Real-Time fMRI

Stephen LaConte

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Classification in Real Time

LaConte et al. *Hum Brain Mapp* (2007)
Outline

• Overview of rtfMRI
• Tracking localized brain regions
• Supervised learning-based rtfMRI
• Resources for getting started
• Technical challenges
• Applications
Chronic Pain:
Continuous display representing percent signal change of rostral anterior cingulate by the size of a virtual fire
Thermometer display showing signal subtraction between right anterior insula and a large reference ROI

Task cues are to the right of the thermometer.
Motion Feedback:
A set of inner, middle, and outer four-way arrows, indicating degree of motion

Task stimuli are presented in the center of the arrows (‘+’ symbol represents the rest condition)
Yellow trace is a running plot of the difference between two brain regions (PPA – SMA)

(Weiskopf et al., 2004)

(Cox et al., 1995)

(Caria et al., 2007)

(Yang et al., 2005)

(deCharms et al. 2005)

(LaConte et al., 2007)

(Eklund et al., 2009)
Cox, R.W., Jesmanowicz, A., Hyde, J.S., 1995

- recursive partial correlation algorithm for fMRI.
- utility of online functional maps
  - monitor data quality
  - evolve experimental protocols more rapidly
  - perform interactive experimental paradigms

(LaConte et al., 2007)

(Eklund et al., 2009)

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Supervised learning / Pattern-based

“move the cursor to the target”
Neural Network:

Using conditions:

- Right hand
- Left hand
- Rest

Subjects controlled a simulated inverted pendulum

(Eklund et al., 2009)
Applications of real-time fMRI

• Monitoring experiments
• Quality assurance
• Surgical planning
• Reading and controlling localized brain function
• Performing adaptive fMRI experiments
• Enabling therapy and rehabilitation
Applications of real-time fMRI

- Monitoring experiments
- Quality assurance
- Surgical planning
- Reading and controlling localized brain function
- Performing adaptive fMRI experiments
- Enabling therapy and rehabilitation
Cohen, 2001
Cohen, 2001
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Localized fMRI signals
Example:
Increasing volitional control over somatomotor cortex

Subjects can learn to control a number of different brain areas

- **Somatomotor cortex**
  - Posse 2001, Yoo 2002, deCharms 2004, Yoo 2004

- **Parahippocampal place area**
  - Weiskopf 2004

- **Amygdala**
  - Posse 2003

- **Insular cortex**
  - Caria 2007

- **Anterior cingulate cortex**
Localized real-time fMRI

- Localized approaches have demonstrated a high degree of potential
- Activated areas are generally noisy
- Generating a map requires
  - Updating statistics at each pixel
  - Time window considerations
  - Interpretation of brain activation
- Tracking a region of interest requires
  - Designation of that region
  - Filtering and spatial averaging
Outline

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Supervised learning applied to fMRI

Step 1: Train with labeled data

Data acquisition → Visual display → Stimulus → Data labels (y) → Time-labeled scans → y_t → Estimated label for time t → Supervised learning

Step 2: Use model to predict/decode

Visual display → Stimulus → Data acquisition → Image data → Model
Temporal Brain State Classification

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Temporal Regression

fMRI experiment

\[ f(x) = x^T \beta + \beta_0 \]

\[ L(y, f(x)) \]
Real-Time Classification

Stimulus Presentation

Exp. Design

Class Training Labels

Stimulus

Data Acquisition

Image Data

Image Recon and SVM Classification

Time-Labeled Scans

Test Data Classifier Output

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Experimental Timing and Classifier Output
(left finger = -1, right finger = +1)

Subject 1 (78 % Accuracy)

Subject 2 (78 % Accuracy)

Subject 3 (79 % Accuracy)

Subject 4 (77 % Accuracy)

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Brain state classification: a variety of cognitive domains.

With the exact same experimental setup (different instructions), subjects can learn to move the arrow

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044

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Stimulus seen by volunteer

Updated fMRI results

Motion tracking and correction

Intensity (brightness) of a single pixel, changing during stimulus conditions

Controller interface for some display parameters

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demonstration experiment

Initial scans

- **Localizer** (9 seconds)
  Acquires images in three planes that enable the operator to locate images during the rest of the session.

- **Anatomical scan** (4.5 minutes)
  High resolution (1 mm³)

fMRI runs: low resolution 3D movies

- **Masking run** (10 seconds)
  A few frames are used that match the resolution of the fMRI runs.
  Image processing is performed to detect ("mask out") brain regions from regions outside the brain. This point in the experiment could also be used to focus the rest of the experiment on a specific anatomical site.

- **Training run** (6 minutes)
  As fMRI brain volumes are being acquired, machine learning algorithms are processing the images and the stimuli/behavior to create a predictive model.

