Hybrid Spectrogram and Waveform Source Separation

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Abstract

Source separation models either work on the spectrogram or waveform domain. In this work, we show how to perform end-to-end hybrid source separation, letting the model decide which domain is best suited for each source, and even combining both. The proposed hybrid version of the Demucs architecture (Défossez et al., 2019) won the Music Demixing Challenge 2021 organized by Sony. This architecture also comes with additional improvements, such as compressed residual branches, local attention or singular value regularization. Overall, a 1.4 dB improvement of the Signal-To-Distortion (SDR) was observed across all sources as measured on the MusDB HQ dataset (Rafii et al., 2019), an improvement confirmed by human subjective evaluation, with an overall quality rated at 2.83 out of 5 (2.36 for the non hybrid Demucs), and absence of contamination at 3.04 (against 2.37 for the non hybrid Demucs and 2.44 for the second ranking model submitted at the competition).

Introduction

Work on music source separation has recently focused on the task of separating 4 well defined instruments in a supervised manner: drums, bass, vocals and other accompaniments. Recent evaluation campaigns (Stöter et al., 2018) have focused on this setting, relying on the standard MusDB benchmark (Rafii et al., 2017). In 2021, Sony organized the Music Demixing Challenge (MDX) (Mitsufuji et al., 2021), an online competition where separation models are evaluated on a completely new and hidden test set composed of 27 tracks.

The challenge featured a number of baselines to start from, which could be divided into two categories: spectrogram or waveform based methods. The former consists in models that are fed with the input spectrogram, either represented by its amplitude, such as Open-Unmix (Stöter et al., 2019) and its variant CrossNet Open-Unmix (Sawata et al., 2020), or as the concatenation of its real and imaginary part, a.k.a Complex-As-Channels (CAC) (Choi et al., 2020), such as LaSAFT (Choi et al., 2021). Similarly, the output can be either a mask on the input spectrogram, complex modulation of the input spectrogram (Kong et al., 2021), or the CAC representation.

On the other hand, waveform based models such as Demucs (Défossez et al., 2019) are directly fed with the raw waveform, and output the raw waveform for each of the source. Most of those methods will perform some kind of learnt time-frequency analysis in its first layers through convolutions, such as Demucs and Conv-TasNet (Luo and Mesgarani, 2019), although some will not rely at all on convolutional layers, like Dual-Path RNN (Luo et al., 2020).

Theoretically, there should be no difference between spectrogram and waveform models, in particular when considering CaC (complex as channels), which is only a linear change of base for the input and output space. However, this would only hold true in the limit of having an infinite amount of training data. With a constrained dataset, such as the 100 songs of MusDB, inductive bias can play an important role. In particular, spectrogram methods varies by more than their input and output space. For instance, with a notion of frequency, it is possible to apply convolutions along frequencies, while waveform methods must use layers that are fully connected with respect to their channels. The final test loss being far from
zero, there will also be artifacts in the separated audio. Different representations will lead to different artifacts, some being more noticeable for the drums and bass (phase inconsistency for spectrogram methods will make the attack sounds hollow), while others are more noticeable for the vocals (vocals separated by Demucs suffer from crunchy static noise).

In this work, we extend the Demucs architecture to perform hybrid waveform/spectrogram domain source separation. The original U-Net architecture (Ronneberger et al., 2015) is extended to provide two parallel branches: one in the time (temporal) and one in the frequency (spectral) domain. We bring other improvements to the architecture, namely compressed residual branches comprising dilated convolutions (Yu and Koltun, 2016), LSTM (Hochreiter and Schmidhuber, 1997) and attention (Vaswani et al., 2017) with a focus on local content. We measure the impact of those changes on the MusDB benchmark and on the MDX hidden test set, as well as subjective evaluations. Hybrid Demucs ranked 1st at the MDX competition when trained only on MusDB, with 7.32 dB of SDR, and 2nd with extra training data allowed.

