Time-Frequency Representations for Music Source Separation

Final project presentation

Sevag Hanssian

MUMT 622, Winter 2021

April 22, 2021

2021-04-20

TF representations for music separation

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Music Source Separation

Musical sources are often categorized as either predominantly harmonic, predominantly percussive, or as singing voice.[1] In this project, I consider both cases (HPSS and harmonic/percussive/vocal)

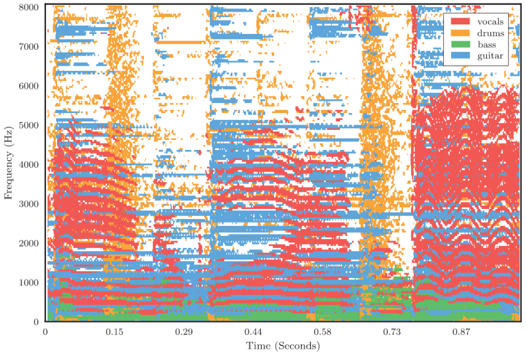
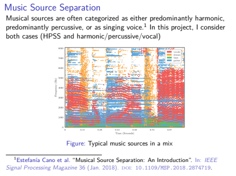


Figure: Typical music sources in a mix

[1] Estefanía Cano et al. "Musical Source Separation: An Introduction". In: *IEEE Signal Processing Magazine* 36 (Jan. 2018). DOI: 10.1109/MSP.2018.2874719.



- steady-state/transient
- tonal/transient in ltfat world

Music Source Separation

A notable property of musical sources is that they are typically *sparse* in the sense that for the majority of points in time and frequency, the sources have very little energy present[2]

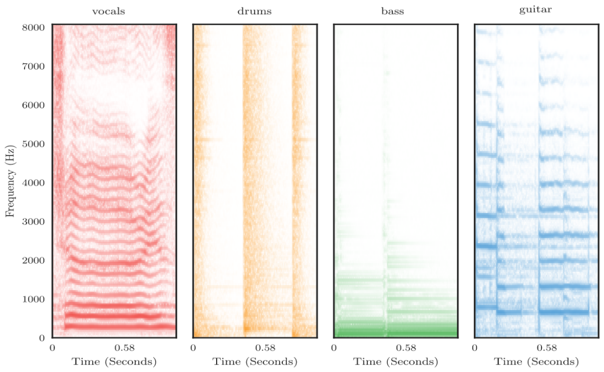


Figure: Typical music sources, separated

[2]Cano et al., 2018.

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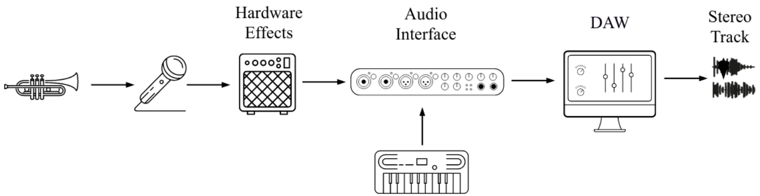
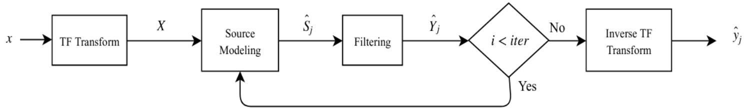


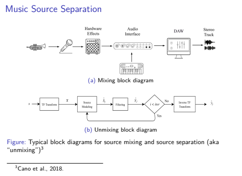
(a) Mixing block diagram



(b) Unmixing block diagram

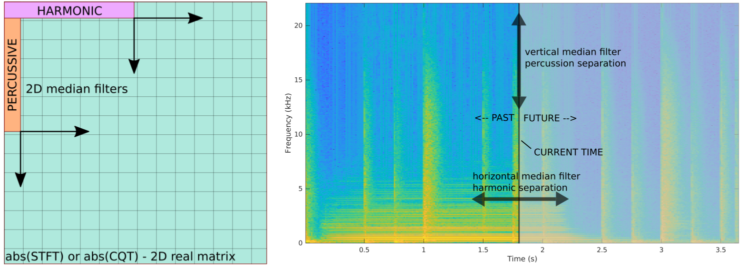
Figure: Typical block diagrams for source mixing and source separation (aka "unmixing")[3]

[3] Cano et al., 2018.



