DEEP LEARNING FOR SPEECH ENHANCEMENT APPLIED TO NON-CONVENTIONAL SOUND CAPTURE DEVICES

Starting date: December 1, 2021 (9 months ago)

Funding: ANR (50% ISL/50% Cnam) - AHEAD project

Artificial Intelligence for Health, Physical Models, Transportation and Defense

PhD student: Julien HAURET[☆]

Director: Éric BAVU[☆]

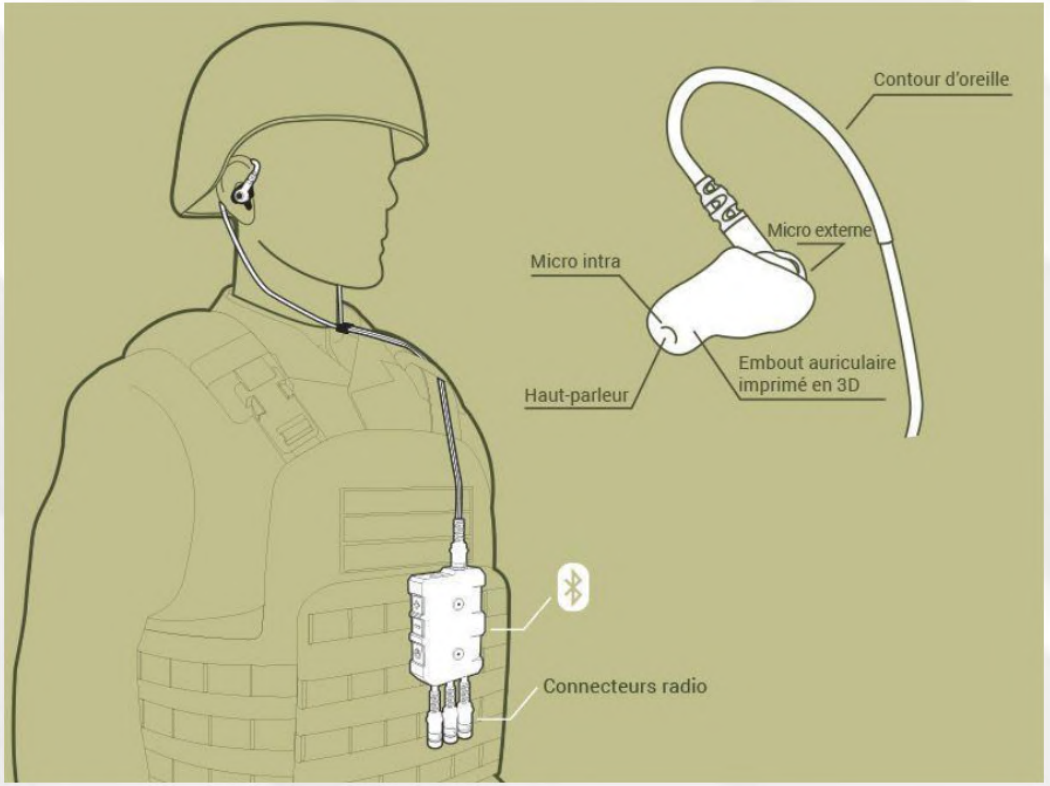
Supervisors: Thomas JOUBAUD[†]**, Véronique ZIMPFER**[†]

☆ : Structural Mechanics and Coupled Systems Laboratory, Conservatoire National des Arts et Metiers

† :Department of Acoustics and Soldier Protection, French-German Research Institute of Saint-Louis