Related work

There exist a number of spectrogram based music source separation architectures. Open-Unmix (Stöter et al., 2019) is based on fully connected layers and a bi-LSTM. It uses multi-channel Wiener filtering (Nugraha et al., 2016) to reduce artifacts. While the original Open-Unmix is trained independently on each source, a multi-target version exists (Sawata et al., 2020), through a shared averaged representation layer. D3Net (Takahashi and Mitsufuji, 2020) is another architecture, based on dilated convolutions connected with dense skip connections. It was before the competition the best performing spectrogram architecture, with an average SDR of 6.0 dB on MusDB. Unlike previous methods which are based on masking, LaSAFT (Choi et al., 2020) uses Complex-As-Channels (Choi et al., 2020) along with a U-Net (Ronneberger et al., 2015) architecture. It is also single-target, however its weights are shared across targets, using a weight modulation mechanism to select a specific source.

Waveform domain source separation was first explored by Lluis et al. (2018), as well as Jansson et al. (2017) and Stoller et al. (2018) with Wave-U-Net. However, those methods were lagging in term of quality, almost 2 dB behind their spectrogram based competitors. Demucs (Défossez et al., 2019) was built upon Wave-U-Net, using faster strided convolutions rather than explicit downsampling, allowing for a much larger number of channels, but potentially introducing aliasing artifacts as noted by Pons et al. (2021), and extra Gated Linear Unit layers (Dauphin et al., 2017) and biLSTM. For the first time, waveform domain methods surpassed spectrogram ones when considering the overall SDR (6.3 dB on MusDB), although its performance is still inferior on the other and vocals sources. Conv-Tasnet (Luo and Mesgarani, 2019), a model based on masking over a learnt time-frequency representation using dilated convolutions, was also adapted to music source separation by Défossez et al. (2019), but suffered from more artifacts and lower SDR.

To the best of our knowledge, no other work has studied true end-to-end hybrid source separation, although other teams in the MDX competition used model blending from different domains as a simpler post-training alternative.

Architecture

In this Section we present the structure of Hybrid Demucs, as well as the other additions that were added to the original Demucs architecture.

Original Demucs

The original Demucs architecture (Défossez et al., 2019) is a U-Net (Ronneberger et al., 2015) encoder/decoder structure. A BiLSTM (Hochreiter and Schmidhuber, 1997) is applied between
the encoder and decoder to provide long range context. The encoder and decoder have a
symmetric structure. Each encoder layer is composed of a convolution with a kernel size of 8,
stride of 4 and doubling the number of channels (except for the first layer, which sets it to
a fix value, typically 48 or 64). It is followed by a ReLU, and a so called 1x1 convolution
with Gated Linear Unit activation (Dauphin et al., 2017), i.e. a convolution with a kernel
size of 1, where the first half of the channels modulates the second half through a sigmoid.
The 1x1 convolution double the channels, and the GLU halves them, keeping them constant
overall. Symetrically, a decoder layer sums the contribution from the U-Net skip connection
and the previous layer, apply a 1x1 convolution with GLU, then a transposed convolution that
halves the number of channels (except for the outermost layer), with a kernel size of 8 and
stride of 4, and a ReLU (except for the outermost layer). There are 6 encoder layers, and 6
decoder layers, for processing 44.1 kHz audio. In order to limit the impact of aliasing from the
outermost layers, the input audio is upsampled by a factor of 2 before entering the encoder,
and downsampled by a factor of 2 when leaving the decoder.

Hybrid Demucs

Overall architecture

Hybrid Demucs extends the original architecture with multi-domain analysis and prediction
capabilities. The model is composed of a temporal branch, a spectral branch, and shared layers.
The temporal branch takes the input waveform and process it like the standard Demucs. It
contains 5 layers, which are going to reduce the number of time steps by a factor of $4^5 = 1024$.
Compared with the original architecture, all ReLU activations are replaced by Gaussian Error
Linear Units (GELU) (Hendrycks and Gimpel, 2016).

The spectral branch takes the spectrogram obtained from a STFT over 4096 time steps, with
a hop length of 1024. Notice that the number of time steps immediately matches that of the
output of the encoder of the temporal branch. In order to reduce the frequency dimension, we
apply the same convolutions as in the temporal branch, but along the frequency dimension.
Each layer reduces by a factor of 4 the number of frequencies, except for the 5th layer, which
reduces by a factor of 8. After being processed by the spectral encoder, the signal has only
one “frequency” left, and the same number of channels and sample rate as the output of the
temporal branch. The temporal and spectral representations are then summed before going
through a shared encoder/decoder layer which further reduces by 2 the number of time steps
(using a kernel size of 4). Its output serves both as the input of the temporal and spectral
decoder. Hybrid Demucs has a dual U-Net structure, with the temporal and spectral branches
having their respective skip connections.

