

# COMPARATIVE EVALUATIONS OF VARIOUS HARMONIC/PERCUSSIVE SOUND SEPARATION ALGORITHMS BASED ON ANISOTROPIC CONTINUITY OF SPECTROGRAM

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## ABSTRACT

In this paper, we explore several algorithms to find the best performing algorithm for harmonic and percussive sound separation (HPSS) based on anisotropic continuity of spectrogram through comparative evaluation of their experimental performance. Separating harmonic and percussive sounds is useful as a preprocessor for many music analysis purposes including chord estimation, rhythm analysis, and other music information retrieval tasks. We have introduced a method called "Harmonic/Percussive Sound Separation" (HPSS), that decomposes a music signal into two components by separating the spectrogram into horizontally-continuous and vertically-continuous components, which roughly correspond to harmonic and percussive sounds, respectively. Many possible ways exist to realize the HPSS algorithm based on this concept while it has been unknown which algorithm performs best. This paper describes the details of five different HPSS algorithms and compares their performances over real music signals.

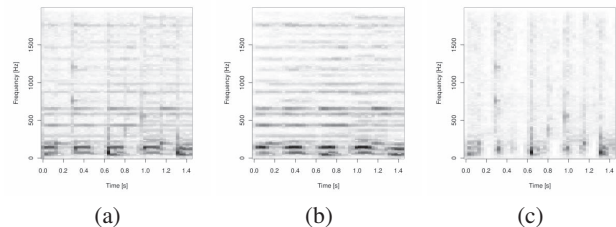
**Index Terms**— Harmonic/percussive sound separation, Music information retrieval, Source Separation

## 1. INTRODUCTION

Music signals are typically composed of harmonic components (such as violin and guitar) and percussive components (such as snare and bass drums), which have very different properties. This paper addresses methods for separating harmonic and percussive components in music signals. Such methods can be used as powerful preprocessors for many music-information-retrieval (MIR) tasks, including chord estimation, melody extraction, and rhythm pattern recognition. They can also be used for music listening applications, which allows the users to control the volumes of drum and other sounds separately. Owing to its potential usefulness, many attempts have been made to develop such methods in the music signal processing area (e.g., [1]).

So far, we have introduced a method called Harmonic/Percussive Sound Separation (HPSS). The key point of this method is that it focuses on the difference in the directions of continuity between the spectrograms of harmonic and percussive components. Specifically, the spectrograms of harmonic components are typically continuous in the time direction, owing to their quasi-stationarity, while the

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**Fig. 1.** Concept of HPSS. (a) Spectrogram of the input signal  $W$ , (b) harmonic component  $H$ , which should be continuous in time, (c) percussive component  $P$ , which should be continuous in frequency.

spectrograms of percussive components are typically continuous in the frequency direction, owing to their impulsiveness. We have verified that HPSS has been effective as a preprocessor for several MIR applications [2], including audio chord estimation [3], rhythm map generation [4], and audio melody extraction [5, 6].

There are many ways to formulate HPSS algorithms based on the concept of the anisotropic continuous of spectrogram, and each algorithm has its own parameters that need to be tuned. Of all these algorithms, we have not yet verified which one performs best in terms of separation performance. We also have not fully investigated which values of the tuning parameters provide the best performance for each of the algorithms. As HPSS can be used as an effective preprocessor for many MIR tasks, it is important to investigate which HPSS variant performs best. This paper describes the details of each HPSS algorithms, and provides comparative evaluation of the devised algorithms using real music signals.

## 2. FRAMEWORK OF HARMONIC/PERCUSSIVE SOUND SEPARATION

In this section, we describe the general framework of HPSS. The method is designed to decompose an input signal  $w(t)$  into harmonic component  $h(t)$  and percussive component  $p(t)$  by a processing on spectrogram domain. That is, given a power spectrogram  $W = \text{STFT}[w(t)] = (W_{t,k})_{1 \leq t \leq T, 1 \leq k \leq K}$  (Fig. 1 (a)), HPSS estimates the spectrogram  $H$  (Fig. 1 (b)) and  $P$  (Fig. 1 (c)), which are continuous in time and in frequency respectively. Generally, HPSS is formulated as a problem to find  $H$  and  $P$  that satisfy following properties:

- (A) Spectrogram  $\mathbf{H}$  should be continuous in time, and  $\mathbf{P}$  should be continuous in frequency.
- (B) Sum of  $\mathbf{H}$  and  $\mathbf{P}$  should be approximately equal to the original spectrogram  $\mathbf{W}$ .
- (C) Each component of the spectrogram should be non-negative, i.e.,  $\forall(\tau, k), H_{\tau,k} \geq 0, P_{\tau,k} \geq 0$ .

