Report Readings: Article 6

AudioMoth: Acoustic Livestock Monitoring Proposal

Francisco Maria Calisto
Instituto Superior Técnico
Lisboa, Portugal
francisco.calisto@tecnico.ulisboa.pt

SUMMARY

This report provides the reading analysis and debate of an *Acoustic Livestock Monitoring Proposal* document supported by the AudioMoth device. In context of this document, it was created for the Advanced Topics in Human-Computer Interaction course of the Computer Science and Engineering Doctoral Program at IST of ULisboa - Portugal (EU).

This document describes a proposal development and concept of an acoustic detector, namely called as *AudioMoth*. It is briefly outlined several potential case studies of monitoring animal for livestock production. As an example, it is used the animal counting, illness or even giving birth, between others, as hypothetical application. With this proposal, it can be demonstrated the potential of *AudioMoth* to enable substantial conversion from passive continuous recording by individual devices, towards smart detection by networks of devices, automatically addressing several animal characteristics. One characteristic, can be the communications between animals, taking into account the animal sound patterns of a livestock production. Since the fact that, in a period of time, each animal communicate at least one time. From here, an algorithm for logging animal sound events, has the potential to identify animal issues on a herd during that period of time. With this idea, livestock productions could benefit from an autonomous monitoring process of the animal herds. Observing animal patterns and managing animal issues.

Advanced Topics in Human-Computer Interaction, 2018/2019, IST

1 BACKGROUND

It has always been hard, if not impossible, to monitor and keep track of animals' pattern [6]. Knowing animal's patterns will greatly improve livestock production [3, 4]. Traditional livestock monitoring methods are limited by being resource intensive and invasive. This then led to an improving need on the field of livestock monitoring methods. In this regard, the idea of acoustically monitoring animals (Figure 1) came up. As a matter of fact, animal acoustical monitoring allow continuous remote data collection, and can serve productions across an inexpensive assemble collar for device recording. Therefore, it is a viable method for characterizing animal productions.

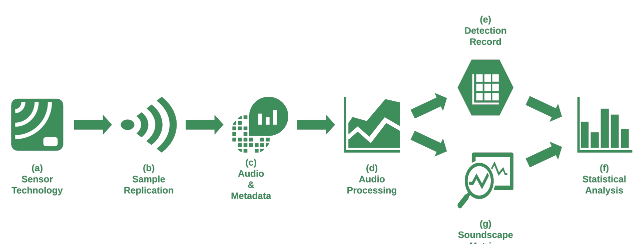

Figure 1: Passive Acoustic Monitoring (PAM) workflow proposal. Pipeline for the current application of PAM technologies, to identify challenges and research priorities at each stage. The Figure show each stage of the process regarding potential use of the (a) Sensor Technology (*AudioMoth*).

Passive acoustic sensors have become an increasingly potential for animal monitoring. Many animals emit acoustic signals that encode information regarding their presence, health condition and activities [1]. However, opportunities to acoustically examine livestock productions have historically been limited by technological constrains and costs. This situation is fast improving. For instance, the release of *AudioMoth* [7], as a low-cost sensor, has seen broad uptake for study goals at ranging from population control to activity state [8, 12].

The passive acoustic approaches have long been applied to monitor visually cryptic livestock productions such as sheep, cow and pig breeding [5]. These established acoustic examination methods typically involves livestock counting to identify each animal on a herd. This process, is done by moving the herd to an animal sleeve, counting one by one. But, in recent years, their scopes has expanded with the arrival of novel proposed acoustic sensors.

The proposed use of acoustic sensors make possible of sensing technologies. Many animals actively produce sound for communication. Also, typical livestock species emit sounds that can be labelled, enabling to create a complete dataset [14]. This dataset is suitable for algorithm development, thus leading to the development of Passive Acoustic Monitoring (PAM) [16].

The PAM involves recording sound using passive acoustic sensors (Figure 1), like *AudioMoth*, and subsequently deriving relevant data from audio (e.g., counting number of animals, epidemic situations and animal events). Vocalising animals can leak information into their surrounding regarding their behaviour, presence and interactions in time and space [10].

