TUTORIAL Model-based fMRI

Birte Toussaint



Methods & Models for fMRI Analysis 3 December 2019



ETH

Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Prerequisites

- Previously preprocessed data files
 - or: run *teach_prepro_subject('path/to/Sub01', 1)* on raw functional scans
- Behavioural data
 - BehaviorSummary files in /Sub01/behav/
- Tapas toolbox
 - added to MATLAB path by running tapas_init

Behavioural parameters

- BehaviorSummary files contain:
 - tLeftStim & tRightStim: presentation time of left/ right arrow
 - tLeftPress & tRightPress → time of left/ right button presses
- Generate input and response vectors
 - run teach_analyse_behaviour_hgf('path/to/Sub01')
 - → BehavHGF files
 - **inputs u:** experimental stimuli (left arrow = 0; right arrow = 1)
 - **responses y:** vector of Sub01's button presses (left = 0; right = 1)

Steps for model-based fMRI

- 1. Choose a model
- 2. Find best-fitting parameters of model to behavioral data
- 3. Generate model-based time series
- 4. Convolve time series with HRF
- 5. Regress against fMRI data

1. Choose a model

Level 3: Phasic volatility

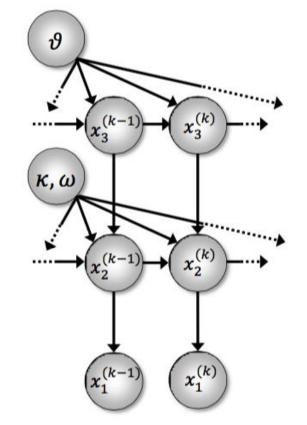
 $p(x_3^{(k)}) \sim \mathcal{N}(x_3^{(k-1)}, \vartheta)$

Level 2: Tendency towards category 1

$$p(x_2^{(k)}) \sim \mathcal{N}(x_2^{(k-1)}, e^{(\kappa x_3^{(k-1)} + \omega)})$$

Level 1: Stimulus category

$$p(x_1 = 1) = \frac{1}{1 + e^{-x_2}}$$



Mathys et al., Front Hum Neurosci, 2011

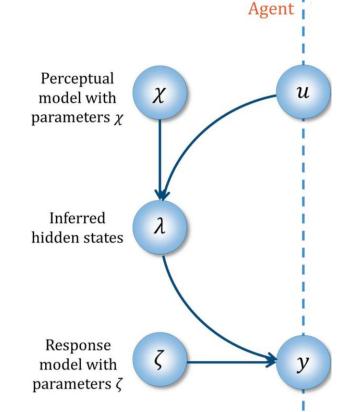
Specify model priors

- Decide which parameter(s) to estimate
 - example: κ_2 (coupling strength between levels 1 and 2)
- Adjust HGF configuration file
 - Open /tapas/HGF/tapas_hgf_binary_config.m

```
% Kappas
% Format: row vector of length n_levels-1.
% Fixing log(kappa1) to log(1) leads to the original HGF model.
% Higher log(kappas) should be fixed (preferably to log(1)) if the
% observation model does not use mu i+1 (kappa then determines the
% scaling of x i+1).
                                                   set prior variance of \kappa_2 > 0
c.logkamu = [log(1), log(1)];
                         4^2; % estimate kappa2 to free the parameter
c.logkasa = [
                  0,
% Omegas
% Format: row vector of length n_levels.
                                                   set prior variance of \omega_1 and
% Undefined (therefore NaN) at the first level.
                                                  -\omega_2 to 0: we don't want to
c.ommu = [NaN, -3, -6];
c.omsa = [NaN, 0,
                                                   estimate them
```

Specify model priors

- You can just use the following file, which is already adjusted:
 - teach_tapas_hgf_binary_config.m
- Load behavioural parameters:
 - BehavHGF02.mat
- Use tapas_fitModel to estimate parameters:
 - est = tapas_fitModel(responses, inputs, <prc_model>, <obs_model>, <opt_algo>);



Specify model priors

• Find Bayes optimal parameters:

leave empty: optimal parameter values are independent of responses

bayes_opt = tapas_fitModel([], u, 'teach_tapas_hgf_binary_config',
'tapas_bayes_optimal_binary_config',
'tapas_quasinewton_optim_config');

