MADRID
inter.noise 2019
June 16 - 19
NOISE CONTROL FOR A BETTER ENVIRONMENT

Challenges in automatic parametrization algorithms for acoustic noise controlling.

Garrido-Sanchez, Pablo[1]
University of Granada
Department of Electronics and Computer Technology

Roldán-Aranda, Andrés[2]
University of Granada
Department of Electronics and Computer Technology

ABSTRACT

This paper presents results of recent work on automatic techniques for optimizing parameters in acoustic noise emission control devices based on a dynamics compressor model. First, the dynamics compressor is presented as an acoustic noise adequation system. The main concerns about how the dynamics compression algorithm is applied to an audio line are discussed in detail, seeking for the emitted noise level to be kept below acoustic healthy criterion. After the discussion, relying on the referred models, the fundamental configurable parameters of these audio processing topologies are described. Likewise, and considering the noise controlling purposes, quality score functions are defined in order to compare the performance of a certain topology using different configurations. These score functions consider both emission noise criterions and audio line quality degradation. Thereafter, so as to achieving a compromise solution between audio quality and noise level, the optimizable variable space provided by the audio dynamics compressor —in its noise limiting configuration— is treated using different machine learning techniques and automatic optimization procedures, i.e. genetic algorithms. Finally, the results show these approaches using automatic parametrization techniques, while conclusions include core challenges in order to optimize the quality of processed audio signal while keeping noise levels below governmental regulation thresholds.

Keywords: noise control algorithms, automatic parametrization, signal processing
I-INCE Classification of Subject Number: 38

1. INTRODUCTION

Audio line signal processing has been increasingly relevant in acoustic noise control systems. These systems combines analog and digital signal processors in order to adjust the emitted acoustic noise levels within healthy thresholds [1]. Signal processing of the signal involves a high performance software running in dedicated hardware that is able to ensure real-time signal processing and healthy acoustical noise emissions [2].

---

[1] pablogs@ugr.es
[2] amroldan@ugr.es

These acoustic noise limiting algorithms could be implemented using several approaches [3], but certainly one of the most significant ones is the use of a tuned dynamics compressor. This paper presents a set of tools and ideas in order to automatically precalculate best configuration parameters of an acoustic noise limiter based on the dynamics compressor model.

Noise limiting dynamic compressor scoring models from the literature are used in order to achieve this purpose. The main scope of this scoring procedures is to evaluate audio quality and acoustical healthiness. Hence, this paper differentiates three different algorithms groups:

- **The acoustical noise limiting algorithm**: represents the software running in the audio processing noise limiter. In this case, it is always a modified version of a dynamics compressor configured with certain parameters.

- **The scoring algorithm**: represents a theoretical framework where different configurations of the acoustical noise limiting algorithm can be compared. It returns a unique and comparable score that can be minimized that takes into account resulting sound quality and acoustical healthiness criterions.

- **The optimization algorithm**: the key point of this document. This algorithm uses the scoring algorithm in order to obtain the best configuration parameters for the acoustic noise limiting algorithm.

2. THE DYNAMICS COMPRESSOR AS NOISE LIMITER

2.1 Dynamics compressor operation and parameters

As it has been said previously, dynamics compressors are one of the most used approaches in order to control the acoustic noise levels of and audio chain. These sorts of acoustical noise limiting algorithm maintain a signal below a preset threshold.

It is clear that, if a digital or analog algorithm maintains the amplitude of a signal below some threshold, the acoustical pressure signal generated by the loudspeaker transduction will also be bounded to a limit (ideally a limit that keeps a linear and direct relation with the dynamics compression algorithm thresholds).

The dynamics compressor applies a variable gain to the signal in order to adequate it to the configured threshold. It also takes into account two timing parameters: the attack and release times. Both of them describe how fast the gain value changes once the input signal has overcome the threshold [4].

This way, a dynamic compressor acting as acoustic noise limiter expects to have 3-tupla input configuration parameters and an audio input signal. When the audio signal amplitude is below the configured threshold, the dynamics compressor generates an output audio signal identical to the input one. Once the threshold is overcome, it starts to apply a negative gain in order to maintain the amplitude below the threshold. This gain may not be applied instantaneously, so the attack time indicates how long it takes to apply the mentioned gain. Eventually, the input signal may drop below the threshold again. In such case, the release time indicates how long it takes to push off the applied (negative) gain.

One more parameter can be configured in a dynamics compressor: the gain-ratio. It indicates how much gain is applied to the output once the input has overcome the threshold. This parameter is not relevant in the present document and it is assumed to be ∞:1 for all the exposed cases.

