Decoding auditory attention in polyphonic music based on EEG: a new dataset and a preliminary study

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AESoP Symposium 2019, Leuven, Belgium

MIPFRONTIERS PROJECT
This project has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skodowsa-Curie grant agreement No. 765068.

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Introduction

Auditory Attention Decoding

Auditory attention decoding *aims at determining, from the brain's activity, which sound source a subject is "focusing on" while listening to a complex auditory scene.*

State of the Art

- Previous works to decode the **attended speaker** in **multi-speaker environments** [Mesgarani and Chang, 2012, O'sullivan et al., 2014, Crosse et al., 2016];
- the **neural activity** tracks dynamic changes in the speech stimulus;
- a feature representation (*amplitude envelope, magnitude spectrogram, ...*) of the attended speech stimulus is reconstructed from the **unaveraged EEG** response.

How can we transpose this problem to **music***?*

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Auditory Attention Decoding

Study Case:

Detect and characterize auditory attention to **an instrument in polyphonic music**.

Useful for

improving **MIR tasks** such as *music transcription*, *score following*, *source separation*...

However...

- musical stimuli are **complex**;
- musical stimuli are intrinsically **different from speech**;
- there is a **lack of data**.
- previous works: [Treder et al., 2014].

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Data & Methods

Dataset

MAD-EEG[1]**:** 20-channel surface electroencephalographic (EEG) signals recorded from 8 subjects while they were attending to a particular instrument in polyphonic music.

Each attended instrument was previously heard in solo, as part of a *training phase*.

Features

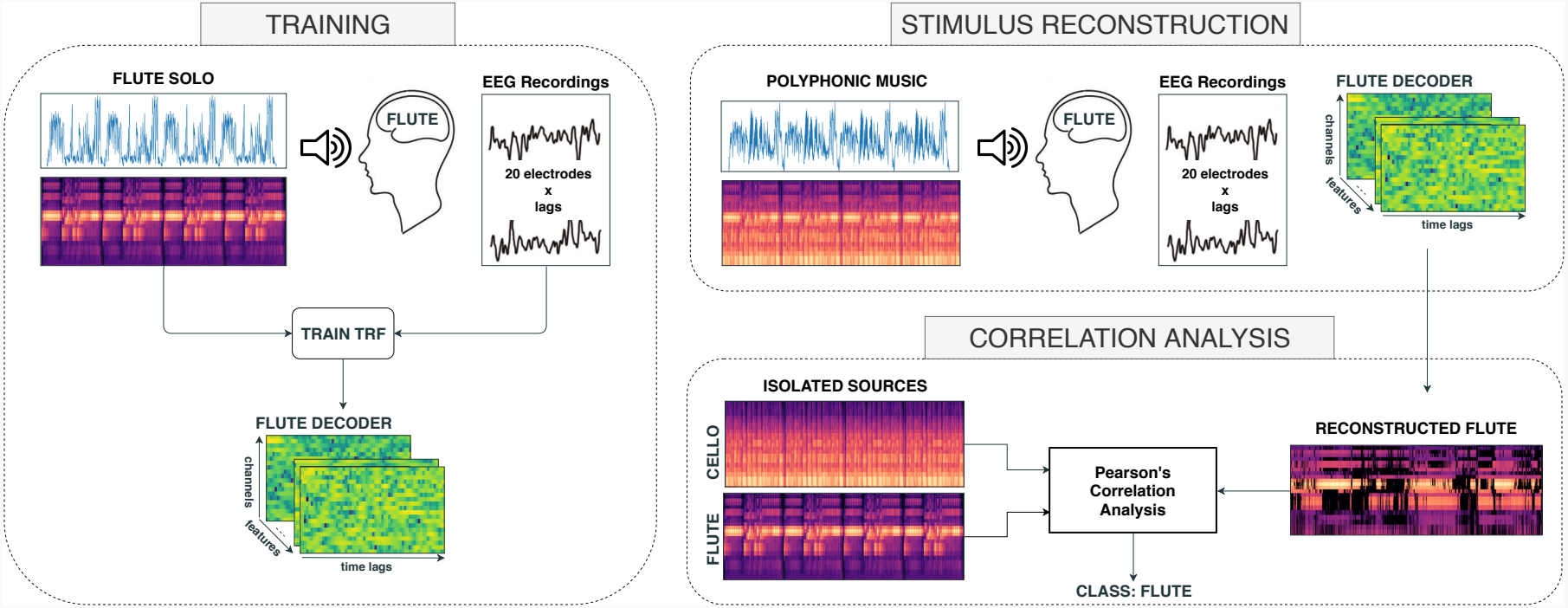
- **well-synchronized** musical stimuli and EEG responses;
- **real music compositions**;

Stimuli variants

- **number and type of instrument**s in the mixture;
- **melody/rhythmical pattern** that is played;
- **music genre**;
- **spatial rendering**.

