs could be linked to respiratory diseases and thus to their welfare [8,9]. Therefore, vocalisation could be useful for assessing the animal's condition. Furthermore, the use of technology to monitor these vocalisations opens new possibilities as they can be monitored automatically and continuously. In the past numerous research studies on pig vocalisations in stressful situations have focussed on analysing high frequency calls.

In these studies on high frequency vocalisations during different situations were analysed such as diverse castration practices [10-12], cold [13] or warm [14] temperatures. Other examples were the simulated crushing of piglets [15] or an electric shock or anticipation to the electric shock [16]. For the remainder of the paper, these high frequency calls are called screams. They are defined as vocalisations containing considerable high frequency content and having a larger amplitude than other vocalisations [17]. For the difference between screams and squeals the reader is referred to literature [18].

These previous studies had one limitation, they focused on analysing screams while ignoring other sounds present in a pig barn. Two exceptions conducted analysis on three sound types: screaming, squealing and grunting sounds [18,19]. However, these are not the only sounds present in a pig barn. For instance other vocalisations such as barks, coughs or environmental sounds

such as the automated feeder, drinking nipple and the farmer are present. For some of these sounds such as coughs [20] and barks [21], separate studies have been performed in analysing them. In general, a new approach is needed that identifies the features that discern screams from all other sounds in a pig barn. These other sounds do not have to be identified in this new approach.

When discerning screams in this new approach, the initial condition requires features with physical meaning [22]. Features such as loudness, duration, fundamental frequency and formant structure [23] are defined as sound parameters which are simply interpreted and physically related to vocalisation. However, speech processing terms such as autoregressive or cepstral coefficients [24], are generally much harder to interpret.

The need for rigorous classification with explicit rules is the next condition for identifying screams. Such rules comprise a set of readily interpretable requirements. For instance, a decision tree with conditions has such rules. An Artificial Neural Network (ANN), however, gives little explicit information about the decision making [25]. For example, ANN can be used for automated stress vocalisation detection of pigs which is called STREMOD0 [26,27]. However, by using an ANN and autoregressive coefficients this method was unable to interpret sound features.

Using features with physical meaning and explicit rules as explained in previous two paragraphs offers the possibility to develop an automated scream detection method. The advantages of this approach over STREMOD0 [26] are that the results can be interpreted and that the approach can be adapted online to changing situations. (1) Our new approach offers the possibility to interpret different classes of screams. Moreover, (2) the rigorous classification can be adapted to each specific situation. For instance, during feeding time, more screams are expected due to competition between animals and this does not

necessarily indicate serious stressful situation. While screams detected during night time would indicate serious stressful situation. So during feeding time, only screams indicating serious stressful situation should be detected. Such screams could have more high frequency content [11] or have a longer duration [6]. While during night time every scream should be detected.

The purpose of this study is to investigate what sound features define a pig scream as a pig scream and how they differ from other sounds in a pig barn. To achieve this goal an automated scream detection method was developed based on sound recordings made in a real scale experimental pig barn. This method is supposed to discern screams from other sounds present. These other sounds are not named but represent all sounds originally detected by this method. Moreover, this method should discern them continuously which means once every second. To identify the relevant sound features defining a pig scream a detection method which followed two conditions was constructed. First the calculated features should have a physical meaning and secondly the classification should be made with explicit rules, in order to interpret why a sound is considered a scream. Moreover, special attention during classification was given to features which described the formant structure of screams. Formants are the different spectral peaks in the frequency spectrum of the human voice and are also present in pig screams.

6.2. Material and Methods

6.2.1. Animal and Housing

Two trials were conducted and 24 grower pigs were used in each trial. The animals Rattlerow Seghers x Piétrain Plus, were housed at Agrivet research farm, Merelbeke, Belgium. After the battery period, they were divided into four

groups of six animals (three gilts and three barrows) and each group was assigned to a pen (Fig. 1). Each pen (1.60m x 2.35m) had a fully slatted concrete floor with one feeder space and one nipple drinker. The pens were located in the same compartment and were separated from each other with 1m high solid walls. So physical contact between pigs of adjacent pens was made impossible but they could still hear each other. There was ad libitum access to feed (commercial grower diet) and water during the experiment. Pigs had a timer-controlled 12-hour light period from 07:00 h to 19:00 h. The average weight of the pigs was 20.9kg (SD = 2.1) at start and 32.2kg (SD = 3.8) at end of the first trial and 31.5kg (SD = 3.4) and 43.0kg (SD = 5.5) respectively, in the second trial. The average temperature during the trials was 24.0°C (SD = 1.2). The experiment was approved by the Ethical Committee of the Faculty of Veterinary Medicine at Ghent University (EC2012/125).

