# Precision livestock farming: an overview of image and sound labelling.

E. Tullo[1] I. Fontana[1] and M. Guarino[1]
[1] *Department of Health, Animal Science and Food Safety, Università degli Studi di Milano, via Celoria 10, 20133, Milan, Italy.*
emanuela.tullo@unimi.it

## Abstract

The shift in livestock farming methods from extensive to intensive poses a number of significant challenges for animal welfare, environmental sustainability and food security. Automatic animal monitoring may be one method of supporting farmers in achieving farm sustainability. Precision Livestock Farming (PLF) can combine audio and video information into automated tools that serve as early warning systems for the farmer if health or welfare problems are detected.

First, reliable sounds and images that indicate poor animal welfare must be identified by animal experts. Then, through careful labelling of sounds or images, it is possible to create a complete database which is suitable for algorithm development.

Labelling is an activity which precisely defines and interprets detailed variations in measured field signals. This study will describe sound and image labelling with the aim of developing an automated tool.

**Keywords:** Sound, Image, Labelling, Algorithm, Precision Livestock Farming

## Introduction

In recent decades there has been enormous growth in livestock production, driven by population growth and changes in dietary preferences associated mainly with increasing wealth and urbanisation.

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.

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, fed with industrial feeds instead of natural forages.
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 animals (Guarino, 2005).

Poor housing, crowding and lack of food in intensive farming systems can often cause welfare problems. The increase in the number of animals being reared also leads to a higher likelihood of creating pandemics of zoonotic origin, with several diseases such as Avian Flu (2003) and H1N1 Flu (2009) outbreaks occurring in Europe in recent years.

Zoonoses are diseases that are transmissible between animals and humans. Humans can acquire these infections directly from contact with sick or carrier animals, contaminated foodstuffs, or from other environmental sources (Lahuerta et al., 2011). It is important to control the spread of these diseases and the use of medication is becoming very important as a means of avoiding disease transfer from animals to humans. This is especially true in livestock and poultry, where antimicrobials are used to prevent disease and to treat infections. Furthermore, antibiotics are also used to help the animals to grow faster. This over-use of antibiotics leads to the development of antibiotic resistance, which means that some bacteria strains are able to survive exposure to one or more antibiotics. This resistance has several negative aspects both in human and animals, such as increased morbidity and mortality due to inappropriate therapy and the increase in costs for medical treatment (Acar, 1997).

Experience in Europe shows that changing animal husbandry practices and removing growth-promoting antimicrobials from feed results in decreased resistance in animals without loss of productivity or loss of value in food animals (Shea, 2003).

In order to arrest the current global increase in antibiotic resistance and to reduce costs related to diseases and veterinary interventions, the methodology must include the elimination 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.

## Precision livestock farming

Information technology (IT) is continuously making remarkable progress in terms of technical efficiency. In particular, production methods and reductions in device size and energy consumption have made the technology cheaper and more accessible.

When recent progress in IT and sensors is combined with the use of internet connections, it is possible to implement new technologies which are complementary to industrial production based on animal biology. These new technologies can provide methods of supporting the farmer, providing him with an early warning system for automatic, non-invasive identification of production, health and welfare problems on farms.

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 of animals and their biological response. The PLF approach can easily be applied to different aspects of management, with a focus on the animals and/or the environment, and at different scales, from the individual to the entire flock/herd (Wathes, 2010). PLF can also be used to aid the management of some complex biological production processes, for example in food strategies, to control the growth rate and to monitor the animal activity (Halachmi et al., 2002; Aerts et al., 2003a; Aerts et al., 2003b; Costa et al., 2007).The aim of these technical tools is not to replace, but to support the farmer who always remains the most important element of good animal management (Costa et al., 2007).

The definition of PLF is 'the application of the principles and techniques of process engineering to livestock farming to monitor, model and manage animal production' (Wathes, 2010). According to Wathes (2010) PLF relies on four essential elements:

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 or growth rate;
4. Actuators and a model-based predictive controller for the process inputs.

