Neural Field Dynamics for Motion Perception

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Abstract

In this paper we present a model for the perception of apparent motion based on dynamic neural fields. We show that both, the organization of percepts and their specific dynamical properties can be derived from the same perceptual dynamics. We show that neural fields adequately formalize this perceptual dynamics. This leads to a model that is sufficient in the sense that it reproduces correctly the perceptual organization of motion. We show that the model allows also to identify elements which are necessary for understanding perceptual organization together with the dynamic properties of the percepts (e.g. hysteresis and its link to switching rates). Such elements are an activation dynamics which is coupled to adaptation processes with different time-scales, and different mechanisms for perceptual switching. We show how the model can be linked quantitatively to a large set of psychophysical data for the motion quartet.

1 Introduction

Motion percepts have dynamic properties like temporal integration of relevant information [16] and visual inertia [4]. Moreover, motion perception shows essentially nonlinear properties like multi-stability and hysteresis [9,17]. Recently, these specific dynamic properties of motion percepts were measured in quantitative detail in psychophysical experiments [9,10]. In addition, it has been argued that cooperative neural networks can be used to solve the motion correspondence problem and allow to reproduce the formation of actual percepts [6,14]. This leads to the hypothesis that perceptual organization and the dynamic properties of percepts can be derived from a single *perceptual dynamics* signifying that the formation of motion percepts is based on a well defined dynamical process.

The aim of this paper is to evaluate this hypothesis based on psychophysical data using an adequate mathematical framework which allows to deal at the same time with a distributed representation of local information and dynamic self-organization phenomena. We propose the *dynamic neural field* as a suitable theoretical concept, in terms of which models can be formulated that can be related quantitatively to psychophysical data. We first show that the dynamic neural field model is *sufficient* to understand the perceptual organization of motion and its dynamical properties. Then we show how that model can be used to identify *necessary* components of the perceptual dynamics. This allows to construct a model that is *minimal* by containing only necessary components and nevertheless capturing the relevant dynamic phenomena of perceptual organization. We believe that this model reveals essential functional components of perceptual organization in general, and allows an analysis how these components interact dynamically during the formation of percepts.

2 Neural Field Model for the Perception of Apparent Motion

The model is based on the following basic concepts: (1) *Distributed neural representation of motion* in an abstract neural representation field: The percept can be characterized by a distribution of neural activation[1] u over a 4-dimensional perceptual space[2] (cf. [15]). It is parameterized by the retinal position of local motion (x, y) and the perceived motion vector in polar coordinates (v, ϕ). At each point of the activation field $u(\mathbf{z}; t) = u(x, y, v, \phi; t)$ the local activations u are thresholded by a sigmoidal function f. The value $f(u(\mathbf{z}; t))$ signifies the (gradual) presence of the corresponding motion specified by $\mathbf{z}$ ($f(u) \approx 1$: present, $f(u) \approx 0$: not present) in the percept. (2) *Neural dynamics:* Each point of the neural activation field is governed by a neural dynamics derived from a continuous neural network model by Amari [1]:

$$\begin{aligned} \tau\,\dot{u}(\mathbf{z}, t) &= -u(\mathbf{z}, t) + \int w(\mathbf{z} - \mathbf{z}')f(u(\mathbf{z}', t))\,d\mathbf{z}' + \xi(\mathbf{z}, \mathbf{t}) \\ &\quad + S(\mathbf{z}, t) - h \end{aligned} \tag{1}$$

We stress the following basic properties of the model: (1) The *time-scale* τ for the local neural dynamics is well-defined. (2) The threshold function, f, makes the system qualitatively *nonlinear.* (3) The neural field has recurrent *cooperative interactions* characterized by the convolution kernel $w(\mathbf{z}) = w(x, y, v, \phi)$. By choosing this interaction structure the space of stable dynamical patterns is strongly reduced, as compared, for instance, to general Hopfield-type (fully connected) network. The kernel also introduces a *topology* over the space of interactions which is crucial both, mathematically to generate stability properties of the neural field, and empirically to account for the topology of interaction effects in perceptual organization. The shape of the functional interaction kernel can be reconstructed from a set of psychophysical experiments[3]. (4) *Stochastic* contributions, $\xi(\mathbf{z}, \mathbf{t})$, are not only necessary to account for fluctuations of the perceptual state, but also to prevent the field from relaxation to spurious (perceptually irrelevant) stable states[4]. For ambiguous stimulation, fluctuations force a perceptual decision. (5) The feed-forward *stimulus signal* $S(\mathbf{z}, t)$ may be viewed as output of a preceding stage of local motion detectors. It represents the

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[1] The neural activation should be interpreted as average activation of functional neural ensembles rather than as single neuron activity. A direct connection between neural field models and neurophysiological data can be achieved using adequate population coding techniques [11].

