External noise yields a surprise: What template?

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Overview

Detection of patterns in noise

- Why noise masking is a powerful technique
- The Lu-Dosher framework: useful black boxes

Graham-Nachmias experiment in noise (detect $1^{st}+3^{rd}$)

Rating scale methods for isolating sources of noise

- A faster classification image method
- Double pass and other methods

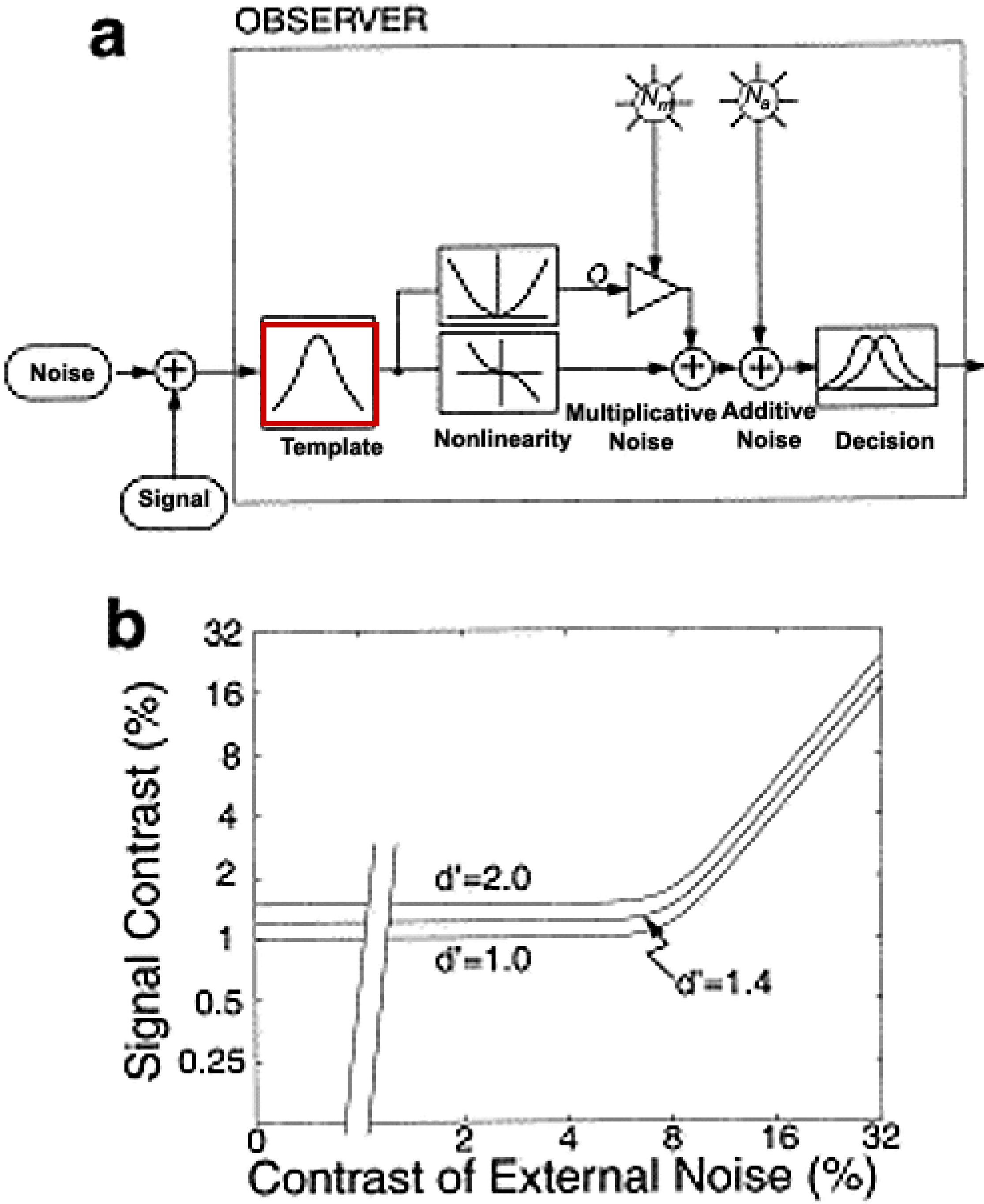
Can the black boxes be unblackened?

The Lu-Dosher model

- Single template
- Constant power nonlinearity
- Multiplicative noise
- Simple decision stage

Alternative models

- Multiple templates
- More complex nonlinearities
- Keep multiplicative noise
- Complex decision stages



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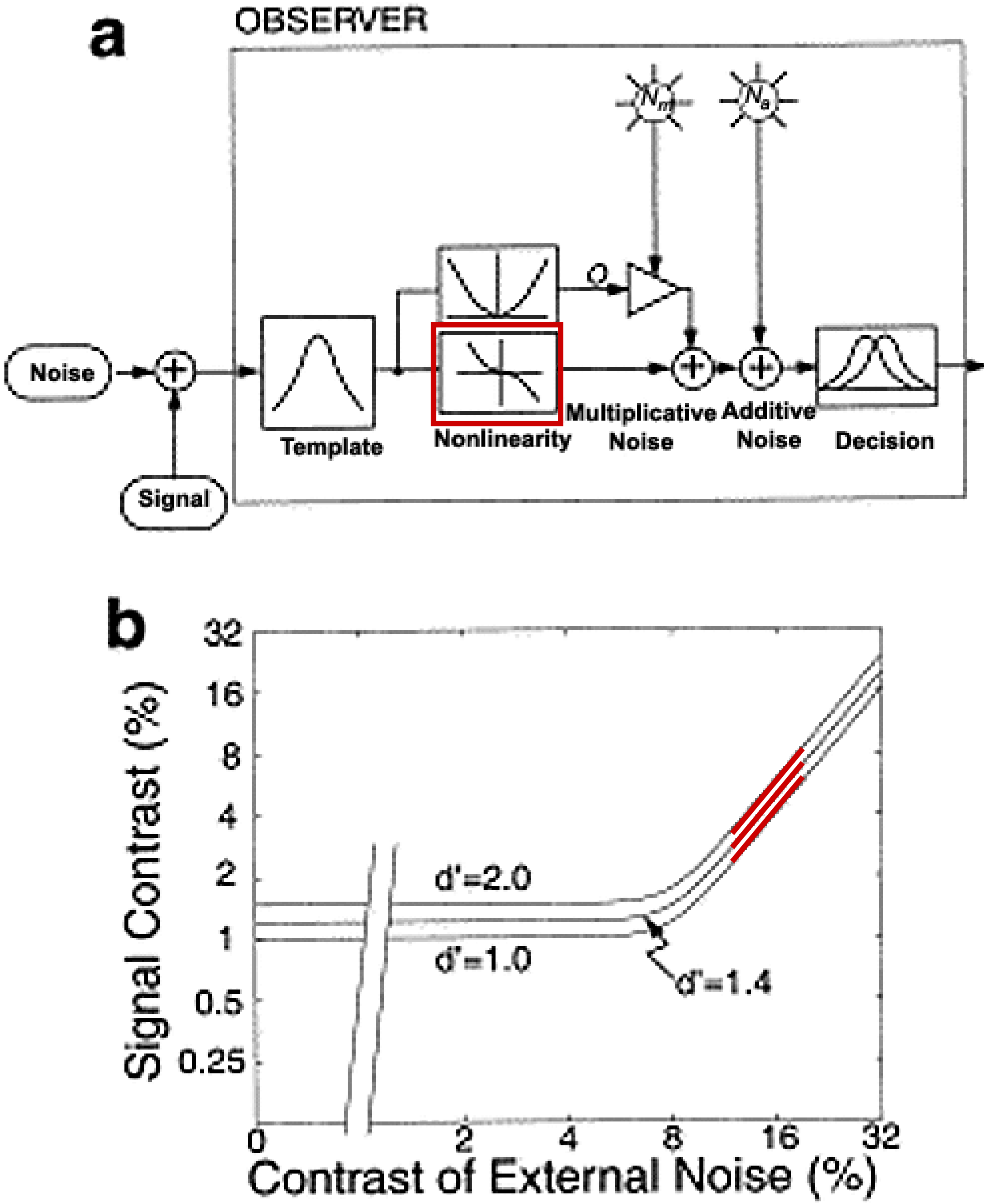

