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GENERALIZED WIENER FILTERING WITH FRACTIONAL POWER SPECTROGRAMS

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ABSTRACT

In the recent years, many studies have focused on the single-sensor separation of independent waveforms using so-called soft-masking strategies, where the short term Fourier transform of the mixture is multiplied element-wise by a ratio of spectrogram models. When the signals are wide-sense stationary, this strategy is theoretically justified as an optimal Wiener filtering: the power spectrograms of the sources are supposed to add up to yield the power spectrogram of the mixture. However, experience shows that using fractional spectrograms instead, such as the amplitude, yields good performance in practice, because they experimentally better fit the additivity assumption. To the best of our knowledge, no probabilistic interpretation of this filtering procedure was available to date. In this paper, we show that assuming the additivity of fractional spectrograms for the purpose of building soft-masks can be understood as separating locally stationary $\alpha$-stable harmonizable processes, $\alpha$-harmonizable in short, thus justifying the procedure theoretically.

Index Terms—audio source separation, probability theory, harmonizable processes, $\alpha$-stable random variables, soft-masks

I. INTRODUCTION

In the past ten years, much research has focused on the \textit{demixing} of musical signals. The objective of such research is to process a musical track so as to recover the original individual sounds that were used for its making. For instance, such a process would permit to automatically recover the voice signal from a song and thus automatically generate a karaoke version as well as solo vocals that could be used for resampling. In the scientific community, each constitutive component — or \textit{stem} — from the mixture is called a \textit{source}, and the problem of demixing is commonly called \textit{audio source separation} \cite{6, 32, 25, 19}. In the literature, both single-channel and multichannel audio source separation have been considered, depending on the number of channels of the mixture signal. For the sake of simplicity, we will only consider the single channel case in this study and leave the multichannel case for future developments.

For achieving single channel audio source separation, an efficient approach is focused on a \textit{filtering} paradigm: each source estimate is obtained by applying a time-varying filter to the mixture. In practice, a time-frequency (TF) representation of the mixture is computed, such as its short-term Fourier transform (STFT), and each source is recovered by multiplying each element in this representation by a gain between 1 and 0, according to whether this point is identified as rather belonging to this source or not, respectively \cite{4, 34, 8, 3}. For one given source, those gains form a \textit{time-frequency mask}, and several ways of designing such masks have been considered in the past.

In the audio source separation literature, an important path of research is to consider the devising of TF masks as a \textit{classification} problem. In that setting, the entries of the mask are either 0 or 1: it is typically assumed that only one source is active for any TF bin, so that the problem becomes to determine the source to which each entry of the mixture STFT is associated to. The separation algorithm hence inputs the mixture and performs a multi-class classification task, where each class corresponds to one source. Among those techniques, we can mention the celebrated DUET \cite{34} and ADRESS \cite{2} algorithms, that classify TF bins according to panning positions in the stereo plane. In the single-sensor case, other works attempt to separate sources with binary masks by using harmonicity assumptions: a melody line is first extracted, and then a binary comb-filter is generated to extract the corresponding source \cite{27}. Other recent research considers deep neural network structures to generate the binary mask used to separate target sources \cite{33}.

Even if reducing the separation problem to a classification task is convenient, it comes with the drawback of bringing a characteristic and annoying \textit{musical noise}, due to abrupt phase and amplitude transitions in the estimates. To address this issue, many researchers have focused on a \textit{soft masking} strategy, where the TF mask is no longer binary, but rather lies in the continuous $[0,1]$ interval. It has long been acknowledged that such strategies have the noticeable advantage of strongly reducing musical noise. Many different approaches were undertaken in the past for the purpose of building a soft TF mask. Among them, we can mention some studies where this mask is based on a divergence measure between the mixture and some model for the source: the further the observation is from the model, the smaller the weight, as in \cite{21, 10, 26}. This approach has the advantage of requiring a model only for the target source to separate, but has the inconvenient to be impractical if more than one source is to be extracted from the mixture.