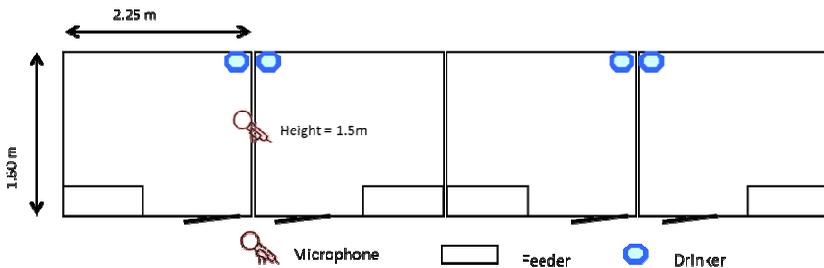


Fig. 1. Ground plan of the pig compartment. Each pen had six animals, one feeder and one drinker. One microphone recorded the sound.

6.2.2. Experiment and Data collection

Each trial lasted 15 days in which two treatments, experienced as stressful by pigs were applied. Prior to each trial pigs had 7 days of adaptation to their new environment. During the trial, on day six, the animals from two randomly chosen pens (P1 and P2) were mixed between 7:00h and 8:00h. For this

purpose, three animals of P1 were exchanged with three animals of P2. On day eleven, P1 and P2 were subjected to feed deprivation which started at 12:00h and ended 24 hours later.

The sound data were recorded with a microphone (C-4 Small Diaphragm Condenser Mic, Behringer, Germany) at a height of 1.5 m and a sound card (Delta 1010LT, M-audio, Cumberland, United States) with a precision of 16 bit and a sampling frequency of 22050 Hz. The microphone was positioned as seen in Fig. 1, so it recorded sounds of all four pens. In total 720 hours of sound data were collected.

One remarkable situation occurred during the recordings. For all hours our compartment was acoustically separated from the neighbouring compartment. Except one hour when most pigs in this neighbouring compartment were screaming at the same time. The sound power was loud enough to be heard through the separating wall. This occurrence was considered when developing the algorithm.

6.2.3. Labelling of Sound Data

In order to develop a classifier, i.e., a system to classify pig vocalisations as screams, a reference data set is needed. Because the collected sound possessed screams but it carried no information when screams occurred. The reference was built via labelling by a human observer, who indicated the beginning and end of each scream, using the computer program Adobe Audition (Adobe Systems, San José, US) [28,29]. This human observer, experienced in labelling pig vocalisation, labelled 7 hours of sound data. These hours were chosen randomly except one. This hour contained the vocalisations in which pigs regained access to the feeder after the second stressful treatment. In this paper a distinction is made between the first 6 hours and the last hour. The former

consist of 312 screams and the latter consists of 38 screams. Moreover, to assess the labelling performance, the human observer labelled the same 10 minutes on two different occasions. However, this person was unaware of this. The correlation between these labelled files was calculated to assess if this person labelled consistently. This calculation was based on literature for pig stress vocalisations [26]. A correlation of 0.83 ($P < 0.001$) was achieved which was deemed sufficient.

6.2.4. Classifier overview

The classifier consisted of four parts: (1) the data transformation, (2) the event detection, (3) the feature calculation and (4) the classification. Fig. 2 shows the scheme of the classifier. In the following paragraphs different elements of the classifier will be explained and their combination will be discussed.

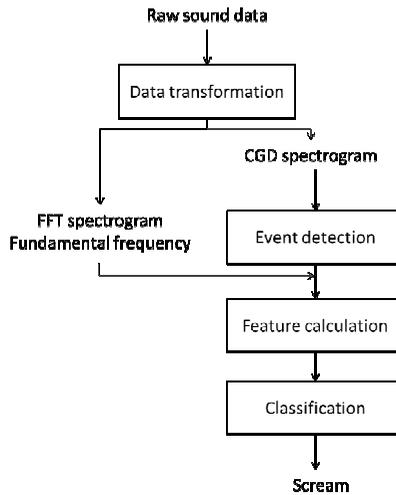


Fig. 2. overview of the classifier elements. The rectangles represent the four parts. The raw data is transformed into an output that indicates if a scream is present. (CGD = Chirp Group Delay, FFT = Fast Fourier Transform)

6.2.5. Data transformation

To obtain different frequency information, the sound data were transformed using three techniques: (1) the Fast Fourier Transform (FFT), (2) the Chirp Group Delay (CGD) [30] and (3) the fundamental frequency calculation. The FFT analysed high frequency content and CGD analysed formant structure. The fundamental frequency provided the longest periodic pattern in the sound, which in human vocalisation is produced by the glottis. The implementation originally used for calculating fundamental frequency of pig coughs was adopted [31].

