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A Multidimensional Technique for Sound Quality Assessment

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Summary
One approach to improving sound quality is to create a preference map on the basis of several acoustic parameters relevant to auditory perception. The map is derived from several stages of subjective testing, acoustic analysis, and auditory modeling. The multidimensional scaling technique CLASCAL reveals common perceptual dimensions shared by sets of sounds samples, perceptual features specific to each sound, and the different subject classes among listeners. The listeners are asked to judge the degree of dissimilarity of all pairs of sounds on a continuous scale. The analysis gives a perceptual spatial representation of the sounds. From this analysis, acoustic and auditory modelling analyses can be performed to determine the stimulus parameters that are strongly correlated with different perceptual dimensions and, where possible, with the specific features. The next stage in the analysis involves determining the probability of one sound being preferred to another. An analysis of the data allows a projection of the structure of listeners' preferences onto the physical parameter space underlying the previously determined multidimensional perceptual space. In many cases, it is found that the physical parameters having the most effect on the listeners' preferences are dependent on the set of stimuli being compared. Furthermore, when one stimulus parameter is kept constant across trials, this may alter the effects of other parameters on the listeners' preferences. Therefore context effects must be taken into account in multidimensional sound quality analysis, particularly since the qualitative aspects of most sounds are clearly multidimensional.

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1. Introduction

Noises emitted by domestic sound objects (e.g., light switches, vacuum cleaners, and coffee machines) or equipment (e.g., car motors, air conditioners, and windshield wipers) are sources whose intrinsic perceptual and acoustic properties can be characterized and evaluated by classical methods of experimental assessment [1, 2] and measurement [3]. Concerning the characterization of the quality or annoyance associated with a sound object, it is important to define the appropriate techniques in order to allow designers to define the acoustic properties of a product based on perceptual data derived from human listeners. In addition, certain acoustic aspects contribute in a significant way to the auditory image projected by the object that produces them and are important for emphasizing its identity, ergonomics, esthetics, and functionality.

The problem is that the sounds are complex and thus have a multidimensional nature from both acoustical and perceptual points of view. Further, not all of the possible dimensions have been characterized psychophysically. It is thus necessary at this stage in the development of sound quality research to determine the number of salient perceptual dimensions for a corpus of sounds associated with a given type of object, as well as their auditory and physical nature, in order to characterize the sonic identity of the object type under study. Subsequently, it is necessary to determine in a similar way the multidimensional nature of the quality or annoyance created by a sound source and thus to determine the combined or independent contributions of the salient perceptual dimensions. However, the large majority of studies of sound quality often adopt the method of magnitude estimation [4] or the method of predefined semantic differentials [5]. In the former case, the human listener must give a numerical value that is proportional to unpleasantness, for example, and the data analysis yields a unidimensional unpleasantness scale. This scale cannot be used to deduce the contribution of different auditory attributes and acoustic parameters to the position of each judged sound source on the scale. In the latter case, the listener evaluates the sounds on different continuous scales, the extremities of which are defined by opposing adjectives: bright/dull, loud/soft, agreeable/disagreeable, etc. Each scale thus defined allows a measurement of the predefined auditory (semantic) attributes without specifying their perceptual salience. These methods thus have limits in their ability to characterize the quality of sound objects, particularly when the salient perceptual, acoustic, and semantic properties of the objects are not known in advance.

Research in the cognitive psychology of audition reveals the interest of multidimensional analysis methods in order to characterize perceptually the dimensions of the timbre of musical instruments [6, 7]. Recently at IRCAM [8], a three-dimensional perceptual space was obtained using the multidimensional scaling program CLASCAL [9]. A quantitative correlation was established between acoustic parameters and the coordinates of the instrument sounds in the perceptual space, one dimension having a spectral nature, another a temporal nature, and the last a spectrotemporal nature [10].

