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# **A GENETIC APPROACH FOR THE INTERACTIVE DESIGN OF SOUNDS: APPLICATION TO ELECTRIC VEHICLES**

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## **Abstract**

This chapter deals with the integration of user's perceptions into the design process of products. Beyond the traditional approaches using predefined Design of Experiments (DOE) to study the effect of design variables of stimuli on human perceptions (classical in sensory analysis), methods based on Interactive Evolutionary computation (IEC) present a great interest. They are efficient to deal with complex optimization problems, where the derivative is unavailable, and can take into account perceptual assessments in the course of the solution search. In this chapter, we propose to show how Interactive Genetic Algorithms (IGA), a particular class of IEC, can be implemented for sound design. We illustrate the method with a particular application, the design of alert sounds for Electric Vehicles (EVs). EVs being very quite at low speed, it is necessary to add warning sounds but this can represent an annoyance if they are poorly designed. We describe a perceptual experiment in which the detectability and the unpleasantness of synthesized sounds are optimized with IGA. Results show that the quality of the sounds designed by the IGA method is significantly higher than different propositions of a designer, validating the relevance of the approach.

## **Keywords:**

Sound design; electric vehicle; interactive optimization; interactive genetic algorithm; User centred design; sound quality; detectability; unpleasantness; masking effect

## **1 INTRODUCTION**

In today's increasingly competitive market, industrials need to reach all the components of customer expectations. These expectations can be translated into functional specifications, such as the fuel economy or the power of a car, or represented by more subjective requirements, such as the "pleasantness" of a motor sound. Recently, an increasing number of businesses are realizing that to gain a competitive edge, they must win the customers' hearts as well as their minds. Emotions elicited by product appearance can enhance the pleasure of using things and design for emotions is now an important topic in engineering design (Barnes & Lillford, 2009). The development of successful products requires the control of product semantics, the "symbolic qualities of man-made forms in the context of their use and application of this knowledge to industrial design" (Krippendorff & Butter, 1984). To manage the risks of design projects, and increase the consistency between the positioning of a product and its design, companies must check that the product matches specific semantic dimensions, in accordance with marketing or design briefs (Kaul & Rao, 1995). For example, the motor sound of a sporty car must inspire "sportiness" to customers, and the company must check from the early stages of the project that the design decisions agree with this connotation for the considered market segment. The challenge for designers is to understand what "sportiness" means to customers, in order to translate it into relevant acoustic attributes. Even if designers are trained and skilled to understand customers, capture trends and make innovative proposals, discrepancies may occur between designers' and users' product perception (Hsu et al., 2000). Furthermore, users are not designers and it is illusory to ask them directly what design attributes would be relevant (users are generally unable to give an opinion on a prospective product until they see it). Companies, despite having well defined product needs, may encounter difficulties anticipating the customers' reactions to a design and the control of product semantics remains an important problem in product design (Hsiao & Wang, 1998). Therefore, to assist designers in their design decisions and to confirm their proposals, an active research field in product design concerns the analysis of end-users' evaluations, in order to extract useful information to take design decisions (Orsborn et al., 2009 - Hoyle et al., 2009).

In this context, a first category of methods concerns the modeling of customers' perceptions or preferences according to a given set of parameterized products (modeling of perceptual data). These methods use the Design of Experiments theory (DOE) and assume a model between the perceptual dimensions and the design variables. Conjoint analysis (CA) (Green & Rao, 1971), the typical decomposition method of preference, initiated in marketing, belongs too this category, and has several applications in design (Wassenaar et al., 2005). A model (generally linear without interaction) explaining the preference by design attributes is assumed and various statistical procedures and design of experiments are proposed to estimate the coefficients of the model. For product design, the presentation of the samples is generally visual and a new discipline, visual conjoint analysis, has been emerging in engineering design (Vriens et al., 1998), including Virtual Reality techniques for product presentations (Tovares et al., 2014). Many works address limitations of CA, concerning in particular the difficulty in the definition of the experimental design (Kuhfeld, 1997) or the importance of interactions between attributes (Green & Srinivasan, 1990). For visual studies that concern shape parameters of a product, interactions between features seem to be particularly important (Sylcott et al., 2015) since they are not considered in the majority of conjoint studies. Beyond customer preferences, the conjoint analysis framework has been extended to study semantic or sensory dimensions. From ratings or choices of participants according to a given semantic dimension, a statistical model is fitted to the data to study the value participants give to specific product features. This process was for example used in (Reid et al., 2010) to study the environmental friendliness of car silhouette and to propose optimal designs.

Another model-based approach is the Japanese *Kansei engineering*, a design method to account for user's feelings and perceptions (Nagamachi, 1995). From subjective measurements of the user's "Kansei", generally using the semantic differential method and adjective pairs, different statistical models are proposed to translate the user's perceptions into design elements and make design decisions (Nagamachi, 2011). The estimation of the statistical models can be made with the Quantification theory type I (Hayashi, 1952) with maximization of the correlation coefficients or with the least square method. The influence of slight changes in product attributes on user emotions using a linear model is for example presented in (Artacho et al., 2010). All these approaches have subjective assessments of users in common and assume a mathematical model (defined a priori) between the perceptions/preferences and the design attributes. An optimum of this model can be defined to constitute the "optimal" product according to a semantic dimension or preference.

A second category of methods for the analysis of users' evaluations is not model-based and uses human-computer interactions. These methods are model-free in content (contrary to CA, there is no model of the behavior of the respondent), but model-driven for the solution search. In this case, an algorithm gradually refines the propositions made to the users, for example with interactive evolutionary computation (IEC), a category of methods where the user plays the role of the evaluator in an evolutionary process (Takagi, 2001). In IEC, the user assesses the fitness of the population (adaptation of the population to the problem), using choices or ratings for example. IEC have been applied to many domains (music, writing, education, food industry, etc.) involving different sensory modalities. Particular cases of IEC are IGA (Interactive Genetic Algorithms), where genetic operators such as recombination, crossover, and mutation are used to modify design samples. This method has been used for example to capture aesthetic intention of participants for the design of cartoons (Gu et al., 2006), car silhouettes (Yannou et al., 2008) or for preference modeling (Kelly et al., 2011). IGA have also been tested in our previous studies for the design of drinking glasses (Poirson et al., 2011) or car dashboards (Poirson et al., 2013) which have confirmed their utility in extracting designs trends and to obtain a final product solution that optimizes a determined semantic dimension. IGA have the great advantage of not needing restrictive assumptions concerning the preference model of the participant. Interaction effects are in fact implicitly integrated in the course of the model driven search in the solution space.