There could be principally two approached to obtain spectrograms  $\mathbf{H}$  and  $\mathbf{P}$  that satisfy these properties. An approach is to simply extract the horizontal lines and the vertical lines from spectrograms, by applying image-processing techniques, such as low-pass filtering in time and frequency directions respectively. The other approach is to obtain the power spectrograms by optimizing a criterion that measure (A) above, under the condition that the constraints (B) and (C) should be satisfied. Details of those methods are described in the following sections.

After estimating the power spectrograms, we should apply time-frequency masking to estimate the waveform  $h(t)$  and  $p(t)$  from the estimated power spectrograms  $\mathbf{H}$  and  $\mathbf{P}$ . In this procedure, we also have a choice what type of time-frequency mask to apply. In this paper, we consider following 3 choices: (a) we do not apply any time-frequency masks, but calculate the amplitude from estimated power spectrogram directly, which will be referred to as ‘‘None,’’ (b) estimate the amplitude by Wiener masking, and (c) by binary masking.

### 3. FORMULATIONS OF HPSS

#### 3.1. Power Spectrogram Estimation based on Low-Pass Filtering of Spectrogram

As mentioned in the previous section, the simplest way to achieve the concept of HPSS is to extract the horizontal and vertical lines from the spectrogram by applying low-pass filtering, and regard them  $\mathbf{H}$  and  $\mathbf{P}$  respectively as follows,

$$H_{t,k}^\gamma = \sum_{\tau} W_{t+\tau,k}^\gamma f(\tau), \quad P_{t,k}^\gamma = \sum_{\kappa} W_{t,k+\kappa}^\gamma g(\kappa), \quad (1)$$

where  $f(\tau), g(\kappa)$  are low-pass filters, and  $\gamma$  is an exponential factor to suppress the effects of relatively strong components, and the value is preferable to be around 0.3 to 0.5. Hereafter, we call this algorithm as ‘‘2DF.’’

As to thus derived power spectrograms, it is conceivable that most percussive components are suppressed in  $H_{t,k}$ , because percussive components are instantaneous and it should easily be filtered out by low-pass filtering. Similarly, most harmonic components should be suppressed in  $P_{t,k}$ . The forms of  $f$  and  $g$  are arbitrary, but in this paper we used the following forms for simplicity:

$$f(\tau) = 1 - \cos(2\pi\tau/I), \quad -I \leq \tau \leq I, \quad (2)$$

$$g(\kappa) = c\{1 - \cos(2\pi\kappa/J)\}, \quad -J \leq \kappa \leq J, \quad (3)$$

where  $I, J$  and  $c$  are constants to be tuned.

#### 3.2. Power Spectrogram Estimation based on Optimization Approach

Power-spectrogram-estimation by optimizing the continuity criteria is also an effective approach. The objective functions of HPSS we have considered are listed in Fig. 2. In this section, we describe the explicit form and the design concepts of each term of the objective functions, and show the way to solve the optimization problems.

All objective functions in Fig. 2 have terms  $\Omega_H(\mathbf{H}^\gamma)$  and  $\Omega_P(\mathbf{P}^\gamma)$ . These terms reflect the concept (A), i.e., they are the

$$J_1(\mathbf{H}, \mathbf{P}; \gamma, \kappa) = \Omega_H(\mathbf{H}^\gamma) + \kappa\Omega_P(\mathbf{P}^\gamma) \quad (4)$$

$$J_2(\mathbf{H}, \mathbf{P}; \gamma, a, b) = \Omega_H(\mathbf{H}^\gamma) + a\Omega_P(\mathbf{P}^\gamma) + b \sum_{t,k} (W_{t,k}^\gamma - H_{t,k}^\gamma - P_{t,k}^\gamma)^2. \quad (5)$$

$$J_3(\mathbf{H}, \mathbf{P}; \gamma, \sigma_H, \sigma_P) = \Omega_H(\mathbf{H}^\gamma)/\sigma_H^2 + \Omega_P(\mathbf{P}^\gamma)/\sigma_P^2 + D_I(\mathbf{W}|\mathbf{H} + \mathbf{P}) \quad (6)$$

**Fig. 2.** Three types of objective functions of HPSS, derived from the continuity criteria (A) and the constraints (B) and (C) described in section 2.