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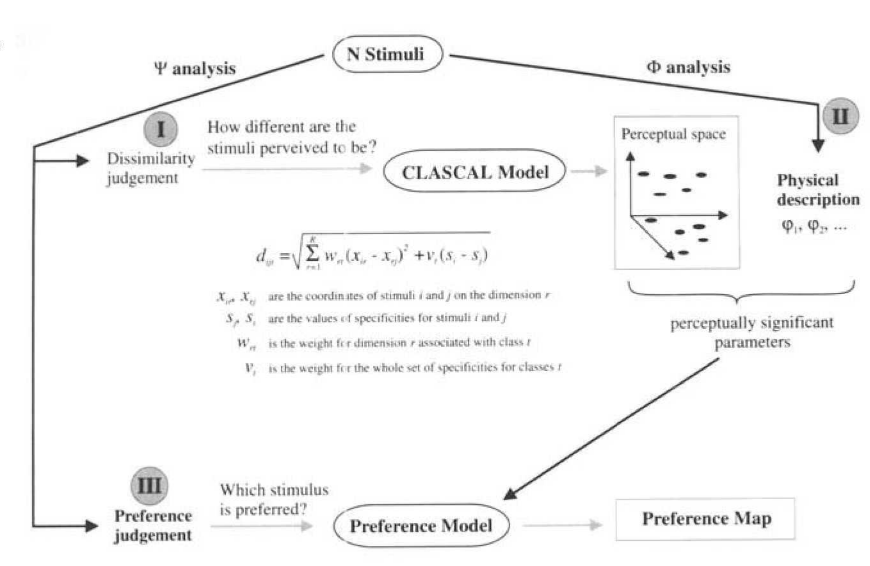

Figure 1. Global schema of the subjective characterization approach, involving multidimensional scaling of dissimilarity judgements (I), acoustic analyses and correlations with the perceptual space (II), and construction of a multidimensional preference map (III).

This approach is valid for other types of sound objects. This article proposes a general method for characterizing sound quality on the basis of objective criteria. The different stages of the method as well as the precautions to be taken in using it will be discussed below, with a study performed on interior car sounds being used as an example [11, 12]. This study was performed at IRCAM in collaboration with the automobile manufacturers Renault and PSA Citroën and falls under the framework of a contractual agreement. Due to confidentiality constraints, the description will remain formal without explicitly describing the results obtained (identity of sound sources and exact nature of acoustic parameters). This constraint does not, however, affect the main aim of the article, which is the presentation of the experimental methods and data analysis techniques employed to explore sound quality in all its natural sonic complexity.

A global view of the method showing the relations among the different stages is presented in Figure 1. At the outset, the sound corpus must be defined and the sounds carefully selected in order to obtain a relatively homogeneous corpus (section 2). As a function of the class of sound object(s) being studied the panel of listeners must be selected according to appropriate criteria (section 3). Globally, a first step consists in determining the perceptual attributes common to the panel of listeners that are used to compare sounds to one another (section 4). A multidimensional scaling analysis (CLASCAL) yields a spatial model that can be represented graphically and which reveals the perceptual structure underlying the listeners' judgments in terms of continuous dimensions shared by all the sound samples and specific features (specificities) of each sound. The CLASCAL output also allows an analysis of different judgment strategies used by listeners, corresponding to their grouping into latent classes. A subsequent acoustic analysis phase attempts to determine the acoustic and psychoacoustic parameters of the sound signals that are correlated with the positions of the samples along the perceptual dimensions (section 5). In the last stage, the degree of preference (or, inversely, annoyance) associated with each sound is evaluated as a function of the perceptually significant acoustic parameters revealed in the previous stage (section 6). The advantage of this approach is that it does not limit the exploration and characterization of the components of sound quality to parameters that are already known. It provides a method for finding new perceptually salient parameters that engineers had not imagined, but that listeners hear and use in their evaluations anyway.

