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Comparison of spectral subtraction noise reduction algorithms

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ABSTRACT

Noise in media is any undesirable signal that masks relevant information content. The addition of noise to real-world data in any context is practically inevitable.
Noise reduction algorithms in the past have tackled the problem, albeit compromising on adaptability to multiple real-world uses.
This research tests the performance of spectral subtraction noise reduction algorithms across varied categories of real-world noise.
It was observed that non-stationary spectral subtraction performed generally better in most categories of noise.
In some, however, most notably in ‘animal sounds’ and ‘music,’ stationary spectral subtraction performed better.
These results exemplify the performance and versatility of spectral subtraction algorithms.
The category specific results can be used to employ specific spectral subtraction algorithms at specific tasks for optimum performance.

INTRODUCTION

To a layperson, noise may merely be an inconvenience in audio consumption. However, in many fields, noise reduction is a necessity.
Most prevalent methods of noise reduction are either not adequately versatile and/or are wastefully time and resource extensive.
Spectral subtraction provides a hybrid approach to noise reduction that incorporates versatility and efficient resource usage.

OBJECTIVE

To determine whether non-stationary spectral subtraction is more effective at noise reduction compared to stationary spectral subtraction in 5 categories of noise.
The hypothesis was that non-stationary spectral subtraction outperforms stationary spectral subtraction in all categories.

METHODS AND TESTING

The procedure for testing a sample on either of the algorithms included three primary steps.

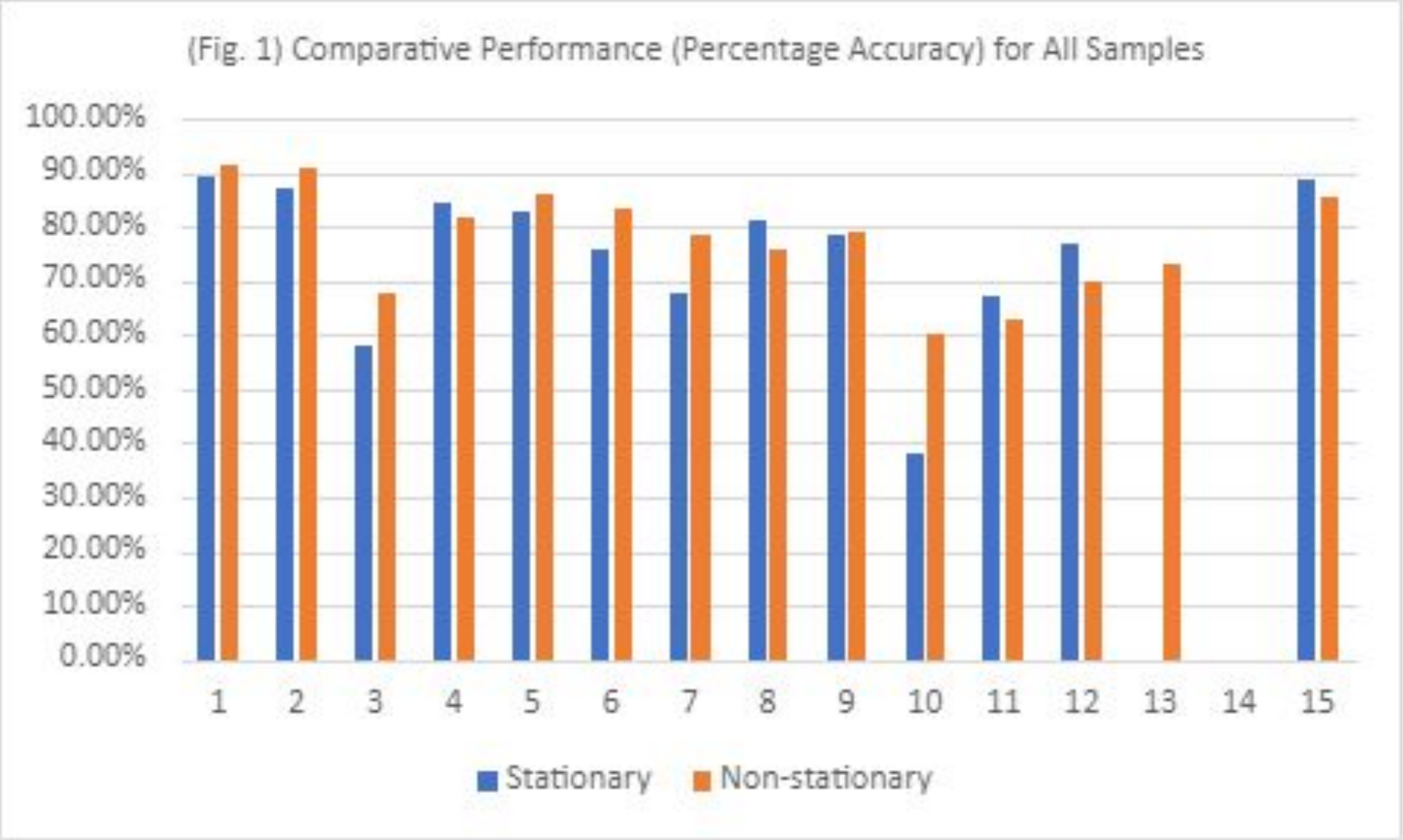
1. An original audio sample in appropriate WAV format was made accessible to the algorithms.
2. Configurable synthetic noise was added to the original sample to obtain the noisy sample.
3. The noisy sample was passed through stationary and non-stationary spectral subtraction to obtain the denoised samples.