The output of the spectral branch is inverted with the ISTFT, and summed with the temporal
branch output, giving the final model prediction. Due to this overall design, the model is free
to use whichever representation is most convenient for different parts of the signal, even within
one source, and can freely share information between the two representations. The hybrid
architecture is represented on 1.

Padding for easy alignment

One difficulty was to properly align the spectral and temporal representations for any input
length. For an input length $L$, kernel size $K$, stride $S$ and padding on each side $P$, the output
of a convolution is of length $(L - K + 2 * P)/S + 1$. Following the practice from models like
MelGAN (Kumar et al., 2019) we pad by $P = (K - S)/2$, giving an output of $L/S$, so that
matching the overall stride is now sufficient to exactly match the length of the spectral and
temporal representations. We apply this padding both for the STFT, and convolution layers in
the temporal encoders.
Figure 1: Hybrid Demucs architecture. The input waveform is processed both through a temporal encoder, and first through the STFT followed by a spectral encoder. The two representations are summed when their dimensions align. The decoder is built symmetrically. The output spectrogram go through the ISTFT and is summed with the waveform outputs, giving the final model output. The Z prefix is used for spectral layers, and T prefix for the temporal ones.

Frequency-wise convolutions

In the spectral branch, we use frequency-wise convolutions, dividing the number of frequency bins by 4 with every layer. For simplicity we drop the highest bin, giving 2048 frequency bins after the STFT. The input of the 5th layer has 8 frequency bins, which we reduce to 1 with a convolution with a kernel size of 8 and no padding. It has been noted that unlike the time axis, the distribution of musical signals is not truly invariant to translation along the frequency axis. Instruments have specific pitch range, vocals have well defined formants etc. To account for that, Isik et al. (2020) suggest injecting an embedding of the frequency before applying the convolution. We use the same approach, with the addition that we smooth the initial embedding so that close frequencies have similar embeddings. We inject this embedding just before the second encoder layer. We also investigated using specific weights for different frequency bands. This however turned out more complex for a similar result.
Spectrogram representation

We investigated both with representing the spectrogram as complex numbers (Choi et al., 2020) or as amplitude spectrograms. We also experimented with using Wiener filtering (Nugraha et al., 2016), using Open-Unmix differentiable implementation (Stöter et al., 2019), which uses an iterative procedure. Using more iterations at evaluation time is usually optimal, but sadly doesn't work well with the hybrid approach, as changing the spectrogram output, without the waveform output being able to adapt will drastically reduce the SDR, and using a high number of iterations at train time is prohibitively slow. In all cases, we differentiably transform the spectrogram branch output to a waveform, summed to the waveform branch output, and the final loss is applied in the waveform domain.

Compressed residual branches

The original Demucs encoder layer is composed of a convolution with kernel size of 8 and stride of 4, followed by a ReLU, and of a convolution with kernel size of 1 followed by a GLU. Between those two convolutions, we introduce two compressed residual branches, composed of dilated convolutions, and for the innermost layers, a biLSTM with limited span and local attention. Remember that after the first convolution of the 5th layer, the temporal and spectral branches have the same shape. The 5th layer of each branch actually only contains this convolution, with the compressed residual branch and 1x1 convolution being shared.

Inside a residual branch, all convolutions are with respect to the time dimension, and different frequency bins are processed separately. There are two compressed residual branch per encoder layer. Both are composed of a convolution with a kernel size of 3, stride of 1, dilation of 1 for the first branch and 2 for the second, and 4 times less output dimensions than the input, followed by layer normalization (Ba et al., 2016) and a GELU activation.

For the 5th and 6th encoder layers, long range context is processed through a local attention layer (see definition hereafter) as well as a biLSTM with 2 layers, inserted with a skip connection, and with a maximum span of 200 steps. In practice, the input is splitted into frames of 200 time steps, with a stride of 100 steps. Each frame is processed concurrently, and for any time step, the output from the frame for which it is the furthest away from the edge is kept.

Finally, and for all layers, a final convolution with a kernel size of 1 outputs twice as many channels as the input dimension of the residual branch, followed by a GLU. This output is then summed with the original input, after having been scaled through a LayerScale layer (Touvron et al., 2021), with an initial scale of $1e^{-3}$. A complete representation of the compressed residual branches is given on 2.

