Application of Artificial Neural Networks for Understanding the Quality and Masculinity Perception of Electric Shavers

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Introduction

In this work annoyance and masculinity estimations of electric shaver and trimmer devices are studied. Most of the society, either use the electric shaver devices directly, or be exposed to electric shaver sounds. Different brands with different designs in market are competing with each other to take the advantage. For the advertisement purposes, besides being ethically questionable, gender based approaches are used quite often. Masculinity, for example, takes a great role on shaver marketing. For that reason, it is one of the main keystones of that study, to understand if there is an understandable perception of a sound to be masculine.

Subjective jury testing is the traditional way in sound quality assessments, despite the fact that it is both expensive and time consuming. However, contemporary studies in that field mostly focus on developing new methodologies that can replace, or at least mimic, subjective jury testing, mainly artificial neural networks (ANNs) [1,2]. In this study, artificial neural networks are used as an indexing/forecasting tool for annoyance and masculinity estimations. Advantages and disadvantages of using ANNs for sound quality estimations are examined by conducting sensitivity analyses on different neural network architectures.

Methodology

In this study, listening tests are conducted with the different shaver recordings. At the same time, different psychoacoustical parameters are calculated. Calculated parameters are considered as inputs, meanwhile, estimations obtained from listening tests are regarded as targets for artificial neural network structures. By using the inputs and targets, artificial neural network is trained, such that it is expected to get compatible outputs with results obtained from listening tests. Ultimate aim is to obtain a neural network, as a black-box tool, to mimic subjective decision making process on annoyance and masculinity estimations.

For both studies, annoyance and masculinity, different neural network sets are obtained, and considering the performance of all neural networks, best performing neural network is selected as an indexing/forecasting tool.

Sound Samples

27 different stimuli are used in that study. All of them are real recordings and no synthesized stimuli is used. Recordings are performed binaurally by using Head Acoustics binaural headset BHS II in an anechoic environment. During recordings, SQuadriga frontend of Head Acoustics is used with the Head Recorder software. Shavers are recorded in their no contact, idle running mode. Having the fact that contact with skin surface changes the sound emission characteristics of the equipment, basic consumer selection process is selected as a case study, in which the unit is not in contact with skin and equipment is nearly 20 cm far away from the listener's ear, directly in front of the listener's head. Equipment are connected to the power supply during recording, since different charging conditions might change the rotating speed of the equipment resulting in different sound emissions. Figure 1 and Figure 2 shows example spectrograms used in this study.

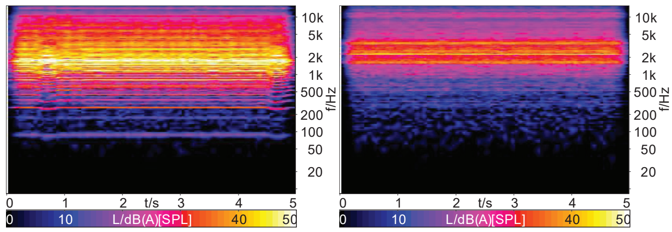

Figure 1: Spectrogram of two sound samples, having the highest (left) and lowest (right) annoyance estimations

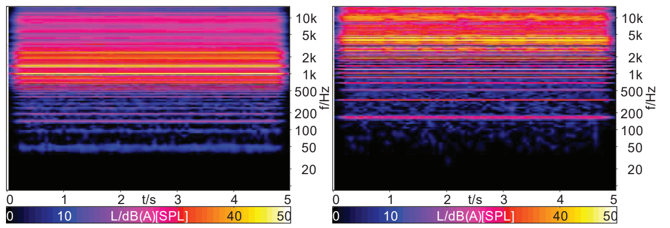

Figure 2: Spectrogram of two sound samples, having the highest (left) and lowest (right) masculinity estimations

Listening Tests

Binaurally recorded sound samples are presented to the 12 participants, 2 women and 10 men aged between 22 and 53, through Sennheiser HD600 headphones. Experiments are conducted in a sound attenuating room. Stimuli are presented in random order and 5 random stimuli are presented before the test as sample stimuli. Every stimuli is presented twice, to check inter-individual validity. The subjects then asked to evaluate the annoyance and masculinity of the sounds on a quasi-continuous scale (from 0 to 100) with equidistance neighboring categories (not at all, slightly, moderately, very, extremely) is used for evaluation of the experiments.