2. Establishment of the Sound Corpus

In order to ensure a realistic restitution of the sound field in the experimental situation that is as close as possible to the original conditions, it is necessary to use binaural techniques [13]. The car sounds used in the study were recorded digitally by the automobile manufacturers with a dummy-head system seated in each car in the front passenger seat with the car running on a test track. The sounds were reproduced in the experiments by IRCAMs ISPW real-time digital signal processing environment [14], using the MAX application on the NeXT workstation. All sounds were edited to 5 s in duration with 50 ms attack and decay ramps, taking care to avoid sounds with recording artifacts. The three important points for sound restitution are the following:

- the specifications of the binaural recording conditions,
- the inverse filtering that compensates for the effects of the transfer function of the sound acquisition and presentation systems, and
- the calibration of the sound level for headphone presentation.

An alternative to dummy-head recordings may also be used and is often sufficient, if not as realistic: simple stereo microphone recordings. A recent study [15] on urban sound environments has shown that a stereo record-

Table I. Composition of four groups of car sounds used.

	Motor speed 1	Motor speed 2
Loudness variable	Group 1	Group 2
Loudness equalized	Group 3	Group 4

ing with cardioid microphones spaced 60 cm apart with a 100° opening conserves the ecologically valid character of sound samples played back over loudspeakers. Certain acoustic characteristics perceptually dominate and overpower other, less salient ones. This is often the case with loudness, for example. Two sounds that differ mainly in terms of loudness will be judged different according to this dimension, with little contribution from other dimensions of variation being taken into account. In order to eliminate overly obvious parameters, it is sometimes necessary to equalize a corpus of sounds along these parameters, such as loudness, duration, and pitch. However, in order to study the influence of loudness, pitch, and broadband noise level (the latter two being related here to motor speed and car speed) on the perceptual representation, four groups of 16 car sounds were used. The cars were the same for each group. Two combinations of motor speed and gear setting were employed. In the first part of the study, the loudness was not modified and the sounds were presented as they would have been perceived in the car interior. In the second part, the loudness of the sound samples was equalized over each of the two sound sets. The composition of the four groups is summarized in Table I.

An initial listening to the sound samples is important to discern salient perceptual properties that might influence the judgments of subjects in the main experiments. In fact, it is necessary to avoid characteristics that are too recognizable in certain samples, due either to their strong identity or to recording artifacts. The set of cars tested corresponded to the same price range. There was no risk that individual cars would be recognized. It is possible to determine more precisely the structure of the corpus used by classing the sounds according to different predefined dominant criteria. A cluster analysis [15] can reveal the degree of homogeneity of the sound corpus. If the tree structure obtained reveals a strong categorization of the corpus, it is advisable to determine which categories best represent the objectives of the study in order to obtain appropriate stimuli.

3. Subject Selection

According to the type of study, it is generally advisable not to use subjects having too great a knowledge of the test product that could induce biases in their judgments. A car mechanic, for example, would listen in a different, much more analytical way than an average listener (one might speak of professional "deformation"). In the present study, subjects aged 25 to 45 years were recruited from a list of volunteers such that an equal repartition of sex and age category were obtained. 30 subjects were recruited for both the dissimilarity (section 4) and preference (section 6) studies and an additional 30 were recruited for the preference study. The subjects were required to have a driving permit and a car of the appropriate price range had to be owned by someone in their immediate family. They were reimbursed for their participation.

4. Dissimilarity Scaling: The CLASCAL Program

4.1. Apparatus

The digitized sounds were processed by inverse filtering on a NeXT computer equipped with an ISPW card and the MAX program. They were subsequently converted to analog signals with ProPort converters before being amplified through a Canford stereo amplifier and sent to AKG 1000 open-air headphones. The experiment was run in the PsiExp computer environment [16] which provides stimulus presentation, data acquisition, and graphic interface for the subject.

