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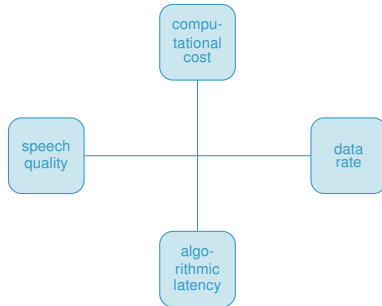


Sparse Reconstruction of Quantized Speech Signals

Christoph Brauer, Timo Gerkmann and Dirk Lorenz

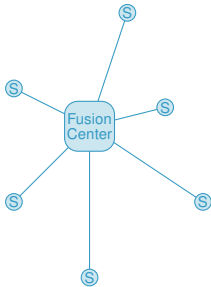
Joint Annual Meeting of GAMM and DMV, March 10, 2016

Speech Coding



- encoding of analog signals
- decoding of encoded signals
- goal: find a good trade-off between different target values
- requirements depend on the regarded application

Wireless Acoustic Sensor Networks



- *“a next-generation technology for audio acquisition and processing”*
- encoding by distributed, small, cheap sensors
- decoding by a powerful central processor
- applications include hearing aids, hands-free telephony, acoustic monitoring and ambient intelligence

Wireless Acoustic Sensor Networks

sound source

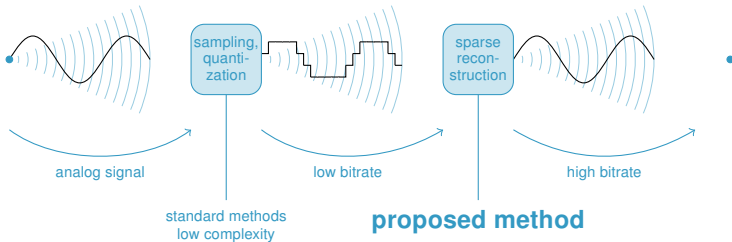
sensors

limited capacity

fusion center

powerful

output device



Wireless Acoustic Sensor Networks

sound source

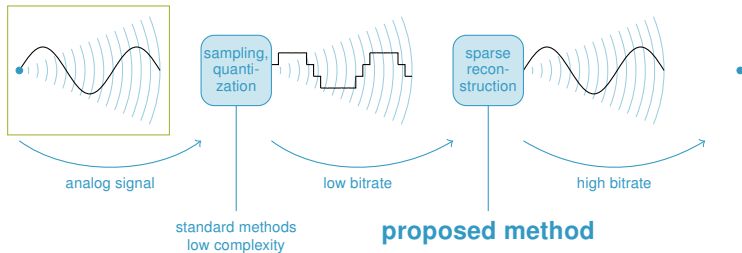
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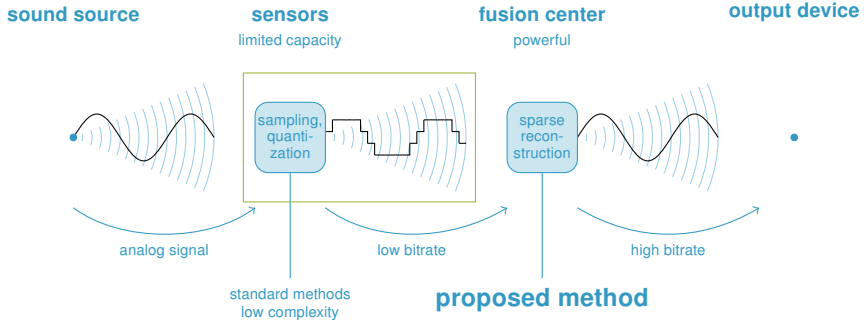
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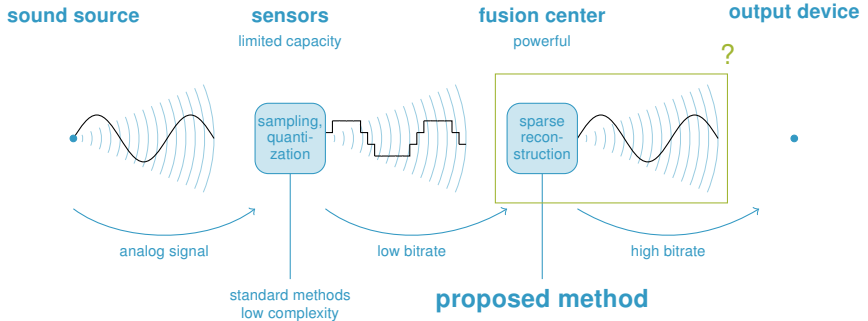
output device



Wireless Acoustic Sensor Networks



Wireless Acoustic Sensor Networks



Outline

- **Introduction**
- **Encoding**
 - Sampling
 - Quantization
- **Decoding**
 - General Approach
 - Uniform Quantization
 - Non-Uniform Quantization
 - Algorithm
- **Numerical Experiments**
- **Conclusion**

