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# Computational Nonlinear Dynamics Model of Percept Switching with Ambiguous Stimuli

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Simulation results of bistable perception due to ambiguous visual stimuli are presented which are obtained with a nonlinear dynamics model using delayed perception–attention–memory coupling. Percept reversals are induced by attention fatigue with an attention bias which balances the relative percept duration. Periodic stimulus simulations as a function of stimulus off-time yields the reversal rate variation in surprisingly good quantitative agreement with classical experimental results reported in the literature [1] when selecting a fatigue time constant of 1 – 2 s. Coupling of the bias to the perception state introduces memory effects which are quantified through the Hurst parameter H, exhibiting significant long range correlations (H > 0.5) in agreement with recent experimental results [2]. Percept transition times of 150 – 200 ms and mean percept dwell times of 3 – 5 s as reported in the literature, are correctly predicted if a feedback delay of 40 ms is assumed as mentioned in the literature (e.g. [21]).

**Keywords:** cognitive bistability, modelling, nonlinear dynamics, perception, attention, Hurst parameter

## 1 Introduction

In the present work new simulation results of a nonlinear dynamics model of cognitive multistability [3] are presented. Multistable perception is the spontaneous involuntary switching of conscious awareness between the different percepts of an ambiguous stimulus. It is excited with different methods and stimuli such as binocular rivalry [5], perspective reversal, e.g. with the famous Necker cube [6][7][25], and ambiguous motion displays [8]. Bistability provides an unique approach to fundamental questions of perception and consciousness because it allows for the direct measurement of the switching of subjective perception under constant external stimulus (e.g. [9][10][11][12] [13]). Various aspects of the present model were described in previous papers [3][14][15] where results on stability, typical time scales, statistics of perceptual dominance times, and memory effects were compared with experimental results found in the literature. The present simulation results are compared with two different experiments: classical results of Orbach et.al. [1][6] addressing percept stabilization due to periodic interruption of stimulus, and recently discovered long range correlations of the perceptual duration times [2] via determination of the self similarity (Hurst) parameter H (> 0.5) of the dwell time series.

Concerning theoretical modeling there is an ongoing discussion on the predominance of stochastic [16] [17] versus deterministic [3] [18][19] background of multistability, and on the importance of neural or attentional fatigue [6][19] versus memory effects [1][17]. The synergetic model of Ditzinger & Haken [19] is based on two separate sets of coupled nonlinear dynamics equations for the two perception state order parameters and the corresponding attention (control) parameters. According to the experimentally supported satiation (neuronal fatigue) hypothesis [6], quasiperiodic transitions between different attractor states of the perception order parameter are induced by a slow time variation of the attention (control) parameter due to perception–attention coupling. Following [19] and supported by recent experimental results in [4][25][29] the present model couples the dynamics of a macroscopic (behavioral) perception state order parameter with an adaptive attention control parameter, corresponding to feedback gain with delay and additive noise [3]. Memory effects are introduced by allowing for the adaptation of the originally constant attention bias parameter which balances the subjective preference of one of the two percepts.
By including an additive attention noise term the model explains the experimental finding that deterministic as well as stochastic dynamics determines the measured reversal time statistics for different multistability phenomena.
In section 2 the theoretical approach is described. Computer simulations of perception time series are presented in section 3, adressing percept stabilization with interrupted stimulus in 3.1 and predicting long range correlations with adaptive bias under constant stimulus in 3.2. Discussion of results and the conclusion follows in section 4.

# 2 Theory

## 2.1 The Recursive Mean Field Interference Model

After reviewing important features of the present model I will add some aspects not mentioned in previous papers [3][14][15]. In agreement with the widely accepted view of reentrant synchronous interactions between distant neuronal groups within the thalamo-cortical system leading to conscious perception (e.g. [13][22][25][29]), the present model assumes superimposition of coherent fields $a(\Phi_1(t))$, $b(\Phi_2(t)$ representing the possible percepts P1, P2, and recursive processes to determine the multistable perception dynamics. Like [19] it utilizes perception-attention coupling, however within a delayed reentrant loop modulating the phase difference $\Delta\Phi = \Phi_1 - \Phi_2$, with attention identified with feedback gain [3][26], and adaptive attention bias balancing preference between percepts via learning and memory. This approach results in a phase dynamics $\Delta\Phi(t)$ formalized by a recursive cosinuidal mapping function. The architecture is motivated by thalamo-cortical (TC) reentrant loops as proposed within the dynamical core hypothesis of consciousness [13] and within the discussion of bottom-up and top-down aspects of visual attention [26]. The present approach is furthermore motivated by the mean field phase oscillator theory of coupled neuronal columns in the visual cortex [23]. It describes via the circle (sine) map the synchronization of neural self oscillations as the physiological basis of dynamic temporal binding which in turn is thought to be cruical for the selection of perceptually or behavioraly relevant information [10][11][12]. Accordingly Figure 1 depicts within a block diagram important modules of the attentionally modulated visual perception system. The diagram is based on classical brain circuit schematics (e.g. [27]) and extends a figure in [26] depicting the attentional top-down modulation of the dorsal ("where") and ventral ("what") streams of information.