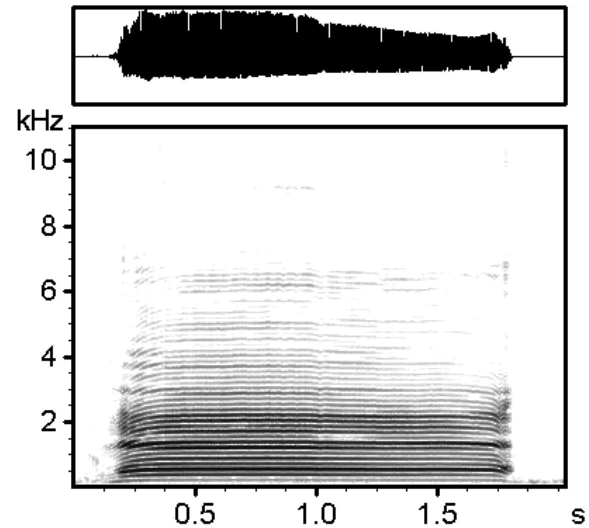

Figure 2: Sheep sound recording sample. A description of externally recorded sample in different poses. From this image we can have an idea of how is the behavior of sheep vocalization and what to expect.

2 ANALYSIS

To improve possibilities for PAM, I emphasize the need for collaborative work to develop standardized methods and analysis regarding the independent monitoring of the livestock production domain. This section is addressing a descriptive analysis of the potential for a novel robust theoretical and analytical framework for monitoring vocalizing livestock productions. The current applications of PAM technologies, identify challenges and research priorities at each stage of the PAM pipeline (Figure 1), as well as significant emerging trends for PAM in research.

The workflow (Figure 1) is presented as (a) commercial acoustic sensors (*AudioMoth*) installation; (b) comparison of audio data collected using different sensor models and sampling protocols; (c) recording and storing audio; (d) processing sound files and metadata; (e) sound identification pipeline for spatially and temporally explicit record of animal call detections; (f) statistical analysis of animal data; and (g) finding patterns of animal acoustic indicators.

Commercial acoustic sensors (Figure 1.a) are now comparable to image processing in terms of user-accessibility and durability [6]. The programmable schedules and onboard metadata collection, allow for extended autonomous deployments with flexible sampling regimes within improved battery life and storage. On the other hand, costs have limited scalability, with ubiquitous models in comparison to the image acquisition hardware.

By using different sensor models and sampling protocols, we can achieve a higher understanding of the comparability for audio data collected. The use of different sensor models and sampling protocols across different environments is also an ongoing challenge (Figure 1.b). PAM studies commonly deploy static sensors (analogous to image processing) either standalone, in multi-sensor networks, or in linked arrays to allow for sound localization. In particular cases, the use of these components (*e.g.*, microphones) might involve trade-offs between sensor data quality and cost. For instance, if showing inconsistent frequency response, vulnerable to environmental damage, or lower signal-to-noise ratios. A critical question concerns how much data can be a sacrifice without comprising the capacity to derive sufficient information from audio. The answer may vary taxonomically since each specific individual animal is intrinsically hard to distinguish between others.

Recording and storing audio at sufficient quality (Figure 1.c) is therefore crucial, alongside with detailed metadata. Both recording parameters and sensor type are also providing opportunities to address additional questions. Another possible solution, to data capacity issues, could be reducing the stored amount of audio. For instance, by applying algorithms that only trigger recording when monitorization is needed or applying onboard thresholds. However, discarding audio data is undesirable. Still, some degree of prior filtering can prevent datasets becoming large, as well as if we combine it with wireless data transmission, we could facilitate real-time livestock monitoring and reporting across animal productions.

The complexity of environmental audio (*e.g.*, communication between animal individuals, localization or vocal health issues) offers a useful real-world test for new methods (Figure 1.d). The involvement of the Machine Learning (ML) and Computer Vision (CV) in PAM is driving analytical advantages benefitting the economy and financial cost-cutting of animal production.