In order to calculate these transformations, sound data was divided into 30ms hamming windows [32] with a 15ms overlap. This duration was chosen similar to speech analysis in which 20-40ms windows are used.[33]. Calculating the transformations on each window provided time frequency information. An example is presented for both FFT and CGD in Fig. 3. To further reduce FFT and CGD data, the frequency resolution was lowered into 24 Mel-spaced frequency bands. This experimental scale is used to resemble human perception of sound frequency, particularly fundamental frequency [34].

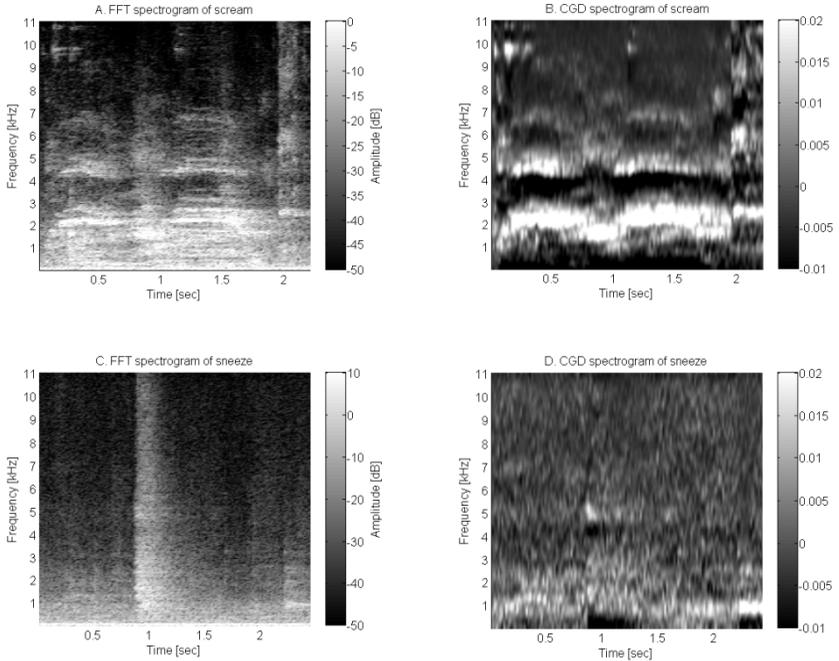


Fig. 3. The FFT spectrograms and GCD spectrograms. The upper two figures show the same screams, the lower figures show the same sneeze. The left figures depict the spectrogram made from FFT while the figures on the right side depict the spectrogram made from CGD. The formant structure of a scream is visible (B). These formants are the whiter values in the CGD spectrogram. It is not straightforward to find the same structure in the FFT spectrogram. Because the difference between the formant value and the surrounding values is much bigger relative to the maximum and minimum values of the CGD compared to the FFT.

6.2.6. Event detection

The event detection is based on a method for detecting sound events needed for human cough detection [35]. This method adopts two thresholds. One threshold detects peaks in the sound data while the second threshold detects the starting and ending time of the peaks. However, the peaks were found in the standard

deviation of the sound data while in the current study, the peaks were found in feature 6 from Table 1. This feature 6 will be described in following paragraph. This feature was chosen because it detected 84% of the labelled screams resulting in 261 screams and only 4552 other sounds. These 261 screams were found in 231 sound events. This means that several sound events consisted of multiple labelled screams.

6.2.7. Feature Calculation

A total of 10 features were calculated from the data transformations for each sound event. These can be ordered into several categories as shown in Table 1. These categories assessed the sound power, the high frequency content, the formant structure, the variability and the duration of the sound events. The aim was to give these categories a physical meaning that can be interpreted easily.

Table 1. *The features used by the scream detection algorithm*

Feature category	Feature nr	Feature description
Event power	1	Mean of the spectrogram
High frequency content	2	Mean of the 12 higher frequencies in the FFT spectrogram
	3	Fundamental frequency
Formant structure	4	Maximum value of CGD spectrogram
	5	Number of values in CGD spectrogram above a threshold
	6	Squared error on line fit through mean vales of CGD spectrogram
	7	Third FFT value from mean values CGD spectrogram
	8	Third FFT value normalised by DC value from mean values CGD spectrogram
Event variability	9	Standard deviation of CGD spectrum
Event duration	10	The duration of the sound event [seconds]

The first feature category is the power and has only one feature. This feature is calculated from the mean value of the FFT spectrogram. Screams are one of the louder sounds in a pig barn and this feature considered this. This feature is less stable because the distance between the animal and the microphone is variable, meaning the value changes. A solution would be to determine the ratio of the sound power to the medial level of all spectra [19].

The second category calculated two features that examined the higher frequency content. The power of the higher frequencies was calculated by taking the mean value of the twelve highest frequencies from the FFT spectrogram and consequently the mean over all windows belonging to the scream. The second feature was the fundamental frequency of pig screams which was already calculated in the data transformation.

