FAST BLACK-BOX OPTIMIZERS FOR LOW DELAY AUDIO SOURCE SEPARATION

TECHNISCHE UNIVERSITÄT ILMENAU

GERALD SCHULLER

ILMENAU UNIVERSITY OF TECHNOLOGY, GERMANY

ABSTRACT

- **Objective:** Demonstrates the significant advancements in black box optimizers for signal processing, especially under tight time constraints, as illustrated by an audio source separation case study.
- **Comparison** of black box optimizers, all suitable for high-dimensional problems.
- **Key Finding:** Emphasizes the importance of selecting and adapting an optimizer to the specific application needs.
- **Top Performer:** Identifies the "Random Directions" optimizer as consistently among the best for optimizing objective or loss functions and for minimizing processing time.

INTRODUCTION

- **Objective:** Illustrates the advancements in black-box optimizers for signal processing, especially for real-time applications like audio source separation, highlighting their efficiency even with limited time budgets.
- **Historical Context:** Digital signal processing has always been intertwined with optimization, from filter design to adaptive filters and filter banks. Traditional methods often relied on gradient descent, suitable mainly for convex functions.
- **Challenges with Non-Convex Functions:** Introduces difficulties in optimizing non-convex functions for applications like multichannel blind source separation and the use of recurrent neural networks (RNNs), which suffer from vanishing gradients.
- **Advantages of Black-Box Optimizers:** Demonstrates how black-box optimizers can tackle challenges unmanageable by gradient descent, such as in RNNs or cases with non-differentiable loss functions. Highlights their potential for embedded device applications where implementing gradient-based methods is impractical. Package: "**Pypop7**".
- **Focus on Random Directions Optimizer:** The introduction mentions the effectiveness of the "Random Directions" optimizer in achieving good outcomes in objective or loss function minimization and processing time efficiency compared to other black-box optimization methods.
- **Applications and Implications:** Suggests applications across various fields, from embedded device adaptation for speech recognition to adversarial machine learning, reinforcing the versatility and significance of black-box optimization in modern signal processing challenges.

THE METHOD OF RANDOM DIRECTIONS

- **Purpose:** Designed to optimize signal processing applications like low delay filter banks and multichannel blind audio source separation, which are challenging due to their nonlinear structure and high rate of local minima.
- **Strategy:** Utilizes normal distributed search vectors with a slowly shrinking standard deviation, akin to simulated annealing, to navigate the optimization landscape without relying on gradient information.
- **Random Subspaces:** Enhances optimization efficiency by introducing random subspaces in updates, which is beneficial for high-dimensional objective functions.
- **Line Search:** Employs a line search on successful directions as direction estimates to efficiently navigate towards the objective function's minimum.
- **Stability and Performance:** Maintains the original argument if it remains the best option, ensuring that optimization does not regress, thereby enhancing stability and performance.
- **Application Success:** Demonstrated effectiveness in optimizing audio source separation and large, difficult neural networks, like Recurrent Neural Networks (RNNs), by overcoming traditional challenges such as vanishing gradients.