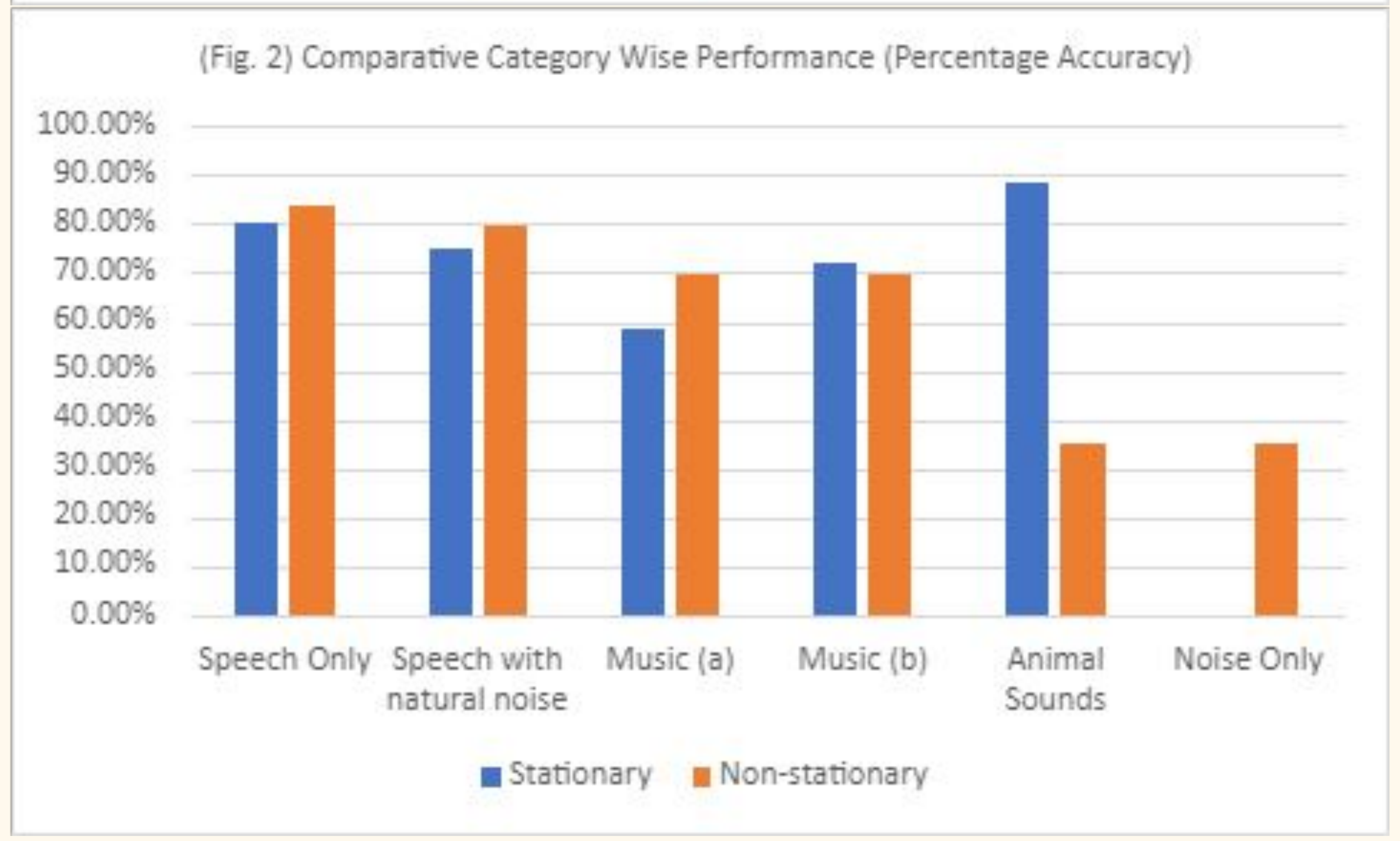
The two algorithms were tested on a direct percentage similarity (normalized cross-correlation) figure of the original audio and the noise reduced audio. Sounds and graphs of the original , noisy and noise reduced samples were also studied.

RESULTS

A category wise breakdown (fig. 2) of the results is as follows:

1. Speech only: Non-stationary spectral subtraction performed better.
2. Speech with natural noise: Non-stationary spectral subtraction performed better.
3. a. Music without speech: Stationary spectral subtraction performed better.
   b. Music with speech: Non-stationary spectral subtraction performed better.
4. Animal sounds: Stationary spectral subtraction performed better.
5. Noise only: Although the score was 0, it was noted that stationary spectral subtraction performed better when listening to the samples





DISCUSSION

The anomaly in performance between the two algorithms was only noted in categories with no human speech. This may have been because the algorithms were trained to denoise human speech primarily.

CONCLUSIONS

Both algorithms performed substantially well on the varied categories.
Non-stationary spectral subtraction performed better in samples where human speech was the target: speech only and speech with natural noise.
Stationary spectral subtraction performed better when denoising music and animal sounds.

LIMITATIONS

The quantitative test used in the procedure was based on comparison to the ‘ideal’ noise-reduced sample. This was assumed to be the original sample since denoising an synthetically noised sample should return the original input.
However, in some categories, the original sample may have contained noise prior to the addition of synthetic noise. This may have affected the reliability of the similarity test.
Furthermore, the study failed to expand the comparison to other prevalent methods of noise reduction.

REFERENCES

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