

Audio Dequantization Using (Co)Sparse (Non)Convex Methods

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Abstract

The paper deals with the hitherto neglected topic of audio dequantization. It reviews the state-of-the-art sparsity-based approaches and proposes several new methods. Convex as well as non-convex approaches are included, and all the presented formulations come in both the synthesis and analysis variants. In the experiments the methods are evaluated using the signal-to-distortion ratio (SDR) and PEMO-Q, a perceptually motivated metric.

Introduction

- Quantization
 - Nonlinear limitation of signal values.
 - Necessary step in signal digitization.
 - Number of quantization levels, word length w (bps).
 - Mid-riser uniform quantization

$$(x^q)_n = \text{sgn}^+(x_n) \Delta \left(\left\lfloor \frac{|x_n|}{\Delta} \right\rfloor + \frac{1}{2} \right),$$

where $\Delta = 2^{-w+1}$ is the quantization step.

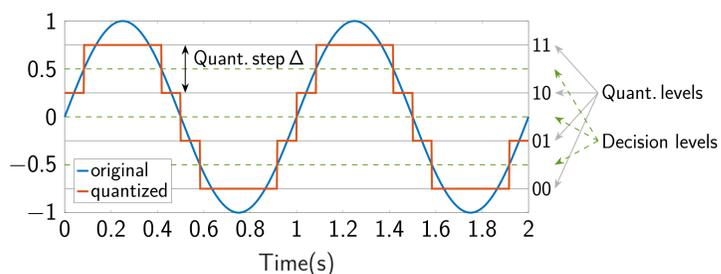


Figure 1: Demonstration of mid-riser quantization.

- Dequantization
 - Inverse problem to quantization.
 - Restore the quantized observation to be as close to the original signal as possible.
 - Ill-posed without additional knowledge.
 - Assumption of sparsity w.r.t. STFT.
- Motivation
 - Enhance standard 16-bit audio.
 - Restore audio in special cases, where less than standard bit depth had to be used (scenario for the paper).
 - Enhance audio generated by Flow-based Neural Vocoder.
 - The goal is not to compete with current lossy compression standards.

Problem formulations

- Consistent ℓ_1 minimization

$$\arg \min_{\mathbf{c} \in \mathbb{C}^Q} \|\mathbf{c}\|_1 \quad \text{s.t.} \quad A^* \mathbf{c} \in \Gamma \quad (1a)$$

$$\arg \min_{\mathbf{x} \in \mathbb{R}^P} \|\mathbf{A}\mathbf{x}\|_1 \quad \text{s.t.} \quad \mathbf{x} \in \Gamma \quad (1b)$$

- Inconsistent ℓ_1 minimization

$$\arg \min_{\mathbf{c} \in \mathbb{C}^Q} \lambda \|\mathbf{c}\|_1 + \frac{1}{2} d_{\Gamma}^2(A^* \mathbf{c}) \quad (2a)$$

$$\arg \min_{\mathbf{x} \in \mathbb{R}^P} \lambda \|\mathbf{A}\mathbf{x}\|_1 + \frac{1}{2} d_{\Gamma}^2(\mathbf{x}) \quad (2b)$$

- Nonconvex ℓ_0 approximation

$$\arg \min_{\mathbf{c}, \mathbf{z} \in \mathbb{C}^Q} \|\mathbf{z}\|_0 \quad \text{s.t.} \quad A^* \mathbf{c} \in \Gamma, \|\mathbf{c} - \mathbf{z}\|_2 \leq \epsilon \quad (3a)$$

$$\arg \min_{\mathbf{x} \in \mathbb{R}^P, \mathbf{c} \in \mathbb{C}^Q} \|\mathbf{c}\|_0 \quad \text{s.t.} \quad \mathbf{x} \in \Gamma, \|\mathbf{x} - A^* \mathbf{c}\|_2 \leq \epsilon \quad (3b)$$

$$\arg \min_{\mathbf{x} \in \mathbb{R}^P, \mathbf{c} \in \mathbb{C}^Q} \|\mathbf{c}\|_0 \quad \text{s.t.} \quad \mathbf{x} \in \Gamma, \|\mathbf{A}\mathbf{x} - \mathbf{c}\|_2 \leq \epsilon \quad (3c)$$

- Set of feasible solutions

$$\Gamma = \{\mathbf{x} \in \mathbb{R}^P \mid \|\mathbf{x} - \mathbf{x}^q\|_{\infty} < \Delta/2\}$$

$\mathbf{c}, \mathbf{z} \in \mathbb{C}^Q$ signal coefficients,
 $\mathbf{x} \in \mathbb{R}^P$ signal in time domain,
 $A: \mathbb{R}^P \rightarrow \mathbb{C}^Q$ analysis operator,
 $d_{\Gamma}(\cdot)$ distance from the set Γ .