The most popular approach to soft-masking for source separation today is based on estimating a nonnegative time-frequency energy distribution for each source, which is most commonly called a \textit{“spectrogram”} in a loose acceptation. Then, the soft mask is computed for each source as the ratio of its estimated spectrogram and some model for the source: the further the observation is from the model, the smaller the weight, as in \cite{21, 10, 26}. This approach has the advantage of requiring a model only for the target source to separate, but has the inconvenient to be impractical if more than one source is to be extracted from the mixture.

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the spectrograms to be used must hence be estimates of PSDs, i.e. squared modulus of STFTs. We should emphasize here that this acceptance is actually the original and only rigorous one.

However, much research undertaken in the recent years has commonly understood the term “spectrogram” with a different meaning. Instead of seeing it as an estimate of the PSD, many researchers have used the word “spectrogram” to denote the modulus of the STFT raised to some arbitrary exponent $\alpha \in [0, 2]$ (see [29], [11], [14], [30]). Choosing $\alpha = 1$ is common. In the sequel, the term $\alpha$-spectrogram will be used for clarity to denote this wider acceptance of the word. Just like in the WSS case with $\alpha = 2$, it is then typically assumed that the $\alpha$-spectrograms of the sources add up to form the $\alpha$-spectrogram of the mixture, and soft masks are derived in the same way as for the Wiener filter. Experience shows that such a procedure does often lead to improved performance. However, no theoretical foundation was available to explain and support this approach: to the best of our knowledge, both additivity of the $\alpha$-spectrograms and soft-masking filtering are only justified theoretically for $\alpha = 2$.

In this paper, we show that using general $\alpha$-spectrograms for sources modeling and separation is the optimal procedure if the sources are not understood as WSS processes, but rather as locally stationary stable harmonizable processes [28], $\alpha$-harmonizable processes in short. Note that for $\alpha = 2$, such processes coincide with Gaussian processes [18]. They fall under the umbrella of $\alpha$-stable distributions [24], [28]. Several studies demonstrated that those distributions are often better models for audio signals than the Gaussian distribution, due to their ability to handle very large deviations from the mean, which is important for such impulsive phenomena as music or sound signals in general that exhibit a large number of outliers.

As can be noticed in Fig. 1, the additivity assumption (1) is not always true even though $\alpha = 2$: $\alpha$-spectrograms of the sources and the $\alpha$-spectrogram of the mixture, as a function of $\alpha$. Minimal values are marked with a circle.

$$p(f, n) \triangleq |x(f, n)|.$$  

Throughout this paper, the $\alpha$-spectrogram $p^\alpha$ is defined as $p^\alpha(f, n) \triangleq p(f, n)^\alpha$. Similarly, $p^\alpha_j$ corresponds to the $\alpha$-spectrogram of source $j$. As we see, the 2-spectrogram is the power spectrogram, which is the estimate of the PSD.

Most audio source separation methods can be understood as assuming that we basically have:

$$\forall (f, n), \quad p^\alpha(f, n) \approx \sum_{j=1}^{J} p^\alpha_j (f, n). \quad (1)$$

As seen above, this assumption is justified theoretically when $\alpha = 2$ if we assume that the sources are locally stationary Gaussian processes [18]. For any other $\alpha \in [0, 2]$, no such probabilistic framework is available even though (1) is often assumed [29], [11], [14], [30].

II-B. Experimental study

The objective of this section is to study the validity of the additivity assumption (1) for $\alpha$-spectrograms, as a function of $\alpha$. To this purpose, we consider the 8 complete songs of different musical genres found in the QUASI database, for which the constitutive sources are available. For a set of 50 $\alpha$ values ranging from 0.2 to 2, we computed the $\alpha$-dispersion between the mixture $\alpha$-spectrogram and the sum of the $\alpha$-spectrograms of the sources:

$$L_\alpha(f, n) = \left| p^\alpha(f, n) - \sum_{j=1}^{J} p^\alpha_j (f, n) \right|^{1/\alpha}, \quad (2)$$

as well as the popular Itakura-Saito (IS) and Kullback-Leibler (KL) divergences, commonly used in audio source separation [9], [7]. Then, the average of each divergence over all songs and all TF bins was computed, as a function of $\alpha$. The results are displayed in Fig. 1.