Local attention

Local attention builds on regular attention (Vaswani et al., 2017) but replaces positional embedding by a controllable penalty term that penalizes attending to positions that are far away. Formally, the attention weights from position $i$ to position $j$ is given by

$$w_{i,j} = \text{softmax}(Q_i^T K_j - \sum_{k=1}^{4} k\beta_{i,k}|i - j|)$$

where $Q_i$ are the queries and $K_j$ are the keys. The values $\beta_{i,k}$ are obtained as the output of a linear layer, initialized so that they are initially very close to 0. Having multiple $\beta_{i,k}$ with different weights $k$ allows the network to efficiently reduce its receptive field without requiring $\beta_{i,k}$ to take large values. In practice, we use a sigmoid activation to derive the values $\beta_{i,k}$.

Interestingly, a similar idea has been developed in NLP (Press et al., 2021), although with a fixed penalty rather than a dynamic and learnt one done here.
Figure 2: Representation of the compressed residual branches that are added to each encoder layer. For the 5th and 6th layer, a BiLSTM and a local attention layer are added.

Stabilizing training

We observed that Demucs training could be unstable, especially as we added more layers and increased the training set size with 150 extra songs. Loading the model just before its divergence point, we realized that the weights for the innermost encoder and decoder layers would get very large eigen values.

A first solution is to use group normalization (with 4 groups) just after the non residual convolutions for the layers 5 and 6 of the encoder and the decoder. Using normalization on all layers deteriorates performance, but using it only on the innermost layers seems to stabilize training without hurting performance. Interestingly, when the training is stable (in particular when trained only on MusDB), using normalization was at best neutral with respect to the separation score, but never improved it, and considerably slowed down convergence during the first half of the epochs. When the training was unstable, using normalization would improve the overall performance as it allows the model to train for a larger number of epochs.

A second solution we investigated was to use singular value regularization (Yoshida and Miyato, 2017). While previous work used the power method iterative procedure, we obtained better and faster approximations of the largest singular value using a low rank SVD method (Halko et al., 2011). This solution has the advantage of always improving generalization, even when the training was already stable. Sadly, it was not sufficient on its own to remove entirely instabilities, but only to reduce them. Another down side was the longer training time due to the extra low rank SVD evaluation. In the end, in order to both achieve the best performance and remove entirely training instabilities, the two solutions were combined.
Experimental Results

**Important:** The results presented in this section are results obtained as part of the MDX challenge. We provide easier to reproduce results and detailed ablation that were conducted after the challenge in the Section “Reproducibility and Ablation” hereafter.

Datasets

The 2021 MDX challenge (Mitsufuji et al., 2021) offered two tracks: Track A, where only MusDB HQ (Rafii et al., 2019) could be used for training, and Track B, where any data could be used. MusDB HQ, released under mixed licensing, is composed of 150 tracks, including 86 for the train set, 14 for the valid, and 50 for the test set. For Track B, we additionally trained using 150 tracks for an internal dataset, and repurpose the test set of MusDB as training data, keeping only the original validation set for model selection. Models are evaluated either through the MDX AI Crowd API, or on the MusDB HQ test set.

Realistic remix of tracks

We achieved further gains, by fine tuning the models on a specifically crafted dataset, and with longer training samples (30 seconds instead of 10). This dataset was built by combining stems from separate tracks, while respecting a number of conditions, in particular beat matching and pitch compatibility. Note that training from scratch on this dataset led to worse performance, likely because the model could rely too much on melodic structure, while random remixing forces the model to separate without this information.

We use librosa (McFee et al., 2015) for both beat tracking and tempo estimation, as well as chromagram estimation. Beat tracking is applied only on the drum source, while chromagram estimation is applied on the bass line. We aggregate the chromagram over time to a single chroma distribution and find the optimal pitch shift between two stems to maximize overlap (as measured by the L1 distance). We assume that the optimal shift for the bass line is the same for the vocals and accompaniments. Similarly, we align the tempo and first beat. In order to limit artifacts, we only allow two stems to blend if they require less than 3 semi-tones of shift and 15% of tempo change.