The formant structure was the third feature category and contained the most features. As seen in Fig. 3, screams exhibit a formant structure that is visible in the CGD spectrogram and this feature will therefore be used in the third category. The first two features were directly calculated from the CGD spectrogram. With these features the maximum value and the amount of values higher than a threshold was assessed. This threshold was calculated with the technique described in the next section 'Classification'. The three other formant structure features required the mean values of each frequency value over all time windows of the event. These are shown by the CGD values in Fig. 4 b. For the third feature a straight line was fitted through these values. The squared error between this line and the mean values was minimised. This resulting squared error was defined as the third feature because a line cannot resemble a formant structure and thus the squared error value of a scream will be higher. For the fourth and fifth feature the formant structure was interpreted by applying an FFT on these mean values. This is the same technique as used in

the data transformation paragraph but now applied on different data. As sounds with a formant structure have more fluctuating values compared to other sounds (for instance in Fig. 3) they will have larger values at higher frequencies compared to the zero frequency.

Within the fourth feature category, the event variability in the CGD spectrogram was determined by calculating the standard deviation values. For instance the CGD of screams vary more than other sounds. For comparison the spectrogram of a sneeze is also given in Fig. 3. The last feature category is the sound event duration. This was calculated from sounds found in the event detection.

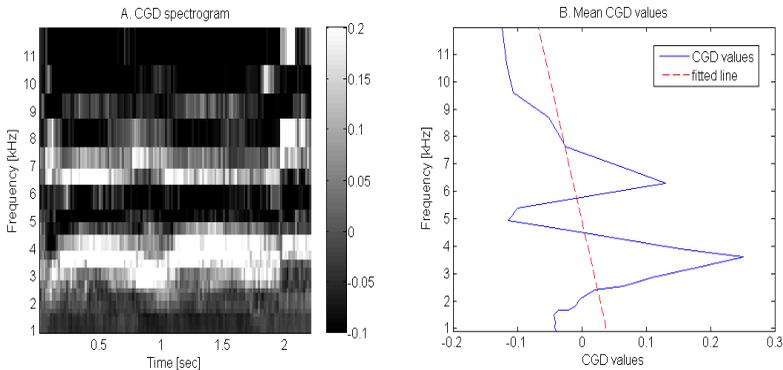


Fig. 4. The Mel CGD spectrogram. The left figure (A) shows the CGD spectrogram with Mel frequency resolution. The right figure (B) shows the corresponding mean values of each frequency value from the Mel CGD spectrogram. This figure further shows the straight line fitted through these mean values.

6.2.8. Classification

Before the classification a preselection of sound events was made based on the labelled data. An event could be a scream if its duration (feature 10) was longer than 0.4s. This threshold was experimentally defined, based on the labelled data. While looking closer at the data it was discovered that screams belonged to the higher values of each feature. However, it also appeared that not every scream had high values for each feature. For example, some screams had a long duration but a low sound power while others were short but had a high sound power.

To cope with the demand for a classification with explicit rules and with the two facts discovered in last paragraph, a threshold was determined for each feature. This threshold split the dataset in two per feature and was made in the same way as a classification tree when splitting by using the Gini Diversity index [36,37]. This index measured the purity of two datasets. Purity is a measure which indicates the homogeneity of a dataset. Several thresholds in ascending order were applied and consequently the threshold that maximised the purity was chosen. Because not every scream had high values for each feature, thresholds were combined into a simple voting system [38]. Each feature had one vote to decide if a sound belonged to a scream or not. These vote were later summed together.

Having a classifier with votes offers the possibility to make the classifier adaptive. As discussed in the introduction, during feeding time, screams related more to serious stressful situation should be detected. This could mean screams with a higher vote or screams for which one threshold was increased such as the duration [6]. While during night time, screams with a lower vote could be detected instead.

6.2.9. Construction of the classifier

The four different parts: data transformation, event detection, feature calculation and classification were combined as depicted in Fig. 2. The data were first transformed from time series into time-frequency representations in order to calculate the events and feature values. Afterwards the event detection constructed the sound intervals that possibly contained a scream. Subsequently the features were computed for these sound intervals of interest. Finally, the classification decided if a sound event was a scream.

6.2.10. Validation of the classifier

The classifier was constructed from six of the seven hours of labelled data. The sound events were extracted from these six hours with the event detection as described in a previous paragraph. This resulted in screams and other sounds. The other sounds comprised of other vocalisations and other environmental sounds. Two third of these sound events were randomly selected as training set for construction of the classifier. The remaining one third was selected to validate the classifier. The criteria to assess the results were sensitivity, specificity, precision and the Receiver Operating Characteristic (ROC curve) [39].

$$\text{sensitivity} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}}$$

(1)

$$\textit{specificity} = \frac{\textit{number of true negatives}}{\textit{number of true negatives} + \textit{number of false positives}}$$

(2)

$$\textit{precision} = \frac{\textit{number of true positives}}{\textit{number of true positives} + \textit{number of false positives}}$$

(3)

The ROC curve plots the True Positive Rate (TPR = sensitivity) versus the False Positive Rate (FPR = 1 – specificity) for various number of required votes. The ROC curve’s purpose was to determine the number of votes required to classify a sound as a scream. Because sensitivity and specificity could be easily compared in this curve.