[2] To keep the model simple we restrict ourselves to the simplest case: 2-dimensional motion in the retinal plane.

[3] So far we have analyzed only 3-dimensional models with v = const. It remains to be clarified if the convolution form can be retained for competition along the v-dimension.

[4] These states can be identified with local minima of the associated potential function.

capacity of the stimulus to specify the motion percept. Only stimulated local motions ($S > 0$) participate in the cooperation process. (6) Finally, the constant parameter h fixes the perceptual threshold.

The percept results from two distinct contributions to the vector-field of the neural field dynamics: The *non-autonomous part* of equation (1) expresses the direct influence of the stimulus on the percept. The *autonomous part* restricts the space of possible stable solutions in a specific way which represents internal hypotheses of the nervous system about the structure of biologically meaningful visual stimuli. Examples are the smoothness of the motion-field (cf. [18]) or the Gestalt-law of "common fate".

3 Sufficiency of the Neural Organization Field

To evaluate if the proposed mathematical framework is sufficient to account for typical phenomena in motion perception we derived a set of critical properties of motion perception known from psychophysical experiments. (1) Localized motion stimuli lead to localized activation patterns (percepts) in the neural field. This reflects that coherently moving objects are represented by local motion percepts. (2) The model predicts the correctly organized percept for simple motion stimuli such as the motion quartet [9,10]. For the quartet this implies perceptual multi-stability and the suppression of potentially perceivable elementary motions. (3) Stable solutions of the model for random-dot stimuli correspond with solutions of the motion correspondence-problem. This shows that a one-layer neural dynamics is sufficient for the solution of the motion correspondence problem (cf. [8,14]). (4) Experimental results on *visual inertia* can be accounted for in *quantitative* detail (cf. figure 1). Inertia results from the continuous variation of the perceptual state over time with a well-defined time constant. (5) We were able to reproduce global cooperative effects (see figure 2 for an example, cf. [3]). We also reproduced the distance dependence of motion-entrainment/contrast effects, cf. [13]. (6) Presentation of ambiguous stimuli reveals dynamic stability properties of the model. We found multi-stability and hysteresis for motion-quartets and ambiguous random-dot stimuli (cf. [9] and [5]). (7) For symmetric ambiguous stimuli spontaneous symmetry-breaking occurs through fluctuations on an adequate intermediate time scale. Only one of the perceptual alternatives is stably observed over typical time scales [5,9]. (8) A quantitative account for the statistics of perceptual switching can be obtained for the motion quartet stimulus [10]. (9) The neural organization field reproduces the dependence of motion coherence and transparency on the angle difference of the component grating [12]. This is possible because the neural activation dynamics allows the co-existence of different motion percepts at the same position contrary to cooperative neural models which are based on a winner-takes-all mechanism. The highly cooperative perceptual organization dynamics shows a bifurcation as a function of the angular difference of the component gratings.

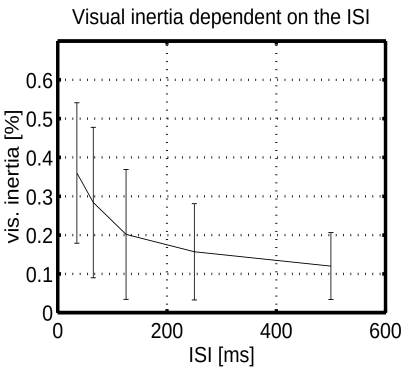

figure 1: Simulated visual inertia dependent on ISI corresponding to the results of Anstis & Ramachandran [4].

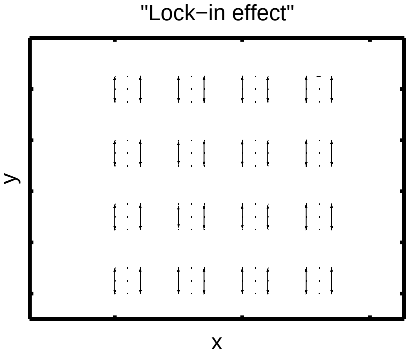

figure 2: Cooperative "lock-in" for multiple quartet-stimuli, cf. [3]. The length of the arrows corresponds to the perceptual strength of the local motions.

4 Necessary Components of the Perceptual Dynamics

By detailed *quantitative* comparison between the model and psychophysical results for *motion quartet* displays (figure 3) we were able to identify *necessary* components of the perceptual dynamics. The motion quartet is particularly well suited for quantitative assessment of the dynamic properties of biological percepts for two reasons: (1) Its temporal and geometrical structure can be quantified simply and completely. (2) The direct observation of switches between two distinct perceptual alternatives makes the dynamic properties of the percepts measurable.