- **Feedback run** (6 minutes)
  Uses the training run model. Specifically, the model is applied to each image as it is acquired, allowing prediction of psychological state. In other words, the model is used to decode the stimulus/behavioral conditions that are associated with the current image. The output of the model is converted into a control signal that can modify the stimulus being presented to the volunteer.

LaConte, *NeuroImage* (2011)
Basic Benchmarks

• Classifier safety factor > 20,000x.
  – Approximately 1μsec / dot product.

• Network/AFNI Transfers > 20x volumes
  – Approximately 100 μsec / slice to transfer
Effect of training with task transition images

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Effect of training with task transition images

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Effect of training with task transition images

testing last 20 of 30 s (10 of 15 images)

Discarded Transition Images

all images exclude 1 exclude 2 exclude 3

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Responsiveness to stimulus changes

Average classifier output

The model trained without transition images is more stable

The model trained without transition images is more sluggish

Individual classifier output with behavioral data

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Classification of “transition” images

LaConte, et al. (2007) Hum Brain Mapp. 28: 1033-1044
Outline

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Resources

• Review Articles

• Software
  – TurboFire (Gebris et al. 2000)
  – Turbo-Brain Voyager (Goebel, 2001)
  – AFNI (Cox, 1996)
3ds svm

LaConte Lab

3ds svm is a command line program and plugin for AFNI, built around SVM-Light. It provides the ability to analyze functional magnetic resonance imaging (fMRI) data as described in (LaConte et al., 2005).

Features:
- Reading AFNI-supported binary image formats
- Marking or erasing brain regions
- Classifying training samples
- Visualizing alpha as time series and linear weight vectors as functional overlays
- Classifying multiple categories

Supervised learning with 3ds svm can be used for predicting brain states to enhance understanding of brain systems, complementing the conventional technique of spatial mapping. The figure below illustrates the classification process supported by 3ds svm. For each time point, the brain voxel intensities can be represented in a high-dimensional vector space. During an fMRI experiment, each image is a point in the vector space. At these points, a classification model can be estimated to divide voxels between experimental stimuli. After the model is determined, independent data can be assigned a class membership.

- 3ds svm is a command line program and plugin for AFNI, built around SVM-Light. It provides the ability to analyze functional magnetic resonance imaging (fMRI) data as described in (LaConte et al., 2005)
- http://lacontelab.org/3dsvm.html
3dsvm features

• Distributed with AFNI
• Reading AFNI-supported formats (including NIfTI)
  • Thus all preprocessing and data manipulation of the major software packages
• Classification and regression
• Masking of variables (brain pixels)
• Censoring training samples
• Visualizing alphas as time series and linear weight vectors as functional maps
• Multi-class classification
• Non-linear kernels
• Real-time fMRI
3dsvm tour: basic steps

- **Prepare training and test data sets**
  - fMRI (3D+t)
  - Labels (1D) – labels for test data are optional (needed to calculate accuracy)
  - Mask for training data (3D) – 3dsvm considers mask to be part of the model it generates

- **3dsvm training**
  - Creates a model that can be tested with independent data
  - For convenience, inspecting the model
    - Model alphas (1D)
    - Weight vector map (3D)

- **3dsvm testing**
  - Calculates class and/or distance measure for each new timepoint
  - Prediction accuracy (if test set labels are available)
3dsvm tour: plugin snapshot

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3dsvm tour: command line

Training - 3dsvm -trainvol run1+orig \n    -trainlabels run1_categories.1D \n    -mask mask+orig \n    -model model_run1

Testing - 3dsvm -testvol run2+orig \n    -model model_run1+orig \n    -predictions pred2_model1
#!/bin/csh

# example by Prashant Prasad

3dsvm -trainvol volreg_run1_PPA+orig \
    -trainlabels LABEL_PPA_1.1D \
    -mask automask_run1_PPA+orig \
    -bucket bucket_run1_PPA \
    -model model_run1_PPA

3dsvm -classout \
    -testvol volreg_run2_PPA+orig \
    -testlabels LABEL_PPA_2.1D \
    -model model_run1_PPA+orig \
    -predictions pred_run2_frmRun1_classout

3dsvm -testvol volreg_run2_PPA+orig \
    -testlabels LABEL_PPA_2.1D \
    -model model_run1_PPA+orig \
    -predictions pred_run2_frmRun1

# optional, move bucket files to Talairach
# @auto_tlrc -base TT_N27+tlrc -input anatomical_PPA+orig
# @auto_tlrc -apar anatomical_PPA_at+tlrc -input bucket_run1_PPA_0_1+orig -dxyz 4
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3dsvm Plugin Screenshot
Support Vector Machine Analysis

