

Statistical Estimation of Emotion in Functional Magnetic Resonance Imaging

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Abstract: This paper proposes a model to perform fMRI analysis using Bayesian Estimator by introducing Koay Inversing Technique to estimate parameter (prior). Prior which forms the major part of the Bayesian Estimator using which the Posterior Probability is calculated. The intensity of the voxels is measured and the voxel group which has the high intensity is recognised. The Bayesian estimator along with koay Inversing Technique is used to estimate the emotional responses of the subjects and the results are generated with respect to Canonical and GLM Contrast.

Key words: Auto-regressive modeling • Bayesian statistics • Functional MRI data analysis • Koay Inversion Technique

INTRODUCTION

Magnetic Resonance Imaging (MRI) is used to view or analyze the structural integrity of a brain, whereas fMRI is used to study the activations that takes place in the brain under the influence of a stimuli.

Bold: Blood-oxygen-level dependent contrast imaging, or BOLD-contrast imaging, is a method used in fMRI to detect different parts of the brain, which is active at any given time.

HRF: Hemodynamic Response function is the measurement of the amount of blood flow to the region of interest in the brain.

Methods

Stimuli: The stimuli that is used in this paper are of two types,

- House
- Cat

The stimuli were given at an interval of 2.5 seconds and with duration of 0.5 seconds.

Procedure: This experiment consisted of 12 runs and the dataset was obtained from Open Fmri.com

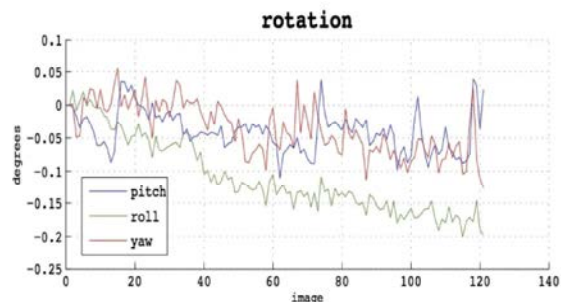


Fig. 1: Correlates to the amount of deviation required by the slices to align that has been spatially deviated have been subjected to during the data collection of the fMRI image

fMRI Pre-Processing: The fMRI data were pre-processed and analysed using the software package SPM12 pre-processing consisted of slice-timing correction and sequential coregistration. Transformation parameters for structural images were then applied to functional images (anatomical) to normalize them to the brain template. Functional images were resampled to a resolution of 1.5 _ 1.5 _ 1.5 mm and spatially smoothed with a kernel of 8 mm full-width-at-half-maximum during normalization.

Slice-Timing correction: The algorithm for slice timing correction uses sinc interpolation between time points, which is accomplished by a Fourier transform of the signal at each voxel. The Fourier transform renders any signal as



Fig. 2: Correlatesto the amount of slice deviated to align to its reference slice

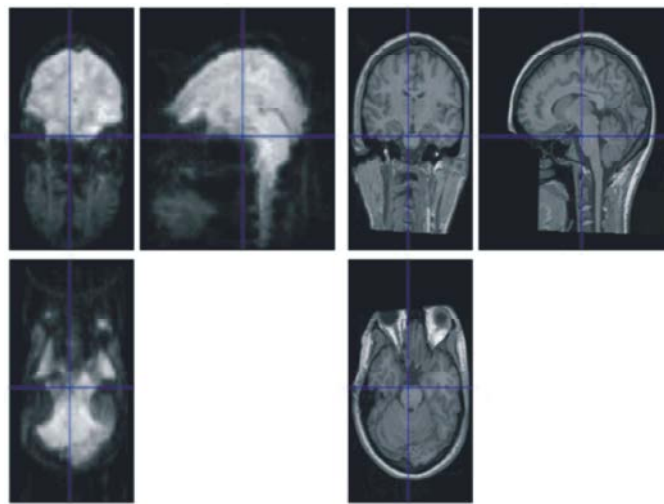


Fig. 3: Indicates that the fMRI image is aligned to its anatomical image.

the sum of some collection of scaled and phase-shifted sine waves; once you have the signal in that form, you can simply shift all the sines on a given slice of the brain forward or backward by the appropriate amount to get the appropriate interpolation. The time-slice correction is done using the SPM 12 Toolbox in which the image is aligned to the reference image provided.

