CHAPTER 5

Results

5.1. An Overview

5.1.1. Computation. *These event related potentials supply a solid resource of data for the investigation of human brain behaviour. The low signal-to-noise ratio as well as many other possible components within the signal tend to complicate any analysis of a single ERP. Here we initially attempted to implement the features that wavelets provide but concluded that his methodology by itself was not able to effectively visualise (or characterise) the MMN component. Indeed tracing the ERP energy movement across the individual electrodes was possibly too ambitious owing to the overlap in the time-frequency space of the varied ERP and EEG components*[1]*, also the averaging within the signal as well as any linear model predictions may have "smoothed" out any such energy traces.*

This wavelet approach, where we simply decomposed each electrode signal into components within a series of fixed frequency bands to define the energy in the signal combined with a linear prediction model, nevertheless, provided us with a method to represent the onset of increased activity during these MMN trials. Exploratory spatial data analysis highlighted that within our representation we did indeed have varying degrees of spatial correlation across the electrodes and that such could not be assumed to be isotropic. This implies that the spatial distribution of energy changes across time.[2] *Advised by the texts Diggle* [**Diggle, 2007**] *and Banerjee* [**Banerjee, 2004**]*, we constructed such spatial models using the spBayes* [**Finley, 2007**] *and geoR* [**Ribero, 2001**] *packages from R. The Bayesian Hierarchical modeling, (from spBayes) allowed us to not only summarize uncertainty at different levels, but choose spatial or non spatial covariance matrices as well as provide full Bayesian specification. The geoR package had limited prior specifications and we even though we used maximum likelihood methods to estimate our spatial*

[1]EEG data is correlated across frequency bands and the orthogonality principles of wavelet methods impose that any decomposition yields series of components in different frequency bands which are not correlated to each other

[2]In effect here we had a spatial-temporal point process: i.e. collection of points where each point represents the time and the location of an event.

parameters this was cumbersome in comparison. However, geoR did provide a method to easily allow for anisotropy. While anisotropy was evident it did not have a major effect on the models, at some levels a "better" (as per the AIC), model resulted by not including correction for any directional affect.

Overall the variability within the spBayes package for the Bayesian specifications permitted us to run simple models with good observable results as well allowing us to continually adjust our priors and hyperparameters with the aim of reducing the model's DIC. Consideration was given to including the z parameter[3]*, from the spherical representation, into the regression formula section of the spherical model i.e. $Y \backsim z$, we used; $Y \backsim 1$. However no readily noticable improvement was observed by including z in the spBayes generated model, therefore no indepth investigation of a 3D representation was undertaken.*[4]

5.1.2. A Conclusion. *Wavelet methodology to extract the energy within the signal, at various resolution levels, combined with the geoR package to then estimate our initial spatial parameters used in a Bayesian hierarchical model allows us to provide a representation of how energy activity within these trials behave. However we simply cannot continue to move to higher energy levels to improve time resolution using the wavelet transforms, as the signal energy returned in the transform reduces at higher levels. It was not evident how to gauge the size of the MMN responses owing to the energy altering across the levels. Nevertheless at the levels used; i.e. 3 and 4 , we have shown that we can at least approximate when activity begins to increase during a trial as well as compare specific trials to illustrate when the energy related to the MMN response begins to increase. Researchers have previously shown this detection to often be difficult to observe and indeed have had problems within some trials obtaining levels of significance,* [**Pettigrew, 2004**]*. Here we have used a number of models in an attempt to provide a suitable outcome.*

An overview of our results at energy level 3 (Table 5.1), highlights that at this level of resolution we are able illustrate at which time location the onset of activity associated with the MMN response begins. However when comparing similar trial types in an attempt to elucidate in which trial the MMN response showed an earlier onset, such was not always possible.

[3]Here the z parameter represents the height or vertical co-ordinate of the electrode in question, see page 53.

[4]I only became aware of the SpherWave, "An R package for analysing Scattered Spherical data by Spherical Wavelets $\backsim$ carries out the wavelet transform of functions on the sphere" quite late in the development of this paper and have not attempted to use such.

TABLE 5.1. All Models $\sim$ Latency of Response at level 3

	MMN Trials			
	Time location of activity onset at energy level 3			
Model	*day* $\rightarrow$ *gay*	*de* $\rightarrow$ *ge*	*de* $\rightarrow$ *day*	*day* $\rightarrow$ *de*
Bayesian Hierarchical	*4*	*4*	*3*	*4*
Kriging	*4*	*4*	*3*	*4*
Log Normal Kriging	*4*	*4*	*3*	*4*
Spherical Bayesian Hierarchical	*4*	*4*	*3*	*4*

At level 3 none of the models used could clearly determine in which of the trials, day $\rightarrow$ *gay or de* $\rightarrow$ *ge, the onset of activity occurred first. However in comparing real word deviants among non-word standards to non-word deviants among word standards i.e. de* $\rightarrow$ *day to day* $\rightarrow$ *de, we could demonstrate the latency of the MMN response to be earlier in the de* $\rightarrow$ *day trial.*

TABLE 5.2. Bayesian Models $\sim$ Latency of Response at level 4

	MMN Trials	
	Time location of activity onset at energy level 4	
Model	*day* $\rightarrow$ *gay*	*de* $\rightarrow$ *ge*
Bayesian Hierarchical	*11*	*7*
Spherical Bayesian Hierarchical	*11*	*7*

By moving to the next level of resolution and comparing the"fine acoustic speech contrasts", day $\rightarrow$ *gay and de* $\rightarrow$ *ge, the Bayesian based model, using either projection, provided a method to determine this latency of activity onset, Table 5.2.*

Overall, we have been able to illustrate the latency of MMN responses in both the types of trials considered here and compare these similar trial types against each other for such latency, although any attempt to demonstrate which trial produced a larger MMN response was hindered by the altering levels of signal power across the resolution levels as well as possibly because of the averaging of the signal in regards to latency and strength at the initial recording stage. Nevertheless we have been able to confirm some of the findings that previous researchers have produced as well as demonstrating some responses that these researchers had only hypothesized, [**Pettigrew, 2004**]*. Our models have enabled us to show that the non-real word deviant de*$\rightarrow$ *ge, had an earlier latency of MMN response than the real word deviant day* $\rightarrow$ *gay, as well as being able to show that the direction of transition in the de* $\rightleftharpoons$ *day trials, alters the latency of response.*

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