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A Recursive Attention – Perception Chaotic Attractor Model of Cognitive Multistability

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Introduction

Attneave (1971) and Lehky (1988) pointed out the similarity of cognitive bistability and electronic multivibrator circuits and suggested analogous neural structures with locking into alternative schemata and exhibiting fatigue. In contrast to the microscopic neural approach I propose to model the dynamics of the macroscopic behavioral variables perception and attention by a phase feedback equivalent circuit which is related to the mean field theory of temporal binding (Schuster & Wagner 1990). Based on a previously outlined nonlinear dynamics model (Fürstenau, 2003), I show that the spontaneous reversals between two perception states with an ambiguous stimulus, e.g. the perspective switching of the Necker-cube, can be explained as self - oscillation between chaotic attractors in attention - perception phase space. The perception state variable is represented by the phase v of a recursive cosinuidal mapping function with feedback delay time T and attention control parameter G. G is proportional to feedback gain g of a corresponding equivalent circuit representing the dynamics of behavioral variables v, G. According to Hillyard, Vogel & Luck (1999) a difference between bias and gain control mechanisms of attention is observed. Like in the multistability model of Ditzinger & Haken (e.g. Haken (1996)) the perception variable is treated as order parameter within the formal framework of Synergetics, with the slowly time varying attention parameter G(t) exhibiting satuation or adaptation. The important aspect of the present approach is the neurophysiologically motivated delay T, giving rise to the chaotic attractors in agreement with Freeman et.al. (e.g. Freeman 2000). The statistical analysis of simulated time series predicts gamma distributions of the perceptual reversal times with mean values and variance in reasonable agreement with experimental results of Borsellino et.al. (1972).

The recursive attention - perception model

The present approach is closely related to the mean field phase oscillator theory of coupled neural groups in the visual cortex (Schuster & Wagner 1990) which was used for modeling the synchronization of neural oscillations as the physiological basis of dynamic temporal binding (Engel et. al.1999). As a kind of minimum architecture allowing for multistability via coupling of the attention and perception dynamics I suggest a nonlinar delayed phase feedback model. An example of a corresponding equivalent circuit from the optics domain was described e.g. in (Watts & Fürstenau, 1989). A simplified block diagram is shown in Figure 1, depicting interference between coherent fields which are associated with the different interpretations of the stimulus. The coupled perception (v_t) – attention (G_t) dynamics for small damping τ is approximated by the recursive equations (time steps t_j = j T, j = 1,2,…):

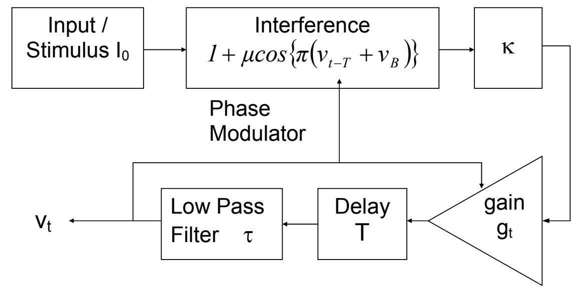

Figure 1: Nonlinear delayed phase feedback equivalent circuit. Interference = superposition of separate coherent phase shifted fields with difference of meaning (contrast) μ, excited by stimulus I_0. v_t = perception state (phase variable), g_t ~ attention (control parameter), κ = conversion factor, τ = damping time

$$v_{t+T} = \frac{G}{1+\tau}\left[1+\mu cos(\pi(v_t+v_B))\right]+\frac{\tau}{1+\tau}v_t \tag{1a}$$

$$G_{t+T} = G_0(v_b - v_t)/\gamma + G_t(1-1/\tau_G) + L(t) \tag{1b}$$

Here G_t is a discrete version of a similar attention equation used in the Ditzinger&Haken model. The relative duration of the dominant and suppressed phase of a percept is determined by the bias parameter v_b. In a first approach to model the random disturbances due to dissipative processes a δ-correlated stochastic (Langevin) force L(t) with random amplitude r s_j , $-1 \le s_j \le 1$ is included in (1b), similar to (Haken 1996) and (Lehky 1988). It adds pushes of random amplitude to G_t .