Annoyance and masculinity estimations of 27 stimuli are presented in a box plot in Figure 3 and Figure 4. Results are averaged for each test subject and for each repetition of the stimuli. Median values are shown in red and mean values are the geometric centers of the represented boxes. Upper and lower edge of the boxes are the 25th and 75th percentiles of the population, and extreme data points (outliers) are plotted individually as red plus signs.

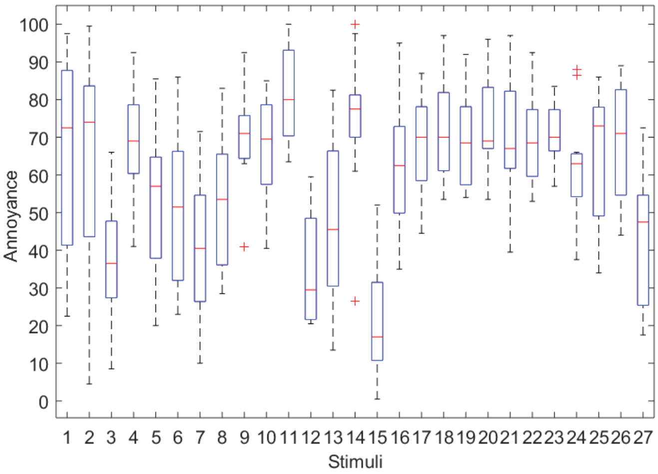

Figure 3: Annoyance ratings of the shaver sounds

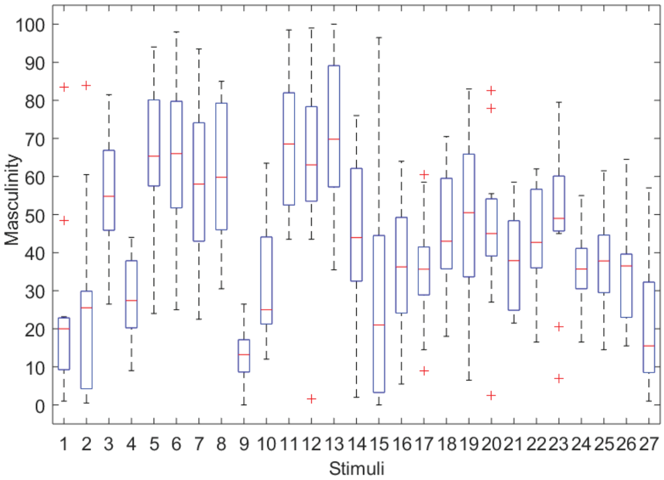

Figure 4: Masculinity ratings of shaver sounds

Correlations

Psychoacoustical metrics are calculated in Head ArtemiS software. For the left and right ear recordings parameters are calculated and mean values are obtained for single value estimations. Considered acoustical variables are loudness, roughness, sharpness and tonality. Loudness calculations are based on DIN45631/A1 standard; sharpness calculations are based on Aures model; roughness calculations are based on Aures model and tonality calculations are based on DIN 45681 standard including 50% overlapping.

In Table 1 and

Table 2, correlation between the annoyance/ masculinity estimations and calculated psychoacoustical parameters are given respectively. Values with two star refers to the correlations with p<0.01 while one star refers to p<0.05.

