The nonlinearity in texture segregation is not rectification

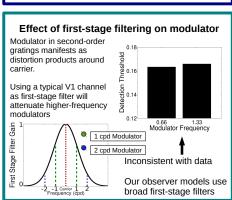
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Background The Filter Rectify Filter (FRF) FRF model model has been successfully applied to explain many aspects of second-order (or texture-defined) vision. We examine the frequency bandwidth of the second-stage filter in two experiments: Experiment 1: no evidence for frequency tuning Experiment 2: frequency tuning consistent with previous estimates [1,2] Both consistent with an Second-stage additional nonlinearity that filter labels dominant texture

Stimuli Orientation-modulated sine wave gratings Vary target modulator amplitude Exp 1: highpass or lowpass noise added to target modulator



Experiment 1: Critical-band-masking Plaid noise, constant Add lowpass or highpass noise to noise spectral density modulator (second-order noise) "Highpass" noise Vary noise cutoff across blocks actually 0 to carrier frea/2 Noise near the channel center Lowpass should raise threshold Highpass Modulator Channels should be centered on frequency modulator FRF model predicts 0.0755 S-shaped threshold elevation Simulated 0.0503 Noise should not affect FRF threshold outside of 0.0252 observer reasonable channel Human data not S-shaped Noise cutoff (cpd) Noise elevates threshold regardless of frequency — no evidence for tuning **Experiment 2:** Human data 🔘 🔿 **Detection vs. discrimination** Task: 2x2 AFC Detection and Frequency: discrimination High Low performance similar at threshold for verv different modulator frequencies Implies independent Second First mechanisms that are interval interval frequency tuned

Labeled-lines paradigm for orientation-

Consistent with similar experiment on contrast

We estimate channel bandwidths from data

Suggests fixed width channels of 1-1.5

covering a variety of high/low frequency pairs

modulated gratings

octave bandwidth

modulated gratings [2]

Orientation-labeling model Some existing evidence points to extraction of dominant response as a nonlinearity in second-order vision [3, 4]. Our model: 4 cpd carrier, 0.5 cpd modulator 1) Filter and rectify \longrightarrow texture energy image E(x, y)0 Model 2) Estimate distributions for textures T1 and T2 from E Human data 3) Label points T1 or T2 based on texture-energy (Labeling) I predictic responses E(x, y) in neighborhood around (x, y), assume independence of neighbors 4) Apply second-stage filter to the orientation-labeled (binary) image to detect modulator noise cutoff (cpd) modulator freq weight w from probability of neighbor sharing the same "stripe" as location (x, y). ZMW/Model 0.66 vs. 1.33 cpd Interval Frequency 0.875 Distant Step 1 Steps 2-3 Step 4 Model modulator frequencies 0.625 Experiment 1: No tuning for noise frequency abeling) I. predictio 0.3 0.45 0.6 Experiment 2: Preserves tuning for ZMW/Model 0.91 vs. 1.08 cpd frequency discrimination Similar channel bandwidth estimates Summary Similar Modulator Critical-band-masking data Frequencies inconsistent with FRF given 0.3 0.45 plausible second F modulation contrast Detection vs. discrimination data Estimated channel bandwidth consistent with previous bandwidth estimates Model ons Bandwidth (octaves) Nonlinearity that labels dominant texture accounts for both Human data ling) I dictic References

Mean modulator frequency (cpd)