Median filtering HPSS

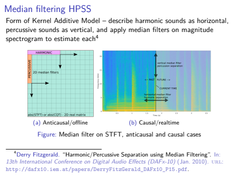
Form of Kernel Additive Model – describe harmonic sounds as horizontal, percussive sounds as vertical, and apply median filters on magnitude spectrogram to estimate each[4]



(a) Anticausal/offline (b) Causal/realtime

Figure: Median filter on STFT, anticausal and causal cases

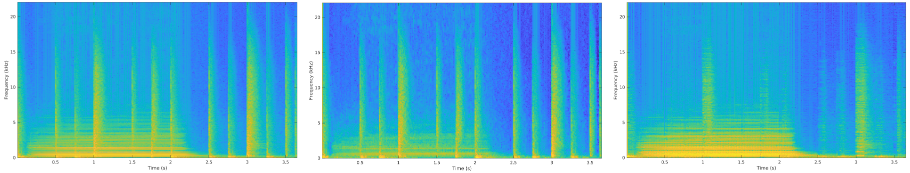
[4] Derry Fitzgerald. "Harmonic/Percussive Separation using Median Filtering". In: *13th International Conference on Digital Audio Effects (DAFx-10)* (Jan. 2010). URL: http://dafx10.iem.at/papers/DerryFitzGerald_DAFx10_P15.pdf.



- sliding STFT, perform causal median filtering, then invert
- keep several columns of STFT in memory, perform windowing + overlap-add – presented this in 501

Median filtering HPSS

Use harmonic and percussive magnitude spectrogram estimates to compute soft masks[5] or hard masks:[6]



(a) Mixed signal (b) Percussive separation (c) Harmonic separation

Figure: Example of median filtering HPSS

Originally based on STFT spectrogram. CQT works fine too.

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[5] Fitzgerald, 2010.

[6] Jonathan Driedger, Meinard Müller, and Sascha Disch. *Extending Harmonic-Percussive Separation of Audio Signals*. Jan. 2014. URL: https://www.audiolabs-erlangen.de/content/05-fau/assistant/00-driedger/01-publications/2014_DriedgerMuellerDisch_ExtensionsHPSeparation_ISMIR.pdf.

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Median filtering HPSS

Soft mask, Wiener filter:[7]

$$M_{\text{harmonic}} = \frac{|\hat{S}_{\text{harmonic}}|^2}{|\hat{S}_{\text{harmonic}}|^2 + |\hat{S}_{\text{percussive}}|^2}$$

Hard mask, binary mask:[8]

$$M_{\text{harmonic}} = \frac{|\hat{S}_{\text{percussive}}|}{|\hat{S}_{\text{harmonic}}| + \epsilon} > \beta$$

Setting $\beta > 1.0$ leads to a third residual component:

$$M_{\text{residual}} = 1 - (M_{\text{harmonic}} + M_{\text{percussive}})$$

Soft mask gives higher audio quality[9]

[7] Fitzgerald, 2010.
[8] Driedger, Müller, and Disch, 2014.
[9] Gerkmann and Vincent, 2018.

Median filtering HPSS
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- define how different harmonic and percussive should be

Iterative median filtering HPSS

2-pass HPSS,[10] , harmonic/percussive/vocal:[11]

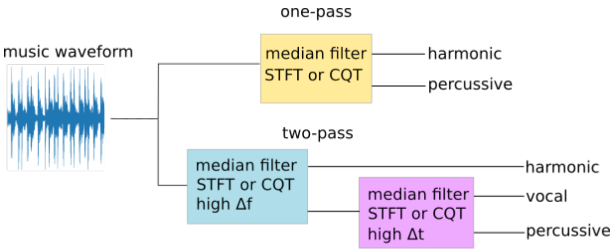
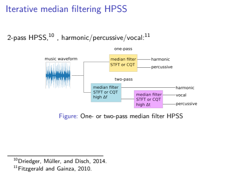


Figure: One- or two-pass median filter HPSS

[10] Driedger, Müller, and Disch, 2014.
[11] Fitzgerald and Gainza, 2010.



HPSS MATLAB pseudocode

$s =$ mixed audio
$\hat{S} = \text{STFT}(s)$ **or CQT**
$S = \text{abs}(\hat{S})$
$H = \text{medianfilter}(S, l_H, \text{axis} = 2)$
$P = \text{medianfilter}(S, l_P, \text{axis} = 1)$
soft $M_H = \frac{H^p}{H^p + P^p}, M_P = \frac{P^p}{H^p + P^p}$
hard $M_H = \frac{H}{P+\epsilon} \geq \beta, M_P = \frac{P}{H+\epsilon} > \beta$
$\hat{H} = \hat{S} \cdot M_H$
$\hat{P} = \hat{S} \cdot M_P$
$h = \text{ISTFT}(\hat{H})$ **or ICQT**
$p = \text{ISTFT}(\hat{P})$ **or ICQT**

