Contrast−response functions, Fisher information, and contrast decoding performance

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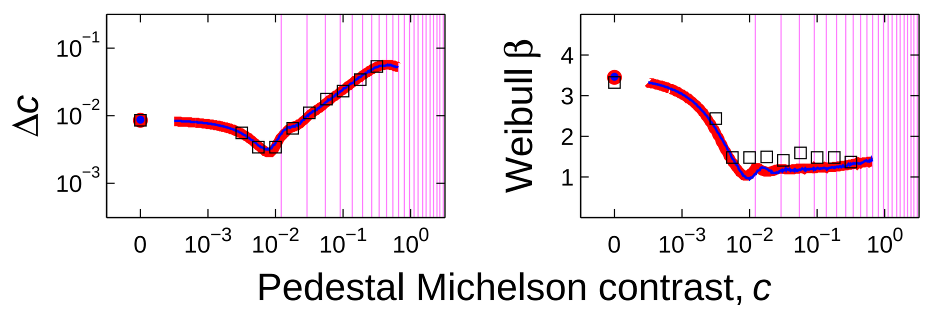
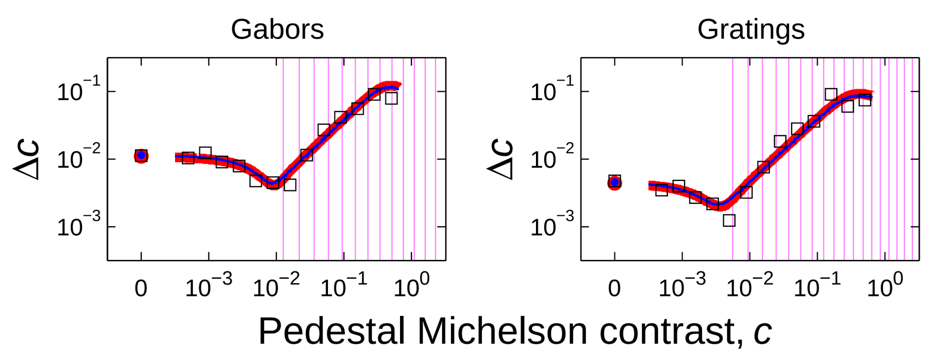
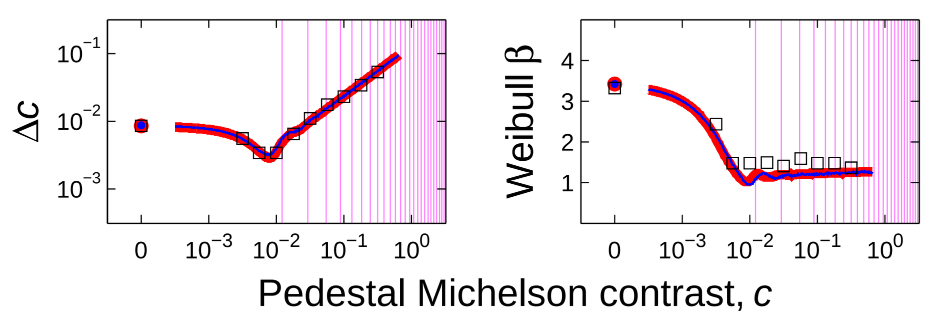
Model 4: Meese, Georgeson & Baker (2006)
Model fitted to contrast thresholds
Parameter−free prediction of Weibull β



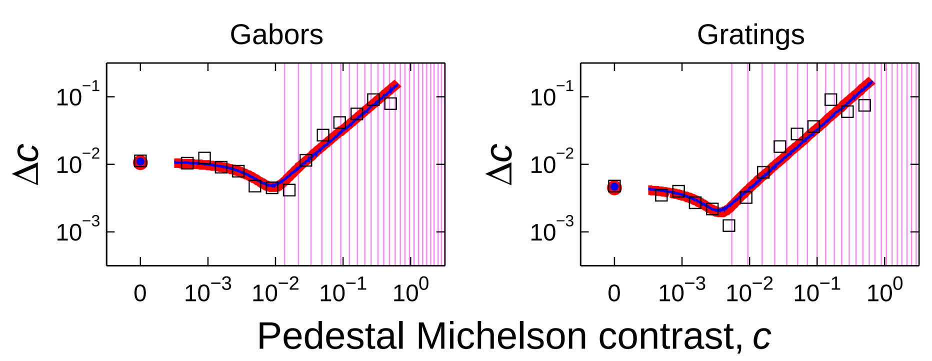
Model 4: Chirimuuta & Tolhurst (2005)
Model fitted to contrast thresholds



Model 3: Meese, Georgeson & Baker (2006)
Model fitted to contrast thresholds
Parameter−free prediction of Weibull β