**Table 1.** List of the parameters and their candidate values.

Parameter	Value
$\gamma$ in Eq. 1, 4, 5	0.3, 0.5, 1.0
$\kappa$ in Eq. 4 for HM1	0.25, 0.5, 0.6, 0.9, 1, 1.2, 1.5, 2, 4
$\kappa$ in Eq. 4 for HM2	$0.8 + 0.04n, (n = 1 \dots 9)$
$a$ in Eq. 5	0.5, 1, 2
$b$ in Eq. 5 and $c$ in Eq. 2	0.25, 0.5, 0.6, 0.9, 1, 1.2, 1.5, 2, 4
$\sigma_H, \sigma_P$ in Eq. 6	0.1, 0.3, 0.5
$I, J$ in Eq. 2, 3	3, 10, 20
Frame length $L$	256, 512, 1024 points (16 kHz)
Time-frequency mask	None, Wiener, Binary

continuity criterion of the spectrogram  $\mathbf{H}$  and  $\mathbf{P}$  in the respective directions. Although there could be many types of specific form of the continuity criterion of the spectrogram, one of the simplest form is the norm of the differences between the neighboring bins of spectrogram. That is, the continuity of spectrogram in time and in frequency can be evaluated by the following criteria respectively.

$$\Omega_H(\mathbf{H}^\gamma) = \sum_{\tau=0}^{T-1} \sum_{k=0}^K (H_{\tau+1,k}^\gamma - H_{\tau,k}^\gamma)^2, \quad (7)$$

$$\Omega_P(\mathbf{P}^\gamma) = \sum_{\tau=0}^T \sum_{k=0}^{K-1} (P_{\tau,k+1}^\gamma - P_{\tau,k}^\gamma)^2. \quad (8)$$

##### 3.2.1. Optimization under Hard Mixing Constraint

Eq. 4 in Fig. 2 consists of only the continuity criterion (A). In this case, inconveniently, the solution that optimize the criterion is trivial, and the sum of the spectrograms does not suffice the concept (B). Therefore, we had to make constraints on the spectrogram based on the concept (B). One of the simplest constraint is the following one, which is based on the assumption that the spectrogram is additive, i.e.,  $H_{t,k}^\xi + P_{t,k}^\xi - W_{t,k}^\xi = 0$ , where  $\xi$  is an exponential factor. For  $\xi$ , we consider two feasible parameter settings in this paper,  $\xi = \gamma$  and  $\xi = 2\gamma$ .

When  $\xi = \gamma$ , the objective function  $J_1(\mathbf{H}, \mathbf{P}; \gamma, \kappa)$  can be minimized by iterating the following formulae [7],

$$H_{\tau,k}^\gamma \leftarrow \min(\max(H_{\tau,k}^\gamma + \beta/4, 0), W_{\tau,k}^\gamma), \quad (9)$$

$$P_{\tau,k}^\gamma \leftarrow W_{\tau,k}^\gamma - H_{\tau,k}^\gamma, \quad (10)$$

$$\text{where } \beta = (1 + \kappa)^{-1} \{ (H_{\tau+1,k}^\gamma - 2H_{\tau,k}^\gamma + H_{\tau-1,k}^\gamma) - \kappa(P_{\tau,k+1}^\gamma - 2P_{\tau,k}^\gamma + P_{\tau,k-1}^\gamma) \}. \quad (11)$$

Hereafter, we refer to this algorithm as ‘‘HM1.’’ As for  $\gamma$  and  $\xi$ , if  $\gamma = \xi = 0.5$  is satisfied, the condition  $h(t) + p(t) = w(t)$  is