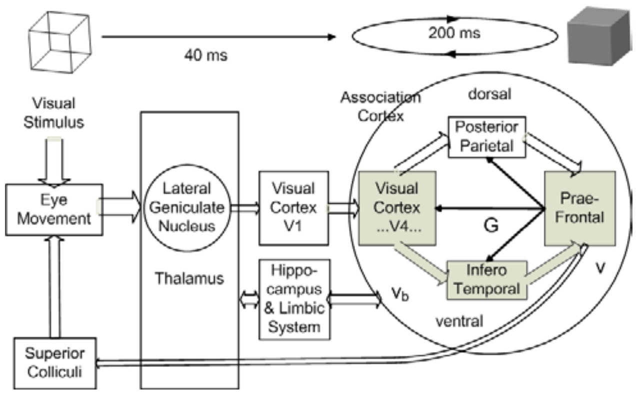



**Fig. 1.** Schematic of visual information flow within the thalamo-cortical system, with indication of bottom-up streams and attentional top-down modulation (black arrows) of ventral ("what") and dorsal ("where") pathways resulting in recurrent v-G-$v_b$ loops (based on [26][27]) with feedforward and reentrant delay $T \approx 40$ ms [21]. Top sketch shows time scales of disambiguation process.

Within the present model it is assumed that for the emergence of the conscious percept, feedforward preprocessing of the stimulus up to the Primary Visual Cortex V1 as well as the loop via superior colliculi can be neglected. The main processing takes place within recurrent TC-loops under covert attention (e.g. [9][22][26]). The model architecture is suggested to basically represent the ventral ("what") V2/V4–InferoTemporal (IF)–PraeFrontal (PF)–V2/V4 loop and the TC-hippocampal (memory) loop as target structure. Recent experimental evidence on perception–attention coupling with ambiguous stimuli was based on EEG recording of frontal theta and occipital alpha bands [25]and eye blink rate measurement [4]. According to Hillyard et.al. [28] stimulus-evoked neuronal activity can be modified by an attentional induced additive bias or by a true gain modulation (present model parameters $v_b(t)$ and g(t)). Increase of gain g(t) is correlated with increased blood flow through the respective cortical areas. Consequently in the present model, like in [19], the feedback gain serves as adaptive control parameter ($g \sim$ attention parameter G) which induces the rapid transitions between the alternative stationary perception states P1 and P2, through attention fatigue [6][19]. The reentrant coherent field superimposition yields an overdamped feedback system with a first order dynamical equation. The resulting phase oscillator equation (1) is similar to the phase attractive circle map of Kelso et.al. [24]. The complete dynamics is described by three coupled equations for the perception state order parameter (phase difference $v(t) = \Delta\Phi/\pi$), the attention control parameter G(t), and for the attention bias or preference $v_b(t)$. The full model is built upon a set of three perception-attention-memory (PAM) equations for each percept $P_i$, i = 1,2,..., n, with inhibiting (phase) coupling $-c_{ij}\, v_j$ , $i \neq j$, in the nonlinear mapping functions, comparable to [19].

$$\tau \dot{v}^{i}_{t+T} + v^{i}_{t+T} = G^{i}_{t}\left[1+\mu^{i}\cos\left(\pi\left(v^{i}_{t} - \sum_{i\neq j}^{n} c_{ij} v^{j}_{t} + v_B\right)\right)\right] . \quad \textbf{(1)}$$

$$\dot{G}^{i}_{t} = \left(v^{i}_{b} - v^{i}_{t}\right)/\gamma + \left(G_{mean} - G^{i}_{t}\right)/\tau_G + L_t \; . \quad \textbf{(2)}$$

