Audio restoration using plug-and-play approach

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***Abstract*—This document is a model and instructions for LaTeX. This and the IEEEtran.cls file define the components of your paper [title, text, heads, etc.]. *CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.**

***Index Terms*—speech enhancement, deep learning, Douglas-Rachford algorithm**

I. Introduction

Audio enhancement tasks mostly face problems like missing or damaged samples, noise, or clipping. If we consider speech signal, we should not avoid the intelligibility problems. Each problem has developed its own way of enhancing the signal. Nowadays, the bestway to differentiate algorithms is with two categories: conventional (autoregressive models, sparsity-based) and solutions using deep learning.

In conventional methods dominates Janssen [1] and Etter [2]. These approaches are based on autoregressive signal modeling [3]. Sparse signal representation has changed efficiency of restoration, mainly because increase of computing power. The information hidden in frequency representation (using proper time-frequency analysis) is sparse, i.e. we do not need each spectral coefficient to repair the signal with improved subjective results. The most advanced works using sparsity are [4]–[7].

Deep learning algorithms have also made their own progress in this area. The most efficient neural network models are autoencoders, recurrent neural networks (RNNs) and Generative Adversial Network (GAN). Current state-of-the-art deep learned algorithms are Speech Enhancement GAN (SEGAN) [8], NSNet [9], FullSubNet [10].

In [11] was introduced Plug-and-Play method for image restoration. The idea of a hybrid model, combining conventional approach (convex minimization) with deep learning, has shown succesful. Our motivation is to transform this model to audio problems with minor differences. We replace Alternating Direction Multiplier Method (ADMM) with Douglas-Rachford algorithm (DR algorithm). Denoiser will be chosen from state-of-the-art audio denoisers.

II. Prerequsities

In this section we introduce our task in mathematical view and compose minimazation task.

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A. Task formulation

We consider column vector $s \in \mathbb{R}^L$ as our observed single-channel signal of length L.

B. Douglas-Rachford algorithm

III. Plug-and-Play inpainting

A. general algorithm

B. choice of denoiser

C. Denoisers

IV. Testing data and evaluation

V. Conclusion

Acknowledgment

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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