Understanding Chimpanzee Acoustic Signatures and Meaning

Research Proposal

Yusuf Brima

brima.yusuf@aims.ac.rw

April 2021

1 Introduction

Individual Recognition (IR) among primates and other social animals has been extensively researched and documented. The process of IR involves two-way communication, that of a recognizer (receiver) and the individual being recognized (signaler) [1]. Research in this direction has shed light on the remarkable ability of primates and social animals to recognize individuals with remarkable dexterity across modalities. The evolution of language (a tool for individual recognition) in primates and other species, has been one of the principal factors determining social organization, interaction, and behavior. IR is the key, that leads to the formation of groups as it intermediates trust and social stability [1]. The ubiquity of IR as a signaling mechanism indicates its widespread evolutionary benefit for social animals as distinctiveness has a high fitness payoff.

2 Literature

Primates that live in habitats with limited visual contact notably use acoustic signals as the main tools for IR [2]. As reported by Fischer et al. [3], who conducted a longitudinal study of vocal variations in free-ranging female chacma baboons (Papio Cynocephalus Ursinus) with regards to context, type of predator, and its distinctiveness in the Moremi Game Reserve, Botswana. Kojima et al. [4], conducted a study on identifying vocalizers using an auditory-visual matching-to-sample task with a female chimpanzee species(Pan troglodytes). In that experiment, the primate successfully achieved the task of picking the vocalizer in response to pant hoots, pant grunts, and screams vocalizations. [5], conducted an ontogeny contact call study in rhesus macaques (Macaca mulatta), during the early developmental stage to determine which factors may influence vocal variations. Lemasson et al. [6], have reported vocal plasticity among Campbell's monkeys (Cercopithecus campbelli) especially amongst females when group compositionality changes.

3 Hypothesis

The identification of acoustic signatures using state-of-the-art deep learning techniques is very significant in determining the evolutionary function and the type of information being transmitted among primates and can help shed light on the precursors of high-level lingual cognition.

4 Research Problem

Knowing the form of vocal signals is very useful in shedding light on the evolutionary function [7]. However, data collection, preprocessing, and analysis are cumbersome and challenging for empirical research. A case in point is the tremendous difficulty and time-consuming nature of traditional approaches of gathering bio-acoustic signals to identify individuals and call types [8]. The traditional approaches, that rely on intuition and domain knowledge, are frequently error-prone due to their manual nature feature and parameter selection which can introduce observer and selection bias in empirical analysis. Recent progress in the field of Machine Learning, however, has shown the applicability of deep learning techniques to potentially augment and boost traditional bio-acoustic methods as well as provide an end-to-end method for the identification of individuals, species, call type, and call function, thus eliminating observer bias [9, 10, 11, 12, 13].

5 Research Goal

The goal of this work is to utilize recent deep learning algorithms to complement traditional bio-acoustic methods to help understand acoustic signatures and call meaning of chimpanzees. The project aims to help shed light on acoustic signals and function thus giving a deeper understanding of the evolutionary precursors of high-level cognition and communication.

6 Research Objective

The objectives of this work are to:

1. Understand the effect of long-distance calls and drumming patterns of chimpanzees as to whether such an acoustic signal can be linked to a distinct individual as well as the behavioral outcome of such signal.

2. Propose a method for vocal feature extraction using cepstral coefficients or similar methods to improve the performance of call and drumming pattern identification

3. Correctly classify species, call type, and caller identity using Deep Neural Networks.

4. Study the effect of acoustical modification (e.g., pitch shift and filtration) on the performance of the proposed algorithm.

7 Open Questions

- Can the analysis of mirror neuron activities to study call type and drumming patterns in primates help characterize the meaning and evolutionary behavioural mechanism of such acoustic signals?
- Can Convolutional Neural Netowork (CNN) models use low-level representations of acoustic data (segmented spectrograms with deltas) be use to effectively recognize long-distance call types and drumming patterns amongst chimpanzees?

8 Methods

This research seeks to explore state-of-the-art deep learning, which has shown promise in bio-acoustic signal analysis. Fig. 1, gives a depiction of the proposed approach where low-level representation of acoustic data are segmented using Short Time Fourier Transform (STFT) followed by cepstral feature extraction which will be used for training and testing a deep neural network for the detection and classification of call types and drumming patterns amongst chimpanzees. This will help to expand the body of scientific knowledge on the evolutionary meaning of these acoustic signals and their behavioral interpretations as tools for understanding the precursors of high-level cognition, communication, and reasoning.

