DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

UNIVERSITÀ DEGLI STUDI DI PADOVA

SIGNET

Learned Spike Encoding of the Channel Response for Low-Power Environment Sensing

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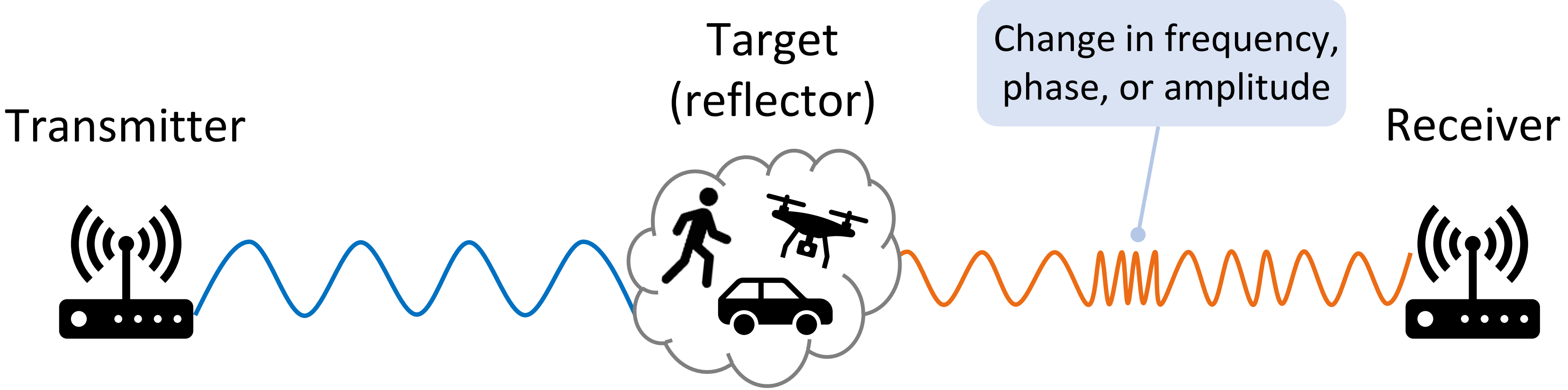
Radio Frequency sensing

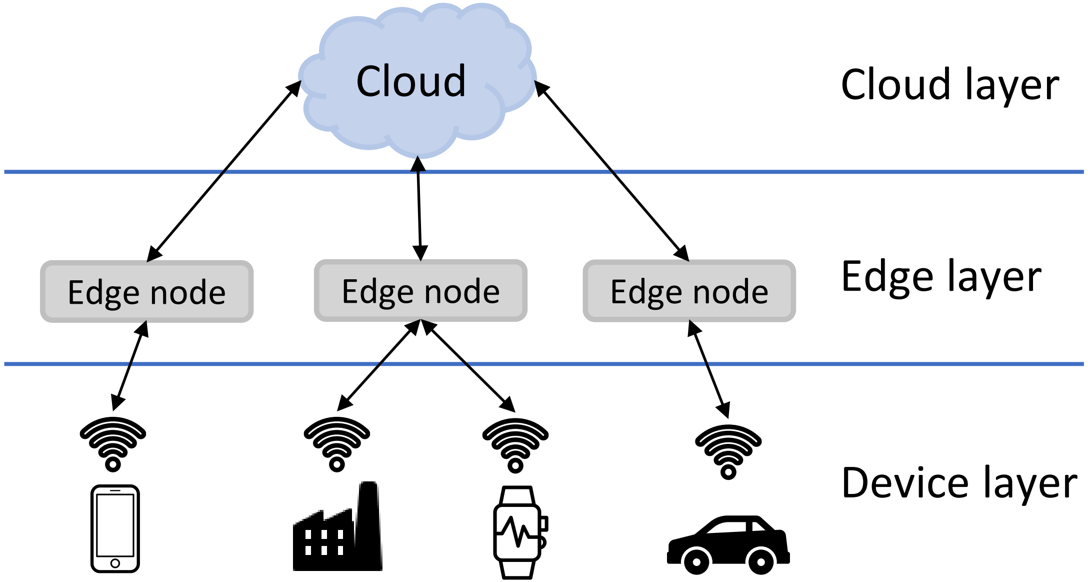


- Radio Detection and Ranging (RADAR) principle

Why radio signals instead of cameras?

