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Modeling Vibrotactile Detection by Logistic Regression

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ABSTRACT
In this study we introduce logistic regression as a method for modeling, in this case the user's detection rate, to more easily show cross-effecting factors, necessary in order to design an adaptive system. Previously such effects have been investigated by a variety of linear regression type methods but these are not well suited for developing adaptive systems. We investigate the method on a qualitative and quantitative dataset with ages spanning from seven to 79 years under indoor and outdoor experimental settings. The results show that the method is indeed a suitable candidate for quantification of, in this instance vibrotactile information, and for the future design of user-adaptive vibrotactile displays. More generally the model shows potential for designing a variety of adaptive systems.

Author Keywords
Vibro tactile signals, detection rates, identifying cross-impacting factors, logistic regression, method

ACM Classification Keywords
H.5.m. Information interfaces and presentation

INTRODUCTION
Recent advances with wearable computing, vibration, pervasive and ubiquitous technologies and information distribution in our surrounding environment support new ways to live out our daily activities. Much work in the vibrotactile field supports special use instances such as navigation for sight-impaired [8] and provision for combat soldiers [2]. Here, we address regular use for a general public audience, but in order to realise the potential of these technologies and to make them adaptive to the user we need to investigate and quantify the factors that impact on vibrotactile performance. Previous research has demonstrated that both age and context have a significant effect on detection rate of vibrotactile information [1, 3, 4, 5]. However, these studies largely concentrate on perception thresholds in broad age intervals (e.g. 10-30, 50-70), which are not suitable for the development of automatically adaptive vibrotactile systems.

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In this study we propose the use of logistic regression to quantify the detection rate of vibrotactile sensations and identify impacting factors. Factors tested are vibration intensity, age, situation (lab-field), skinfold, and the effect of gender. We work with logistic regression as it is a known method for modeling in experiments where a yes/no outcome is required. Logistic regression is used extensively for example, in testing dose-response effects from medicine, pesticides, drugs etc. Here, the method can predict if the vibrations displayed are detected or not, and gives information on how much the amplitude of the vibration needs to be increased, so we can expect that vibrations are detectable.

The work is part of a larger research project where we investigate how to develop models that are able to adapt to the most dominant factors influencing in this instance, detection rate. In turn such models can pave the way for the design of adaptive vibrotactile systems, which display vibrations that are not too high or low in amplitude and consequently not annoying for the user. Additionally using such a customised system can ensure future designs with optimised power consumption.

LOGISTIC REGRESSION MODELING
Logistic regression is often used in cases where the response variable is categorical, usually in the form of a success or failure outcome: in this case 'detection' or 'none detection' of a vibration stimuli. The response data can be then coupled with the predictor variables—in this case age, gender, situation, situation, and vibration intensity. Using a logistic function to model the detection or miss of a vibration, will then give us the resulting probability between 0 and 1 for detection of a vibration. The model is mathetically defined by the following formula:

$$\boldsymbol{f(z) = \frac{1}{1 + e^{-z}}}$$

where z is a linear combination; $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \cdots \beta_i x_i$ of the explanatory varibles x_i (age, gender, skinfold etc.) and the regression coefficients β_i describe the contribution of variable x_i. To determine the regression coefficients, the model is estimated by maximum likelihood. Once the explanatory variables are determined, it is a matter of inputting the contribution of the predictor variable, to predict the detection rate. The regression coefficients can be examined using a likelihood ratio test, comparing the deviance of the predictor model with a null

model with a chi-square distribution. In this way it can be estimated how significantly the explanatory variable contributes to the model or whether it should be discarded from the model.

The model results in a stretch "S" shape curve (see Figure 2, 3). At the start of the curve only few vibrations are detected. As the amplitude of the vibrations are increased the detection rate, as expected, increases until it reaches a level where close to all vibrations are detected. In a perfect adaptive system the vibration amplitude should be adjusted to be at the intensity level where the curve saturates, that is where the curve flattens at almost 100% detection. For a more detailed detailed review of regression modelling, see [9].

EXPERIMENT

To investigate the model's usefulness, and because we lacked a reference data set (usual with logistic regression method modeling), we modeled detection rate for a dataset from a larger research project regarding vibrotactile interfaces. The project involved analysis of 1152 detection rate recordings from 42 persons with a continuous age span distribution ranging from seven to 79 years (see figure 1 for detailed age distribution), in two situations: 1) a controlled indoor laboratory setting and 2) an outdoor experimental urban environment [6].