These two categories of methods (DOE and IGA) are very different in nature and comparative studies between them are very rare in the engineering design literature. A comparison is presented in (Teichert & Shehu, 2007), where the authors expose a simple case study on the design of a bottle with three attributes. The authors conclude on the superiority of interactive evolutionary algorithms to elicit the optimum product, but without explanations for the reason behind this superiority. The fields of

application of DOE and IGA are different but they share the same general goal: developing products that satisfy consumer's needs and desires, on the basis of customer's surveys. Both methods are clearly in competition for the optimization of products in a design space according to user perception of a given semantic dimension. DOE allows for the definition of "optimal" products and the generation of predictions in the design space, while IGA is oriented towards the search for the "optimal" product in the design space. They can also both be employed to "optimize" a given product according to a semantic or sensory dimension, on the basis of customers' surveys.

We propose in this chapter to study the efficiency of Interactive Genetic Algorithms for the design of sounds. Sounds are nowadays used for many applications during our interaction with complex products. They can be used to present information to the user (auditory display), to give a feedback on the state of a Human Machine Interface (HMI), to alert the user on potential dangers of a situation (aircraft or vehicle navigation systems (Stenton & Edworthy, 1999) or even to elicit a positive emotional state and to connote the design of a product with particular semantic dimensions (sounds of vehicles for example) (Roussarie et al., 2004). The design of such functional sounds is a complex design problem that necessitates coping with many constraints and dealing with perceptual aspects. In addition to the expertise of a designer, hearing tests are required in order to understand the complex relationships between acoustic parameters and perceptual dimensions.

For warning sounds in particular, knowledge of the effect of sound parameters on the perceived urgency is important to give precise recommendations (Edworthy, Loxley & Dennis, 1991). Recently, new-in car technologies led to an increasing number of sound interfaces, for example for navigation or driver assistance systems (autonomous vehicle). Many studies propose an experimental approach with hearing tests to understand human perceptions for sounds design. In (Marshall, Lee & Austria, 2007), different hearing scenarii are proposed to study two objectives, annoyance and urgency, with a fixed design of experiments. In addition to the perceived urgency, other dimensions such as the criticality level or the severity level of alarms can be studied (Sousa et al., 2016), so as the influence of ambient noise conditions (Singer et al., 2015).

Another typical example of sound design concerns Electric vehicles (EV) or hybrids that may be dangerous because too silent at low speed (under 30 km/h). Yet, several countries such as Japan and the United States of America already decided that adding artificial sounds to EVs is compulsory (Konet et al., 2011). Many studies have been conducted to recommend design guidance for external sound generation systems for EVs (Senselab, 2011), (Robart et al., 2013), (Singh et al., 2014).

To study and understand human reaction to sounds, experiments use generally a parameterized sound synthesis and classical model-based design of experiments (for example D-optimal DOE) (Kuhfeld, 1997). The limitation of such approach is that a model between the acoustic parameters and the perceptual dimension must be assumed in advance, given that the exact form of the model is generally unknown.

Concerning sounds, IGA have been used in sound design for musical compositions (Biles, 2007) or to design sign sounds (Miki et al., 2006). Subtle perceptual phenomenon can then be taken into account for the optimization of products involving sensory constraints (Wakefield et al., 2005). A study using IGA for the design of sounds for Electric Vehicles can be found in (Petiot, Legeay & Lagrange, 2019), where an exploration of the tradeoff between detectability and unpleasantness of the sounds is proposed, showing the efficiency of the approach. The present chapter is in the continuity of this work.

The first objective is to describe how the optimization of the tradeoff detectability/unpleasantness of EV sounds can be made with IGA. A second objective of the chapter is to assess the efficiency of the design solutions compared to different designs and current proposals of a designer. For this, hearing tests based on synthesized alert sounds were proposed to a panel of participants in an interactive experiment. In a second experiment, the efficiency of the design solutions provided by different design methods was assessed.

The remainder of the chapter is organized as follows. Section 2 presents a short background on interactive Genetic Algorithms (IGA) and their use in product design. Section 3 presents the application on EV with a Material and Methods section (presentation of the sound synthesis method, description of the tasks given to the participants and the sound stimuli used, methods used for the

analysis of the results) and a Results section. The concluding section provides implications for sound design and perspectives.

## 2 BACKGROUND ON IGA

### 2.1 Principles

Genetic Algorithms (GA) are evolutionary optimization methods (Goldberg, 1989). The principle of GA is based on iterative generations of populations of individuals, converging step by step toward solutions, which are adapted to the problem. Based on the principle of Darwin’s natural evolution theory, the algorithm proceeds to a selection of parents, which will spread their genetic dominant heritage in the next generation, suitable to a desired objective. Classically, the fitness evaluation of the individuals is calculated numerically with a mathematical function known beforehand. A particular category of GA, Interactive Genetic Algorithms (IGA) introduces the user in the optimization loop to assess the fitness. In each iteration, the user selects solutions (products) that he/she considers as the most interesting for the desired objective. After a number of iterations, the method may converge towards solutions that fulfill the user’s objective. These algorithms are used for example to explore design spaces and to encourage creativity (Kim & Cho, 2006), (Qian & Ben-Arieh, 2009). Since the user decides the individual fitness, there is no need for a prior and unique formulation of the fitness function. For some applications, such as exploring semantic dimensions (Poirson et al., 2013) or integrating complex perceptual processes (Wakefield et al., 2005) (Lee & Chang, 2010), this advantage is crucial.