<table>
<thead>
<tr>
<th>Real-time</th>
<th>AFNI Plugin: Set Real-Time Options for 3dsvm – An AFNI SVM-Light Plugin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>Run &amp; Keep</td>
</tr>
<tr>
<td>Train Data</td>
<td></td>
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<tr>
<td>Train Params</td>
<td>Type: classification</td>
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<tr>
<td>Labels</td>
<td>Choose Time series</td>
</tr>
<tr>
<td>Mask</td>
<td>-- Choose Dataset --</td>
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<tr>
<td>Kernel</td>
<td>Linear</td>
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<tr>
<td>Model Output</td>
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<tr>
<td>Model Inspection</td>
<td>Prefix</td>
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<tr>
<td>Testing</td>
<td>SIM Prefix</td>
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<td>Test Data</td>
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<tr>
<td>TCP/IP</td>
<td>IP</td>
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<tr>
<td>Predictions</td>
<td>Prefix (1D)</td>
</tr>
</tbody>
</table>

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3dsvm real-time

plugout_drive -com "3DSVM -rt_train -trainlabels run1_categories.1D -mask mask+orig -model model_run1

plugout_drive -com "3DSVM -rt_test -rt_ip 10.10.10.2 -rt_port 5000 -model model_run1+orig -predictions pred_run2"
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• Overview of rtfMRI
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• Applications
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces
Future Challenges

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

- capability of multi-session and group-based SVM models
  - handling movement between runs within a session
  - progressive training and testing across sessions
  - using group models to affect rehabilitation/therapy
Future Challenges

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

- requires that the SVM model and the test data be spatially aligned

- investigate alignment strategies
  - classification accuracy
  - computational demands
Future Challenges

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

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Spatial Transforms

R: training data space

S: testing data space

N: “normalized” brain space

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Future Challenges

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

Processor:
Intel Xeon Quad Core E5462 (2.80 GHz)
Memory:
16GB DDR2 SDRAM @ 800 MHz
Future Challenges

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

### Percent prediction accuracies

<table>
<thead>
<tr>
<th>training data</th>
<th>Tapping</th>
<th>MSIT</th>
<th>Tapping</th>
<th>MSIT</th>
<th>Tapping</th>
<th>MSIT</th>
<th>Tapping</th>
<th>MSIT</th>
<th>Tapping</th>
<th>MSIT</th>
<th>Tapping</th>
<th>MSIT</th>
</tr>
</thead>
<tbody>
<tr>
<td>single run</td>
<td>90.83±7.23</td>
<td>69.44±9.05</td>
<td>90.71±7.61</td>
<td>69.48±9.11</td>
<td>90.79±7.39</td>
<td>69.46±9.00</td>
<td>91.12±7.17</td>
<td>69.26±8.93</td>
<td>93.33±7.40</td>
<td>72.01±8.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 runs combined</td>
<td>93.96±5.84</td>
<td>73.21±8.54</td>
<td>93.98±6.10</td>
<td>73.59±8.28</td>
<td>94.01±5.67</td>
<td>73.31±8.62</td>
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</table>

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Future Challenges

(LaConte, NeuroImage, 2011)

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Spatial transformation of support vector machine models for multi-session and group real-time fMRI

• alignment across scanning sessions is comparable to alignment within a scanning session
• no deleterious interpolation error effects
• model-to-scan alignment is feasible for real-time fMRI
• group SVM models can be used in real-time experiments
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
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- Feedback and feedback interfaces

Brain state feedback requires a training data and a model

- There are likely important differences between feedback and no-feedback variations of a task
- Given a start-up model, it might be possible to proceed to continuous training and feedback, leading to progressively more accurate feedback
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
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- Feedback and feedback interfaces

Feedback runs differ from no-feedback runs

Feedback (FB): Brain Controls Needle

No Feedback (noFB): Computer Controls Needle
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
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Feedback runs differ from no-feedback runs

We have initial data suggesting that these permutations may not be completely identical. Specifically, we see a slight tendency for higher prediction accuracy in Run 4 (regardless of training run) compared to Runs 1–3 (across all training run permutations). If this is the case,
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
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Feedback runs differ from no-feedback runs

(Papageorgiou, et al. 2009)
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Feedback runs differ from no-feedback runs

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Humans Out-Learning the Machine

<table>
<thead>
<tr>
<th>SVR Predicted Rate [Hz]</th>
<th>True Tapping Rate [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
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<tr>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>SVR Predicted Rate [Hz]</th>
<th>Time [Sec]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>200</td>
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<tr>
<td>4</td>
<td>300</td>
</tr>
<tr>
<td>5</td>
<td>400</td>
</tr>
</tbody>
</table>

SVR predicted rate

True rate

Diagram showing the comparison between SVR predicted rate and true tapping rate over time.
Future Challenges

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Humans Out-Learning the Machine

- Complex Motor:
  - Finger Sequence
    - short-term motor learning
  - Regression: button press rate
    - Regression error correlation with mean button press rate
    - (0.75, 0.94, 0.94, 0.80, 0.91, 0.99, 0.99).