Metrics

The MDX challenge introduced a novel Signal-To-Distortion measure. Another SDR measure existed, as introduced by Vincent et al. (2006). The advantage of the new definition is its simplicity and fast evaluation. The new definition is simply defined as

\[
SDR = 10 \log_{10} \frac{\sum_n || s(n) ||^2 + \epsilon}{\sum_n || s(n) - \hat{s}(n) ||^2 + \epsilon},
\]

where \(s\) is the ground truth source, \(\hat{s}\) the estimated source, and \(n\) the time index. In order to reliably compare to previous work, we will refer to this new SDR definition as \(nSDR\), and to the old definition as \(SDR\). Note that when using \(nSDR\) on the MDX test set, the metric is defined as the average across all songs. The evaluation on the MusDB test set follows the traditional median across the songs of the median over all 1 second segments of each song.

Models

The model submitted to the competitions were actually bags of 4 models. For Track A, we had to mix hybrid and non hybrid Demucs models, as the hybrid ones were having worse performance on the bass source. On Track B, we used only hybrid models, as the extra training

\[\text{1} https://github.com/sigsep/website/blob/master/content/datasets/assets/tracklist.csv\]

\[\text{2} https://www.aicrowd.com/challenges/music-demixing-challenge-ismir-2021\]
data allowed them to perform better for all sources. Note that a mix of Hybrid models using CaC or real masking were used, mostly because it was too costly to reevaluate all models for the competition. For details on the exact architecture and hyper-parameter used, we refer the reader to our Github repository facebookresearch/demucs.

For the baselines, we report the numbers from the top participants at the MDX competition (Mitsufuji et al., 2021). We focus particularly on the KUIELAB-MDX-Net model, which came in second. This model builds on (Choi et al., 2020) and combines a pure spectrogram model with the prediction from the original Demucs (Défossez et al., 2019) model for the drums and bass sources. When comparing models on MusDB, we also report the numbers for some of the best performing methods outside of the MDX competition, namely D3Net (Takahashi and Mitsufuji, 2020) and ResUNetDecouple+ (Kong et al., 2021), as well as the original Demucs model (Défossez et al., 2019). Note that those models were evaluated on MusDB (not HQ) which lacks the frequency content between 16 kHz and 22 kHz. This can bias the metrics.

Results on MDX

We provide the results from the top participants at the MDX competition on Table 1 for the track A (trained on MusDB HQ only) and on Table 2 for track B (any training data). We also report for track A the metrics for the Demucs architecture improved with the residual branches, but without the spectrogram branch. The hybrid approach especially improves the nSDR on the Other and Vocals source. Despite this improvement, the Hybrid Demucs model is still performing worse than the KUIELAB-MDX-Net on those two sources. On Track B, we notice again that the Hybrid Demucs architecture is very strong on the Drums and Bass source, while lagging behind on the Other and Vocals source.

Table 1: Results of Hybrid Demucs on the MDX test set, when trained only on MusDB (track A) using the nSDR metric.

| Method          | All   | Drums | Bass | Other   | Vocals |
|-----------------|-------|-------|------|---------|--------|
| Hybrid Demucs   | 7.33  | 8.04  | 8.12 | 5.19    | 7.97   |
| KUIELAB-MDX-Net | 7.24  | 7.17  | 7.23 | 5.63    | 8.90   |
| Music_AI        | 6.88  | 7.37  | 7.27 | 5.09    | 7.79   |

Table 2: Results of Hybrid Demucs on the MDX test set, when trained with extra training (track B) using the nSDR metric.

| Method          | All   | Drums | Bass | Other   | Vocals |
|-----------------|-------|-------|------|---------|--------|
| Hybrid Demucs   | 8.11  | 8.85  | 8.86 | 5.98    | 8.76   |
| KUIELAB-MDX-Net | 7.37  | 7.55  | 7.50 | 5.53    | 8.89   |
| AudioShake      | 8.33  | 8.66  | 8.34 | 6.51    | 9.79   |

Results on MusDB

We show on Table 3 the SDR metrics as measured on the MusDB dataset. Again, Hybrid Demucs achieves the best performance for the Drums and Bass source, while improving quite a lot over waveform only Demucs for the Other and Vocals, but not enough to surpass KUIELAB-MDX-Net, which is purely spectrogram based for those two sources. Interestingly, the best performance on the Vocals source is also achieved by ResUNetDecouple+ (Kong et al., 2021), which uses a novel complex modulation of the input spectrogram.
Human evaluations