Encoding

sound source

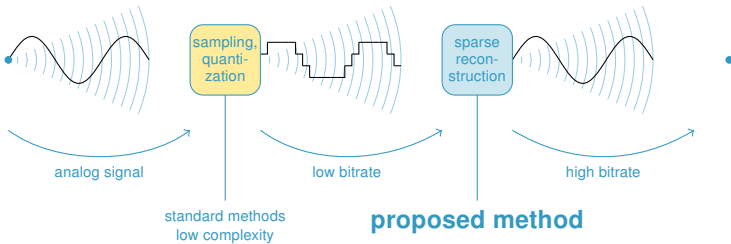
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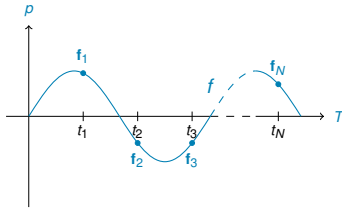
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output device

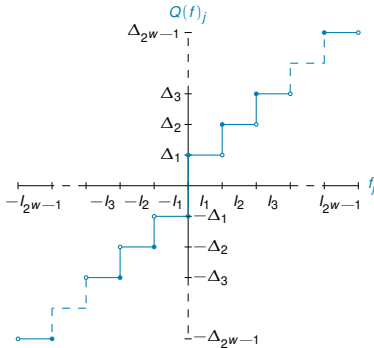


Sampling



- $f : T \rightarrow (-1, 1)$ analog signal
- $t_j \in T$ equidistant points
- $\mathbf{f} \in (-1, 1)^N$ with $\mathbf{f}_j = f(t_j)$ sampled signal

Quantization

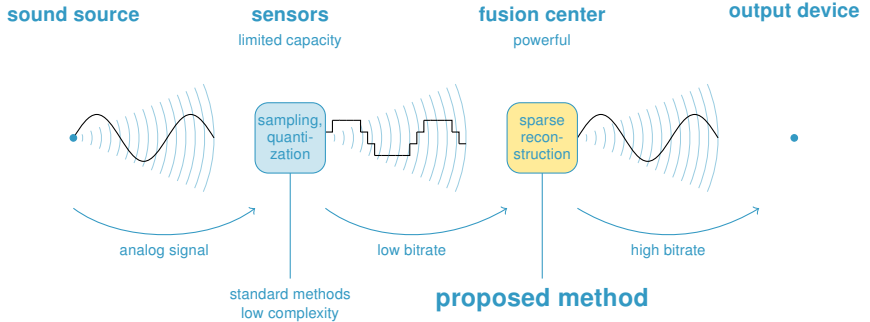


- $\mathbf{f} \in (-1, 1)^N$ speech signal
- $Q : (-1, 1)^N \rightarrow (-1, 1)^N$
- $w \in \mathbb{N}$ word length

Quantization Function

$$Q(\mathbf{f})_j = \text{sign}^+(\mathbf{f}_j) \Delta_l \quad \text{if} \quad |\mathbf{f}_j| \in I_l$$

Decoding



General Approach

- $Q(\mathbf{f})$ is given
- seek to find \mathbf{x} that approximates \mathbf{f}

Priors

1. $Q(\mathbf{x}) = Q(\mathbf{f})$
2. $\mathbf{x} = \Psi \mathbf{a}$ for full-rank matrix $\Psi \in \mathbb{R}^{N \times N}$ and sparse \mathbf{a}

General Approach

Optimization Problem

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 \quad \text{s.t. } Q(\Psi \mathbf{a}) = Q(\mathbf{f})$$

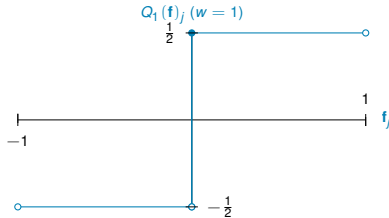
- constraint has a linear reformulation

Relaxed Optimization Problem

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 \quad \text{s.t. } \forall j : (\Psi \mathbf{a})_j \in \overline{I_{Q(\mathbf{f})_j}}$$

- if Q is given, we need the intervals $\overline{I_{Q(\mathbf{f})_j}}$

Uniform Quantization

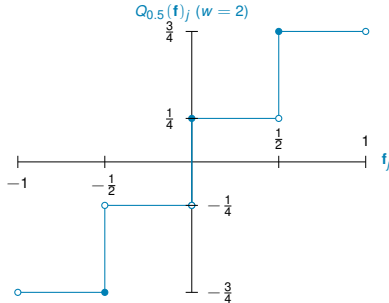


- w is given
- $\Delta = 2^{-w+1}$
- $I_l = [(l-1)\Delta, l\Delta)$
- $\Delta_l = (l - \frac{1}{2})\Delta$
- $\bar{I}_l = \{ |x - \Delta_l| \leq \frac{\Delta}{2} \}$
- $\overline{I_{Q_\Delta(\mathbf{f})_j}} = \{ |x - Q_\Delta(\mathbf{f})_j| \leq \frac{\Delta}{2} \}$