II-C. Discussion

As can be noticed in Fig. 1, the additivity assumption (1) is not equally valid for all $\alpha$. On the contrary, we clearly see that a value $\alpha \approx 1$ is much more empirically appropriate than the value $\alpha = 2$, for all divergences considered.

\[ \hat{\alpha} \] denotes a definition.

\[ \text{www.tsi.telecom-paristech.fr/aao/en/2012/03/12/quasi/} \]
This result has already been noticed, e.g. in [13, 17], and demonstrates that assuming additivity of the power spectrograms, even if justified theoretically under Gaussian assumptions, is not mostly appropriate. On the contrary, assuming additivity of the moduli $p_j$ of the STFT of the sources for audio processing, as in most Probabilistic Latent Component Analysis studies (PLCA, see [30] and references therein), is indeed a good idea.4

However, this empirical fact does raise an important question. When estimates of the $\alpha$-spectrograms $p_j^\alpha$ of the sources have been obtained by any appropriate method, the estimation of the STFT of source $j$ is then typically achieved through:

$$s_j(f,n) = \frac{p_j^\alpha(f,n)}{\sum_j p_j^\alpha(f,n)} x(f,n),$$  

(3)

which we call an $\alpha$-Wiener filter in the following. Is this procedure any good and does it come with any flavor of optimality? If so, in which we call an $\alpha$-Wiener filter in the following. Is this procedure any good and does it come with any flavor of optimality? If so, in which

III. $\alpha$-HARMONIZABLE PROCESSES

We define an $\alpha$-harmonizable process as a process that can locally be approximated as a stationary harmonizable $\alpha$-stable process. In practice, the audio is split into overlapping frames, which are then assumed independent and each one of them is assumed stationary $\alpha$-stable harmonizable.

In this section, we briefly present stationary $\alpha$-stable harmonizable processes, which have been the topic of much research since the 70s and are particular cases of $\alpha$-stable processes [23], [28], [24], [31], [12]. Since we only consider isotropic complex S$\alpha$S r.v., we do not linger on the topic of the so-called “spectral measure” of $[v_1^T v_2^T]^T$, which is important for general S$\alpha$S multivariate distributions [28, p. 65].

III-B. Isotropic complex S$\alpha$S random variables

Because it will be useful in the sequel, we mention here that a complex random variable (r.v.) $z = v_1 + iv_2$ is called S$\alpha$S if the random vector $[v_1^T v_2^T]^T$ is S$\alpha$S. A particular case of interest in our context is the special case where a complex S$\alpha$S r.v. $z$ is isotropic, or circular, abbreviated S$\alpha$S$c$, meaning that:

$$\forall \theta \in [0, 2\pi[, \exp(i\theta)z \overset{d}{=} z.$$  

It can be shown that in the Gaussian case $\alpha = 2$ this is equivalent to $v_1$ and $v_2$ being independent and identically distributed (i.i.d.) Gaussian r.v., whereas for the case $\alpha < 2$, isotropy leads to the particular characteristic function [28, p. 85]:

$$z = v_1 + iv_2 \sim S\alpha S_c$$

$$\Rightarrow E[\exp(i (\theta_1 v_1 + \theta_2 v_2))] = \exp(-\sigma^\alpha |\theta|^\alpha),$$  

(5)

where $|\theta|$ is the Euclidean norm of the vector $[\theta_1, \theta_2]$, and $\sigma > 0$ is a scale parameter. The real and imaginary parts of an isotropic complex S$\alpha$S$c$ r.v. are not independent in general. As can be seen, the isotropic complex S$\alpha$S$c$ distribution is only parameterized by the scale parameter $\sigma$. For convenience, we denote it $S\alpha S_c(\sigma^\alpha)$.