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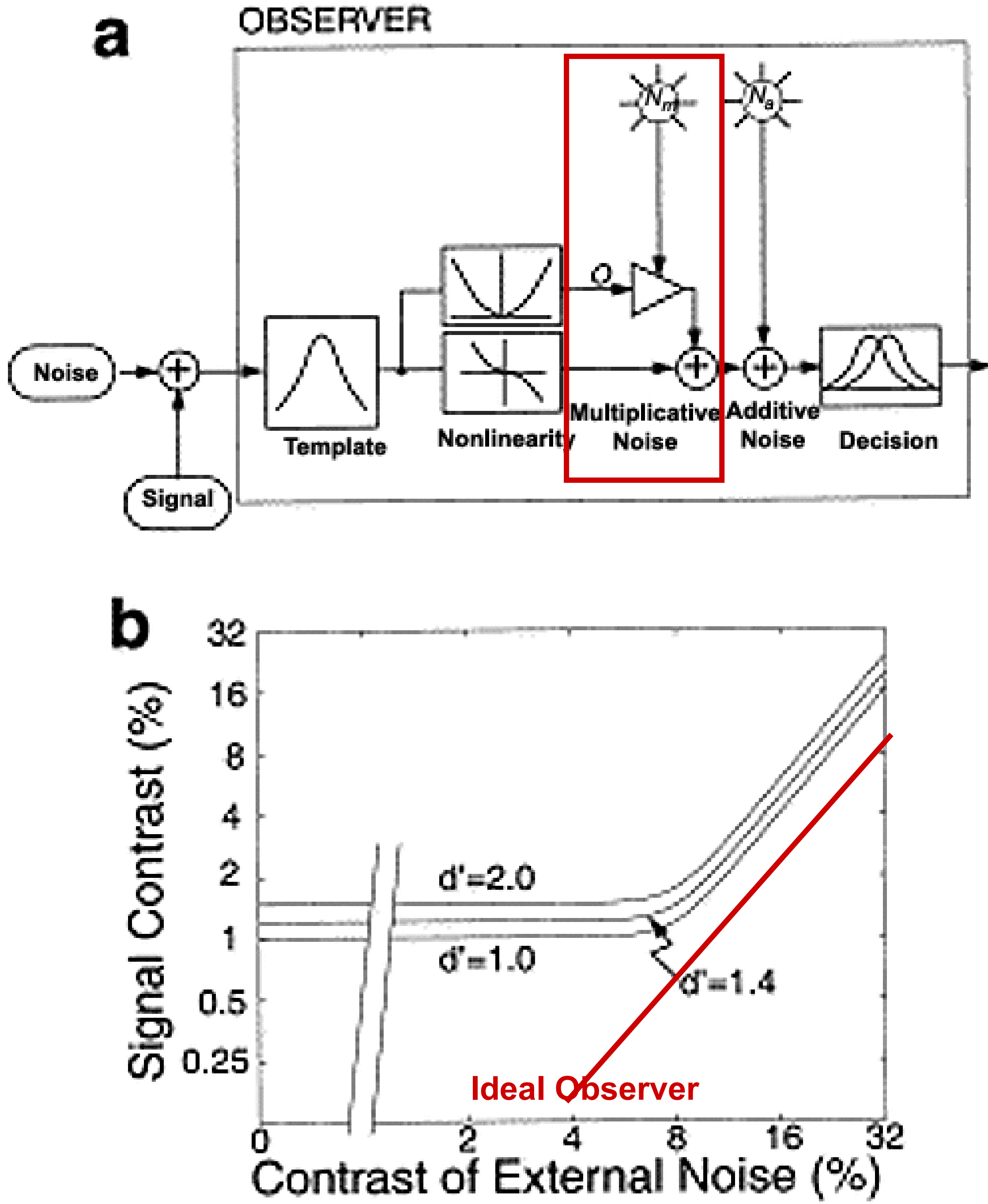

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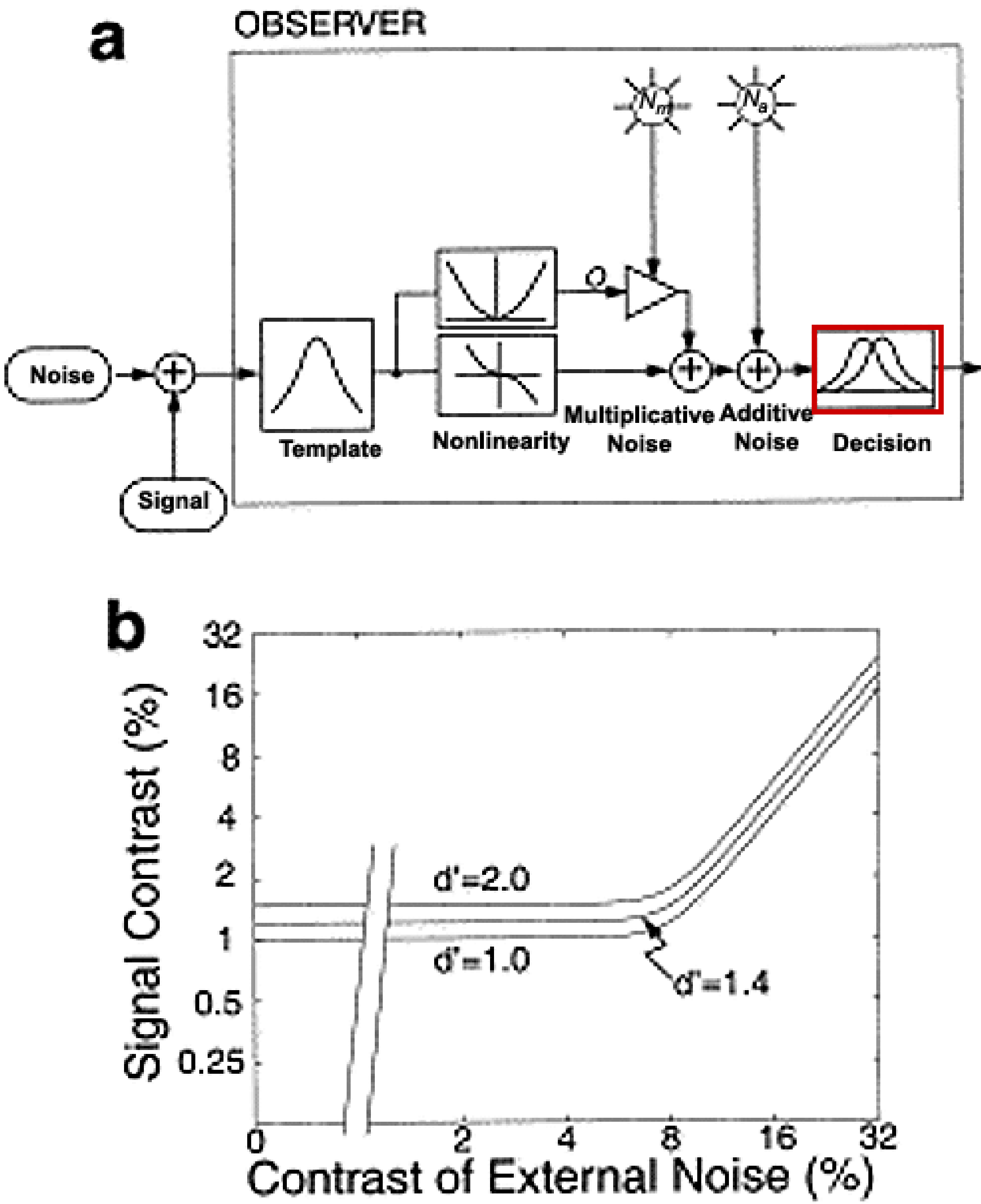


The Graham-Nachmias Experiment Plus Noise

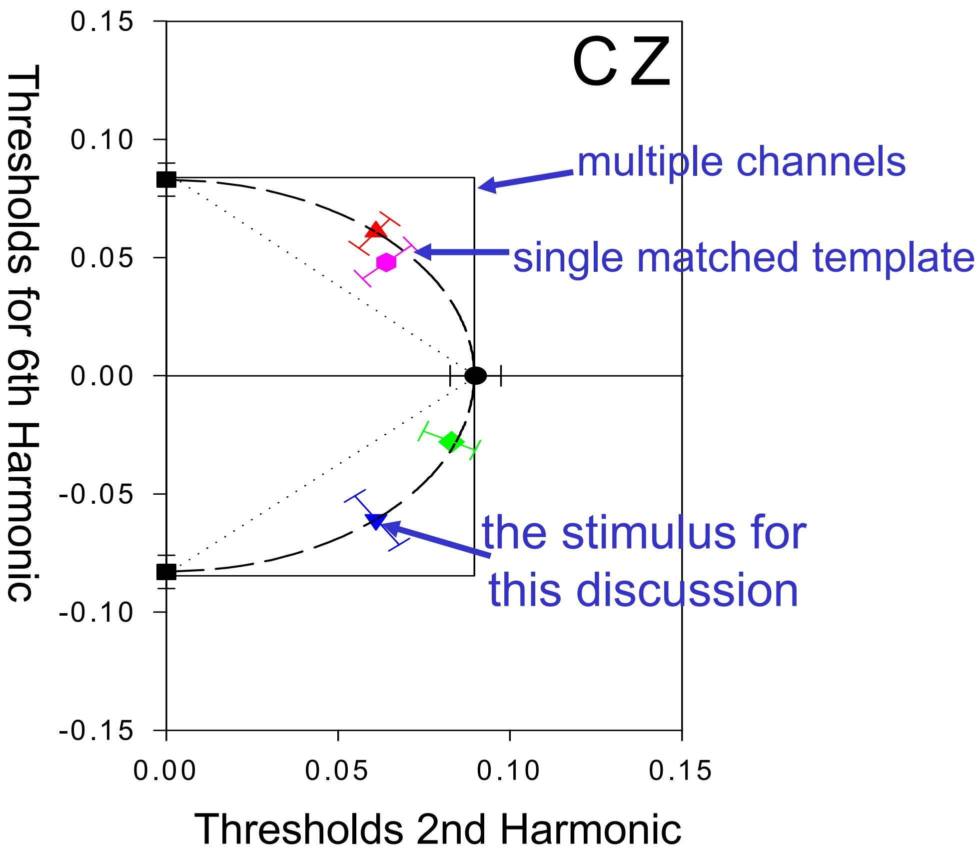
2^{nd} plus 6^{th} test pattern

2^{nd} plus 6^{th} plus noise

$P(x) = c(\cos(2x) - \cos(6x))$

$N(x) = \Sigma_f \, a_f \cos(fx) + b_f \sin(fx)$

for f=1 to 7



Our thresholds lie near the curve

$c_2^2/th_2^2 + c_6^2/th_6^2 = 1$,

compatible with a matched template model. However, the double-pass analysis will raise doubts about the single template hypothesis.

Trial	Stimulus level	test contrast		external noise		total contrast		response	
		T_2	T_6	N_2	N_6	C_2	C_6	pass1	pass2
1	1	0	0	.02	-.03	.02	-.03	1	1
2	2	.08	-.08	-.01	-.02	.07	-.10	2	1
3	1	0	0	-.02	.06	-.02	.06	2	1
4	4	.24	-.24	.05	-.03	.29	-.27	4	4
5	1	0	0	.06	.03	.06	.03	1	1
	etc.								