Optimization Problem

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 \quad \text{s.t.} \quad \|\Psi \mathbf{a} - Q_\Delta(\mathbf{f})\|_\infty \leq \frac{\Delta}{2}$$

Uniform Quantization

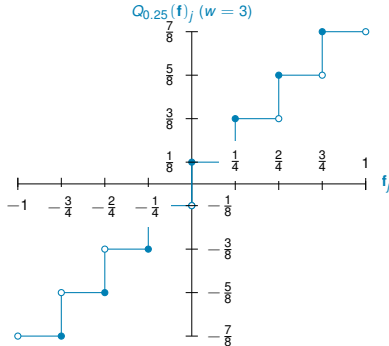


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Uniform Quantization

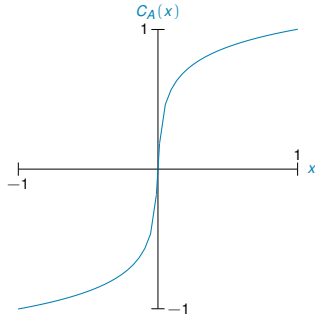


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Optimization Problem

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 \quad \text{s.t.} \quad \|\Psi \mathbf{a} - Q_\Delta(\mathbf{f})\|_\infty \leq \frac{\Delta}{2}$$

Non-Uniform Quantization

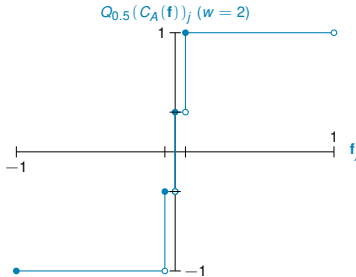


- Δ and Δ_i as before
- $C_A : (-1, 1) \rightarrow (-1, 1)$ odd, continuous and strictly monotonically increasing
- $Q_A(\mathbf{f}) = Q_\Delta(C_A(\mathbf{f}))$

A-law

$$C_A(x) = \begin{cases} \text{sign}(x) \frac{1 + \ln A|x|}{1 + \ln A} & , \text{ if } |x| \geq \frac{1}{A} \\ \text{sign}(x) \frac{A|x|}{1 + \ln A} & , \text{ else} \end{cases}$$

Non-Uniform Quantization

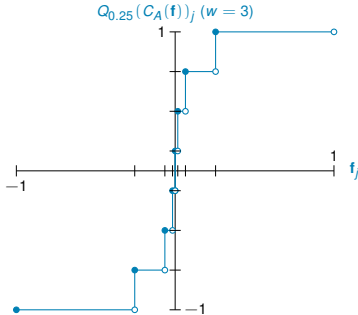


$$\begin{aligned}
 Q_{\Delta}(C_A(\mathbf{f}_j)) &= \Delta_l \\
 \Leftrightarrow C_A(\mathbf{f}_j) &\in [\Delta_l - \frac{\Delta}{2}, \Delta_l + \frac{\Delta}{2}) \\
 \Leftrightarrow \mathbf{f}_j &\in \underbrace{[C_A^{-1}(\Delta_l - \frac{\Delta}{2}), C_A^{-1}(\Delta_l + \frac{\Delta}{2})]}_{=I_{\Delta_l}}
 \end{aligned}$$

New Interval

$$\overline{I_{Q_A(\mathbf{f})_j}} = [C_A^{-1}(Q_A(\mathbf{f})_j - \frac{\Delta}{2}), C_A^{-1}(Q_A(\mathbf{f})_j + \frac{\Delta}{2})]$$

Non-Uniform Quantization



$$\begin{aligned}
 Q_{\Delta}(C_A(\mathbf{f}_j)) &= \Delta_l \\
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New Interval

$$I_{Q_A(\mathbf{f})_j} = [C_A^{-1}(Q_A(\mathbf{f})_j - \frac{\Delta}{2}), C_A^{-1}(Q_A(\mathbf{f})_j + \frac{\Delta}{2})]$$

Non-Uniform Quantization

- $\alpha := C_A^{-1}(Q_A(\mathbf{f}) - \frac{\Delta}{2})$
- $\beta := C_A^{-1}(Q_A(\mathbf{f}) + \frac{\Delta}{2})$

New Optimization Problem

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 \quad \text{s.t. } \alpha \leq \Psi \mathbf{a} \leq \beta$$

Algorithm

- $\Omega_1 = \{\|\mathbf{x} - Q_\Delta(\mathbf{f})\| \leq \frac{\Delta}{2}\}$
- $\Omega_2 = \{\alpha \leq \mathbf{x} \leq \beta\}$
- Writing $\Omega = \Omega_1$ and $\Omega = \Omega_2$, respectively, we can reformulate above problems as saddle point problems:

$$\min_{\mathbf{a} \in \mathbb{R}^N} \|\mathbf{a}\|_1 + I_\Omega(\Psi \mathbf{a}) = \min_{\mathbf{a} \in \mathbb{R}^N} \max_{\mathbf{y} \in \mathbb{R}^N} \|\mathbf{a}\|_1 + \langle \mathbf{y}, \Psi \mathbf{a} \rangle + I_\Omega^*(\mathbf{y})$$