A total of 10 minutes of the 7th hour was used for a different validation. This validation calculated the correlation between labelling result and algorithm result. In this way it provided an indication if labelled screams followed the same pattern as found by the algorithm. This correlation was calculated as proposed by Schön et al. [26] for stress vocalisations. The remaining 50 minutes of the last hour were not used as they consisted of only 4 labelled screams as opposed to the 34 labelled screams in the chosen 10 minutes.

6.2.11. Assessing the defining features of a scream

The resulting classification structure allowed assessing each feature and the corresponding threshold for their share in the final vote. For instance, the percentage of true positives that satisfied a specific feature threshold was

calculated. Or in other words, the percentage of true positives that received a vote from this specific feature threshold. This allowed explaining which feature thresholds contributed more to the scream detection. This analysis was expanded to two other sets: all labelled screams and all other sounds, providing the TPR and FPR per feature threshold. These analyses were applied to the combined training and validation dataset.

6.3. Results

In accordance with the event selection 4783 sound events were found. A total of 231 events agreed with screams found by human labelling. After preselection as described in the section about classification 563 sound events remained. A total 213 events contained labelled screams. These 563 sound events were subsequently subjected to the final classification as shown in **Errore. L'origine riferimento non è stata trovata..**

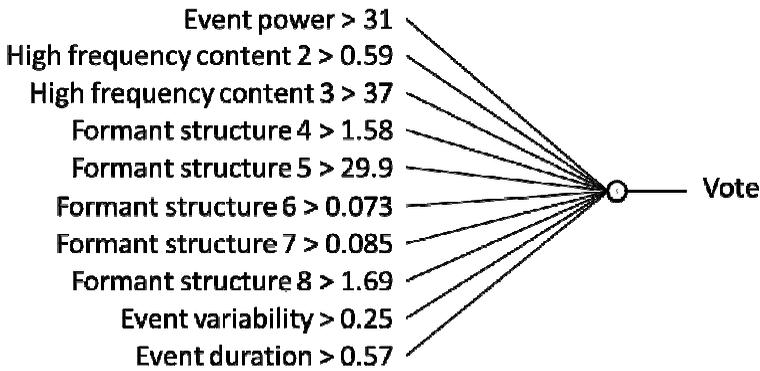


Fig. 5. The resulting classification. These were the found thresholds for each feature after applying the gini index to all sound events in the training dataset. Each line resembles on feature with acompagning threshold. When an event's feature value was above the threshold value, the sound event received one vote. All ten votes were subsequently summed together for one sound event.

Fig. 6 depicts the ROC-curve for the various numbers of votes required for classification as a scream. According to ROC the training set had consistently higher sensitivity (or TPR) values than the validation set. On average it was 0.07 (or 7%) higher. Furthermore, the desired sensitivity and specificity could be chosen based on this curve. The remainder of the results were calculated with six as the minimal number of votes required. The reason for choosing six is explained in the discussion.

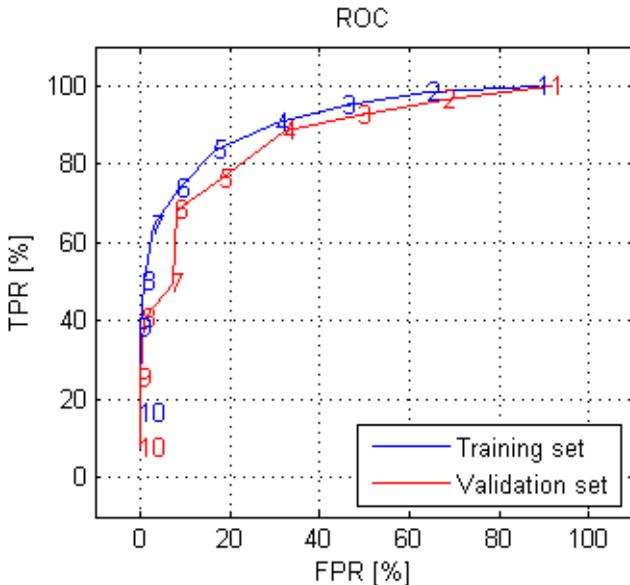


Fig. 6. The two ROC curves. They showing the True and False positive Rates (TPR and FPR). The numbers on the plots give the minimal required votes for the training and validation set.