Privacy

Edge computing



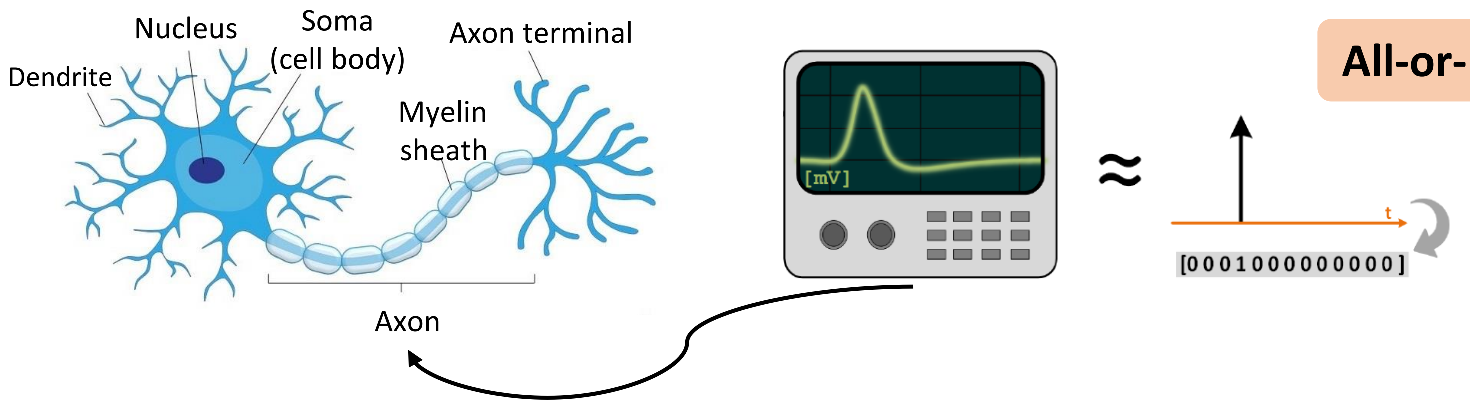
Complex Deep Learning models are run in the cloud

NEW PARADIGM:
Bring computation here

↓

Accuracy-efficiency trade-off

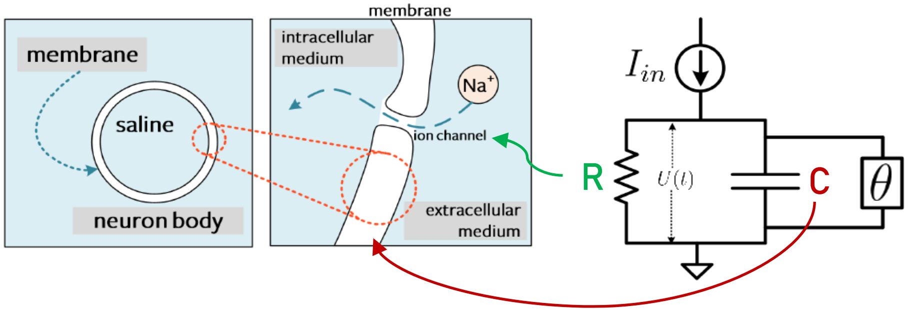
Spiking Neural Networks



All-or-nothing event

- **1.** Biological neurons communicate via **action potentials**, or *spikes*
- **2.** Biological neurons spend most of their time at rest
- **3.** Event-based processing

The Leaky Integrate and Fire (LIF) neuron



$$\tau \frac{dU(t)}{dt} = -U(t) + I_{in}(t)R$$

τ: time constant of the circuit

$U(t)$: membrane potential

$I_{in}(t)$: input current

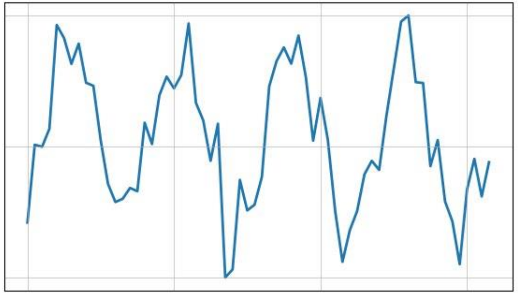
Find approximate solution with *Forward Euler Method*

$$\beta = e^{-1/\tau}$$

$$U[t] = \underbrace{\beta}_{\text{decay}} U[t-1] + \underbrace{WX[t]}_{\text{input}} - \underbrace{S[t-1]\theta}_{\text{reset}}$$

$$S[t] = \begin{cases} 1, & \text{if } U[t] > \theta \\ 0, & \text{otherwise} \end{cases}$$

Spike encoding



Consider also negative spikes

$$[0\,0\,-1\,0\,0\cdots0\,1\,0]$$

GOAL

- Sparsity
- Preserve spectral content

Temporal Contrast encoding

- Keep track of temporal changes in the signal
- Inaccurate and dense encoding

What if we **learned** the spike encoding?

