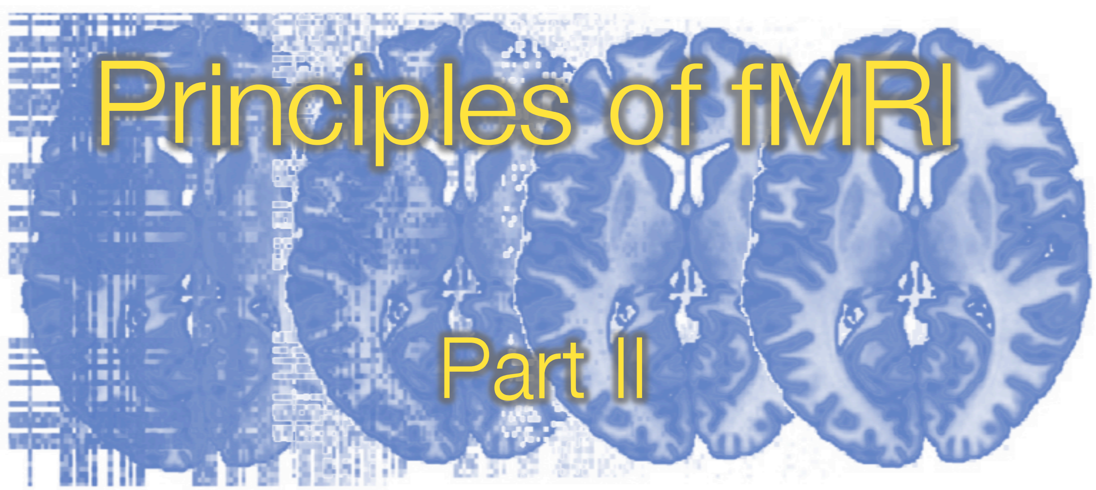
Principles of fMRI

Part II



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Eight principles of fMRI design

Principles of fMRI

1) Sample size.
2) Scan time.
3) Number of conditions.
4) Grouping of events.
5) Temporal frequencies.
6) Randomization.
7) Nonlinearity.
8) Optimization.

Many considerations and rules

Computer-aided design can help!

Computer-aided design

Search through random designs and identify the best

Generate random designs and test:
- OptSeq (Doug Greve)

Generate random designs and optimize:
- Genetic algorithm (Wager & Nichols, Kao)

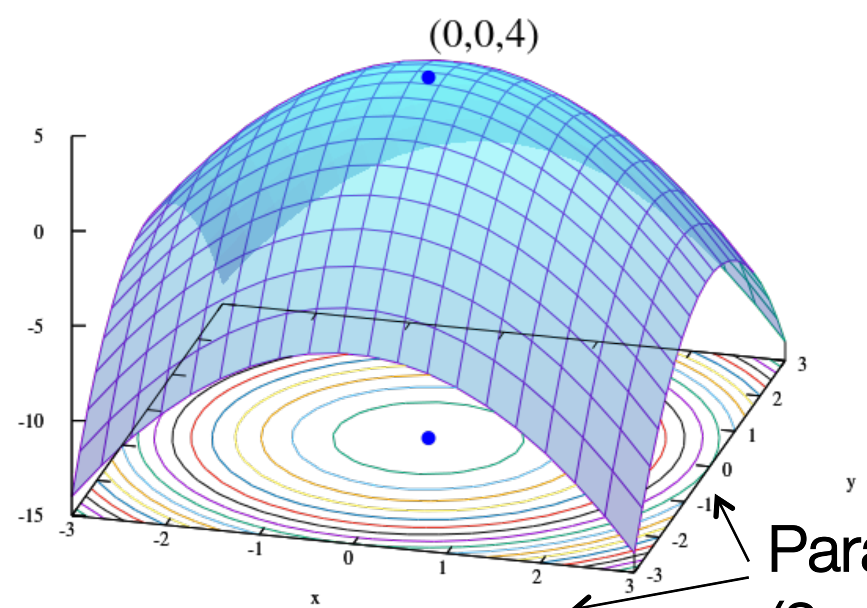
Mathematical sequences
- M-sequence program (Buracas).