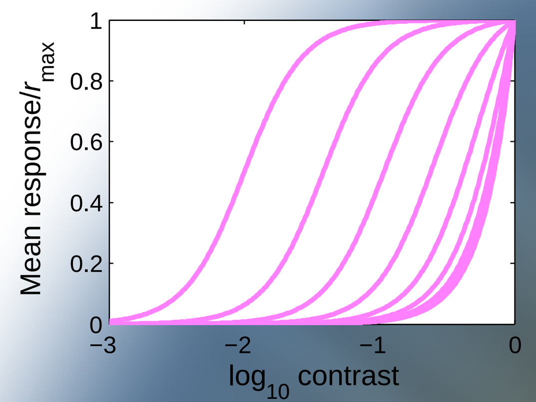


Model 3: Chirimuuta & Tolhurst (2005)
Model fitted to contrast thresholds



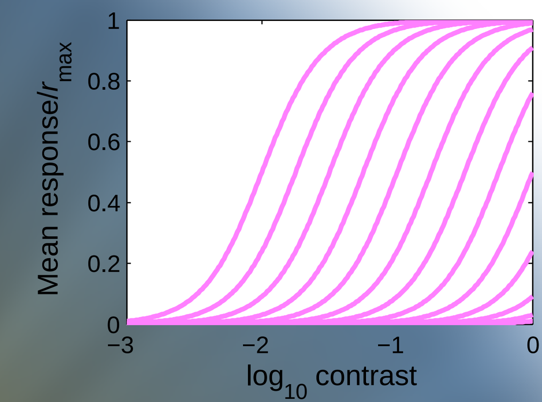
Model 4

Exponential c_{50} distribution, r_{100} fixed
q, ρ_{100}, m, z_{min} and z_{max} fitted



Model 1

Uniform c_{50} distribution, r_{max} fixed
q, ρ_{100} and z_{min} fitted



Tolhurst and colleagues developed a Bayesian model for decoding contrast from a population of spiking neurons with Naka−Rushton contrast−response functions (Clatworthy et al, 2003; Chirimuuta et al, 2003). The model chooses the most likely contrast, given the neural response. Chirimuuta and Tolhurst (2005) attempted to fit this model to contrast discrimination data, but concluded that the Naka−Rushton function "is a poor basis for modelling contrast coding by V1, unless a small 'hard threshold' is incorporated" (p. 2957). They claimed that, without a threshold on the contrast−response function, their Bayesian decoding model was unable to account for

- the depth of the dip in dipper functions for contrast discrimination
- the steepness of the psychometric function for detection (Weibull $\beta \approx 3$)

To fit a 14−data−point dipper function, Chirimuuta and Tolhurst (2005) used an arbitrary population of neurons with 18 free parameters, including a threshold on the contrast−response function.

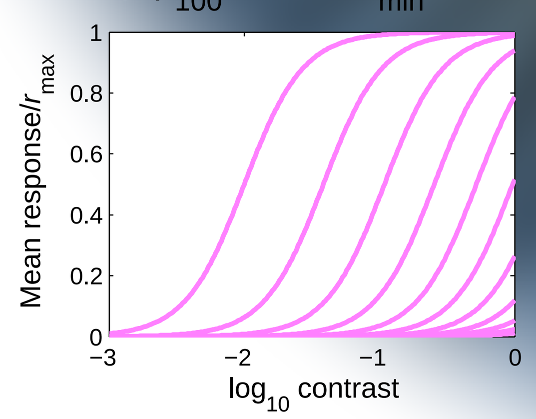
Chirimuuta and Tolhurst used complex distributions of semi−saturation contrast (c_{50}). We show that the Bayesian decoder can fit many contrast discrimination dipper functions if we use a population of neurons with a standard Naka−Rushton function (no threshold) and c_{50} uniformly distributed along the log contrast axis. With r_{max} constant across the population of neurons (Model 1) we get Weber's Law for high pedestal contrasts. A shallower slope can be obtained by scaling r_{max} to keep a constant response (r_{100}) to max contrast (Model 2), or by using an exponential distribution of c_{50} values (Model 3), or both (Model 4).

We used Fisher information and probability theory to derive equations that predict the Bayesian decoder's performance levels. As shown, the equations accurately predict the model's performance. The equations allow fast fitting of the model parameters.

The equations explain the change in psychometric function slope (Weibull β) with increasing pedestal. For detection, it turns out that $\beta = q$, the Naka−Rushton exponent; with increasing pedestal contrast, β asymptotes to about 1.3, regardless of the model parameters. Without a threshold, Chirimuuta and Tolhurst always got $\beta \approx 2$ for detection because they fixed q at 2. Their hard threshold increased the Weibull β because a threshold has a similar effect to increasing q.