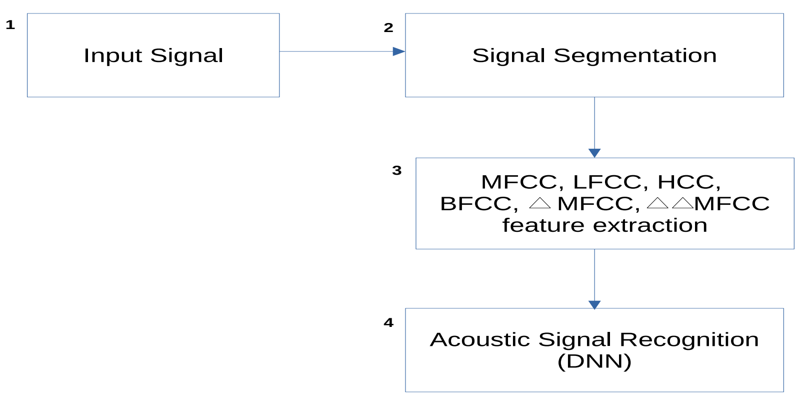

Figure 1: End-to-end system model for call type and drumming pattern recognition using deep learning: (1) Input signal is read; (2) input signal is segmented into Short Time Fourier Transforms (STFT); (3) Linear Frequency Cepstral Coefficients (LFCC), first-order Linear Frequency Cepstral Coefficients (△ LFCC),second-order Linear Frequency Cepstral Coefficients (△△ LFCC), Mel Frequency Cepstral Coefficient (MFCC), Homomorphic Cepstral Coefficients (HCC), and Bark-Frequency Cepstral Coefficients (BFCC) are extracted; (4) A deep neural network is used to classify the extracted features

References

[1] E. A. Tibbetts and J. Dale, "Individual recognition: it is good to be different," *Trends in ecology & evolution*, vol. 22, no. 10, pp. 529–537, 2007.

[2] A. Mielke and K. Zuberbühler, "A method for automated individual, species and call type recognition in free-ranging animals," *Animal Behaviour*, vol. 86, no. 2, pp. 475–482, 2013.

[3] J. Fischer, K. Hammerschmidt, D. L. Cheney, and R. M. Seyfarth, "Acoustic features of female chacma baboon barks," *Ethology*, vol. 107, no. 1, pp. 33–54, 2001.

[4] S. Kojima, A. Izumi, and M. Ceugniet, "Identification of vocalizers by pant hoots, pant grunts and screams in a chimpanzee," *Primates*, vol. 44, no. 3, pp. 225–230, 2003.

[5] K. Hammerschmidt, J. D. Newman, M. Champoux, and S. J. Suomi, "Changes in rhesus macaque 'coo'vocalizations during early development," *Ethology*, vol. 106, no. 10, pp. 873–886, 2000.

[6] A. Lemasson, M. Hausberger, and K. Zuberbühler, "Socially meaningful vocal plasticity in adult campbell's monkeys (cercopithecus campbelli)." *Journal of Comparative Psychology*, vol. 119, no. 2, p. 220, 2005.

[7] P. Marler, "The logical analysis of animal communication," *Journal of theoretical biology*, vol. 1, no. 3, pp. 295–317, 1961.

[8] K. Adi, M. T. Johnson, and T. S. Osiejuk, "Acoustic censusing using automatic vocalization classification and identity recognition," *The Journal of the Acoustical Society of America*, vol. 127, no. 2, pp. 874–883, 2010.

[9] T. Grill and J. Schlüter, "Two convolutional neural networks for bird detection in audio signals," in *2017 25th European Signal Processing Conference (EUSIPCO)*. IEEE, 2017, pp. 1764–1768.

[10] I. Himawan, M. Towsey, B. Law, and P. Roe, "Deep learning techniques for koala activity detection." in *INTERSPEECH*, 2018, pp. 2107–2111.

[11] W. L. Allen and J. P. Higham, "Assessing the potential information content of multicomponent visual signals: a machine learning approach," *Proceedings of the Royal Society B: Biological Sciences*, vol. 282, no. 1802, p. 20142284, 2015.

[12] C. Bergler, H. Schröter, R. X. Cheng, V. Barth, M. Weber, E. Nöth, H. Hofer, and A. Maier, "Orca-spot: An automatic killer whale sound detection toolkit using deep learning," *Scientific reports*, vol. 9, no. 1, pp. 1–17, 2019.

[13] G. Dezecache, K. Zuberbühler, M. Davila-Ross, and C. D. Dahl, "A machine learning approach to infant distress calls and maternal behaviour of wild chimpanzees," *Animal Cognition*, pp. 1–13, 2020.