Algorithm

Chambolle-Pock-Iteration

- 1 $\mathbf{a}^{i+1} = \text{prox}_{\tau\|\cdot\|_1}(\mathbf{a}^i - \tau\Psi^\top \mathbf{y}^i)$
- 2 $\bar{\mathbf{a}}^{i+1} = 2\mathbf{a}^{i+1} - \mathbf{a}^i$
- 3 $\mathbf{y}^{i+1} = \text{prox}_{\sigma I_\Omega^*}(\mathbf{y}^i + \sigma\Psi\bar{\mathbf{a}}^{i+1})$

- *Proximal operator* for convex $F : \mathbb{R}^N \rightarrow \mathbb{R}$:

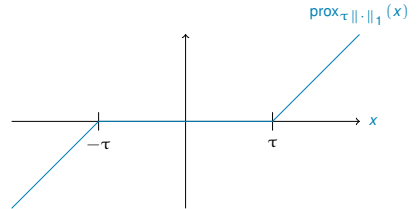
$$\text{prox}_{\lambda F}(\mathbf{x}) := \underset{\mathbf{y} \in \mathbb{R}^n}{\text{argmin}} \lambda F(\mathbf{y}) + \frac{1}{2} \|\mathbf{x} - \mathbf{y}\|_2^2$$

- Has closed-form for $\tau\|\cdot\|_1$ and σI_Ω^* :

Algorithm

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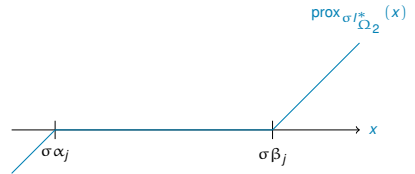


- $\text{prox}_{\tau \|\cdot\|_1}(\mathbf{a}) = \mathbf{a} - \mathcal{P}_{\{\|\cdot\|_\infty \leq \tau\}}(\mathbf{a})$
- $\text{prox}_{\sigma I_{\Omega_1}^*}(\mathbf{y}) = \text{prox}_{\frac{\sigma \Delta}{2} \|\cdot\|_1}(\mathbf{y} - \sigma Q_\Delta(\mathbf{f}))$
- $\text{prox}_{\sigma I_{\Omega_2}^*}(\mathbf{y}) = \mathbf{y} - \mathcal{P}_{\{\sigma \alpha \leq \cdot \leq \sigma \beta\}}(\mathbf{y})$