### 2.2 Implementation of IGA

After a definition of the design variables of the product and their corresponding levels, a coding of the designs, represented by a chromosome, is proposed. Our implementation uses a binary coding and discrete-valued variables, but continuous variables may also be used. A more complete description of the implementation of our IGA can be found in (Poirson et al., 2013). The IGA creates an initial population of individuals (e.g. pictures or sounds) by randomly generating the chromosomes and presents them to the user. Based on personal criteria, and according to the instructions given to the user for the experiment, the user has to assess the “fitness” of each individual of the population. Two main protocols can be used for this assessment: (1) a choice of a subset of individuals (for example 1 or 2 designs) – this process is convenient for example for pictures or shapes, where the assessment of the participant can be immediate (Poirson et al., 2013). It is not well adapted to sounds because the short time memory of the participant cannot be activated, given that sounds, contrary to pictures, are embedded in time - (2) a rating of each design on a rating scale – this process is convenient for sounds, the sound being rated just after its listening. From these assessments of the fitness, a new population of individuals is then created using genetic operators applied to each design of the previous population. The general framework for a user-test using IGA (applied to sounds) is presented in Figure 1.

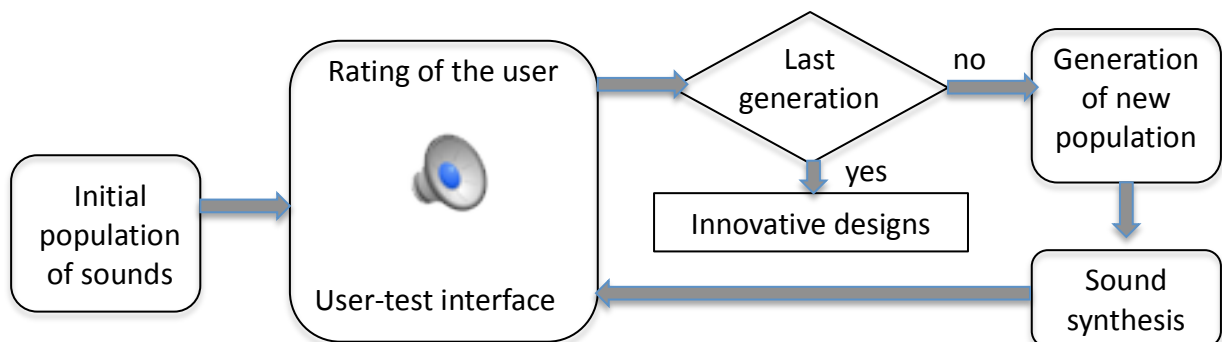


Figure 1: Framework of the iterative user-test of sounds using IGA

The generation of the new population uses genetic operators, mainly crossover, mutation, and selection. In our implementation of IGA, the algorithm is controlled by 3 parameters: the crossover rate ( $c_r$ ), the mutation rate ( $m_r$ ) and the selection rate ( $s_r$ ). These values are chosen between 0 and 1 in such a way that  $c_r + m_r + s_r = 1$ . The choice of the operator applied to each individual  $i$  is made

randomly according to the following process: an indicator,  $rand(i)$ , is randomly chosen between 0 and 1 from a uniform distribution:

- If  $rand(i) < c_r$ , the operation applied is a crossover (single point crossover – the second parent is chosen randomly in the population (see after))
- If  $c_r \leq rand(i) \leq c_r + m_r$ , the operation is a mutation (random mutation of one variable)
- If  $rand(i) > c_r + m_r$ , the operation is a selection (simple duplication of the individual)

A fourth parameter can be added for the generation of populations: the roulette wheel  $w_r$ . In the crossover operation, the probability that an individual is the second parent in the crossover operation depends on its fitness, and can also be increased by the weight  $w_r > 1$ . The number of individuals per generation does not depend on the IGA methodology. It is chosen according to the number of variables and levels and the possible fatigue of the participants. This set of parameters allows the management of different strategies for the solution search, and control the convergence properties of the process. For example, with the set ( $c_r = s_r = 0$ ,  $m_r = 1$ ), the strategy corresponds to a random search in the design space. A very eugenist strategy can be obtained for example with ( $c_r = 1$ ,  $s_r = m_r = 0$ ) and  $w_r \gg 0$  (very aggressive strategy that may converge fast but to local minima).

Figure 2 presents the general mechanism of our implementation of IGAs: after the rating of the fitness of each individual of the population, the next population is created by applying either a selection (copy) or a mutation or a crossover.

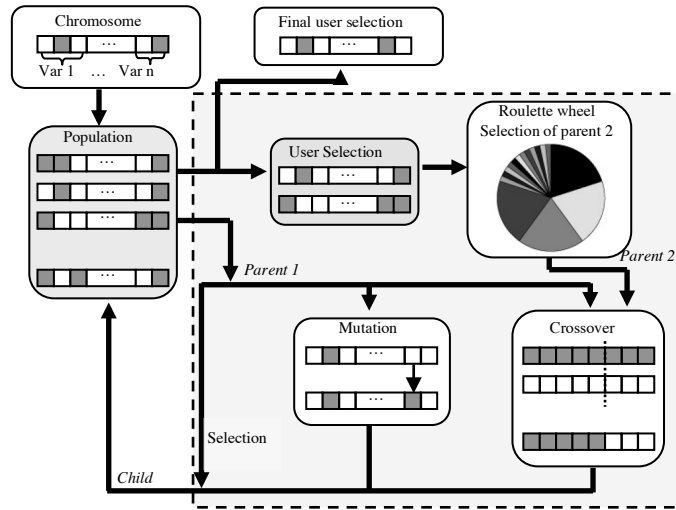


Figure 2: Synoptic of the IGA process for the generation of a new population

The tuning of the parameters of IGA is a complex problem that depends mainly on the size of the design space and the maximum number of generations allowed. A balance between quality of the solutions and participant fatigue is necessary (Wang et al., 2006): not too few generations because poor solutions may be obtained, and not too much generations because inconsistent ratings of the participants due to fatigue may occur. An automatic process was implemented to tune the different parameters of our IGA (Poirson et al., 2013). This process uses simulated “virtual” users and a “target” product in the design space (defined by target values of the design variables). To simulate the choices of a virtual user, a distance function between the individuals of the population and the target is computed. By launching several simulations in the same conditions (Monte Carlo method), an average estimate of the convergence rates of the IGA is computed, given the value of the parameters. This process allows the experimenter to determine the “optimal” tuning of the parameters, given a maximum number of generations allowed.

