PAPER TEMPLATE FOR ISMIR 2015

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ABSTRACT

The abstract should be placed at the top left column and should contain about 150-200 words.

1. INTRODUCTION

Audio Source separation is a challenging task and fully automatic system is still out of reach, but a number of algorithm involving a human operator are starting to yield satisfactory results. Supervised algorithms use high-level musical information to improve the separation quality of the algorithm. In the context of blind source separation, Non-negative Matrix Factorization (NMF) is a widely used method for source separation. The goal of NMF is to approximate a data matrix $V \in \mathbb{R}_+^{n\times m}$ as $V \approx \tilde{V} = WH$ with $W \in \mathbb{R}_+^{n\times k}$, $H \in \mathbb{R}_+^{k\times m}$ and where k is the rank of factorization [1]. In audio signal processing, the input data is usually a Time-Frequency (TF) representation such as a short time Fourier transform (STFT) or a constant-Q transform spectrogram. Blind source separation is a difficult problem and the plain NMF decomposition does not provide satisfying results. To perform a satisfying results, it is necessary to exploit various features that make each sources distinguishable from one another. Supervised algorithms in the NMF framework exploit training data or prior information in order to guide the decomposition process. For example information from the scores or from midi signals [2] can be used to initialize the learning process. The downside of this approach is that it requires well organized prior information that is not always available. Another supervised method consists in performing prior training on specific databases. For example a dictionary matrix W_{train} can be learnt from a big database in order to separate an instrument [3, 4]. A common method to build a dictionary for NMF is to perform a decomposition on a large training set. After the convergence, the W matrix from the decomposition is used as the dictionary matrix W_{train} in the separation [3]. Another method is detailed in [4], a dictionary matrix is created by extracting template spectra from isolated drum samples. The dictionary is then used in a NMF decomposition to perform drum transcription. This method requires minimum tuning from the user. However, the dictionary should match the target instrument for satisfying performances. The problem of recent method using dictionary matrices is that, within a database, an instrument can sound differently depending on the recording condition and post processing treatment. In order to represent correctly one instrument, ones can decide to learn a dictionary on a large database, however, the problem of overfitting the data exist. In order to overcome this problem and to be able to build effective dictionaries we decided to use genre specific training data. Genre specific information can provide an insight on the structure of the audio signal. Music from the same genre share similar chords and rhythm and the resemblance between two pieces of music have been used to perform chord transcription [5, 6] or for downbeat detection [7]. In this paper, we focus on the task of harmonic/percussive source separation (HPSS) using the method developed in [8]. We adapt the method to be used with a drum dictionary to extract the percussive instruments. This method is explained in detail in the preprint. The main contribution of this article is that we developed a genre specific method to build a drum NMF dictionary that obtains consistent results on a HPSS task. Overall using a fixed dictionary for drum extraction is an underused method in the literature as it is difficult to create a drum dictionary that provide robust results on a large variety of signal. By using genre specific dictionary we were able to improve the separation score and decrease the computation time as the dictionary are smaller in size.

2. DATABASE

The dataset is taken from medley-dB [9], it is composed of polyphonic real-world music excerpts. It has 122 music signals and 89 of them contain percussive instruments, harmonic instruments and vocals. The signals that do not contain a percussive part are not part of the evaluation.

3. CONSTRUCTION OF THE DICTIONARY

3.1 Supervised NMF for source separation

The NMF model is:

$$V \approx \tilde{V} = WH. \tag{1}$$

If V is the power spectrum of a drum signal, The matrix W is a *dictionary* or a set of *patterns* that codes the frequency information of the data. This dictionary can then be used to extract a specific instrument from a mixture [3, 10]. However, building a dictionary specific to an instrument and that performs well on a large database is a complicated problem. Here we will use genre specific drum dictionary. The medley-dB database has information on the genre of music. We will used the dictionary to

3.2 Construction of the dictionary

We decide to use a NMF decomposition for the dictionary. The audio drum signal are from the database [11] and we also used isolated drum sound found on the internet (The dictionary signal used are available on your website). We concatenated 33 isolated strike on different element of different drum kit to have a wide variety of sounds. The power spectrum of STFT of the drum signal is used as the input for the NMF. We perform an NMF on the test decomposition and we use different rank of factorization to obtain different dictionary.

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$$E = mc^2 \tag{2}$$

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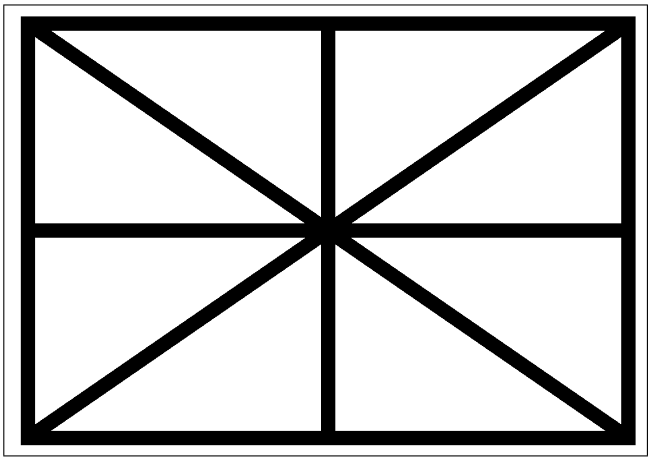

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9. CITATIONS

10. REFERENCES

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