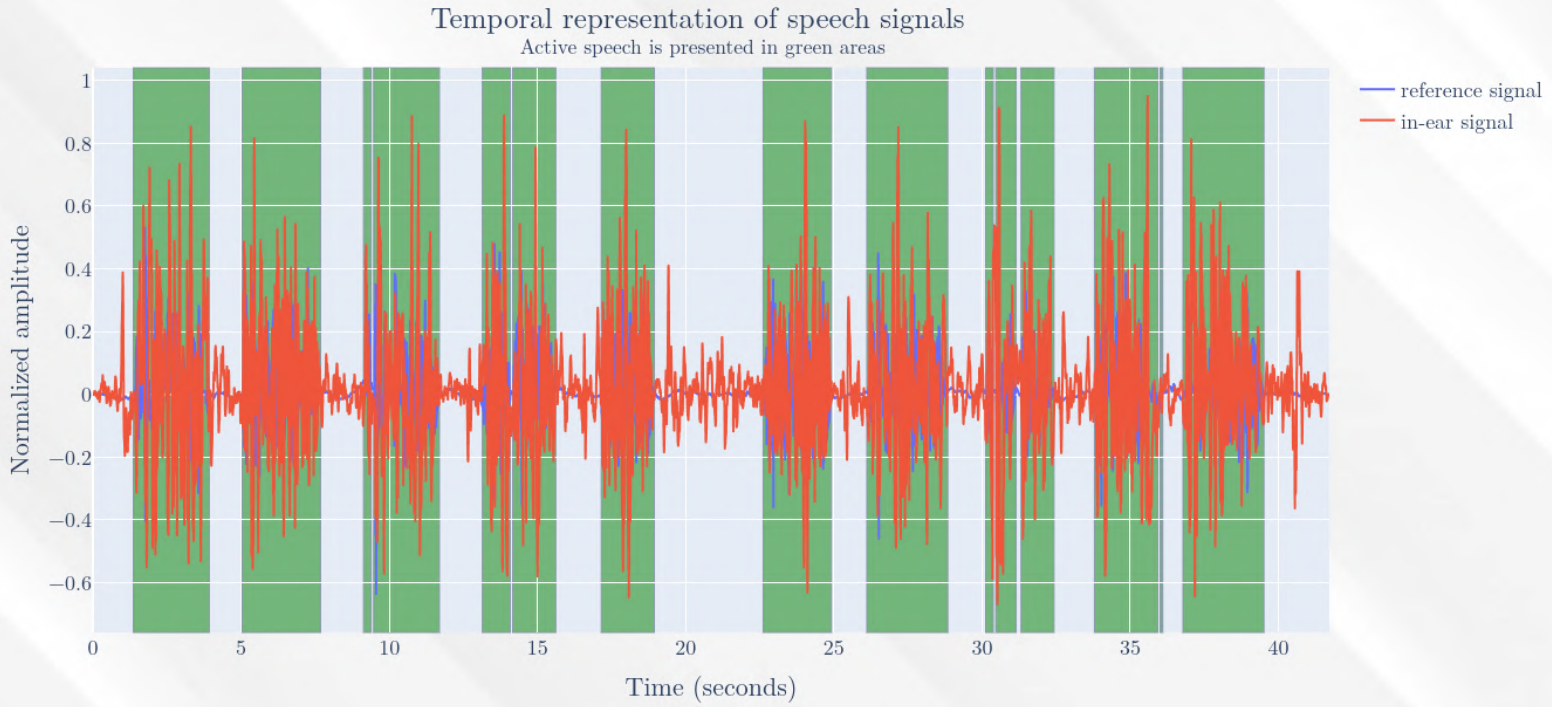
CONTEXT

BANG PROTOTYPE



Bouchon Auriculaire de Nouvelle Génération

TEMPORAL REPRESENTATION



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SPECTROGRAM

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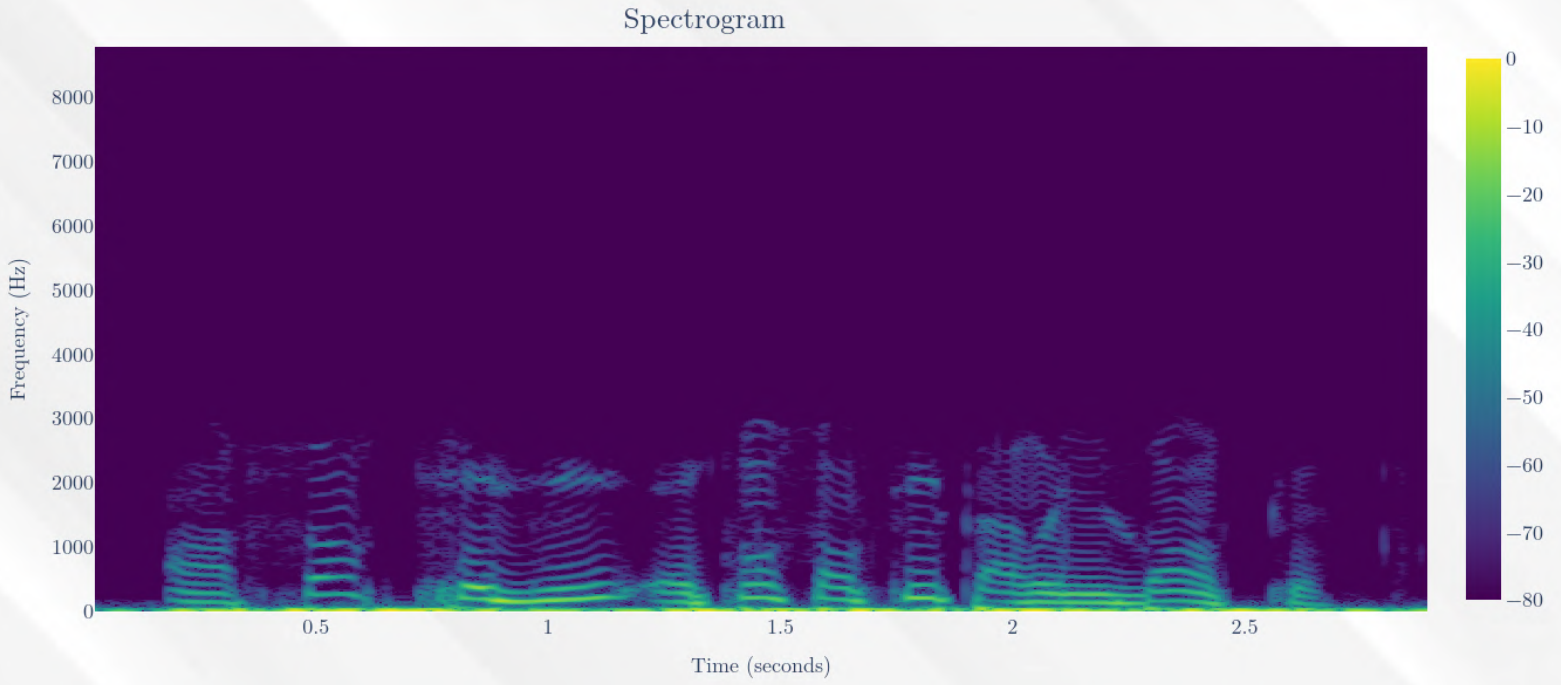
IN-EAR SIGNAL



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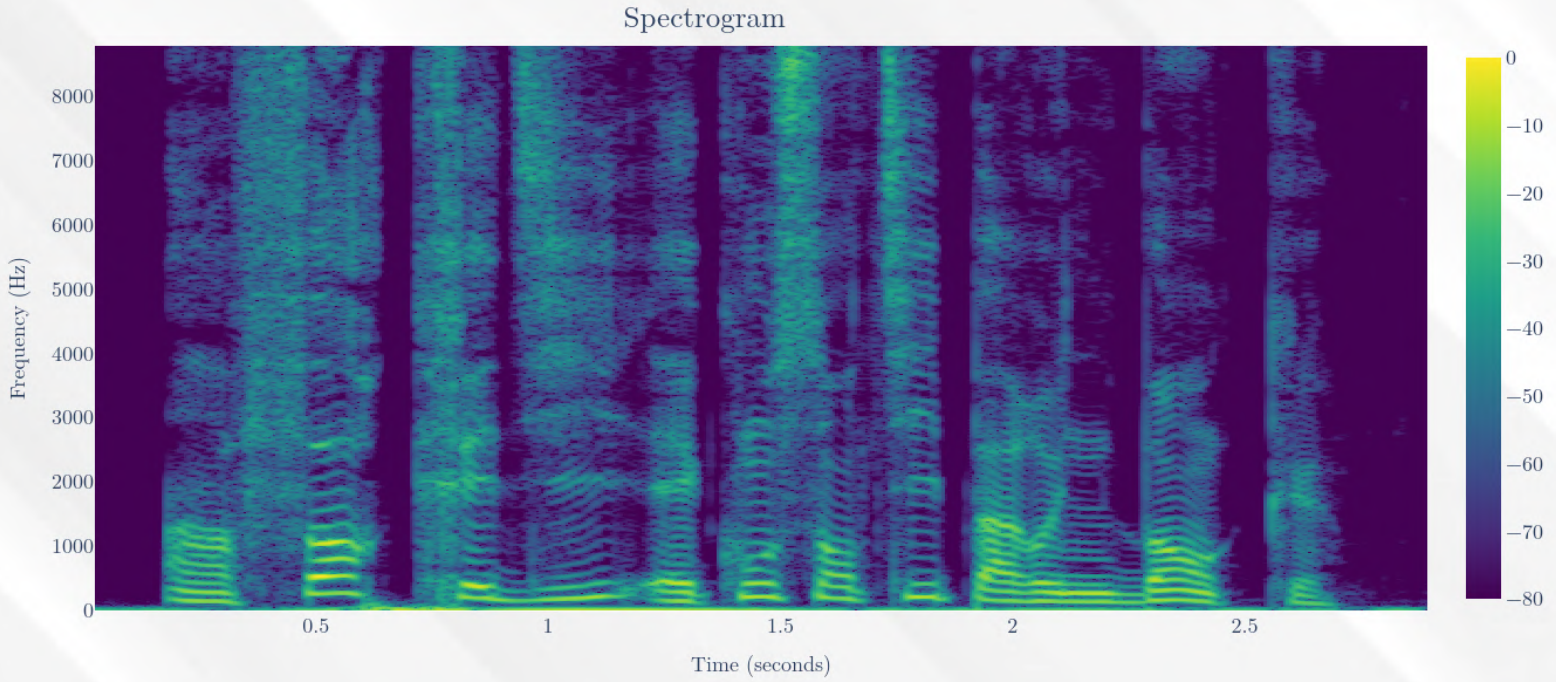
REFERENCE SIGNAL



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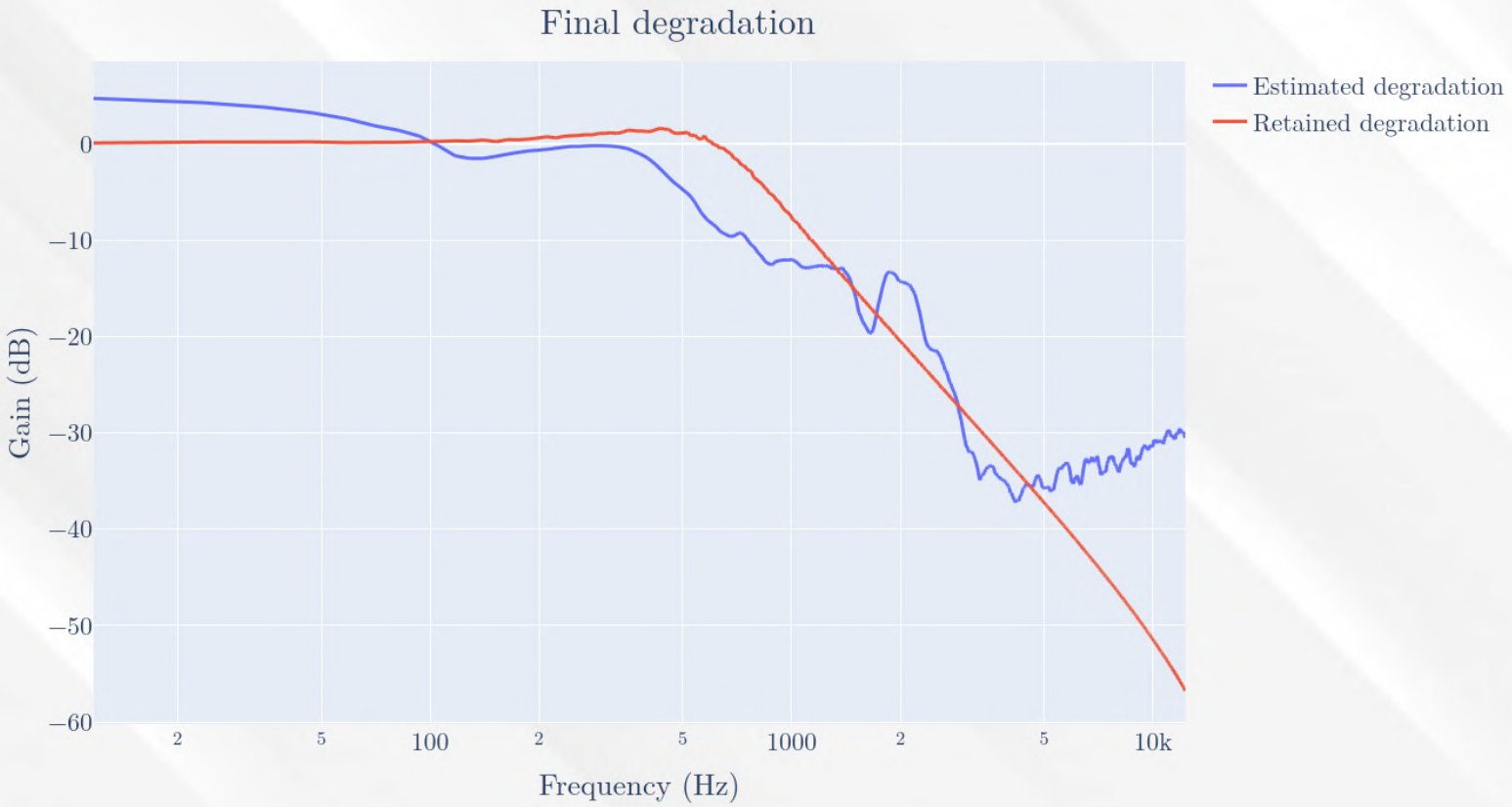
SOURCE FILTER MODEL



