

Copyright is owned by the Author of the thesis. Permission is given for a copy to be downloaded by an individual for the purpose of research and private study only. The thesis may not be reproduced elsewhere without the permission of the Author.

Multi-Step Look-Ahead Adaptive Designs for the Estimation of Sensory Thresholds

A thesis presented in partial fulfilment of the requirements
for the degree of

Master of Applied Statistics

at Massey University, Albany, New Zealand

Mark William Wohlers

Student ID # 10148537
2013

Abstract

The estimation of sensory thresholds is an important part of the psychophysics field. The point at which a physical stimulus becomes detectable can vary from trial to trial within as well as between subjects. Often the probability of detection is modelled over a range of stimulus intensities using an assumed psychometric curve which has the threshold as a parameter. To estimate the threshold with a reasonable accuracy often requires careful placement of the stimulus levels when the total number of trials are limited. There have been a number of design schemes proposed over the years to find the optimum placement strategy to minimise a given loss function. Some of the most successful have been Bayesian adaptive designs which select the next signal intensity based on prior knowledge and the responses observed up until that point. A critical step in the adaptive designs is the choice of threshold estimator and error term, also known as the loss function, to be minimised by the design scheme. A sub-class of these look-ahead a short number of trials to calculate the expected loss function given the current posterior distribution. However sometimes it is not possible to adjust the signal after every test. Olfactory sensory threshold tests, for example, can require a large setup time. In this situation a number of sensory tests may be grouped into sessions, with any design alterations occurring between these. However this would require a look-ahead design with a number of steps equal to the number of samples in a session.

Most of the look-ahead designs have been restricted to one or two steps due to the little performance increase gained by increasing them and the computational limitations at the time they were suggested. The first point is not relevant to situations where the step size must be larger, and the second point may be less true today due to advances in computer power. This investigation demonstrates that it is possible to implement multi-step look-ahead adaptive designs in a computationally efficient manner for sessions up to sizes of twelve samples. Based on Monte-Carlo simulations, these multi-step look-ahead designs also provide encouraging results in terms of performance in minimising a number of loss functions.

Acknowledgements

It is a pleasure to have the opportunity to thank the many people who have helped me along the way to completing this thesis. The New Zealand Institute for Plant and Food Research Ltd was kind enough to allow me to continue to work full-time while studying. Many of my co-workers also deserve a special mention. In particular I would like to thank Nihal De Silva and the Biometrics team for their continued encouragement to further my study and Sara Jaeger along with the rest of the sensory team for being instrumental in inspiring my interest in the area.

My supervisor Barry McDonald has my thanks for his guidance and invaluable suggestions while writing this.

Lastly I would like to give a special thanks to my wife Evelyn for her never ending support and encouragement throughout this long journey. To her I dedicate this thesis.

Contents

Table of Figures	vi
Table of Tables	vii
1 Background	1
2 Literature Review	3
2.1 Test Protocols: Yes-No and n-AFC Experiments.....	4
2.2 Methods for Estimating the Psychometric Curve	6
2.2.1 Method of Constant Stimuli.....	6
2.2.2 Method of Limits.....	7
2.2.3 Method of Adjustment	7
2.2.4 PEST.....	7
2.2.5 Staircase Procedures.....	8
2.2.6 Maximum Likelihood Adaptive Procedures	8
2.2.7 Bayesian Adaptive Procedures.....	9
2.2.8 ASTM method	15
2.3 Odour Detection Experiments at The New Zealand Institute for Plant and Food Research.....	16
2.4 Difficulties Implementing Standard Adaptive Procedures with Olfactory and Taste Threshold Estimation	17
2.5 Proposed Adaptive Threshold Estimation for Olfactory and Taste Experiments.	18
3 Methods.....	21
3.1 Software	21
3.1.1 Numpy and Scipy.....	22
3.1.2 Matplotlib.....	22
3.1.3 PyMC	22
3.1.4 Playdoh.....	22
3.1.5 Numdifftools	22
3.1.6 Numexpr	22
3.1.7 ffnet.....	23
3.1.8 OpenOpt.....	23
3.2 ASTM method	23
3.3 Threshold Estimation using the Psychometric Function.....	25