[1] G. Cantisani, G. Trégoat, S. Essid, G. Richard, *"MAD-EEG: an EEG dataset for decoding auditory attention to a target instrument in polyphonic music"*, SMM19 workshop, 2019

Goal & Pipeline

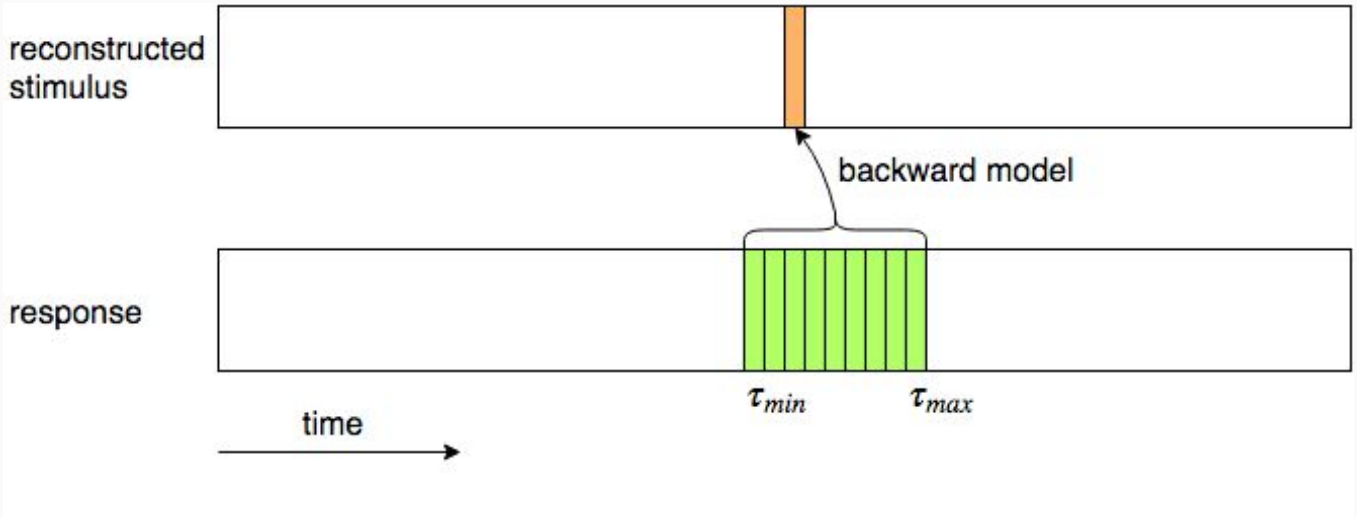


For each of the 8 subjects train on 14 solos, test on 40 duets and 24 trios.

Stimulus Reconstruction

A stimulus representation $\hat{s}$ is estimated from multi-channel neural data r through a model g which behaves like a *multi-channel Wiener filter*:

$$\hat{s}(t,f) = \sum_{n} \sum_{\tau} g(\tau, f, n) r(t-\tau, n)$$



The filter is learned by solving a **linear regression** problem: $\sum_t \sum_f [s(t,f) - \hat{s}(t,f)]^2$

Results & Discussion

Research questions

- *Are we* **tracking attention** *or a general music entertainment*?
- *Are we tracking the* **target instrument**?
- *Which is the most suitable* **audio descriptor** *for such a task*?
- *How much* **variants in the stimuli** *influence the performances*?