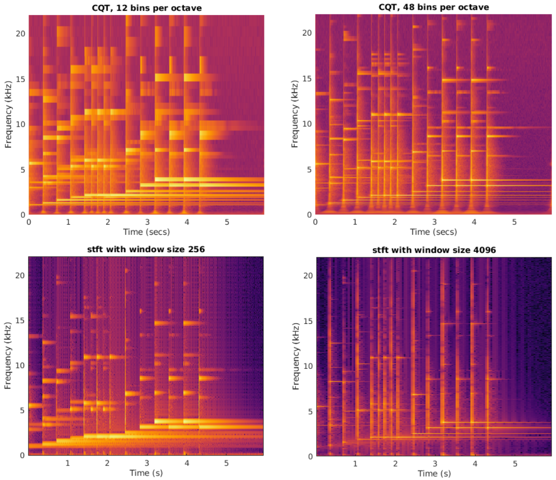
$s =$ mixed audio
$\hat{S}1 = \text{STFT}(s)$ **or CQT**
1-pass algorithm $\rightarrow \hat{H}1, \hat{P}1$
final harmonic $h1 = \text{ISTFT}(\hat{H}1)$ **or ICQT**
$p1 = \text{ISTFT}(\hat{P}1)$ **or ICQT**
$\hat{S}2 = \text{STFT}(p1)$ **or CQT**
1-pass algorithm $\rightarrow \hat{H}2, \hat{P}2$
$h2 = \text{ISTFT}(\hat{H}2)$ **or ICQT**
final percussive $p1 = \text{ISTFT}(\hat{P}2)$ **or ICQT**

Listing 1: 1- and 2-pass median filtering HPSS algorithms

HPSS MATLAB pseudocode
Listing 1: 1- and 2-pass median filtering HPSS algorithms

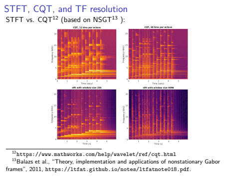
STFT, CQT, and TF resolution

STFT vs. CQT[12] (based on NSGT[13]):



[12]https://www.mathworks.com/help/wavelet/ref/cqt.html

[13]Balazs et al., "Theory, implementation and applications of nonstationary Gabor frames", 2011, https://ltfat.github.io/notes/ltfatnote018.pdf.



- glockenspiel = default file of ltfat, the canonical sound for tonal/transient
- loaded by gspi function
- look how good the cqt is – original motivation for this project, can we take the simple median filter algorithm and make it better with a better tf representation

Sparsity, entropy, and two window sizes

Sparsity and entropy are complementary concepts:[14]

- *Sparsity* is the property of concentrating most of the energy of x in few coefficients of w
- *Entropy* is the property of not concentrating most of the probability mass in few atoms of p – in other words, the entropy of a random variable is a concept of information theory that characterizes the unpredictability inherent in its outcomes

In every algorithm shown, the common element is a 2 dictionary wide + narrow window analysis, to represent tonal and transient parts of the input signal sparsely – or, to represent tonal and transient parts of the input signal with low entropy/high significance

[14] Paul Honeine. *Entropy of Overcomplete Kernel Dictionaries*. 2014. arXiv: 1411.0161 [cs.IT]. URL: https://arxiv.org/pdf/1411.0161.pdf; Giancarlo Pastor et al. *Mathematics of Sparsity and Entropy: Axioms, Core Functions and Sparse Recovery*. 2015. arXiv: 1501.05126 [cs.IT].

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TF representations for music separation

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Structured sparsity

Group-LASSO:[15] Lasso shrinkage (aka linear least squares regression[16] [17]) to the transform coefficients in the time and frequency dimensions

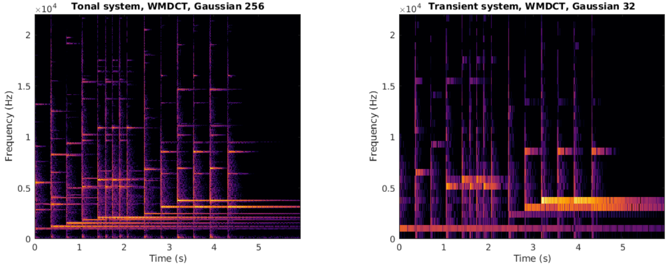
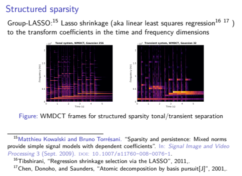


Figure: WMDCT frames for structured sparsity tonal/transient separation

[15] Matthieu Kowalski and Bruno Torrésani. "Sparsity and persistence: Mixed norms provide simple signal models with dependent coefficients". In: *Signal Image and Video Processing* 3 (Sept. 2009). DOI: 10.1007/s11760-008-0076-1.