4.2. Procedure

The experiment was performed in four sessions with one session for each gear setting/motor speed combination, with and without loudness equalization. All 120 different pairs between the 16 car sounds were presented in each session. At the beginning of the session, the subject listened to all the samples in a random order to get a sense of the range of variation possible. Next, 15 training trials were presented to give the subject the possibility to become familiar with the rating task. On each trial a pair of sounds was presented, separated by a 1-s silence. The subject saw a horizontal slider on the computer screen with a cursor that could be moved with the computer mouse. The scale was labelled "Very Similar" at the left end and "Very Dissimilar" at the right end. A judgment was made by moving the cursor to the desired position on the slider and clicking on a button to record it in the computer. The initial position of the cursor was random on each trial and the subject had to move it at least once before entering the judgment. Once the judgment was entered the program proceeded automatically to the next trial. The judgments were coded on a scale from 0 (very similar) to 1 (very dissimilar), for example. The scale could equally well vary from 0 to any positive number.

4.3. Multidimensional scaling analysis with CLASCAL

The data used in a multidimensional scaling (MDS) analysis consist of judgments of dissimilarity between each pair of the stimuli under consideration, i.e. $N(N-1)/2$ judgments for N stimuli from each subject. The dissimilarities are modelled as distances in an extended Euclidean space of R dimensions. In the spatial representation of the N stimuli a large dissimilarity is represented by a large distance. The CLASCAL model for the distance between

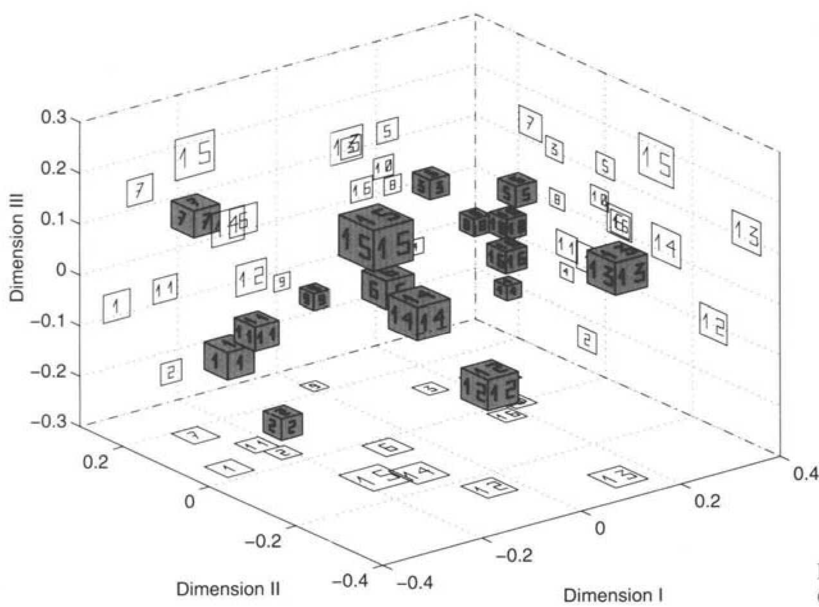

Figure 2. Perceptual space of the stimuli from Group 3 derived from dissimilarity scaling.

stimulus i and stimulus j developed by Winsberg and De Soete [9, 17] and presented in Figure 1, postulates common dimensions shared by all stimuli, specific attributes or specificities particular to each stimulus, and latent classes each of which have different saliences or weights for each of the common dimensions and the set of specificities. Maximum likelihood estimates of the model parameters are determined (that is the coordinates of each stimulus on each dimension of the common space, the specifities of the stimuli, the dimension weights for each class, and the proportion of subjects in each class). An EM (expectation-maximization) algorithm is used to determine the class structure. (See [9] for a complete description of the CLASCAL algorithm and the latent class approch to MDS. Space does not permit an adequate description here.) The class structure is latent; there is no apriori assumption concerning the latent class to which a given subject belongs. Model selection, including the choice of the appropriate number of latent classes, the number of common dimensions, and the presence or absence of specificities, is based on the BIC statistic which is information based and depends on the log likelihood, the number of model parameters, and the number of observations [18], as well as on a Monte Carlo procedure [19]. Models with the lowest BIC values are chosen. The Monte Carlo procedure is used to determine the appropriate number of latent classes and to verify the spatial model. (See [9] for a discussion on model selection.) The CLASCAL analyses yield a spatial representation of the N stimuli on the R dimensions, the specificity of each stimulus, the probability that each subject belongs to each latent class (generally equal to one for one of the classes) and the weights or saliences of each perceptual dimension for each class. Also included in the output results are the model variance, the log likelihood, the value of the BIC statistic, and the results of the Monte Carlo procedure if used.