Quartet stimuli produce local activated zones in the perceptual organization field (cf. figure 3). Integrating over each of the four (potentially) activated zones that represent the possible elementary motions[5] leads to a discrete network model with only four model neurons. This simplified model approximates the behavior of the complete neural field for the quartet stimulus. The interaction-matrix of the discrete model is *not* symmetric for quartet geometries other than square (aspect ratios other than 1.) That asymmetric case violates *detailed balance*[6] [7] and as a result the network has much more complicated stochastic behavior than Hopfield-networks.

The discrete approximation was fitted quantitatively to a large experimental data set [9,10]. This involved a mathematical and numerical analysis of the stable and unstable states, the stochastical dynamics for un-symmetric weight-matrices, the switching behavior and switching-time statistics. The quantitative

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[5] Based on time-scale arguments we neglect the difference between forward and backward motion.

[6] This is equivalent to the absence of an equivalent classical potential for the dynamics

results reveal *necessary properties* of the perceptual dynamics: (1) The dynamics of the individual formal neurons in the discrete limit must be extended by two adaptation processes with very distinct time-scales. This can be mathematically expressed by introducing an adaptation dynamics for the thresholds h of the elementary motions. The biological processes which might be reflected by these time-scales might include the relatively fast intra-cortical inhibition ($\tau_1 \approx 600$ ms) and slower processes of neural fatigue ($\tau_2 > 60$ s). (2) Two different mechanisms of perceptual switching, stochastical fluctuations and adaptation, could be contrasted, and their relative contribution to perceptual switching have been determined. The quantitative results suggest that both mechanisms must substantially be involved in the formation of visual motion percepts.

Including these additional necessary components into the perceptual dynamics leads to a *minimal model* for the motion quartet that reproduces *quantitatively* a large set of experimental details: a) dependence of the stationary percept probabilities on the stimulus geometry (aspect ratio): The perceptual alternative with shorter motion matches occurs with higher probability. b) dynamic stability of the perceptual alternatives as measured with different methods: Displays with extreme aspect ratios are more stable that display with aspect ratio 1. c) stochastic switching behavior and switching-time statistics: More stable displays lead to less switches. The switching times vary over time. Switches can occur without time delay. d) reciprocal interdependence between adaptation and stability: stable percepts adapt more and adaptation changes the stability.

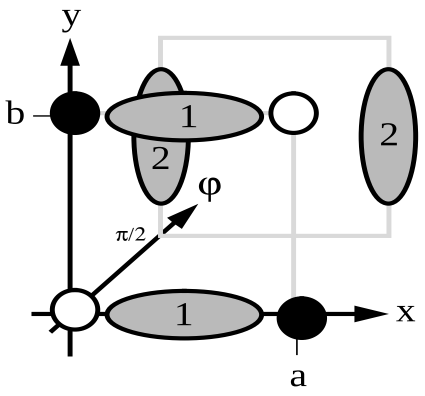

figure 3: The motion quartet consists of two pairs of dots flashing in alternating sequence (black dots: first frame; white dots: second frame; etc.). The geometry is determined by the side-length a and b. The percept is multi-stable and depends on the aspect ratio b/a. The stimulus causes local activated zones in the 3-dimensional projection of the motion organization field. Exclusively, either horizontal motion (zones 1) or vertical motion (zones 2) is seen.

5 Conclusions

We have evaluated the hypothesis that perceptual organization and dynamic properties of percepts both can be derived from a single perceptual dynamics. As adequate mathematical language to describe this perceptual dynamics we proposed a dynamic neural-field model which allows to treat distributed representation of information and dynamic self-organization phenoma within the same context. Our aim was to isolate the set of functional components which is sufficient and necessary to capture the dynamic aspects of perceptual organization in motion perception. We have shown that the neural field model is sufficient in the sense that it captures characteristic (dynamic) properties of motion perception (solution of the correspondence problem, dynamic stability, visual inertia, cooperative effects, perceptual switching and its statistics, transparency percepts). A detailed quantitative comparison of the model to experimental data revealed necessary features of the perceptual dynamics (topology of the cooperative interactions in the perceptual space, presence of adaptation and its relation to the neural activation, stochastical switching). We conclude that dynamic effects in motion perception and the perceptual organization are consequences of a single underlying perceptual dynamics. It was shown that this dynamics can be mathematically adequately described and analyzed and how its characteristic parameters can be determined in psychophysical experiments. This leads to the interpretation that motion perception must be interpreted as dynamical self-organization process. We have isolated functional components of this process and have analyzed how they interact. We believe also that we have developed a methodology which allows an analysis of dynamic perceptual organization processes in general.

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