DYNAMIC FIELD THEORY OF SEQUENTIAL EFFECTS

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Abstract

Dynamic Field Theory (DFT; Erlhagen & Schöner, 2002) provides a framework how sensorimotor and perceptual decision making may arise from population representations by taking into account principles of Dynamic Systems Theory (Schöner, 2002). From a theoretical standpoint decision making may be divided into estimation –choosing from a continuum of choices by estimating the current stimulus value – and categorization –sorting the stimulus value into a finite number of discrete categories based on preinformation. DFT provides a framework how current stimulus information and preinformation may be flexibly combined and weighted according to current situational constraints (Wilimzig, 2006; Wilimzig & Schöner, 2006) such that the system may flexibly switch between estimation and categorization behavior. Sequential effects emerge from the representation of preinformation in this account.

Daily life behavior involves both categorical decisions as well as selecting from continuous ranges of behaviors. In a visual scene, for instance, humans may recognize objects as belonging to categories (e.g., chairs, pencils) but may also estimate their pose, their size, or feature values such as colors etc.. In psychophysical paradigms, perceptual tasks often take the form of categorical choices (via labelling, categorizing, discrimination, etc.), while sensorimotor tasks typically involve choosing among a continuum (pointing to locations, remembering a place, etc.). However, this does not refer to a general difference between perceptual and sensorimotor decision making as movements may also be essentially categorical in nature if the perceptual layout allows only a finite number of movement goals (e. g., button pressing) or when the subject has to decide with which hand or finger to respond. On the other hand, perceptual decisions may require to select among a continuum of choices when subjects are asked to rate stimuli on continuous or fine-grained scales (e.g, matching perceived intensity to a corresponding force on a dynanometer, Stevens, Mark & Stevens, 1966). Thus, the nervous system seems to be capable of flexibly switching between categorical and continuous decisions for the same sensorimotor or perceptual dimensions. How may the nervous system structure itself to achieve this flexibility and how does this relates to principles of population activation?

Neurophysiological evidence suggests that features are represented in continuous feature maps, in which populations of neurons with broad tuning curves are activated. Across neocortex and other parts of the central nervous system, the location of neurons in the network determines what information these neurons encode (space code principle). In many cortical areas, topographic mapping makes that neighboring neurons encode similar kinds of information. Independently of topography (anatomical coordinates), neuronal representations of parameters can be constructed by sorting neurons according to what they code (functional coordinates) (Georgopoulos et al., 1982). Neuronal interaction is sensitive to this metric structure of representations, meaning that neurons representing similar information excite each other while neurons representing dissimilar information inhibit each other. Wilson and Cowan (1973) as well as Amari (1977) have shown that the processing of information in such cortical and subcortical networks is mathematically well described by continuous dimensions with an associated metric defined by interaction

Dynamic Field Theory

Dynamic Field Theory (Thelen et al., 2001; Erlhagen & Schöner, 2002) is an approach to the representation of stimulus and response parameters that takes their natural metric structure into account while also being consistent with basic neurophysiological principles (Amari, 1977). Within Dynamic Field Theory (DFT), task and stimulus parameters define the dimensions of a functional space, over which an activation field is defined. The activation field evolves continuously in time under the influence of inputs and brain-like interactions within the field. Two sources of inputs feed into the field: Inputs may derive from current sensory stimulation (stimuli), but also from prior knowledge about possible choices, memory traces of prior activation or subthreshold cues. Such prior information preshapes the activation field through sub-thresholded distributions of activation. Thus, an imperative stimululs does not impinge upon a perfectly homogeneous "blank" state, but instead encounters a prestructured activation field that reflects the perceptual and behavioral context in which the stimulus is presented (Erlhagen & Schöner, 2002).

Localized peaks of activation represent perceptual or motor decisions as interaction is sufficiently strong to be capable of making detection decisions (Bicho, Mallet & Schoner, 2000) or selecting one out of a set of behavioral options (Kopecz & Schöner, 1995). Based on the notion of population distributions of activation (Erlhagen et al., 1999), Dynamic Field Theory is thus a process model of neuronal decision making.