Table 1: Correlation between psychoacoustical parameters and annoyance

R	Annoyance	Loudness	Roughness	Sharpness	Tonality
Annoyance	1.000	0.808**	0.082	0.661**	0.086
Loudness		1.000	-0.129	0.551**	-0.272
Roughness			1.000	0.098	0.292
Sharpness	sym.			1.000	-0.131
Tonality					1.000

Table 2: Correlation between psychoacoustical parameters and masculinity

R	Masculinity	Loudness	Roughness	Sharpness	Tonality
Masculinity	1.000	-0.237	0.598**	-0.385*	0.370*
Loudness		1.000	-0.129	0.551**	-0.272
Roughness			1.000	0.098	0.292
Sharpness	sym.			1.000	-0.131
Tonality					1.000

Artificial Neural Networks

Artificial neural networks are being used in recent sound quality studies very often [3,4]. The connections between the neurons, called weights, are adjusted from the relation between calculated psychoacoustical parameters and estimations obtained from jury tests; hence adjusted – or trained – neural network can be used as a nonlinear curve fitting tool.

There are different parameters need to be considered for tailoring a neural network architecture. In this study, some of those parameters are kept constant while some of them being parametric. At the end, 30 different neural network are obtained for each estimation and performance of the different neural networks are compared with each other to find the most efficient ANN architecture. Table 3 shows the values that kept parametric during the study, while division of data into training and validation is similar for all cases (70% training, 30% validation and test) and function type within the cells are being kept as sigmoid functions for all cases.

Table 3: Parameters need to be considered for an ANN design

Number of training sets	5 different states
Training function	•Levenberg-Marquardt •Bayesian regularization •Scaled conjugate gradient
Network size – hidden layer size	•5 neurons in hidden layer •10 neurons in hidden layer
Result: 5*3*2 = **30 different neural networks**	

Performance Analyses

In order to compare the performances of different neural network architectures, a performance parameter is needed. For that reason, performance parameter is defined as the mean squared error (MSE) between the calculated outputs from ANN and targets obtained from listening tests. Performance values are calculated for all stimuli for all 30 different neural network structures. In Figure 5 and Figure 6, results obtained from best and worst neural networks in terms of their performances in annoyance and masculinity estimations are given, respectively. It can be observed that, trying to tailor the neural network with highest performance is crucial, since the black lines in both figures follow almost the same path that listening tests indicate, while the results given in red have deviates from the target results highly.

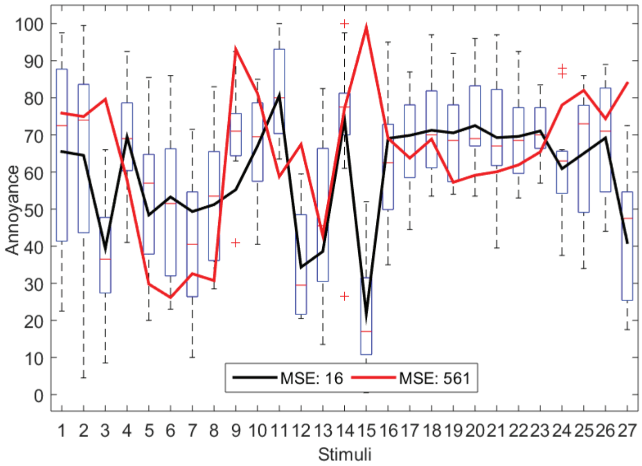

Figure 5: Annoyance estimations versus ANN results, boxplot show the annoyance estimations obtained from listening tests, while the black and red lines shows the neural network results with best and worst performances

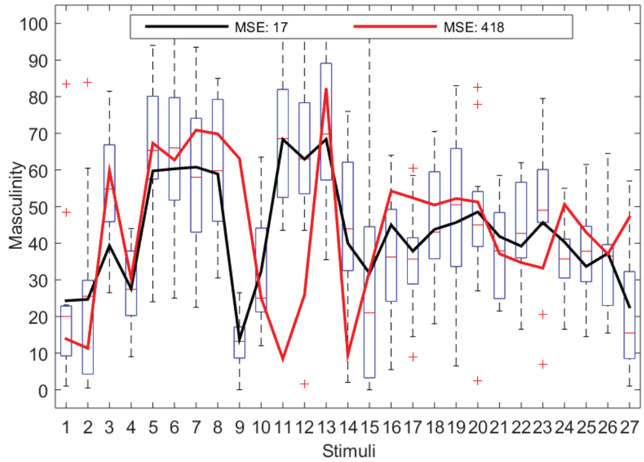

Figure 6: Masculinity estimations versus ANN results, boxplot show the annoyance estimations obtained from listening tests, while the black and red lines shows the neural network results with best and worst performances

