The Counter-Change Model of Motion Perception: An Account Based on Dynamic Field Theory

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Abstract. Motion perception is theoretically understood as the detection of sequential optical changes at two locations in the visual array. Experiments on generalized apparent motion have demonstrated, however, that sequentiality is not necessarily required for the detection of motion [1] leading to instantaneous counter-change as an alternative theoretical view of motion detection [2]. Here we generalize the counter-change model to spatially and temporally continuous motion. Transients detected within the receptive fields of edge filters are combined in a space-time continuous neural dynamics, in which nonlinear neural interaction leads to the detection decision. We show that the model enables the detection of continuous motion while also accounting for psychophysical results on generalized apparent motion.

Keywords: Motion Detection, Neural Dynamics, Neural Fields.

1 Introduction

Although the detection of motion has been well studied both experimentally and theoretically, newer research has uncovered an aspect not accounted for by classical theory [3]. The critical question is if motion detection is indeed fundamentally based on sequential changes in the visual array as posited in the established theory [4,5,6]. In generalized apparent motion [7] two patches of brightness are simultaneously visible, but undergo a step-change in luminance. Motion is seen from locations that change luminance toward the background to locations that change luminance away from the background [3]. Motion is strongest when the luminance changes at the two locations occur simultaneously. In fact, motion from the "toward" location to the "away" location can be seen even when the "away" change precedes the "toward" change ("back to the future motion") [1]. This points to a mechanism of motion detection that does not rely on sequentiality, but instead on simultaneous counter-changes of luminance at two spatial locations [2]. This paper extends the counter-change model of motion perception

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[2] by embedding it in a spatial and temporal continuum. Using Dynamic Field Theory, a variant of neural dynamics in which the activity of neural populations is captured in spatially and temporally continuous neural fields [8], we show how a dynamical instability accounts for the detection threshold of counter-change motion perception.

2 The Dynamic Field Model of Counter-Change Motion Detection

Figure 1 provides a survey over the model, which we will explain now following the computational stream. In this paper the model is only elaborated for one spatial dimension, although generalization to two-dimensional space is straightforward.

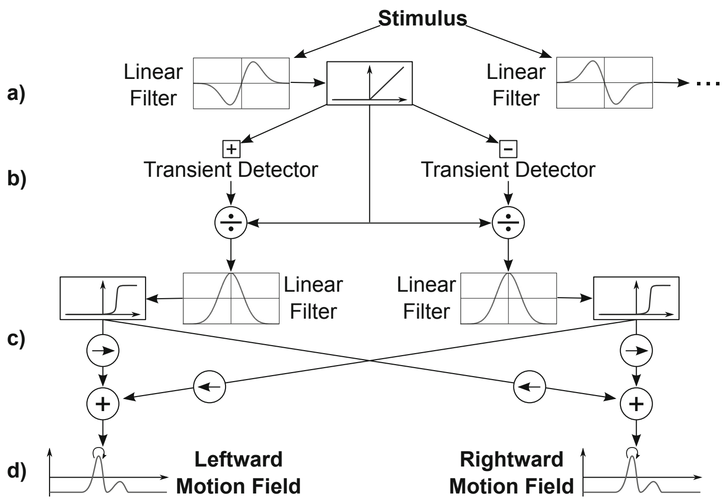

Fig. 1. The counter-change model of motion perception. *a)* Edges are detected in two streams for the two edge polarities, of which only one is illustrated. *b)* Positive (*"away"*) and negative (*"toward"*) transient changes are detected in parallel filters, followed by divisive normalization. *c)* The "toward" signal from one location and the "away" signal from another location are converted into a spatial code and then summed. *d)* Motion detection happens through a detection instability in a Dynamic Field.

Edge detectors. Spatial preprocessing consists of edge detection, so that spatially homogenous input is suppressed. Two subunits respond to dark-bright or bright-dark edges, respectively. The edge detectors are linear filters with derivative of Gaussian shaped Kernels:

$$K_{\text{edge}}(x) = \frac{x}{\sqrt{2\pi}s_e^3} \exp\left(-\frac{1}{2}\left(\frac{x}{s_e}\right)^2\right) \tag{1}$$

where s_e is the standard deviation of the Gaussian. Negative activation is filtered out by the subsequent half-wave rectification so that each edge detector responds only to edges of its preferred polarity (orientation in 2D).