We trivially have:

$$z_1 \sim S\alpha S_c(\sigma_1^\alpha) \text{ and } z_2 \sim S\alpha S_c(\sigma_2^\alpha) \Rightarrow z_1 + z_2 \sim S\alpha S_c(\sigma_1^\alpha + \sigma_2^\alpha).$$  

(6)

III-C. Stationary harmonizable $\alpha$-stable processes

An harmonizable process $\tilde{z}(t)$ is defined as the inverse Fourier transform of a complex random measure $z(\omega)$ with independent increments:

$$\tilde{z}(t) = \int_{-\infty}^{\infty} \exp(i\omega t) z(\omega) d\omega.$$  

(7)

In expression (7), the r.v. $z(\omega)$ may be understood as the spectrum of $\tilde{z}$, taken at angular frequency $\omega$. Stating that $z$ has independent increments basically means that all frequencies of the spectrum of $\tilde{z}$ are asymptotically independent, if the frame is long enough. It is a classical result that when $z(\omega)$ is an isotropic complex Gaussian random measure, $\tilde{z}(t)$ is furthermore stationary. Since audio signals can be considered stationary for the whole duration of each frame, assuming $z(\omega)$ to be an isotropic complex Gaussian is a popular assumption in the audio processing literature (see e.g. [18]).

However, assuming an isotropic complex Gaussian spectral measure is not the only way of guaranteeing that an harmonizable process $\tilde{z}$ is stationary. In particular, a very important result in our context [28, p. 292] is that taking $z$ as an isotropic complex S$\alpha$S random measure is equivalent to having $\tilde{z}$ being both a stationary and an S$\alpha$S random process, which is the natural extension of the Gaussian case to $\alpha < 2$. We then model $z(\omega) \sim S\alpha S_c(\sigma^\alpha(\omega))$, where $\sigma^\alpha(\omega)$ is called the fractional power spectral density of $\tilde{z}$ [31], abbreviated $\alpha$-PSD in the following.

4Remarkably, Fig. 1 also suggests to use KL rather than IS for $\alpha = 1$, and IS rather than KL for $\alpha = 2$, as done in the literature.
The main interest of the $\alpha$-harmonizable model is to account for signals that both include large deviations and are stationary. It is thus interesting for audio signals, because they are stationary on short time-frames and often feature large dynamic ranges.

III-D. Separation

Let the $J$ source waveforms $s_1, \ldots, s_J$ defined in section II be modeled as independent $\alpha$-harmonizable processes. Due to the stability property (4), their mixture $x$ is also $\alpha$-harmonizable and using (6), we have:

$$x(f, n) \sim S \alpha S_c \left( \sum_{j=1}^{J} \sigma_j^\alpha(f, n) \right),$$

where $\sigma_j^\alpha$ is the $\alpha$-PSD of source $j$. Since the $\alpha$-spectrogram $p_j^\alpha$ defined in section II is an estimate of the $\alpha$-PSD, we see that the $\alpha$-harmonizable model indeed leads to the additivity assumption (1) over the $\alpha$-spectrograms of the sources.

Now, given $x(f, n)$ and assuming the $\alpha$-PSD $\sigma_j^\alpha$ of the sources are known, is there a way to estimate $s_j(f, n)$ in order to proceed to source separation? Interestingly, the answer is yes. If $0 < \alpha < 2$, and considering that (i) $x(f, n)$ is the sum of $J$ independent $S \alpha S_c$, t.v. $s_j(f, n)$ and that (ii) $x(f, n)$ and $s_j(f, n)$ are jointly $S \alpha S_c$, we have:

$$E[s_j(f, n) | x(f, n), \{\sigma_j^\alpha\}] = \frac{\sigma_j^\alpha(f, n)}{\sum_{j'} \sigma_j^\alpha(f, n)} x(f, n).$$

Equation (3) can thus be interpreted as a practical estimate $\hat{s}_j(f, n)$ of $s_j(f, n)$ given $x(f, n)$, where the $\alpha$-PSD $\sigma_j^\alpha$ in equation (8) has been replaced by its estimate $p_j^\alpha$. We can conclude that for $0 < \alpha < 2$, the $\alpha$-Wiener filter corresponds to estimating the separated sources as their conditional expectation given the mixture $x$ under an $\alpha$-harmonizable model.