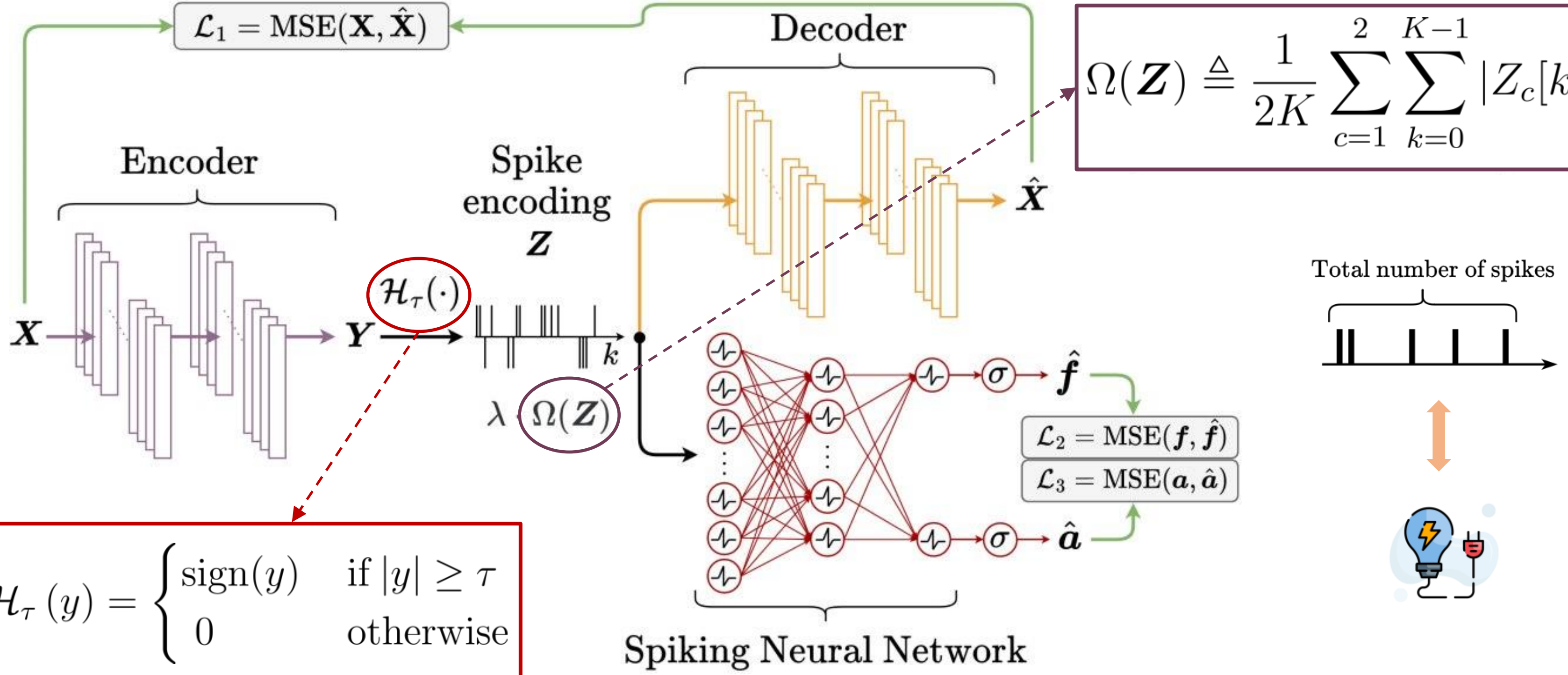
Signal model

$$x[k] \triangleq x(kT) = \sum_{m=1}^{M} \underbrace{a_m e^{j(2\pi f_m kT + \phi_m)}}_{\text{complex sinusoid}} + \underbrace{w(kT)}_{\text{Gaussian noise}}, \quad k = 0, \ldots, K-1$$