[16] Tibshirani, "Regression shrinkage selection via the LASSO", 2011,.

[17] Chen, Donoho, and Saunders, "Atomic decomposition by basis pursuit[J]", 2001,.



Structured sparsity

WMDCT[18] + Group-LASSO – "audioshrink"[19]

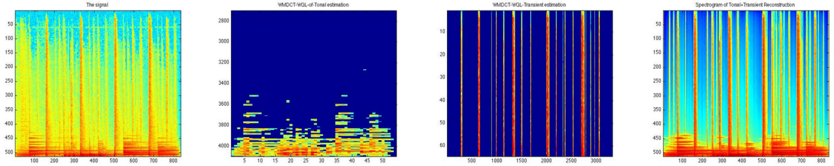


Figure: Audioshrink for tonal/transient separation in jazz music

Use 2 WMDCT transforms (wide + narrow window) + Group-LASSO to shrink input signal into significant coefficients in "time" and "frequency" groups

[18] Kai Siedenburg and Monika Doerfler. "Structured sparsity for audio signals". In: *Proc. of the 14th International Conference on Digital Audio Effects (DAFx-11), Paris, France*. Jan. 2011.

[19] `https://homepage.univie.ac.at/monika.doerfler/StrucAudio.html`, `https://ltfat.github.io/doc/demos/demo_audioshrink.html`

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[19] https://homepage.univie.ac.at/monika.doerfler/StrucAudio.html, https://ltfat.github.io/doc/demos/demo_audioshrink.html

Audioshrink MATLAB pseudocode

f = mixed audio
$F1 = \text{frametight}(\text{frame}(\text{wmdct}, \text{gauss}, \text{winsize}_h))$ **WMDCT**
$F2 = \text{frametight}(\text{frame}(\text{wmdct}, \text{gauss}, \text{winsize}_p))$
$c1 = \text{franagrouplasso}(F1, f, \lambda_h, \text{soft}, \text{freq})$
$c2 = \text{franagrouplasso}(F2, f, \lambda_p, \text{soft}, \text{time})$
$xh = \text{frsyn}(F1, c1)$ **Inverse WMDCT**
$xp = \text{frsyn}(F2, c2)$

Listing 2: WMDCTLasso tonal/transient separation algorithm

franagrouplasso in LTFAT solves the Group-LASSO regression problem in the time-frequency domain
Soft thresholding vs. hard thresholding – similar to soft/hard masking

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$c2 = \text{franagrouplasso}(F2, f, \lambda_p, \text{soft}, \text{time})$
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Rényi entropy vs. Lasso

- Using Lasso-like methods ($l1, 2$ norm in linear least squares regression) assumes that the underlying systems are linear Gaussian, or approximately so[20]
- If the system is not linear-Gaussian, linear least squares regression can lead to suboptimal results
- Rényi entropy, which is an adaptation of Shannon entropy[21] is a measure of information in signal processing, and can be used as an optimization target (i.e., loss function) without imposing restrictions on the system being optimized

[20] Ed Beadle et al. "An Overview of Renyi Entropy and Some Potential Applications". In: Nov. 2008, pp. 1698–1704. DOI: 10.1109/ACSSC.2008.5074715.

[21] A. Rényi. "On Measures of Entropy and Information". In: *Proceedings IV Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, 20-30 June 1961* 1 (1961), pp. 547–561; C. E. Shannon. "A mathematical theory of communication". In: *The Bell System Technical Journal* 27.3 (1948), pp. 379–423. DOI: 10.1002/j.1538-7305.1948.tb01338.x.

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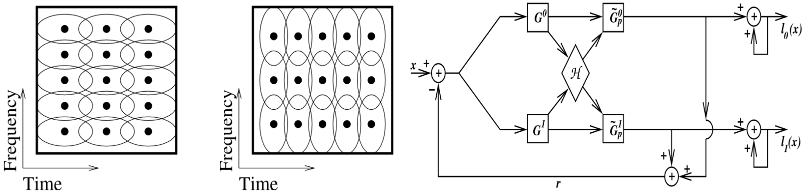
Time-Frequency Jigsaw Puzzle

1. Create time-frequency "super-tiles" by superimposing a large window + small window Gabor analysis
2. Use Rényi entropy to set coefficients to zero where sound has more entropy than random white noise



(a) TF supertiles (b) Entropy criterion

Figure: TF Jigsaw Puzzle tonal/transient separation[22]

[22] Florent Jaillet and Bruno Torrésani. "Time-Frequency Jigsaw Puzzle: adaptive multiwindow and multilayered Gabor expansions". In: *International Journal of Wavelets, Multiresolution and Information Processing* 05 (Mar. 2007). DOI: 10.1142/S0219691307001768.

