

# The Bayesian Power Imaging (BPI) test for task/control experiments

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## 1 Introduction

There has been considerable interest in the use of Bayesian formulations and approaches in the solution of the biomagnetic inverse problem [1,2,3,4]. The Bayesian Power Imaging (BPI) method is a new Bayesian approach that is introduced in [5]. In this companion paper, the BPI method is extended to analyze not one but two sets of experimental data in order to highlight the differences in their underlying source structures.

## 2 Methods

The BPI method as described in [5] is a fusion of the Bayesian approach detailed in [4] and the direct power algorithm derived in [6]. The method provides a means of calculating the probability that features of an activation map are due to meaningful sources as opposed to noise.

In order to highlight aspects of the BPI method that are central to the comparison calculations set out in this paper, we will summarise the relevant features of [5]. The first step in the BPI method is to determine the *a-posteriori* distribution of the expected measurements for each channel, given the *a-priori* probability distribution of the current and the data.

The means of this distribution are then used in the direct power method of [6] to calculate the activation  $A$  of the  $\theta$  th voxel;

$$A_{\theta}(m) = \sum_{k=1}^3 \left( m^T \psi_{\theta}^k \right)^2$$

where  $\psi_{\theta}^k = (P^2 + D)^{-1} P L_{\theta}^k$  and  $L_{\theta}^k$  is the measurement vector due to a current dipole at the position labelled  $\theta$  and direction  $k$ .

$P$  and  $D$  are the Gram-Schmidt matrix and the covariance matrix respectively.

In order to determine the probability distribution on the activation we use the *a-posteriori* distribution on the measurement channels. This results in quadratic forms in Gaussian random variables which are evaluated using Monte-Carlo integration.

The calculation proceeds on a voxel by voxel basis and generates a significance or probability map by comparing the activation distribution due to the data with that due to random noise. The value at each voxel of the map is the probability that the activation at the voxel cannot be explained (to a chosen statistical level) by the noise.

This probability is given by;

$$P_{\theta}(A_{\theta}(m)) = \frac{1}{N} \sum_{i=1}^N \Phi[A_{\theta}(m) - T - A_{\theta}(z_i)]$$

Here  $A_{\theta}(m)$  and  $A_{\theta}(z_i)$  are the activations of voxel  $\theta$  due to the measurement vector  $m$  and the  $i$  th noise vector  $z_i$ .  $\Phi$  denotes the Heaviside step function and  $N$  is the number of trials or noise vectors in the ensemble. A threshold  $T(A_{\theta}(m))$  is included to allow the exclusion of large regions of low significance from the resulting map.

The probability  $P_{\theta}$  is a measure of the significance of the activation on a voxel compared with that produced by noise. In effect, we are comparing the data against a prior model which, in this instance, is characterized by random noise. In so far as random noise simulates uncorrelated detector noise this prior model could be considered as equivalent to an idealised 'empty room' experiment.

Other prior models can be used. Data from real 'empty room' experiments would allow the examination of the significance of a response within the context of environmental noise and instrumental artifacts. Similarly, using data from a pre-stimulus period, would help to identify significance to features corresponding to the evoked response within the context of other subject derived sources, both cerebral and non-cerebral.

This paper is focused on the use of the BPI to determine the significance of differences in the responses recorded in two otherwise identical experiments involving different stimuli or tasks. This is a very common paradigm in brain research where a variation of stimulus is used to identify a specific aspect of brain function. Using the BPI formulation, one experiment becomes the prior model against which the other is compared. The map

of significant differences then indicates areas where the prior model is not a good explanation of the experiment, i.e. where the responses are different. There is a complication. The Monte-Carlo calculation requires the comparison of the data against many datasets representative of the prior model. Here our prior model consists of a single dataset. In order to proceed we subtract the activation of the prior model from that of the experiment to give a difference map. We then evaluate the significance of this difference map against the random noise as previously to determine the probability that the differences are not due solely to noise. If the difference map is denoted by

$$\Delta A_\theta = A_\theta(m_1) - A_\theta(m_2)$$

then

$$P_\theta(\Delta A_\theta) = \frac{1}{N} \sum_{i=1}^N \Phi[\Delta A_\theta - T - A_\theta(z_i)]$$

Either of the two one-sided probabilities can be found by switching the role of prior model and experiment between the two datasets.