**Table 2.** Parameter sets that optimize the criteria.

Method	Parameter set that maximizes SDR of $\mathbf{H}$	Parameter set that maximizes SDR of $\mathbf{P}$	Parameter set that maximizes average SDR	Parameter set that maximizes average SIR
HM1	$L = 512, \gamma = 0.3,$ $\kappa = 1, \text{Wiener}$	$L = 1024, \gamma = 1,$ $\kappa = 0.25, \text{None}$	$L = 1024, \gamma = 0.5,$ $\kappa = 1.2, \text{Wiener}$	$L = 1024, \gamma = 0.3,$ $\kappa = 1, \text{Binary}$
HM2	$L = 256, \gamma = 1,$ $\kappa = 0.92, \text{None}$	$L = 1024, \gamma = 1,$ $\kappa = 1.12, \text{None}$	$L = 1024, \gamma = 1,$ $\kappa = 1, \text{Wiener}$	$L = 1024, \gamma = 1,$ $\kappa = 1.12, \text{Binary}$
SE	$L = 512, a = 1, b = 1,$ $\gamma = 1, \text{Wiener}$	$L = 512, a = 2, b = 4,$ $\gamma = 0.5, \text{None}$	$L = 512, a = 4, b = 2,$ $\gamma = 1, \text{Wiener}$	$L = 512, a = 1.2, b = 2,$ $\gamma = 0.3, \text{Binary}$
Idiv	$L = 512, \sigma_{\mathbf{H}} = 0.5,$ $\sigma_{\mathbf{P}} = 0.1, \text{Wiener}$	$L = 1024, \sigma_{\mathbf{H}} = 0.1,$ $\sigma_{\mathbf{P}} = 0.5, \text{Wiener}$	$L = 1024, \sigma_{\mathbf{H}} = 0.1,$ $\sigma_{\mathbf{P}} = 0.5, \text{Wiener}$	$L = 1024, \sigma_{\mathbf{H}} = 0.1,$ $\sigma_{\mathbf{P}} = 0.5, \text{Binary}$
2DF	$L = 256, \gamma = 0.5, c = 2,$ $I = 10, J = 10, \text{Wiener}$	$L = 512, \gamma = 0.5, c = 0.6,$ $I = 10, J = 3, \text{Wiener}$	$L = 256, \gamma = 0.5, c = 4,$ $I = 10, J = 10, \text{Wiener}$	$L = 1024, \gamma = 0.5, c =$ $0.25, I = 20, J = 3, \text{Binary}$

strictly satisfied. However, it is also possible to set the parameter other than 0.5, such as 0.3, to suppress the effects from the very strong components.

When  $\xi = 2\gamma$ , assuming that  $\kappa \approx 1$ , the objective function can be minimized by iterating the following formulae [5],

$$H_{\tau,k}^{2\gamma} \leftarrow \alpha_{\tau,k} W_{\tau,k}^{2\gamma} / (\alpha_{\tau,k} + \beta_{\tau,k}), \quad (12)$$

$$P_{\tau,k}^{2\gamma} \leftarrow \beta_{\tau,k} W_{\tau,k}^{2\gamma} / (\alpha_{\tau,k} + \beta_{\tau,k}), \quad (13)$$

$$\text{where } \alpha_{\tau,k} = (H_{\tau+1,k}^{\gamma} + H_{\tau-1,k}^{\gamma})^2, \quad (14)$$

$$\beta_{\tau,k} = \kappa^2 (P_{\tau,k+1}^{\gamma} + P_{\tau,k-1}^{\gamma})^2. \quad (15)$$

Hereafter, we refer to this algorithm as ‘‘HM2.’’ If we set  $\xi = 0.5$ , the method is advantageous because the constraint  $h(t) + p(t) = w(t)$  is strictly satisfied. Besides, the dynamic range of the power spectrogram is sufficiently suppressed, because the value of  $\gamma$  is 0.25, which is sufficiently small.

### 3.2.2. Simultaneous Optimization of Continuity and Error Criteria

Another way to realize the concept (B) is to add a criterion to the objective function (Eq. 5 and Eq. 6), that measures the error between the sum  $\mathbf{H} + \mathbf{P}$  and the original spectrogram  $\mathbf{W}$ ,

The objective function Eq. 5 is based on the square error of the both spectrograms. This function can be minimized by iterating the following formulae, and we refer to this algorithm as ‘‘SE,’’

$$H_{t,k}^{\gamma} \leftarrow \frac{(H_{t+1,k}^{\gamma} + H_{t-1,k}^{\gamma}) + b(W_{t,k}^{\gamma} - P_{t,k}^{\gamma})}{2 + b}, \quad (16)$$

$$P_{t,k}^{\gamma} \leftarrow \frac{a(P_{t,k+1}^{\gamma} + P_{t,k-1}^{\gamma}) + b(W_{t,k}^{\gamma} - H_{t,k}^{\gamma})}{2a + b}. \quad (17)$$