Sensitivity Analyses

Using artificial neural networks as an indexing tool, instead of equations including multiple linear regressions or piecewise continuous functions, has also some shortcomings. The biggest problem of using an ANN is, it is not possible to obtain the explicit formulation between the input parameters and output values, which is valuable for a psychoacoustical study. However, a sensitivity analyses can be performed instead, to understand the response of an ANN system for a defined percentage change in input parameters.

For the sensitivity analyses, 16 new inputs are created. Those new inputs are created by decreasing one of the input parameters by 5, 10, 20 and 30 percent while keeping the others constant. For all 4 inputs, 16 new stimuli are created accordingly. Table 4 shows the methodology for creating inputs for sensitivity analyses. It should be noted that, newly created stimuli consist of mathematically defined numbers, even though the physical sense might not be exactly realistic. Numbers given in Table 4 are selected as 100, instead of their exact numbers, in order to make it easier to understand the underlying structure. Figure 7 and Figure 8 shows the results obtained from sensitivity analyses. First stimuli in both figures shows the result from control group, and the rest are the newly generated 16 stimuli.

It is observed that, the behavior of best performing network for annoyance, is coherent with the results obtained from linear correlations, however the results from masculinity network shows different trends. Green ticks and red crosses represents the areas that the resulting trends are coherent with the linear correlations or not, respectively.

In order to understand the reason behind the different responses of linear regression tools and results obtained from ANN, which is a nonlinear curve fitting tool in that case, correlation values of each test subject are investigated in detail. Table 5 and Table 6 shows the correlations between input and output parameters, for annoyance and masculinity estimations, for all subjects. Some of the subjects had to be eliminated because of the high inter-individual differences between repeated stimuli or highly outsider behavior.

Table 4: Inputs used for sensitivity analyses (numbers are representative)

	Loudness	Roughness	Sharpness	Tonality	Annoyance	Masculinity
Control Group:1	100	100	100	100	100	100
2	95	100	100	100	% Change?	
3	90	100	100	100		
4	80	100	100	100		
5	70	100	100	100		
6	100	95	100	100		
7	100	90	100	100		
8	100	80	100	100		
9	100	70	100	100		
10	100	100	95	100		
11	100	100	90	100		
12	100	100	80	100		
13	100	100	70	100		
14	100	100	100	95		
15	100	100	100	90		
16	100	100	100	80		
17	100	100	100	70		

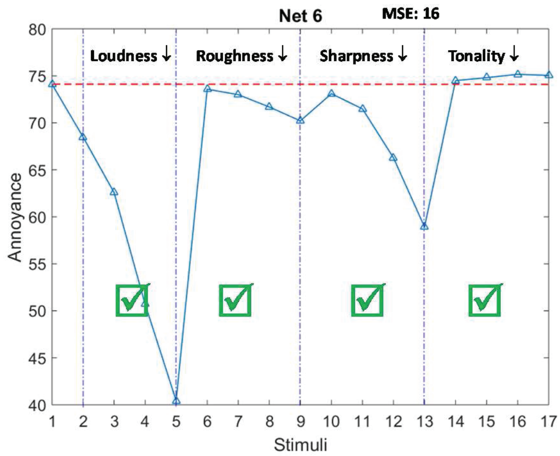

Figure 7: Results of sensitivity analyses for best performing network for annoyance