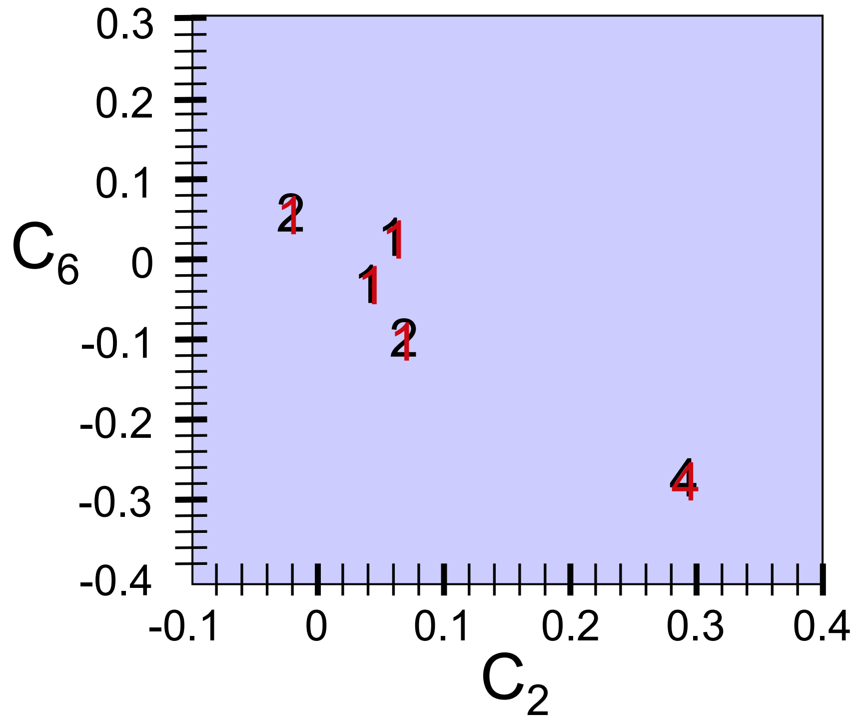
Rating scale method of constant stimuli

Four stimulus levels (1,2,3,4) were randomly intermixed:
The lowest level had zero contrast (before noise)

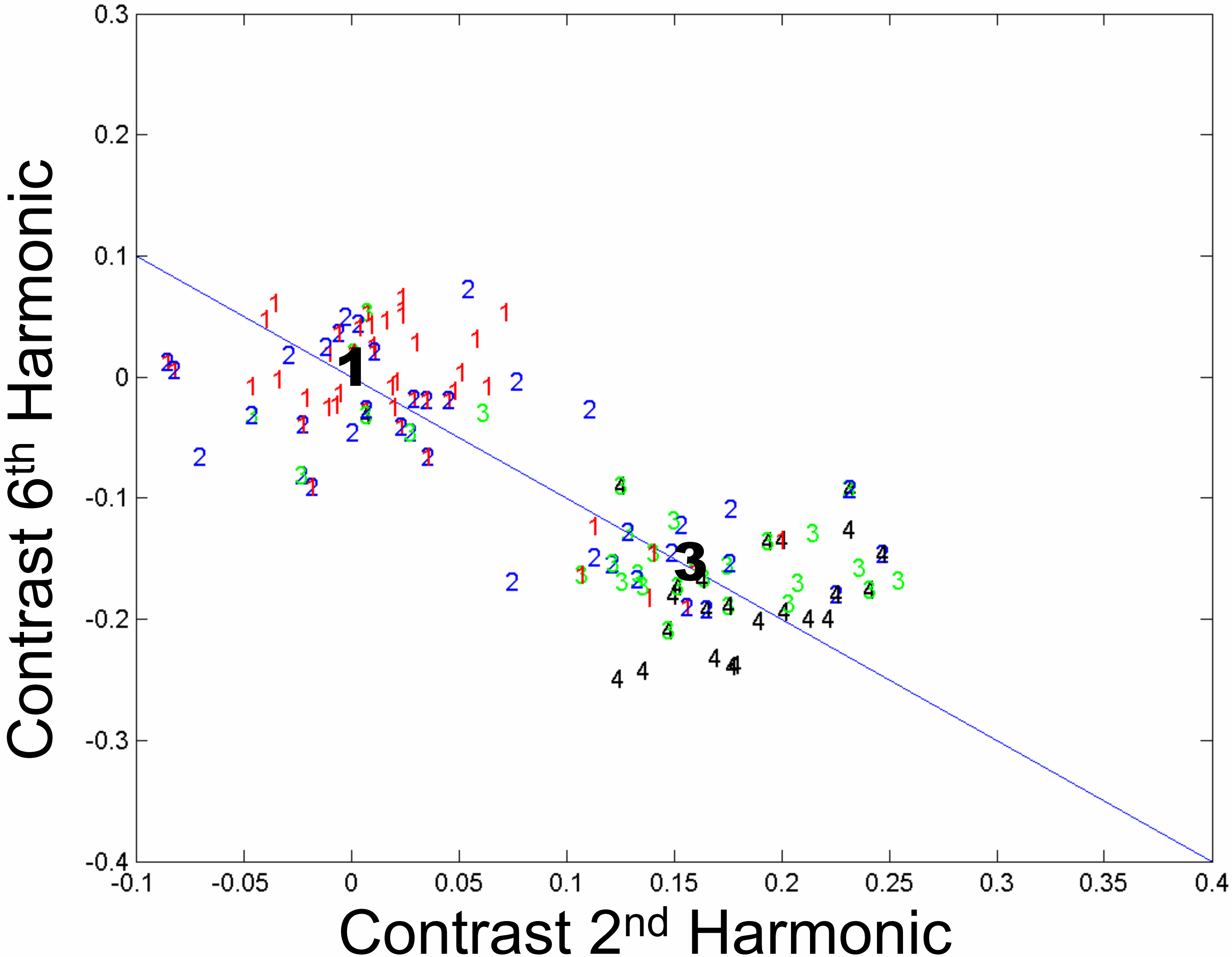
One of four responses (1,2,3,4) was given to each presentation.

Trial	Stimulus level	test contrast		external noise		total contrast		response	
		T_2	T_6	N_2	N_6	C_2	C_6	pass1	pass2
1	1	0	0	.02	-.03	.02	-.03	1	1
2	2	.08	-.08	-.01	-.02	.07	-.10	2	1
3	1	0	0	-.02	.06	-.02	.06	2	1
4	4	.24	-.24	.05	-.03	.29	-.27	4	4
5	1	0	0	.06	.03	.06	.03	1	1
	etc.								