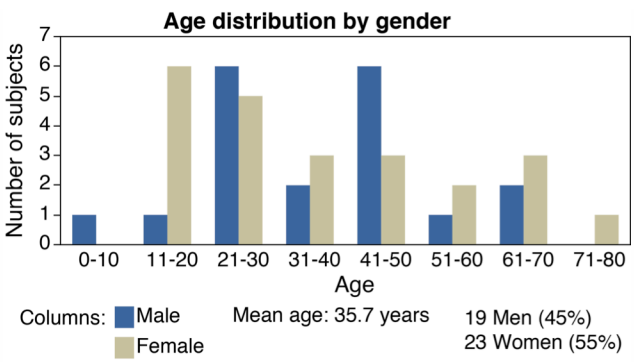

Figure 1: Age distribution among participants

In the trial the participants wore a belt containing vibrators that vibrated at random intervals and intensity for 500ms. The vibration amplitude ranged linearly from 0.1g at 65hz to 0.36g at 155hz, controlled by a PWM signal at a resolution of 80 intensities, down-sampled to ten intensity levels, for statistical analysis. Whenever the participants felt a vibration they responded by pushing a button. The belt logged the vibration intensities and button pushes. The explanatory variables investigated in this study are vibration intensity, age, situation (lab-field), skinfold, and the effect of gender on the detection rate of the vibration stimulus. Based on previous research we expected vibration intensity and age to have a significant effect [3, 4]. At the end of the experiment, we had obtained 1152 observations, which were then investigated with a full second order model, that is, only the interactions between two main explanatory variables are considered [9]. The analysis is done using the statistical software JMP 9.0.2.

RESULTS

From the analysis using the full second order model (#1), see table 1, it was evident that the variables vibration intensity, age and situation (between laboratory and field) were the variables that significantly contributed to explanation of the detection rate. Skinfold measurement and gender were not significant variables. Consequently, a simpler second order model (#2) composed of only vibration intensity, age and situation and their three cross effects as explanatory variables, was investigated.

The results of this #2 model are reported in table 2, where we found that the cross effect (age x situation) and consequently a final model (#3) without this effect was estimated. The #3 model was significant ($p<0.0001$) with the regression coefficients as reported in table 3. As expected increasing vibration intensity (0.255) has a positive effect on the detection rate whereas increasing age (-0.031) and the activity of the situation (lab-field) (-0.993) has a negative influence. That is, as you become older or if the activity load requires more of your attention, your detection rate decreases. This simpler second order #3 model was used to generate figures 2 and 3.

Results of #1 model: full second order model

Effect	Estimate coefficient variables	Std. Error	χ^2	$p > \chi^2$
Intercept	-0.098	0.1958	0.25	0.6156
Age	-0.035	0.0047	56.22	<.0001*
Intensity	0.373	0.0382	95.23	<.0001*
Situation	0.510	0.0708	51.86	<.0001*
Gender	-0.061	0.0660	0.88	0.3487
Skinfold	0.00	0.0074	0.05	0.8154
Cross effects omitted for legibility				

Table 1. Results for the logistic regression model #1.

Results of #2 model

Effect	Estimate coefficient variables	Std. Error	χ^2	$p > \chi^2$
Intercept	-0.131	0.1515	0.75	0.3875
Age	-0.031	0.0041	56.82	<.0001*
Situation	0.496	0.0690	51.61	<.0001*
Intensity	0.343	0.0364	88.83	<.0001*
(Age-35.4) x (Intensity-3.84)	-0.004	0.0018	5.83	0.0157*
(Situation) x (Intensity-3.84)	0.093	0.0352	7.03	0.0080*
(Age-35.4) x Situation	-0.002	0.0045	0.23	0.6345

Table 2. Results of the logistics regression model #2, where skinfold and gender has been left out as explanatory variables. 35.4 is the mean age and 3.84 the mean intensity.

Results of #3 model

Effect	Estimate coefficient variables	Std. Error	χ^2	$p > \chi^2$
Intercept	-0.296	0.1850	2.56	0.1095
Age	-0.031	0.0041	58.12	<.0001*
Situation	-0.993	0.1380	51.80	<.0001*
Intensity	0.255	0.0367	48.11	<.0001*
(Age-35.4) x (Intensity-3.84)	-0.004	0.0016	5.90	0.0151*
(Situation) x (Intensity-3.84)	0.171	0.0624	7.54	0.0060*

Table 3. Results of the logistic regression model #3 where the age x situation cross effect was left out, leaving only significant explanatory variables. 35.4 is the mean age and 3.84 the mean intensity.

Figure 2 illustrates how the method is able to model decreased ability to detect vibrations with increasing age from 10 to 80 years for the laboratory situation. As an example, a 10 year old is expected to have a detect rate of 75% at vibration intensity of circa 3 whereas for an 80 year old person it will expected that s/he only detects about 25% percent of the same vibrations under laboratory conditions.