IV. EVALUATION

IV-A. Data and metrics

For evaluating the performance of the proposed $\alpha$-Wiener filter for source separation, we processed the 8 songs of the QUASI database in the following way:

First, the $\alpha$-spectrograms $p_j^\alpha$ of the true sources were computed. Then, separation was performed through (3) to obtain the best possible estimates $\hat{s}_j$ under an $\alpha$-harmonizable model. After this, the resulting waveforms were obtained through an inverse STFT.

For evaluation, all separated sources were split into 30s excerpts, yielding a total of 182 separated source excerpts. The Perceptual Similarity Measure (PSM) from PEMO-Q [15] was finally used to compare the estimated sources with the true ones, on all the excerpts and for 19 values of $\alpha$ between 0.2 and 2. The PSM lies between 0 (mediocre) to 1 (identical) and is frequently used in assessing audio quality. Results are displayed in Fig. 2.

IV-B. Discussion

Similarity Measure between the true sources and those obtained by the $\alpha$-Wiener filter (3), as a function of $\alpha$. $\alpha = 2$ corresponds to classical Wiener filtering. The best performance is marked with a circle.

First, we see that choosing an $\alpha$-harmonizable model with $\alpha < 2$ does improve the separation performance. In particular, the classical 2-Wiener filter is outperformed in our experiments by an $\alpha$-Wiener filter with $\alpha \approx 1.2$, even if the improvement is only of a few percents.

Second, these scores correspond to the oracle performance of the method, i.e. when the true $\alpha$-spectrograms of the sources are known. In real applications, they need to be estimated from the mixture and the additivity assumption (1) is critical for this purpose. Since we saw in section II that (1) is much better verified when $\alpha \approx 1$ than in the Gaussian case, we see that the $\alpha$-harmonizable model may be advantageous in practice, because it is the only one we know of that justifies both this popular assumption and the resulting filtering procedure (3).

V. CONCLUSION

In a single channel audio source separation context, it is often convenient to assume some linear relationship between the spectrogram of the mixture and the spectrograms of the sources. Identifying the spectrograms of the sources is indeed important to devise soft TF masks used for separation.

When we model the sources as independent and locally wide-sense stationary processes, we have recalled that this assumption is valid for power spectrograms. In that case, a natural TF mask is the classical Wiener filter.

However and as we empirically showed here, assuming the power spectrograms of the sources to add up to form the power spectrogram of the mixture is generally a rough assumption for real audio signals. After introducing the $\alpha$-spectrogram as the magnitude of the STFT raised to the power $\alpha \in [0, 2]$, we demonstrated that the additivity assumption rather holds for $\alpha$-spectrograms for some $\alpha < 2$. This fact has already been pointed out by some studies in the dedicated literature.

In this paper, we have modeled the sources as locally stationary $\alpha$-stable harmonizable processes, abbreviated $\alpha$-harmonizable, and showed that this naturally leads to the additivity of their $\alpha$-spectrograms. Furthermore, that probabilistic framework does yield a natural way of separating such signals through a soft TF mask which is analogous to the Wiener filter.

This study could be extended in two main and important directions. First, the case of multichannel mixtures is important for audio processing, because audio signals often come in several channels, as in stereophonic music. Second, this paper was only concerned with the oracle performance of the separation of stationary $\alpha$-harmonizable processes, i.e. assuming that the true $\alpha$-spectrograms were known. An interesting question concerns the implications of this model with respect to the blind estimation of the $\alpha$-spectrograms of the sources when only the mixture is available.
VI. REFERENCES