In general, the reliability of PLF is determined primarily by the animal and all the physiological variables that can/must be continuously measured, such as weight, activity, behaviour, food intake, noise produced, body temperature, heart or respiratory rate, etc. Continuous measurement means that, depending on the variable in question, the frequency of measurements must be high/elevated. Other requirements include the capability to provide reliable prediction and, along with on-line measurement, integration of the algorithms that are necessary for automatic animal monitoring in order to implement correct control strategies (Guarino, 2005).

Possible approaches to automatic monitoring systems may be based on sound, images and collection of environmental data.

One of these "monitoring technologies" is bioacoustics. This cross-disciplinary science investigates sound production, dispersion and reception in biological organisms (Fletcher, 2004) and offers several advantages in terms of the detection of relevant sounds linked to the physiological status, activity, health and mental status of reared animals. Bioacoustics has been used to evaluate conditions such as stress and welfare through screams, calls and vocalizations (Moura et al., 2008; Ferrari et al., 2013), and to assess health by monitoring coughs and sneezes (Aerts et al., 2005; Ferrari et al., 2008; Silva et al., 2009; Ferrari et al., 2010). Furthermore it is a simple, cheap and non-invasive technology.

For example, respiratory diseases are one of the most prevailing pathologies in pig farming and veterinarians use cough sounds as a method of diagnosing respiratory diseases.

Cough sounds can only be assessed during a visit to the farm and an automatic monitoring tool for animals' coughs can contribute to improved farm management through opportune treatments (Silva et al., 2009).

Another approach to animal status assessment traditionally includes manual and visual scoring, but the large number of man-hours required for these methods involves high costs, and use of a sensor attached to the animals can be invasive and may alter the outcome (Cangar et al., 2008). For this reason, the use of automatically collected images to analyse farming systems is becoming more and more common. It is relatively cheap since it requires a small number of cameras and a computer, it is non-invasive and it gives access to more frequent data over long period. In addition to this, large numbers of dependent variables can easily be calculated (Cangar et al., 2008).

Image analysis has been widely used in many species to investigate thermal comfort (Shao&Xin, 2008), behaviour (Leroy et al., 2006), activity (Costa et al., 2009; Aydin et al., 2010), growth trends (De Wet et al., 2003; Demmers et al., 2012), welfare (Leroy et al., 2006; Viazzi et al., 2011) and health problems (Cangar et al., 2008; Song et al., 2008).

First of all, reliable standardised indicators of poor animal health and welfare status must be identified by animal experts. Standardising objectively measurable welfare indicators could improve systems for monitoring animal welfare at farm level and help to identify stressful practices so that preventive and corrective action can be taken within the growth cycle of the animals (Candiani et al., 2008). These indicators provide the basis for identifying the sounds and images that can be used to develop an analysis algorithm which is capable, on the basis of continuous monitoring, to predict and manage animal health and/or welfare, or take control actions (climate control, feeding strategies, etc.).

Sounds and images which identify behaviours or symptoms related to welfare and health indicators must be recorded. The next step involves the expertise of people who can extract and label the sounds or images that can provide evidence of problems on the farm.

## Sound labelling

Sound labelling involves the extraction and classification of individual animal sounds on the basis of the amplitude or frequency of the sound signal in audio files recorded on the farm. The labellers identify sounds that are of interest on the basis of the key indicators and golden standards provided by veterinarians and ethologists.

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 and their accuracy and interpretation/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 for the evaluation of audio amplitude or the spectrum of the sound, which reveals audio frequency (Figure 1).