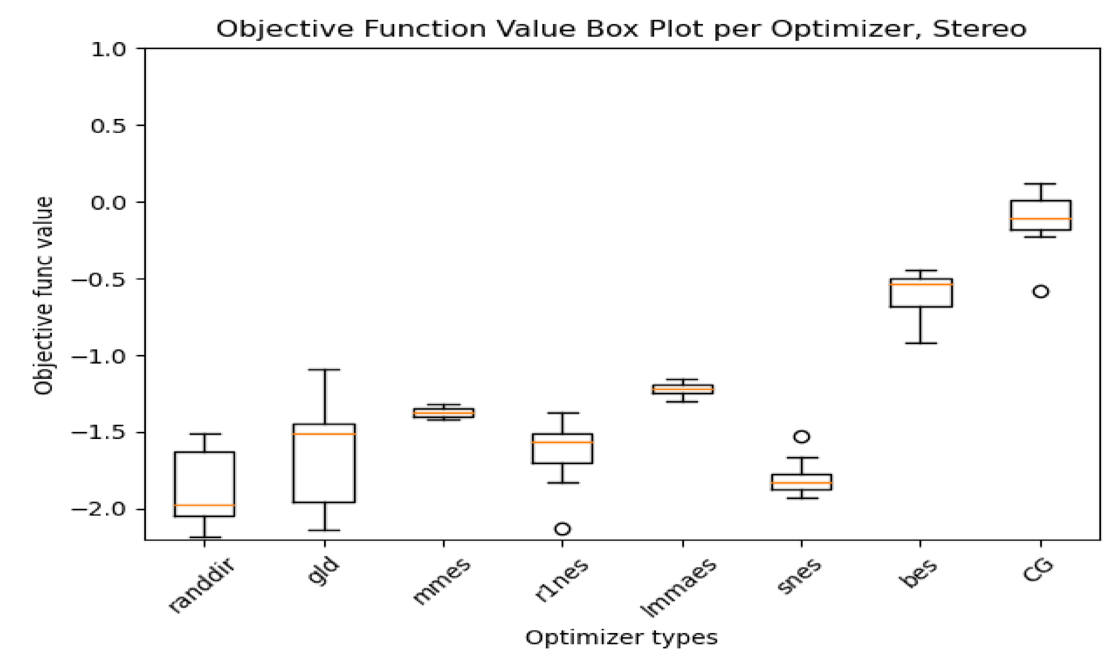
ALG. RANDOM DIRECTIONS

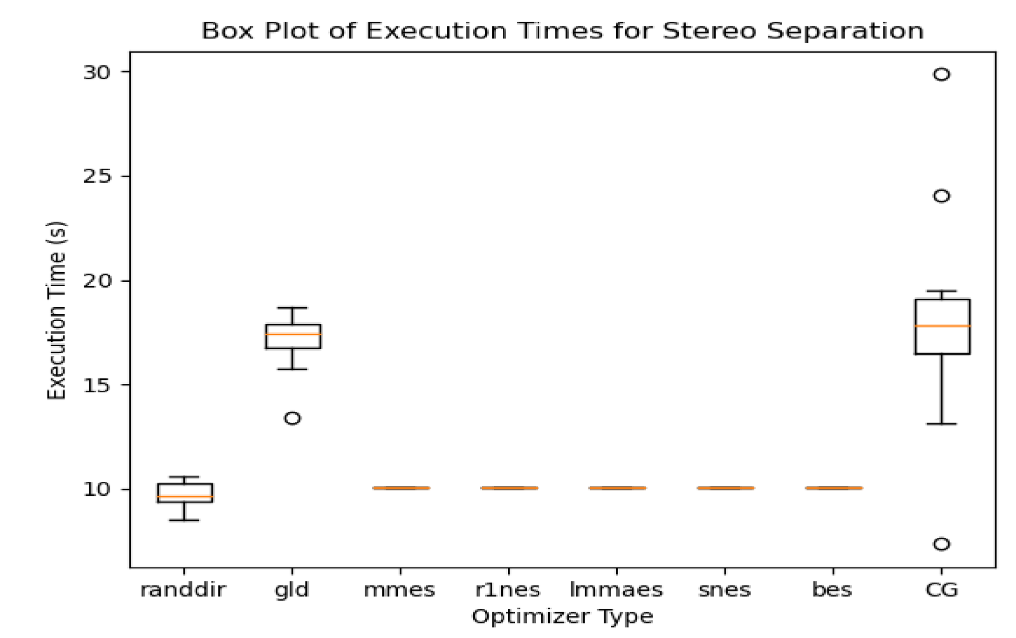
Input: $f(c)$: $\mathbb{R}^n \rightarrow \mathbb{R}$: Objective function to be minimized
c_0: Starting point coefficient vector,
T: Number of iterations,
P: Number of parallel processes,
startingscale: Standard deviation at the start
endscale: Standard deviation at the end
Initialization: $c_{best} = c_0$
for m=0,...,T **do**
  $scale = endscale + (startingscale - endscale) \cdot ((1.0 - m/iterations)^2)$
  Parallel Processing:
    generate P search vectors v_r with std deviation "scale" and zero mean on **random subsets** of coefficients;
    compute $f(c_{best} + v_r)$
  find best update vector: $v_{best} = \arg\min_{v_r} \{f(c_{best} + v) \mid v = v_r\}$
  if $f(c_{best} + v_{best}) < f(c_{best})$ **then**
    Find new c_{best} with coarse line search along successful vector v_{best},
    $k_{best} = \arg\min_k f(c_{best} + 2^k v_{best})$, $k = (-8, \ldots, 8)$ (Line search)
    $c_{best} = c_{best} + 2^{k_{best}} v_{best}$
  end
end
return x_{best}

Algorithm 1: The method of Random Directions.

BSS EVALUATION

Office room sim., RT60=0.1s, Separation





CONCLUSIONS

- **Efficacy of Black Box Optimization:** Black box optimization is shown to be highly effective for real-time audio signal processing tasks, like time domain blind audio source separation.
- **Suitability for Specific Applications:** It's crucial to select and use a suitable optimizer for the specific application to achieve optimal results.
- **Outstanding Performance of Random Directions:** The Random Directions optimizer is highlighted for its excellence in minimizing the objective or loss function efficiently and quickly among the tested black box optimizers.