- Set the prior mean of κ_2 to the Bayes optimal value
 - Adjust tapas_hgf_binary_config.m

```
% Kappas
% Format: row vector of length n_levels-1.
% Fixing log(kappa1) to log(1) leads to the original HGF model.
% Higher log(kappas) should be fixed (preferably to log(1)) if the
% observation model does not use mu_i+1 (kappa then determines the
% scaling of x_i+1).
c.logkamu = [log(1), 0.090349]; % Bayes optimal prior
c.logkasa = [ 0, 4^2]; bayes_opt.p_prc.ka(2)
```

or use teach_tapas_hgf_binary_config_adjusted.m

2. Find best-fitting parameters of model to behavioral data

• Fit an HGF to the data:

est = tapas_fitModel(y, u, 'teach_tapas_hgf_binary_config_adjusted',
'tapas_unitsq_sgm_config', 'tapas_quasinewton_optim_config');

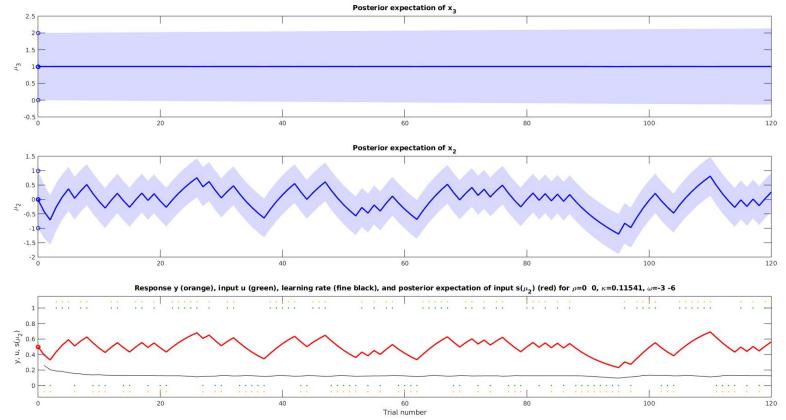
Results:

Parameter estimates for the perceptual model: mu_0: [NaN 0 1] sa_0: [NaN 1 1] rho: [NaN 0 0] ka: [1 0.1154] om: [NaN -3 -6] Parameter estimates for the observation model: ze: 0.6961 Model quality: LME (more is better): -96.8247 AIC (less is better): 176.4899 BIC (less is better): 182.0649 AIC and BIC are approximations to -2*LME = 193.6495.

2. Find best-fitting parameters of model to behavioral data

• Visualise the inferred belief trajectories:

tapas_hgf_binary_plotTraj(est)



3. Generate model-based time series

• Model outputs:

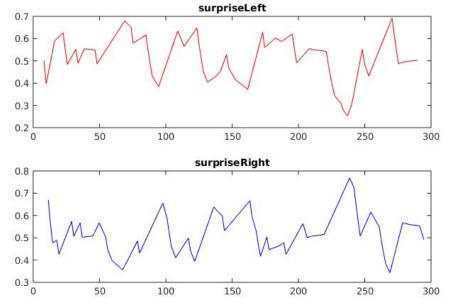
E 1x1 struct with 11	The second se	est.traj	1
Field ∠	Value	Field 🛆	Value
± y	120x1 double	🕂 mu	120x3 double
u	120x1 double	🛨 sa	120x3 double
🚽 ign	[]	🕂 muhat	120x3 double
🛨 irr	[]	🕂 sahat	120x3 double
🗄 c_prc	1x1 struct	Ηv	120x3 double
E c_obs	1×1 struct		120x2 double
E c_opt	1×1 struct	🕂 da	120x3 double
🗉 optim	1x1 struct	🕂 ud	120x3 double
E p_prc	1x1 struct	🖶 psi	120x3 double
🗄 p_obs	1x1 struct	🕂 epsi	120x3 double
🗉 traj	1×1 struct	H wt	120x3 double
raioctorios of th	e environmental state	s Sympodic	tion errors