### 3 APPLICATION OF IGA TO THE DESIGN OF SOUNDS

#### 3.1 The design problem: sounds for electric vehicles (EV)

Electric vehicles (EVs) and hybrid vehicles are becoming a serious alternative to internal combustion engine cars (Gillibrand et al., 2011). However, at low speed (under 30 km/h), EVs are very quiet and may be dangerous for pedestrian or visually impaired peoples who have to rely on auditory cues when intending to cross a road (Parizet et al., 2014). Regulation concerning the sounds of electric cars is still under study. Nevertheless, several countries such as Japan and the United States of America already decided that adding artificial sounds to EVs is compulsory (Konet et al., 2011). Car manufacturers started to design warning sound generator devices, named for instance AVAS (Approaching vehicle Audible System), VSP (Vehicle Sound for Pedestrian), VPNS (Vehicle Proximity Notification Systems)...

The sonification of EVs is a complex design problem, with many constraints and stakeholders involved. Stakeholders include cyclists and pedestrians some of whom might have difficulties hearing warning sounds in a urban environment, drivers who expect audio-feedback on the performance of the car, and other third parties who prefer not to be disturbed by additional sounds (Petiot et al., 2013). The main difficulty in the design concerns the tradeoff between detectability and acceptance of the EV sound (Lee et al., 2017).

It is indeed clear that EV sounds may be masked by the background noise of the environment, making them hard to detect. And a naïve solution consisting in a simple increase of the sound level to reduce the masking effect may have dramatic consequences on the sound pollution of cities. There is then clearly a conflict between detectability and annoyance for the perception of EV sounds. Different studies addressed this problem (Campillo-Davo & Rassili, 2016), (Lee et al., 2017), (Parizet et al., 2014). All these studies are based on hearing tests of a predefined set of sound stimuli (classical DOE). They produced interesting results to give recommendations for the design of sounds by the fitting of a model between the perceptual dimensions and the sounds parameters. This data modeling stage may constitute a limitation for the optimization of sounds, given the number of parameters of the sounds and the possible interaction between them. For these reasons, the IGA approach should be a valuable alternative.

#### 3.2 Material and methods

##### 3.2.1 EV Sound synthesis

##### COMPONENTS OF THE SOUND

The EV sounds were synthesized using the mathematical modeling software *Matlab* and the additive synthesis technique. In order to generate different but plausible sounds for an electric car, after an analysis of current sounds of different carmakers (Misdariis et al., 2012) and personal propositions (Petiot et al., 2013), four main components of the sound were considered. The components are also named design factors in this chapter:

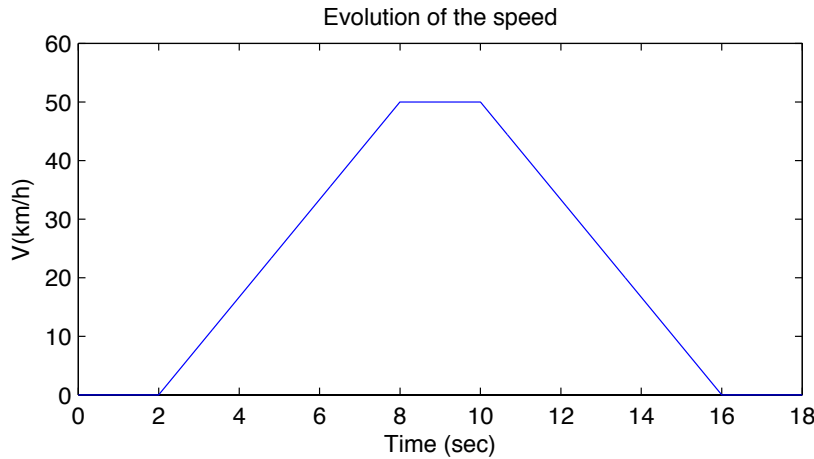
- Component C1 “A thermic motor sound”. This component synthesizes the first harmonics of a classical 4-stroke internal combustion engine (H0.5, H1, H1.5, H2, H4, H6 – H1 correspond to the rotation frequency of the engine),
- Component C2 “A Harmonic Sound”. This component synthesizes different musical ‘notes’, harmonic, that constitute a chord (chord with 2, 3, or 4 notes),
- Component C3 and C4: “A broad band Noise” (granular synthesis). These components synthesize two filtered noises.

The final temporal signal of the EV sound  $s(t)$  is simply a weighted sum of these different components (equation 1).

$$s(t) = a_{c1}.C1(t) + a_{c2}.C2(t) + a_{c3}.C3(t) + a_{c4}.C4(t) \quad (1)$$

In addition, different parametric filters were applied to the final sound: (1) a sweeping filter (envelop filter), which changes the harmonics amplitude in function of time – (2) a flanging filter (swept comb filter effect), which produces time variations of the frequency spectrum.

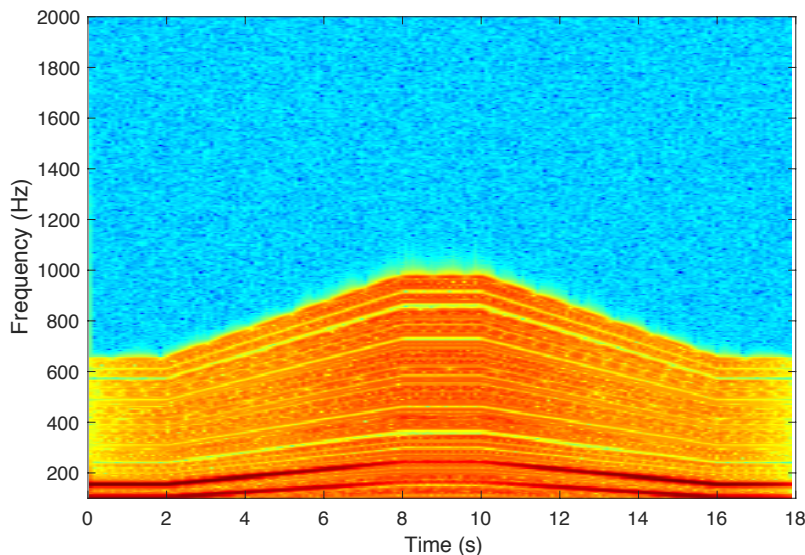
Since it is out of the scope of this chapter to describe all the parameters of the synthesizer (there are more than 70 independent parameters to define a sound), we can mention that all the frequencies and amplitudes of the components are adjustable, to create credible and original sounds, as well as the filters parameters. The sound is not constant but ‘played’ by a control parameter of the car: the speed. To make the sound evolve with the speed of the car, we choose to adjust the frequencies and the amplitudes of the different components according to the speed with parameterized patterns. Figure 3 presents a typical pattern of speed with four phases of driving: idling (2s), acceleration (6s), constant speed (2s - typically: 50km/h), deceleration and idling.