Figure 1 shows how the dynamics compressor and limiters behave on the output levels depending on signal input levels.

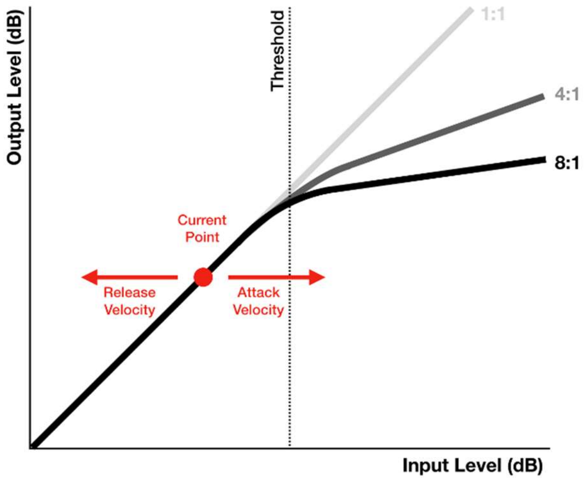

Figure 1. Dynamics compressor input to output diagram and gain point mobility depending on attack and release times.

2.2 Common Topologies

The mentioned acoustical noise limiting algorithms based on the dynamics compressor need a certain topology in order to actually control the acoustic pressure.

The most common topology, exposed in Figure 2, relies on an audio chain where the noise controlling device is placed just before the power amplifiers and the loudspeakers system. The audio source and the optional audio effects (AFX) and equalization (EQ) must be placed before the acoustical noise controlling device.

This way, it can be guaranteed that the audio signal levels after the controlling device are adequate and will produce a bounded acoustical noise emission.

Beyond this audio chain, it is recommended to acquire the actual acoustical signal from the place where the audio chain is performing and from a sensitive surrounding location. Both signals must come from a calibrated acoustical sensor. These acoustical sensors must provide the noise limiting algorithm with an accurate reference of how much noise there is in the analysed places. Taking into account the information retrieved, the acoustical noise limiting algorithm may act over the input signal in order to adequate it.

It is relevant to note that the algorithm can also act detached from these sensors relaying on a previous digital or electrical calibration against acoustic pressure. The authors explain this possibility extensively in [3].

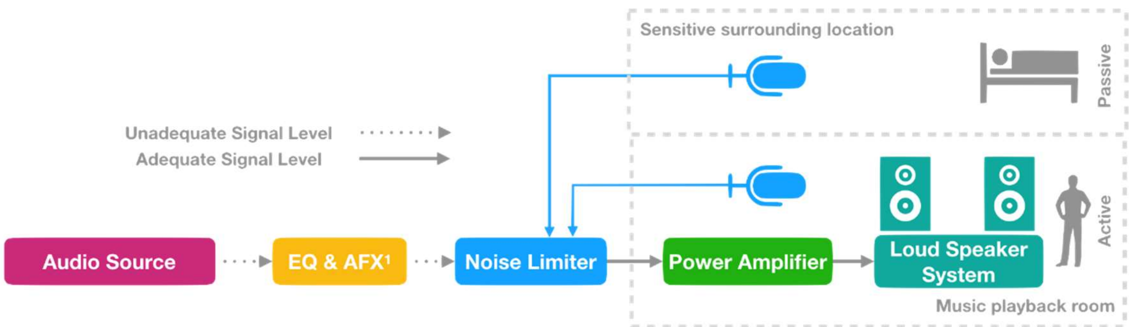

Figure 2. Audio chain with acoustic noise limiting architecture and active and passive acoustic noise sensors.

3. ALGORITHMS SCORING FRAMEWORK

In order to evaluate the performance of the acoustical noise limiting algorithm shown in the previous section, a scoring or evaluation algorithm from the literature is used [5] with some modifications. These mechanisms rely on a theoretical background that involves two mains considerations:

1. The modification and degradation of the audio signal. This component takes into account the non-linearities and the spectral distortions of the output signal with regard to the input signal.
2. The annoyance generated by the audio chain in sensitive surrounding locations (such as private dwellings, hospitals or conference rooms) and the healthiness of the acoustic levels inside the playback room.