- T: sampling time
- M: # of sinusoids
- K: window length

- Each sinusoidal component accounts for **one** moving reflector
- **Dataset**: 3,000 windows for each M=1,…,5

Network architecture



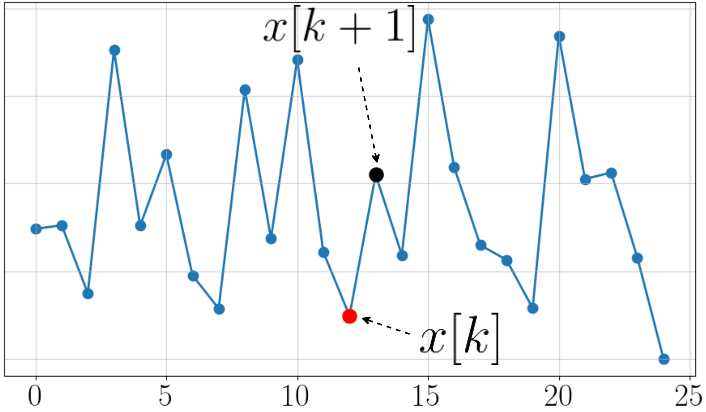
$$\Omega(\boldsymbol{Z}) \triangleq \frac{1}{2K} \sum_{c=1}^{2} \sum_{k=0}^{K-1} |Z_c[k]|$$

$$\mathcal{H}_\tau(y) = \begin{cases} \mathrm{sign}(y) & \text{if } |y| \geq \tau \\ 0 & \text{otherwise} \end{cases}$$

Comparison with Temporal Contrast methods

- Threshold-based representation (TBR)
- Step-forward (SF)
- Moving-window (MW)

- channel reconstruction
- spectral components
- sparsity
- robustness to noise



$$\begin{cases} x[k+1]-x[k] & > thr. \longrightarrow \text{spike} = 1 \\ x[k+1]-x[k] & < -thr. \longrightarrow \text{spike} = -1 \end{cases}$$

Channel reconstruction

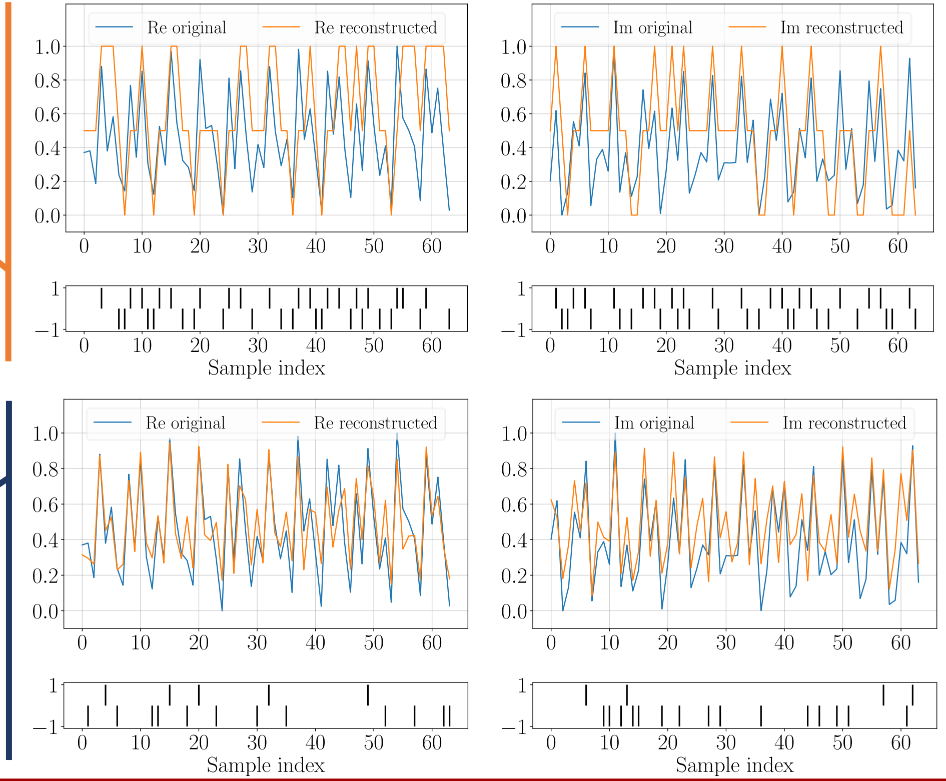
Metric: *Per-window* Root Mean Squared Error