*Figure 3: Typical pattern of speed versus time for the simulation of the EV sound*

Mapping the speed of the car with the parameters of the sound (frequencies and amplitudes of the components) makes the sounds evolve and “simulates” the movement of the car. Analogous to an internal combustion engine, for this mapping, the rule used is that the frequencies of the components increase, when the speed increases. This pattern creates realistic conditions to facilitate the perception of speed, acceleration or deceleration.

An example of the spectrogram of an EV sound, playing the previous speed pattern, is given in Figure 4. The sound is made of a broadband noise (component C3 - 50-650Hz, central frequency = 300Hz), the frequency range of which increases with the speed of the car. A thermic motor sound (component C1) is added, below 200Hz.



*Figure 4: Spectrogram of an EV sound with components C1 (motor sound) and C3 (broad band noise), playing the speed pattern presented in Figure 3*



## DESIGN VARIABLES OF THE EV SOUND

Among the different synthesis parameters of the sounds, it is necessary to define which one are manipulated by the IGA and coded in the genome (space of exploration of the genetic code). After several tests, the following 6 variables, and their corresponding levels, were chosen as factors (table 1). The four first factors (**C1**, **C2**, **C3**, **C4**) control the frequencies of the components C1, C2, C3, C4, the factor **Amp** control the relative amplitude of the different components, and the **Filter** controls the use of different filters to alter the global sound. 4 levels were chosen for each factor. The setting of the levels of the factors required many adjustments (not reported here) to get a large diversity of sounds and to obtain audible differences between sounds but with still convenient sounds.

Table 1. Definition of the 6 factors (design variables) and their levels

Factor	Variable	Level 1	Level 2	Level 3	Level 4
<b>C1</b>	Fundamental frequency of C1	70Hz	100Hz	130Hz	160Hz
<b>C2</b>	Fundamental frequency of C2	100Hz	150Hz	200Hz	250Hz
<b>C3</b>	Central frequency of C3	100Hz	200Hz	300Hz	400Hz
<b>C4</b>	Central frequency of C4	500Hz	600Hz	700Hz	800Hz
<b>Amp</b>	Amplitude of C1, C2, C3, C4	$a_{C1} = 2$ $a_{C2} = 1$ $a_{C3} = 0.75$ $a_{C4} = 0$	$a_{C1} = 0.5$ $a_{C2} = 0.75$ $a_{C3} = 1.5$ $a_{C4} = 0.33$	$a_{C1} = 0.25$ $a_{C2} = 0.5$ $a_{C3} = 0.1$ $a_{C4} = 0.25$	$a_{C1} = 0$ $a_{C2} = 0.1$ $a_{C3} = 0.1$ $a_{C4} = 0.5$
<b>Filter</b>	Type of filter	None	Sweeping filter	Flanger	Sweep+flanger

With these six factors and four level, the design space counts  $4^6 = 4096$  possible designs (all the possible combinations of the full factorial).

### 3.2.2 Scenario and Sound stimuli

Given that the objective of the test is to assess the reaction time associated to the detection of the EV sound, the sound must be incorporated in a background noise (masking signal). The background noise considered in the study corresponds to a two-lane street in downtown. The soundscape was synthesized with the *SimScene* software<sup>1</sup> (Rossignol et al., 2015), from real recordings in a city. To be used as background noise, the soundscape must not contain any strong emergent event (horns, car passing, ...) (Kerber & Fastl, 2008). The level of the background noise was adjusted to a convenient level and kept constant for all the stimuli proposed in the hearing test. To avoid the potential fatigue of the participant due to the repetition of the same background noise during the test, the part of the audio file selected (15 seconds) was randomly chosen in the total background noise (duration 1mn).

The scenario chosen for the test corresponds to the following situation (Misdariis et al., 2013): a pedestrian located on the sidewalk of a street waits before crossing (Figure 5). An EV may pass by, coming either from the right or from the left. The listener is static, and must indicate when he/she detects the EV.

<sup>1</sup> Open-source project available at: <https://bitbucket.org/mlagrange/simscene>

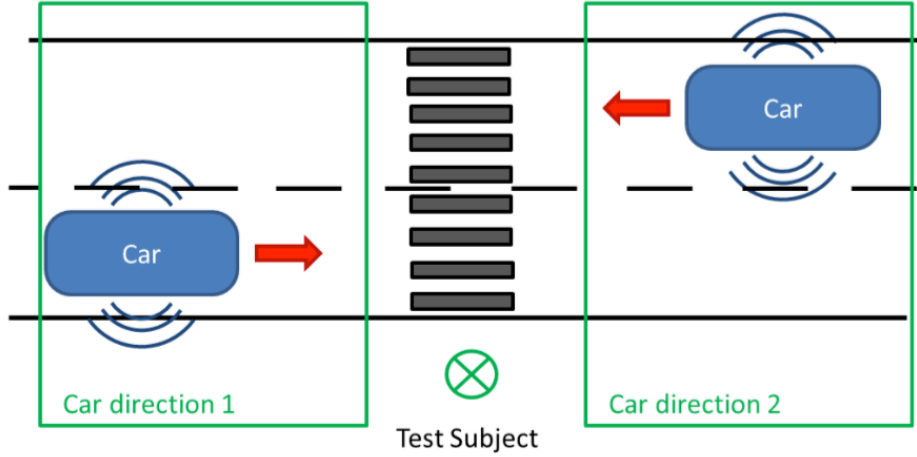


Figure 5: Passing-by scenario for the hearing test: pedestrian located on the sidewalk of a street

To obtain a pseudo-realistic passing-by scenario, the following properties have been implemented:

- The sound level of the EV is modulated according to the vehicle/listener distance. The model used, based on acoustic theory, considers the EV as a monopole and provides a sound level inversely proportional to the distance to the listener ( $1/r$ ) (see Figure 6) (Misdariis et al., 2013), (Lee et al., 2017),
- The speed of the EV is 25km/h, and accelerate to 30km/h in the approach phase
- The duration of the sound stimuli is 15 seconds,
- The Doppler effect (shifting in frequency due to the speed of the source) is taken into account for a more realistic experience,
- The direction of the car (from the right or from the left) is randomly chosen,
- The panning of the EV sound is managed in such a way that the source goes progressively from one canal (left or right, depending of the direction of the EV) to the other (right or left) according to the position of the vehicle

Figure 6 describes the assembly of the background and the EV sounds and their respective sound level evolution.