As depicted in Table 2 when choosing six as minimal number of votes, the sensitivity of the training set was higher than the validation set but the specificity and precision was lower. Moreover the correlation between the labelled data and the screams found by the algorithm was 79.95% ($P < 0.001$).

Table 2. *The sensitivity, specificity and precision.*

	Training set	Validation set	All sets
Number screams	134	79	213
Number of others	238	112	350
Sensitivity	73.9 %	68.5%	71.8%
Specificity	91.2%	92.0%	91.4%
Precision	82.5%	85.7%	83.6%

The sensitivity, specificity and precision of both sets separately and combined when six votes are required. The number of others refers to sound events that are not screams.

Furthermore the share of each feature and corresponding threshold is indicated in Table 3. This allowed to discuss the importance of each feature in defining a scream. From this table it became clear that the percentage of true positives (TP) for all feature thresholds except for feature ‘Formant structure 4’ had percentages higher than 75%. ‘Formant structure 4’ had 30.1%. The percentages of all scream events performed poorer than the TPs because the True Negatives (TN) were included in the computation. Overall every percentage was higher than 50% except again for feature ‘Formant structure 4’. The third row gives the same analysis for all the other sounds. Every value was lower than 50% and remarkably ‘Formant structure 4’ also scored the lowest value with 3.7%. The different percentages of feature ‘Formant structure 4’ are caused by applying the Ginny Diversity index [36] in the classification. This index maximises the purity and this resulted in 21.6% and 3.7% of screams and

other sounds, respectively. It could be that ‘Formant structure 4’ is feature for a specific class of screams and not in general of pig screams.

Table 3. Performance of the features.

	Event Power	min frequency content 2	min frequency content 3	Formant structure 4	Formant structure 5	Formant structure 6	Formant structure 7	Formant structure 8	Event variability	Event duration
TP	93.5 %	74.5 %	85.6 %	30. 1%	86.9 %	93.5 %	93.5 %	86.9 %	75.2 %	91.5 %
Screams (TP+FN)	85.4 %	59.6 %	78.4 %	21. 6%	66.2 %	79.8 %	82.2 %	69.5 %	57.3 %	85.4 %
Others (TN+FP)	24.5 %	13.4 %	32.3 %	3.7 %	10.6 %	44.3 %	45.1 %	25.1 %	12.6 %	52.0 %

The percentage of True Positives (TP), all screams and other sounds that satisfy each feature’s threshold. Or in other words the percentage of TPs that receive a vote from each threshold

6.4. Discussion

The purpose of this paper was to investigate what sound features define a pig scream as a pig scream and how they differ from other sounds in a pig barn. To achieve this, a classifier using features with physical meaning was constructed. This ability is one advantage of the method compared with STREMOD0 [26]. A total of 10 features were developed which belonged to 5 categories: The

power, the higher frequency content, the formant structure, the variability and the duration of each sound event. Subsequently a classifier based on explicit rules was developed and was depicted in **Errore. L'origine riferimento non è stata trovata.**. The performance of the classifier is first examined, the adaptive ability of the classifier is shortly discussed and afterwards the discerning sound features are discussed.

6.4.1. Performance of the classifier

Performance of the classifier is displayed in Fig. 6. Increasing the number of minimal votes required, decreased the TPR and increased the FPR. Because other sound events, such as coughs or sneezes are usually more prevalent in pig barns, a high specificity was desired, whereas sensitivity was of less importance. Six was, therefore, selected as the minimal number of votes as this gave a specificity higher than 90%. Moreover, this gave eventually 92% specificity, 69% sensitivity and 86% precision for the validation set (Table 2).

The scream detection method performance could be compared with a system called STREMOD0 [26]. Although there are several differences such as the target vocalisation: screams compared to stress vocalisation; a cautious comparison is made. The sensitivity and specificity obtained by STREMOD0, 99.3 % and 98.6 %, respectively were better than our method. Moreover, their results were obtained from sounds recorded in a noise-reduced chamber with less sound reflections [40]. Our results, however, were obtained in a real scale experimental pig barn with additional sounds, such as pigs playing with chains. In reality, there will be other sounds present during screaming sounds. Another reason for our lower sensitivity and specificity is the classifier's complexity.

STREMODO used a complex ANN with 194 perceptron and 4 layers while we used 10 thresholds and a voting system.

Another way to compare STREMODO with our developed algorithm is by calculating the correlation between our algorithm and the labeller for 10 minutes. For STREMODO this feature was calculated in commercial pig barn hence this is comparable to our set-up. Our method achieved a correlation of 0.80 ($P < 0.001$), which was comparable with the correlation obtained by STREMODO (0.84; $P < 0.001$) in which six experts labelled pig screams.