Genetic algorithms

- Evolutionarily inspired optimization of problems with rough ‘fitness landscape’: When the solution is not convex

Simple convex fitness landscape

Fitness or goodness of the design →



Parameter space (2 parameters)

e.g., Goldberg & Holland 1988

Genetic algorithms

Principles of fMRI

- Evolutionarily inspired optimization of problems with rough ‘fitness landscape’: When the solution is not convex

1
2
4
2
3
1
1
…

The “DNA” : Design parameters

- Which of 4 event types to present in a time slot

Generate design matrix and test efficiency

e.g., Wager & Nichols 2003

Genetic algorithms

A “generation”:
Population of designs

1	2	4	3
2	4	2	3
4	3	2	4
2	3	1	1
3	1	1	1
1	2	4	2
1	2	3	4
…	…	…	…
↓	↓	↓	↓
e1	e2	e3	e4

e4 ← Fitness (efficiency)

“Crossover”:
Generating new designs

1	4	→	1
2	2		2
4	2		4
2	1		2
3	1		1
1	4		4
1	3		3
…	…		…

Crossover: Jumps across fitness landscape
Can jump over local optima to find global optimum

- *e.g., Goldberg & Holland 1988*

Benefits over random search

Principles of fMRI

- Perhaps random search would do just as well?

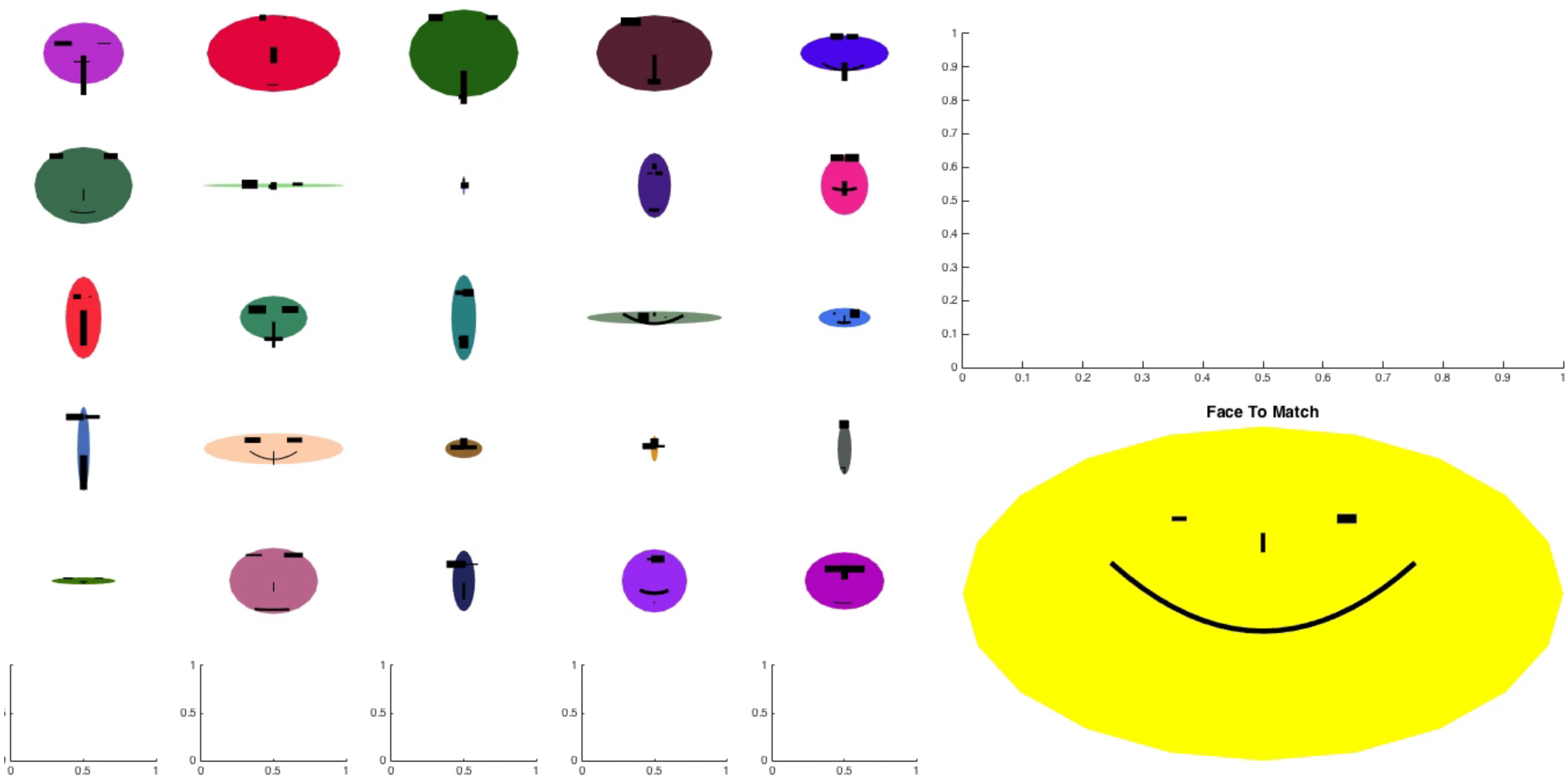
Many choices!!