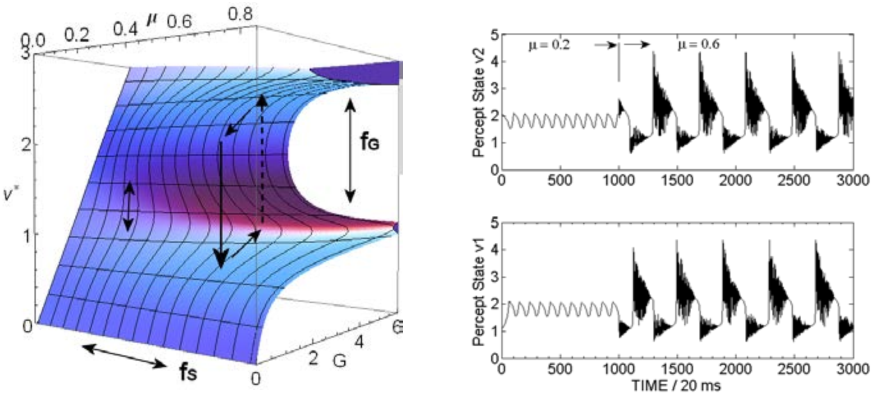
$$\dot{v}^{i}_{bt} = \left(v^{i}_{b_e} - v^{i}_{bt}\right)M/\tau_L + \left(\overline{v}^{i}_{t} - v^{i}_{b_t}\right)/\tau_M \, . \quad \textbf{(3)}$$

In the computer experiments of section 3, however, like in previous publications, for the bistable case a reduced model with a single set of PAM equations will be used. This is justified by the fact that without noise the system behavior is completely redundant with regard to perception states i = 1, 2 (P1, P2) as will be shown in section 2.2 (see also [19]). The advantage of reduced number of parameters has to be payed for by slightly unsymmetric behavior of P1, P2 time series (slightly different mean dwell times with symmetric bias $v_b$)

The reduced model system behavior can be understood as follows. An ambiguous stimulus with strength I and difference of meaning $\mu$ (interference contrast $0 \leq \mu \leq 1$) of the two possible percepts P1, P2 excites two corresponding hypothetical mean fields [$a_1$, $a_2$] representing percept possibilities, with phase difference $\Delta\Phi$. A recurrent process is established by feedback of the output $U \sim |a_1 + a_2|^2$ after amplification (feedback gain g) with delay T into $\Delta\Phi$ via a hypothetical phase modulation mechanism $\Delta\Phi = \pi U/U_{\pi}. = \pi v$. As a quantitative estimate for T the reentrant (feedback) processing delay of ≈ 40 ms within the association cortex is assumed as mentioned by Lamme [21]. The nonlinear rhs. of equ. (1) describes the conventional interference between two coherent fields. In what follows I assume the phase bias $v_B = 0$ mod 2. In agreement with Itti & Koch [26] the attention parameter $G(t) \sim \kappa\, I_0\, g(t)$ is the product of feedback gain g(t) and input (stimulus) strength $I_0$ (=1 in what follows). The attention dynamics is determined by the attention bias $v_b$ (determining the relative preference of P1 and P2), fatigue time constant $\gamma$, recovery time constant $\tau_G$, and $G_{mean} = 0.5(3 - \mu)/(1 - \mu^2)$ = center between turning points of stationary hysteresis v*(G) (see below). Following [19], the random noise due to physically required dissipative processes is added to the attention equation G(t) as a stochastic Langevin force L(t) with band limited white noise power $J_{\omega}$. The attention bias or preference dynamics $dv_b/dt$ is modelled as the sum of a learning term $M(v_t,v_b,v_{be})(v_{be} - v_b)/\tau_L$, and of a memory component $(\langle v_t\rangle - v_b)/\tau_M$ which couples $v_b$ to the low pass filtered perception state. Learning of an unfamiliar (weak) percept $P_j$ is active only in the initial phase of the time series if a $P_j$ association is low and a fluctuation induced jump into the weak $P_j$-perception state from $P_i$ occurs, switching M from 0 to 1.