Transient detectors. Transient changes in the output of the edge filters are detected by dynamical neurons. Two subunits respond to either a positive ("away") or a negative ("toward") change in the edge signal:

$$\tau_{exc}\dot{u}(x,t) = -u(x,t) - v(x,t) \pm S_{\text{edge}}(x,t) \quad (2)$$

$$\tau_{inh}\dot{v}(x,t) = -v(x,t) \pm S_{\text{edge}}(x,t). \quad (3)$$

Here, u and v are the activation of the excitatory and inhibitory neuron, respectively, τ is a parameter that fixes the time scale, and S_{edge} is the response of one of the edge detectors. For the "away" subunit, the neurons receive positive input ($+S_{\text{edge}}$) and for the "toward" subunit, negative input ($-S_{\text{edge}}$). The half-wave rectified response of the excitatory neuron is the output of the transient detector.

When a step increase in input occurs it drives the excitatory neuron and the inhibitory neuron. The faster time scale, τ_{exc}, of the excitatory unit leads to an initial rise of activation of that unit before it is returned to its initial state by the inhibitory unit. The excitatory unit is at zero, while the inhibitory unit exactly counter-balances the shifted input into the excitatory unit. The rectified response of the excitatory neuron is, therefore, a purely transient response to tonic change of its input, whose size and duration depends on the time scales of two units. The polarity of input from the edge detectors determines if the transient detector is an "away" or a "toward" unit. As long as "toward" and "away" subunits have identical parameter values, there is strictly no sequentiality to the detection mechanism. (Below we shall see how asymmetries between the subunits may arise).

The strength of the rectified transient response of the excitatory unit depends on the strength of input, that is, on the amount by which the edge changes in contrast. Experimentally, however, psychometrical functions were found to be best characterized by the background relative luminance contrast *BRLC* [9]. This quantity is defined for step changes in luminance as: $BRLC = (L_2 - L_1)/(L_m - L_b)$, where L_1 is the luminance before, L_2 after the step change. L_b is the background luminance and $L_m = (L_1 + L_2)/2$ the temporally averaged luminance (analogous definitions for contrast across an edge). Psychometric curves determined by varying the step change at different levels of average or background luminance are aligned when computed against BRLC [9]. Thus, the stronger an edge on average, the larger the change required to generate the same motion strength.

To reflect this dependency, the transient signals are divided by the edge signal (Figure 1b). This amounts to normalizing to the latest value of the edge strength rather than to a temporal average but is nevertheless sufficient to capture the BRLC scaling law. Note that $L_2 > L_m$ for "away" changes and $L_2 < L_m$ for "toward" changes, so that "away" changes are more strongly compressed by this division than "toward" changes, an asymmetry consistent with differences between regular and "back-to-the-future" motion observed psychophysically [1] (see below).

Motion detection by a Dynamic Field. We postulate that a field of motion detectors, $u(x,t)$, receives input from the transient "toward" and "away" signals. Each location, x, in the field represents one particular motion localized in space, while the level of activation, $u(x,t)$, represents the strength of that motion [8]. To provide input to such an activation field, the transient signals are converted into space code by applying a spatial kernel that projects the transient signal originating from a given localized edge filter onto a range of locations (point spread function). The transient signal is passed through a sigmoidal nonlinearity which effectively normalizes input. As a result, the strength of the transient signal is reflected in the width of the excited region of the activation field rather than in the amplitude of input to the field.

The "toward" and "away" transient signals that project onto a single location in the field originate from edge detectors that look at two spatial locations shifted against each other. Motion direction is determined from the spatial shift and the counter-change combination of "toward" and "away". Leftward motion is driven by a transient "away" signal at a location to the left of the location from which a transient "toward" signal is obtained. Rightward motion is driven by a transient "away" signal from a location to the right of the location from which the "toward" signal is obtained.

The neural dynamics of the field has this form [8]:

$$\tau \dot{u}(x,t) = -u(x,t) - h + S(x,t) + \int dx' K(x-x')\sigma(u(x',t)) \tag{4}$$

where h is the resting level, K the interaction kernel, σ a sigmoid nonlinear function and S the input of the combined transient signals for the corresponding motion direction and location. The neural representation of a detected motion at time t and position x is $\sigma(u(x,t))$.

The parameters of the sigmoid output function and the resting level h are such that input from only one of the two component transient signals leaves the field below the threshold of the sigmoid. The threshold is pierced only when input from both "toward" and "away" transient signals overlaps consistent with the counter-change rule. When this happens, the detection instability [8] is induced. Excitatory interaction among neighboring field sites generates a self-stabilized peak of activation that represents the detection of motion. That peak has a minimal size contributed by neural interaction that is a step change larger than the size of sub-threshold activation peaks. This step change signals the detection decision. The peak size also reflects the strengths of both inputs to the field, however.