6.4.2. Adaptive ability classifier

One of the mentioned advantages of this new approach over STREMODO [26] was the adaptive ability of the automated detection method. The developed detection allows for an adaptive threshold both on the number of votes as for each of the ten features. For instance, it is very easy to increase a threshold on the duration feature during feeding time so that calls associated with serious stressful situation are detected [6]. Or to decrease the number of required votes during the night time to certainly detect all screams. This would be possible as the number of other sounds also decreases during the night. In general, the sensitivity, specificity and precision should always be considered when adapting these thresholds. However, this was not developed in this study as more labelled sound files during different situations were necessary than currently available to validate this.

6.4.3. Features defining a pig scream

The goal of this study was to define what features make a pig scream a pig scream. The percentage of screams satisfying each threshold in the classifier were given (Table 3). Consequently, identifying the defining scream sound features in our experimental pig barn was now possible. Generalisation to other pig barns should be done with caution as for instance, sound from an automatic feeder may be present. In following paragraphs each feature category will be investigated.

(1) A scream should have a certain power (feature 1). This is evident as screams are one of the louder sounds in a pig barn. This corresponded with literature in which the mean relative sound energy of screaming was 15dB higher than grunting and squealing [19]. According to Table 3, the power was one of the most defining sound features of a scream. In total 93% true positives received a vote from this feature. While only 24% of the found other sounds in this dataset conformed to this threshold. Furthermore among all features, the difference in percentage between screams and other sounds was highest for this feature, attaining 61%.

(2) Screams have more higher frequency content than other sounds as seen in Table 1. The two features that described the higher frequency content showed this (Mean of the 12 higher frequencies in the FFT spectrogram and fundamental frequency; Table 1). This corresponds with literature in which the peak and main frequencies of screams were significantly higher than grunts [18]. However, they did not consider every sound in a pig barn while this paper considered all sounds present during the labelled hours for this specific pig barn. According to Table 3 75% and 85% of the true positives received votes from feature 2 and 3, respectively.

(3) A scream should have a formant structure. In this study, there were five features assessing the formant structure. These features did not specify the exact values of the formants as in literature [41] but attempted to give an indication if a formant structure was present. Furthermore, a data representation called Chirp Group Delay (CGD) [30] was applied for the first time on animal vocalisations while previous studies applied LPC coefficients to represent this structure in stress vocalisations [26,41]. Moreover, other sounds present in a pig barn such as barks [21] and coughs [42] were shown to possess certain formant structure but these sounds were not included in this research paper. The performance of the first formant feature (maximum value of CGD spectrogram) was poor at first sight according to Table 3. Only 30% of the TPs received a vote. According to the last row, however, only 4% of the other sounds received votes from this feature. This feature had, therefore, low sensitivity but high specificity. The other four features accounted for at least 87% of the TPs and except for feature 6 and 7 the other sounds received low percentage of votes. In general they performed well on separating screams from other sounds.

(4) Screams should vary considerably (Standard deviation of CGD spectrum; Table 1), meaning that feature 9 should be higher than 0.25 as seen in Fig. 5. Because 75% of the TPs and only 13% of the other sound received votes, this indicated a defining sound feature of screams.

(5) Finally, screams should possess a minimal duration. Because before classification, the sound events shorter than 0.4 seconds were omitted. In accordance with this preselection 563 out of 4783 sound events were removed based on duration. Furthermore, after classification 85% of the produced screams had a longer duration than 0.57s compared to only 52% of the other sounds as seen in Table 3. This is in agreement with literature on young pigs in which longer calls were more associated with negative situations [6] and in

which scream duration was significantly longer than grunts or squeals [19]. However, in literature on older pigs such as sows, calls which were not screams were found to be longer than 1s [43]. Moreover, in literature screams were found to have a duration between 0.3s and 3s [5] or on average 1s [17] while pig coughs had an average duration of 0.43s or 0.67s for non infectious and infectious coughs, respectively [44].

The previous paragraphs discussed the performance of different features characterising a scream. However, the automated scream detection considered a combination of these features, because no single feature defines a scream. This was demonstrated in Fig. 6: which shows FPR declined faster than TPR when the number of votes required increased. Furthermore, screams did not need to conform to all feature thresholds, only to the number of required votes. However, the most salient features can be derived from Table 3. The event power and formant feature 5 defined screams most clearly, because these have the highest difference between votes for TPs and other sounds, of 69% and 76%, respectively. Furthermore these features account for at least 87% of the TPs. Other salient features include the event duration and formant feature 6 and 7 as they account for 91%, 93% and 93% of the TPs, respectively.

6.5. Conclusion

This paper investigated which sound features define a pig scream in a pig barn. A classifier was constructed with a deliberate focus on explicit rules based and features with physical meaning. The resulting classifier had 71.83% sensitivity, 91.43% specificity and 83.61% precision. According to the classifier, a scream should have a high sound power, a formant structure and a certain duration.

