Multi-band Masking for Waveform-based Singing Voice Separation

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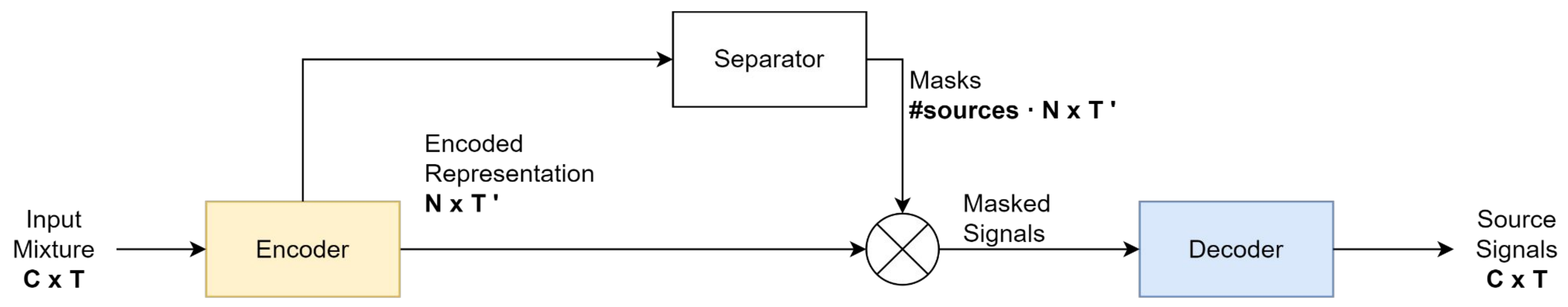
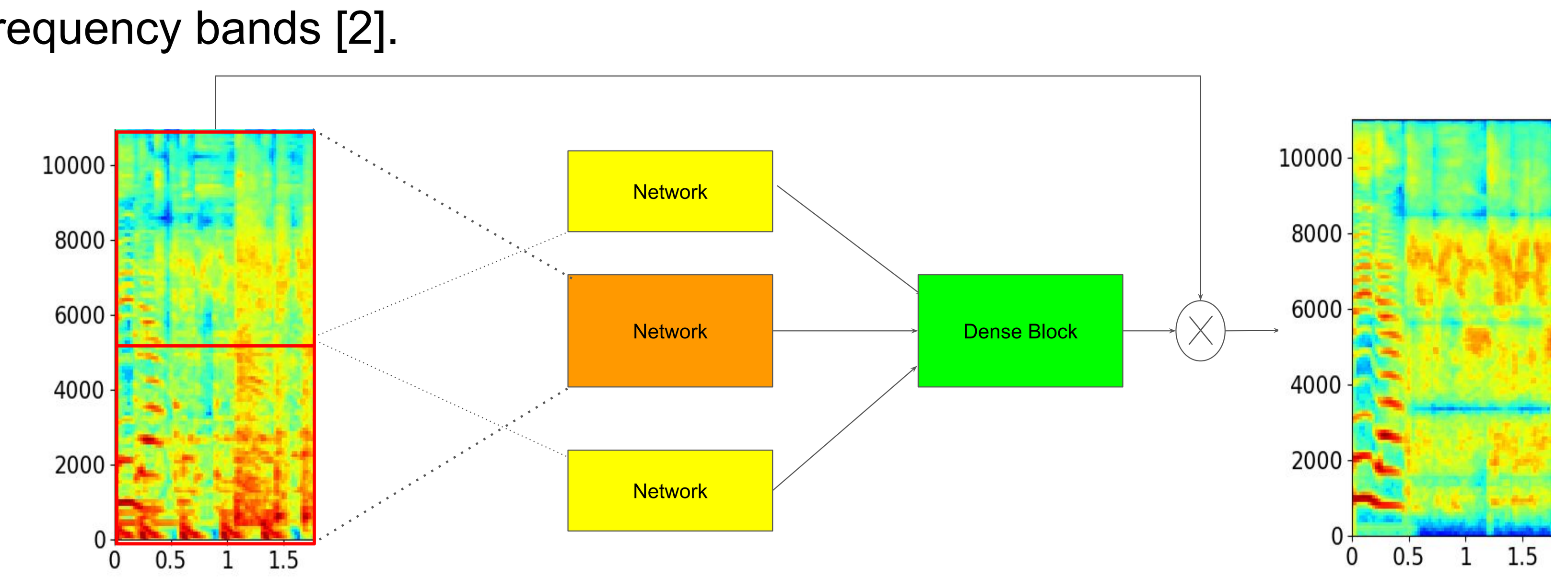
1. Introduction

- Singing voice separation: The task of isolating the vocals from a musical mixture.
- Waveform-level architectures following an **Encoder-Separator-Decoder** schema, such as the Conv-TasNet [1], are currently prominent in the literature.