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- i.e. good tonal/good transient
- high entropy = indicating sound is poorly represented

TFJigsaw

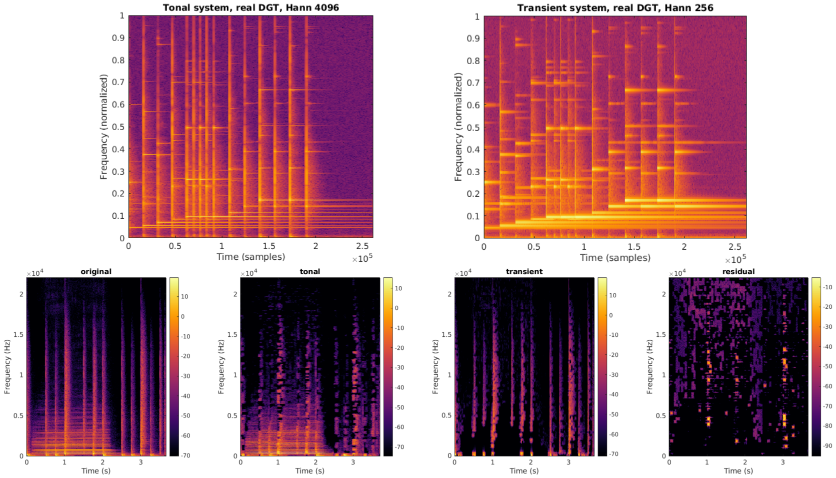
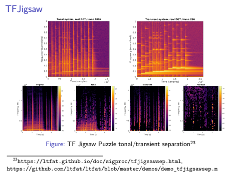


Figure: TF Jigsaw Puzzle tonal/transient separation[23]

[23] https://ltfat.github.io/doc/sigproc/tfjigsawsep.html, https://github.com/ltfat/ltfat/blob/master/demos/demo_tfjigsawsep.m



- Hann DGT = stft, basically

TFJigsaw MATLAB pseudocode

f = mixed audio
a, M, winsize, $b\{1,2\}$ = Gabor systems 1 and 2 configuration
$r\{1,2\}$ = significance level of tonal and transient layer re: white noise ref
$[\text{ref}1, \text{ref}2]$ =
↪ generate estimate of random white noise entropy within supertile
$[\text{tau}1, \text{tau}2] = [\text{ref}1 \cdot r1, \text{ref}2 \cdot r2]$
$c1 = \text{DGTReal}(f, \text{winsize}1, a1, M1)$ **Discrete Gabor Transform**
$c2 = \text{DGTReal}(f, \text{winsize}2, a2, M2)$
for all time and frequency supertiles
    $f\{1,2\}$ = frequency supertile location, Gabor system 1,2
    $t\{1,2\}$ = time supertile location, Gabor system 1,2
    $[c1, c2] = \text{decision}(c1, c2, f1, f2, t1, t2, \text{tau}1, \text{tau}2)$
endfor
$f_{\text{tonal}} = \text{IDGTReal}(c1)$ **Inverse discrete Gabor Transform**
$f_{\text{transient}} = \text{IDGTReal}(c2)$

Listing 3: TFJigsaw tonal/transient separation algorithm

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f = mixed audio
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↪ generate estimate of random white noise entropy within supertile
$[\text{tau}1, \text{tau}2] = [\text{ref}1 \cdot r1, \text{ref}2 \cdot r2]$
$c1 = \text{DGTReal}(f, \text{winsize}1, a1, M1)$ Discrete Gabor Transform
$c2 = \text{DGTReal}(f, \text{winsize}2, a2, M2)$
for all time and frequency supertiles
$f\{1,2\}$ = frequency supertile location, Gabor system 1,2
$t\{1,2\}$ = time supertile location, Gabor system 1,2
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endfor
$f_{\text{tonal}} = \text{IDGTReal}(c1)$ Inverse discrete Gabor Transform
$f_{\text{transient}} = \text{IDGTReal}(c2)$
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Evaluation testbench

Inspired by SigSep[24], SISEC (Signal Separation Evaluation Campaign):

- BSS[25] (BSSv4 variant[26]) and PEASS[27] (MATLAB toolkit[28]). BSS vs. PEASS?[29] BSSv4 is used widely in modern literature,[30] but perceptual measures are important! Use PEASS
- Testing files: MUSDB18-HQ [31]
- MATLAB/Python testbench using file system + JSON interchanges
- Open-Unmix[32] as a reference, open, near-SOTA neural solution
- Compare different configurations of each algorithm in "group stages," winners move to next stage and may be combined in hybrid algorithms

[24] `https://sigsep.github.io/`
[25] Vincent, Gribonval, and Févotte, 2006.
[26] `https://github.com/sigsep/bsseval`
[27] Emiya et al., 2011.
[28] `http://bass-db.gforge.inria.fr/peass/`
[29] Ward et al., 2018.
[30] Stöter, Liutkus, and Ito, 2018.
[31] Rafii et al., 2019.
[32] Stöter et al., 2019.