Coregistration: Spatial coregistration refers to intrasubject registration, namely the alignment of functional and structural data from individual participants. This is usually done when reference anatomical data sets acquired in separate sessions are available for each participant. Spatial coregistration includes computing a transformational matrix specifying the transformation parameters and applying it to the data of interest.

fMRI Bayesian Estimation: Statistical parametric maps were evaluated by multiple regressions of the data onto a model of the hemodynamic response The duration for

each image was 0.5 sec. Regressors were convolved with the canonical hemodynamic response function in SPM12. A temporal high-pass filter with a cutoff of 128 sec was applied. Contrasts of each of the two conditions in the factorial design for each participant. In order to test whether there is neural substrate, the hemodynamic response of which is always stronger to one of the two images in a consistent way for all two emotional conditions, results were then calculated the conjunction of the following contrast house Vs cat.

Statistical Analysis: An fMRI time series is the set of values recorded at a particular pixel over the course of the frames of the image. These are collected together into the dimensional vector.

Then the following linear model may be introduced to analyze the data:

$$x = A\theta + B\psi + e = C\varphi + e, \quad e \sim N[0, \sigma^2 I].$$

In this equation and are known matrices of dimension and respectively is known as the experimental design matrix and its columns reflect the expected effects in the data shall be termed the nuisance matrix and its columns contain unwanted effects such as a nonzero mean or systematic drift. In general, is nonzero. The parameters and are unknown and dimensional vectors representing the contributions to the data of the response and nuisance signals, respectively. They shall be called the amplitudes. To simplify the notation the matrix and vector are introduced. Finally, is the unknown variance of the distribution from which the random noise variable is assumed to have been drawn [6].

Bayes' Theorem and the Posterior Distribution: With known values for the parameters the probability density for obtaining the data would be

$$p(\mathbf{x}|\boldsymbol{\varphi}, \sigma^2) = (2\pi\sigma^2)^{-P/2} \cdot \exp\left[-\frac{(\mathbf{x} - \mathbf{C}\boldsymbol{\varphi})^T(\mathbf{x} - \mathbf{C}\boldsymbol{\varphi})}{2\sigma^2}\right].$$

When the parameters are unknown the problem is to make inferences about them from knowledge of the data. In a Bayesian formulation this means constructing the posterior probability density function (pdf) utilizing the Bayes theorem which states that This is done by,

$$p(\boldsymbol{\varphi}, \sigma^2|\mathbf{x}) = \frac{p(\mathbf{x}|\boldsymbol{\varphi}, \sigma^2)p(\boldsymbol{\varphi}, \sigma^2)}{p(\mathbf{x})}.$$

In this equation is called the *prior* distribution of the parameters. Its role is to express all prior knowledge the analyst may have about the values the parameters may take. The factor is a function of the known data only, so it is constant with respect to the parameters. Also, since the data are known and the parameters are unknown, the sampling density may be relabeled as In this form it is called the likelihood function. The posterior distribution is now

$$p(\boldsymbol{\varphi}, \sigma^2|\mathbf{x}) \propto l(\boldsymbol{\varphi}, \sigma^2; \mathbf{x})p(\boldsymbol{\varphi}, \sigma^2).$$

The proportionality becomes equality when the unknown constant is determined by normalization [6].

Choosing the Prior Distribution: When constructing the prior distribution it is important to first determine which of the parameters are independently distributed. Then, if there is some information about the values a particular

parameter may take, this should be introduced to quantify the functional form of the prior. In the case of fMRI data, nothing is known about the parameters *a priori*. In the Bayesian approach, this state of ignorance about the model parameters is expressed by noninformative prior distributions. In the Bayesian approach, this state of ignorance about the model parameters is expressed by noninformative prior distributions. For a location parameter, where a change in the data only affects the location of the likelihood function in the parameter space, a noninformative prior must be locally uniform. Most parameters, however, are not location parameters. In such cases, a transformation of the parameter must be found so that the new transformed parameter becomes a location parameter for which a locally uniform prior may be used. The prior distribution for the original parameter is then proportional to the Jacobian of the transformation. Unfortunately, it is usually impossible, or at least very difficult, to find an exact transformation of the parameters so that a locally uniform prior may be used. Hence we put forth a technique to generate prior probability koay inversion techniquesolving the estimating equations, based on the sample mean and the sample standard deviation, simultaneously [6].

The fixed point SNR is expressed as,

$$g(\theta) = \sqrt{\xi(\theta) [1 + r^2] - 2},$$

where θ is the ratio of the parameters,

$$\xi(\theta) = 2 + \theta^2 - \frac{\pi}{8} \exp(-\theta^2/2) \left[(2 + \theta^2)I_0(\theta^2/4) + \theta^2 I_1(\theta^2/4) \right]^2,$$

where I_0 and I_1 are modified Bessel functions of the first kind.