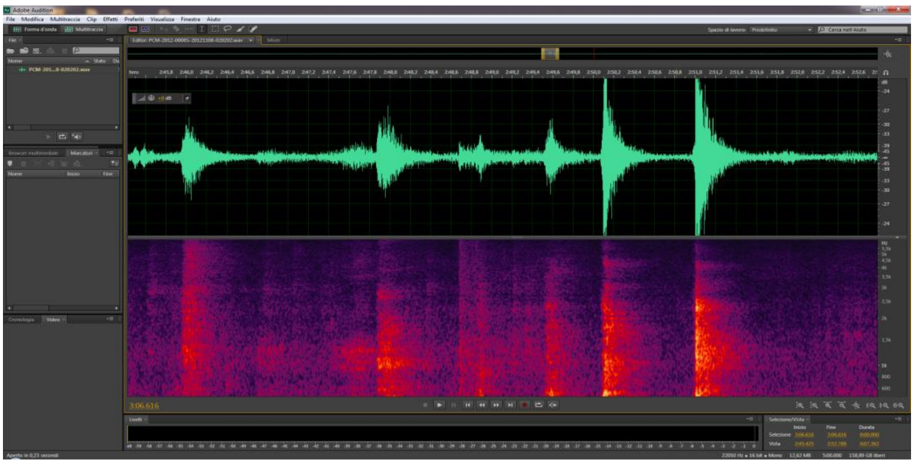

Figure 1. Screenshot of Adobe® Audition®. Waveform (upper part) and spectral display (lower part) of an audio file.

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

The spectral display (Figure 1, lower part) shows a waveform by its frequency components, where the x−axis (horizontal ruler) measures time and the y−axis (vertical ruler) measures frequency. This view allows the analysis of audio data in which frequencies are most prevalent. Colours range from dark blue, indicating low−amplitude frequencies, to bright yellow, indicating high−amplitude frequencies (Adobe® Systems Incorporated, 2003).

While listening to the audio files it is possible to zoom in and out in the two domains (frequency and amplitude) in order to visualize clearly the energy envelope of each sound.

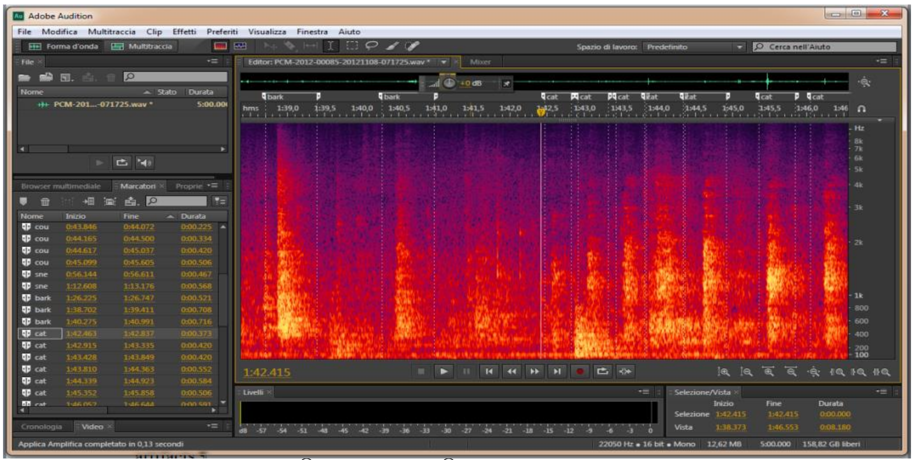

Figure 2. Screenshot of Adobe® Audition®. Spectral display of an audio file with the insertion of labels describing a cough attack (CAT).

When a sound of interest (e.g. a cough, sneeze or vocalisation) is detected, the labeller can mark it and can insert a label describing the sound (Figure 2). For each sound, the start, end and duration is automatically recorded.

**Video labelling**

Video labelling is precise detection of the occurrence of behaviours of interest performed by the group of animals or individuals and is performed by manual extraction and classification of individual frames of a video recorded at the farm. 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 the video where behaviours, activity and occupation can be measured and labelled (Figure 3).

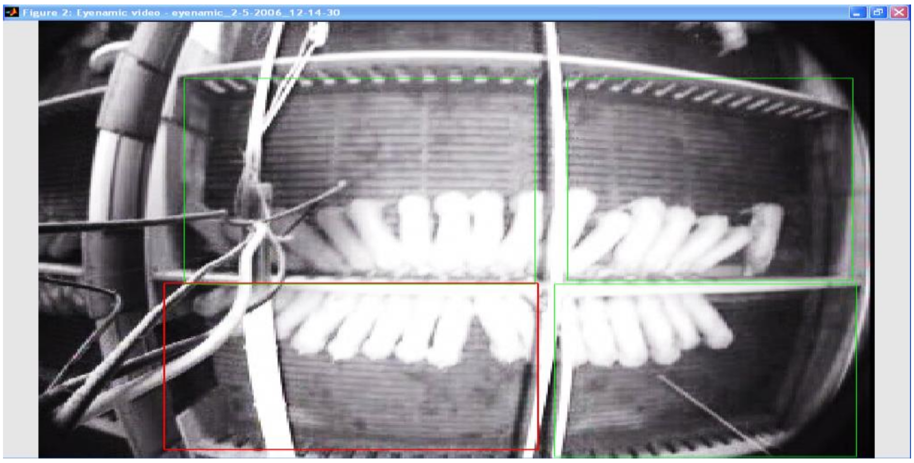


Figure 3. Definition of zones of interest inside the video where behaviours, activity and occupation can be measured and labelled