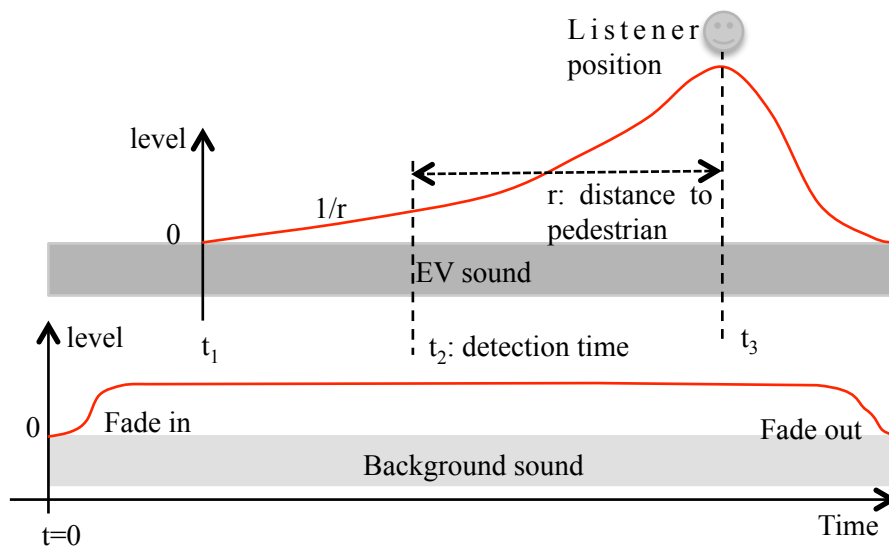


Figure 6: Timeline of the assembly of the background and the EV sound, with their respective level evolution

We can mention that for experimental reasons related to the test duration, the attenuation function of the EV sound is asymmetrical, as in (Misdariis et al., 2013) (the attenuation is more fast than the increase of the sound level). Of course this aspect does not affect the detectability of the EV sound, which always occurs in the approach phase.

### 3.2.3 Experiment

The objective of the experiment is to assess the detectability and the unpleasantness of EV sounds.

15 participants (12 males), with no reported auditory deficiencies, performed the experiments. The audio stimuli were presented with the same hardware desktop configuration, sound card and software, as well as *Beyerdynamics DT-990* headphones in a quiet environment. The same sound output level was set by the experimenter for all computers. Instructions were given to the participants at the beginning of the experiment, mainly to explain how to assess the detection time.

After selecting a sound (“select” button Figure 7), participants had to strike the “space bar” to start playing the stimuli ( $t = 0$ ), and next strike the “a” key as soon as they detect the EV coming from the left, or the “e” key if it is coming from the right. This allows the definition of the detection time  $t_2$  (see Figure 6). The detection duration  $D_d$  is then given by (equation 2).

$$D_d = t_2 - t_1 \quad (2)$$

In case the participant did not strike any key, or strike a key before  $t_1$  (starting time of the EV), the detection duration was arbitrarily set to the maximum value, and a warning was recorded. In case the participant struck the wrong key (mistake in the direction of the EV), the detection duration was still computed, but a warning was recorded. The change in the direction of the car in the protocol is very important to be able to detect “false alarm” cases, where the participants strike the key before detecting the car. Furthermore, to avoid habituation of the participant in the detection time, the starting time  $t_1$  of the EV sound in the mixture (Figure 6) was not always the same, and was randomly chosen in the interval  $[1, 3]$  seconds.

After assessing the detectability of the sound, participants were asked to rate the unpleasantness  $Un_s$  of the sound on a structured semantic scale (Figure 7 – from “0”: not at all unpleasant to “10”: very unpleasant)). To explain this semantic dimension unpleasantness, the following information was given to the participants « If the car passed by your house during a calm moment, how unpleasant would the sound be? ». They were able to play again the stimuli, but of course it was not possible to assess again the detectability (given that they already heard the sound and knew the direction of the car).

Figure 7: Interface for the assessment of the detectability and the unpleasantness of a sound stimulus (structured rating scale).

### 3.2.4 IGA test

The assessment of the EV sound according to detectability and unpleasantness has been included in an IGA iterative experiment. The problem of IGA tests is to manage a good balance between convergence properties and fatigue of the participant. After different tests, we considered that the assessment of 11 populations of 9 sounds was enough to not fatigue the participant. This corresponds

to a test duration of around 35mn. An automatic process was implemented to tune the different parameters of our IGA (Poirson et al., 2010). The optimal tuning parameters of the IGA are as follows:

- Wheelrate:  $w_r = 14$
- Crossrate:  $c_r = 0.65$
- Mutation rate:  $m_r = 0.3$
- Selection rate  $s_r = 0.05$

The fitness of the individuals was computed from the detectability and unpleasantness assessments (equation 3). The following form was defined, according to the detection duration  $D_d$  and the unpleasantness rating score  $Un_s$ :

$$fitness = a \left( 1 - \frac{D_d}{t_3 - t_1} \right) + \frac{1}{2} (10 - Un_s) \quad (3)$$

The higher the *unpleasantness*, and the higher the *detection duration*, the lower the *fitness*. The parameter  $a$  represents the relative contribution of the detection time to the fitness. After several tests, it was set to  $a = 5$  to give a similar importance to detectability and unpleasantness given the variance in the population. At the end of the IGA test, the individual (EV sound) with the highest fitness  $IGA_{opt}$  in the last population can be defined for each participant.