SUMMARY

GOAL

Improving speech intelligibility with in-the-ear transducers

CONSTRAINTS

- Light hardware
- Real-time processing
- Robustness to speaker's indentity

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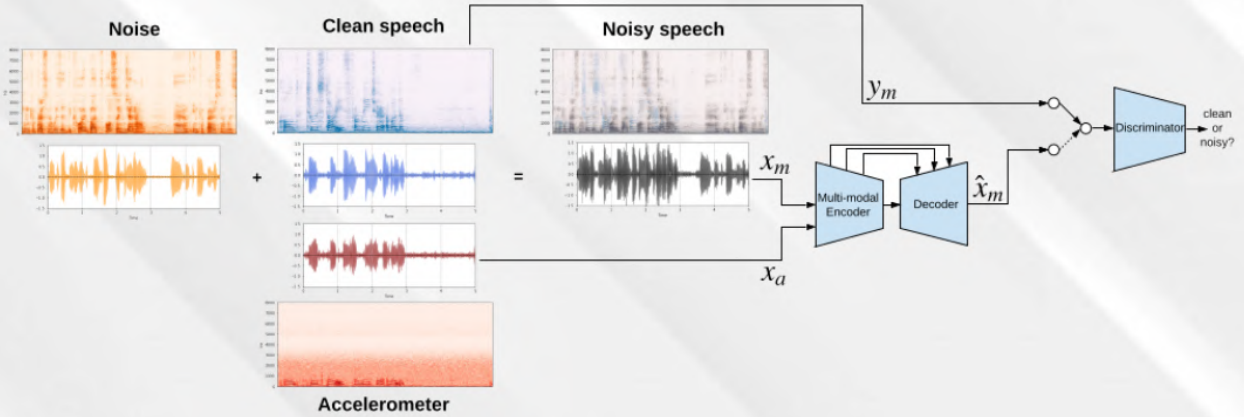
SEANET

presented at INTERSPEECH 2020 by Google Research

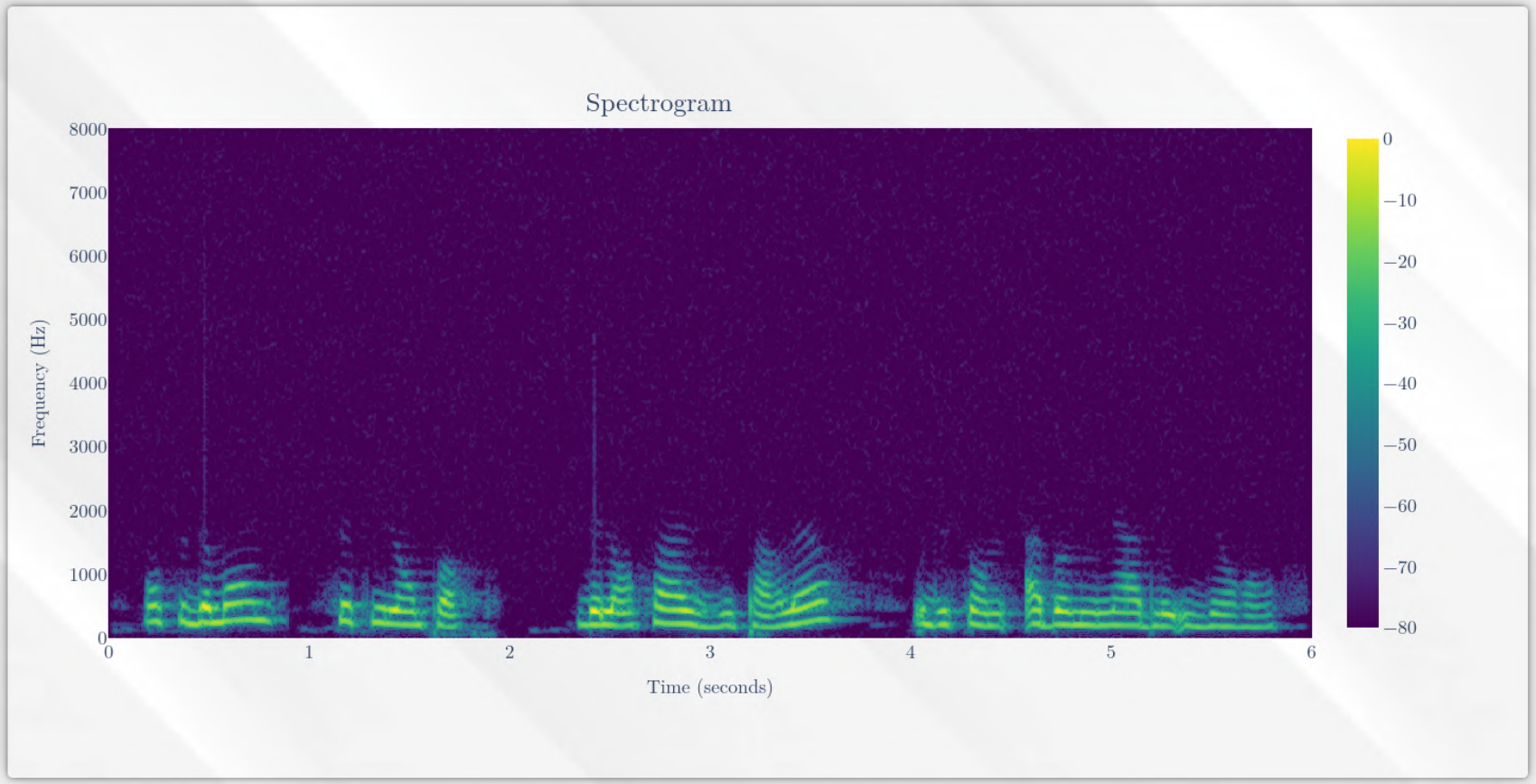
PRINCIPLE

$$\mathcal{L}_{gen} = \mathcal{L}_{rec} + \lambda \mathcal{L}_{adv} \qquad \mathcal{L}_{dis} = \mathcal{L}_{adv\ fake} + \mathcal{L}_{adv\ real}$$



Model overview

RESULTS



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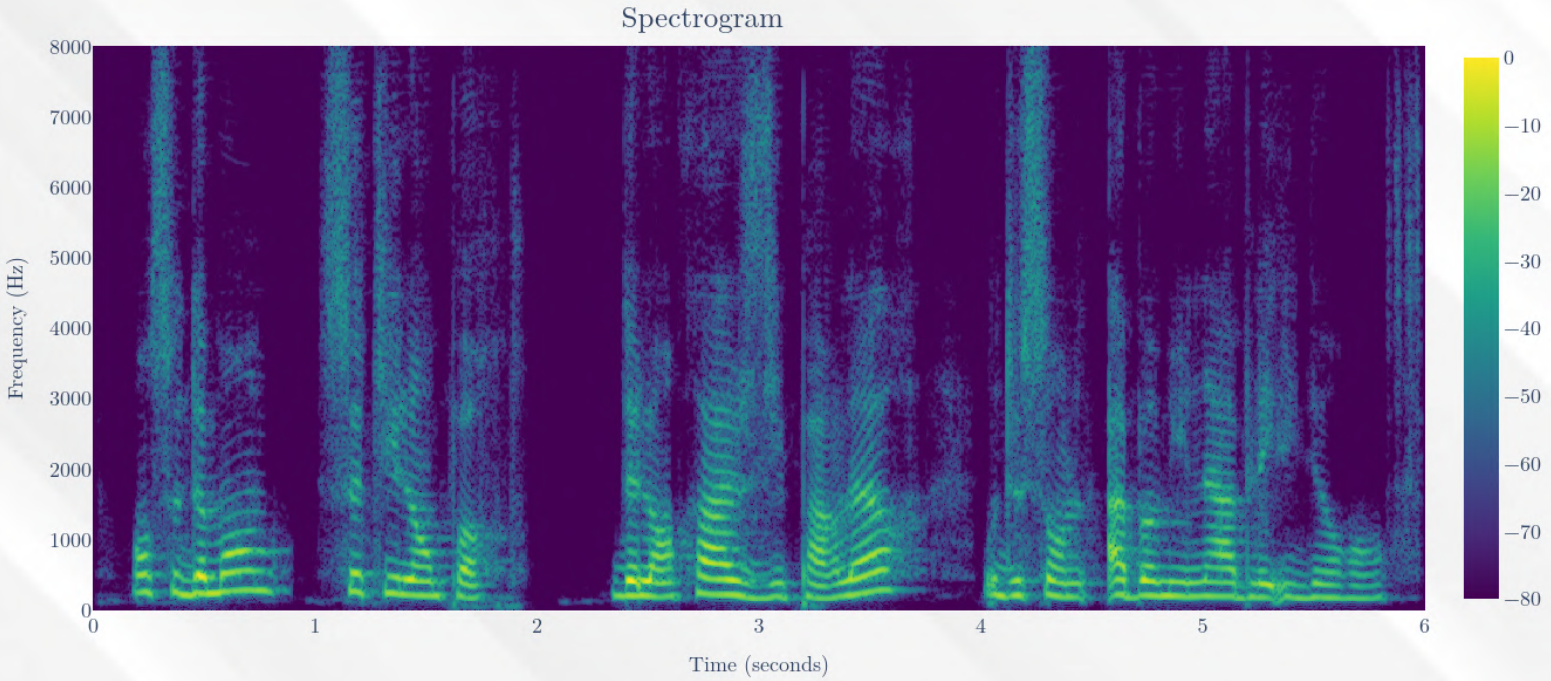
RESULTS