To estimate activity or occupation, the pen floor area must be converted into pixels in the image and then the pixel intensity is used to evaluate animal activity.

In order to support and speed up visual labelling, a labelling tool (Figure 4) was developed in MATLAB©It is based on the principle that relates changes in pixel intensity to a good estimation of animal activity (*activity index, Figure 4b*).

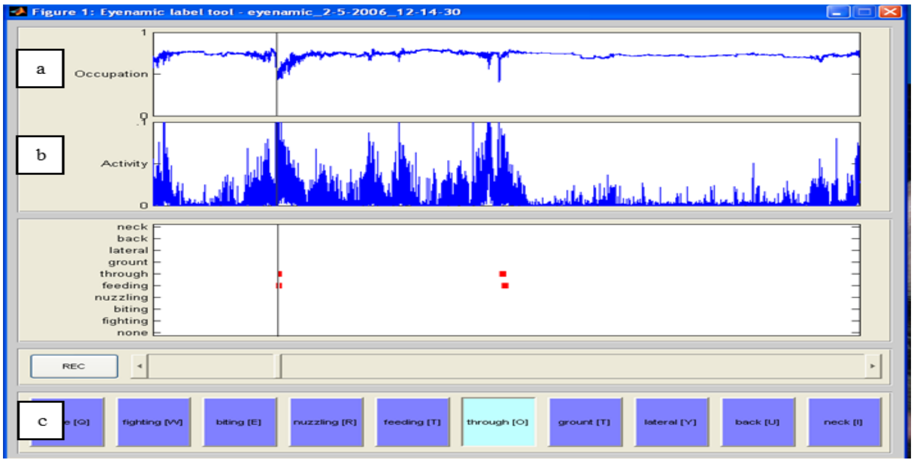


Figure 4. Screenshot of Labelling Tool. a) Occupation index. b) Activity index. c) Customisable buttons

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 that is considered in the Labelling tool is the *occupation index* (Figure 4*a*); this parameter indicates the ratio between the zone occupied by animals and the total area of the pen. By aassociating those two parameters, the software creates threshold values for animal activity, making it possible to skip those periods of the day when animals move out of necessity (e.g. feeding, drinking time).

This tool is helpful in detecting periods of increased activity and by fast forwarding the video 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 (Figure 4c).

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).

## Conclusions

The essential prerequisite for the development of a reliable algorithm for automatic identification of health and welfare problems on farms is the accuracy of the data collected. 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 and manpower. For these reasons, an accurate labelling tool should be developed. This goal will be reached through accurate validation of the output from the labelling tool (audio or video) against data collected by means of manual labelling procedures.
In order to achieve highly accurate and useful labelling, key indicators and golden standards must be clear and precise. For this reason, it is desirable to have close cooperation between animal health/welfare experts and labellers. Each labeller must be trained according to key indicators and golden standards; he/she must be competent and skilled in animal physiology, welfare and behaviour in order to understand the importance of the labelling procedure.

## References


Acar, J. F. (1997). Consequences of Bacterial Resistance to Antibiotics in Medical Practice. Clinical Infectious Diseases 24(Supplement 1): S17-S18.

Adobe® Systems Incorporated (2003). Adobe® Audition™ User Guide for Windows®.

Aerts, J. M., Jans, P., et al. (2005). Labeling of cough data from pigs for on-line disease monitoring by sound analysis. Transactions of the ASAE 48(1): 351-354.

Aerts, J. M., Van Buggenhout, S., et al. (2003a). Active Control of the Growth Trajectory of Broiler Chickens based on On-Line Animal Responses. Poultry Science 82(12): 1853-1862.