LaConte – UCLA NITP 2011
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
- Detecting and correcting temporal non-stationarity
- Feedback and feedback interfaces

Humans Out-Learning the Machine

Button Press and Estimation Error
Future Challenges

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Humans Out-Learning the Machine
Future Challenges

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• Model-to-scan alignment
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Humans Out-Learning the Machine

• Human learning makes training data less relevant.
• Performance measures corresponded to observed “learning” in activation patterns.
• A control experiment: paced motor task
Future Challenges

(LaConte, NeuroImage, 2011)

- Model-to-scan alignment
- Model updates during real-time feedback
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- Feedback and feedback interfaces

Can interfaces be optimized by studying reward processing to promote learning/plasticity?

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Outline

- Overview of rtfMRI
- Tracking localized brain regions
- Supervised learning-based rtfMRI
- Resources for getting started
- Technical challenges
- Applications
Support Vector Machine Maps of Real-Time Tasks

Right vs. Left Tapping
Crave vs. Don’t Crave
Fast vs. Slow Counting

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Substance dependent individuals are characterized in part by susceptibility to drug cue-induced craving.
Pathophysiology and treatment of substance dependence
(With Pearl Chiu)
Pathophysiology and treatment of substance dependence
(With Pearl Chiu)

Successful “Crave” block

Non-successful “Don’t Crave” block

Figure 1: Number of successful blocks per subject for “Don’t crave” and “Crave” conditions

Figure 2: Side-by-side comparison of session 1 and session 2 for subjects who have returned for the second time point.
Speech: Covert counting
(Papageorgiou, Lisinski, McHenry, White)

run 1
Fast vs. Slow SVM
Neurofeedback
Group A
30-40 s
Run 2
Fast vs. Slow SVM
Neurofeedback
Group B
4 s
Run 3
Fast vs. Slow SVM
Neurofeedback
Group C
15-20 s
Run 4
Fast vs. Slow SVM
Neurofeedback
Group C
30-40 s

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Speech: Covert counting

(Papageorgiou, Lisinski, McHenry, White)
Speech: Covert counting
(Papageorgiou, Lisinski, McHenry, White)

Fast vs. Slow

Speech vs. Rest

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Dynamic Field Corrected Imaging of Speech

(With Brad Sutton)

Sutton et al. JMRI, 2010.
Temporal Classification
(With Brad Sutton)
Decoding speech from structural movies

(With Brad Sutton)

slow counting

fast counting

Cross-validated accuracy 88%
out of 1896 frames
Chance = 50%
Can we decode the words? “Mouth-reading” the mid-sagittal slice
(With Brad Sutton)

cross-validated accuracy 96% out of 48 spoken numbers (chance = 25%)
Can we decode the words?
“Mouth-reading” the mid-sagittal slice
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SVM multi-class

Test Input

SVM_1 (1 vs. 4)

SVM_2 (1 vs. 3)
SVM_3 (2 vs. 4)

SVM_4 (1 vs. 2)
SVM_5 (2 vs. 3)
SVM_6 (3 vs. 4)

Class 1
Class 2
Class 3
Class 4
Can we decode the words?
“Mouth-reading” the mid-sagittal slice

cross-validated
accuracy 96% out of 48 spoken numbers
(chance = 25%)

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Brad Sutton’s SIMULSCAN

Acquisition of dynamic anatomical for every functional slice.

A) Sequence diagram showing the contrast between fMRI and dynamic images over time.

B) Example images showing the sequence of acquisitions.

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Anatomical</th>
<th>Functional</th>
</tr>
</thead>
<tbody>
<tr>
<td>TR per shot</td>
<td>6.5 ms</td>
<td>25.7 ms</td>
</tr>
<tr>
<td>FOV</td>
<td>240 mm</td>
<td>240 mm</td>
</tr>
<tr>
<td>Matrix Size</td>
<td>96 x 96</td>
<td>64 x 64</td>
</tr>
<tr>
<td>TE</td>
<td>1.1 ms</td>
<td>25 ms</td>
</tr>
</tbody>
</table>

Paine, et al.  
Real-Time fMRI

• Adaptive feedback based on classified brain state
  • goes beyond linear systems input-output relationships
  • adaptive fMRI and other RT techniques may provide insights unattainable through traditional stimulus-response experiments

• Applications
  • flexible fMRI experiments, biofeedback rehabilitation, …
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