The objective function Eq. 6 is based on  $I$ -divergence (Kullback-Leibler-divergence), which is known as an effective criterion to measure the divergence between two spectrograms. In this case,  $\gamma$  should be 0.5 for scale invariance, and the updating formulae can be written as follows [2, 8]:

$$H_{\tau,k} \leftarrow \{B_1 + (B_1^2 + 4A_1C_1)^{1/2} / 2A_1\}^2 \quad (18)$$

$$P_{\tau,k} \leftarrow \{B_2 + (B_2^2 + 4A_2C_2)^{1/2} / 2A_2\}^2 \quad (19)$$

$$m_{\tau,k} \leftarrow H_{\tau,k} / (H_{\tau,k} + P_{\tau,k}), \quad (20)$$

$$\text{where } A_1 = 2/\sigma_{\mathbf{H}}^2 + 2, \quad A_2 = 2/\sigma_{\mathbf{P}}^2 + 2, \quad (21)$$

$$B_1 = (H_{\tau+1,k}^{1/2} + H_{\tau-1,k}^{1/2}) / \sigma_{\mathbf{H}}^2, \quad (22)$$

$$B_2 = (P_{\tau,k+1}^{1/2} + P_{\tau,k-1}^{1/2}) / \sigma_{\mathbf{P}}^2, \quad (23)$$

$$C_1 = 2m_{\tau,k}W_{\tau,k}, \quad C_2 = 2(1 - m_{\tau,k})W_{\tau,k}. \quad (24)$$

We refer to this algorithm as ‘‘Idiv.’’

## 4. PERFORMANCE COMPARISON OF HPSS ALGORITHMS

In this section, we first tune the parameters of each HPSS algorithm using real music signals, and then evaluate each algorithm using other music signals. The performance criteria we used were SDR (signal to distortion ratio) of  $\mathbf{H}$ , SDR of  $\mathbf{P}$ , average SDR of  $\mathbf{H}$  and  $\mathbf{P}$ , and average SIR (signal to interference ratio) [9]. High SDR indicates that separated signals have low distortion, and high SIR indicates that there remain few opposite components (e.g., percussive component in  $\mathbf{H}$ ).

### 4.1. Parameter Tuning

Table 1 shows the list of parameters to be determined in this experiment. Because there are many parameters and possible parameter values, there are too many parameter combinations. Therefore, we first selected the candidate parameters, and reduced the permutations to be tested, based on the techniques of design of experiments (DOE) [10]. The data set we used for parameter tuning was the same one to the one which was used in [1]. Part of this data set was extracted from MASS database [11]. The number of music signals was 6, and the genre of each piece was different each other. All clips were 16 kHz-sampled monaural signals, and the duration of each clip was around 10–20 [s].

Table 2 shows the parameter values that optimize the evaluation criteria. Some of parameters to optimize SDR of  $\mathbf{H}$  and SDR of  $\mathbf{P}$  tend to be symmetry, e.g., as to  $(\sigma_{\mathbf{H}}, \sigma_{\mathbf{P}})$ , (0.1, 0.5) is optimal for SDR of  $\mathbf{H}$ , while (0.5, 0.1) is optimal for SDR of  $\mathbf{P}$ . Similar symmetric properties are observed in  $\kappa$  in HM2. The parameter sets that makes the average SDR and SIR optimal were quite similar to the one that optimize the SDR of  $\mathbf{P}$ , possibly because of the biased power ratio of harmonic components to percussive components in a normal music signal.