Algorithm

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Numerical Experiments

sound source

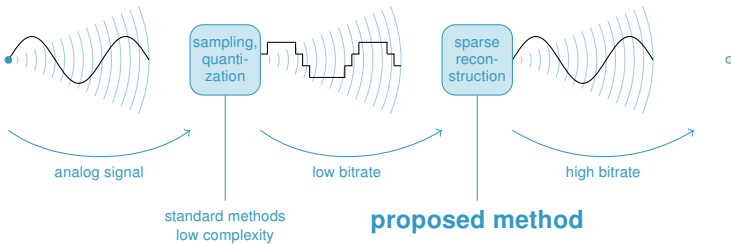
sensors

limited capacity

fusion center

powerful

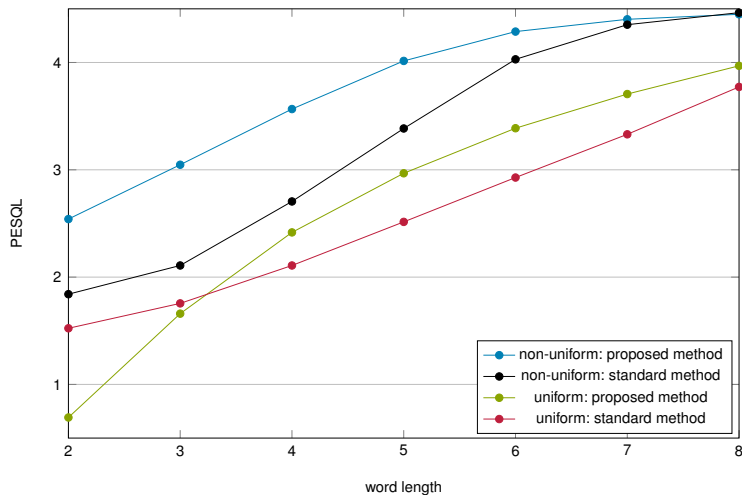
output device



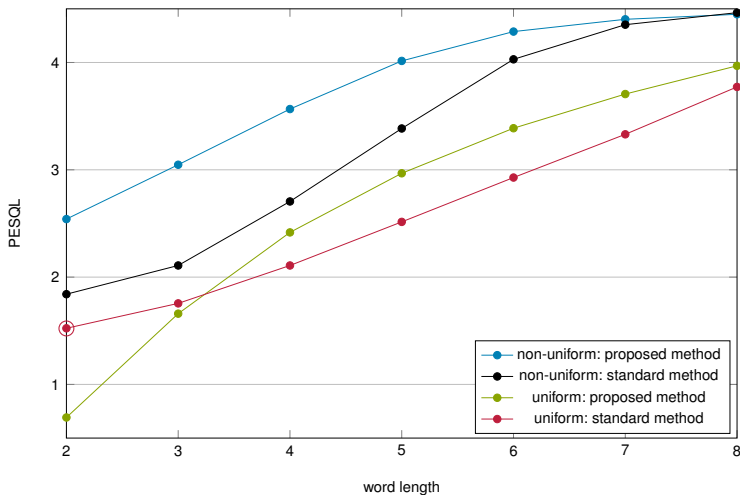
PESQL

- *Perceptual Evaluation of Speech Quality*
- standard measure for speech quality experienced by the user of a telecommunication system
- sampled signal \mathbf{f} is used as reference and compared to reconstructed signal \mathbf{x}
- compared PESQL of our reconstructions to the PESQL of standard reconstructions $Q_{\Delta}(\mathbf{f})$ and $C_A^{-1}(Q_A(\mathbf{f}))$
- results for $w = 2, \dots, 8$ averaged over 720 speech signals from IEEE database