### 3 Results

This extension of the BPI method is illustrated by real and simulated data studies. For both studies the experimental instrument was the Neuromag 122™ full head detector system which consists of 61 pairs of first order gradiometers that measure the tangential gradients of the magnetic field.

#### 3.1 Simulated data study

The simulated data was generated by two current dipoles embedded in a homogeneous sphere. The dipole magnitudes were the same. The source space was a part spherical shell surface of radius 8 cm which covered a 2 radian by 2 radian solid angle in posterior regions of the brain. The surface was divided into 33 by 33 voxels. The arrangement is shown in Figure 1.

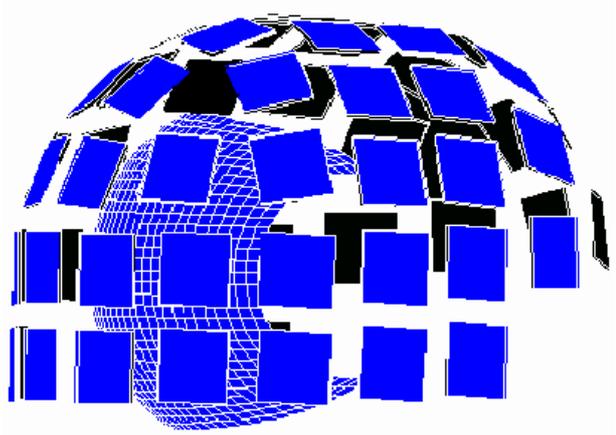


Figure 1 The position of the source space relative to the detector helmet.

The first dataset  $m_1$  was generated with the dipoles at positions (5cm, 12cm) and (10cm, 4cm) relative to the bottom left hand corner of the source space and oriented along the  $x$  and  $y$  axes respectively. For the second dataset,  $m_2$ , the dipole at (5cm, 12cm) was moved 3cm along the  $x$  axis to (8cm, 12cm) without any change in orientation. Uncorrelated Gaussian noise was added to both datasets so that the resulting signal to noise ratio was 10.2.

As in [5], the regularisation parameter  $\zeta$  was calculated as  $0.1 \times \text{trace}(P)/M$  where  $P$  is the Gram-Schmidt matrix and  $M$  is the number of detectors. The number of trials  $N$  in the Monte-Carlo calculation was 1000. The threshold  $T$  was set to two standard deviation above the average activation over the source space.

Figure 2 shows plots, over the full source space, of the activations  $A_\theta(m_1)$  and  $A_\theta(m_2)$  and the two one-sided probability estimates of the differences.

#### 3.1 Real data study

The real data chosen for the second illustration came from an experiment designed to elicit differences between the responses to different stimulus classes [7]. Subjects were shown pictures of human faces, animals, motor bikes and abstract patterns in a random sequence. The task was to identify membership of a stimulus class by a cued key press or deny membership by pressing an alternative key.