Two properties of lesser importance were the high frequency content and the variability of the signal. Furthermore, it was not necessary for a scream to have all these properties.

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CHAPTER 7

7. General discussion and conclusion

The main purpose of PLF is to improve the production efficiency, increasing animal and human health and welfare, through the application of advanced information and technologies, to control the entire production process.

The PLF is a very useful methodology to support the farmer through the application of process engineering at livestock farming to monitor, model and manage animal production. Its employment is due to changes in the livestock sector (from extensive to intensive conditions), the always higher number of animals involved and the changes in the farmer role. PLF aims at considering all the animals as individually different.

This thesis was particularly dedicated to the importance of using new technologies and methodologies to improve animal health, welfare and production.

The objectives of this thesis was the application of sound and image techniques to investigate and solve some common problems at farm level such as specific behaviours or production issues.

Chapter 3 was dedicated to explore the preference and the duration of interest of weaned pigs for two different types of environmental enrichments using labelling techniques and activity monitoring. Image analysis can support farm management- directed to improve animal health and welfare. Presence of available environmental enrichment is an important prerequisite for the welfare of animals reared under intensive farm conditions.

The results received from this experiment suggest that the chain and the wooden block, often used by the farmers as low cost enrichments, are not

effective for the long-term use. In case of short-term use it is advisable to combine the point-source enrichment objects with different characteristics to increase the playing time during the day. Animals lose very soon the interest in the provided materials. The goal is the development of smart enrichments able to motivate the animal attention for long time.

Chapter 4 and 5 are both devoted to the broiler vocalisations study.

In chapter 4 the chicks vocalisation is investigated to define the vocal pattern of this species during the first 5 days of their life. The vocalisations emitted by the chicks during their first 2 days were different. Moreover, the sounds emitted by isolated one day old chicks caused a behavioural reaction in the non-isolated chicks. Indeed, the behaviour of non-isolated chicks responding to the sounds emitted by the isolated chicks was more identified in younger chicks and less in older ones. The sounds emitted by isolated one-day-old chicks were classified as “calling sounds” directed towards their co-specifics, whereas sounds emitted by five day old chicks were better classified as “distress calls” due to social (and physical) isolation.

Hearing is an important sense for birds (Appleby et al., 1992; Tefera, 2012) and animals use vocalisations to express different conditions (Manteuffel et al., 2004; Tefera, 2012; Vandermeulen et al., 2015). "Calling sounds" are vocalisations emitted by very young chicks during the imprinting phase (first two days of life), when birds usually learn fundamental behaviours related to social interaction and vocal communication.

Moreover, in this preliminary study was noticed that there was a decreasing in the peak frequency (Hz) of the vocalisation emitted by the animals while they gradually gained weight.

Chapter 7

Chapter 5 describes the possibility to use sound analysis to monitor the growth changes in the birds during the entire production cycle.

The PF of each vocalisation was evaluated in order to find a relation with the age and consequently with the weight of the birds.

The results indicate that the peak frequency of the sounds emitted by the animals is inversely proportional to the age and the weight of the broilers; specifically the more they grew, the lower the frequency of the sounds emitted by the animals.

This study shows that the methodological approach based on the identification of specific sound frequencies emitted by the animals might be used as an early warning method/system or a continuous monitoring system to evaluate the general status of the animals at farm level. This relation might open the scenario to an automated tool based on vocalisation to predict the weight and the growth trend of the birds.

Clearly, further studies will be necessary to create an accurate weight prediction algorithm based on sounds emitted by the animals.

Anyway, this study proves that audio and video data monitoring might be promising techniques for the development of an automated growth-monitoring tool for the broiler chickens farming.

Chapter 6 describes the process to understand which sound features define a scream and how they differ from other sounds in a pig barn. Pig screams can indicate stressful situation occurring at the piggery. A classifier was constructed with a deliberate focus on explicit rules based and features with physical meaning.

Several sounds in a pig farm can be detected such as sneezes, coughs, cough attacks, barks, grunts, screams and environmental/background noises. For this reason, when monitoring screams, other sounds can interfere with screams detection. Therefore, identifying screams from other sounds is essential. The feature categories to define a scream are:

- A scream should have a certain power (screams are one of the louder sounds in a pig farm).
- Screams have higher frequency content than other sounds (peak and main frequencies of screams were significantly higher than grunts).
- A scream should have a formant structure.
- Screams should vary considerably.
- Screams should have a minimal duration (the sound events shorter than 0.4 seconds were omitted).

The automated scream detection considered a combination of these features, because no single feature defines a scream.

A scream should have a high sound power, a formant structure and a certain duration. Two properties of lesser importance were the high frequency content and the variability of the signal.

List of publication

1. Publication in peer reviewed international journal publications

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2. Publication in international conference proceedings

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