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[28] http://bass-db.gforge.inria.fr/peass/
[29] Ward et al., 2018.
[30] Stöter, Liutkus, and Ito, 2018.
[31] Rafii et al., 2019.
[32] Stöter et al., 2019.

- global score omitted. target, interference, artifact

HPSS – PEASS results

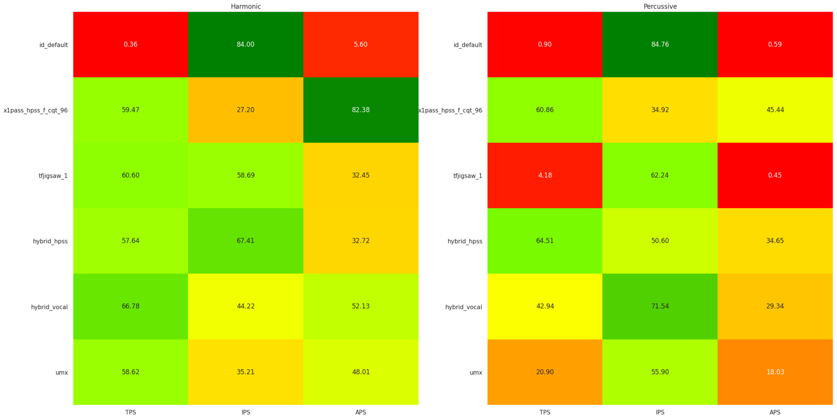
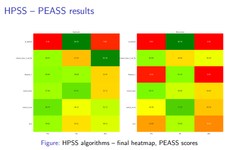


Figure: HPSS algorithms – final heatmap, PEASS scores



HPSS – BSSv4 results

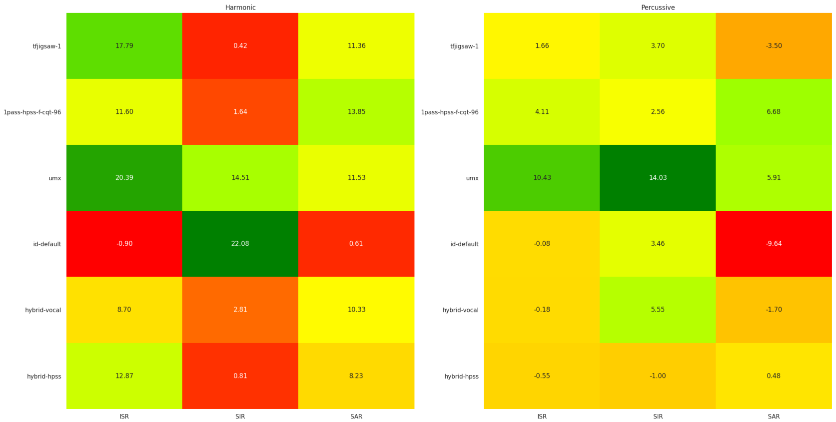


Figure: HPSS algorithms – final heatmap, BSSv4 scores

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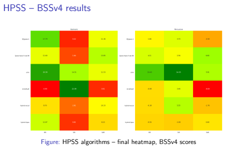
TF representations for music separation

└HPSS – BSSv4 results



HPSS + vocal – PEASS results

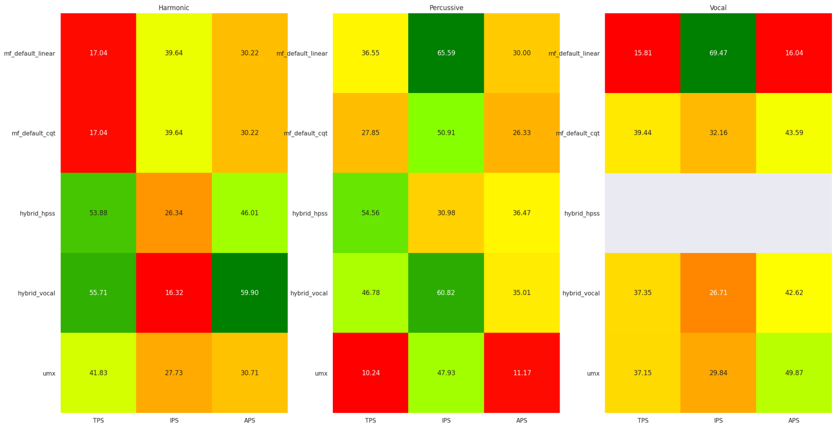
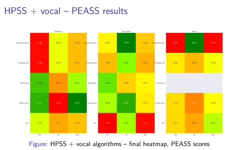