## 2.2 Stationary Solutions and Self-Oscillations

Quasiperiodic switching between two attractor states $v^*_1$(P1) and $v^*_2$(P2) emerges after a node bifurcation of the stationary solution v*(G). It evolves from a monotonous function into a hysteresis (S-shaped) ambiguous one with increasing μ as can be seen in the first order stationary solution of equ. (1) shown in Figure 2a). The stationary solution supports the proposed catastrophe topology of the cognitive multistability dynamics [18]. At the critical value, $\mu_n = 0.18$, the slope of the stationary system state v*(G) becomes infinite, with $(G_n, v_n) \approx (1.5, 1.5)$. For $\mu < \mu_n$ both percepts are fused into a single meaning. For $\mu > \mu_n$ the stationary solution v*(G) becomes multivalued. For maximum contrast μ = 1 the horizontal slope dv/dG = 0 yields $v_i^\infty = 2i - 1$, i = 1,2,3,… as stationary perception levels for $G \rightarrow \infty$. Figure 2b) depicts a numerical solution of the set of two coupled PAM equations with identical parameter values T = 2, τ = 1, γ = 60, $\tau_G = 500$, $c_{ij} = 0.1$, constant attention bias $v_b = 1.5$, noise power $J_\omega = 0$ (time units = sample time $T_S$ = 20 ms), as obtained with a Matlab–Simulink code using the Runge-Kutta solver "ode23tb" [3][14][15].




a) b)

**Fig. 2.** a) First order stationary solution of a single percept equation (1) with arrows indicating g-v phase space trajectories of perceptual self oscillations (frequency $f_G$, vertical) and externally imposed stimulus oscillation μ(t) = 0.2 ⇔ 0.6: (frequency $f_S$, horizontal). b) Numerical solution of the full model equs. (1) (2) (3): over 3000Ts = 1 min, depicting redundancy due to antiphase of $v_1$, $v_2$. Stimulus μ(t) changes at t = 1000 Ts = 20 s from μ = 0.2 to μ = 0.6.

Higher order stationary solutions yield period doubling pitchfork bifurcations [3][14][15] (not shown in Fig. 2a)) on both positive slope regions of the hysteresis curve, with the G-values of the bifurcation points converging at the chaotic boundary according to the Feigenbaum constant $\delta_\infty = 4.6692$ . The corresponding P1-, P2-limit cycle oscillations and chaotic contributions can be seen in Figure 2b) which depicts time series of perceptual switching events of the percept vector [v1, v2] for small and large contrast parameter μ. The small-μ self-oscillations change into pronounced switching between percept-on ($v_i > 2$) and –off ($v_i \approx 1$) with incrasing contrast. In contrast to the quasiperiodic P1-P2 switching the superimposed limit cycle oscillations (> 5 Hz) originate from the finite delay T with the amplitudes corresponding to the pitchfork bifurcation pattern [3][15]. The linear stability analysis of equ.(1) [15] yields Eigenfrequencies $\beta = 2\pi f$ via $\beta\tau = -\tan(\beta T)$ with numerical values f/Hz = 9.1, 20.2, 32.2, 44.5 ... for $\tau$ = 20 ms, T = 40 ms. This spectrum compares reasonably well with typical EEG frequencies as well as fixational eye movements as related external observables.

The percept reversal time period is determined by the slow G(t) dynamics, with fatigue and recovery time constants $\gamma$, $\tau_G$ , leading to the quasiperiodic P1→P2 transitions at the G-extrema. An analytic estimate for small $\mu$ of the expected perceptual self oscillations between the stationary states v*(P1) ⇔ v*(P2) due to the v – G coupling may be obtained by combination of equations (1) and (2) yielding the reversal frequency

$$f_G = f_0\sqrt{1-D^2} \qquad \textbf{(4)}$$

with eigenfrequency $\omega_0 = 1/\sqrt{\gamma(\tau+T)} = 3.73\text{rad/s}$ or $f_0$ = 0.59 Hz = 36 min$^{-1}$ or $T_0$ = 1.7 s. The influence of the damping term can be derived after transformation of the timescale into eigentime $\vartheta = \omega_0 t$ with normalized damping $D = \sqrt{(1-\pi\mu G^*)/(2\omega_0(\tau+T))}$, yielding the reversal rate $f_D$ = 0.55 Hz = 33 min$^{-1}$ in exact agreement with the the numerical solution in Fig.2b). Although the very rough dwell time estimate for a single percept $\Delta(P_i) = T_G / 2 = 1/2f_G$ due to the low hysteresis ($\mu$ = 0.2 ) lies at the lower end of the typical experimental results it nevertheless predicts the correct order of magnitude, e.g. [6][7][16][20].