3.1 Scores

With the purpose of summarizing the used scoring algorithm, two main equations are used. The first of them, named Like-Score, represents the first of the considerations previously mentioned. As shown in Equation 1, it computes the difference between the RMS value of each of the ANSI S1.11 octave bands [6]. These energy differences are weighted using A-weight in order to approximate the human earing system sensitivity to each of these sections of the acoustic spectrum [7].

$$Like - Score = \sum_{b=1}^{bands} Aw_b \times (RMSin_{mean} - RMSout_{mean}) \qquad (1)$$

Equation 3 details the second consideration. It generates a score named NC-score, this name makes an explicit reference to the NC curve defined in ANSI S12.2-2008 [8]. The NC curves define a maximum noise level for each octave band. If a certain acoustical noise analysis of a room keeps below each of these thresholds, it can be said that a certain NC curve is satisfied. For sake of example, a NC criterion between NC-25 and NC-35 is adequate to private dwellings.

Coming back to Equation 3, it computes the RMS energy of each output signal's octave band and compares it to the required NC value (NC_b). To take into account the most unfavourable case, the acoustical noise in a sensitive surrounding location is used, so the received RMS value is estimated using the building transmission coefficient (TX_b).

It is important to point out that this comparison between the received RMS energy inside the sensitive location and the required NC curve uses two different magnitudes: full-scale decibels (dBFS) and acoustic pressure level in decibels (dBSPL). In such a way, a correction or calibration factor between them is used (C_{FS}).

$$\overline{RMSout_{max}} = RMSout_{max} + TX_b + C_{FS} \qquad (2)$$

$$NC - Score = \sum_{b=1}^{bands} \begin{cases} \left| e^{0.01\times(\overline{RMSout_{max}} - NC_b)} - 1 \right| & if\ \overline{RMSout_{max}} \leq NC_b \\ (\overline{RMSout_{max}} - NC_b)^{0.5} & if\ \overline{RMSout_{max}} > NC_b \end{cases} \qquad (3)$$

Once defined both scores, both initial considerations are taken into account. As far as both of them present a lower-is-better optimization approach, it could be reasonable to use the sum of both to obtain a comparison framework.

Henceforth, this acoustical noise algorithm comparison framework is treated as an optimization space where each 3-tupla parameters (dynamics compressor's amplitude threshold, attack time and release time) score with a certain value. The system optimization allows to look for the 3-tupla parameter that performs with less signal degradations and accomplishing a NC curve criterion, ensuring in such that manner a healthy and not-annoying acoustic level in sensitive surrounding locations.

4. PARAMETERS OPTIMIZATION

4.1 Techniques discussion

Given the variable optimization space, some automatic techniques can be proposed. Taking into account the scoring system exposed in the previous section, a three input and one output function can be defined. The computation of this single output relies on the summarized scoring algorithm exposed and can be evaluated in order to minimize the score. As it has been said, the minimum value of this output score implies the parameters set that impacts less over the signal integrity and takes into account the noise generated in the evaluated surrounding location.

As can be seen, the exposed scoring algorithm relies on heuristic in order to evaluate a parameter set. This way, algorithms such as PSO (Particle Swarm Optimization), GA (Greedy Algorithms) or EA (Evolutionary Algorithm) are candidates for the task of optimization. All of these techniques implement mechanisms that obtain an increasing optimal solution for a certain heuristic.

Particle Swarm Optimization is an approximation that allows to solve an optimization problem using a set of candidate solutions. Such solutions are displaced along the search space by speed and position rules that answer to their position's heuristic. The final scope of these procedures is to make the particles cloud converge towards the best possible solutions.

A greedy approach to this optimization problem could evaluate the whole variables space with a certain resolution and iterate increasing the resolution in areas where scores are lower. The main advantage of this method is that the resolution of the search is limited due to the nature of the optimization problem. For example, it can be easily assumed that a difference of 1 ns between two values of attack or release time is not relevant.

However, the authors found in Evolutionary Algorithm an interesting commitment between greedy lookup and swarm optimization. These kind of algorithm moves evaluations points around the best-found heuristics, but they also mix these resulting best heuristics in order to find best solutions. These mixings or mutations, as named in the literature, imply crossing input values of different evaluated points and applying random changes to the input values.

4.2 Evolutionary algorithms

As said in the literature [9], evolutionary algorithms are based on the operation of biological evolution. Given a search space and a scoring or fitting function, the algorithm generates one first "generation" by randomly selecting sets of inputs. After evaluating each "element" of this first generation using the heuristic function, a new "generation" is computed.

This new "generation" is generated by using "elements" with better scores from the previous "generation". In such that way, the "element" from the first generation with the highest score (according to the described heuristic), is added identically to the new "generation". The rest of the elements could be combinations of the last generation's best-scored ones, random mutations, or simply new random elements.