4.4. Results

A single class was sufficient for all data sets. An analysis with the number of dimensions varying between 1 and 6 without specificities and between 1 and 5 with specificities was then performed for a single subject class. BIC indicated that the best model was three-dimensional with specificities for Group 3 and two-dimensional with specificities for the other groups. A graphic representation of the data corresponding to the sounds of Group 3 is given in Figure 2. Each sample is represented in the three-dimensional common space. The specifities of the stimuli are not shown in the figure.

5. Physical Parameters Underlying the Perceptual Space

5.1. Acoustic analysis

Once the perceptual configuration is obtained, it is important to give a physical interpretation. An interpretation means some systematic relationship between the stimulus characteristics and the locations in the space.

An appropriate spectral representation for the signal analyses is chosen. Since the car sounds studied (constant motor speed) had a quasi-stationary character, the method of Welch [20] was used. In order to take into account auditory response as a function of level and frequency, the analytic formulations of different classic weighting functions were used (dBA, dBB, dBC). A physiological modeling approach was also used in which the operation of the peripheral auditory system was considered at two levels: the filtering due to the external and middle ears was modeled with a second-order Butterworth bandpass filter with −3-dB cutoff frequencies of 450 Hz and 8500 Hz [21]. As for the cochlea, Moore and Glasberg's [22] ERB (equivalent

Table II. Correlation coefficients between perceptual coordinates and "objective" parameters. The probability p that the two measures are independent is indicated for $p < 0.01$ (*) and for $p < 0.05$ (†). Parameter φ_1 = Loudness.

	Group 1		Group 2		
Parameter	Dim. 1	Dim. 2	Dim. 1	Dim. 2	
φ_1	-0.92*	-0.06	-0.91*	0.28	
φ_2	0.09	0.80*	–	–	
φ_3	–	–	0.43	-0.88*	

	Group 3			Group 4	
Parameter	Dim. 1	Dim. 2	Dim. 3	Dim. 1	Dim. 2
φ_2	0.35	-0.7*	-0.14	-0.93*	-0.29
φ_3	–	–	–	-0.51†	0.86*
φ_4	-0.81*	0.32	-0.33	–	–
φ_5	-0.32	0.00	-0.83*	–	–

rectangular bandwidth) formula was adopted for auditory filter bandwidths and Patterson *et al.*'s [23] gammatone filters were used. On the bases of these early analysis stages, a set of parameters derived from the psychoacoustic literature [24] and from studies on timbre [10] were calculated. These parameters were chosen by way of an empirical loop that consisted of listening to the sounds with respect to their relative positions in the multidimensional space in order to isolate the kind of variation that characterized a given dimension. Next, hypotheses on the new physical or psychoacoustic indices that were appropriate for the stimuli under study were made, and the analyses were performed to extract the quantitative values. Finally, the correlation of each parameter with the coordinates of the sound samples along the perceptual dimensions was evaluated. A good correlation is taken as an indication that the parameter is a strong candidate for a quantitative predictor of the perceptual dimension.