The percept duration time statistics has been shown in numerous experimental investigations (e.g.[7][20][29]) and different theoretical modelling approaches ([3][19][24]) to correspond to a $\Gamma$-distribution as a reasonable approximation. Time series of the kind shown in Fig. 2b) obtained with the simplified (scalar) model were analyzed in previous publications [3][14][15] with respect to the relative frequencies of perceptual duration times $\Delta$(P1), $\Delta$(P2). The analysis confirmed the $\Gamma$-distribution statistics of percept dwell times as a good approximation, with absolute mean values $\Delta_m$ of some seconds and relative standard deviation $\sigma/\Delta_m \approx 0.5$ [7][20].

# 3 Computer Experiments

In what follows numerical evaluations of the PAM-equations in its reduced scalar form are presented for comparing theoretical predictions with a) experiments addressing fatigue suppression (or percept stabilization) with periodically interrupted ambiguous stimulus [1][6], and b) long range correlations within dwell time series observed under constant stimulus [2].

## 3.1 Perception–Attention Dynamics with Interrupted Stimulus

In this section numerical evaluations of a single set of PAM equations with periodically interrupted stimulus are presented. Figure 3 shows for the same parameter values as Fig. 2b) over a period of $t_{Sim}$ = 2000 $T_S$ = 40 s the time series $\mu$(t), G(t) and v(t), however with noise power $J_\omega$ = 0.001 (noise sample time $t_c$ = 0.1), and $\tau_M$ =

10000, $\tau_L$ = 100000, i.e. effectively constant bias. The periodically interrupted stimulus parameter (contrast) $\mu(t)$ alternates between 0.6 = stimulus-on and 0.1 = stimulus-off with $t_{on} = t_{off}$ = 300 ms.

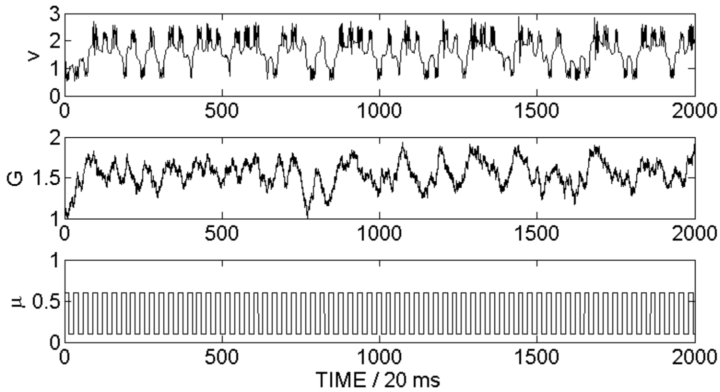



**Fig. 3.** Numerical evaluation of PAM-equations (reduced scalar model) for periodic stimulus with $t_{on} = t_{off}$ = 300 ms. From bottom to top: Stimulus parameter $\mu(t)$ alternating between $\mu$ = 0.6 (on) and 0.1 (off), attention parameter G, perception state v(t). For details see text.

The v(t) dynamics in Fig.3 exhibits the expected quasiperiodic transitions between stationary perception states P1 (near $v^* \approx 1$) and P2 (near $v^* \approx 2.5$). During stimulus on periods the expected superimposed fast limit cycle and chaotic oscillations are observed. The transition time between P1 and P2 is of the order of 8 - 10 $T_S \approx$ 150 - 200 ms, in reasonable agreement with the time interval between stimulus onset and conscious perception [21]. Figure 4 shows model based reversal rates $1/\Delta_m$ as function of $t_{off}$.

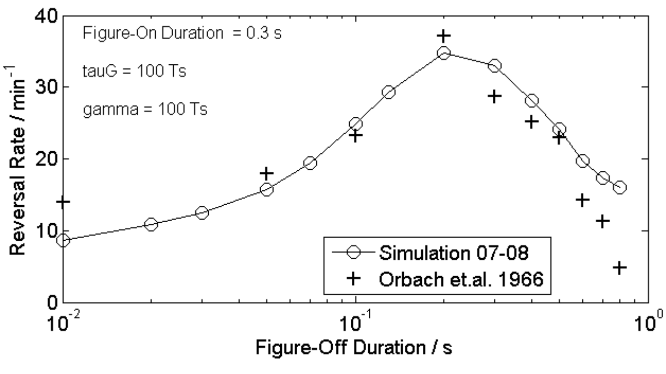



**Fig. 4.** Reversal rate $1/\Delta_m$ obtained from computer experiments for $t_{on}$ = 300 ms and 10 ms $\leq t_{off} \leq$ 800 ms (circles: 100 time series of $t_{Sim}$ = 5000 $T_S$/data point) and experimental values [1] (crosses).