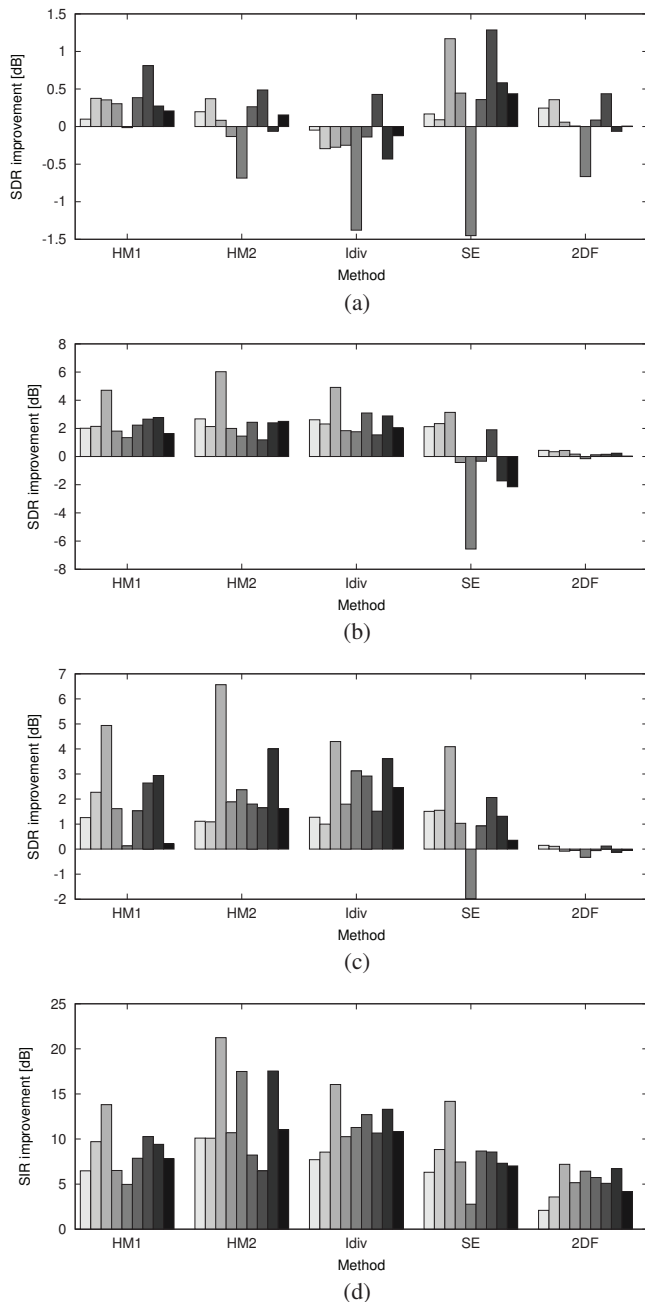
As to time-frequency masking, the result shows that Wiener mask is the best to improve SDR in many cases, while binary mask is more preferable to suppress the volume of interference signal.

### 4.2. Performance Evaluation

We evaluated the performance of each method using the parameters which were decided in the previous section. We examined the performance of the methods using other 9 mixtures, which were used in SiSEC evaluations<sup>1</sup>.

Fig. 3 shows the improvement of SDR and SIR of the signals separated by each method for each mixture. The result shows that

<sup>1</sup><http://sisek.wiki.irisa.fr>



**Fig. 3.** (a) SDR improvement of  $H$  components for 9 songs, (b) SDR improvement of  $P$  components for the 9 songs, (c) average SDR improvement of  $H$  and  $P$  for the 9 songs, (d) average SIR improvement of  $H$  and  $P$  for the 9 songs.

the performance principally depends on the piece, but there are following tendencies: the performance of “2DF” is not as high as other methods totally. There are no algorithms that maximize all the criteria. For example, if we prioritize the SDR of  $H$  over other criteria, the algorithm that performs best is “SE” (Fig. 3 (a)). However, the performance of “SE” is lower than other three methods if we focused on the SDR of  $P$ . If we focused on the average SDR and SIR, “HM2” and “Idiv” outperform other methods as a whole, indicating the comparable performance of each other.

## 5. SUMMARY

In this paper, we described various harmonic/percussive sound separation algorithms, which were based on anisotropic continuity of spectrogram: harmonic component is horizontally continuous and percussive component is vertically continuous. There are many ways to formulate HPSS algorithms based on the concept, and each algorithm has its own parameters that need to be tuned. In this paper we investigated the parameters sets of each HPSS algorithm to maximize several types of criteria, using real music signals. Further, we conducted comparative evaluations of the HPSS algorithms.

According to the experiments, we verified the inclination of parameter sets that maximize the performance of each method. Comparative evaluation based on the determined parameter sets suggests that the algorithm “HM2” and “Idiv” are comparatively better, while they are not necessarily best to improve SDR of harmonic component, i.e., it should depend on the demands from the application. Our future work will include the investigation on the compatibility to applications e.g. chord estimation.

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