Simulated Perception - Attention Dynamics

If μ > 0.18 the stationary solution of (1a) becomes multivalued (hysteresis curve $v_{t+T} = v_t = v^*$, (Fürstenau 2003)) and the delayed feedback system allows for spontaneous transitions between percept P1 corresponding to stationary state $v^* < 1$, and P2, corresponding to $2 < v^* < 3$. Figure 2 shows the numerical evaluation of equations (1) for μ = 0.7, τ/T = 0.03, v_b = 1.5, γ = 170, τ_G = 1400, a random noise amplitude r = 0.025, G_0 = 1 and normalized time with T :=1. The time series of the perception state shows the low frequency self oscillations between P1 (v(t) ≈ 1) and P2 (v(t) ≈ 2), with superimposed high frequency oscillations (f ≥ 1/2T). These low amplitude rapid variations of the perception state are due to a combination of limit cycle oscillations, chaotic trajectories in v_t – G_t - phase space and the

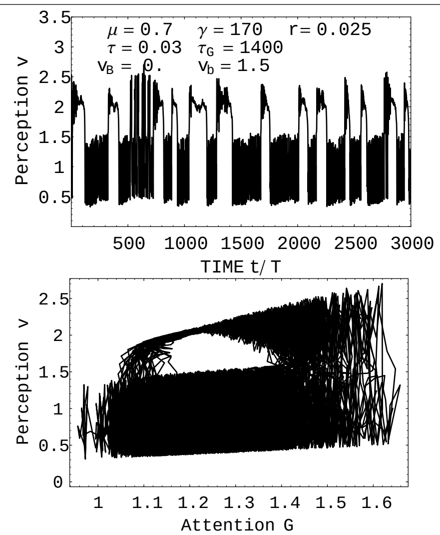

Figure 2: Numerical solution of equ.(1) with 15000 iterations. Top: perception state v_t time series in time units T. Bottom: trajectories in attention – perception phase space.

small random noise (amplitude r = 0.025) of the attention (gain) control parameter. A transition time between P1 and P2 of the order of 5 T is measured. This corresponds to 150 - 200 ms if the recurrence time T is identified with the temporally segmented processing time units of typically 30 - 40 ms as proposed by Pöppel (1990). It is in reasonable agreement with the time interval between (visual) stimulus onset and the beginning of conscious perception (Lamme 2003). The lower graph depicts the trajectories in attention (G) – perception (v) phase space. Besides the limit cycle and chaotic oscillations it exhibits the counterclockwise global movement of v(t) with transitions between P1, P2 due to the coupling with the slowly adapting G(t) (satuation: $v_b - v(t) < 0$ for P2 and $v_b - v(t) > 0$ for P1). The perception speed is determined by $1/\gamma$.

Reversal Time Statistics

Figure 3 depicts the relative frequencies of the perceptual duration times as obtained by averaging 11 time series con-

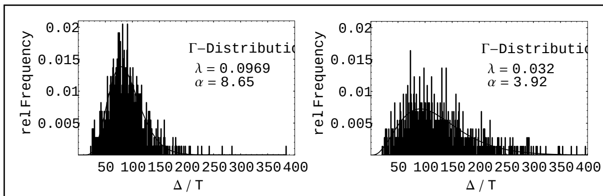

Figure 3 : Relative frequencies of perceptual duration time Δ. Fit with Γ-distribution (solid line). Right: Percept P1 ($v \approx 1$), left: Percept P2 ($v \approx 2$).

sisting of N = 15000 iterations each. Plotted are the two distributions of the perceptual durations Δ(P1), Δ(P2). According to Borsellino et.al. (1972) who evaluated experiments with the Necker cube, the relative frequencies are fitted by a Γ – distribution as probability density with shape parameter α and scale parameter λ, with mean and variance $\Delta_m = \alpha/\lambda$ and $\sigma^2 = \alpha / \lambda^2$ respectively. The X^2 – test suggests acceptance of the Γ-distribution hypothesis for percepts P1, P2 at a significance level of 1%: $X^2(P1,18) = 22.1$, $X^2(P2,19) = 30.3$. For percept P1 mean Δ_m = 123 T, standard deviation σ = 62 T; for P2 Δ_m = 89 T, σ = 30 T. In contrast to (Fürstenau, 2003) with purely deterministic time series, the addition of the small random attention noise L(t) in (1b) leads to a significant increase of the variance, whereas the mean values remain roughly the same, indicating the dominant influence of the deterministic (chaotic) dynamics. The contributions of chaotic dynamics as well as random noise agrees qualitatively with experimental results of Richards, Wilson & Sommer (1994) who separated the chaotic and random contributions of nonlinear perception state time series of quite different visual perception phenomena including multistability. With T = 30 ms e.g. Δ_m (P1) = 3.6 s with σ = 1.8 s, in reasonable agreement with the experimental results of (Borsellino et.al.1972). The model parameter values μ, v_b, τ, γ, τ_G may be tuned to match the inter – subject variations of the experimental results.

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