### 3.2.5 Assessment of sounds proposals

At the end of the IGA test, participants were asked to assess the detectability and unpleasantness of six different EV sound proposals (interface given in Figure 7). Four EV Sounds (*rand1, rand2, rand3, rand4*) were randomly defined in the experimental space, whereas two EV sounds (*Sound1, Sound2*) were designed by a sound designer with instructions for good detectability and good acceptance. In total, each participant had to assess 105 sound stimuli (11\*9 for the IGA + 6 design proposals). For each participant, the *detection time*, *unpleasantness*, *fitness* of his/her best individual  $IGA_{opt}$  was next compared to those of the different sound proposals. In addition to this, the *detection time* was converted into the *distance to pedestrian*, i.e. the distance of the EV to the participant at the instant of detection.

## 3.3 Results

Concerning the detection of the car direction, one participant made more than 50% of errors in the detection direction (problem with the headphone). He was withdrawn of the panel. The other 14 participants made very few errors (less than 5 errors for the 105 stimuli), errors only in the direction of the car due to careless mistakes (strike of the wrong key). Their data were considered as valid.

### 3.3.1 IGA convergence

The average fitness of the population according to the generations for the whole panel of participants is presented in Figure 8.

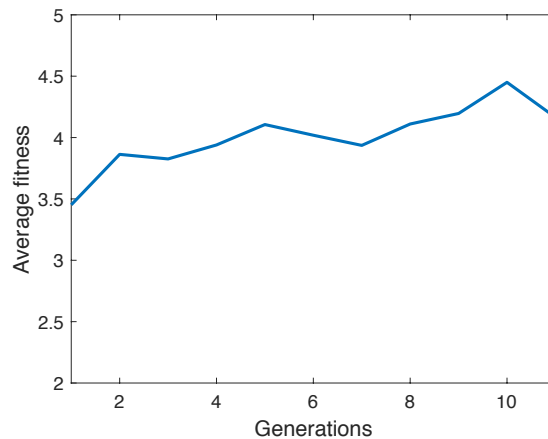


Figure 8: Average fitness of the populations over the generations

An improvement of the fitness is noticed over the generations, sign of the reliability of the experimental protocol for the assessment of the detection time and the unpleasantness, and a correct tuning of the IGA parameters.

### 3.3.2 Analysis of the best IGA sounds

Table 2 shows the occurrences of each level of the variables in the set of  $IGA_{opt}$  sounds. For example, for the fundamental frequency of the motor sound (**C1**), 6 participants chose the level 3 (130Hz), 3 the level 2 (100Hz) or level 4 (160 Hz), and 2 the level 1 (70Hz) for their final sound. To define the variables subjected to the most consensual choice concerning their levels, a multinomial goodness of fit test of the distribution of the occurrences was carried out. Results are presented in Table 2.

Table 2: Occurrences of the levels of the variables in the IGA final choices of the participants (IGA test)

	C1	C2	C3	C4	Amp	Filter
Level 1	2	2	3	5	8	1
Level 2	3	4	4	4	0	4
Level 3	6	3	3	2	3	3
Level 4	3	5	4	2	2	5
Multinomial test Signif.	N.S.	N.S.	N.S.	N.S.	***	N.S.
	***: $p < 0.01$ N.S.: not significant					

Only one variable (**Amp**) obtains occurrences significantly different from a random distribution at the 1% level. For the amplitude of the components of the sounds, the level 1 (strong presence of the thermic motor sound) is by far the most represented. This over-representation could be explained by the “naturalness” of the thermic motor sound in the street, and the habit of people to be surrounded by such noises.

In conclusion, for the whole group, the presence of the thermic motor sound is important for the detectability and the acceptance of the EV sounds. For the other variables (**C1**, **C2**, **C3**, **C4**, **Filter**), there was no significant consensus, mainly because of the small size of the panel of participants. Additional studies are needed to identify the sound that better fits in average the requirement of all participants.

### 3.3.3 Comparison IGA sounds/design proposals

Figure 9 presents, for the panel of 14 participants, the average performances of the sounds proposals and of the best sound  $IGA_{opt}$  according to the two criteria *detection time* and *unpleasantness*. The standard error is also reported for information.

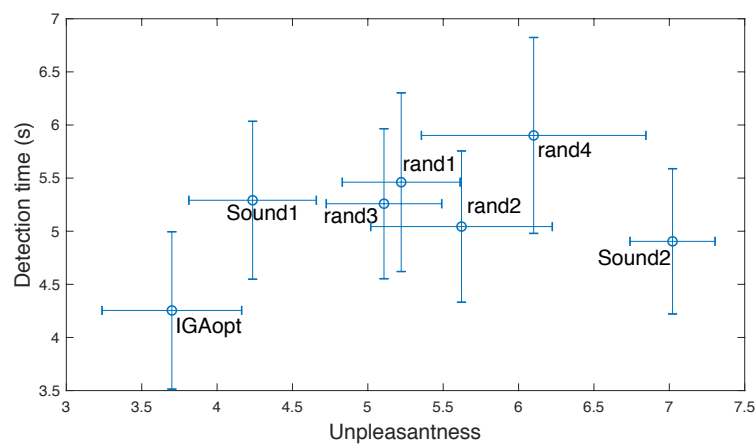


Figure 9: Scatterplot of the average performances of the different EV sounds (detection time vs. unpleasantness) with their standard error.

It is clear on Figure 9 that the  $IGA_{opt}$  sound is Pareto efficient (it dominates all the other proposals, with the lowest detection time and the lowest unpleasantness). In average, the  $IGA_{opt}$  sound obtains the best performances both for *detectability* and *unpleasantness*. The first proposal of the sound designer, *Sound1*, is still not unpleasant, but less detectable than  $IGA_{opt}$ . The second proposal, *Sound2*, is more detectable, but the price to pay is the unpleasantness, that is the largest. The randomly generated sounds (*rand1* to *rand4*) obtain average performances: they are rather unpleasant, and with large detection times.

To investigate the differences in the performances of the sounds, the average scores with their standard errors are presented in Figure 10 left (*Detection time*), Figure 10 right (*distance to pedestrian*), Figure 11 left (*Unpleasantness*), and Figure 11 right (*Fitness*). To study the differences in the average score, a Duncan multiple comparisons test is carried out for every pair of sounds (significant threshold:  $p = 0.05$ ). The results are presented with bold lines connecting the sounds in the figures. When sounds are connected, pairs are not significantly different, whereas they are when not connected.