3.3.1	Maximum Likelihood.....	25
3.3.2	Bayesian Fitting.....	28
3.3.3	Approximating the Loss Function by Simulation	41
3.4	Loss Function Minimisation	41
3.4.1	Minimisation with Continuous Stimulus Levels	42
3.4.2	Minimisation with Discrete Stimulus Levels	43
3.4.3	The Adaptive Procedure	44
3.4.4	Python code	46
4	Results.....	49
4.1	Fitting Bayesian Models through MCMC.....	49
4.1.1	Generating data for Neural Network Training.....	49
4.1.2	Training the Neural network.....	50
4.1.3	Neural Network Performance.....	51
4.1.4	Optimizing based on the Neural Network	55
4.2	D-Optimal Designs	57
4.3	Bayesian Optimal Design using Discrete Priors.....	58
4.3.1	Comparison of Adaptive Schemes	59
4.3.2	Adaptive Schemes Under Misspecified Psychometric Curve.....	63
4.3.3	Comparing Look-Ahead Step Sizes: Minent8 vs. Minent1	68
4.4	ASTM Optimal Design	71
4.5	Discrete Signal Intensities	72
5	Discussion and Suggestions for Future research	74
6	Conclusion.....	79
7	Bibliography	81
Appendix A	R Computer Code.....	86
Appendix B	Python Computer Code.....	87

Table of Figures

Figure 1	An example of a Gumbel psychometric curve	3
Figure 2	A visual summary of common sensory test protocols	5
Figure 3	Parameterisation and forms of psychometric functions	11
Figure 4	Effect of parameterisation of the logistic psychometric curve with standard uniform prior distributions	13
Figure 5	Example of estimated detection probabilities for a psychometric curve at given signal intensities.....	24
Figure 6	Autocorrelation plots for Threshold parameter estimates.....	32
Figure 7	Example of a Neural Network with 3 input, 6 hidden and one target neuron.	35
Figure 8	Example of how the inputs (x) are linked to the outputs (y) via the weights (w) and activation function (g).....	36
Figure 9	Example of a log-sigmoid activation function with $\beta = 5$	36
Figure 10	Scatter plots of the MCMC estimates based on 8 observations vs. the neural network approximations.....	51
Figure 11	Scatter plots of the MCMC estimates based on 32 observations vs. the neural network approximations.....	53
Figure 12	Posterior mean NN approximations versus MCMC means based on 8, 16, 24, and 32 samples. 54	
Figure 13	Logistic Psychometric curves used to generate responses to assess the performance of the NN based adaptive method.....	56
Figure 14	Estimated RMSE for the NN Adaptive Design	57
Figure 15	Logistic Psychometric curves under discrete standard uniform priors	59
Figure 16	RMSE based on 100 samples generated by Logistic Psychometric curves	61
Figure 17	Mean Absolute Errors based on 100 samples generated by Logistic Psychometric curves	62
Figure 18	Categorical Errors based on 100 samples generated by Logistic Psychometric curves	63
Figure 19	Weibull Psychometric curves used to generate misspecified samples	64
Figure 20	RMSE based on 100 samples generated by Weibull Psychometric curves.....	65
Figure 21	Absolute errors based on 100 samples generated by Weibull Psychometric curves	66
Figure 22	Categorical errors based on 100 samples generated by Weibull Psychometric curves	67
Figure 23	Logistic Psychometric curves used to compare the MINENT1 and MINENT8	69
Figure 24	Comparison of the convergence of the MINENT8 (red) versus MINENT1 (black)..	70
Figure 25	Comparison of RMSE for the MINENT1 and MINENT8 procedures	70
Figure 26	ASTM Expected RMSE	72

Table of Tables

Table 1	Example of BET estimates for two panellists. Ticks indicate correct detection at a given concentration, and a cross an incorrect response.	16
Table 2	Variance, Bias, and MSE estimation for teh ASTM method.....	24
Table 3	Regression Summary Statistics for Neural Network Approximation Based on samples of Length 8	52
Table 4	Summary statistics from regressing the MCMC point estimates on the NN approximations based on 32 observations per sample.	53