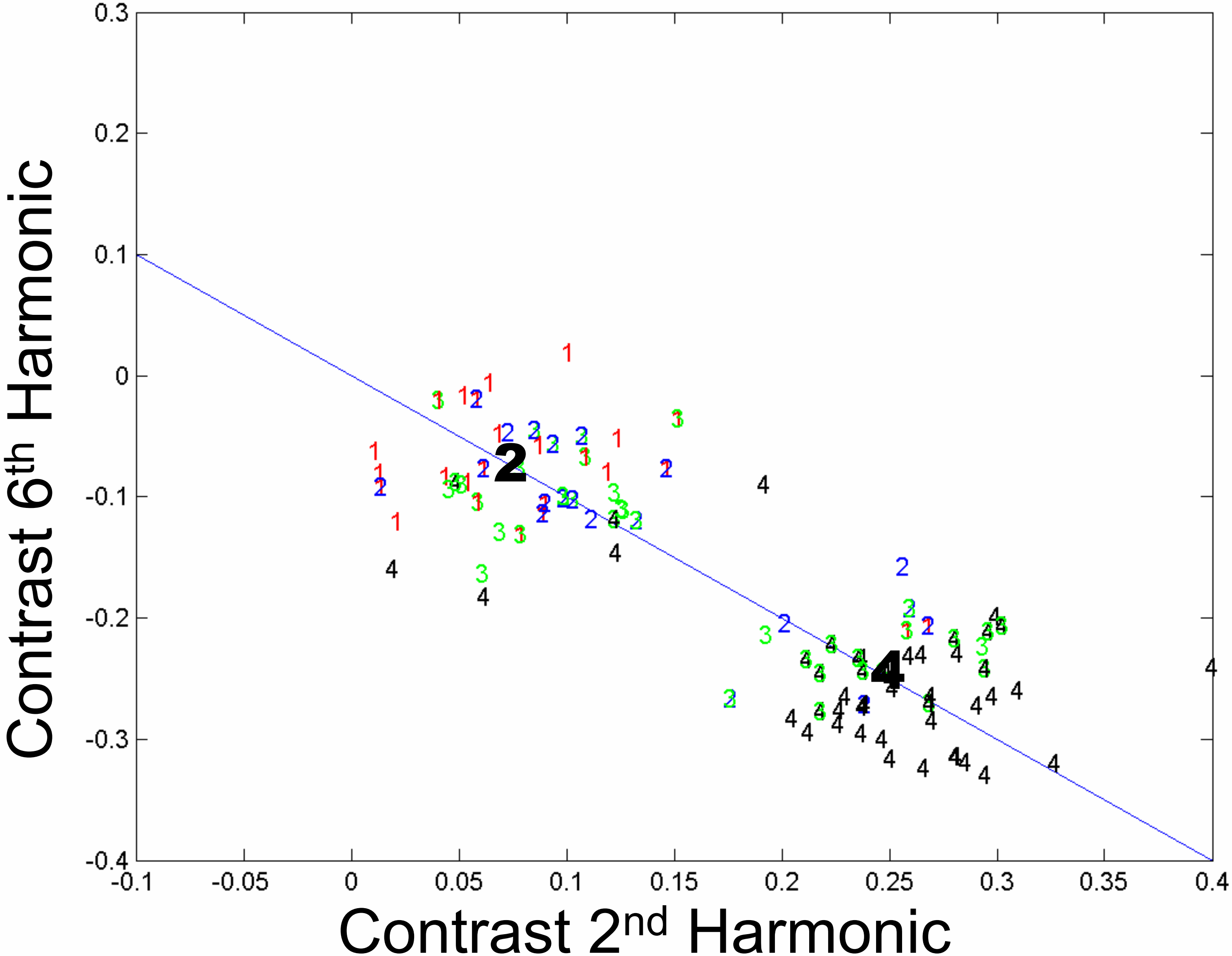
Stimulus plot



2nd and 6th contrasts and responses for levels 1 and 3



2^{nd} and 6^{th} contrasts and responses for levels 2 and 4



The Graham-Nachmias Experiment Plus Noise

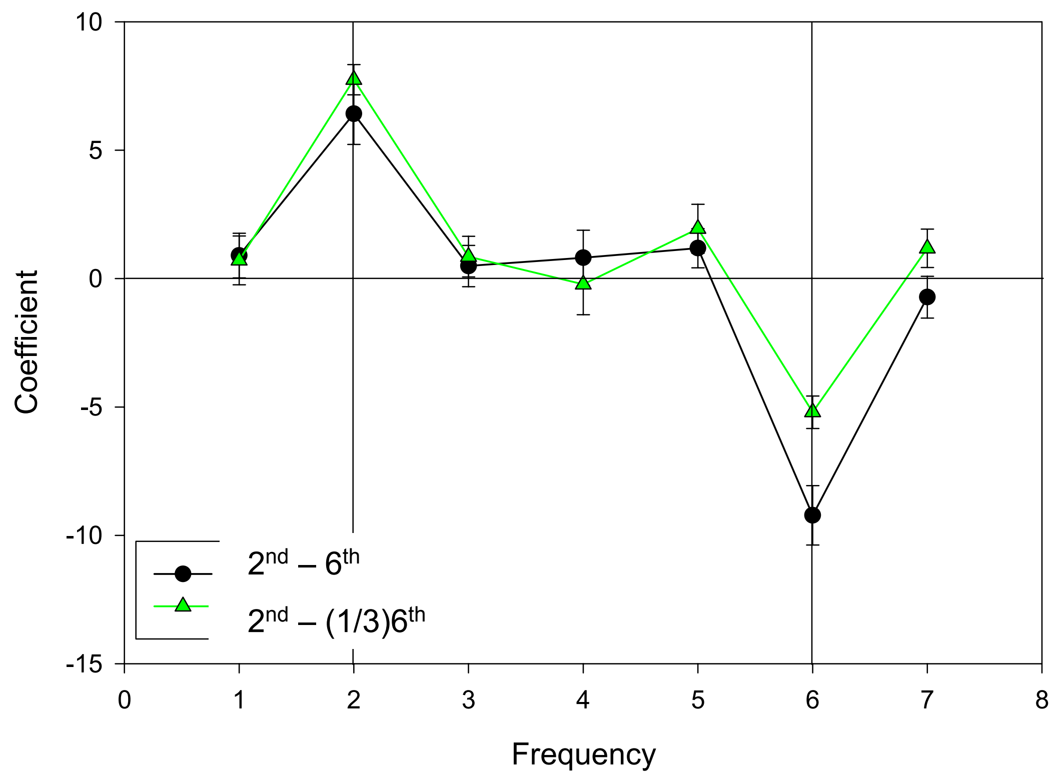
2^{nd} plus 6^{th} test pattern

2^{nd} plus 6^{th} plus noise

Classification profile
The 2 and 6 c/deg components are well matched to the test pattern.

Linear regression allows high quality profiles in less than 800 trials.

Peaks subtract condition



Reverse correlation vs. linear regression

$\text{Resp}(k) = \sum_{x'} \text{Template}(x') \text{ Pattern}(x', k) + \text{Noise}(k)$

or $R(k) = \sum_{x'} T(x') P(x', k) + N_{human}(k)$

$T_{rev\ cor}(x) = \sum_k R(k) P(x,k) = \sum_{x'} T(x') \sum_k P(x',k) P(x,k) + \text{noise}$

$= T(x) + \sum_k N_{human}(k) P(x,k) + \sum_{x'} N_{stim}(x',x) T(x')$

Where $\sum_k P(x',k)P(x,k) = \delta(x,x') + N_{stim}(x,x')$ ($N_{stim} << 1$ for white)

$T_{lin\ reg}(x) = \sum_k R(k) P^{PseudoInv}(x,k)$

$= T(x) + \sum_k N_{human}(k) P^{PseudoInv}(x,k)$

In order to calculate $P^{PseudoInv}$ #trials > #stimulus components

Web site information to be given at end

Reverse correlation vs. linear regression

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or $R(k) = \sum_{x'} T(x') \, P(x', k) + N_{human}(k)$

$T_{rev\ cor}(x) = \sum_k R(k) \, P(x,k) = \sum_{x'} T(x') \sum_k P(x',k) P(x,k) + \text{noise}$

$= T(x) + \sum_k N_{human}(k) \, P(x,k) +$

Where $\sum_k P(x',k) P(x,k) = \delta(x,x') + N_{stim}(x,x')$ ($N_{stim} << 1$ for white)

$T_{lin\ reg}(x) = \sum_k R(k) \, P^{PseudoInv}(x,k)$

$= T(x) + \sum_k N_{human}(k) \, P^{PseudoInv}(x,k)$

In order to calculate $P^{PseudoInv}$ #trials > #stimulus components

For sparse classification images, linear regression with <1/2 the number of trials as reverse correlation can give comparable precision and accuracy.

Trial	Stimulus	test contrast		external noise		total contrast		response	
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5	1	0	0	.06	.03	.06	.03	1	1
	etc.								