Categorical versus Continuous responding

If the neuronal support for decisions is functionally continuous and metric in nature, how may categorical responses emerge from such representations? To categorically react to graded sensory information, prior information is required that represents properties of the categories. When prior activation has the appropriate metric and strength, Dynamic Fields respond in a categorical mode, in which the location of a localized peak of activation is determined by the location of the prior distribution of activation and the generation of the peak driven by a broad boost of activation while the current sensory input is weak (Wilimzig & Schöner, 2006; Wilimzig, 2006). In contrast, the field continuously makes a robust estimation of current parameters, as required for sensorimotor decision making to support pointing or grasping movements, when the current stimulus input is the dominant contribution and prior activation provides a smaller contribution (Erlhagen & Schöner, 2002; see also Wilimzig & Schöner, 2006).

These two response modes lead to opposite experimental signatures such as facilitation for metrically close choices in continuous tasks, e. g. the metric effect (Erlhagen & Schöner, 2002), and inhibition for metrically close choices in categorical tasks, e. g. the well-known bow effect (Lacouture & Marley, 2004; Stewart, Brown & Chater, 2005) in absolute identification tasks. Although signatures of the categorical mode typically occur in cognitive tasks while signatures of the continuous mode occur in sensorimotor tasks, our models show that this depends on the task structure rather than differences in cognitive versus sensorimotor representation. Empirically, we provide evidence that the bow effect may also occur in tasks closer to sensorimotor surfaces when the task requires a categorical response (Wilimzig, Ragert & Dinse, 2006).

Prior information

Prior information may arise from explicit experimental manipulations such as precuing one or a set of potential upcoming stimuli. Within DFT, the most important source of prior information may be derived from prior experience, for instance, by laying down memory traces of previous activation patterns (Thelen et al., 2001; Erlhagen & Schöner, 2002) which accounts for the influence of activation history in the A-not-B paradigm (Thelen et al., 2001) and the influence of the probability of choices (Hyman effect, Erlhagen & Schöner, 2002).

This relatively simple concept of learning as memory traces of (successful) previous actions may account of the emergence of categories from a fundamentally continuous representations. As previous actions play a fundamental role in learning the information necessary for categorization, sequential effects, well-known in psychophysical literature, naturally emerge from this way of representing prior information. Specifically, facilitation for repeated responses inherently arises as prior information for just executed responses is increased. As prior information increases this pre-stimulus activation of respective field sites (Erlhagen & Schöner, 2002), our model not only account for reaction time effects but also for increased pre-target activations shown in the context of eye movements (Dorris, Pare & Munoz, 2000) thus providing a link not only to psychophysical but also to neural studies. By taking into account the time structure of interaction with eary facilitation and late inhibition the model accounts not only for facilitation of return but for inhibition of return as well.

Apart from these effects on the speed of the behavioral reaction, our model accounts for sequential effects on the location of the reaction. In the continuous mode, representing prior activation through sub-thresholded distributions of activation may lead to biases of responses toward previously given responses. In the categorical mode, prior information may induce errors with the speed of errors depending on the respective strength of current and prior inputs.

For these concepts of learning categories by the system bootstrapping itself up from prior responses, the metric structure of the learning stimuli plays an important role. Specifically, if learning stimuli are metrically very close to each other, the system does not learn how to categorize them into different categories, a psychophysical effect that has recently regained interest (McClelland, Fiez & McCandliss, 2002). Furthermore, by taking into account the time structure of interaction, the metric structure of learned categories – i. e. of prior information – changes dynamically over time providing an explanation of the empirically observed prototype-to-exemplar shift in categorization (Smith & Minda, 1998).

In summary, by using a simple learning concept of laying down memory traces, Dynamic Field Models take into account a variety of sequential effects and may also explain relatively complex categorization phenomena. These sequential effects inherently arise from the concept how the systems learns to categorize and how possible choices are represented within continuous neural representations rather than being pre-designed into the system.

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