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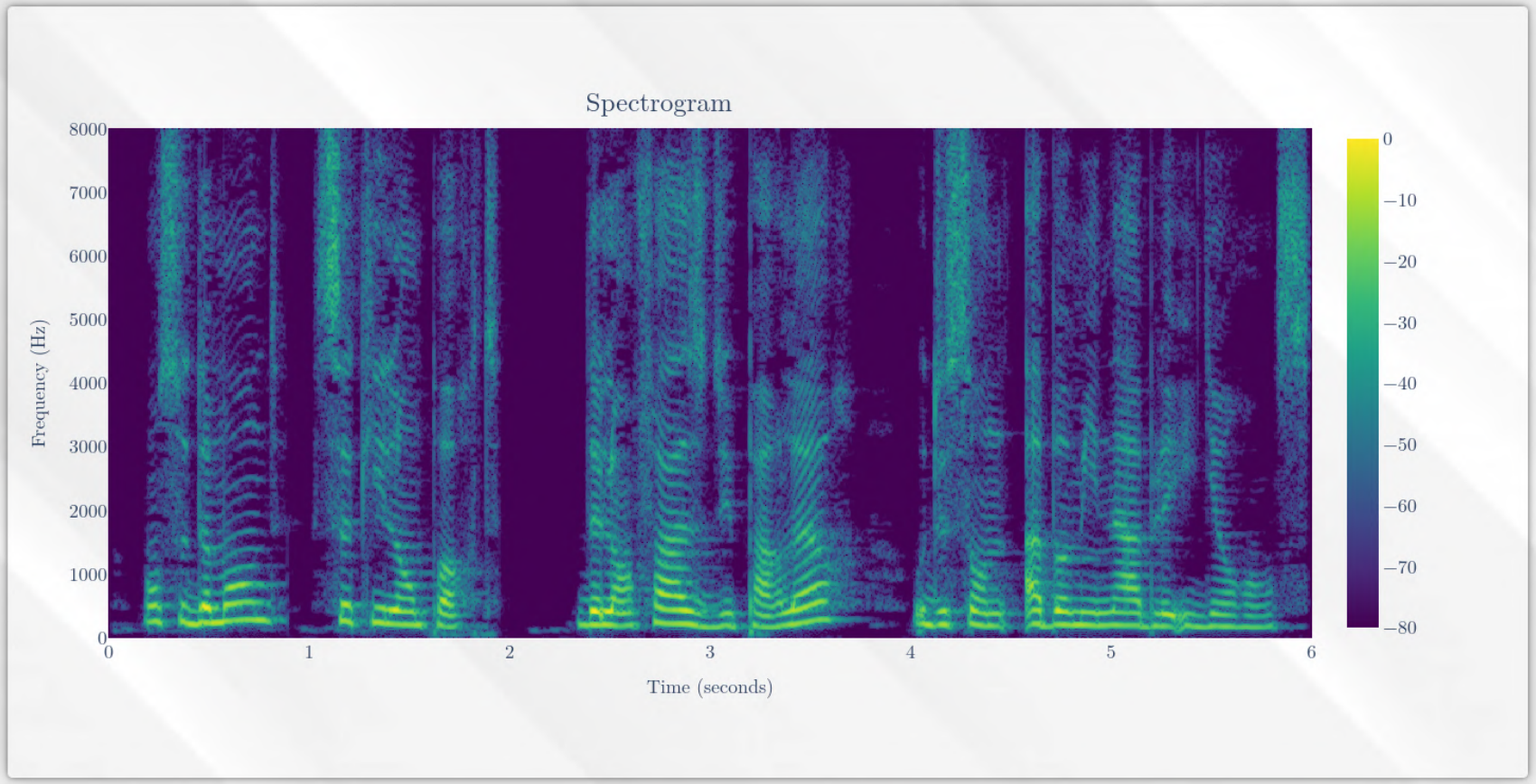
RESULTS



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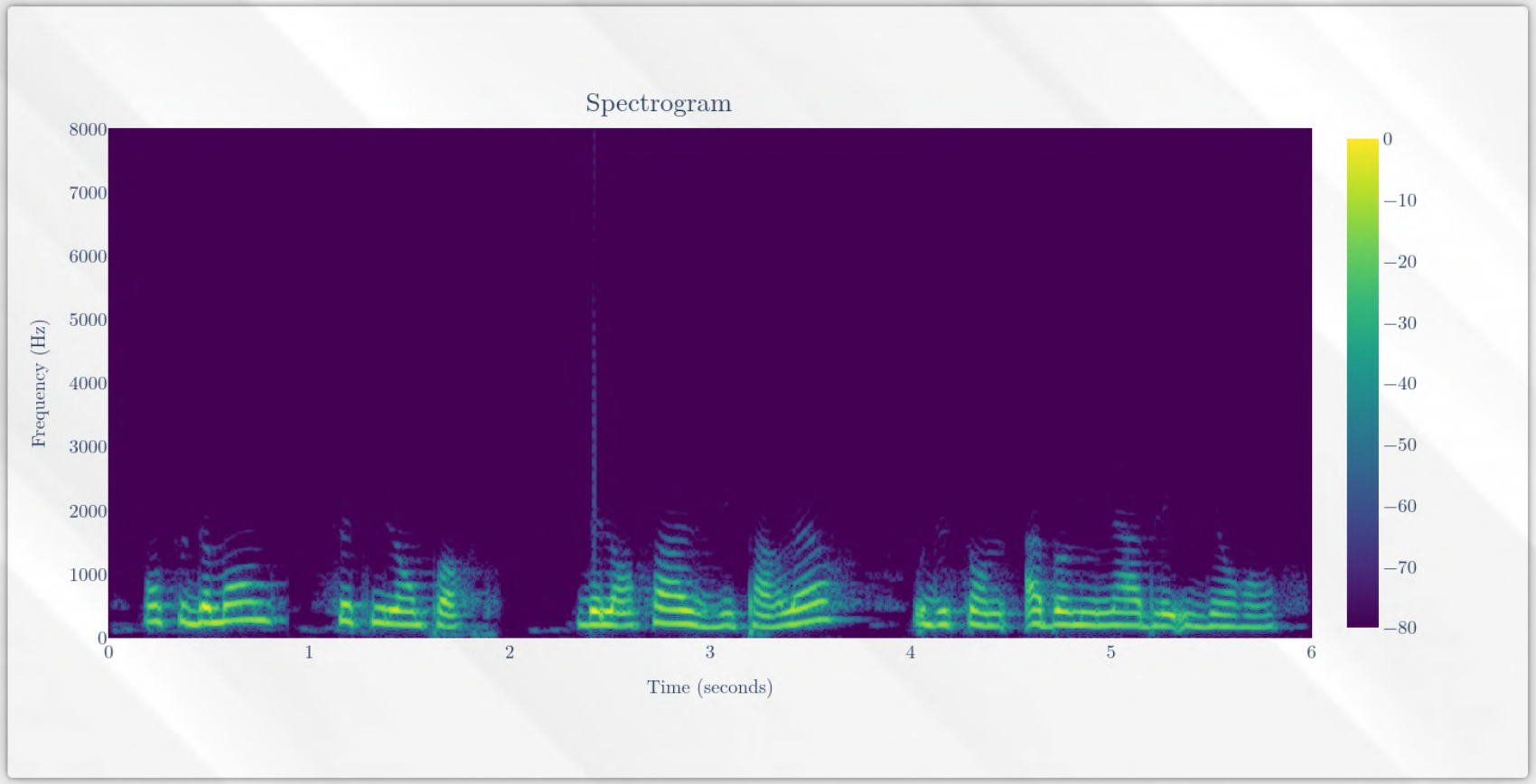
RECONSTRUCTIVE ONLY: RESULTS