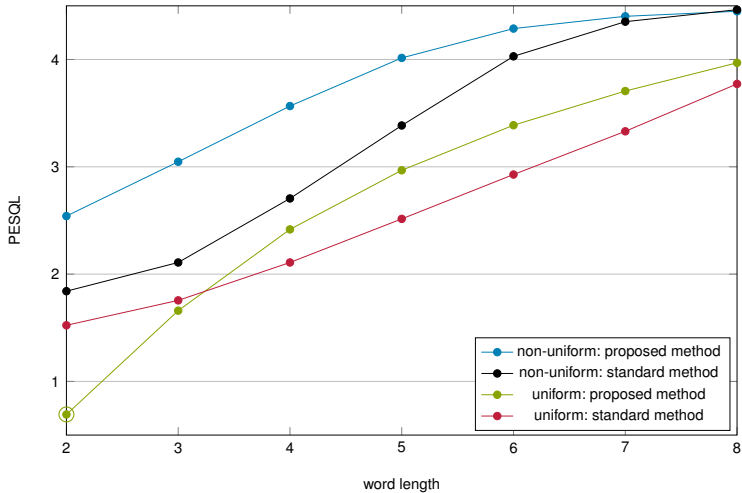
PESQL



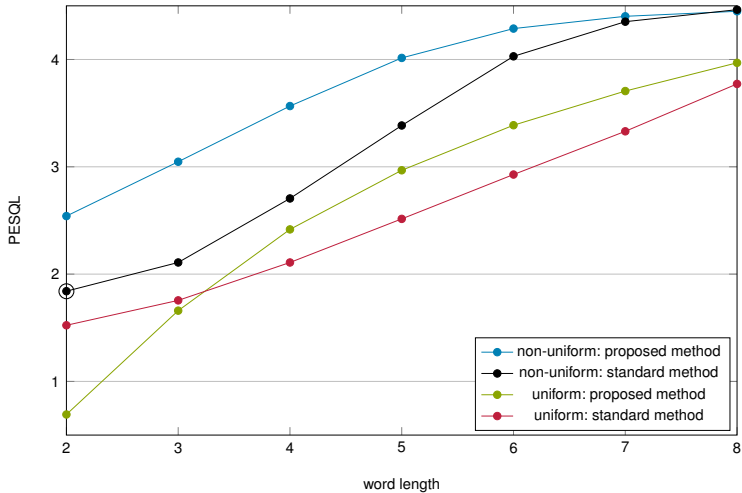
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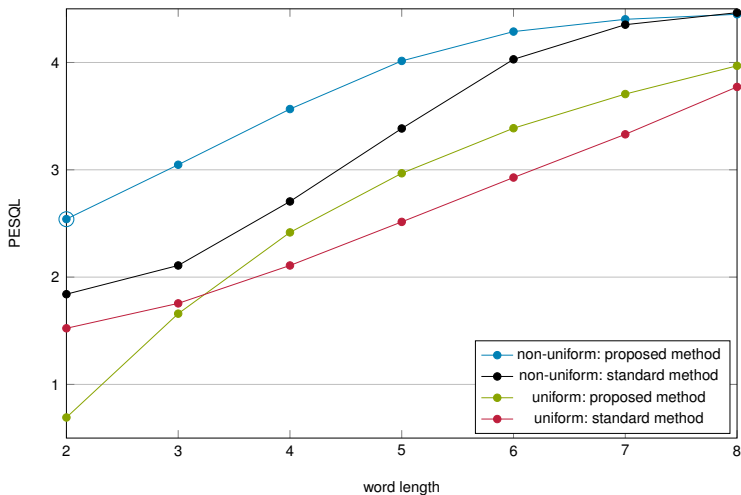
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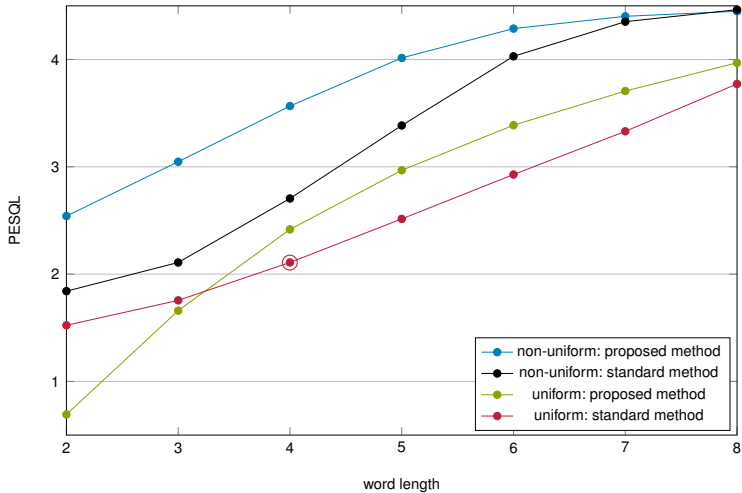
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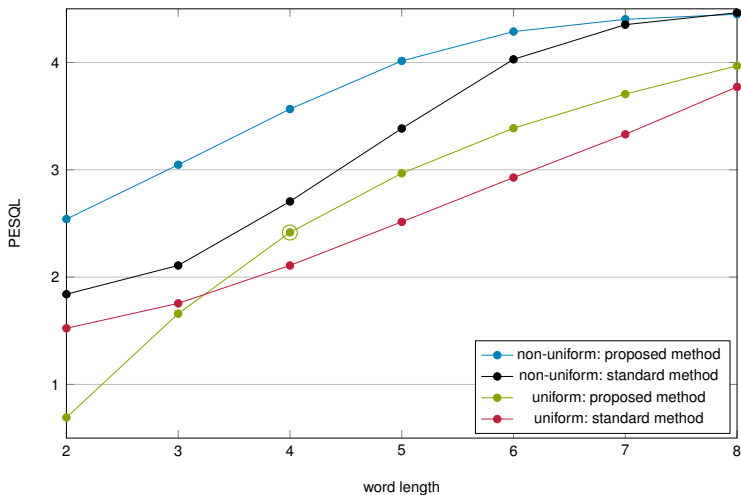
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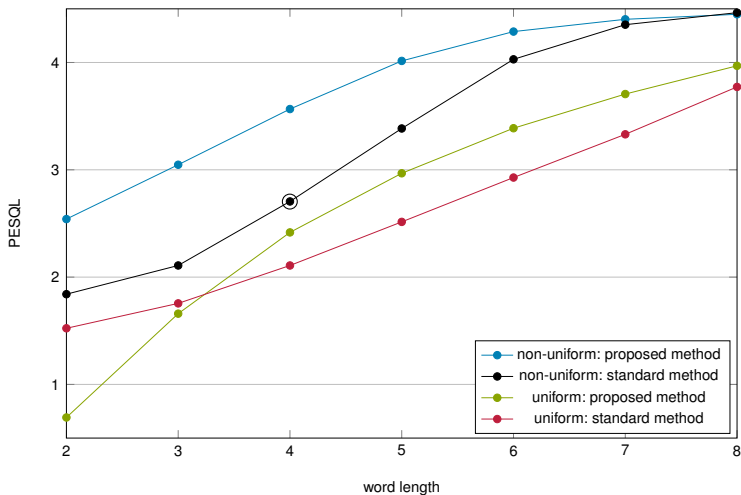
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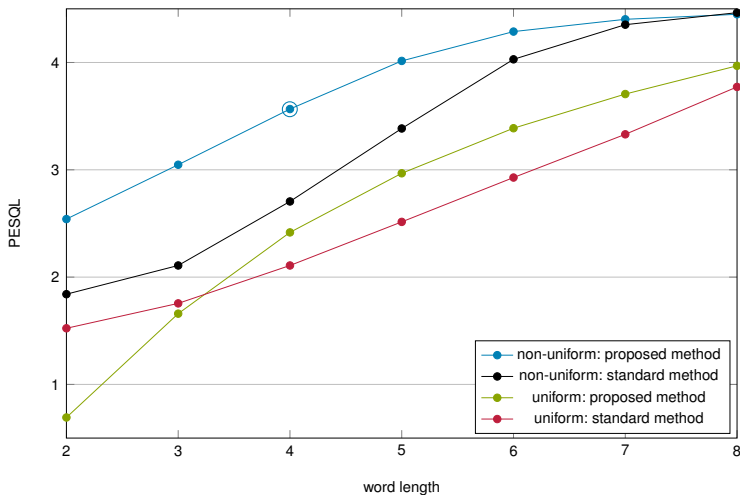
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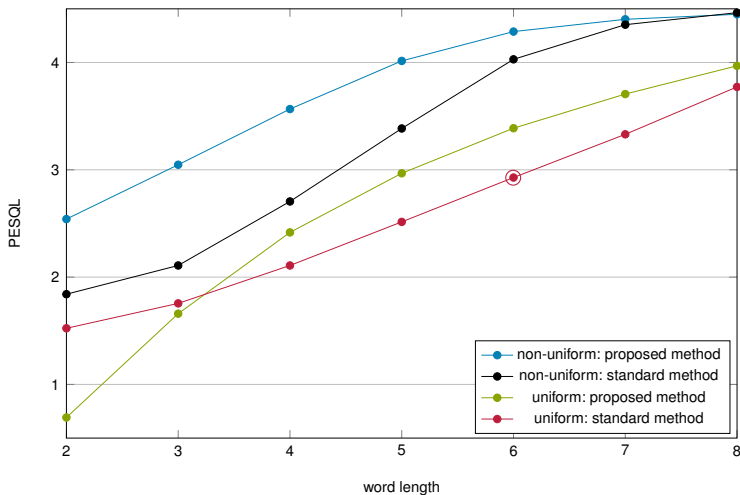
PESQL