3 Results

Three simulations are presented to show that the model accounts for (a) motion detection based on non-sequential information, (b) multiplicative-like combination of local transient activation and (c) the perception of motion for continuous sine wave grating stimuli.

Counter-change motion: regular and back-to-the-future. Gilroy and Hock showed that counter-change motion can be perceived independently of the sequential order of transient events in the stimulus [1]. The stimuli are illustrated in the top panel of Figure 2. A "toward" change occurs on the right, an "away" change on the left. The inter-change-interval (ICI) varies from 0 to 400msec but covers both orders, "toward" preceding "away" (regular motion) and "away" preceding "toward" (back-to-the-future motion). The psychometric curve in panel (c) shows that motion can be seen for both sequential orders, although back-to-the-future motion falls off more rapidly in strength with increasing ICI. Optimal motion perception occurs at $ICI = 0$, when luminance changes simultaneously at the two locations! The model shown in panel (b) matches the psychometric curves.

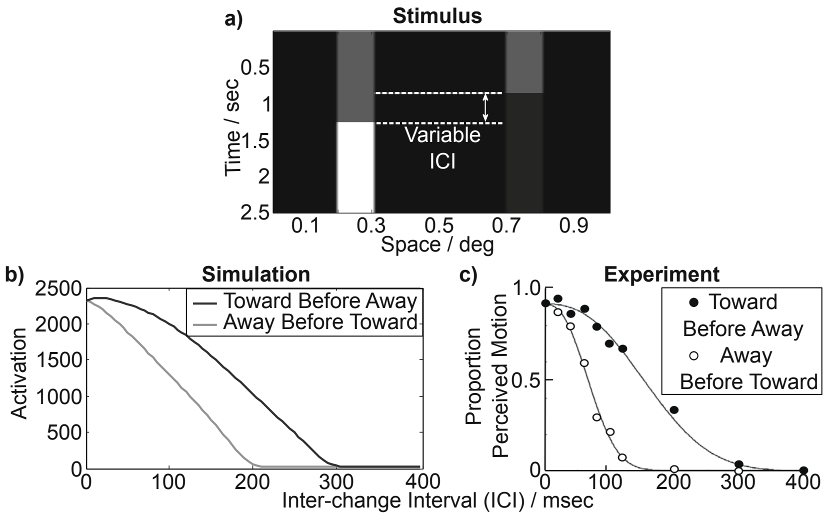

Fig. 2. A single toward and away change. (a) Single element generalized apparent motion stimuli (leftward counterchange motion). The ICI measures the asynchrony of the stimulus changes on the left vs. the right. Both orders, *away before toward* and *toward before away*, are probed. (b) Activation in field for leftward motion at the appropriate location is plotted as a function of ICI for the two orders of change. (c) Experimental results [1] (adapted from [2]) plotted as probability to see motion.

Multiplicative threshold for motion. Gilroy and Hock [10] showed that the psychometric curves obtained from different combinations of $BRLC$ values at the left and right locations of a single generalized apparent motion stimulus were best aligned when plotted against the product of the two BRLC values (rather than the sum or squared sum, for instance). They inferred that counter-change motion detection is based on a multiplicative mechanism.

Here we simulate this paradigm with stimuli illustrated on top of Figure 3. A "toward" change on the right and an "away" change on the left have different $BRLC$ values ranging in varied combinations between 0.2 to 0.4. The model detects leftward motion, the activation of which is plotted against the product, the sum, or the squared sum of the two BRLC values. The product best compresses and aligns the theoretical psychometrical curves. The model thus accounts for the multiplicative pattern observed in experiment, although there is no literal multiplication in the model. Summation with a detection instability in the Dynamic Field lead to this same signature.