A standard sound identification pipeline, harvest a temporally and spatially explicit record for call detections of herds (Figure 1.e). Population inference from PAM herds, as counting number of animals, presents its difficulties. First of all, imperfect animal detection can address the probability of a successful vocalizing detection. However, is not being entirely accurate. It depends on environmental factors, call parameters, vocalizing behavior and, most importantly, its distance from the sensor. Secondly, recorded animal vocalizations are statistically nonindependent [11], for temporal proximity and close spatial, since each vocalization may come from the same individual. For instance, when addressing the animal counting, detection rates may be artificially inflated by individual animals vocalizing close to a sensor for long periods. This issue is present in one of my proposal use cases (Figure 3), since the fact that my idea is to put a collar in several (not all) animal sentinels. A primary uncertain source relates to errors in automated sound identification. Therefore, predicted detections and classifications must be removed in regard for prior modeling. However, false-negatives and false-positives (*e.g.*, due to external noises) may still impact estimates.

Considering a statistical analysis (Figure 1.f), I hope to account these uncertainties. The emergence of less computationally expensive and more accessible inference methods for complex hierarchical models is increasingly enabling multiples sources of uncertainty. These multiple sources of uncertainty are framed to incorporate several spatiotemporal models [2, 9]. For instance, such models can be extended to include associated confidence with automated animal call detections and classifications.

Figure 3: The device attached to the neck of a sheep with a collar. My proposal idea is to do the same as presented on this image. From here, we can provide algorithms audio information of the individual, as well as the surrounding animals. The animals can be ships, cows, pigs, between others.

From PAM data, it presents the challenge of classifying calls from several vocalizing animals of a heard. This approach is made by moving beyond an animal focus and towards deriving community information. For most data heterogeneity, this is currently either impossible or extremely difficult, which emphasizes the need for acoustic indicators (Figure 1.g). The acoustic indicators are, therefore, improving the recorded data. For example, by designating acoustic entropy and dissimilarity indices as acoustic analogs of classical diversity indices [13].

Newer ML methods may offer alternative means to tackle the problem of livestock monitoring. Looking further, by using Computational Neural Networks (CNN) to quantify and separate sound, we can explicitly bypass the issue of noise sensitive. Besides, another promising path involves unsupervised learning of acoustic patterns. Such patterns are directly related to acoustic data. As an example of this, we can use sparse techniques to isolate periodic sound components within call recording [15], which suggest a correlation with animal health issues.

3 DISCUSSION

To conclude, in this document, I outline some main emerging opportunities, from the literature. As PAM moves beyond proof-of-concept towards animal monitoring applications, it outcomes the feasibility of this approach into livestock productions.

The low-cost sensors, like *AudioMoth*, have pushed the bottleneck into the analysis and research stages, where it increasingly requires community efforts. A novel integration between livestock productions and research communities would benefit from it. Not only concerning reducing costs but also, concerning scientific contributions and research opportunities.

The development of *AudioMoth* is, in short, driving demand from the environmental monitoring and conservation community. However, it has an applicability range. From here, I propose the research and development of this device from the livestock domain. This future work aims at providing the community an extensive survey about livestock populations to investigate patterns and behavior on animal productions. A future project like this can promote a huge amount of data, which will contribute to further analyses of long-term livestock population trends to aid in future production efforts.

Emerging networked sensors like this, and onboard analysis pipelines, raise the possibility of using PAM data for livestock monitoring. Deriving detections from sensor networks can provide high spatial and temporal details on data for the livestock activity. This real-time data can, for instance, be applied to count the number of animals on a herd. From here, the livestock productions can surpass the need of counting animals manually. Beyond several barriers, we still face substantial technical difficulties. A particular difficulty is related to the research retardment of the domain. Nonetheless, these prospects represent future work to develop technology that is providing sensitive insights into the effects of improving livestock productions.

In short, purchasing available opportunities to apply novel monitoring techniques can dramatically reduce the financial cost and time commitment required for animal production. Monitoring projects, like the one proposed here, can address more significant questions with access to smart, yet powerful devices, such as *AudioMoth*. With further developments in the new technologies described here, I am sure that we all can get closer, achieving the basic requirements of a more sustainable animal monitoring, by improving it, as well as improving livestock management.