3. Generate model-based time series

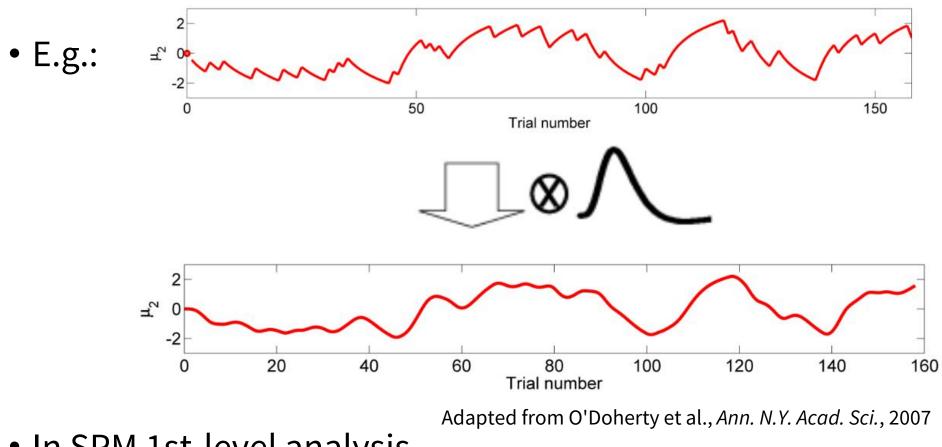
- E.g. time series representing surprise about the arrow direction
- In the Bayesian framework *surprise* is given by the unsigned PE

```
% Extract inferred delta(1): PE about arrow direction
pe = est.traj.da(:,1);
surprise = abs(pe); % take absolute value to get surprise
```

```
% Split into surprise about left vs. right arrow
surpriseLeft = surprise(u==0);
surpriseRight = surprise(u==1);
```