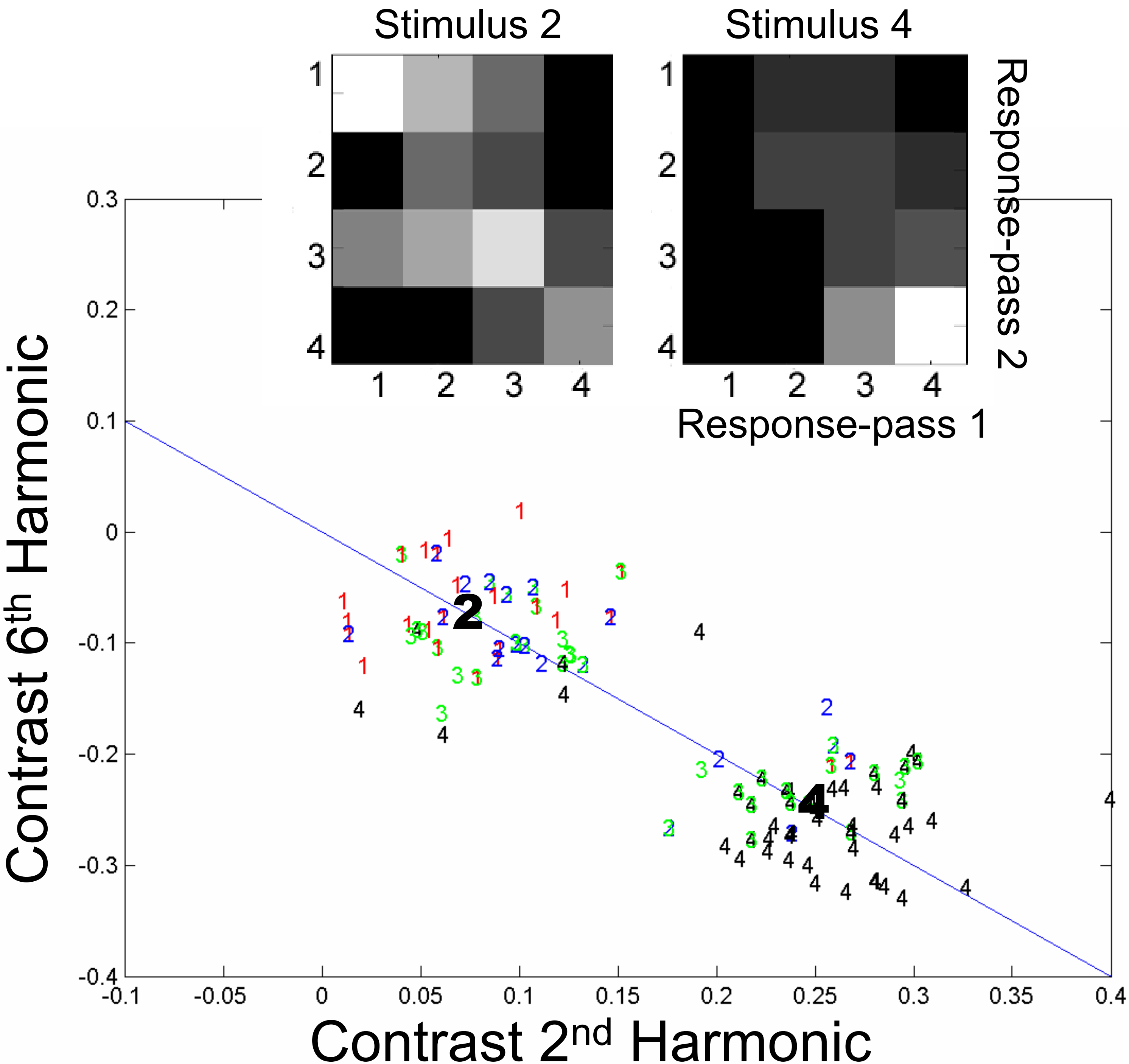
For stimulus level 1

R1 = 1 and R2 = 1 : 2 cases

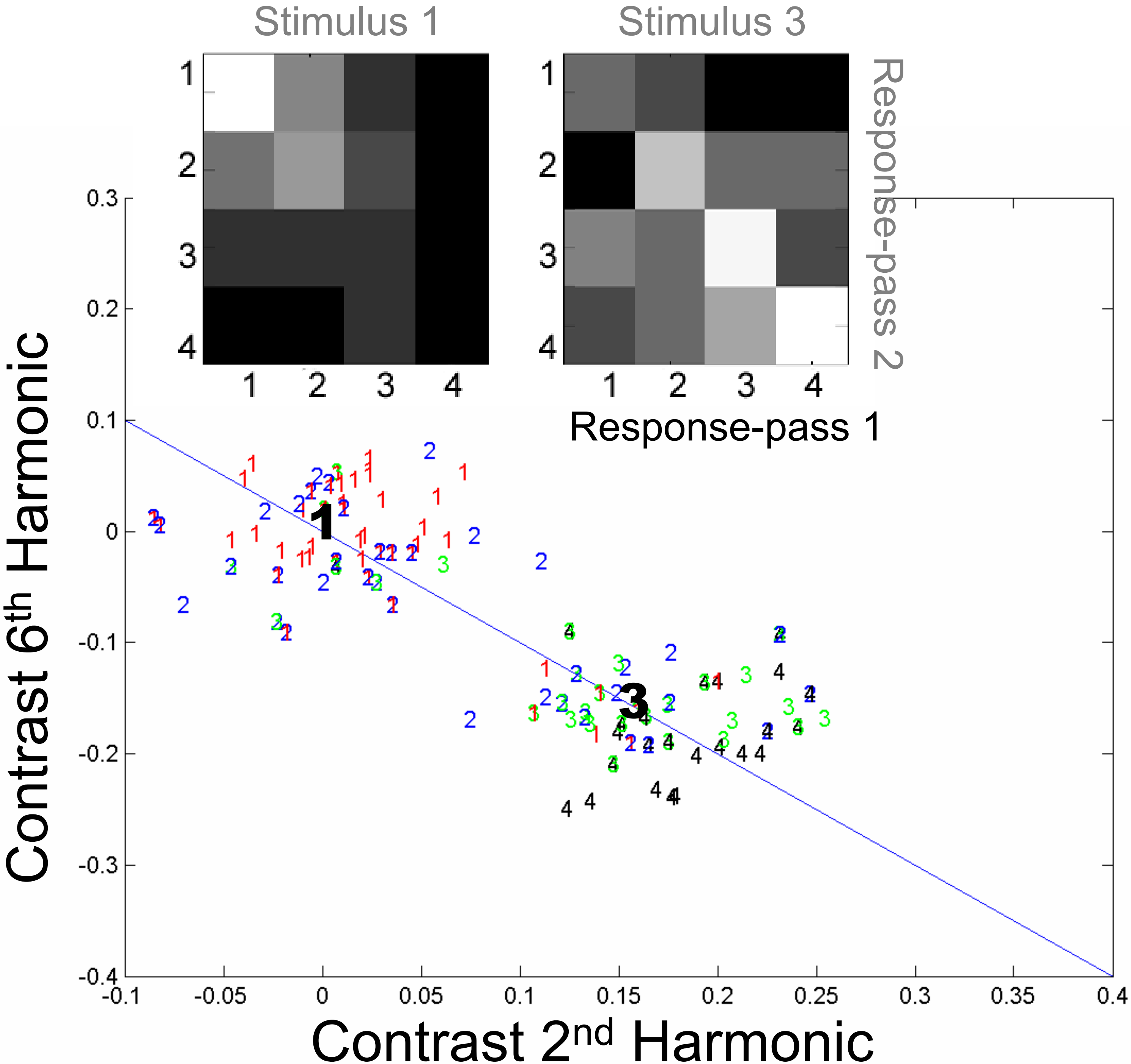
R1 = 2 and R2 = 1 : 1 case

Response 2 \ Response 1	1	2	3	4
1	2	1		
2				
3				
4				

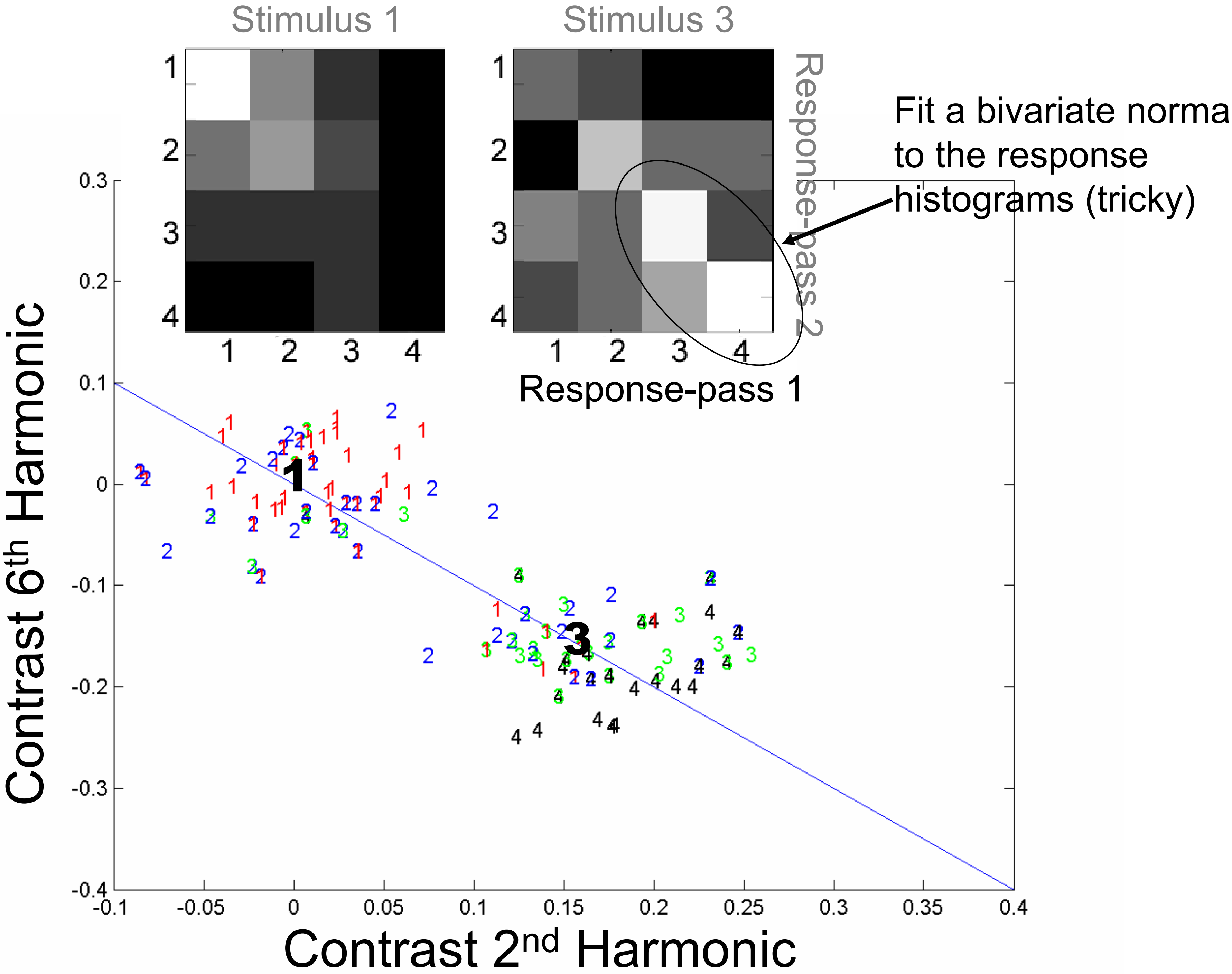
Response histogram for stimulus level 1

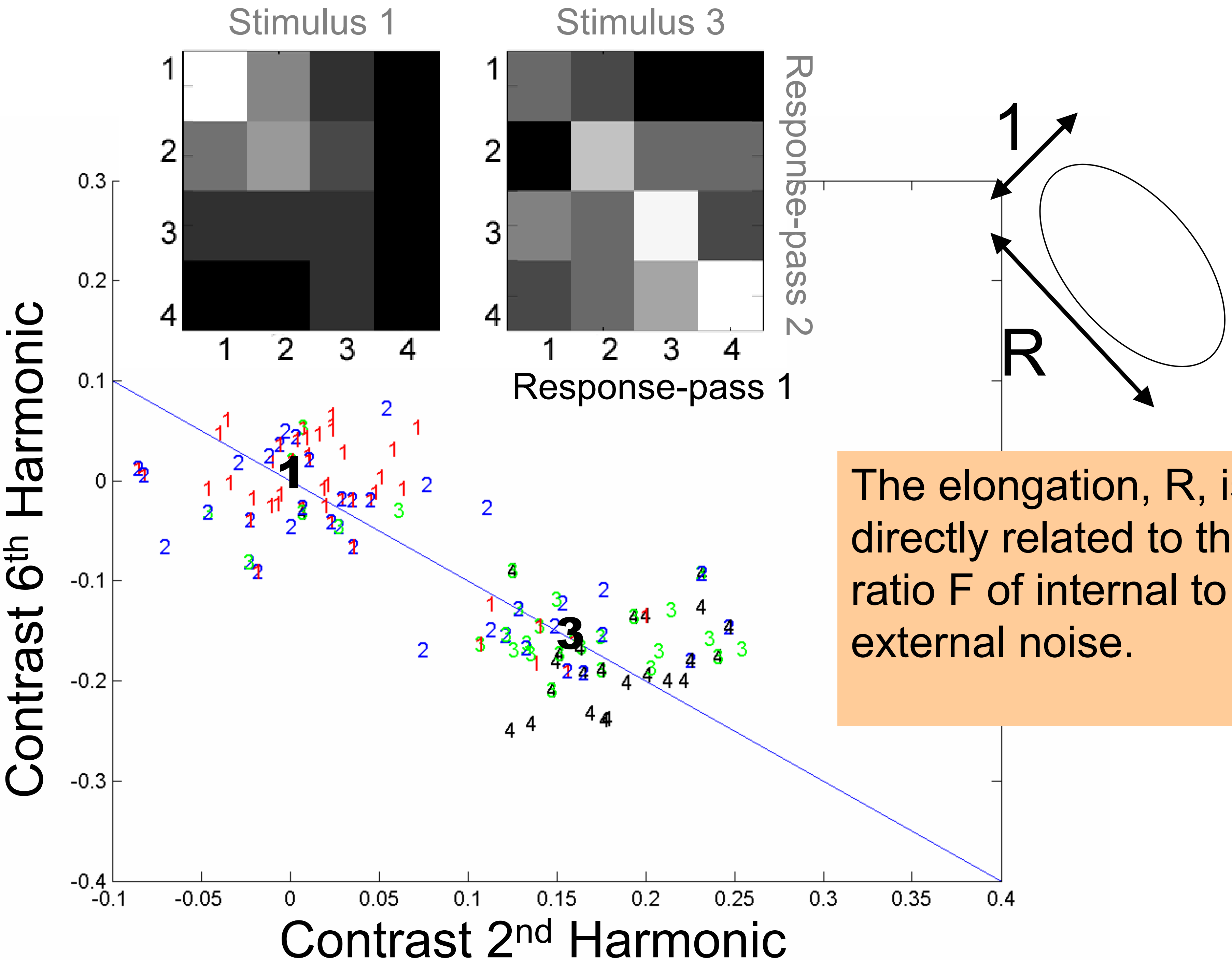


Stimulus 2
Stimulus 4
Response-pass 2
Response-pass 1
Contrast 6th Harmonic
Contrast 2nd Harmonic



