# PERCEPTUALLY-MOTIVATED GENERATION OF ELECTRIC GUITAR TIMBRES USING AN INTERACTIVE GENETIC ALGORITHM

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## ABSTRACT

This paper presents a system for the interactive modification of electric guitar timbre. A genetic algorithm was used to explore the parameter space of a simplified re-amping circuit, which consisted of an initial high-pass filter, a soft-clipping circuit, equalisation and cabinet simulation. This allowed perceptually optimal solutions to be found in the parameter space, e.g. to find sounds that are *"warm", "bright", "heavy"* or any other perceptual quality, as perceived by the user. Such a system could be used to increase accessibility in music production. Additionally, it is hoped that this system can be used in future psychoacoustic experiments investigating the perception of electric guitar timbre, or that of similar instruments.

## 1. INTRODUCTION

In recording electric guitar it is common to place a number of microphones in the vicinity of a loudspeaker cabinet fed by a amplifier. The addition of a DI box (Direct Input/Injection/Interface) allows for an unamplified signal to be captured. This allows the performance to be re-broadcast to an alternative signal chain (processors, amplifiers and microphones) at a later time. The flexibility provided by such an option permits the musician or engineer to tailor the sound of the instrument to better fit the mix, especially once it has started to take shape. However, in communication between musicians and audio engineers there is an inevitable loss of information as sonic concepts are conveyed from one person to another. A form of compromise is often sought.

Technological solutions to this issue have been put forward in recent years. One approach attempts to map audio signals and effect parameters to semantic descriptors [1], e.g. establishing an EQ curve that makes a guitar sound *"heavy"*. If the user is not completely satisfied with the result, the user can be provided with a complete set of controls. This result can then be stored for future use. This framework can make music production more accessible for musicians who may lack the technical training required for certain tasks. However, there is still a loss in information as there may be numerous *"heavy"* presets to choose from, none of which may be suitable for the application.

This paper describes a system which searches for appropriate sounds based on instructions from the user, while the user is not required to make any direct adjustment of parameters if they do not wish to, or if this is not possible. The application here is to guitar re-amping, although the principle could be applied to any number of possible scenarios involving parameter adjustment, such as EQ, panning or level-balancing.

## 2. BACKGROUND

It has been indicated that guitar players and non-players have a similar perception of electric guitar timbre, both groups having perceived a "*brightness*" factor [2]. This factor was found to be well-predicted by Zwicker sharpness, and later, spectral centroid [3]. It was also suggested that the amount of distortion applied and the frequency alterations caused by the application of equalisation were perceived independently. Perhaps paradoxically, the perception of brightness decreases with increased distortion, despite the increased harmonic overtones [3]. "*Wildness*" and "*heaviness*" have been proposed as two perceptual attributes in distorted guitar tones [4]. It has recently been suggested that these were in fact one attribute, referred to as *"power"* of the timbre [5].

In these previous studies, audio stimuli are generated in advance and participants are asked to rate these sounds on particular scales. An alternative methodology is to provide the participants with the entire solution space of the system and seek to map the perceptual quality sought in this space. To this end, this paper uses Evolutionary Computation (EC) to explore the parameter space of the problem. EC is a branch of natural computing based on Darwin's evolutionary theory of natural selection [6]. Solutions are ranked according to their *fitness*, their ability to solve the problem, often determined using a defined function. When the fitness function is evaluated subjectively, this is referred to as Interactive Evolutionary Computation. Such algorithms have previously been used as a means of exploring the parameter space of audio systems, particularly for synthesis, in both interactive [7] and non-interactive implementations [8, 9]. The advantages of EC in perceptual audio optimisation are discussed in an alternate publication [10]. In this paper, the

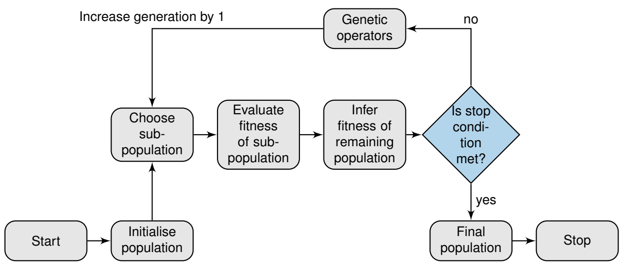


Figure 1: *Flowchart of IGA system. The "evaluate fitness of sub-population" block is expanded in Fig. 2.*

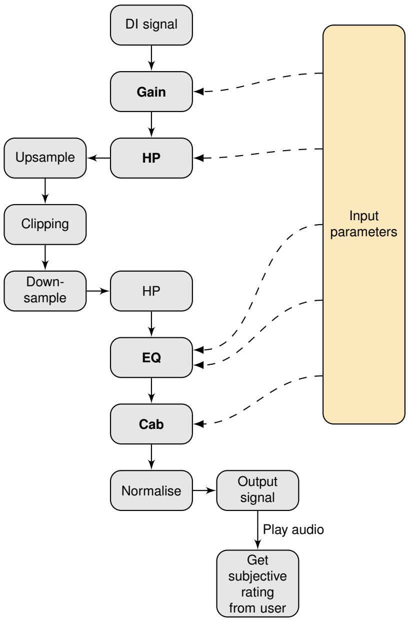


Figure 2: *Flowchart of processing chain, for each generated audio sample. Processes in **bold** are variables to be optimised.*

implementation of an Interactive Genetic Algorithm (IGA) is identical to the author's earlier work [11], in which mixes of multitrack audio were created in accordance with desired perceptual dimensions. An overview of this algorithm is displayed in Fig. 1.