Reconstruction performances

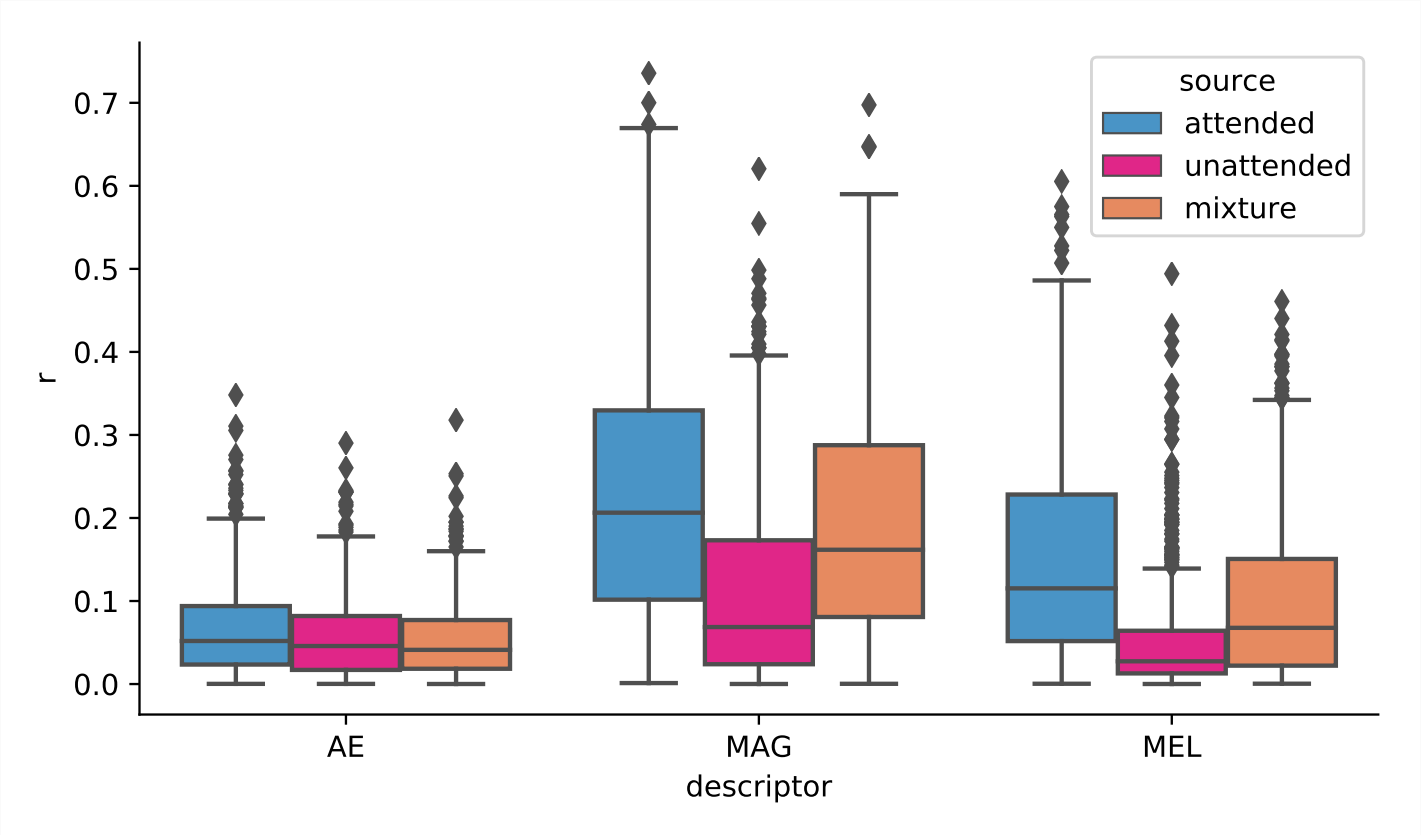


Figure 1: Pearson's correlation coefficients of the reconstructed stimulus with the attended source (blue), the unattended one (pink) and the mixture (orange) for the three audio descriptors.