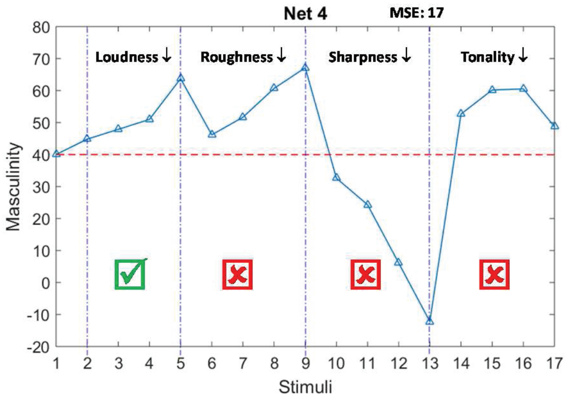

Figure 8: Results of sensitivity analyses for best performing network for masculinity

Table 5: Correlation between psychoacoustical parameters and annoyance for each test subject

	Correlation - Annoyance			
	Loudness	Roughness	Sharpness	Tonality
S1	0,309	0,178	0,312	-0,126
S2	,512**	,527**	,508**	0,308
S3	,725**	-,337*	0,305	-0,062
S4	,614**	,385*	,359*	-0,121
S5	,783**	-0,078	,689**	-0,229
S6	,605**	-0,141	,772**	0,169
S7	,691**	0,185	,433*	-0,28
S8	,714**	0,162	,680**	-0,022
S9	,591**	0,016	,544**	0,199
S10	,530**	0,007	,450**	,415*
S11	,437*	0,059	0,254	,554**
MW	,808**	0,082	,661**	0,086

Table 6: Correlation between psychoacoustical parameters and masculinity for each test subject

	Correlation - Masculinity			
	Loudness	Roughness	Sharpness	Tonality
S1	0,035	,536**	-0,187	,605**
S2	-0,249	,567**	-0,25	,635**
S3	-0,29	,401*	-0,154	,360*
S4	0,071	,474**	0,093	,423*
S5	-,583**	,492**	-,690**	0,228
S6	0,085	,324*	-0,241	,381*
S7	0,312	,392*	,455**	0,182
S8	-0,218	0,293	-,514**	-,329*
S9	0,038	-0,018	-,372*	-0,102
S10	-,532**	,580**	-,440*	0,132
MW	-0,237	,598**	-,385*	,370*

Results and Discussions

Electric shavers, with their quasi-stationary noise characteristics, are selected as a case study for annoyance and masculinity estimations in that work. Listening tests are conducted and linear correlations between psychoacoustical metrics and jury estimations are obtained. For the annoyance study, correlation values indicated that, annoyance is highly correlated with mostly loudness. It should be noted that loudness is also highly, and significantly correlated with sharpness, as the definition implies. However for the masculinity study, linear correlation was not that clear, even though it seems that roughness plays the crucial role in masculinity estimations, the other inputs also have quite high impact, such as sharpness being negatively correlated with masculinity, as expected.

For both masculinity and annoyance estimations, different neural network structures are obtained and compared in terms of their performances. It is observed that selection process of the best performing network in an ANN study is one of the most important step of such approach. Lastly, since it is impossible to obtain explicit mathematical formulation of an ANN structure, a sensitivity analysis is conducted for both best performing neural networks. Response of annoyance network for sensitivity analysis are compatible with the linear correlation tables, however the same situation is not valid for masculinity estimations. Knowing the fact that, ANN fit is compatible with jury estimations for masculinity analyses, detailed analyses of correlations of single subjects are obtained. These results show that, for linear correlation analyses on the basis of subjects, general trend of loudness being the most important parameter can easily be observed for annoyance. However, for the masculinity, the situation is not that clear to deduce a basic trend with the first view. Relation seems more chaotic and more complex than annoyance. For that reason, nonlinear curve fitting tools, such as ANNs, can perform quite better in such complex cases. As a future study, number of subjects should be increased, such that an increased input data might yield in better result with ANNs.

References

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