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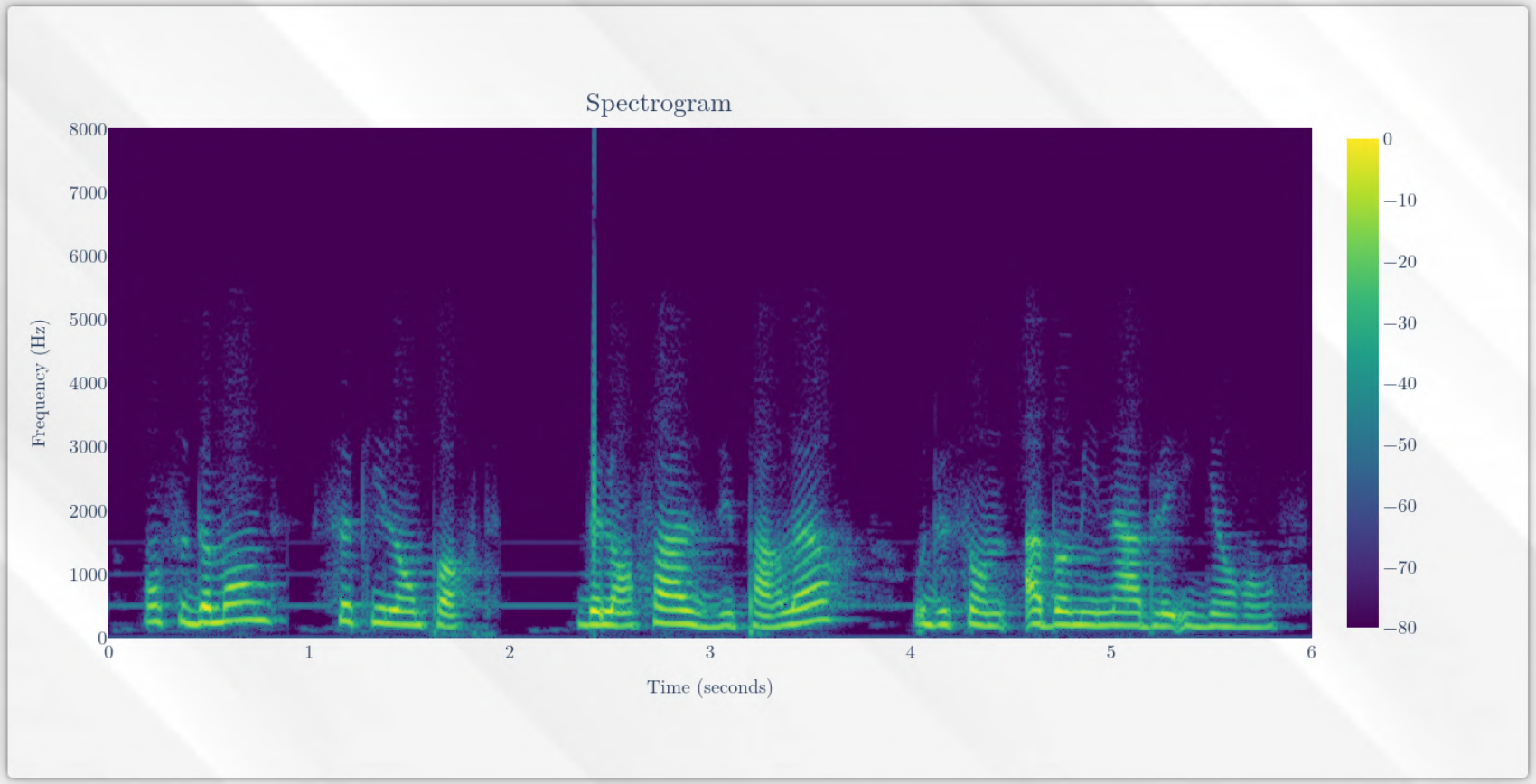

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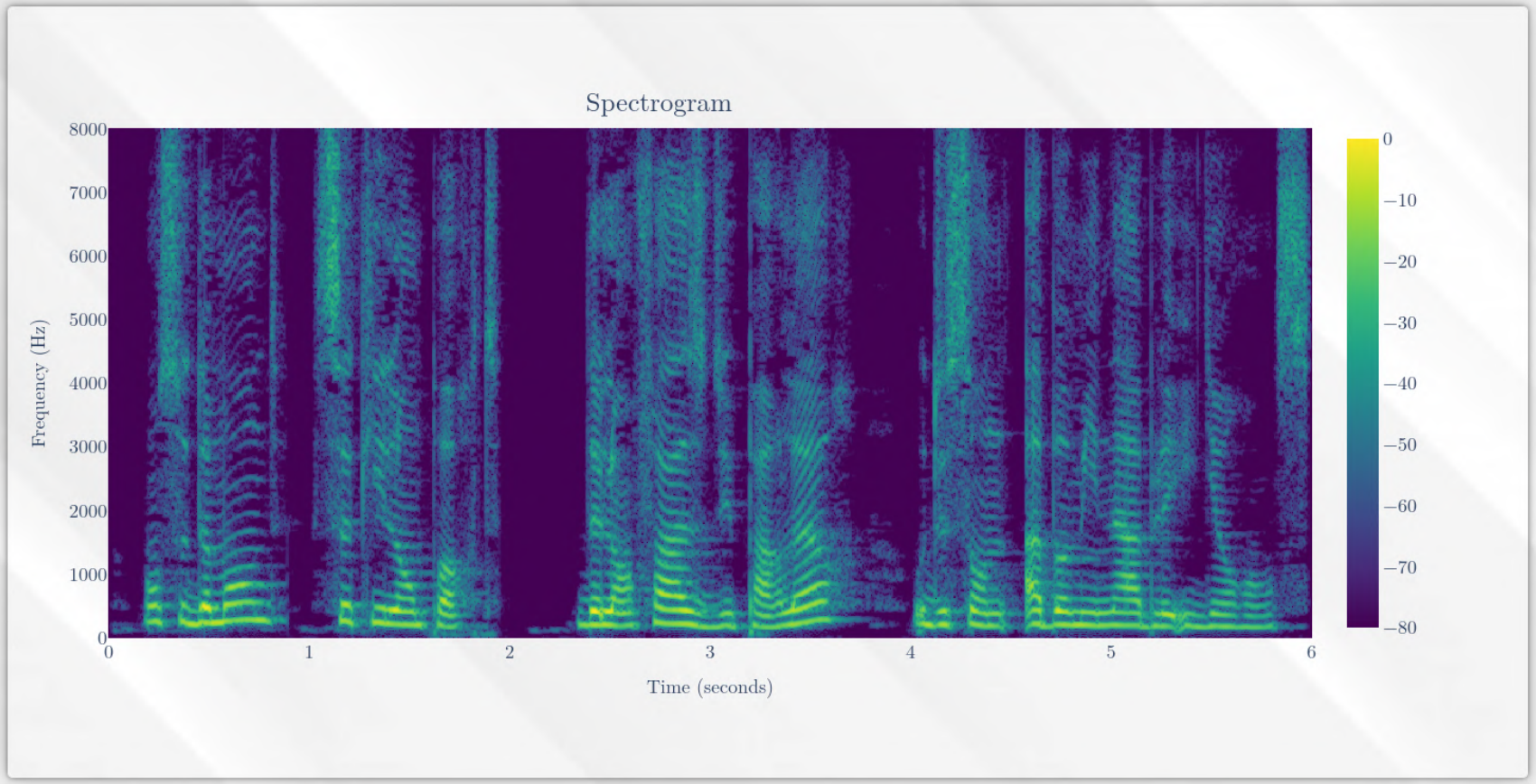
RECONSTRUCTIVE ONLY: RESULTS