Method	Recon. RMSE
TBR	0.374 ± 0.075
SF	0.222 ± 0.044
MW	0.262 ± 0.059
LSE	**0.133 ± 0.028**

LSE = Learned Spike Encoding

SF

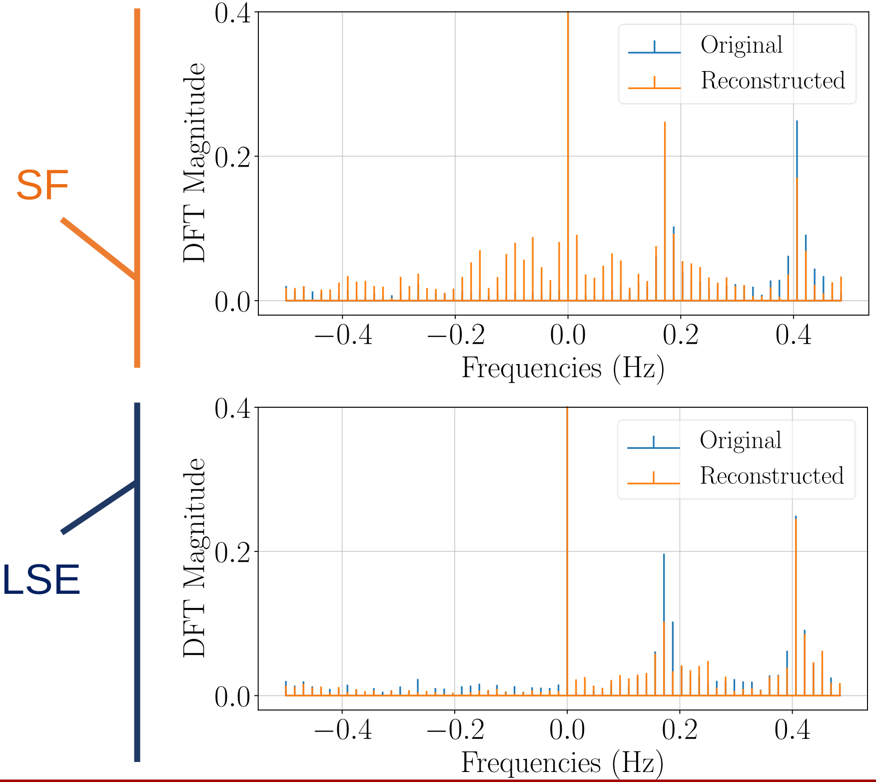
LSE



DFT magnitude reconstruction

Metric: *Per-window* Root Mean Squared Error

Method	$\lvert DFT \rvert^2$ RMSE
TBR	0.043 ± 0.010
SF	0.029 ± 0.009
MW	0.039 ± 0.011
LSE	0.017 ± 0.004