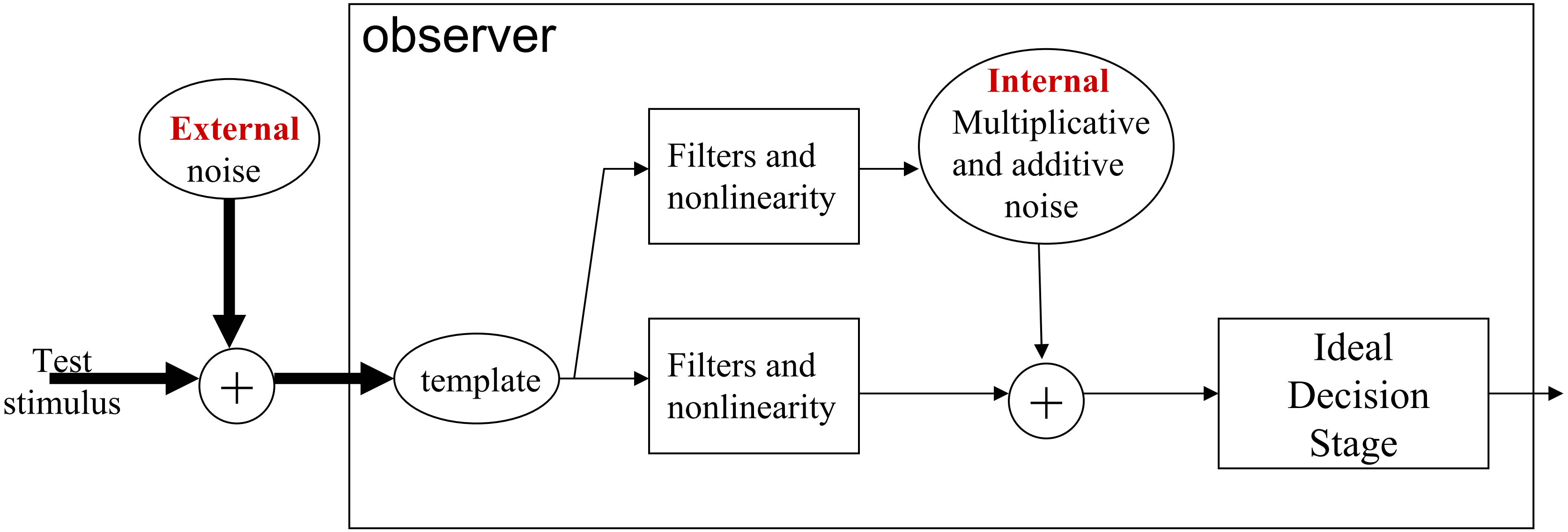
Stimulus 1
Stimulus 3
Response-pass 2
Response-pass 1
Contrast 6th Harmonic
Contrast 2nd Harmonic


Stimulus 1
Stimulus 3
Response-pass 2
Response-pass 1
Fit a bivariate normal to the response histograms (tricky)
Contrast 6th Harmonic
Contrast 2nd Harmonic
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.1
-0.05
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4



The elongation, R, is directly related to the ratio F of internal to external noise.

Two methods for calculating F=internal noise/External noise

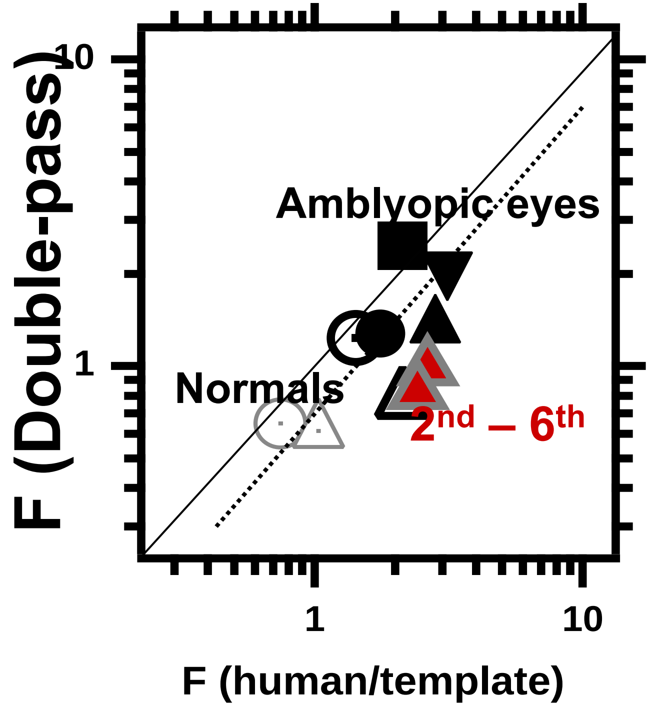


Double pass method: $F = 1/(R^2 - 1)$ where R is elongation of the double pass response ellipse (preceding slide).

d' (efficiency) method: $F = (d'_{template}/d'_{human})^2 - 1$ where $d'_{template}$ is the d' of an ideal observer who uses the template specified by the classification image.

F: Ratio of internal to external noise

For detection of 2nd and 6th
F_{2pass} <= 1 Very promising.
$F_{d'}$ ~ 2.5 Very interesting.



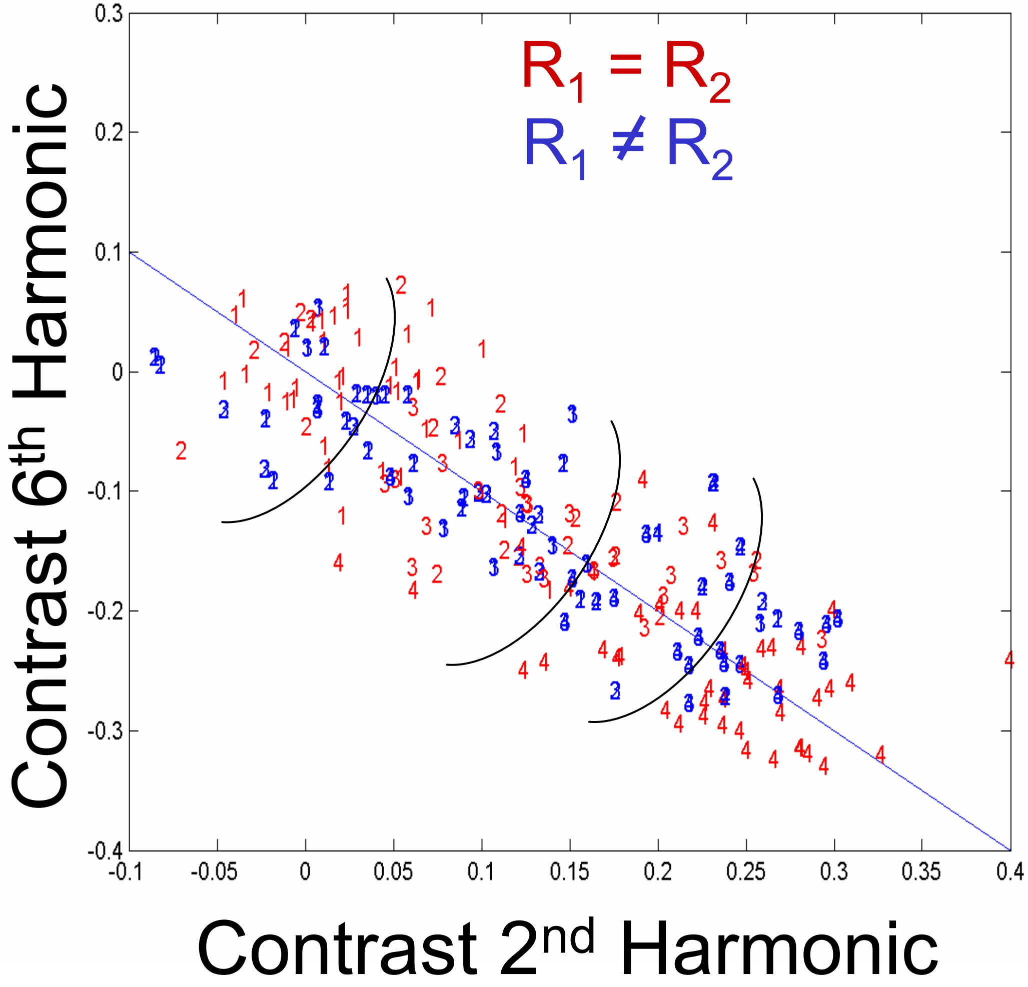
The discrepancy in the two estimates of F indicates incorrect model assumptions.

