Learning to Identify Overlapping and Hidden Cognitive Processes from fMRI Data

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1 Objective

fMRI data analyses typically assume the observed fMRI activation results from the sum of hemodynamic responses (HDRs) generated by known stimuli with known timing. We present an alternative approach that assumes additional activation may be generated by internally initiated cognitive processes, whose timing and identity may be unknown. For example, in an experiment where subjects compare a sentence to a picture to determine whether the two are consistent, we might posit three internal cognitive processes: ComprehendPicture, ComprehendSentence, and ComparePictureToSentence. Onsets of the first two processes might be inferred from stimulus onsets, whereas onset of the third process is unknown. We present a formalism which allows learning the HDRs of such hidden processes, and using these learned models to track hidden cognitive processes given observed fMRI sequences.

2 Methods

We define a Hidden Process Model (HPM) as a set of processes, each described by its characteristic HDRs across multiple voxels in the brain.

2.1 Learning HPMs

First consider learning an HPM (i.e., the HDR for each HPM process) given fMRI data plus the known timing and identity of each process generating the data. This can be accomplished using a variant of the General Linear Model (GLM) as outlined in [Dal99]. The HDR for each process can be estimated using Ordinary Least Squares regression.

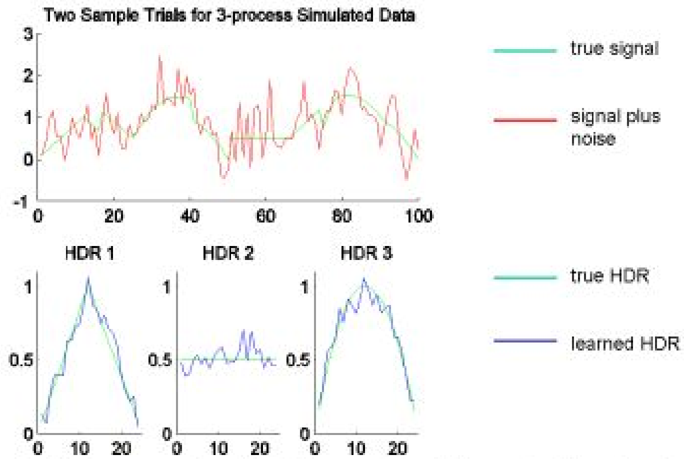

Figure 1. The learner was given 80 training examples with known start times for only the first two processes. It chooses the correct start time (26) for the third process, in addition to learning the HDRs for all three processes.

Second, consider learning HPMs when the exact timing of some processes and the training data are unknown. In this case we employ an EM algorithm to obtain locally maximum likelihood estimates for both the unknown onsets and the HDRs.

2.2 Using HPMs for Tracking

As a byproduct of learning an HPM, the algorithm also determines a locally maximum likelihood assignment of onset times for each hidden process generating the training data. Given a new fMRI data sequence, an HPM, and a hypothesized number of processes, a similar algorithm can be used to determine the maximum likelihood identities and onsets of the hidden processes generating this new data.

3 Results & Discussion

Figure 1 shows the application of HPM learning to synthetic data generated by three hidden processes. Note the ability to accurately learn the hidden process HDRs from noisy data.

Figure 2 shows the application of HPMs to the above ComprehendPicture, ComprehendSentence, ComparePictureToSentence fMRI study. During training, timings were provided for only the first two processes. Timing of the third process was inferred with the HDR.

Table 1 shows the results of applying HPMs to fMRI data in which subjects

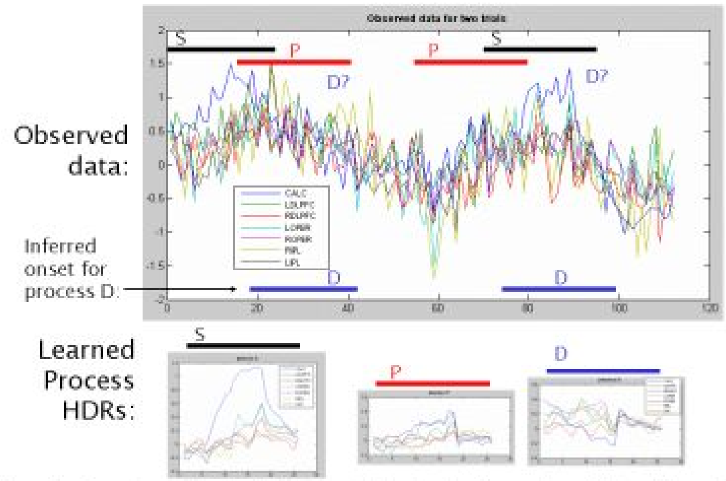

Figure 2. Top: observed fMRI data for two trials showing ComprehendPicture (P) and ComprehendSentence (S) processes. Lower bar shows inferred timing for third process (D). Bottom: learned HDRs per process, for each of seven cortical regions of interest.

viewed words, one every 3-4 seconds. It shows the ability of the learned HPM to predict which process instances were readNoun versus readVerb, over data left out during training. Accuracy is significantly better than random for three out of four subjects, despite the 3-4 second interval between process onsets.

Subject	A	B	C	D
Accuracy	0.683	0.525	0.633	0.733
p-value	$<$0.0001	0.32	0.003	$<$0.0001

Table 1: Accuracies and p-values when predicting left-out data from four subjects in the readNoun-readVerb study. Accuracies for random predictions would be 0.5.

4 Conclusions

Our results demonstrate that our approach can accurately reconstruct the processes in synthetic data, and predict the timing and identities of underlying processes in fMRI data.

5 References & Acknowledgements

[Dal99] Anders Dale. Optimal experimental design for event-related fMRI. Human Brain Mapping, 8:109-114, 1999.