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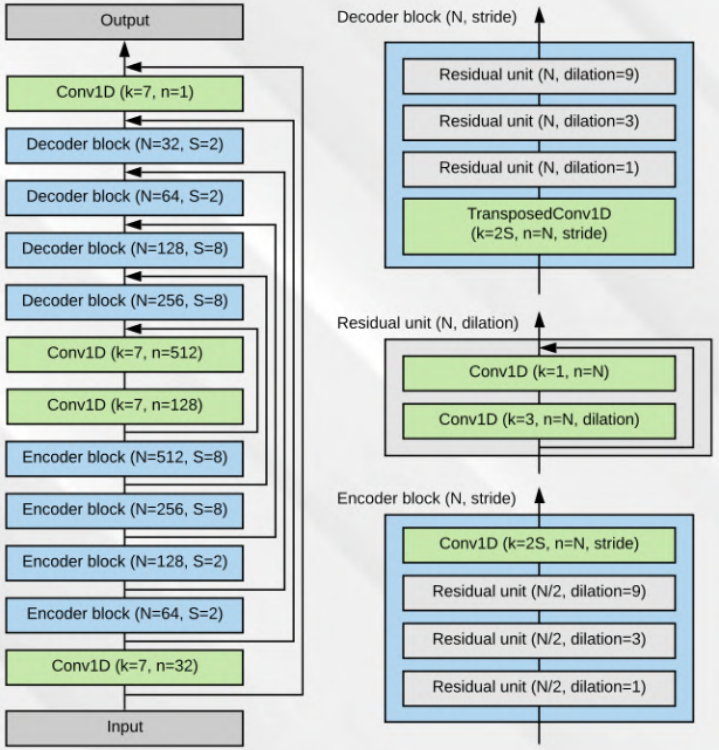
PQMF APPROACH TO LIGHTEN PROCESSING

STARTING POINT



SEANet's generator architecture

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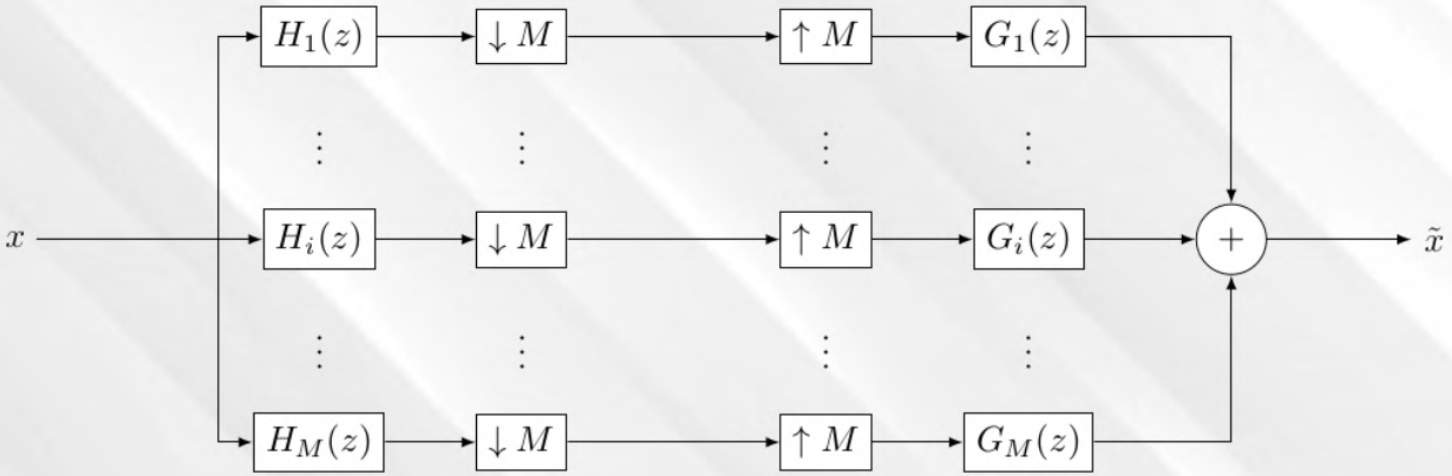
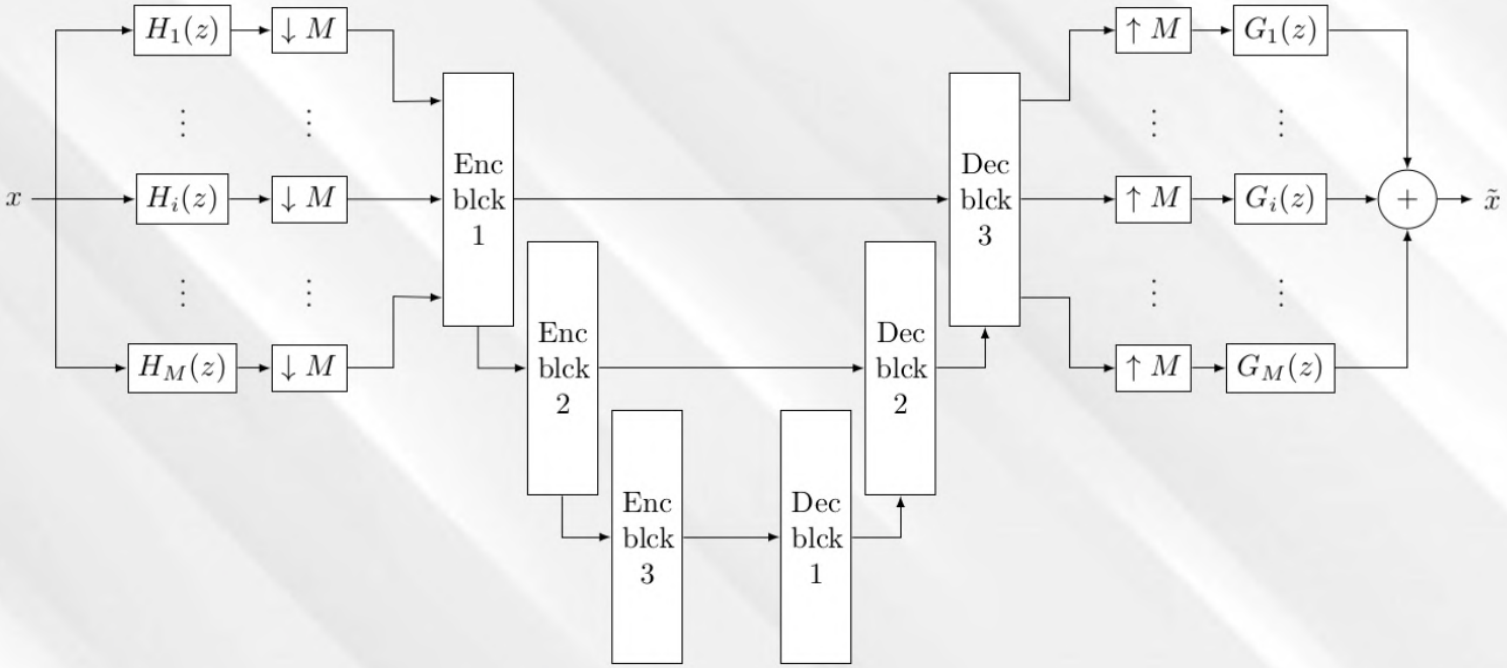


Pseudo Quadrature Mirror Filter (PQMF) banks



PQMF-generator

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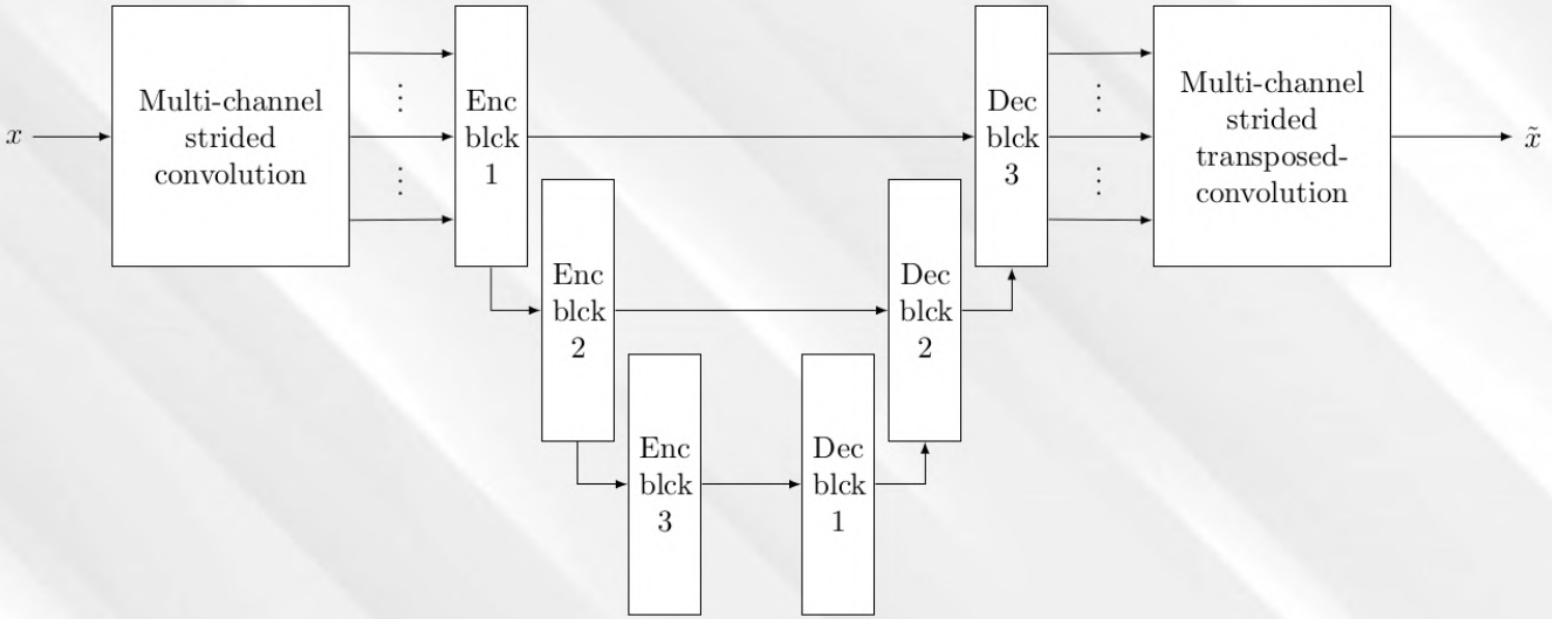