Figure: HPSS + vocal algorithms – final heatmap, PEASS scores

2021-04-20

TF representations for music separation

└HPSS + vocal – PEASS results



HPSS + vocal – BSSv4 results

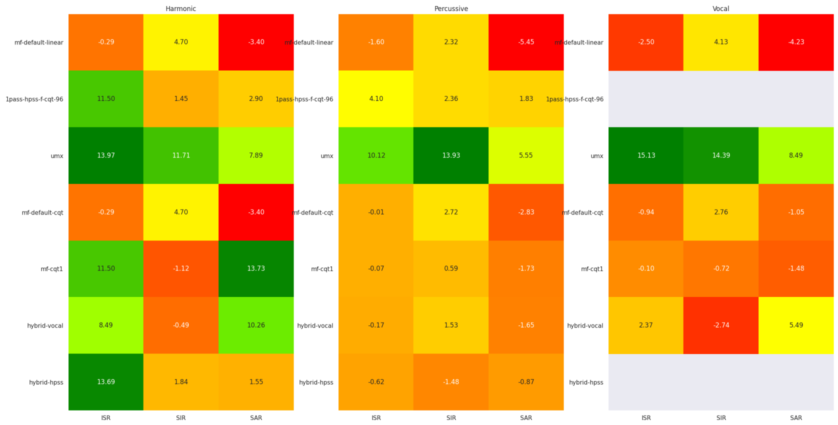


Figure: HPSS + vocal algorithms – final heatmap, BSSv4 scores

2021-04-20

TF representations for music separation

└HPSS + vocal – BSSv4 results

HPSS + vocal – BSSv4 results

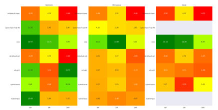
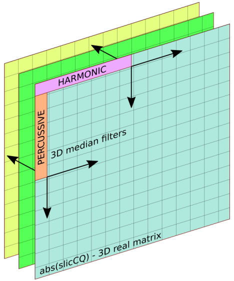


Figure: HPSS + vocal algorithms – final heatmap, BSSv4 scores

Best 1-pass HPSS – CQT-96, sliCQ median filter

Best performing 1-pass offline/anticausal algorithm: CQT with 96 bins-per-octave + median filter + **soft** mask. Realtime/causal: sliCQ[33] with 12 bins-per-octave + median filter + **hard** mask



Realtime STFT:[34] input stream = hop size, $2 \times$ hop ringbuffer (window).
sliCQ transform: input stream = trlen, $4 \times$ trlen ringbuffer (sllen)

[33] Nicki Holighaus et al. "A Framework for Invertible, Real-Time Constant-Q Transforms". In: *IEEE Transactions on Audio, Speech and Language Processing* 21 (Sept. 2012). DOI: 10.1109/TASL.2012.2234114. URL: https://arxiv.org/pdf/1210.0084.pdf.

[34] https://github.com/sevagh/Real-Time-HPSS

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[34] https://github.com/sevagh/Real-Time-HPSS

- 3D sliCQ coefficients can be median filtered, analogous to RGB/RGBA images

Best 2-pass HPSS – hybrid

Hybrid HPSS: combine TFJigsaw and STFT median filtering

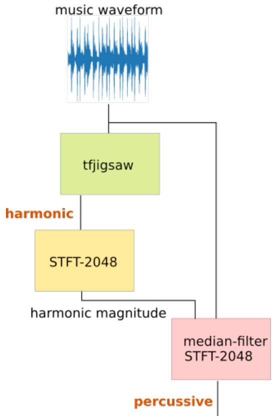

Figure: Block diagram of hybrid HPSS algorithm

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TF representations for music separation

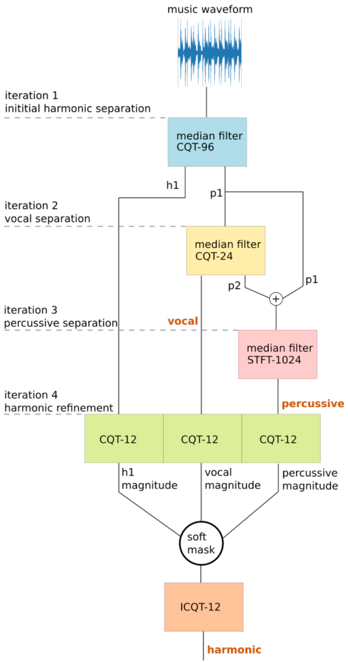
└Best 2-pass HPSS – hybrid

Best 2-pass HPSS – hybrid

Hybrid HPSS: combine TFJigsaw and STFT median filtering

Figure: Block diagram of hybrid HPSS algorithm

Multipass hybrid vocal



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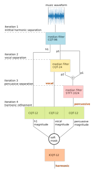
TF representations for music separation