Figure 3 illustrates how the method is able to quantify the effect of moving into an outdoor field situation. From the figure is evident that the detection rate decreases for all ages due to the additive effect of the situation (busy-ness), which gives a general shift in the detection rate in relation

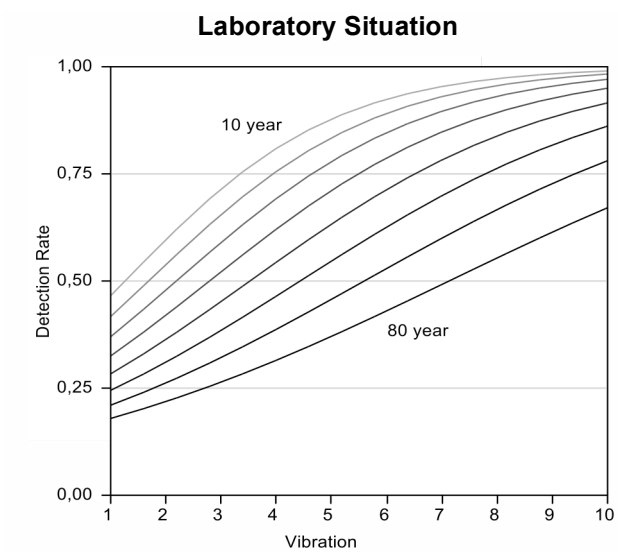

Figure 2. Detection rate with varying intensity in the lab situation, from 10 to 80 years in steps of 10 years.

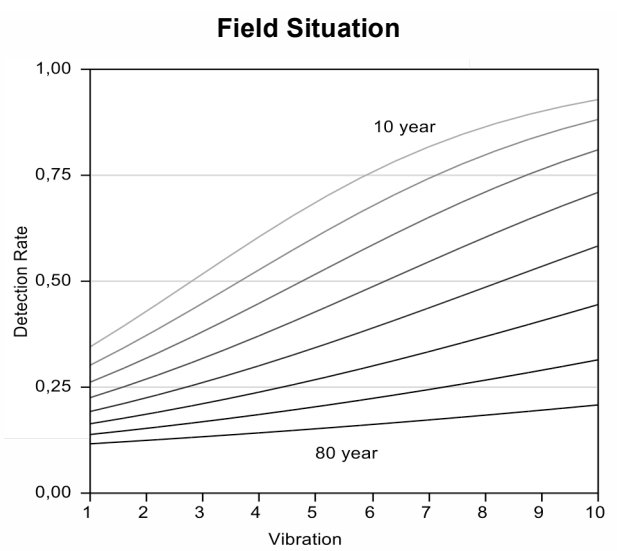

Figure 3. Detection rate with varying intensity in field situation, from 10 to 80 years in steps of 10 years.

to the vibration intensity. The (situation x vibration intensity) cross effect (0.171) together with the negative cross effect (age x vibration intensity) (-0.004) even further enhances the decrease in detection rate with increasing vibration intensity and age. The consequence is a larger spread of the curves with increasing age, that is, younger people are generally better at adapting to the field conditions than the older ones in line with [6].

In sum, our results demonstrate as expected that the detection rate decreases with age and increasing complexity of the situation, that is, moving from laboratory to field conditions. Further, that the two cross effects (age x vibration intensity and situation x vibration intensity) impact detection so that vibration intensity in general has to be increased when activity level increases and this increase needs to be more pronounced with increasing age.

DISCUSSION AND FUTURE WORK

In this paper we proposed using logistic regression to identify variables affecting vibration detection rate. Due to the lack of a reference data set, we have evaluated the applicability of logistic regression for modeling detection rate on a data set with a significant age distribution and under two distinct situations. Our results demonstrate that the logistic regression model is able to quantify the detection rate in-line with what is expected from other studies [1, 3, 4, 5, 7] regarding intensity, age and situation.

The main advantages using the logistic model when compared to a linear model is that the logistic method is able to model how the increased detection will "flatten out" with increasing intensity, especially evident in figure 2. In a practical system this will allow for adjustment of the vibration intensity, so that it can deliver a magnitude just sufficient to achieve a desired detection rate, normally around 95%.

However to further realise this potential in future work in this particular case, several challenges need to be addressed. The age of the user needs to be known, which can be done a priori. More difficult though, is to determine the situation the user is in. In this study we have concentrated on two predetermined discrete situations, however for real life implementation the situation cannot be so pre-determined but has to be estimated semi or fully automatically to adapt vibration intensity to the optimal level. Solving this, calls for research into models that by monitoring the user's activity are able to estimate the situation and potentially the context s/he is in. Input from various sensors monitoring biological and motion information of the user's activity together with environmental data, temperature, wind, time of day, background noise could be sampled with fusion to give an estimate of the current situation. Fortunately in this case, the vibrotactile wearable, by its very nature easily accommodates integrating the necessary sensors for future implementations to address adaptability.

The model was specifically developed based on the case presented. We find that logistic regression is suited for modeling detection rate and impacting factors, and that the model can serve as a suitable tool for developing future user-adaptive systems. While our case investigated only one sense and one position on the body, the method could be applied to other variables, including body sites, activities, demographic variables, and potentially to other senses such as listening or seeing. Logistic regression is a useful method for developing adaptive systems beyond vibrotactile and/or wearables. Having a useful method to quantify both individual and cross-effecting impacting factors, using both qualitative and quantitative data can prove a valuable design, development and evaluation tool for much future research and in many fields.

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