Estimation with the Posterior Distribution: In Bayesian statistics, like statistical analysis in general, there are many ways that an estimate for a parameter may be arrived at. Each of these may be different from the others. For example, two simple methods for obtaining estimates for a parameter are: 1) maximizing the posterior distribution to obtain the most probable value and 2) calculating the expectation value with respect to the posterior distribution. In the context of the GLM it is easy to see that methods 1) and 2) both lead to the ML estimate for the amplitudes. In general, the method of estimation will be dependent on the situation at hand and should be quoted as part of the information about the parameter [6].

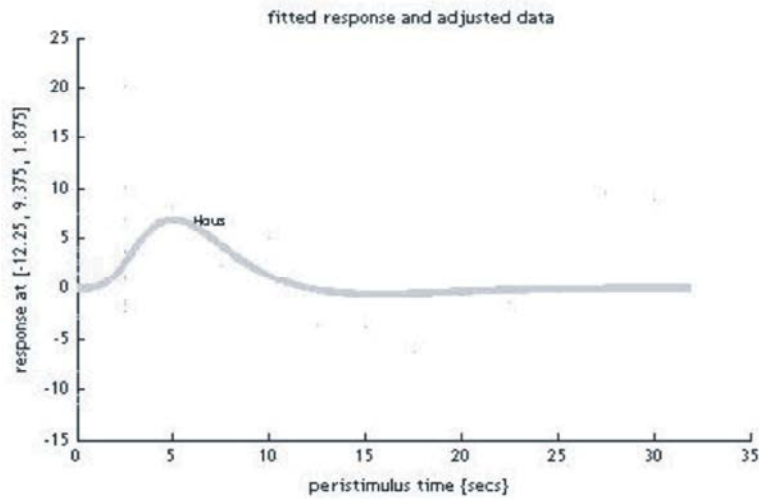


Fig. 4: Indicates the intensity spike in the brain

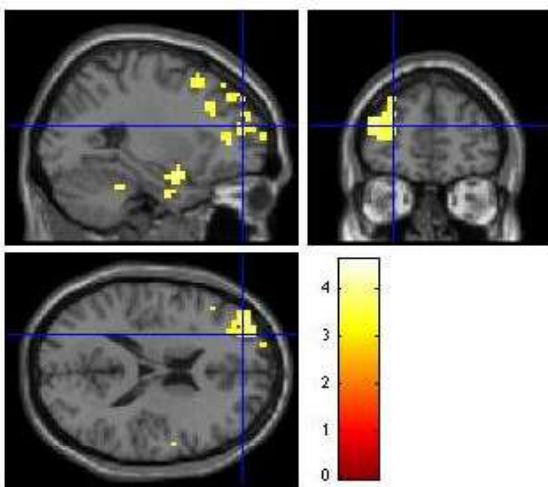


Fig. 5: Indicates the area of the maximum activation in the brain(Canonical)

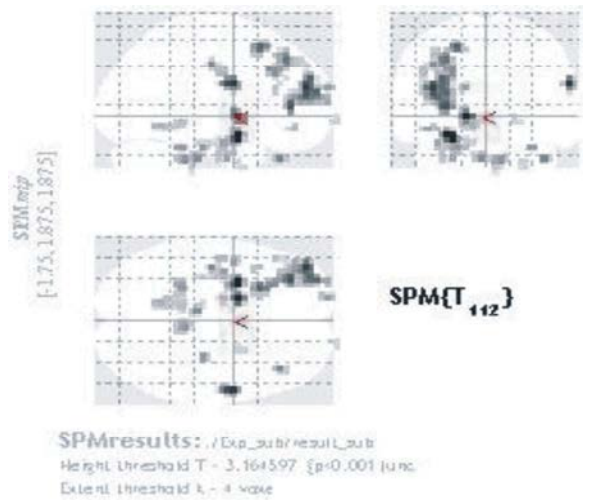


Fig. 6: Indicates the area of the maximum activation in the brain(Bayes estimation)

Inference with the Posterior Distribution: The aim of fMRI data analysis is to declare F pixels (or, more correctly, regions of the brain) either activated or inactivated with respect to the experimental design. Specifically, the task of declaring pixels activated or nonactivated translates into making inferences about the parameters given that the values of and are unknown [6].

$$Q(\varphi) = R(\theta) + S(\chi)$$

where,

$$R(\theta) = (\theta - \hat{\theta})^T A^T (I - P_B) A (\theta - \hat{\theta})$$

$$S(\chi) = (\chi - \hat{\chi})^T B^T B (\chi - \hat{\chi})$$

$$\chi = \psi + (B^T B)^{-1} B^T A \theta$$

And

$$\hat{\theta} = [A^T (I - P_B) A]^{-1} A^T (I - P_B) x$$

$$\hat{\chi} = (B^T B)^{-1} B^T x$$

$$P_B = B (B^T B)^{-1} B^T.$$

Bayesian analysis provides a natural way of achieving this: and are treated as nuisance parameters that are removed from the problem by integrating the posterior distribution over their domain. Prior to this, however, it is convenient to introduce the additional decomposition [6].