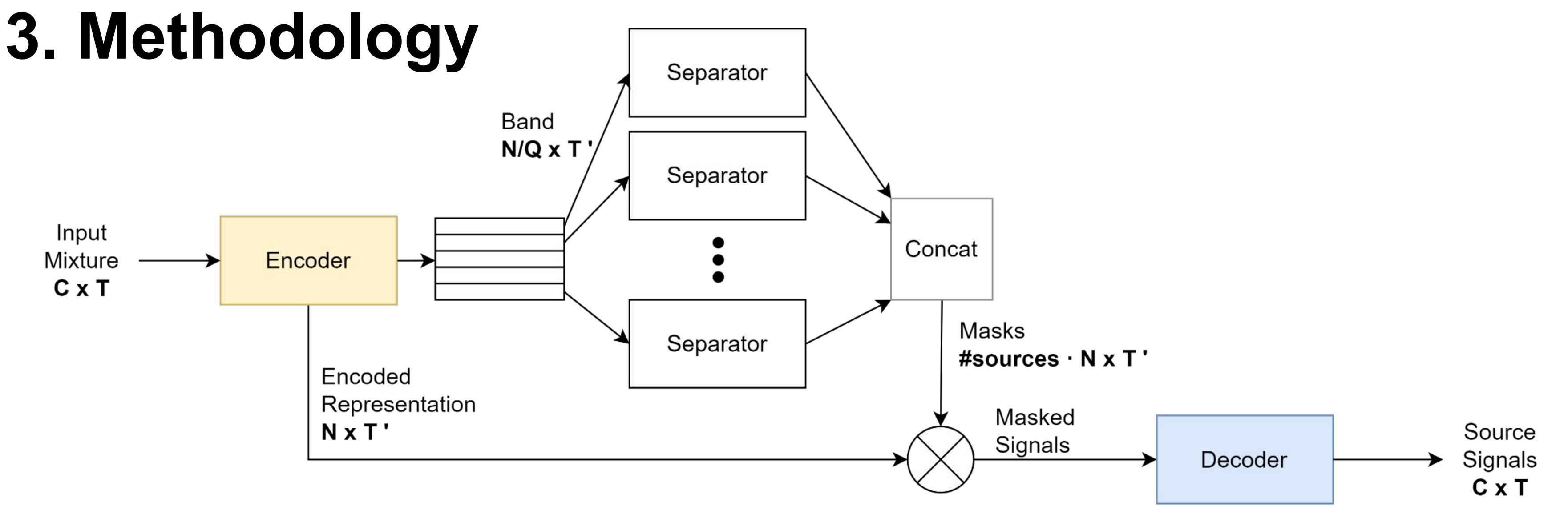
2. Goal and Motivation

- STFT-based architectures for singing voice separation have been shown to achieve higher performance when splitting the input STFT to a number of frequency bands [2].



Goal: Transfer this **multi-band** set-up to waveform-based architectures.