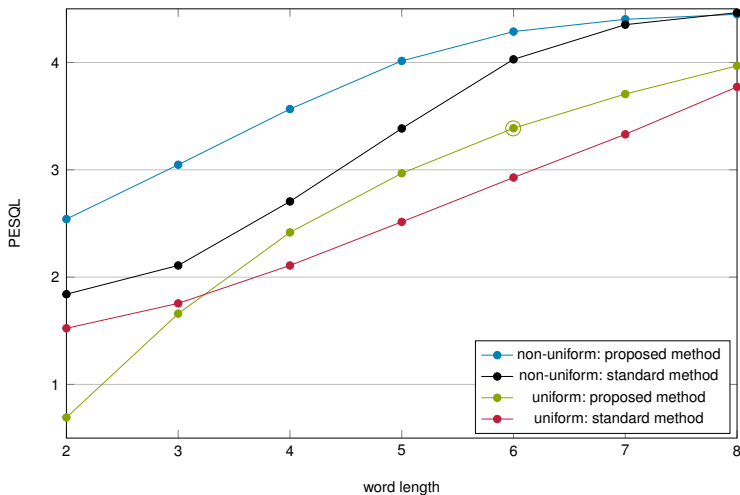
PESQL



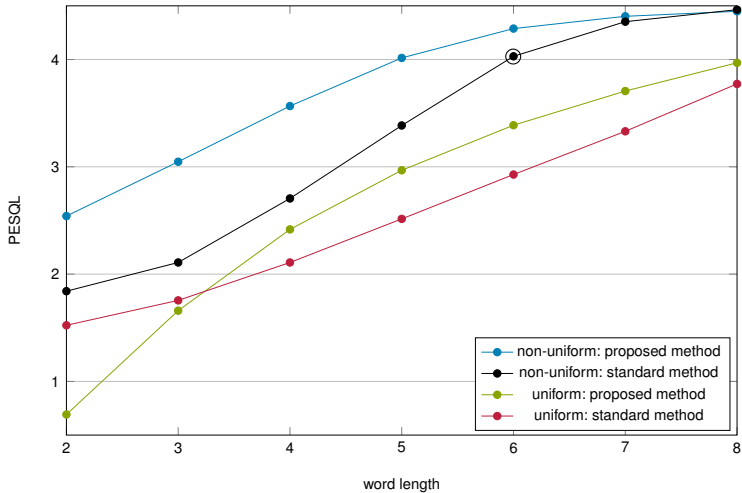
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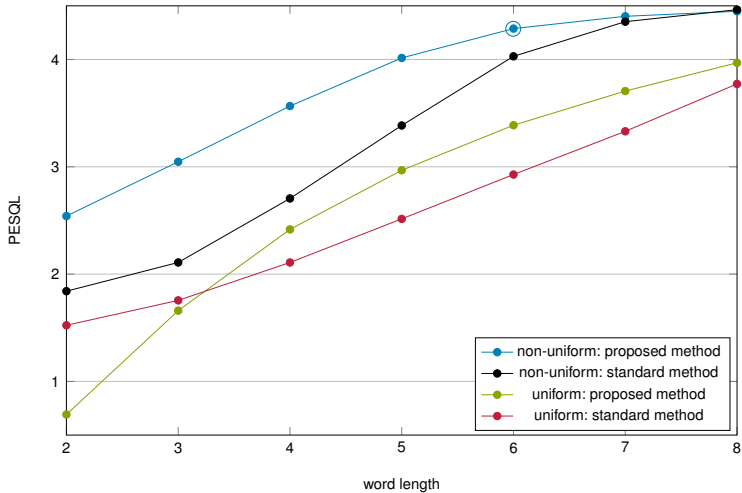
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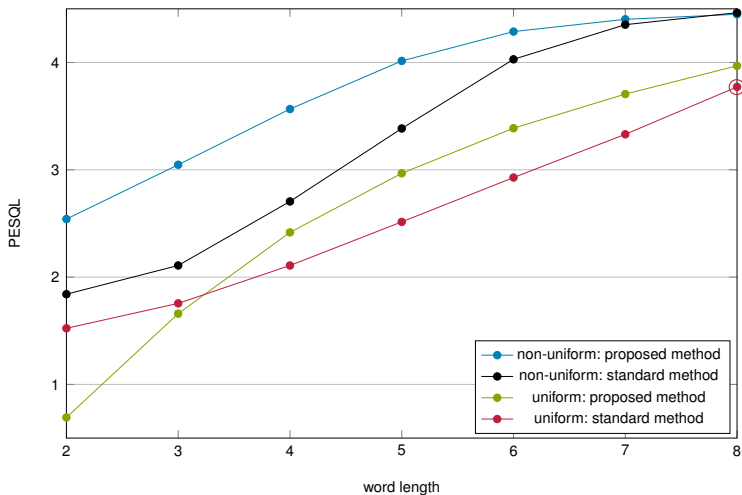
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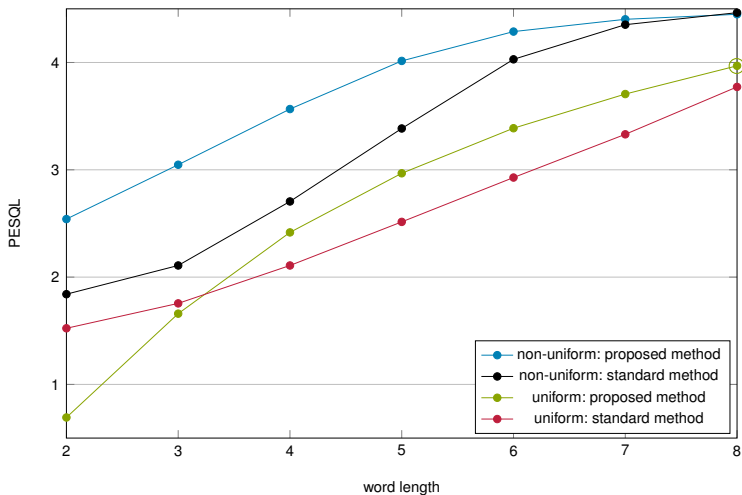
PESQL