1
2
4
2
3
1
1
…

- With a stimulus every 2 sec, and a run of 240 stimuli (6 min), there are 3 x 10^144 possible designs.
- Way more than there are stars in the known universe
- Random search would take forever. Can only test one “galaxy” worth in a computer year.

An example

- Optimizing to match target face:



Wager & Nichols GA

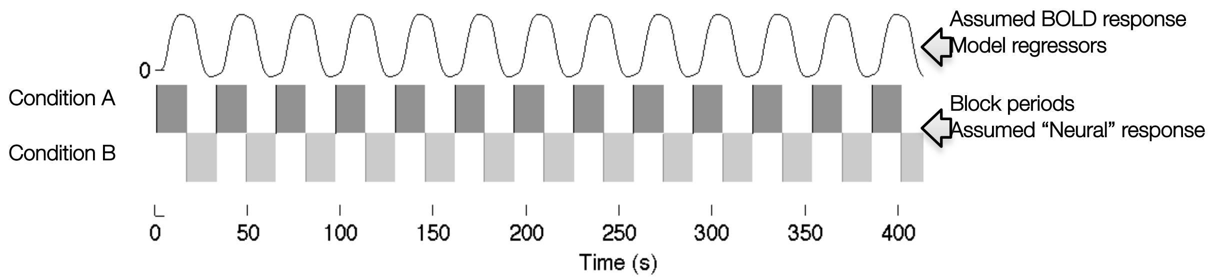
Search through random designs and identify the best ones

- Rapid convergence on optimal designs
- Can optimize across multiple contrasts
- User can specify the relative importance of each contrast
- Account for high-pass filtering and autocorrelation
- Account for nonlinearity (simple model)
- Can optimize for combination of detection power, HRF estimation power, and counterbalancing

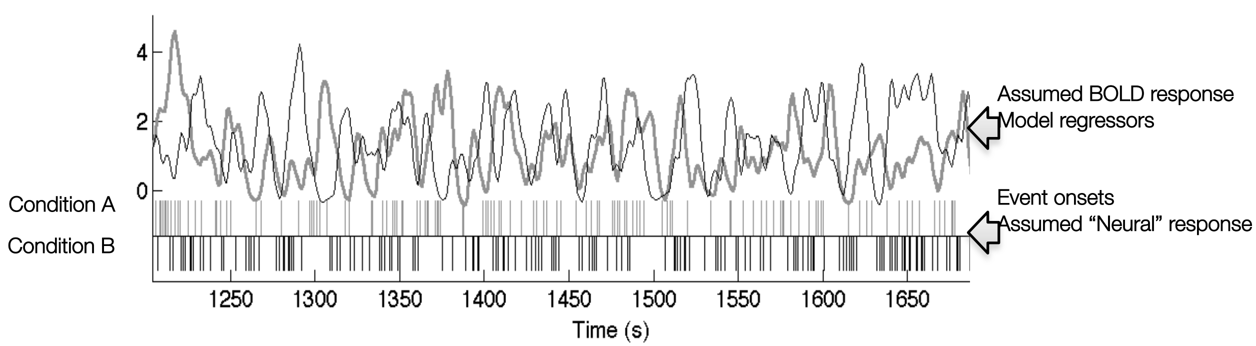
- *At wagerlab.colorado.edu, and on Github in CANlab tools*