Fast PQMF-generator

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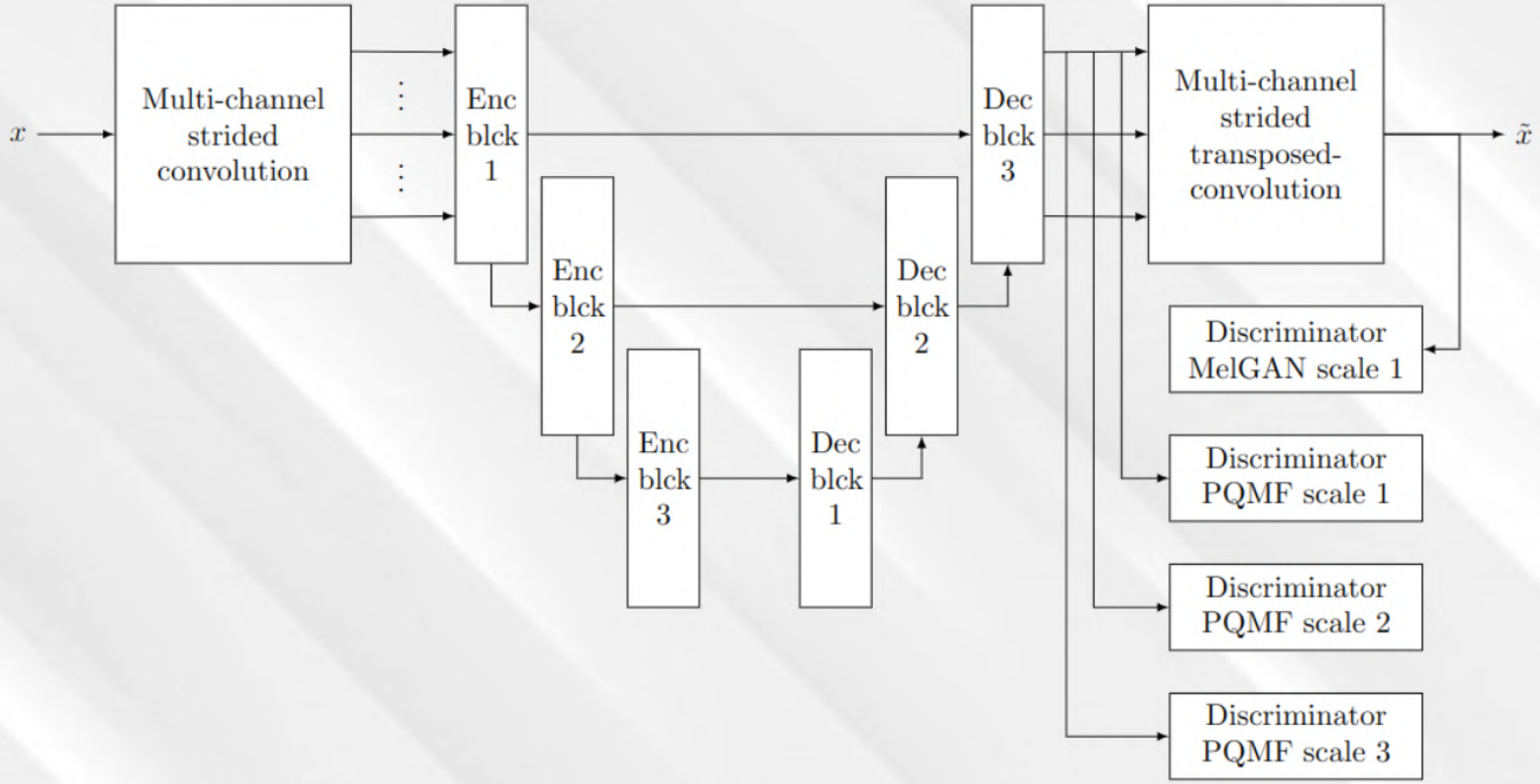

Our PQMF-SEANet

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SUMMARY ON PQMF-SEANET

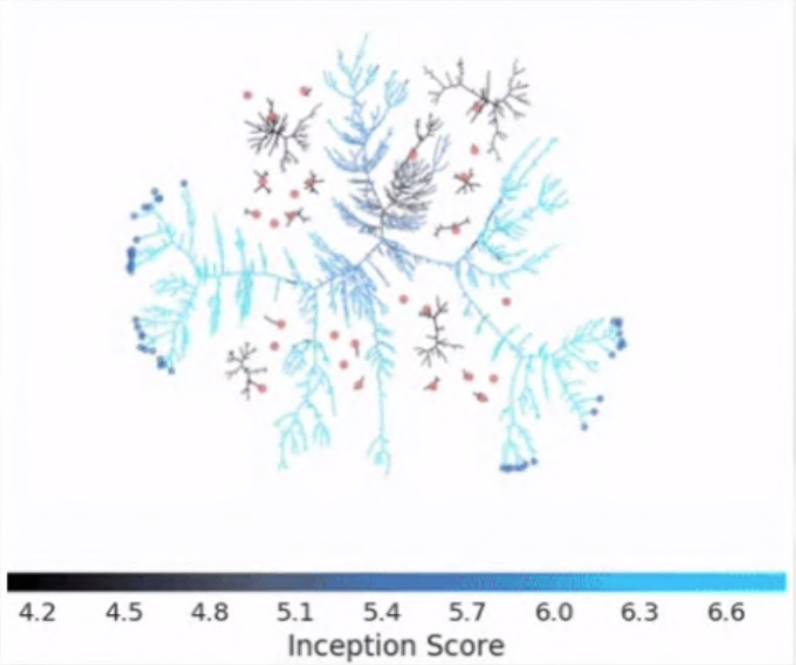
AVANTAGES

- **Memory gain** thanks to the reduction of features' temporal length
- **Gain in inference speed** thanks to the reduced number of layers
- **More flexibility** for processing and discriminators inputs

DISADVANTAGES

- Projection in a non-optimal basis for our problem
- Convolution with large kernels difficult to parallelize