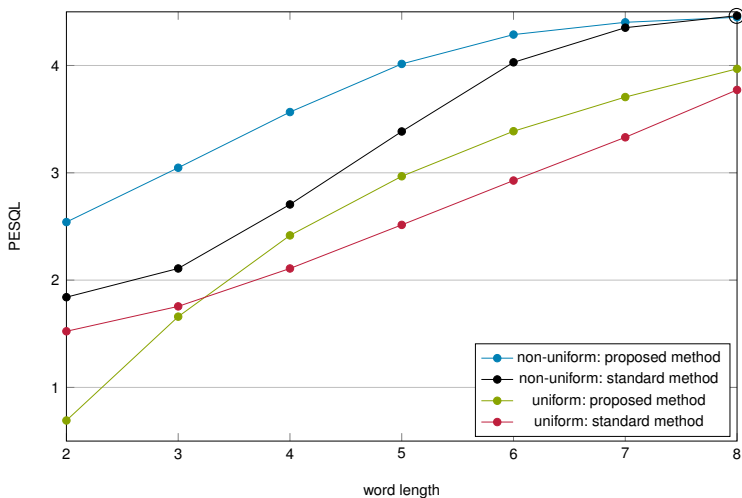
PESQL



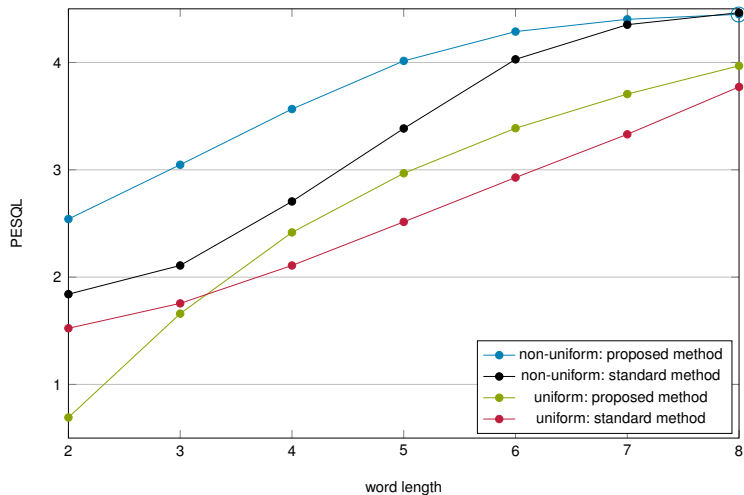
PESQL



PESQL



PESQL



Conclusion

- in *Wireless Acoustic Sensor Networks*, computational and power capacities are distributed asymmetrically between sensors and fusion center
- therefore, the proposed method features low encoding complexity and low datarate
- suitable sparsity priors and convex optimization can increase the perceived speech quality compared to standard methods
- real-time implementation is possible

Questions

Thank You for Your attention!

Slides available under <https://www.tu-braunschweig.de/iaa/personal/brauer>.