Result and Analysis: The GLM has been applied to the fMRI image data with a 1% significance level. The slice

Statistics: p-values adjusted for search volume

set-level		cluster-level				peak-level						mm mm mm		
p	c	P _{FWE-corr}	P _{FDR-corr}	k _c	P _{uncorr}	P _{FWE-corr}	P _{FDR-corr}	T	Z _c	P _{uncorr}				
0.000	19	0.044	0.119	49	0.006	0.096	0.567	4.62	4.41	0.000	-30	2	-17	
						0.926	0.922	3.57	3.47	0.000	-26	-6	-36	
						0.930	0.922	3.56	3.46	0.000	-37	-9	-24	
		0.382	0.389	19	0.067	0.132	0.567	4.53	4.33	0.000	-16	2	-2	
		0.443	0.389	17	0.082	0.231	0.645	4.34	4.16	0.000	58	-2	24	
		0.000	0.000	179	0.000	0.276	0.645	4.28	4.11	0.000	-40	51	21	
						0.444	0.755	4.09	3.94	0.000	-30	39	6	
						0.545	0.755	3.99	3.85	0.000	-30	58	17	
		0.284	0.356	23	0.047	0.537	0.755	4.00	3.86	0.000	-23	17	54	
		0.871	0.685	6	0.286	0.791	0.921	3.75	3.64	0.000	40	32	-36	
		0.412	0.389	18	0.074	0.794	0.921	3.75	3.63	0.000	-40	-17	39	
						0.967	0.943	3.47	3.37	0.000	-33	-9	32	
						0.980	0.943	3.42	3.32	0.000	-47	-13	36	
		0.145	0.246	32	0.022	0.825	0.921	3.72	3.60	0.000	-5	-28	-36	
						0.876	0.921	3.65	3.54	0.000	9	-36	-39	
						0.908	0.943	3.22	3.15	0.001	-12	-24	-22	
		0.792	0.685	8	0.220	0.889	0.921	3.63	3.52	0.000	-23	-39	-28	
		0.936	0.685	4	0.385	0.892	0.921	3.63	3.52	0.000	30	-24	-28	
		0.792	0.685	8	0.220	0.901	0.921	3.61	3.51	0.000	-16	66	21	
		0.936	0.685	4	0.385	0.914	0.922	3.59	3.49	0.000	-44	-2	-13	
		0.169	0.246	30	0.026	0.959	0.943	3.49	3.39	0.000	-12	-54	-9	
						0.984	0.943	3.39	3.30	0.000	-9	-39	-6	
						0.988	0.943	3.37	3.28	0.001	-19	-43	-9	
		0.906	0.685	5	0.331	0.969	0.943	3.46	3.36	0.000	-37	43	-13	
		0.906	0.685	5	0.331	0.977	0.943	3.43	3.33	0.000	-16	-9	-28	
		0.906	0.685	5	0.331	0.980	0.943	3.41	3.32	0.000	-40	17	47	
		0.936	0.685	4	0.385	0.988	0.943	3.37	3.28	0.001	-47	28	21	

table shows 3 local maxima more than 8.0mm apart

Height threshold: T = 3.16, p = 0.001 [0.95]
 Extent threshold: k = 4 voxels, p = 0.418 [0.9]
 Expected voxels per cluster, $\langle k \rangle = 5.7$
 Expected number of clusters, $\langle c \rangle = 2$
 FWEp: 4.818, FDRp: Inf, FWEc: 49, FDRc: 17

Degrees of freedom = [1.0, 112.0]
 FWHM = 12.4 14.7 13.8 mm mm mm; 3.5 3.9 3.7 {voxel:
 Volume: 1675160 - 34035 voxels - 541.6 res
 Voxel size: 3.5 3.8 3.8 mm mm mm; (resel = 51.37 voxel
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Fig. 7: P-values generated by the Bayes estimation

from Experiment of a subject performing the visual task. Activation has been clearly identified in several compact, localized regions. Fig. 4 was taken from the visual stimulation experiment. Distinct activation is apparent in the visual cortex. The final two parts of Fig. 1 are the same slice taken from the same subject for two different experiments. Fig. 5 is from another visual recognition experiment. The task was performed with the opposite hand to that used in Experiment 1, so activation is detected in the opposite side of the brain. The Bayes estimator is used to estimate intensity in the brain of the experiment with a threshold of 3.5 and indicates the value of intensity that was recorded during the performance of the experiment.

The Bayesian estimator is applied to the fMRI image using the Kaoy Inversion Technique.

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