By the use of this kind of procedures, the heuristic function can be optimized. In the current case, the used heuristic is the scoring procedure described in section 3. The "elements" of these optimization problem are 3-tuple of threshold, attack and release time

5. RESULTS

5.1 Scope of application

Let's assume there is a simulated acoustical noise control system composed of a full-spectrum dynamics compressor. This dynamics compressor has a configurable signal threshold, attack time and release time. The goal of this noise control system is to guarantee a NC-35 (Figure 3a) curve in an adjacent location that has an acoustic isolation treatment that accomplishes the attenuation levels exposed in Figure 3b. A calibration parameter of 140 dB is assumed as the reference between the digital full scale and the acoustic pressure generated by the electroacoustical system.

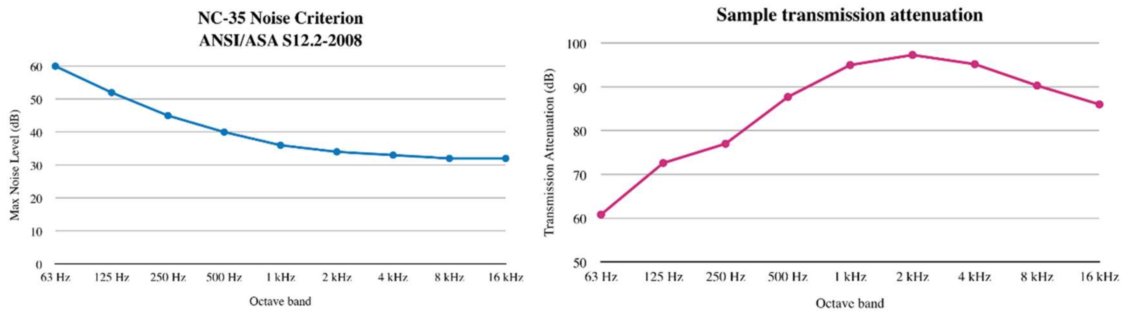

Figure 3a (left). ANSI S12.2-2008 NC-35 curve that represents for example the recommended acoustic noise emissions in a private dwelling. Figure 3b (right). Sample building acoustic isolation levels used for the simulations exposed in this document.

Given this scenario, an evolutionary approach is implemented in order to select the best configuration parameters for a given sample song. This evolutionary algorithm has 20 elements per generation and 50 generations. The "evolution" process includes: the 3 best elements of the last generation, 4 completely random new elements, 4 elements crafted by recombining parameters of the 3 best elements, 4 elements that randomly shift parameters of the 3 best elements (by a gaussian function of $\mu = 1$ and $\sigma^2 = 0.4$) and 5 elements that combine the mentioned random recombining plus gaussian shift.

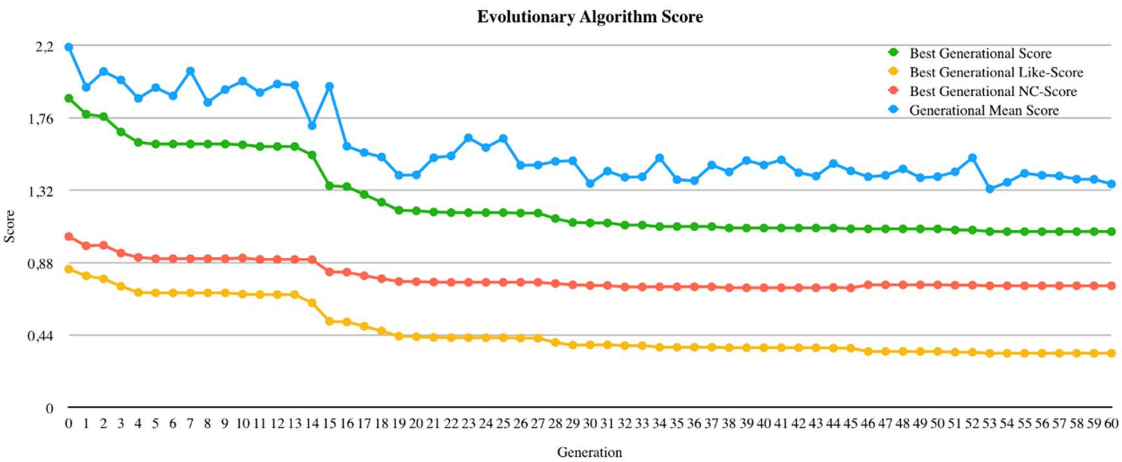

Figure 4. Evolution of the acoustical noise controlled audio chain simulation score along the progress of the proposed evolutionary algorithm approach

Figure 4 shows the evolution of the generation score, defined as the mean score of the elements of a generation, and the best generational score, defined as the score achieved by the best element of every generation.