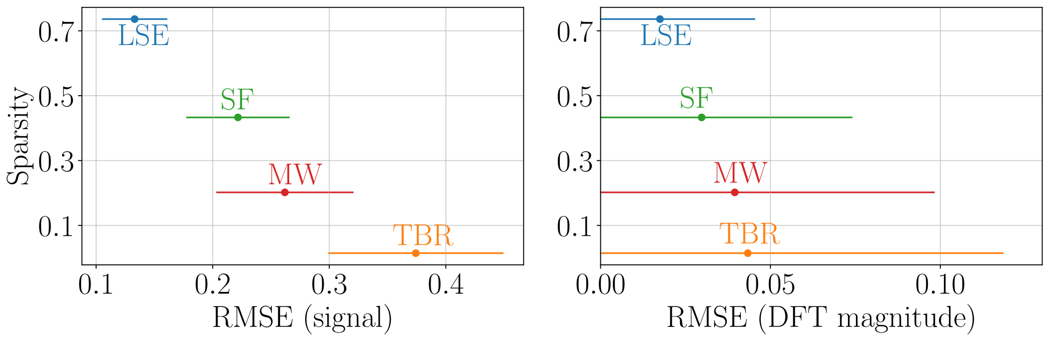


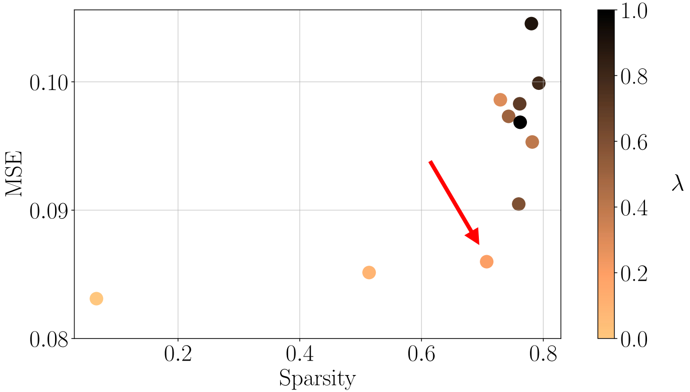
Sparsity of the encoding

Sparsity: Fraction of zeros in the encoding

Method	$\|DFT\|^2$ RMSE
TBR	0.015
SF	0.433
MW	0.202
LSE	0.736

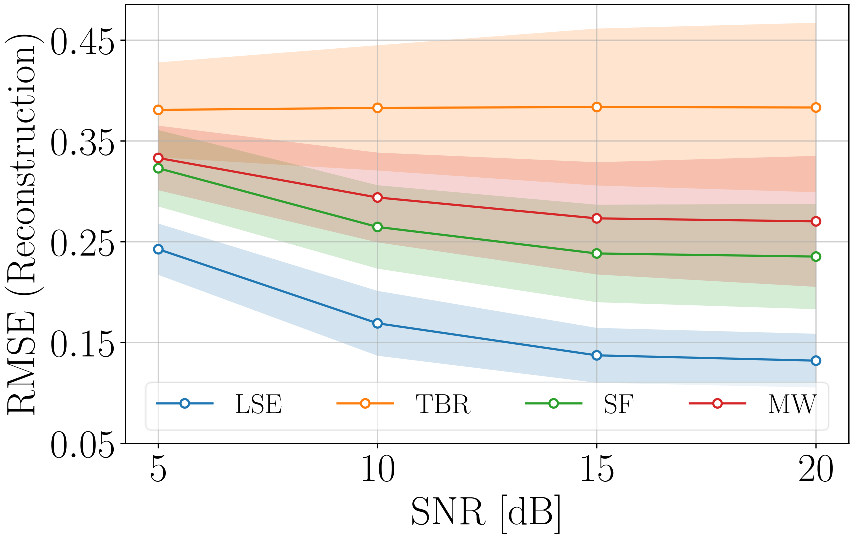
70% higher sparsity than SF

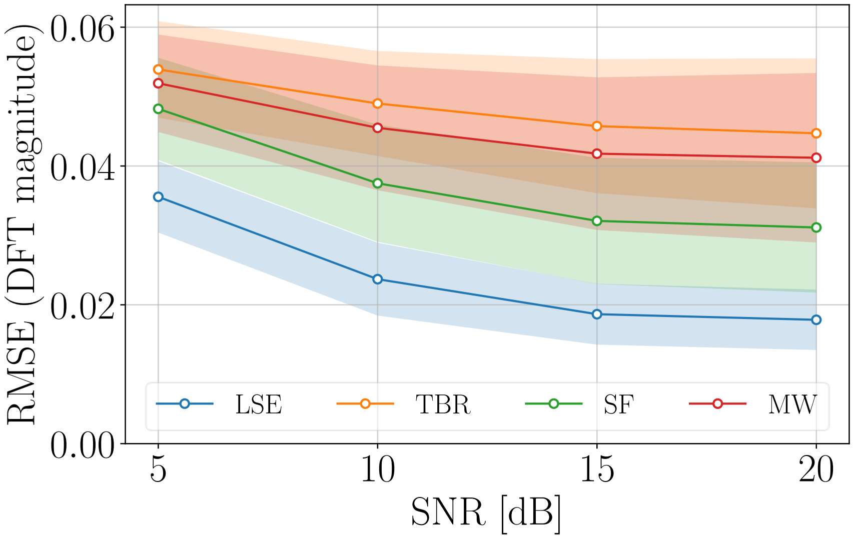




Direct control of the sparsity-accuracy trade-off

Robustness to noise





Channel response reconstruction

|DFT|² reconstruction

Concluding remarks

- Learn a **tailored** spike encoding for RF channel responses
- CAE for encoding + SNN for reconstructing amplitudes and frequencies
- **Lightweight** neural network: <120K parameters, ~2MB of size
- Direct control of the performance-sparsity trade-off

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Thank you

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