Experiments

- Audio database:
 - 10 musical audio excerpts,
 - approximate length 7 seconds,
 - sampling rate 44.1 kHz,
 - bit-depth 16 bps.
- Quantized to 7 different levels
 - $w = 2, 3, \dots, 8$ bps,
 - Mid-riser quantization.
- Signals restored using algorithms based on sparsity.
- Discrete Gabor Transform (DGT/STFT),
 - 8192 samples long Hann window,
 - 75% overlap.
- Evaluation
 - Signal-to-distortion ratio improvement (ΔSDR),
 - PEMO-Q ODG (perceptually motivated metric)

0.0 Imperceptible,
 -1.0 Perceptible, but not annoying,
 -2.0 Slightly annoying,
 -3.0 Annoying,
 -4.0 Very annoying.
- Implementation available on GitHub:
github.com/zawi01/audio_dequantization

Results

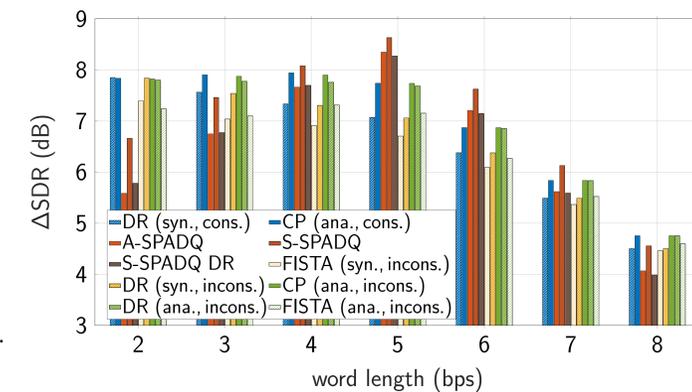


Figure 2: Average performance in terms of ΔSDR .

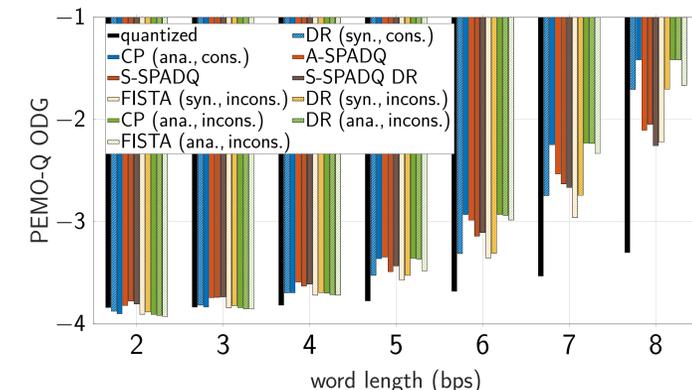
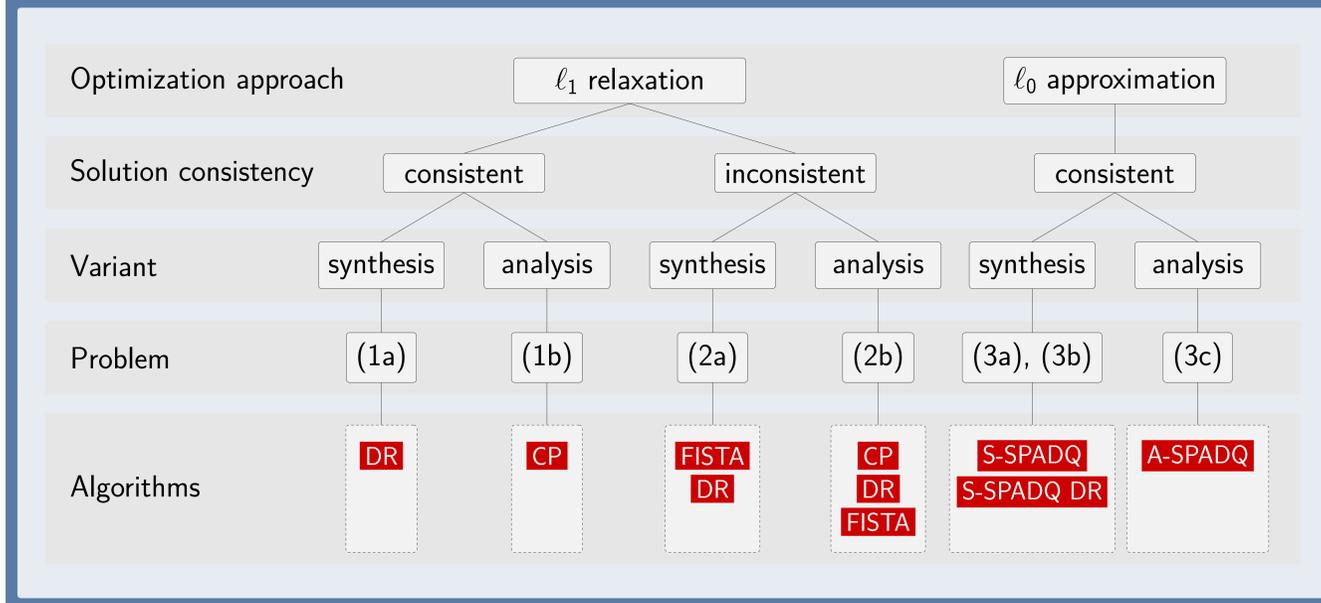


Figure 3: Average performance in terms of PEMO-Q ODG.

Overview of algorithms



Conclusion

- 10 sparsity-based approaches to audio dequantization.
 - Convex ℓ_1 relaxation, nonconvex ℓ_0 approximation.
 - Strict or only approximate compliance of the solution consistency.
 - Synthesis and analysis model.
- All methods improve the quality of the signal.
- No clear winner of all presented methods.
- Analysis model seems to outperform its synthesis counterpart.