A fundamental tradeoff: contrast detection vs. HRF estimation

Blocks of the same trials: Greater power to detect differences among conditions



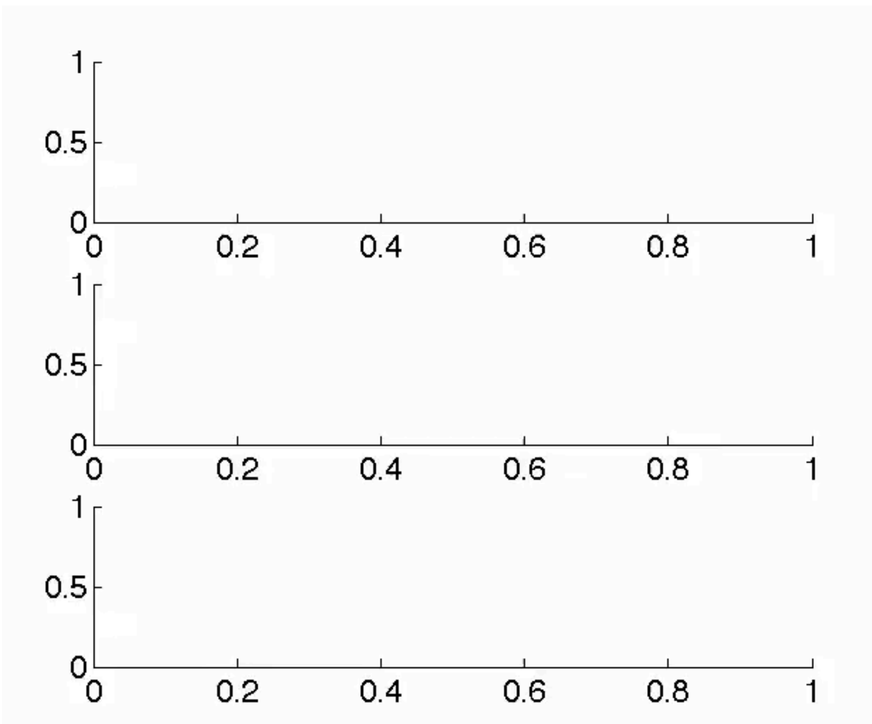
Unpredictable sequences of trials: Greater power to estimate the shape of the hemodynamic response



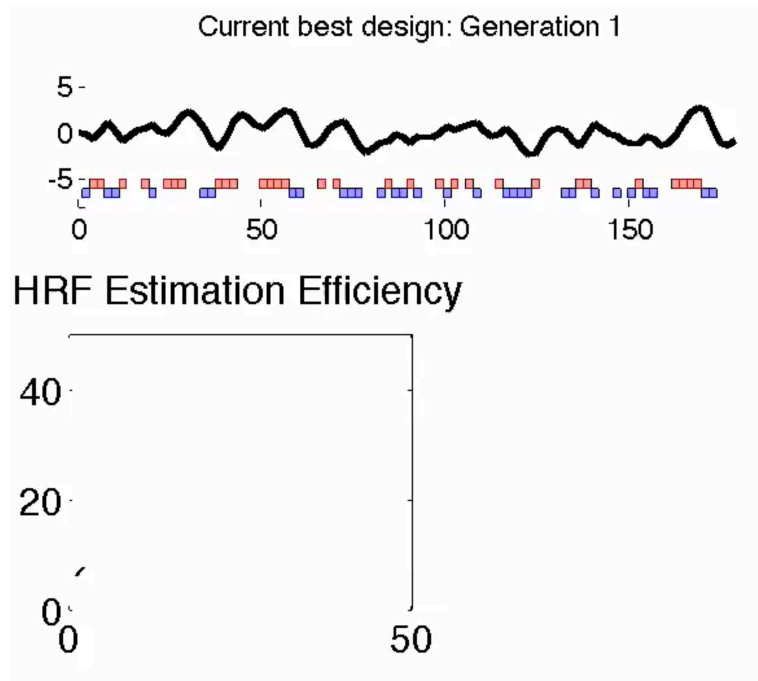
Josephs & Henson, 1999; Wager & Nichols, 2003; Liu, 2004; Smith et al., 2007; Buracas et al., 2004