AUTOMATE THE SEARCH FOR HYPERPARAMETERS



Population based training

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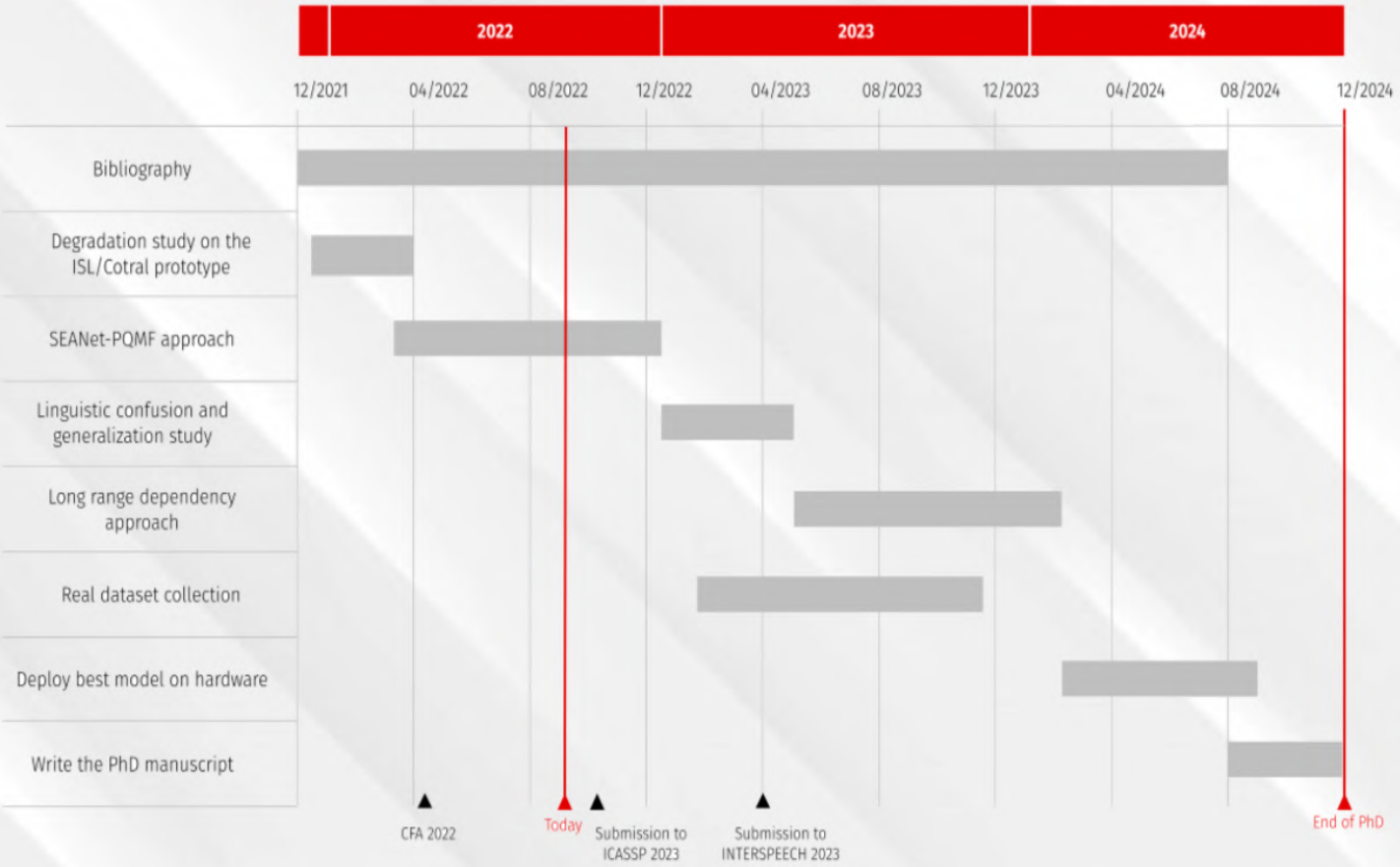
EVALUATION

Signals	PESQ	SI-SDR	SI-SNR	STOI
In-ear	1.246	-6.615	-7.538	0.7178
SEANet baseline	2.321	10.99	10.79	0.8985
Mix	2.573	11.25	11.05	0.8961
PQMF SEANet	2.245	11.52	11.42	0.890
PQMF SEANet + tricks	2.435	11.94	11.84	0.902

TIMELINE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12/2023
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08/2024
12/2024
Bibliography
Degradation study on the ISL/Cotral prototype
SEANet-PQMF approach
Linguistic confusion and generalization study
Long range dependency approach
Real dataset collection
Deploy best model on hardware
Write the PhD manuscript
CFA 2022
Today
Submission to ICASSP 2023
Submission to INTERSPEECH 2023
End of PhD

THANK YOU FOR YOUR ATTENTION

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Title: Deep learning for speech enhancement applied to non-conventional sound capture

contact: julien.hauret@lecnam.net

acknowledgments to: Éric Bavu, Thomas Joubaud, Véronique Zimpfer, Robin Petit

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Cotral Lab

ISL

AGENCE NATIONALE DE LA RECHERCHE ANR

SIGNAL PROCESSING EQUATIONS

Source-Filter model

$$y(t) = (h * x)(t)$$

$$Y(f) = H(f).\, X(f)$$

Transfer function estimation

$$H(f) = \frac{P_{xy}(f)}{P_{xx}(f)}$$

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f).\, P_{yy}(f)}$$

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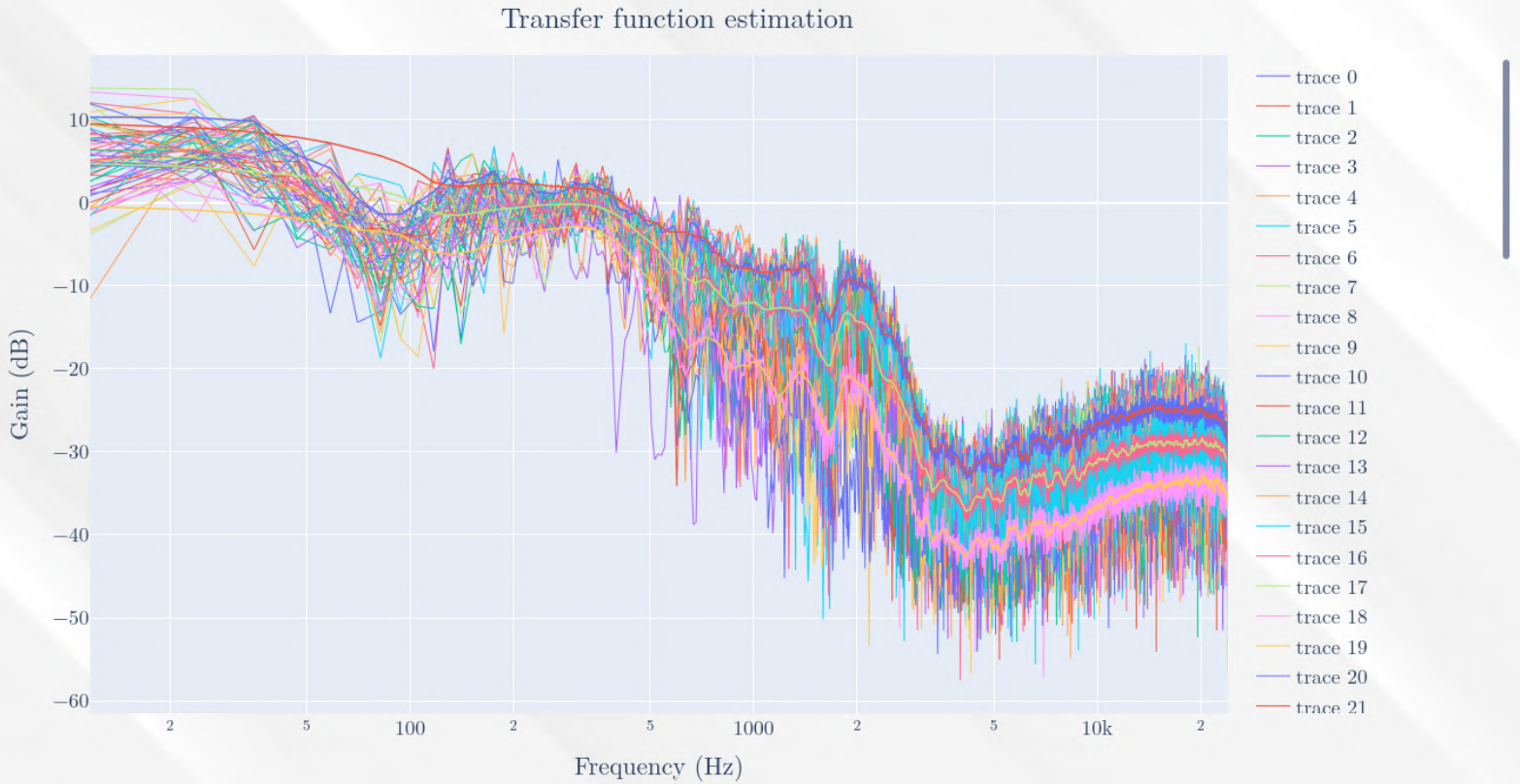
BODE DIAGRAM



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LOSS FUNCTIONS : SEANET

$$\mathcal{L}_D = E_y \left[\frac{1}{K} \sum_k \frac{1}{T_k} \sum_t max(0, 1 - D_{k,t}(y)) \right] + E_x \left[\frac{1}{K} \sum_k \frac{1}{T_k} \sum_t max(0, 1 + D_{k,t}(G(x))) \right]$$

$$\mathcal{L}_G^{adv} = E_x \left[\frac{1}{K} \sum_k \frac{1}{T_k} \sum_t max(0, 1 - D_{k,t}(G(x))) \right]$$

$$\mathcal{L}_G^{rec} = E_x \left[\frac{1}{KL} \sum_{k,l} \frac{1}{T_{k,l}} \sum_t \| D_{k,t}^{(l)}(y) - D_{k,t}^{(l)}(G(x)) \|_{L_1} \right]$$

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PQMF

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