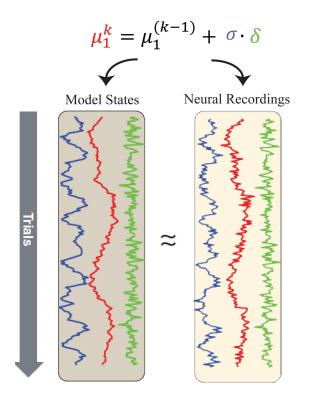


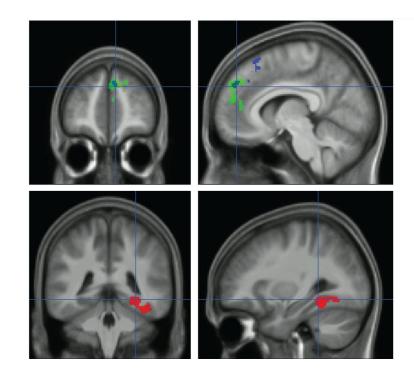
4. Convolve time series with HRF



• In SPM 1st-level analysis

5. Regress against fMRI data





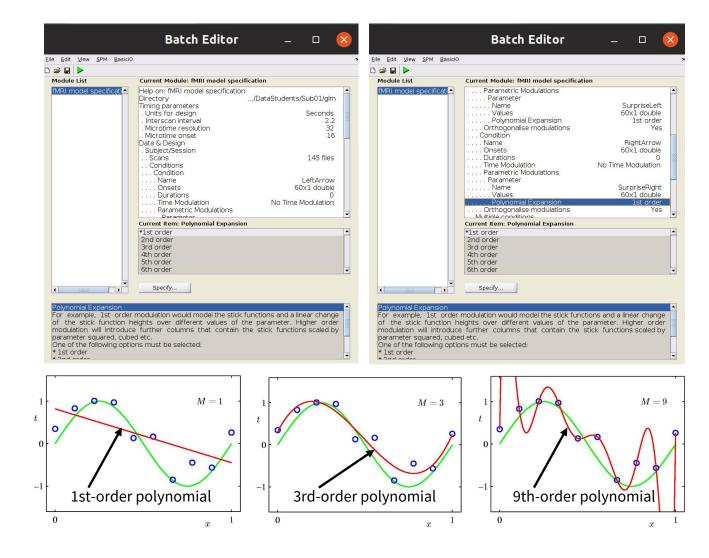
Adapted from Behrens et al., 2010

• In SPM 1st-level analysis

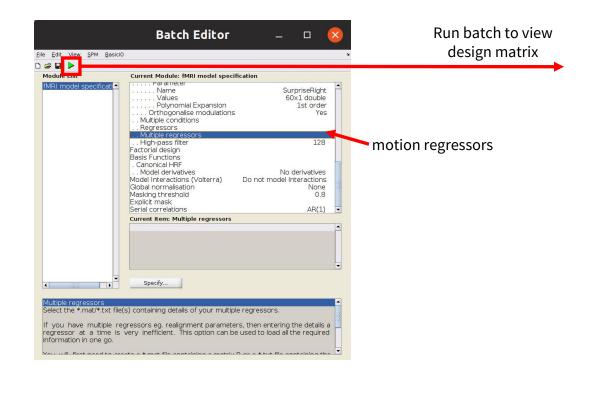
- SPM: Specify 1st-level
- Specify directory:
 - /Sub01/glm/modelbased
- Scanning parameters:
 - TR = 2.2 s
 - 32 slices
- Load data:
 - /Sub01/functional/ s8wafmri02.nii

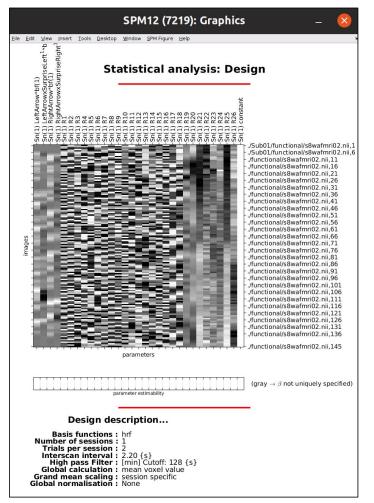
Spatial pre-process Realign (E • Coregister •	Slice t Normal	ine	Smooth egment				
Specify 1st-	_	d estimation Revie	E	📽 🖬 🕨	Batch Edit	or – 🗆	
Specify 2nd-	level	Estim	ate		Module List fMRI model specificati	Current Module: fMRI model Help on: fMRI model specifi	
Inference	Resu					Directory Timing parameters . Units for design . Interscan interval . Microtime resolution . Microtime enset Data & Design . Subject/Session . Conditions . Multiple conditions . Rearessors	9/DataStudents/Sub01/gin Second 2.3 1f 1f5 file
						Multiple regressors High-pass filter Factorial design Basis Functions Cancolcal HDE	128
SPM	for fun	ctional MR	21			Current Item: Scans /home/birtet/polybox/M&Mi	ecture 03.12.19/DataStudents/Su
Display Che	eck Reg	Render •	FMRI -			/home/birtet/polybox/M&Mi /home/birtet/polybox/M&Mi	ecture 03.12.19/DataStudents/Su ecture 03.12.19/DataStudents/Su ecture 03.12.19/DataStudents/Su ecture 03.12.19/DataStudents/Su
Toolbox: •	PPIs	ImCalc	DICOM I		•	Specify	
Help		Batch	Quit	10	Scans Select the fMRI scar orientation, voxel size		I have the same image dimension:
	and the last of the second second	01 1004 2017			C		

- Load regressors:
 - Condition 1: tLeftStim
 - Parametric modulation: SurpriseLeft
 - Condition 2: tRightStim
 - Parametric modulation: SurpriseRight
- Set Durations = 0
- Polynomial Expansion:
 - Choose 1st order