We also performed Mean Opinion Score human evaluations. We re-use the same protocol as in (Défossez et al., 2019): we asked human subjects to evaluate a number of samples based on two criteria: the absence of artifacts, and the absence of bleeding (contamination). Both are evaluated on a scale from 1 to 5, with 5 being the best grade. Each subject is tasked with evaluating 25 samples of 12 seconds, drawn randomly from the 50 test set tracks of MusDB. All subjects have a strong experience with music (amateur and professional musicians, sound engineers etc). The results are given on Table 4 for the quality, and 5 for the bleeding. We observe strong improvements over the original Demucs, although we observe some regression on the bass source when considering quality. The model KUIELAB-MDX-Net that came in second at the MDX competition performs the best on vocals. The Hybrid Demucs architecture however reduces by a large amount bleeding across all sources.

Table 3: Comparison on the MusDB (HQ for Hybrid Demucs) test set, using the original SDR metric. This includes methods that did not participate in the competition. “Mode” indicates if the waveform (W) or spectrogram (S) domain is used. Model with a “*” were evaluated on MusDB HQ.

| Method                | Mode | All Drums | Bass | Other | Vocals |
|-----------------------|------|-----------|------|-------|--------|
| Hybrid Demucs*        | S+W  | 7.68      | 8.24 | 8.76  | 5.59   | 8.13   |
| Demucs v2             | W    | 6.28      | 6.86 | 7.01  | 4.42   | 6.84   |
| KUIELAB-MDX-Net*      | S+W  | 7.47      | 7.20 | 7.83  | 5.90   | 8.97   |
| D3Net                 | S    | 6.01      | 7.01 | 5.25  | 4.53   | 7.24   |
| ResUNetDecouple+      | S    | 6.73      | 6.62 | 6.04  | 5.29   | 8.98   |

Table 4: Mean Opinion Score results when asking to rate the quality and absence of artifacts in the generated samples, from 1 to 5 (5 being the best grade). Standard deviation is around 0.15.

| Method                | All  | Drums | Bass | Other | Vocals |
|-----------------------|------|-------|------|-------|--------|
| Ground Truth          | 4.12 | 4.12  | 4.25 | 3.92  | 4.18   |
| Hybrid Demucs         | 2.83 | 3.18  | 2.58 | 2.98  | 2.55   |
| KUIELAB-MDX-Net       | 2.86 | 2.70  | 2.68 | 2.99  | 3.05   |
| Demucs v2             | 2.36 | 2.62  | 2.89 | 2.31  | 3.17   |

Table 5: Mean Opinion Score results when asking to rate the absence of bleeding between the sources, from 1 to 5 (5 being the best grade). Standard deviation is around 0.15.

| Method                | All  | Drums | Bass | Other | Vocals |
|-----------------------|------|-------|------|-------|--------|
| Ground Truth          | 4.40 | 4.51  | 4.52 | 4.13  | 4.43   |
| Hybrid Demucs         | 3.04 | 2.95  | 3.25 | 3.08  | 2.88   |
| KUIELAB-MDX-Net       | 2.44 | 2.23  | 2.19 | 2.64  | 2.66   |
| Demucs v2             | 2.37 | 2.24  | 2.96 | 1.99  | 2.46   |

Reproducibility and Ablation

In this section, we provide ablation of the performance of the model, as well as a simpler setup for reproducing the performance of the model submitted to MDX Track A. Note that the numbers and analysis presented here might differ slightly from the ones presented up to now, and should be preferred when referring to this work.
Reproducibility

The model submitted to the MDX competition Track A used heterogeneous configurations, as we used any model that was sufficiently trained at any given time. This led to a complex bag of 4 models, some of which were used only for some sources. While suitable for a competition, such a complex model does get in the way of reproducing easily the performance achieved.

The training grids for all the models presented in this section can be found on GitHub repository facebookresearch/demucs, in the file demucs/grids/repro.py, and demucs/grids/repro_ft.py for the fine tuned models.

We reproduced the performance of the model submitted to Track A by training two time domain Demucs (with the residual branches depicted on Figure 2), and two hybrid Demucs using Complex-As-Channels representation. All four models were trained for 600 epochs, using the SVD penalty and exponential moving average on the weights. Within each domain, only the random seed changes between the two models. The four models were fine tuned on the realistic remix of tracks dataset. The predictions of the four models are averaged into the final prediction, with equal weights over all sources.