Reconstruction performances - variants

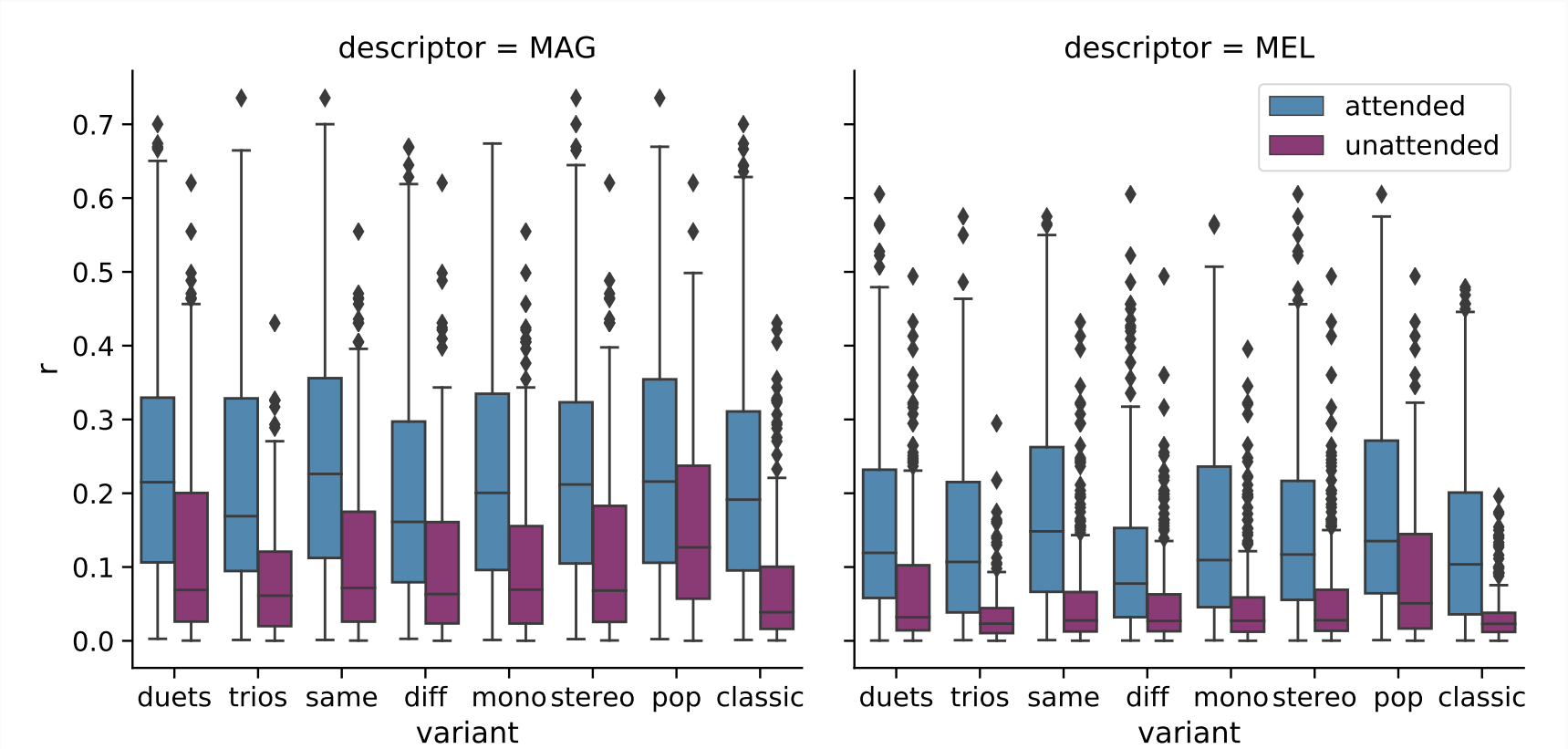


Figure 2: $r_{attended}$ and $r_{unattended}$ scores for the all the stimuli variants. Only MAG and MEL descriptors are considered. $r_{attended}$ and $r_{unattended}$ distributions are significantly different for all the variants ($p < 0.001$, Wilcoxon test).

Decoding performances

	F1 score (%)								
	all	ensemble		melody/rhythm		rendering		genre	
		duets	trios	same	diff	mono	stereo	pop	classic
AE	51 *	58 *	37 n.s.	48 n.s.	53 *	53 *	48 n.s.	54 *	48 n.s.
MAG	72 **	74 **	66 **	76 **	**65** **	73 **	**72** **	**64** **	79 **
MEL	**73** **	**79** **	**73** **	**79** **	60 **	**74** **	71 **	60 **	**83** **

Table 1: F1 scores for different subsets of the test set corresponding to variants in the stimuli and different audio descriptors. "**" denotes high ($p < 0.001$), "*" good ($p < 0.01$), and "n.s." no ($p > 0.05$) statistical significance of the results.