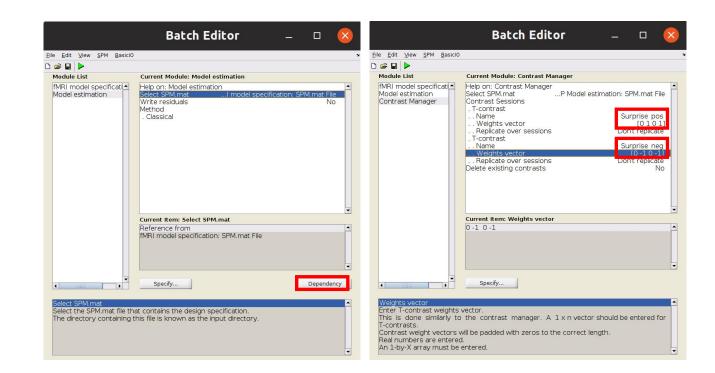


Enter motion regressors
physio_regressors_run02.txt





- Stats: Model estimation
 - Select SPM.mat
 - set Dependency
- Stats: Contrast manager
 - Select SPM.mat
 - set Dependency
 - Contrast Sessions
 - T-contrast: Surprise_pos
 - T-contrast: Surprise_neg
- Run batch



- View results
 - /Sub01/glm/SPM.mat

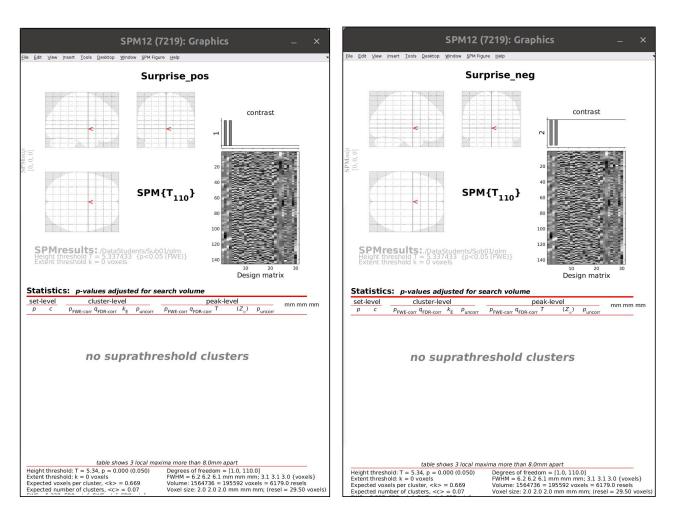
Slice timing	Smooth											
Normalise	Segment											
Model specification, review and estimation												
vel	Review											
evel	Estimate											
Inference Results												
Dynamic Causal Modelling												
SPM for functional MRI												
k Reg Rende	er • FMRI •											
Pls ImC	alc DICOM I											
• Bat	ch Quit											
	Normalise vel vel Results nic Causal Mod or function k Reg Rende Pls ImC											



- Select contrast
 - apply masking: none
 - p val adjustment: none
- → Uncorrected results:
 - brain activity correlates with surprise about arrow direction