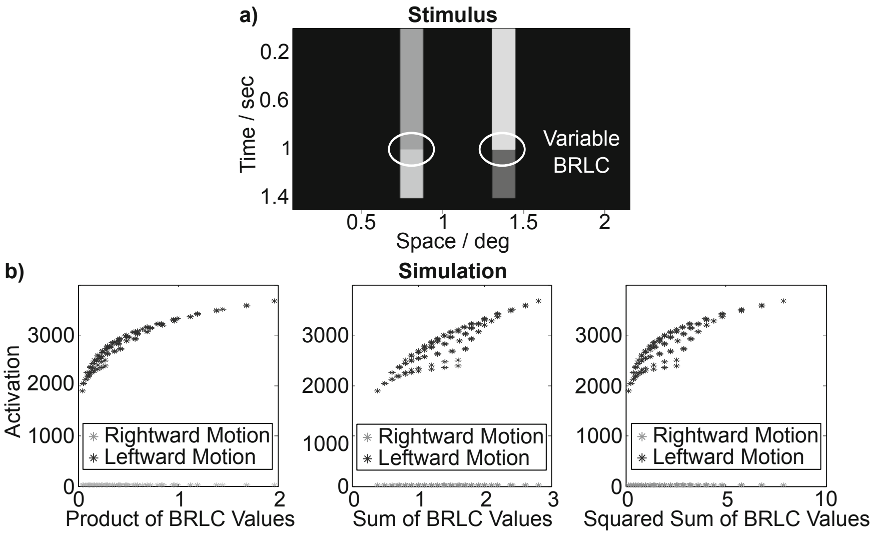

Fig. 3. Simulation with varied combinations of BRLC values: (a) Single element generalized apparent motion stimuli (leftward counterchange motion) with $BRLC$ varied between 0.2 to 0.4 in different combinations. (b) Rightward and leftward motion activation is plotted over the $BRLC$ values combined as a product (*left*), sum (*middle*), or squared sum (*right*).

Continuous Motion. Moving sine wave gratings have been a key paradigm for the experimental and theoretical investigation of the detection of continuous motion [5]. Therefore, we look at how the DFT model detects motion for such stimuli. Figure 4 illustrates a sine wave grating that moves to the right, has constant spatial frequency, and varies in speed.

In contrast to the previous simulations this is not single element motion. The stimulus induces a periodic spatio-temporal pattern of "toward" and "away" signals. As a result, different pairs of these signals indicate motion in either direction. Total supra-threshold activation in the two direction fields is plotted on the right of Figure 4 as a function of stimulus speed. At very small speeds, only rightward motion is detected (matching the veridical direction of motion). At larger speeds, both motion directions are activated, the veridical one more so than the opposite one. Note that the counter-change model as elaborated here does not contain competition between motion directions, although such competition may be required to understand motion patterns. Activation in both fields increases with speed, then plateaus from approximately 0.2 deg/sec on. At larger speeds of approximately 0.8 deg/sec, the wagon wheel illusion arises as back-to-the-future leftward motion increases in strength due to increasing overlap of the associated transient volleys.

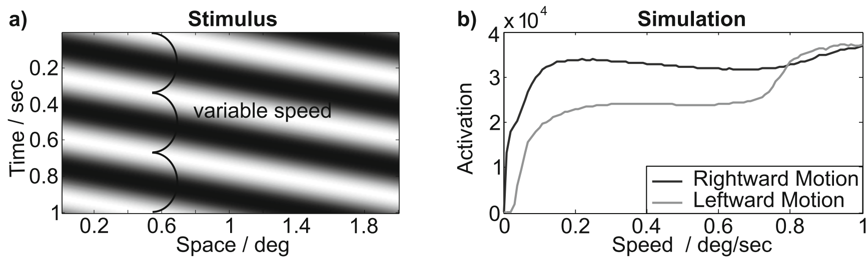

Fig. 4. Simulation of moving sine wave gratings. (*a*) Simulation stimuli whose speed varies between 0 and 1 deg/sec. At constant spatial frequency, temporal frequency is proportional to speed. (*b*) Rightward and leftward motion activation is plotted aganst stimulus speed.

4 Discussion

We showed that a model of counter-change motion detection based in Dynamic Field Theory (DFT) captures psychophysical data from generalized apparent motion while also being able to represent continuous motion. In both domains, we have a much wider range of demonstration than we could present here [11]. In DFT, motion detection is mediated by the detection instability [8], at which neuronal interaction self-stabilizes an activation peak. This accounts for the multiplicative nature of the detection threshold [10]. Conversely, the model extends DFT by showing how the inherently transient nature of motion signals can be integrated into the attractor dynamics of DFT.

Continuous motion is inherently ambiguous in the model, as in classical models of motion detection. This ambiguity is observed in the model at high temporal frequencies in the form of the wagon wheel illusion [12], consistent with similar motion reversals observed for appropriate inter-stimulus intervals [13]. An obvious necessary extension of the present model is to include competitive interaction among motion detectors to account for the perceptual organization of motion patterns. This requires a two-dimensional representation of motion that samples motion direction continuously.

The sequential theory of motion detection embodied in motion energy models has provided accounts for motion detection across a wide range of stimuli, tasks, and species and is firmly grounded in neurophysiology [14] It appears, therefore, unlikely, that the counter-change model would replace motion energy. Nevertheless, motion energy must be complemented by the counter-change concept to understand generalized apparent motion[1,3]. By showing that the counterchange mechanism accounts for continuous motion, we have established counter-change as a viable mechanism for the perception of continuous object motion, possibly at work in parallel to motion energy.

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