Aerts, J. M., Wathes, C. M., et al. (2003b). Dynamic Data-based Modelling of Heat Production and Growth of Broiler Chickens: Development of an Integrated Management System. Biosystems Engineering 84(3): 257-266.

Aydin, A., Cangar, O., et al. (2010). Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. Computers and Electronics in Agriculture 73(2): 194-199.

Candiani, D., Salamano, G., et al. (2008). A Combination of Behavioral and Physiological Indicators for Assessing Pig Welfare on the Farm. Journal of Applied Animal Welfare Science 11(1): 1-13.

Cangar, Ö., Leroy, T., et al. (2008). Automatic real-time monitoring of locomotion and posture behaviour of pregnant cows prior to calving using online image analysis. Computers and Electronics in Agriculture 64(1): 53-60.

Costa, A., Borgonovo, F., et al. (2009). Dust concentration variation in relation to animal activity in a pig barn. Biosystems Engineering 104(1): 118-124.

Costa, A., Borgonovo, F., et al. (2007). Real time monitoring of pig activity: classification and evaluation of pigs' behaviour. Large Animal Review 13(4): 167-172.

De Wet, L., Vranken, E., et al. (2003). Computer-assisted image analysis to quantify daily growth rates of broiler chickens. British Poultry Science 44(4): 524-532.

Demmers, T., Cao, Y., et al. (2012). Simultaneous Monitoring and Control of Pig Growth and Ammonia Emissions. 2012 IX International Livestock Environment Symposium (ILES IX) ILES12-1323.

Ferrari, S., Costa, A., et al. (2013). Heat stress assessment by swine related vocalizations. Livestock Science 151(1): 29-34.

Ferrari, S., Piccinini, R., et al. (2010). Cough sound description in relation to respiratory diseases in dairy calves. Preventive Veterinary Medicine 96(3–4): 276-280.

Ferrari, S., Silva, M., et al. (2008). Cough sound analysis to identify respiratory infection in pigs. Computers and Electronics in Agriculture 64(2): 318-325.

Fletcher, N. H. (2004). A simple frequency-scaling rule for animal communication. The Journal of the Acoustical Society of America 115(5): 2334-2338.

Guarino, M. (2005). La zootecnia di precisione cambierà il nostro futuro? (Livestock precision farming will change our future?). Informatore zootecnico 18-21.

Halachmi, I., Metz, J. H. M., et al. (2002). Case study: Optimal facility allocation in a robotic milking barn. Transactions of the ASAE 45(5): 1539-1546.

Lahuerta, A., Westrell, T., et al. (2011). Zoonoses in the European Union: origin, distribution and dynamics - the EFSA-ECDC summary report 2009. . Euro Surveillance 16(13).

Leroy, T., Vranken, E., et al. (2006). A computer vision method for on-line behavioral quantification of individually caged poultry. Transactions of the ASAE 49(3): 8.

Moura, D. J., Silva, W. T., et al. (2008). Real time computer stress monitoring of piglets using vocalization analysis. Computers and Electronics in Agriculture 64(1): 11-18.

Shao, B. and Xin, H. (2008). A real-time computer vision assessment and control of thermal comfort for group-housed pigs. Computers and Electronics in Agriculture 62(1): 15-21.

Shea, K. M. (2003). Antibiotic Resistance: What Is the Impact of Agricultural Uses of Antibiotics on Children’s Health? Pediatrics 112(Supplement 1): 253-258.

Silva, M., Exadaktylos, V., et al. (2009). The influence of respiratory disease on the energy envelope dynamics of pig cough sounds. Computers and Electronics in Agriculture 69(1): 80-85.

Song, X., Leroy, T., et al. (2008). Automatic detection of lameness in dairy cattle—Vision-based trackway analysis in cow's locomotion. Computers and Electronics in Agriculture 64(1): 39-44.

Viazzi, S., Borgonovo, F., et al. (2011). Real-Time monitoring tool for pig welfare. 5th European Conference on Precision Livestock Farming (ECPLF), Prague, Czech Republic.

Wathes, C. M. (2010). The prospects for precision livestock farming. Journal of the Royal Agricultural Society of England 171: 26-32.