5.2. Correlations

In Table II are presented the correlation coefficients between the perceptual dimensions and the physical or psychoacoustic parameters for each sample group. The probability (p) that the perceptual coordinates and the parameters values are independent (or unrelated) is given as well. The variance in the perceptual dimension "explained" by the predictor parameter can be determined by taking the square of the correlation coefficient. Finally, for each of the dimensions, a quantitative descriptor was determined. It is important to note that in equalizing loudness over the set of samples (Groups 3 and 4), other dimensions emerged that correlated with parameters not revealed in the analysis of Groups 1 and 2 with loudness variation. This kind of context effect is particularly important to emphasize since it demonstrates that the salient perceptual parameters one obtains in such a study depend very strongly on the kinds of physical variation present in the stimulus set. The preference analysis to be examined in the next section will determine the utility for preference of each of the predictor parameters. Those that have a strong weight can thus in turn be equalized over the sound set in a subsequent stage of experimentation. As such, this approach allows a progressive minimization of perceived differences in terms of preference or unpleasantness between the stimuli.

6. Preference Analysis: A Thurstone Case V Preference Model with Spline Transformations

6.1. Procedure

At the beginning of the session, the subject listened to all the samples in a random order to get a sense of the range of variation possible. Then, all pairs of different samples were presented in a random order. On each trial the subject heard a pair of samples only once and had to choose which sound was preferred. The data consist of the proportion of subjects that preferred one sample over another for each of the N stimuli.

6.2. Stages in the preference analysis

This phase of the study attempts to construct a preference map. De Soete and Winsberg [25] developed a Thurstonian pairwise choice model with univariate and multivariate spline transformations. In their preference model the probability that stimulus i is prefered over stimulus j is defined as a function of the difference in "utility" of each stimulus or sample. The preference analysis program developed by De Soete and Winsberg is presently limited to two dimensions, generally considered as adequate to describe a preference space (as is the case with Groups 1, 2, and 4). If three perceptual dimensions are recovered in an MDS analysis (as with Group 3), all pairs of candidates may be tested. The model seeks a function that transforms the values of the physical parameters a_i and b_i, for stimulus i with a utility value, u_i, that depends on the preference probability. The dependence is expressed as follows,

$$p_{ij} = \Phi(u_i - u_j), \tag{1}$$

where p_{ij} is the probability of preferring sample i over sample j, Φ is the cumulative normal (Gaussian) function, and u_i is the utility of sample i.

The greater and more positive the difference in utility between the two samples is, the more sample i will be preferred over sample j.

Two types of models were tested: additive and multivariate. In the additive model (2), it is assumed that the contributions of the two parameters are independent and that the global utility of a sample is the sum of the utilities of each parameter. Thus, u is a function of the predictor parameters (a and b), each having its own transform function (f and g, respectively):

$$u_i = f(a_i) + g(b_i). \tag{2}$$

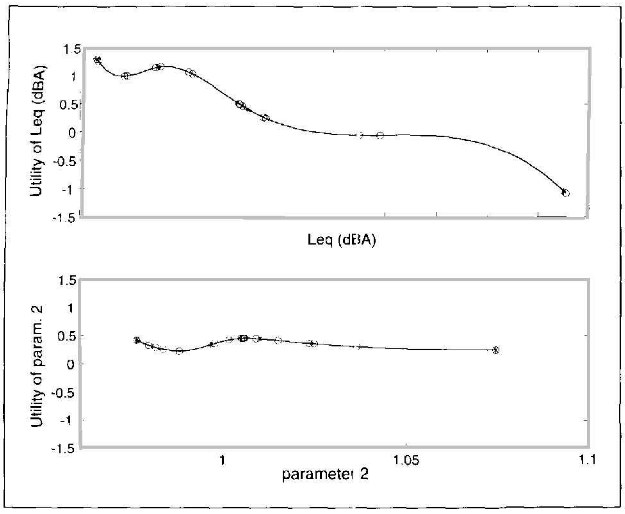

Figure 3. Evolution of the utility of Leq (dBA) and parameter 2 from the stimuli of group 2. The circles (o) correspond to the stimuli and the asterics (*) correspond to the placement of the internal knots of the spline.