Taking into consideration the described system, the optimization process results in a configuration of 0.36 threshold (digital full scale), 0.83 seconds of attack time and 1.68 seconds of release time.

For the sake of simplification and example, previous simulation was repeated with a single modification: fixing the threshold to its estimated optimal value of 0.36. Figure 5 shows a heatmap graph where the scores distribution can be observed. As in the previous results, the combination of an attack time between 0.5 and 1 seconds and a release time between 1 and 2 seconds gives the absolute minimum of the score used as heuristic.

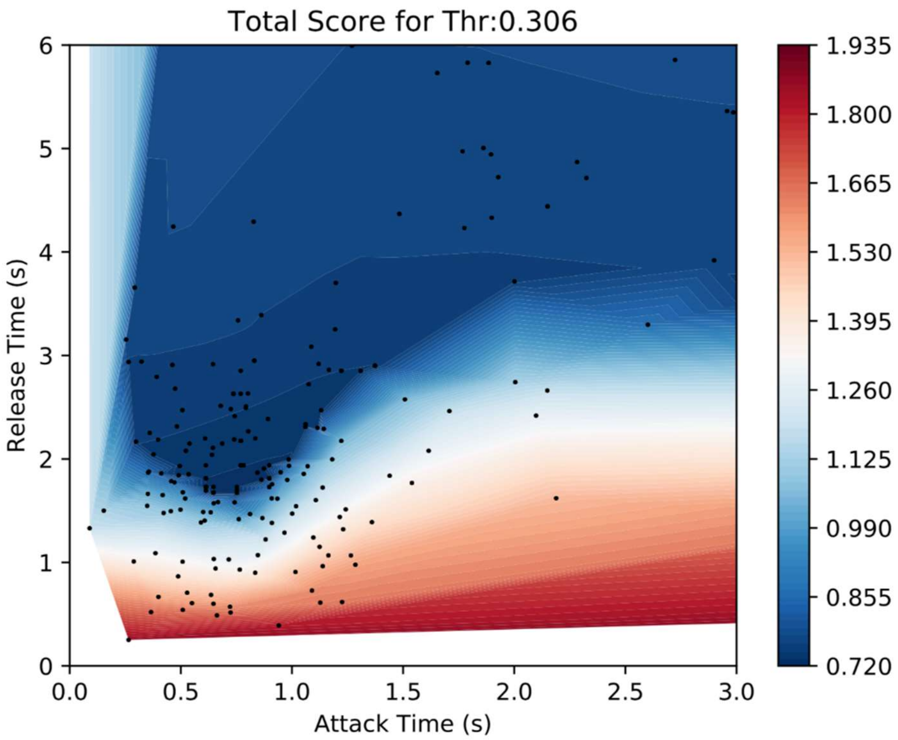

Figure 5. Heatmap representing the evaluation of the heuristic along the optimization space proposed. This simulation fixes the dynamics compressor thresholds to 0.306. Note that the black dots represent the evaluation points selected by the evolutionary algorithm and all of them tend to approximate to the absolute minimum.

5.1 Genre clustering by dynamics compression parameters

In order to validate the explained techniques, the presented optimization techniques have been run with the same underlying assumptions for a genre classified music database. This database considers 10 different music genres: country, jazz, classical, rock, folk, blues, metal, electronic, reggae and rap.

With 5 representative songs for each genre, the optimization mechanism has evaluated the best configuration for the exposed acoustical noise controlled audio line configuration.

Table 1 shows how these parameters, despite being slightly different for each specific song, present a trend for each genre. This trend seems to be related with parameters such as music dynamics, tempo, spectral components or loudness compression of the audio mastering, which is highly dependant on each specific music production.

Table 1. Results of optimization algorithms over a genre sample music library.