Numerical values are determined by evaluation of time series like in Fig.3 with $t_{on}$ = 300 ms and a range of $t_{off}$–values corresponding to experiments reported in [1][6]. A surprisingly good agreement is observed between model simulations and experiments, even with regard to the absolut maximum, indicating the fatigue induced phase-oscillator mechanism to capture essential aspects of the cognitive bistability dynamics.

### 3.2 Memory Effects through Adaptive Bias

In a recent analysis of perceptual dwell time statistics as measured with Necker cube and binocular rivalry experiments Gao et.al. [2] detected significant long range correlations quantified by the Hurst parameter ($H > 0.5$), with $0.6 < H < 0.8$ for 20 subjects who indicated subjective percept switching by pressing a button. With the present model the coupling of the dynamic bias $v_b$ to the perception state leads to long term correlations via memory effects. The left graph of Figure 5 depicts simulated subjective percept switching with dwell times $\Delta(P2)$ versus reversal number.□Simulation parameters are $\mu = 0.6$, $v_{b0} = v_{be} = 1.5$, $T = 2T_S$, $\tau = 0.5$, $\gamma = 60$, $\tau_G = 500$, $J_\omega = 0.004$, dynamic bias (preference) time constants $\tau_M = 3000$, $\tau_L = 100000$. The right graph of Fig. 5 depicts the evaluation of H from 100 time series with simulation length 5000 $T_S$ by employing the log(variance($\Delta$(m))) vs. log(sample size m) method with var($\Delta$(m)) $= s^2 m^{2H-1}$ as used by Gao et.al. [2]. H is determined from the slope of the regression line and includes 95% confidence intervals of parameter estimates.

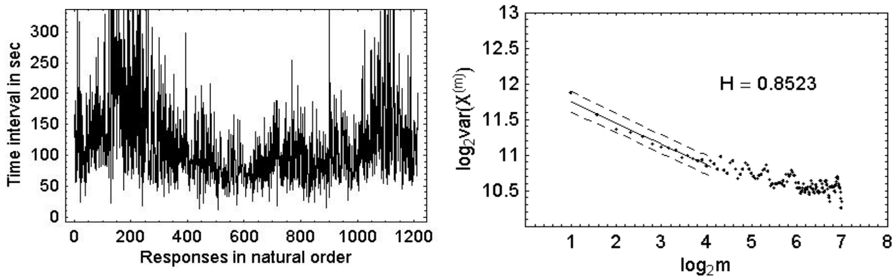



**Fig. 5.** Left: Simulated subjective responses to percept switching depicting dwell times $\Delta$(P2). Right: variance(m) vs. sample time (m) plot of the same simulation runs with linear fit (95% conf. intervals) for estimating H via the slope of the regression line.

It shows significant long range correlations due to the memory effect if the time constant for the attention bias $v_b$ satisfies $\tau_M < 10000\ T_S = 200$ s. The learning component in equ.(3) influences the dynamics only in the initial phase if $|v_{be} - v_b(t=0)| > 0$ and only if $\tau_L < 2000$. Large $\tau_{L,M}$ (vanishing memory change) represent quasi static preference: for $\tau_{M,L} > 10000$ the long range correlations vanish, with $H \approx 0.5$ corresponding to a random walk process (Brownian motion).

## 4 Discussion and Conclusion

For the first time to our knowledge the percept reversal rate of alternating perception states under periodic stimulus and the memory effect of an adaptive perception bias was derived by computer simulations using a single behavioral nonlinear dynamics phase oscillator model based on perception-attention-memory coupling and phase feedback. The PAM model can be mapped to a simplified thalamocortical reentrant circuit including attentional feedback modulation of the ventral stream [26]. For the bistable case the full vector model with a set of PAM equations per perception state can be approximated by a scalar PAM model due to redundancy of the noise-free case, at the cost of slight unsymmetries between $v_1$, $v_2$ time series statistics. The dynamics of the reentrant self oscillator perception circuit is determined by delayed adaptive gain for modeling attention fatigue, with additive attention noise. The attention in turn is biased by an adaptive preference parameter coupled to the perception state for simulating memory effects. Simulated perceptual reversal rates under periodic stimulus provide surprisingly good quantitative agreement with experimental results of Orbach et al. [1][6]. With memory time constants < 200 s reversal time series exhibit long range correlations characterized by a Hurst (self similarity) parameter H > 0.5 in agreement with experimental results of Gao et.al.[2]. The present model supports the early proposal of Poston & Stewart [18] of a deterministic catastrophe topology as the basis of the perception reversal dynamics.

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