Multipass hybrid vocal



HPSS – audio clips

Algorithm	Harmonic	Percussive
Reference mix	h	p
1-pass CQT 96 bins + soft mask [35]	h	p
Realtime sliCQ 12 bins + hard mask	h	p
Iterative Driedger[36]	h	p
Hybrid-HPSS	h	p
UMX	h	p

[35] Fitzgerald, 2010.
[36] Driedger, Müller, and Disch, 2014.

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HPSS + vocal – audio clips

Algorithm	Harmonic	Percussive	Vocal
Reference 🔊 mix	🔊 h	🔊 p	🔊 v
Iterative Fitzgerald, vocal [37]	🔊 h	🔊 p	🔊 v
Iterative Fitzgerald, percussive	🔊 h	🔊 p	🔊 v
Hybrid-Vocal	🔊 h	🔊 p	🔊 v
UMX	🔊 h	🔊 p	🔊 v

[37] Fitzgerald and Gainza, 2010.

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TF representations for music separation

└HPSS + vocal – audio clips

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NSGT in STFT-based neural network

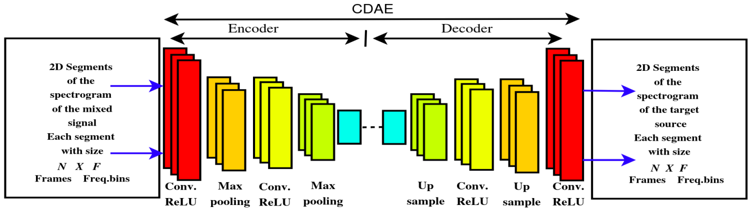
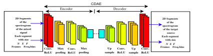


Figure: Convolutional denoising autoencoders[38]

Idea: replace STFT spectrogram with NSGT spectrogram. Both MATLAB Wavelet Toolbox CQT (based on NSGT) and reference Python implementation of NSGT (https://github.com/grrrr/nsgt) can produce a rectangular matrix of TF coefficients, solving a common difficulty of using the CQT in spectrogram-based algorithms.

[38] Emad M. Grais and Mark D. Plumbley. "Single Channel Audio Source Separation using Convolutional Denoising Autoencoders". In: *CoRR* abs/1703.08019 (2017). arXiv: 1703.08019. URL: http://arxiv.org/abs/1703.08019.

NSGT in STFT-based neural network



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NSGT-spectrogram neural network

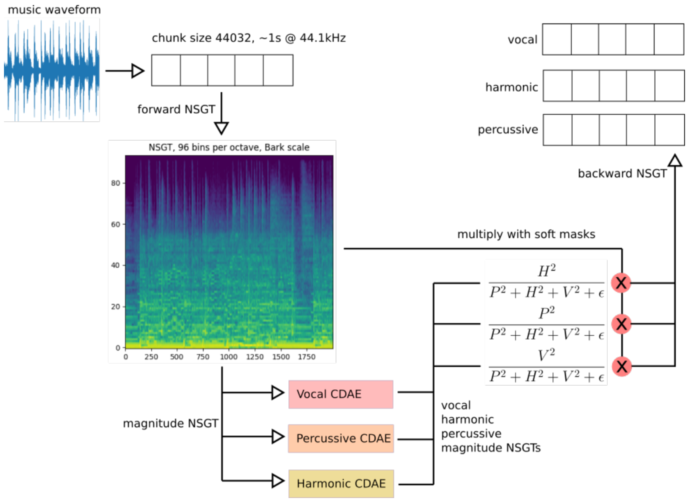

Figure: Toy/demo in https://github.com/sevagh/MiXiN

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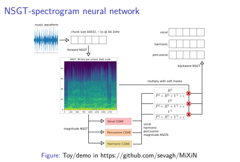
└NSGT-spectrogram neural network



Conclusions

- Real-world application of 622 concepts – sparsity, entropy, overcomplete dictionaries, pursuit
- Swap STFT for "better" TF representations in simple algorithms to improve source separation results
- Competitive PEASS separation results in hybrid algorithms based on advanced DSP/time-frequency analysis (not so good in BSSv4)
- Swap STFT for NSGT in a both traditional DSP algorithms, and machine/deep learning networks – lots of future potential

501 to 622:

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MiXiN (MUMT 622)	h	p

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