Ahumada and Beard have found similar results.

nonlinearities? *But our expts. indicate they are too weak.*
multiple templates? *But our expts. indicate a matched filter.*
inefficient decision stage? uncertainty?
non-straight criterion boundaries?

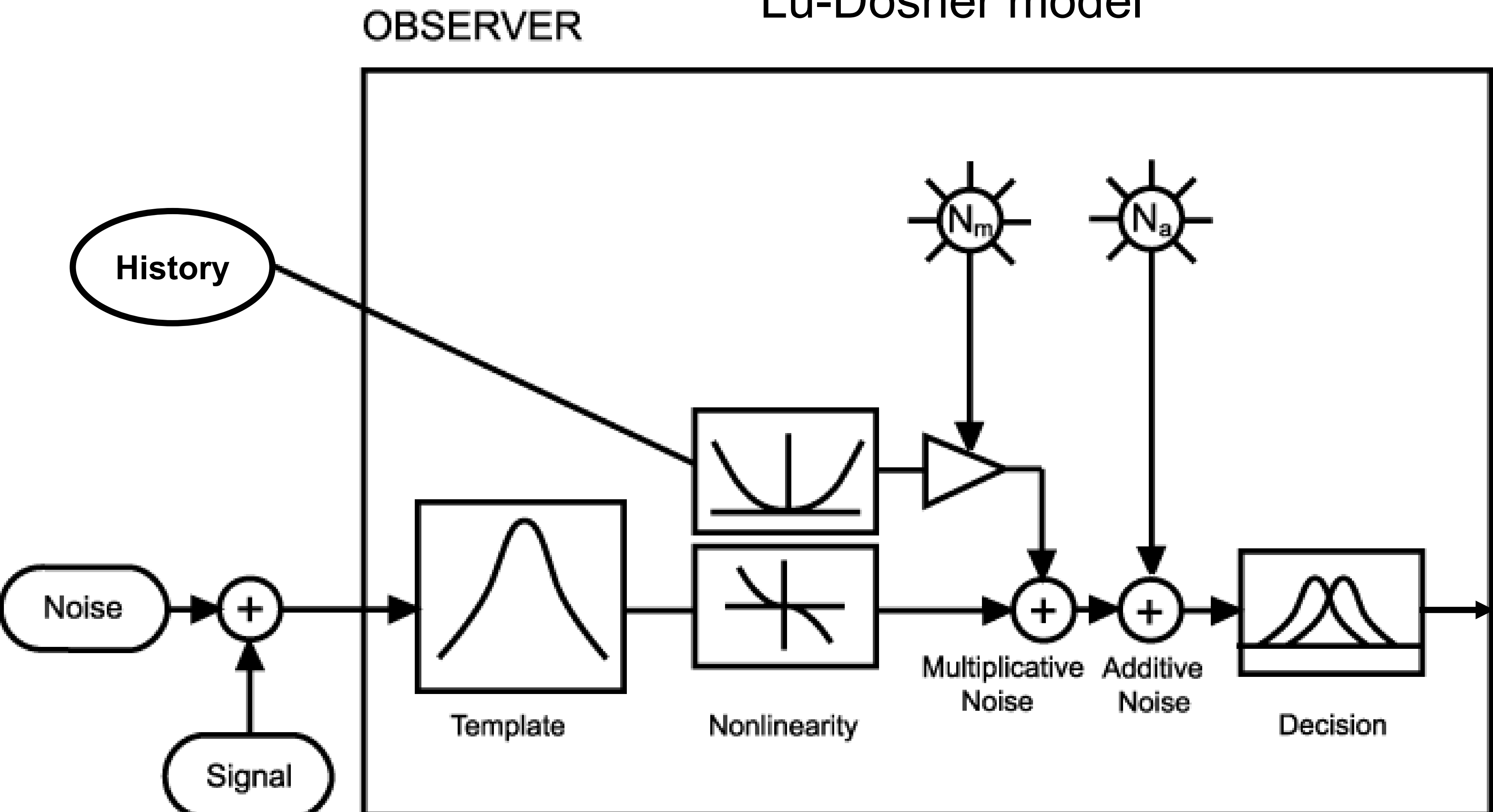
Can one see a pattern in the criteria?
Can one see a pattern in the double pass agreement?
Are the criteria straight as a single template would predict?

Triple pass data as well as broader classification tools may help answer these questions.