## 3. GUITAR RE-AMPING SIGNAL CHAIN

For this work, a simple, yet realistic signal-processing chain was desired. This processing chain is shown in Fig. 2. The four blocks to be optimised are highlighted in **bold** and described here. Gain is simply the amount of dB by which the DI signal is amplified prior to any further processing. This directly influences the result of the clipping stage only, as all other blocks are linear processes. Prior to the clipping stage is a variable high-pass filter. This is a second order Butterworth design, with a corner frequency variable between 100 and 1,000 Hz. The choice of corner frequency determines the spectral content and overall amplitude of the signal to be processed by the clipping stage. Consequently, the distorted tone is greatly influenced by this highpass filter. The clipping stage is an implementation of a cubic function described in [12] (which was modified from [13]). Each of the proposed soft-clipping algorithms from [12] was tested and this cubic soft-clipping was chosen as it exhibited low harmonic instability at low and medium input levels and did not require any additional variables to be specified. The expression is shown in Eqn. 1.

Table 1: System parameters and ranges

| Parameter | Range |
|---|---|
| HP | 100 – 1000 Hz |
| Gain | 0 – 70 dB |
| EQ | $[-40\ 40]$ in PCA dim.1 |
| | $[-40\ 40]$ in PCA dim.2 |
| Cab | Impulse response of 4 cabinet types, labelled A, B, C and D |

$$y(x) = \begin{cases} \mathrm{sgn}(x), & \text{if } |x| > \frac{2}{3} \\ \frac{9x}{4} - \frac{27x^3}{16}, & \text{otherwise} \end{cases} \quad (1)$$

A simple DC blocking filter was implemented after the clipping stage, consisting of an eighth-order Butterworth filter with a fixed cut-off, $f_c = 20$ Hz. For each variable the range (as shown in Table 1) was quantised according to a specified resolution. In this case, a 7-bit resolution was used, providing 128 discrete values for each variable. For HP, these 128 possible values were logarithmically-spaced in the specified range. As there are only four possible cabinet choices in this particular implementation, only a 2-bit resolution was required for that variable.

The EQ block implements an IIR filter to change the tone of the distorted signal. Here the aim was to implement an EQ stage which would cover a wide variety of tones, beyond that of what is common in any specific guitar amp (such as a fixed-frequency or semi-parametric EQ with a small number of bands), while also keeping the number of variables low. This was achieved as follows: a target EQ curve was obtained from a feature-reduced space, comprised of the first two principal components of a library of 731 examples of equalisation (the raw data from [14][1]). These first two components explain roughly 68% of the variance in the total dataset. The range of [-40 40] refers to the units in the PCA-space. A full description of this EQ method has been provided in the author's previous work [15].

Once processed, a fitness function is evaluated. The specific choice of fitness function is flexible and depends on the desired output of the system. In an interactive genetic algorithm, the fitness function is a subjective rating obtained

[1] `http://socialeq.org/data/`

from the user. In this instance, the processed signal is played back to the user and a preference rating is obtained (a value from 1 to 10, where 10 is an output equal to the subjective target). Alternatively, the fitness function could be one of any number of perceptual characteristics, such as brightness, warmth, heaviness or wildness.

## 4. RESULTS AND DISCUSSION

In perceptual tasks, it is not so critical to determine the precise optimal solution but the region of the solution space in which a number of perceptually-similar optimal solutions exist [16]. To achieve this, the optimal values of each parameter are determined by estimating the density of the final population, as in [11]. The data from three trials (one trial each, by three users) are presented here in order to assess the convergence towards an optimal solution. Audio was reproduced over headphones in a quiet environment. The user was asked to optimise the parameters towards a sound which they considered most suitable for that guitar performance. Each processed audio sample was peak normalised.

Figure 3 shows the estimated probability density function of the HP, GAIN, and EQ values in the final population as well as a histogram showing the number of times each CAB value appeared in the final population. Using the peak values of EQ1 and EQ2 from Fig. 3, the modal EQ is determined from this position in the PCA-space and displayed in Fig. 4. For a given user, the peak values for each variable are used to generate the final, presumably optimal, tone. Good agreement can be seen for HP and, to a lesser extent, GAIN. The EQ curves have similar values along dimension 1 (providing a spectral tilt with increased low frequencies) and variations in dimension 2 (providing a mid-range boost/cut — see [15]). In each trial a different cabinet impulse response was ultimately chosen. Therefore, it is hypothesised that the variations in EQ were attempts to correct for the spectral response of the cabinet. This suggests good convergence for most variables but not for the cabinet, perhaps due to the categorical nature of that variable.