The functions f and g are splines; that is, piecewise polynomial functions, the number and order of each polynomial being variable. The order of the spline is taken to be equal to the maximum degree of the polynomial plus one. The junctions between the polynomials of a given spline correspond to the "internal knots" and are of finite number. Attention is restricted to splines with maximal continuity at each knot. That is, for a spline of order k, the function and its $k-2$ derivatives are continuous. The default knot positions are located at a ladder of quantiles, thus an equal number of observations is used to determine each spline parameter. Each spline of a given degree can be represented as a linear combination of a set of basis functions.

In the multivariate model (3), the utility is a function of both parameters:

$$u = f(a, b). \tag{3}$$

This multivariate function is represented by a multivariate spline, that can be defined as a linear combination of tensor products of univariate basis splines. In this model therefore, the effect of one parameter on utility depends on the value of the other parameter.

For a preference matrix and a given set of predictor parameters, a large number of models may be tested by varying the type of model (additive or multivariate) and the order and number of internal knots of the splines. BIC is used to chose between the candidate models. For a given preference matrix, this criterion can also be used to choose from among various pairs of predictor parameters that had more or less similar correlations with the perceptual space. This latter choice is of a heuristic nature, since the correlations with the different perceptual dimensions are also taken into account. In general, the best model is chosen for each set of parameters and the resulting utility functions are examined in order to compare the different sets of parameters in terms of their interpretability. The analyses yield the preference function for each dimension for an additive model, and the preference surface for a multivariate model.

As an example, the utility functions for acoustic level and another parameter (parameter 2) are shown in Figure 3 in which the additive model was retained. Not surprisingly, the utility function for level is more or less monotonic: the more the level increases, the more the utility for preference decreases. The variation in utility with the other parameter is nonmontonic, however its overall influence on preference is comparatively small and is completely overpowered by the effect of level variation. For the level-equalized sample sets, the parameters had more equivalent influence on preference and some of these were clearly nonmonotonic, indicating that there are zones in the middle of the range of variation that are maximally or minimally preferred by the panel of listeners.

7. Conclusions

The data analysis reveals representations of the sets of car sounds that have several perceptual dimensions for both combinations of gear setting and motor speed. The loudness equalization allowed the emergence of other factors contributing both to similarity perception and quite notably to preference. When loudness is a factor in the comparison of car sounds, it clearly dominates the preference judgments. The role of the secondary parameters vary with gear setting and motor speed and globally have less importance in these judgments. Generally, the perceptual salience of the dimensions is not the same for the two gear setting/motor speed combinations, indicating that the relative importance of perceptual cues evolves with changes in car functioning and context (equalized loudness or not).

This method, when applied to very different sets of sound objects (musical instruments and car sounds), thus reveals: 1) a multidimensional mental representation of complex sound events, 2) a close relation between the perceptual dimensions and acoustic properties or their auditory transforms, and 3) specific properties of certain sounds that affect their perception and comparison with other sounds. For musical instrument sounds, differences between listeners in the perceptual importance according to the different dimensions and specificities have also been found. While such differences were not found in the studies on car sounds mentioned above, they should be systematically verified in such experiments in case they do exist. The coherence of the results across these different stimulus sets indicates a great stability in the perceptual processes involved in the appreciation of homogeneous sets of sounds. Further, it is important to emphasize that aside from loudness, none of the objective parameters revealed corresponded to those currently included by default in most sound quality measuring devices. A cautionary note on a methodological issue is warranted here however. In another, similar study with a set of environmental sounds that were extremely heterogeneous, a perceptual structure was found that was strongly categorical in nature and which was associated with a high degree of identification of the individual sound sources by the listeners [26]. Judgments of dissimilarity seemed in this case to be based entirely on the categories that the stimuli belonged to and less to their individual acoustic and sensory properties. Thus, this predominant cognitive factor–recognition, classification, and identification of the sound source [12]–rendered inappropriate the conception of the perceptual space in terms of continuous underlying dimensions. The above techniques of preference analysis are not applicable in such cases and other techniques need to be used. However, for homogenous sound sets, the experimental approach described above is a powerful method for understanding the perceptual underpinnings of sound quality.

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