Optimizing with a genetic algorithm

[A - B] contrast power

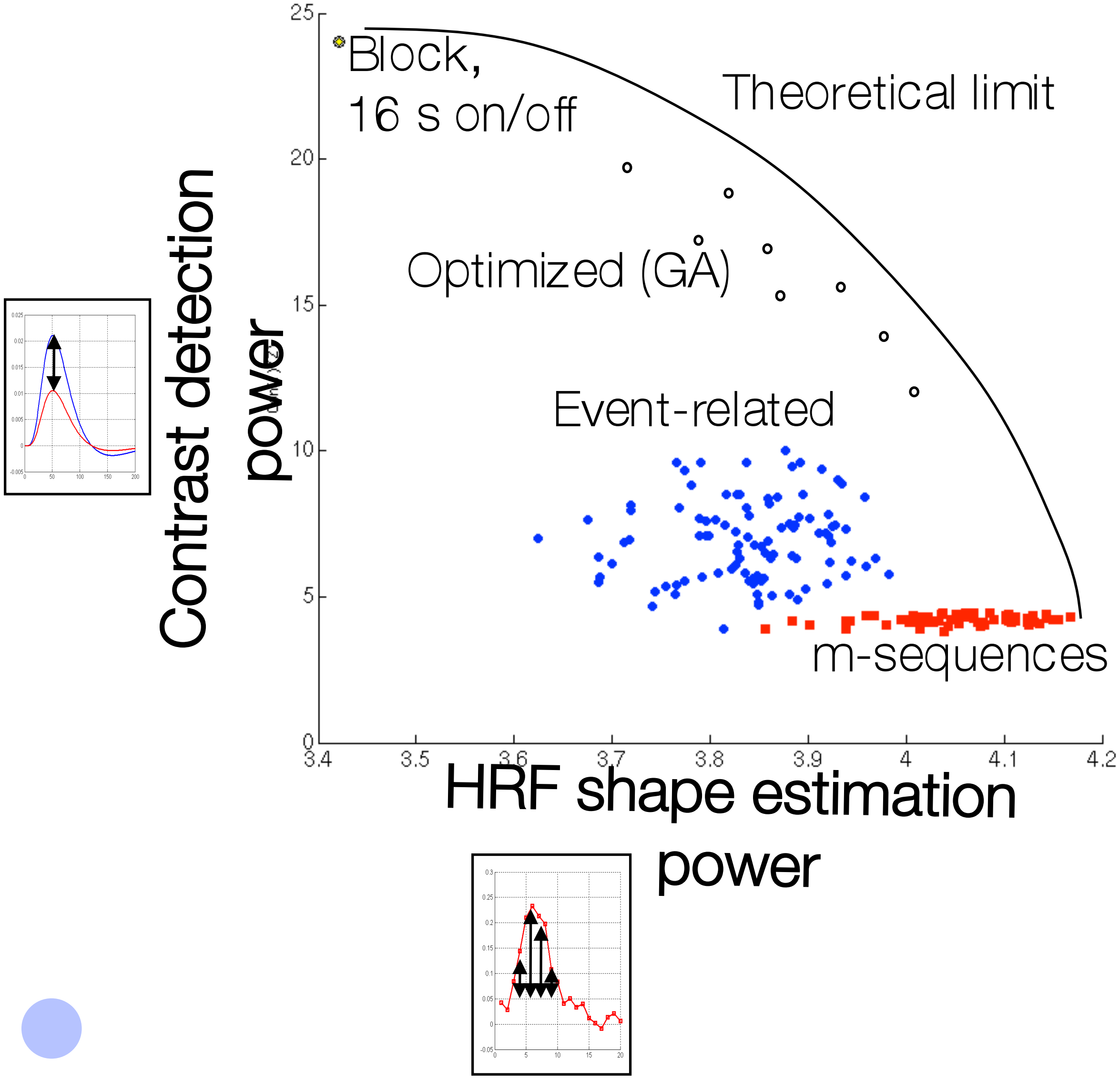


HRF estimation power



Wager & Nichols, 2003

Efficiency summary with different types of designs



Block best for detection

M-sequence best for shape (Buracas et al.)

Event-related designs so-so on both

Optimized designs good tradeoff

End of Module

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