Different acoustic method analyses yield different results

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Introduction

Efficient method analyses are necessary to establish a reliable vocal directory. As the manual classification of vocalizations is slow and subjected to the experimenter's subjectivity, automated acoustics method analysis represent a powerful help to categorize.

In the present study, we compared **four acoustic analysis methods**: a **human analysis**, an **automated graphic analysis** (**Software ANA**), a **half-human half-automated analysis** (Music Browser software) and **an analysis in supervised learning** (EDS software). Vocal recordings of five **African grey parrots** (*Psittacus erithacus*) raised in captivity have been used.

Materials & Methods

Subjects

Five African grey parrots (3 females: Nyanga, Wata, Zoé; 2 males: Léo and Shango) born in captivity and arrived at the laboratory at three months old.

Acoustic analysis methods

1- Human analysis (Avisoft-SASLab Pro V4.40 software)

• One classification based on **various acoustic features**: intensity, frequencies (max, min), bandwidth, duration, *etc.* (56526 vocalizations into 128 different categories) established by an expert

• Two classifications based on various acoustic features (same as previous) established by two non-expert persons on a sample of 2729 vocalizations

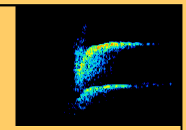
2- Automated graphic analysis (**ANA Software** developed by EVE Laboratory of Rennes – France)
5702 vocalizations
A **correlation index is calculated by comparing the frequencies in various points of each pair of spectrograms**.

3- Mi-human mi-automated analysis (Music Browser software developed by CSL Sony - France**)**
2351 vocalizations
The user defines categories from **specific archetypes and the software determines a model of classification** to distribute all the other sound samples in the vocal categories.

4- An analysis in supervised learning with EDS (developed at the laboratory CSL de Sony) **and Weka Softwares**
2375 vocalizations into 7 categories
EDS identifies **specific acoustic features** (by combining basic features) to separate sound samples into different categories. Weka allows to evaluated the **relevance of the features determined** by EDS.

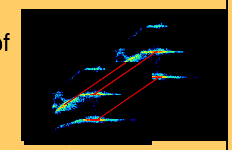
Results

1- Human analysis



The comparison between the classification established by the expert and the one established by the non-expert showed a **recovering of 22.8** and **22.3%**. More categories were described by the expert (**128 against 47 and 42** by the non experts) and mainly regroup **up to 3 vocal categories** of the non-experts.

2- ANA software



The intra-categories correlation indexes of vocalizations are significantly higher than The intercategories correlation index (0,35 ± 0,0076) *vs.* 0,19 ± 0,0037, Mann-Whitney tests).

➡The **correlations intra-categories are weak** for the vocalizations of low frequency

➡**Inaccuracy of the classification** / **Background noise** of the recording masks the vocalizations

3- Music Browser software

A non expert has defined archetypes of 18 different vocal categories. The software automatically classified the other vocalizations in 16 of these 18 categories. Compared to the expert's classification, the software mainly classified the data in **7 of the 18 categories with an overlap of 35 to 77% with the expert classification**.

4- EDS and Weka softwares

Specific acoustic features were identified by EDS. Using the SMO algorythm, Weka classified the rest of the data with an overlap of **0, 25, 35, 79, 93, 94 and 95% according to the categories.**

Discussion

- **Human analyses**: the classification varied according to the experience of the experimenter

- Among the different automated acoustic methods of analysis:

  • the analysis with **ANA** seems **not to be really efficient** when the recordings have background noise

  • the analysis with **EDS and Weka seems to be the most powerful**

  • the **Music Browser analysis** allows a **preliminary and fast classification**

Conclusion

Our study suggests that these methods are promising to conduct powerful and faster categorization of acoustics signals