															C D	1412 /	7240		- hie				~
SPM12 (7219): Graphics – 🛛 🛛 🛛 🛛									SPM12 (7219): Graphics _ ×														
le Edit View Insert Iools Desktop Window SPM Figure Help											Elle Edit View Insert Iools Desktop Window SPM Figure Help 🗙												
Surprise_pos										Surprise_neg													
					contrast									× •			<		2		contrast		
SPM{T ₁₁₀ } SPM{T ₁₀ } SPM{T ₁₀ } SPM{T ₁₀ } SPM{T ₁₀ } SPM{T ₁₀ } SPM{T ₁₁₀ } SPM{T ₁₁₀ } SPM{T ₁₀ } SPM{T ₁										30 rix													
	CS: p-va		-	ed for s	earch v						50	atistic		cluster-le		a tor s	earcn V	oiume	peak-	level			10
p c		cluster- rr q _{FDR-co}		P _{uncorr}	<i>D</i>	rr q _{FDR-co}	peak-lev	(Z_)	P _{uncorr}	mm mm mm				orr q _{FDR-cor}		P _{uncorr}	P _{FWE-c}	orr 9 _{FDR-1}		(Z_)	p _{uncorr}	mm m	m mm
0.685 59	0.008	0.004	66	0.000	0.453	0.751	4.77	4.53	0.000	-36 -32 -10			1.000	0.578	1	0.578	1.000	0.954		9 3.11		-40 34	-16
	0.002	0.002	83	0.000	1.000 0.968 1.000 1.000	0.982 0.882 0.982 0.982	3.31 4.24 3.71 3.46	3.22 4.07 3.60 3.37	0.001 0.000 0.000 0.000	-42 -38 -10 -14 -74 -22 -6 -80 -24 -18 -78 -28													
	1.000	0.578	1	0.578	0.971	0.882	4.23	4.06	0.000	-30 -66 26													
	0.220	0.059	32	0.004	0.975	0.882	4.22	4.05	0.000	64 -38 14 52 -42 14													
	0.569	0.159	22	0.013	0.992	0.982	4.13	3.97	0.000	-20 -82 42													
	1.000	0.578	5	0.201	1.000	0.982	3.32	3.23 3.87	0.001	-24 -90 36 22 -78 30													
	1.000	0.578	2	0.419	1.000	0.982	3.75	3.63	0.000	44 14 16													
	1.000	0.578	2 14	0.419	1.000	0.982	3.69	3.58	0.000	46 -76 -14 -68 -28 14													
	1.000	0.348	3	0.320	1.000	0.982	3.67	3.55	0.000	24 -76 28													
	0.059	0.019	45	0.001	1.000	0.982	3.63	3.52	0.000	22 -70 38													
					1.000	0.982	3.60	3.49	0.000	28 -80 44													
	1.000	0.578	3	0.320	1.000	0.982	3.61	3.50	0.000	-38 -68 -40													
	1.000	0.578	4	0.251	1.000	0.982	3.61	3.50	0.000	52 -64 -12 58 0 40													
	0.971	0.416	12	0.056	1.000	0.982	3.56	3.45	0.000	-18 -68 58													
	1.000	0.578	6	0.163	1.000	0.982	3.55	3.45	0.000	50 -4 18													
		table	shows	3 local ma	xima mor	e than 8	0mm an	art						table s	hows 3	local ma	xima mo	re than 8	8.0mm -	apart			
Height thre	shold: T = 3						edom = [.01		Hei	ght thresh	old: T = 3							= [1.0, 11	0.01		
	shold: $k = 0$		5.001	(1.000)						3.0 {voxels}	Ext	ent thresh	old: $k = 0$) voxels			FWHM	1 = 6.2 6	6.2 6.1 1	mm mm r	mm; 3.1 3.		
Expected voxels per cluster, <k> = 3.273 Volume: 1564736 = 195592 voxels = 6179.0 resels</k>						Exp	ected vox	els per cl	uster, <k></k>			Volun	ne: 1564	1736 = 3	195592 v	oxels = 61	79.0 rese	ls					
Expected n	umber of cl	usters, <	c> = 6	52.44	Voxel	size: 2.0	2.0 2.0 r	nm mm	mm; (rese	el = 29.50 voxels)	Exp	ected nur	nber of cl	usters, <c< td=""><td>> = 62</td><td>.44</td><td>Voxel</td><td>size: 2.0</td><td>0 2.0 2.</td><td>0 mm mn</td><td>n mm; (res</td><td>el = 29.5</td><td>0 voxels)</td></c<>	> = 62	.44	Voxel	size: 2.0	0 2.0 2.	0 mm mn	n mm; (res	el = 29.5	0 voxels)

- Contrasts
 - Significance level
 - Set to 0.05 (FWE)
- \rightarrow FWE-corrected results:
 - correlations not significant when we correct for multiple comparisons



• What questions can we ask?

- What questions can we ask?
 - 1. Where in the brain are PEs (about arrow direction) represented?
 - 2. Are there differences in brain activity depending on whether PEs occur in response to the arrow being presented on the left or right?

- What questions can we ask?
 - 1. Where in the brain are PEs (about arrow direction) represented?

2. Are there differences in brain activity depending on whether PEs occur in response to the arrow being presented on the left or right?

• Different 2nd-level design matrices:

- What questions can we ask?
 - 1. Where in the brain are PEs (about arrow direction) represented?

2. Are there differences in brain activity depending on whether PEs occur in response to the arrow being presented on the left or right?

• Different 2nd-level design matrices:

1. Average over parametric regressors:

• Set surpriseLeft = 1 & surpriseRight = 1, one-same t-test

2. Difference between parametric regressors:

• Set surpriseLeft = 1 & surpriseRight = -1, one-sample t-test