Genre	Best Score (20 gen. @ 20 elem.)	Attack time mean	Attack time stdev	Release time mean	Release time stdev
folk	*0.664*	*10.8 s*	*7.1 s*	*57.6 s*	*96.5 s*
rap	*0.736*	*11.7 s*	*7.2 s*	*50.5 s*	*81.6 s*
jazz	*0.765*	*11.1 s*	*8.5 s*	*1.5 s*	*1.9 s*
blues	*0.880*	*12.9 s*	*6.1 s*	*111.5 s*	*128.8 s*
rock	*0.882*	*10.5 s*	*7.3 s*	*77.2 s*	*132.3 s*
country	*0.883*	*10.3 s*	*7.3 s*	*121.1 s*	*126.1 s*
electronic	*0.929*	*9.4 s*	*8.1 s*	*43.5 s*	*84.7 s*
metal	*0.978*	*9.2 s*	*9.1 s*	*15.3 s*	*28.3 s*
classical	*1.083*	*13. s*	*7.7 s*	*27.2 s*	*30.2 s*
reggae	*1.122*	*8.3 s*	*7.3 s*	*52.6 s*	*91.2 s*
comercial	*1.536*	*.2 s*	*.4 s*	*96.8 s*	*162.5 s*

As further work, taking into account the previous results and dissertation, song depth analysis is proposed before optimization mechanism are applied. That way, applying music information retrieval [10] techniques is proposed in order to fine-tune the optimization process. This sort of fine-tune processes could include selective limiting of the range of the optimization parameters or selecting accurate initial conditions in order to force the evolution of the optimization along the best path.

7. CONCLUSIONS

In this study, an acoustical noise optimization is proposed. The main target of this optimization is to evaluate the usage of evolutionary algorithms in acoustical noise limiting system based on a dynamics compressor model.

The document explains theimplementation of the dynamics compressor model so it can act as an acoustical noise limiter. Taking into account these implementation considerations, a performance scoring system is applied to these configurations.

With this scoring or evaluation mechanisms, an optimization problem is defined. The minimization of this optimizable space is supposed to produce an optimal configuration parameter set for the noise limiting architecture.

As a result, a case study of the presented optimization mechanism is evaluated. In this case study, the dynamics compressor parametrization space is evaluated using evolutionary algorithms, and it is proven that these algorithms can converge to the desired heuristic minimums. However, an extension of the proof of concept to a small music database shows this automatic parametrization does not have a high correlation with the music genre. In this way, music information retrieval techniques are proposed in order to fine-tune the optimization algorithms.

8. ACKNOWLEDGEMENTS

This research was supported by Ruido de Fondo SL and University of Granada. We would also like to show our gratitude to the PhD program at the University of Granada’s Escuela de Posgrado for funding this investigation.

8. REFERENCES

[1] P. Garrido-Sanchez, J. C. Martinez-Durillo, and A. Roldán-Aranda, “An advanced mixed-signal processing platform with high performance SoCs,” in *URSI 2018*, 2018.

[2] “DECRETO 6/2012, de 17 de enero.” Boletin Oficial de la Junta de Andalucia, pp. 7–37, 2012.

[3] P. Garrido-Sanchez, J.-A. Almagro-Pastor, and A. Roldan-Aranda, “Acoustic noise emissions limiting algorithms: Taxonomy and Proposals,” *XI Congr. Iberoam. Acústica; X Congr. Ibérico Acústica; 49º Congr. Español Acústica - TECNIACUSTICA’18*.

[4] D. Giannoulis, M. Massberg, and J. D. Reiss, “Digital dynamic range compressor design - A tutorial and analysis,” *AES J. Audio Eng. Soc.*, vol. 60, no. 6, pp. 399–408, 2012.

[5] P. Garrido-sanchez and A. R. Aranda, “Acoustic noise limiter evaluation framework,” *Sound Music Comput. Conf. SMC 2019*.

[6] American National Standards Institute, “ANSI S1.11: Specification for Octave, Half-Octave, and Third Octave Band Filter Sets,” vol. 552, p. 31pp, 2009.

[7] International Electrotechnical Commission, “IEC 61672-1:2013: A Standard for Sound Level Meters Explained,” p. 103, 2013.

[8] “ANSI/ASA S12.2: Criteria for Evaluating Room Noise.” 2018.

[9] P. A. Vikhar, “Evolutionary algorithms: A critical review and its future prospects,” *Proc. - Int. Conf. Glob. Trends Signal Process. Inf. Comput. Commun. ICGTSPICC 2016*, pp. 261–265, 2017.

[10] M. Leman, M. A. Casey, R. Veltkamp, M. Slaney, C. Rhodes, and M. Goto, “Content-Based Music Information Retrieval: Current Directions and Future Challenges,” *Proc. IEEE*, vol. 96, no. 4, pp. 668–696, 2008.