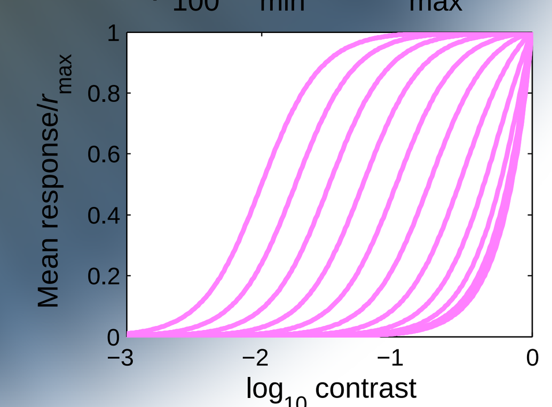
Model 3

Exponential c_{50} distribution, r_{max} fixed
q, ρ_{100}, m and z_{min} fitted

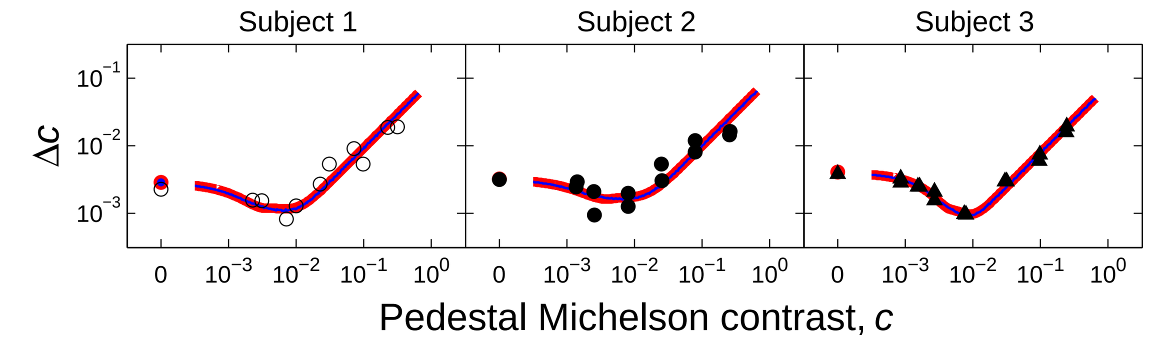


Model 2

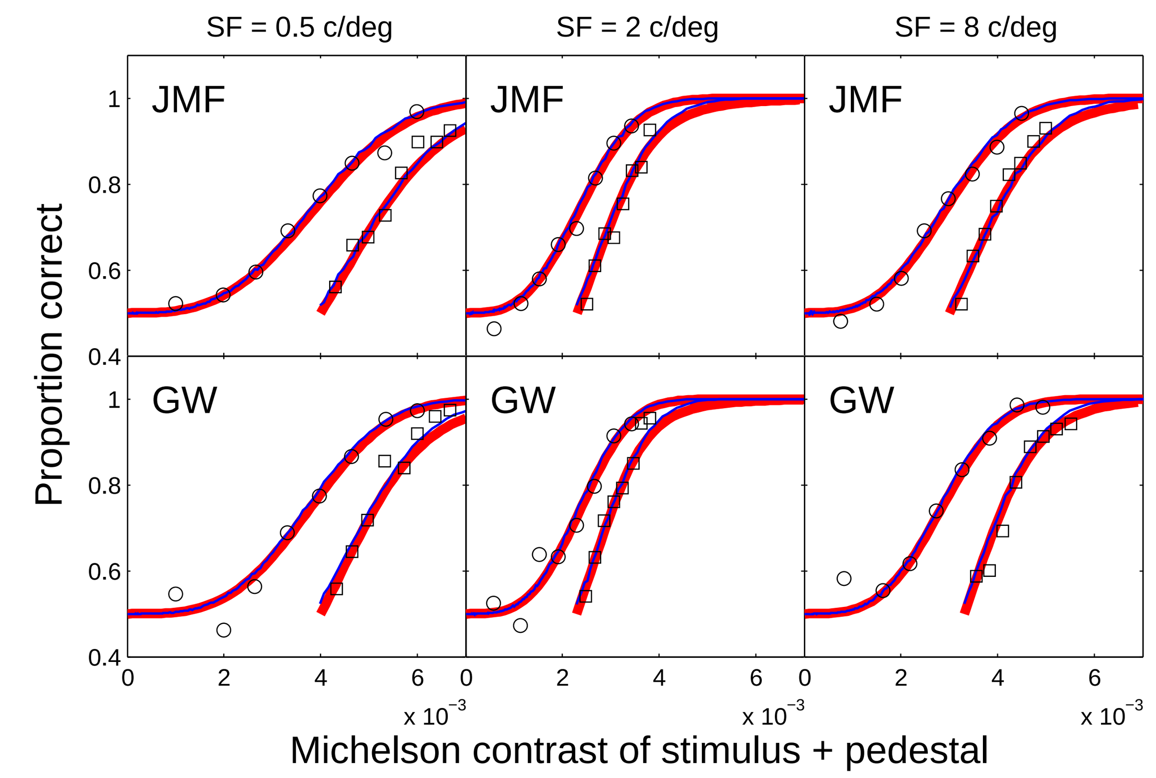
Uniform c_{50} distribution, r_{100} fixed
q, ρ_{100}, z_{min} and z_{max} fitted