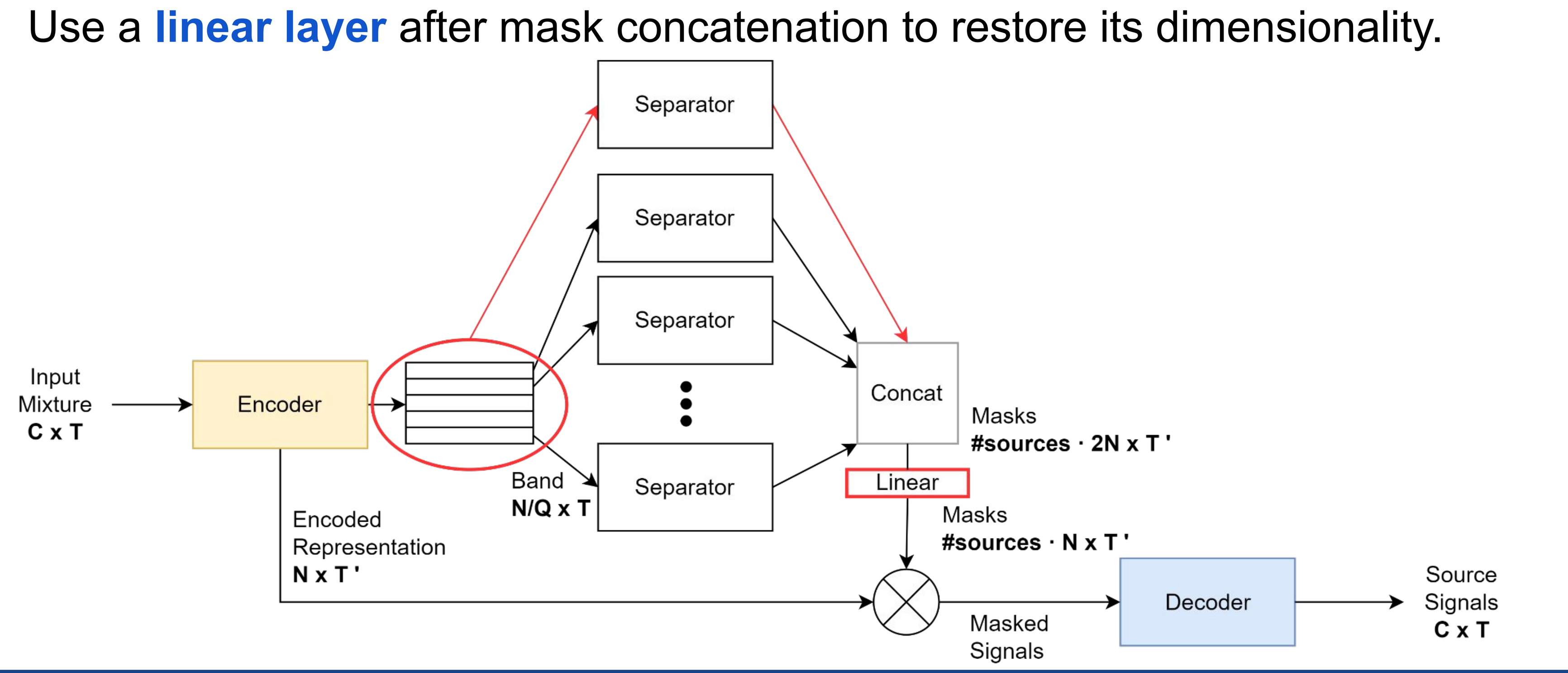
3. Methodology



- Encoder: Learns a **latent representation**, which is split into Q sub-bands
- Separators: Process each sub-band **individually**, each producing a mask for its subspace. The masks are then concatenated before element-wise multiplication with the encoded latent representation.
- Decoder: **Retrieves** the source signals.

Variant including full-band masking: Similar to above, but additionally:

- Include an **additional** separator for the full latent space (Q+1 separators in total)
- Use a **linear layer** after mask concatenation to restore its dimensionality.



4. Model Configurations

- M1: Conv-TasNet baseline [1], as implemented in [3].
- M2-4: Models with a different number and structure of latent bands.
- M5-6: Models with a pretrained latent space, only training the separators.
- S1-2: Models with the more complex encoder/decoder presented in [4].

Model	Description	#Params
M1	Baseline	6.6M
M2	2 Bands	6.58M
M3	2 Bands +1 Full-Band	12.97M
M4	4 Bands	6.71M
M5	2 Bands + Frozen enc/dec	6.56M
M6	2 Bands + Sorted enc/dec	6.56M
S1	Stronger enc/dec	7.32M
S2	Stronger enc/dec + 2 bands	7.31M