As a first ablation, we also form one bag composed of the two time domain only models, and another bag with the two hybrid models only. For fairness, we evaluate each model twice with a random shift, which is known to improve the performance (Défossez et al., 2019). We also compare to the original Demucs model, retrained on MusDB HQ, using 10 random shifts, as done in (Défossez et al., 2019).

The results are presented on Table 6. We reach an overall SDR of 7.64 dB, just 0.04 dB of the model submitted to MDX Track A. We notice a difference in performance between time only, and hybrid only bags only for the bass source and the other source. We still decided to use the same weights over all sources for each type of model for simplicity. We can see the advantage of averaging multiple models, as the combination of both time only and hybrid only model surpasses either ones individually for instance on the drums or the vocals sources. Note however that when training with extra training data, e.g. for the MDX Track B models, the hybrid models were always better than the time only ones.

Table 6: Comparison on the MusDB HQ test set, using the original SDR metric of different bags of models, as well as with the original Demucs v2 model retrained on MusDB HQ. “Mode” indicates if the waveform (W) or spectrogram (S) domain is used.

| Method          | Mode   | All  | Drums | Bass | Other | Vocals |
|-----------------|--------|------|-------|------|-------|-------|
| Bag time + hybrid | S+W    | 7.64 | 8.12  | 8.43 | 5.65  | 8.35  |
| Bag time only   | W      | 7.27 | 7.57  | 8.38 | 5.17  | 7.96  |
| Bag hybrid only | S+W    | 7.34 | 7.96  | 7.85 | 5.63  | 7.95  |
| Demucs v2 HQ    | W      | 6.17 | 6.54  | 7.08 | 4.21  | 6.85  |

Ablation

We report on Table 7 a short ablation study of the model. We start from a time only improved Demucs, e.g. trained with residual branches, local attention and svd penalty. We can first observe the effect of fine tuning on a set of realistic remixes, which improves by 0.3 dB the SDR overall. Further gains are achieved using the bagging. Using Exponential Moving Average on the weights improves the SDR by 0.2dB. The effect of the SVD penalty is more contrasted, with on overall gain of 0.1dB, mainly due to the improved vocals (+0.7 dB), but with a deterioration on the drums source (-0.4 dB).

Finally, removing the LSTM or the local attention in the residual branches lead to a strong decrease of the SDR. Interestingly, the local attention is the most important, despite the absence of positional embedding. One decision taken during the challenge was to switch to
GELU instead of ReLU. The ablation indicates that no real gain is achieved here.

**Table 7:** Ablation study, all models are trained and evaluated on MusDB HQ. The base model is a time only improved Demucs, with local attention, residual branches and svd penalty. Note that we report single model performance instead of bags of model.

| Model                              | All  | Drums | Bass  | Other | Vocals |
|------------------------------------|------|-------|-------|-------|--------|
| Improved Time Demucs               | 6.83 | 7.06  | 7.78  | 4.81  | 7.65   |
| + fine tuning                      | 7.11 | 7.42  | 8.18  | 5.08  | 7.75   |
| + fine tuning and bagging          | 7.27 | 7.57  | 8.38  | 5.17  | 7.96   |
| - LSTM in branch                   | 6.44 | 6.66  | 6.68  | 4.89  | 7.54   |
| - Local Attention                  | 6.29 | 6.39  | 6.76  | 4.68  | 7.33   |
| - SVD penalty                      | 6.73 | 7.45  | 8.01  | 4.48  | 6.98   |
| - EMA on weights                   | 6.63 | 6.99  | 7.36  | 4.74  | 7.43   |
| - GELU + ReLU                      | 6.84 | 7.19  | 7.81  | 4.73  | 7.63   |

**Conclusion**

We introduced a number of architectural changes to the Demucs architecture that greatly improved the quality of source separation for music. On the MusDB HQ benchmark, the gain is around 1.4 dB. Those changes include compressed residual branches with local attention and chunked biLSTM, and most importantly, a novel hybrid spectrogram/temporal domain U-Net structure, with parallel temporal and spectrogram branches, that merge into a common core. Those changes allowed to achieve the first rank at the 2021 Sony Music DemiXing challenge, and translated into strong improvements of the overall quality and absence of bleeding between sources as measured by human evaluations. For all its gain, one limitation of our approach is the increased complexity of the U-Net encoder/decoder, requiring careful alignment of the temporal and spectral signals through well shaped convolutions.
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