Model 1: Nachmias & Sansbury (1974)



Model 1: Foley & Legge (1981)
Model fitted to detection psychometric function (circles)
Parameter−free prediction of discrimination psychometric function (squares)



Key to lines and symbols

- Model performance predicted from our equations
- Model performance determined from Monte Carlo simulations
- Semi−saturation contrasts of neurons
- ○ ● ▲ □ Psychophysical data

Model parameters

Mean response, r, of neuron is given by the Naka−Rushton function:

$r = r_{max}c^q/(c_{50}^q + c^q) = r_{max}10^{qu}/(10^{qz} + 10^{qu})$

c is Michelson contrast

$u = \log_{10}c$

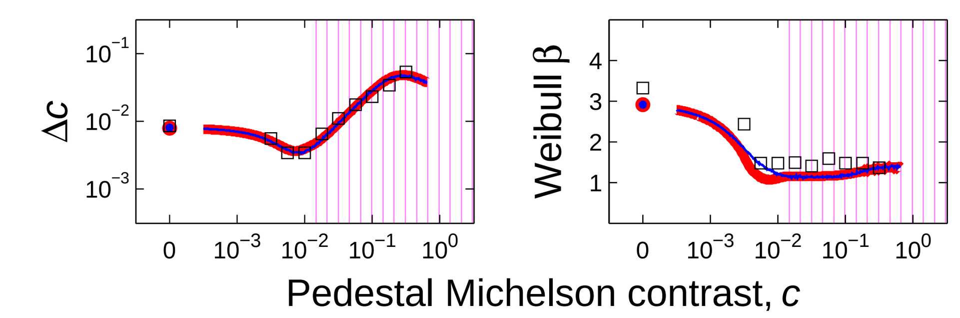
c_{50} is semi−saturation contrast

$z = \log_{10}c_{50}$

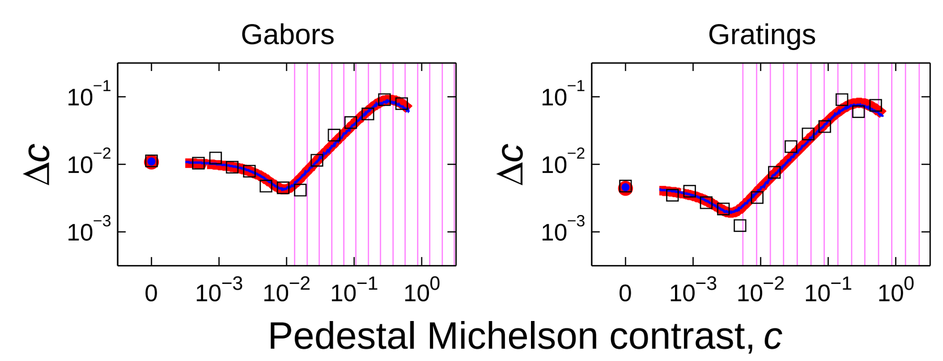
z_{min} and z_{max} are the min and max values of z in the neural population

z either has a uniform distribution with density ρ_{100} neurons per log contrast unit (Models 1 and 2), or has an exponential distribution with density $\rho(z) = \rho_{100}e^{mz}$ (Models 3 and 4)

Model 2: Meese, Georgeson & Baker (2006)
Model fitted to contrast thresholds
Parameter−free prediction of Weibull β



Model 2: Chirimuuta & Tolhurst (2005)
Model fitted to contrast thresholds



References

Chirimuuta, M., Clatworthy, P. L., & Tolhurst, D. J. (2003). *JOSA*, *A*, **20**, 1253−1260.
Chirimuuta, M. & Tolhurst, D. J. (2005). *Vis Res*, **45**, 2943−2959.
Clatworthy, P. L., Chirimuuta, M., Lauritzen, J. S., & Tolhurst, D. J. (2003). *Vis Res*, **43**, 1983−2001.
Foley, J. M. & Legge, G. E. (1981). *Vis Res*, **21**, 1041−1053.
Meese, T., Georgeson, M. A., & Baker, D. H. (2006). *JOV*, **6**, 1224−1243.
Nachmias, J. & Sansbury, R. V. (1974). *Vis Res*, **14**, 1039−1042.

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