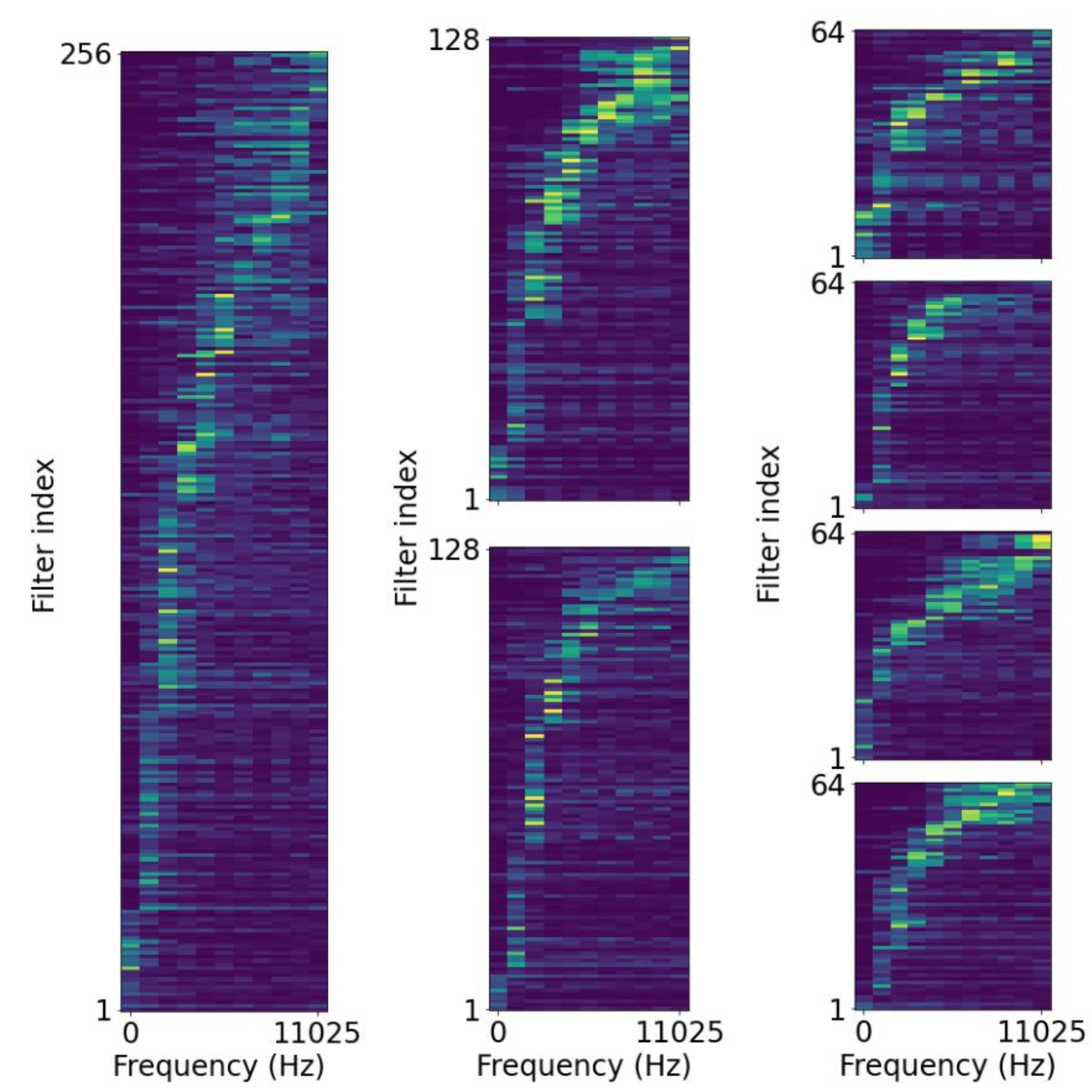
5. Experimental Setup

- Dataset used: MUSDB18 [5] (predefined train-validation-test split)
- Training details: 150 epochs (early stopping at 20 epochs), Adam (lr = 0.0001), L1 loss, on-the-fly augmentation (as in [4]).
- Evaluation protocol: Median-of-medians [6] as implemented by BSSEval4.

6. Results and Discussion

		M1	M2	M3	M4	M5	M6	S1	S2
Voc.	SDR	5.81	**6.37**	5.94	6.05	**6.31**	**6.26**	6.39	6.36
	SIR	14.13	14.25	14.23	14.61	**15.29**	**15.21**	14.39	14.92
	SAR	6.59	**7.12**	6.78	6.98	**6.75**	**6.88**	6.82	7.09
Acc.	SDR	11.78	**12.21**	11.76	11.66	**12.36**	11.91	12.23	12.03
	SIR	16.01	**16.69**	16.01	16.04	**17.07**	**16.54**	17.57	17.51
	SAR	14.24	**14.52**	14.37	14.10	14.11	14.29	14.20	14.07

- Models M2 and M5 record the overall best performance.
- **Splitting** the latent space into multiple sub-bands leads to **improved** performance, but **further increasing** the number of sub-bands results in **narrower spaces** per separator and thus diminishing returns.
- The full-band separator fails to provide any benefit.
- The technique works equally well with an **arbitrary**, **pre-trained frontend**, while manually crafting bands by **spectral content** does not provide additional gains.
- No additional gains from the models utilizing the **more sophisticated encoder**.



- The top subspace of M2 contains more high-frequency and less narrow filters than the bottom, but the **overall filter distribution** matches that of the M1 model.
- On the other hand, the sub-spaces of M4 have **more visible differences** in terms of central frequencies and bandwidth.

7. Conclusions

- Proposed a **multi-band**, **multi-separator** extension for waveform-based audio source separation architectures.
- **Improved** performance in singing voice separation over a single-band Conv-TasNet.
- The technique is also able to **adapt** at frozen, predefined latent spaces.

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