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Perceived Music Reconstruction by EEG Signals

by

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A report on work done upto aformentioned date to

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Abstract

We intend to use Music information retrieval techniques and develop some of them on our own which were originally developed to process audio recordings and adapt them for the analysis of corresponding brain activity data. We analyse the brain activity data by using EEG signals. We point out similarities and differences in processing audio and EEG data and show to which extent the music features can be accurately reconstructed. We also present our analysis and inferences done on the OpenMIIR dataset.
We expect your guidance in this project in terms of technical aspects and in deciding the course of the project.

Contents

Abbreviations

ICA	**I**ndependent **C**omponent **A**nanlysis
STFT	**S**hort **T**ime **F**ourier **T**ransform
PICA	**P**robabilistic **I**ndependent **C**omponent **A**nanlysis

Chapter 1

Introduction

It has been shown that oscillatory neural activity is sensitive to accented tones in a rhythmic sequence rhythmic sequence. Our entire analysis is based on one assumption that the neural activity associated with music perception is synchronized with the actual recordings. or example, if there's a onset in the recoding, there would be an onset in he perceived music as well. We wish to conduct this analysis on the public domain OpenMIIR dataset of EEG recordings taken during music perception and imagination. The biggest challenge involved in this task is the extremely noisy nature of the EEG signal. We would be appying several denoising techniques like PCA, ICA(Blind Source Seperation), SSP based filtering, Wavelet transform denoising,Wavelet Packet Transform, Non-Linear Adaptive filtering,etc. This raises the question whether Music Information Retrieval techniques originally developed to detect beats and extract the tempo from music recordings could also be used for the analysis of corresponding EEG signals. One could argue that as the brain processes the perceived music, it generates a transformed representation which is captured by the EEG electrodes. Hence, the recorded EEG signal could in principle be seen as a mid-level representation of the original music piece that has been heavily distorted by two consecutive black-box filtersthe brain and the EEG equipment.

1.1 Dataset

In this study, we use a subset of the OpenMIIR dataset a public domain dataset of EEG recordings taken during music perception and imagination.These stimuli were selected from well-known pieces of different genres. They span several musical dimensions such as meter, tempo, instrumentation (ranging from piano to orchestra) and the presence of lyrics (singing or no singing present). All stimuli were normalized in volume and kept similar in length, while ensuring that they all contained complete musical phrases starting from the beginning of the piece. The EEG recording sessions consisted of five trials $t \epsilon T := \{1, ..., 5\}$ in which all stimuli $s \epsilon S := \{01, 02, 03, 04, 11, 12, 13, 14, 21, 22, 23, 24\}$ were presented in randomize order. This results in total of 300 trials for 5 (example) participants, 60 trials per particpant 25 trials per stimulus. EEG was recorded with a BioSemi Active-Two system using 64+2 EEG channels at 512 Hz. Horizontal and vertical electrooculography (EOG) channels were used to record eye movements.

1.2 Data Preprocessing

EEG pre-processing comprised the removal and interpolation of bad channels as well as the reduction of arifacts using techniques like Independent component analysis to remove occular artifacts, etc. The following preprocessing techniques have been tried out:

- There are in total 69 channels out of which 64 are EEG channels and the remaining 5 channels are EOG channels which record the occular activity. The occular activity introduces noisy artifacts in the EEG signal. We cross-correlated the 5 EOG channels with each 64 EEG channels and filtered out the bad EEG channels which displayed a high correlation value.

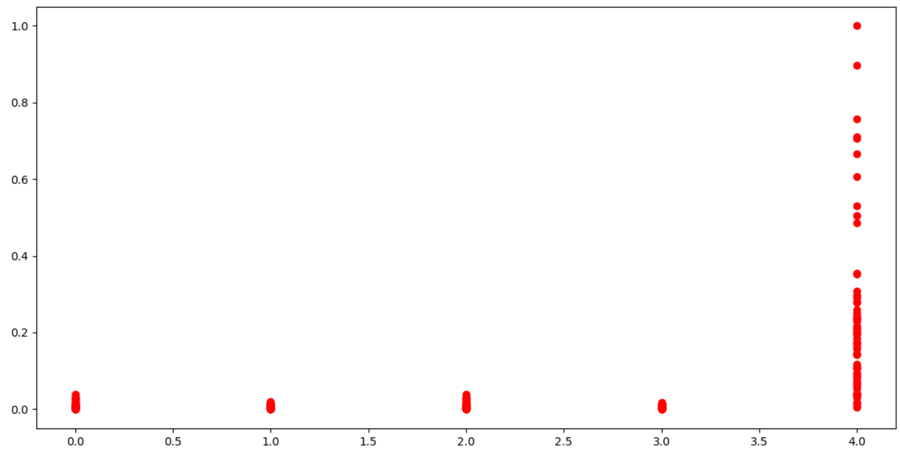
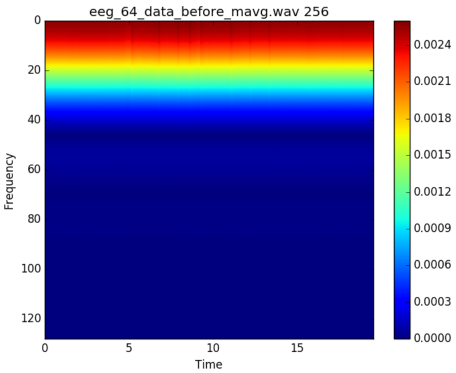
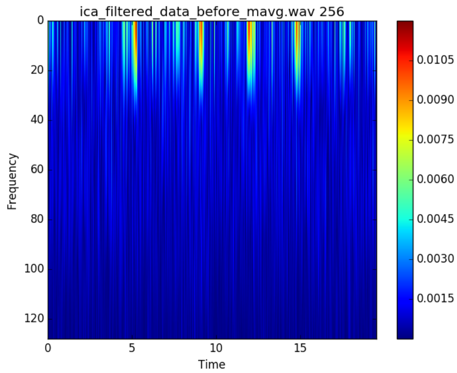