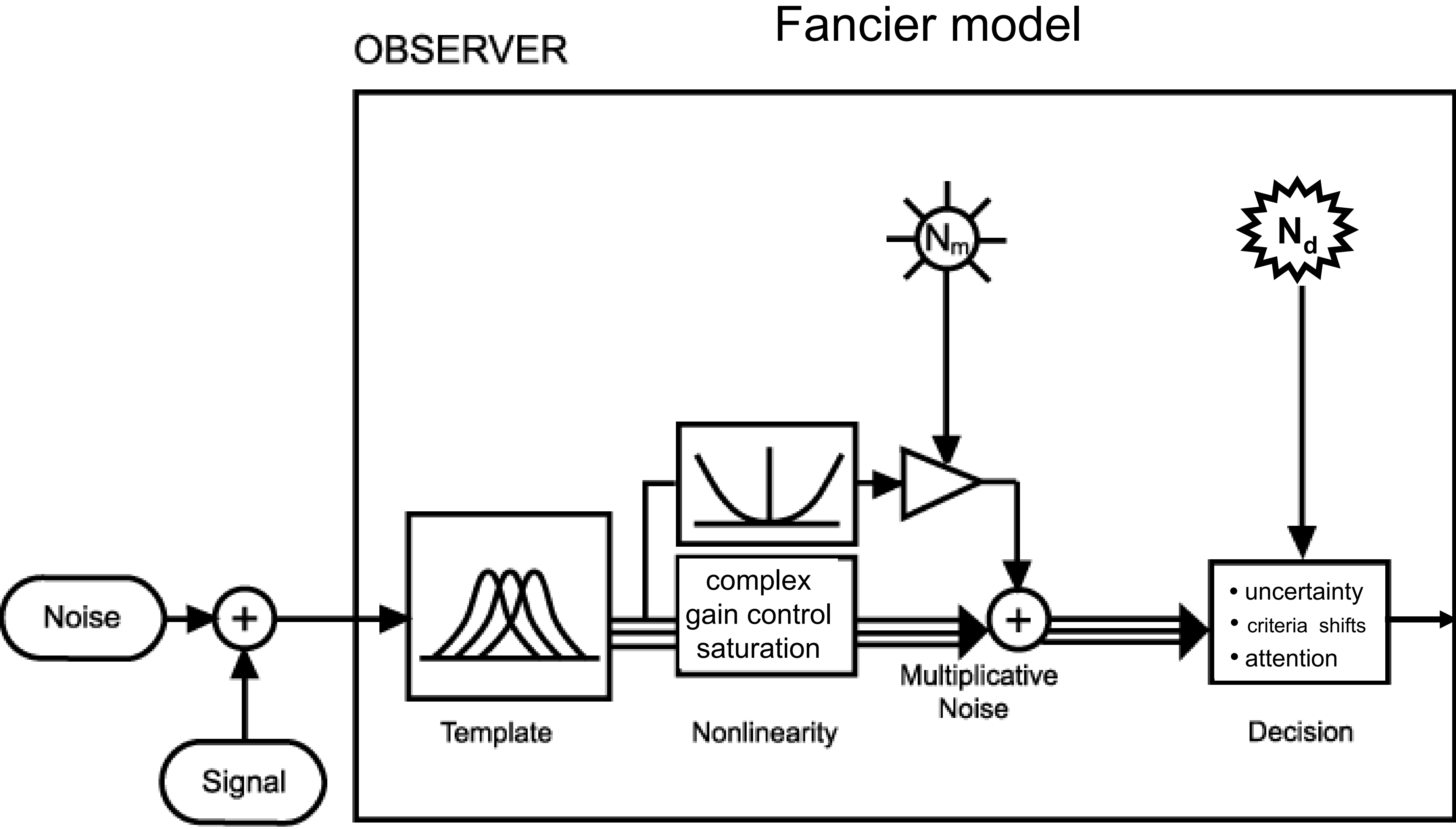


Summary

Lu-Dosher model



Summary

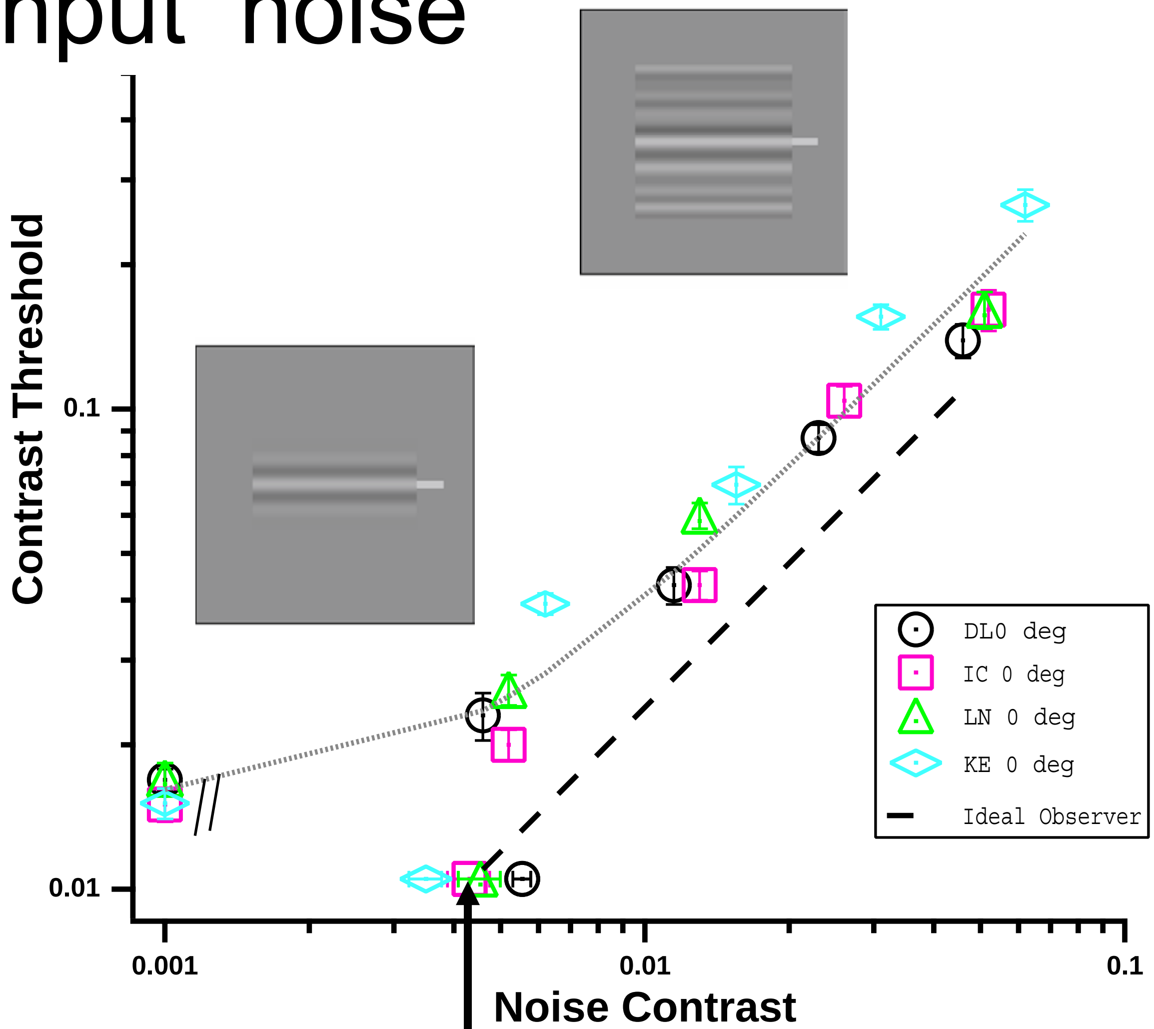

Fancier model
OBSERVER
Noise
Signal
+
Template
complex
gain control
saturation
Nonlinearity
N_m
Multiplicative
Noise
+
N_d
• uncertainty
• criteria shifts
• attention
Decision

Acknowledgments

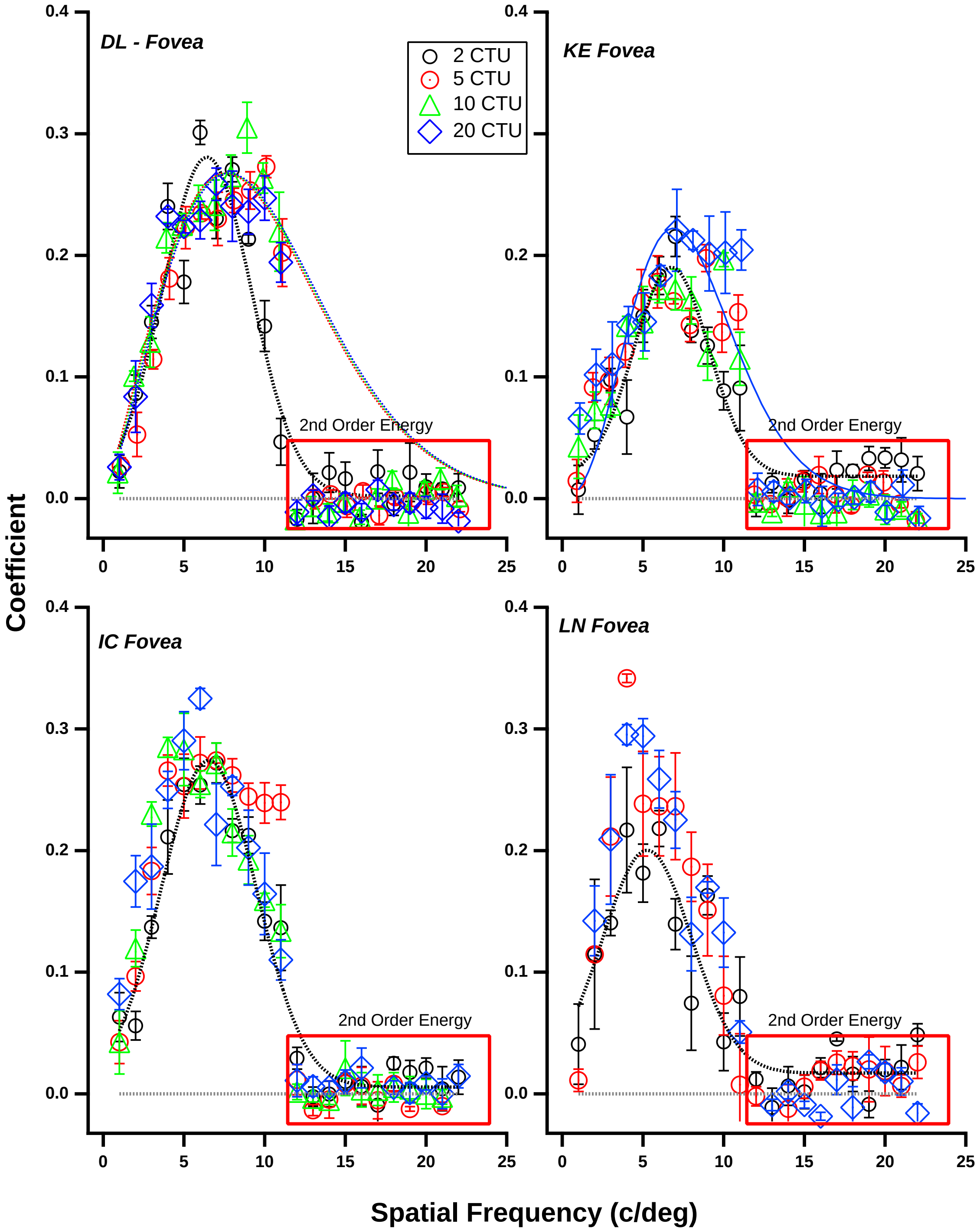
Thom Carney– for help with Winvis
Alex Tauras – for help with figures
NEI – for help with funds

This talk will be found at:
cornea.berkeley.edu

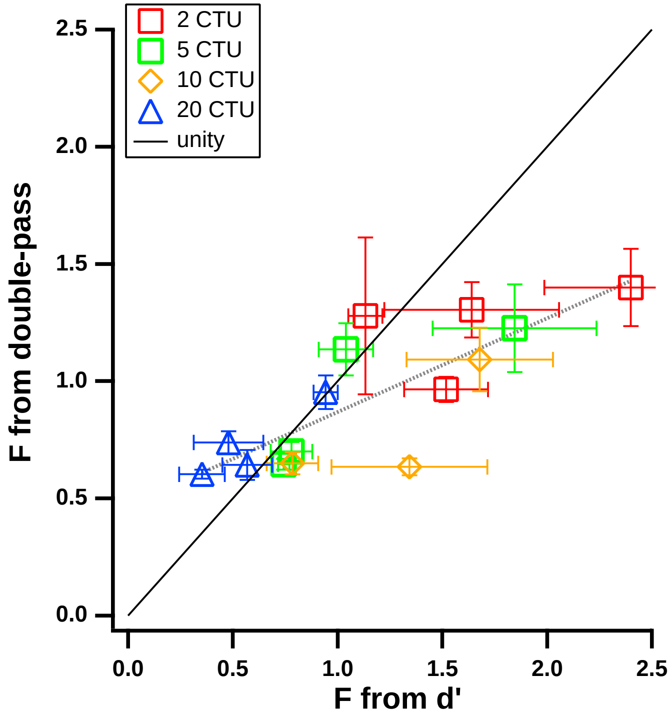
Experiment to measure equivalent input noise

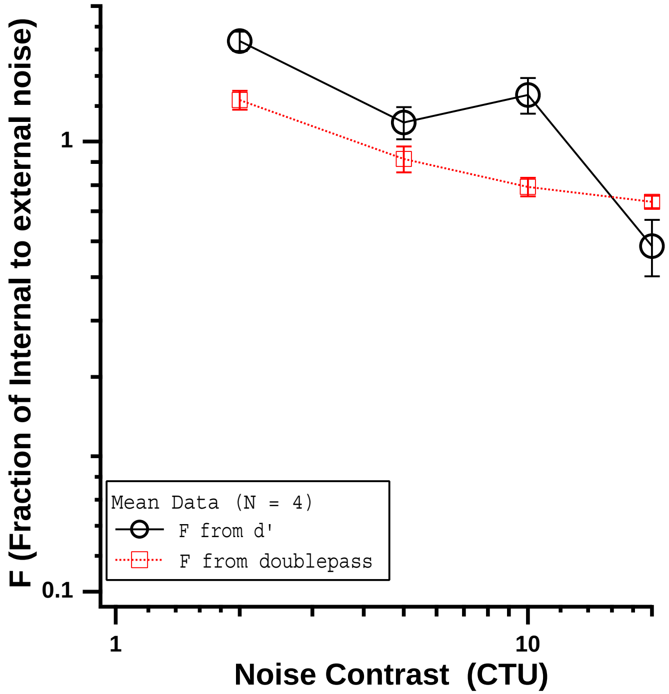


Input noise



DL - Fovea
KE Fovea
IC Fovea
LN Fovea
2 CTU
5 CTU
10 CTU
20 CTU
2nd Order Energy
Coefficient
Spatial Frequency (c/deg)


2 CTU
5 CTU
10 CTU
20 CTU
unity
F from double-pass
F from d'
0.0
0.5
1.0
1.5
2.0
2.5


F (Fraction of Internal to external noise)
Noise Contrast (CTU)
Mean Data (N = 4)
F from d'
F from doublepass
1
10
0.1