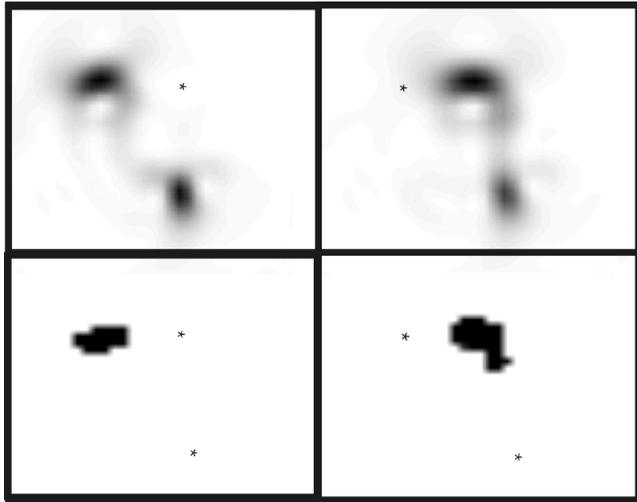


Figure 2 The two upper maps are the activation maps  $A_\theta(m_1)$  and  $A_\theta(m_2)$  corresponding to the initial (left) and final (right) positions of the dipoles. The left lower map shows the map of significant differences derived from one sided probability calculations. For the left map the first data set was compared with a prior defined by the second data set. The right lower map was generated by reversing the roles of data and model. Each map is a two-dimensional projection of the source space. The dipole positions are indicated by asterisks.

The goal was to identify any response that was face specific. We have reported such a face specific response at  $\sim 150$  ms after stimulus onset, with the main centre of activation in inferior occipito-temporal cortex [7]. For the present study we used averaged data from one subject who demonstrated such face specificity weakly. MRI data was available for this subject.

The BPI method was applied using a source space consisting of the entire brain. The activation maps for the latency corresponding to the peak in the global signal power (160 ms) are complex with significant activity widespread over the occipital, temporal and parietal regions. The difference algorithm was also used with the responses to animals in the role of the prior model.

Figure 3 is derived from the one-sided probability that the activation of the face response is significantly greater than the activation of the animal response. For simplicity the figure shows those regions where, to a high probability, the animal data prior does not explain the face response.

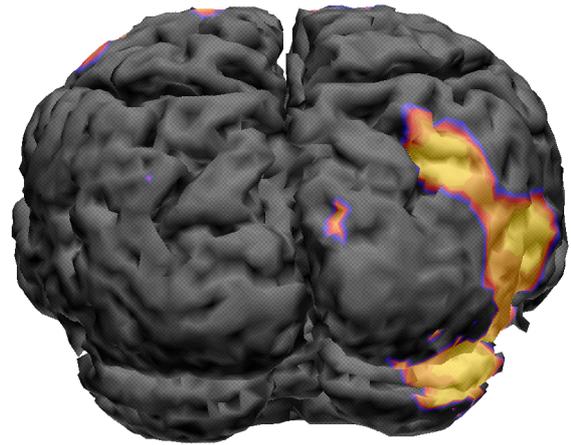


Figure 3 The regions on the brain surface where the response to the face stimuli cannot be explained by the prior animal response model.

#### 4 Discussion

The simulation study provides a simple illustration of the use of the BPI method to identify activation differences. The activation maps correspond closely to the known dipolar source structure with the usual smearing introduced by the choice of basis and regularisation. The thresholded maps of significant differences identify correctly the regions where there are significant differences between the two experiments. It should be noted that the source regions linked to the stationary dipole do not appear in the map of significant differences.

The illustration based on the real data has provided a means of quantifying face specificity in source space. Figure 3 shows that, for this subject, face specificity is associated with right occipito-temporal regions. Both inferior and superior regions are indicated. This is broadly in line with previous source analyses which were reported alongside a statistical analysis of face specificity carried out in data space [7].

The identification of the anatomical regions in Figure 3 is not robust. The full analysis of the sources will require further refinement of the source space as well as careful optimisation of the regularisation conditions, the weighting distribution, and the noise covariance assumptions. However, the example does illustrate how the BPI method can be used to identify source regions where the activity is a significant function of the stimulus. It is worth noting that, once again, the strong occipital activity found in both the face and animal responses disappear in the map of the significant differences.

There is considerable interest in the comparison of MEG images with the results obtained by other functional imaging methods, for example fMRI. The BPI method is used here in a directly analogous way to the subtraction techniques employed in fMRI. This enables easier comparison between the modalities.

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