FIGURE 1.1: Correlation of EEG channels with EOG channels.

- ICA has been extensively used as an effective filtering technique for EEG channels. We applied ICA and we got some interesting results which we want to analyse further. The following plots are STFT of the signals. Since music information

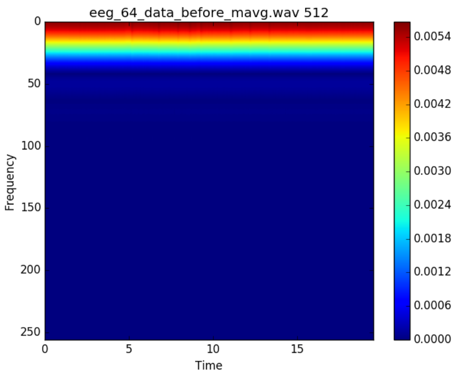


(a) Without ICA

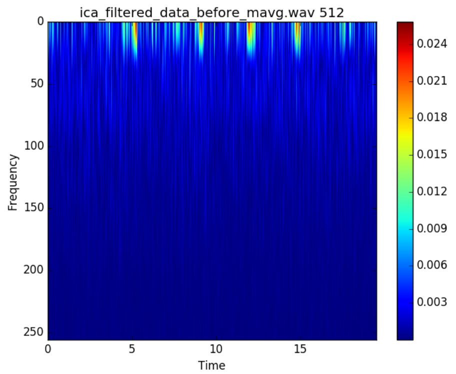


(b) With ICA

Figure 1.2: Sampled at 256 Hz



(a) Without ICA

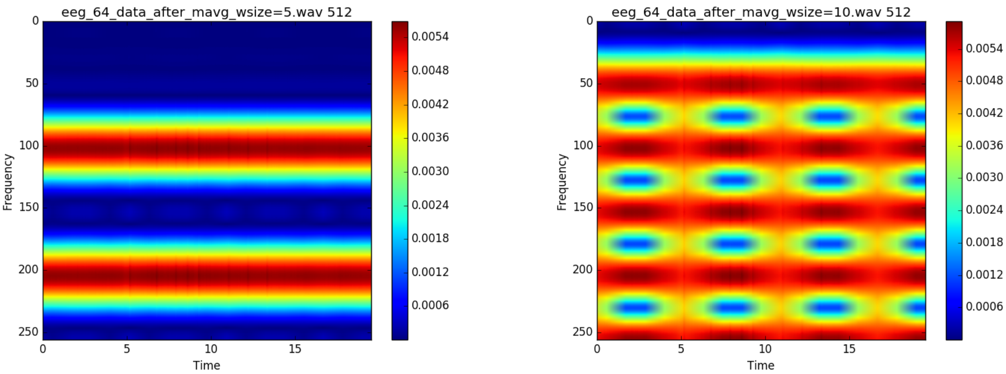


(b) With ICA

Figure 1.3: Sampled at 512 Hz

is embedded in the frequency content, we applied STFT. We are reading up on PICA, a variant of ICA and planning to implement it on the raw data.

- We calculated the moving average by specifying a window-size and subtracted it from the EEG signal.



(a) Window Size = 5

(b) Window Size = 10

FIGURE 1.4: Sampled at 512 Hz without applying ICA

Appendix A

An Appendix

ICA

We could view a measurement as an estimate of a single source corrupted by some random fluctuations (e.g. additive white noise). Instead, we assert that a measurement can be a combination of many distinct sources each different from random noise. The broad topic of separating mixed sources has a name -blind source separation (BSS). As of todays writing, solving an arbitrary BSS problem is often intractable. However, a small subset of these types of problem have been solved only as recently as the last two decades this is the provenance of independent component analysis (ICA).

Solving blind source separation using ICA has two related interpretations filtering and dimensional reduction. If each source can be identified, a practitioner might choose to selectively delete or retain a single source (e.g. a persons voice, above). This is a filtering operation in the sense that some aspect of the data is selectively removed or retained. A filtering operation is equivalent to projecting out some aspect (or dimension) of the data in other words a prescription for dimensional reduction. Filtering data based on ICA has found many applications including the analysis of photographic images, medical signals (e.g. EEG, MEG, MRI, etc.), biological assays (e.g. micro-arrays, gene chips, etc.) and most notably audio signal processing.

Quick Summary of ICA

- Subtract off the mean of the data in each dimension.

- Whiten the data by calculating the eigenvectors of the covariance of the data.
- Identify final rotation matrix that optimizes statistical independence