REFERENCES

[1] Jack W Bradbury and Sandra L Vehrencamp. 1998. Principles of animal communication. (1998).

[2] Marconi Campos-Cerqueira and T Mitchell Aide. 2016. Improving distribution data of threatened species by combining acoustic monitoring and occupancy modelling. *Methods in Ecology and Evolution* 7, 11 (2016), 1340–1348.

[3] Dena J Clink, Henry Bernard, Margaret C Crofoot, and Andrew J Marshall. 2017. Investigating individual vocal signatures and small-scale patterns of geographic variation in female Bornean gibbon (Hylobates muelleri) great calls. *International Journal of Primatology* 38, 4 (2017), 656–671.

[4] Alice Eldridge, Michael Casey, Paola Moscoso, and Mika Peck. 2016. A new method for ecoacoustics? Toward the extraction and evaluation of ecologically-meaningful soundscape components using sparse coding methods. *PeerJ* 4 (2016), e2108.

[5] AR Frost, CP Schofield, SA Beaulah, TT Mottram, JA Lines, and CM Wathes. 1997. A review of livestock monitoring and the need for integrated systems. *Computers and electronics in agriculture* 17, 2 (1997), 139–159.

[6] Rory Gibb, Ella Browning, Paul Glover-Kapfer, and Kate E Jones. 2018. Emerging opportunities and challenges for passive acoustics in ecological assessment and monitoring. *Methods in Ecology and Evolution* (2018).

[7] Andrew P Hill, Peter Prince, Evelyn Piña Covarrubias, C Patrick Doncaster, Jake L Snaddon, and Alex Rogers. 2018. AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment. *Methods in Ecology and Evolution* 9, 5 (2018), 1199–1211.

[8] Kate E Jones, Jon A Russ, Andriy-Taras Bashta, Zoltálan Bilhari, Colin Catto, István Csősz, Alexander Gorbachev, Páleter Győrfi, Alice Hughes, Igor Ivashkiv, et al. 2013. Indicator bats program: a system for the global acoustic monitoring of bats. *Biodiversity monitoring and conservation: bridging the gap between global commitment and local action* (2013), 211–247.

[9] Ammie K Kalan, Roger Mundry, Oliver JJ Wagner, Stefanie Heinicke, Christophe Boesch, and Hjalmar S Kühl. 2015. Towards the automated detection and occupancy estimation of primates using passive acoustic monitoring. *Ecological Indicators* 54 (2015), 217–226.

[10] Arik Kershenbaum, Daniel T Blumstein, Marie A Roch, Çağlar Akçay, Gregory Backus, Mark A Bee, Kirsten Bohn, Yan Cao, Gerald Carter, Cristiane Caesar, et al. 2016. Acoustic sequences in non-human animals: a tutorial review and prospectus. *Biological Reviews* 91, 1 (2016), 13–52.

[11] Tim CD Lucas, Elizabeth A Moorcroft, Robin Freeman, J Marcus Rowcliffe, and Kate E Jones. 2015. A generalised random encounter model for estimating animal density with remote sensor data. *Methods in Ecology and Evolution* 6, 5 (2015), 500–509.

[12] Stuart E Newson, Hazel E Evans, and Simon Gillings. 2015. A novel citizen science approach for large-scale standardised monitoring of bat activity and distribution, evaluated in eastern England. *Biological Conservation* 191 (2015), 38–49.

[13] Jérôme Sueur, Sandrine Pavoine, Olivier Hamerlynck, and Stéphanie Duvail. 2008. Rapid acoustic survey for biodiversity appraisal. *PloS one* 3, 12 (2008), e4065.

[14] E Tullo, I Fontana, and M Guarino. 2013. Precision livestock farming: an overview of image and sound labelling. In *European Conference on Precision Livestock Farming 2013:(PLF) EC-PLF*. KU Leuven, 30–38.

[15] Wendy J Underwood. 2002. Pain and distress in agricultural animals. *Journal of the American Veterinary Medical Association* 221, 2 (2002), 208–211.

[16] Walter MX Zimmer. 2011. *Passive acoustic monitoring of cetaceans*. Cambridge University Press.