The obvious application of this system is as an interface for the audition and selection of guitar tones. However, in that capacity, the system can be used for the generation of stimuli in psychoacoustic experiments on the nature of qualities such as brightness, wildness and heaviness. Further investigations include the perception of how such qualites relate to the concept of preference. The multi-modal nature is also of interest — is our perception of guitar tone influenced by the visual design of a virtual amp, or by the fashion sense of the recording artist?

## 5. CONCLUSIONS AND FURTHER WORK

This preliminary investigation illustrates that an interactive evolutionary algorithm is a viable method for the audition

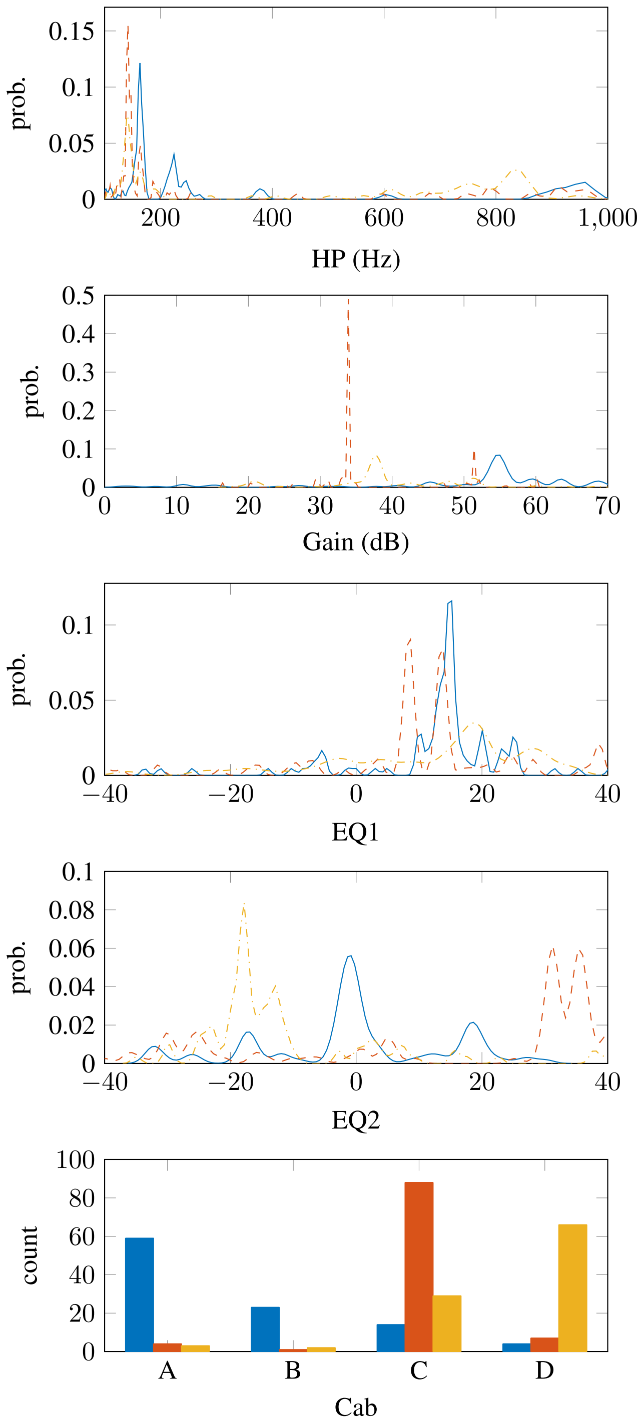


Figure 3: *Estimated distribution of parameters in final population. Solid line (in blue) represents trial #1, dashed line (in red) represents trial #2 and the dash-dotted line (in yellow) represents trial #3.*

and comparison of electric guitar tones, towards perceptual optimisation. This has the potential to act as an assistive tool in recording and mixing processes. The system proposed in this paper used a rather simple model of an electric

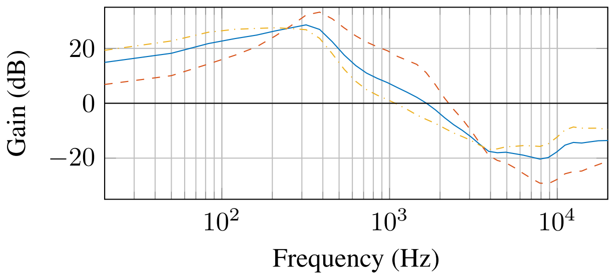


Figure 4: *Modal EQ curve from final populations, from the peak values of EQ1 and EQ2 shown in Fig. 3.*

guitar signal chain. A more detailed model would include the modelling of specific circuits (such as commonly used distortion and overdrive pedals [17]) and the non-linearities of the loudspeaker [18]. Since the categorical nature of the amplifier cabinet choice appears a barrier to convergence in the optimisation, a parametric model could be beneficial.

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