Reconstruction performances

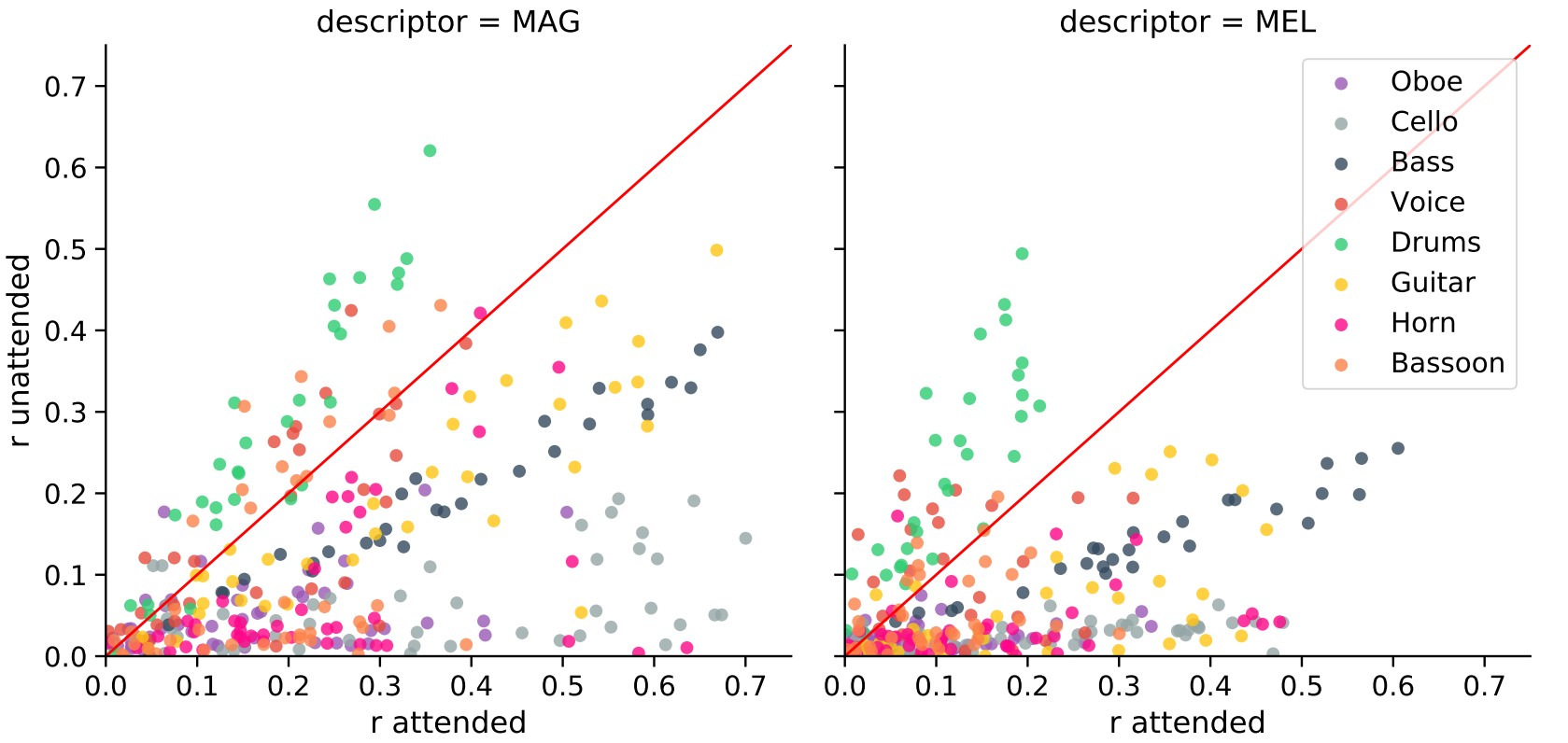


Figure 3: $r_{attended}$ against $r_{unattended}$ (only duets) for the MAG and MEL descriptors. The instruments are marked with different colors.

Conclusions

Conclusions

Take-home

- the model is **tracking attention** and not a general entertainment to the music;
- the neural activity tracks **musically relevant features of the attended source**;
- MAD-EEG: a **new dataset** to study the problem (soon available online!).

Limitations

- **limited generalization capability**;
- the model is tracking mostly the **pitch/harmonic contour** of the attended source;
- the **more instruments** in the mixture, the **more difficult** is the attention task.

Contributions

- G. Cantisani, S. Essid, G. Richard, *"EEG-based decoding of auditory attention to a target instrument in polyphonic music"*, WASPAA, 2019
- G. Cantisani, G. Trégoat, S. Essid, G. Richard, *"MAD-EEG: an EEG dataset for decoding auditory attention to a target instrument in polyphonic music"*, SMM19, 2019

Data soon available on our lab's web page
`https://www.tsi.telecom-paristech.fr/aao/en/2019/07/19/mad-eeg/`

Thank you for the attention!

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