

Mathematical Morphological Filtering with a Self-adaptive Reconstruction Technique and Application to Local Seismic Data

Rigobert Tibi

Sandia National Laboratories (SNL)



INTRODUCTION AND MAIN RESULTS

Mathematical morphological filtering (MMF) stems from the branch of mathematics referred to as mathematical morphology, which is based on set-theoretic concepts. MMF is efficient for low SNR data, and significantly outperforms frequency filtering (FF) in that SNR range. The results suggest that in an operational setting, MMF cannot replace FF; however, detection can be improved if MMF is used to supplement FF in some scenarios.



Introduction

- Mathematical morphological filtering (MMF) is a less known method of noise suppression.
- It stems from the branch of mathematics referred to as mathematical morphology, which is based on set-theoretic concepts.
- In contrast to frequency filtering (FF), which operates on frequency information and hence requires Fourier transforms, MMF leverages waveform shape and works entirely in the time domain.

Objectives

Noise Suppression Method	Drawbacks
Frequency filtering	Inadequate when signal and noise share the same frequency band; causes significant distortion in amplitudes
Machine learning denoising	Requires pre-trained model for the region of interest, which necessitates a lot of resources
Wavelet-based thresholding	Causes significant distortion in amplitudes; can introduce artefacts in the waveforms

- The purpose of this work is to improve signals from local-distance events (both earthquakes and explosions) and avoid issues associated with other noise suppression methods.

ACKNOWLEDGMENTS: Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525. The views expressed here do not necessarily reflect the views of the United States Government, the United States Department of Energy. This research was funded by the National Nuclear Security Administration, Defense Nuclear Nonproliferation Research and Development (NNSA DNN R&D).

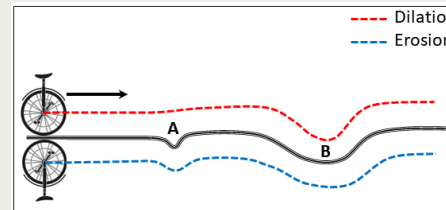
Methods

Morphological Operations

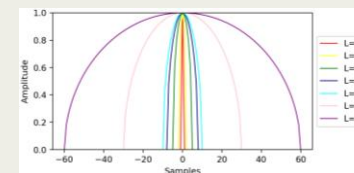
- The key element of morphological operations is the structuring element (SE).
- The shape and size of SE determine the outcome of the morphological operation.
- MMF relies on 2 basic morphological operations (dilation & erosion) and compound operations involving the two.

$$\text{Dilation: } (F \oplus S)(n) = \max [F(n - m) + S(m) \mid n \in P, (n - m) \in Q]$$

$$\text{Erosion: } (F \ominus S)(n) = \min [F(n + m) - S(m) \mid n \in P, (n + m) \in Q]$$



The selected SEs are symmetric elliptical, with the general form: $S_{(A,L)}(m) = A\sqrt{1 - (m/L)^2}$, where $m \in [-L, L]$, $L > 0$ is the length (in samples), and A the amplitude, with $A = 0.2(\max(|F(n)|))$



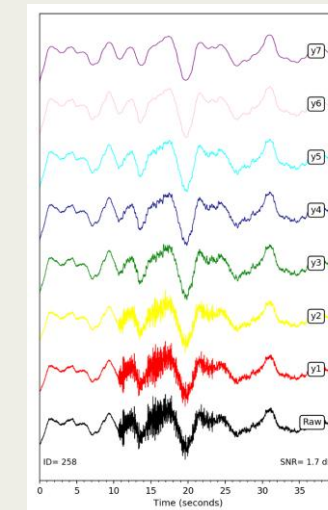
Methods (continued)

Multi-scale Morphological Decomposition

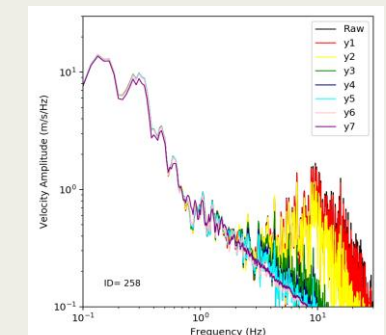
- Opening:** $(F \circ S)(n) = ((F \ominus S) \oplus S)(n)$
- Closing:** $(F \bullet S)(n) = ((F \oplus S) \ominus S)(n)$
- Open-closing:** $(F \sqcup S)(n) = ((F \circ S) \bullet S)(n)$
- Close-Opening:** $(F \sqcap S)(n) = ((F \bullet S) \circ S)(n)$

$$y_i(n) = \frac{(F \sqcup S_i)(n) + (F \sqcap S_i)(n)}{2}, i = 1, \dots, 7$$

$$\begin{cases} f_1(n) = F(n) - y_1(n) \\ f_i(n) = y_{i-1}(n) - y_i(n), i = 2, \dots, 7 \\ f_8(n) = y_7(n) \end{cases}$$