According to *detection time*, there is no significant difference between two groups of sounds (Figure 10 left): (*rand2*, *Sound2*,  $IGA_{opt}$ ) and (*rand4*, *rand1*, *Sound1*, *rand3*, *rand2*, *Sound2*). With *detection time* only, the  $IGA_{opt}$  sound does not outrank two other proposals, particularly the sound designer proposal *Sound2*. Concerning the *distance to pedestrian*, Figure 10 (right) shows that some proposals (*rand4*, *rand1*) may be dangerous because detected under the stopping distance of the vehicle (considered as 11m at 30km/h). These sounds do not allow the EV (and the pedestrian!) to stay in a safety zone with regard to a blind detectability.

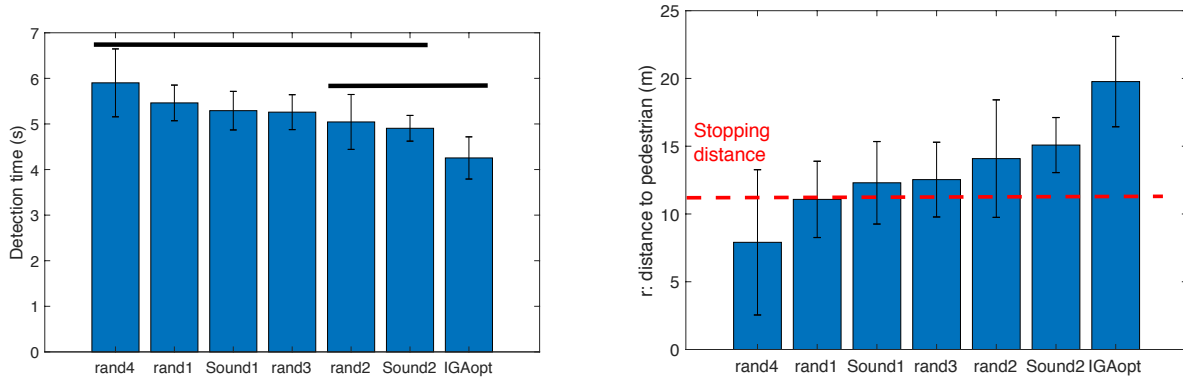


Figure 10: Bar graph of the average value of the *Detection time* (left) and *distance to pedestrian* (right) for the different EV sounds. Non significant differences between pairs of sounds ( $p > .05$ ) are linked with an horizontal line (Duncan multiple comparison test).

According to *Unpleasantness* (Figure 11 left), there is no significant difference between three groups of sounds. Again the  $IGA_{opt}$  sound does not outrank all the proposals, particularly the sound designer proposal *Sound1*. When global fitness is considered (Figure 11 right),  $IGA_{opt}$  is then significantly different of all the other proposals. This result shows that the IGA allows a conjoint optimization of the two conflicting criteria.

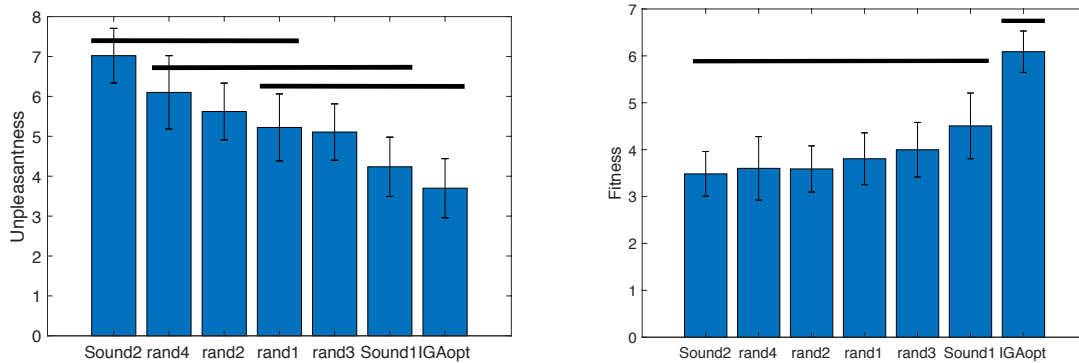


Figure 11: Bar graph of the average value of the Unpleasantness (left) and Fitness (right) for the different EV sounds. Non significant differences between pairs of sounds ( $p > .05$ ) are linked with an horizontal line (Duncan multiple comparison test).

These results are average results for the whole panel. At the individual level, the IGA sounds got the best fitness for 7 participants out of 14. The IGA procedure is interesting to define convenient EV sounds, optimized for unpleasantness and detectability. It allows ones to uncover tradeoffs between detectability and unpleasantness.

We are of course aware that a larger panel of participants should be necessary to support the conclusions in a real design project. It should also be interesting to confirm the generalizability of the results, by defining evaluations protocols in various environmental situations.

In our experiment, the same experimental protocol is used for the optimization and for the evaluation, what could constitute a limitation. Validation tests in a real environment should be necessary to prove with an independent experiment that the IGA process is efficient to design EV sounds. This will be conducted in future experiments. The positive results are nevertheless encouraging given the small number of studies on the interactive optimization of sounds.

## 4 CONCLUSION

This chapter presented how Interactive Genetic Algorithm can be implemented to design EV sounds that are detectable but not unpleasant. The results show an optimization of the fitness of synthesized sounds, from perceptual assessments of participants.

The designed experimental protocol provided a realistic assessment of the detection time. With hearing tests, and inclusions of the EV sounds in a background sound, assessments of the *detection time* and the *unpleasantness* of the sounds were provided. The results show the potential of the method: the IGA algorithm is effective for the design of efficient sounds. Comparisons between sound proposals showed that in average, the sound provided by the IGA was significantly more efficient. The IGA method can be considered as a valuable alternative to help the design of sounds, or to select particular acoustic attributes in a pilot study.

Several perspectives can be drawn for this project. Other perceptual dimensions should be included in the objectives of the project, for example aesthetical or emotional dimensions. A next stage of the project will be to explain the performances in detectability and unpleasantness with sound parameters (spectral or spectro-temporal). This will be important to be able to draw solid recommendations to a sound designer and to improve the design of sounds for EVs.

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