$$F = (F - y_1) + (y_1 - y_2) + (y_2 - y_3) + \dots + (y_6 - y_7) + y_7$$





Rigobert Tibi

P3.5-177

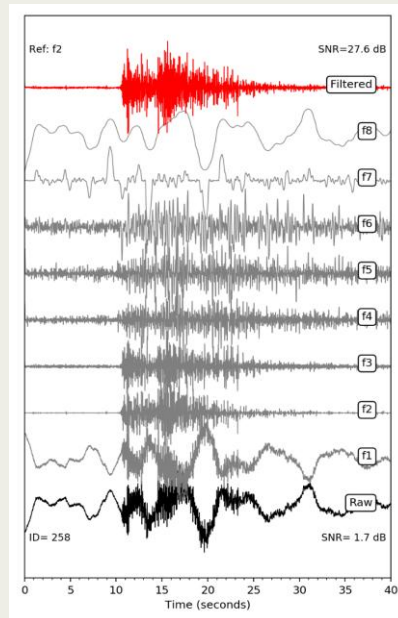
Methods (continued)

Morphological Reconstruction & MMF

$$F_{fil}(n) = \sum_{i=1}^8 \lambda_i f_i(n)$$

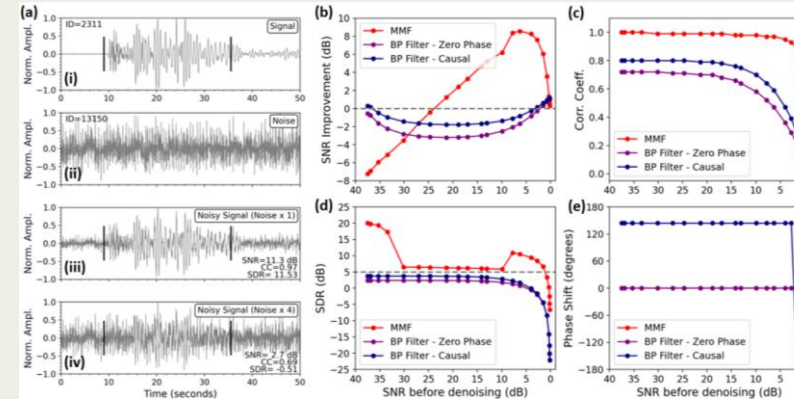
$$\begin{cases} \lambda_{i,ref} = 1, \text{ if } CC_{i,ref} \geq 0.2 \\ \lambda_{i,ref} = (SNR_i / SNR_{ref}) |CC_{i,ref}|, \text{ if } CC_{i,ref} < 0.2 \end{cases}$$

$$F_{fil} = \lambda_1 f_1 + \lambda_2 f_2 + \lambda_3 f_3 + \dots + \lambda_7 f_7 + \lambda_8 f_8$$



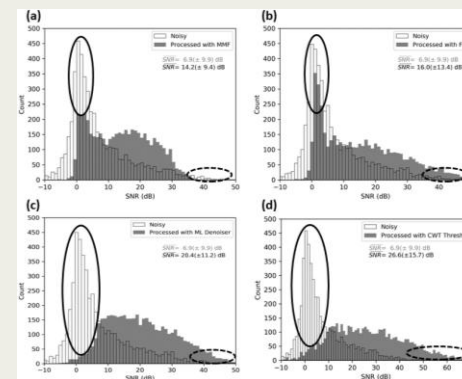
Results

Effect of Input Seismogram Quality



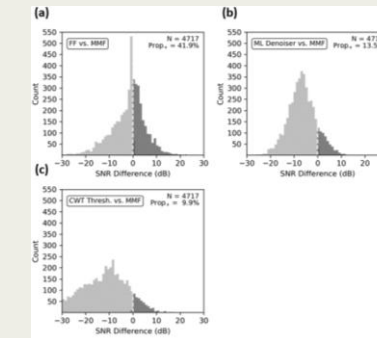
MMF is efficient for low input SNR, and significantly outperforms FF in that SNR range.

Comparison with some Established Noise Suppression Methods



Comparison based on a dataset of >4700 constructed noisy waveforms.

Results (continued)



- For ~42% of the dataset, MMF outperforms FF; and the SNR gain achieved by MMF is as high as ~23 dB.
- This proportion is only ~10%–14% for ML denoising and CWT thresholding.

Conclusions

- As noise suppression method, MMF is efficient for low-SNR data and significantly outperforms FF in that SNR range.
- For most of waveforms, FF, ML denoising, and CWT thresholding result in higher SNRs compared with MMF; however, for ~42% of the waveforms, MMF outperforms FF.
- Compared to ML denoising and CWT thresholding, this proportion drops to ~10%–14%.
- The results suggest that in an operational setting, MMF cannot replace the other noise suppression methods; however, detection can be improved if MMF is used to supplement them in some scenarios.
- MMF could help detect signals in problematic low-SNR data, which are currently being missed particularly when using FF alone.