Stable Representations of Dynamic Stimuli in Perceptual Decision Making

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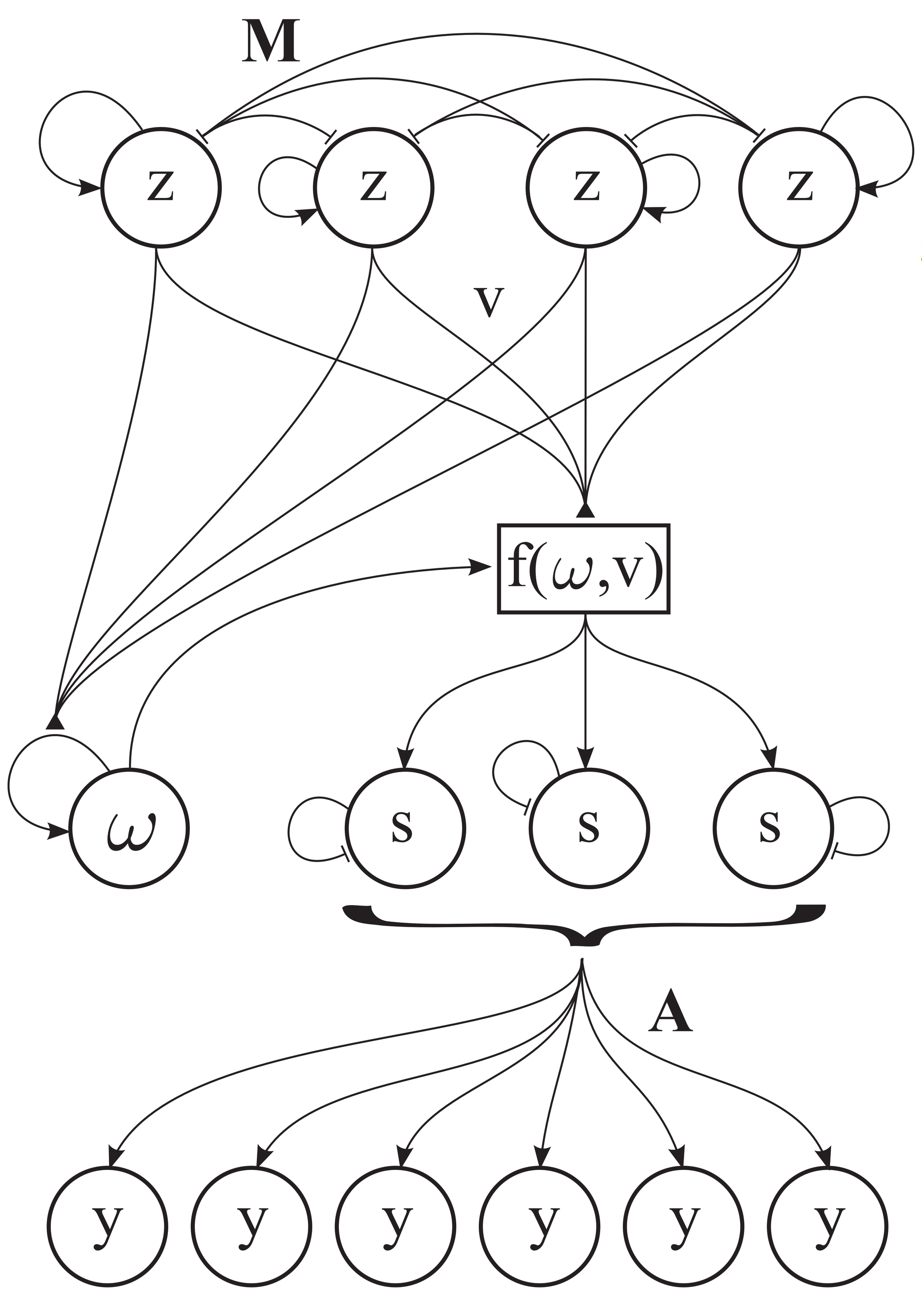
Abstract

Models of perceptual decision making, which are based on dynamic stimuli such as random dot motion, are predominantly concerned with how evidence for a stimulus is accumulated over time [e.g., 1,2]. However, it is unclear how the brain derives this evidence from the sensory dynamics. While it is conceivable that simple feature-detecting neurons can, for example, directly signal evidence for motion in a specific direction, it is less clear how evidence for complex motion, such as human movements, is computed from sensory input. Here we present such a model of the perceptual lower level system which is based on probabilistic inference for dynamical systems and can be used to provide input for higher level decision making systems. We illustrate this mechanism using two simulations. First we show that the system can handle the conventional random dot motion paradigm, and secondly, that it can also infer, i.e. recognize, complex dot motion as generated by human walking movements (cf. point light walkers) in an online fashion. The present model is implemented by a neuronal network and computes stable percepts rapidly, thereby enabling both fast decision (reaction) times and high accuracy.

A generative model for switching dynamic processes



switching dynamics
(Hopfield network)

$$\dot{\mathbf{z}} = k\left(\mathbf{M}\boldsymbol{\sigma}(\mathbf{z}) + b^{\mathrm{lin}}(g\mathbf{1} - \mathbf{z})\right) + \mathbf{w}$$

$$\mathbf{M} = b^{\mathrm{lat}}(-\mathbf{1} + \mathbf{I})$$

$$\mathbf{v} = \boldsymbol{\sigma}^{v}(\mathbf{z})$$

observation dynamics
(dynamic movement primitives)

$$\dot{\omega} = f_{\omega}(\mathbf{v})$$

$$\dot{\mathbf{s}} = a\left(\mathbf{f}(\omega, \mathbf{v}) - \mathbf{s}\right)$$

$$\mathbf{f}(\omega, \mathbf{v}) = \frac{\mathbf{k}(\omega)^{T}}{\mathbf{1}^{T}\mathbf{k}(\omega)}\mathbf{W}(\mathbf{v})$$

observations
(stimulus)

$$\mathbf{y} = \mathbf{A}\mathbf{s} + \mathbf{b}$$

Online Bayesian inference

$$d\mathbf{x} = \begin{bmatrix} -\mathbf{w} \\ k\left(\mathbf{M}\boldsymbol{\sigma}(\mathbf{z}) + b^{\mathrm{lin}}(g\mathbf{1} - \mathbf{z})\right) + \mathbf{w} \\ f_{\omega}(\mathbf{v}) \\ a\left(\mathbf{f}(\omega, \mathbf{v}) - \mathbf{s}\right) \end{bmatrix} dt + \mathbf{B}d\boldsymbol{\epsilon}_x$$

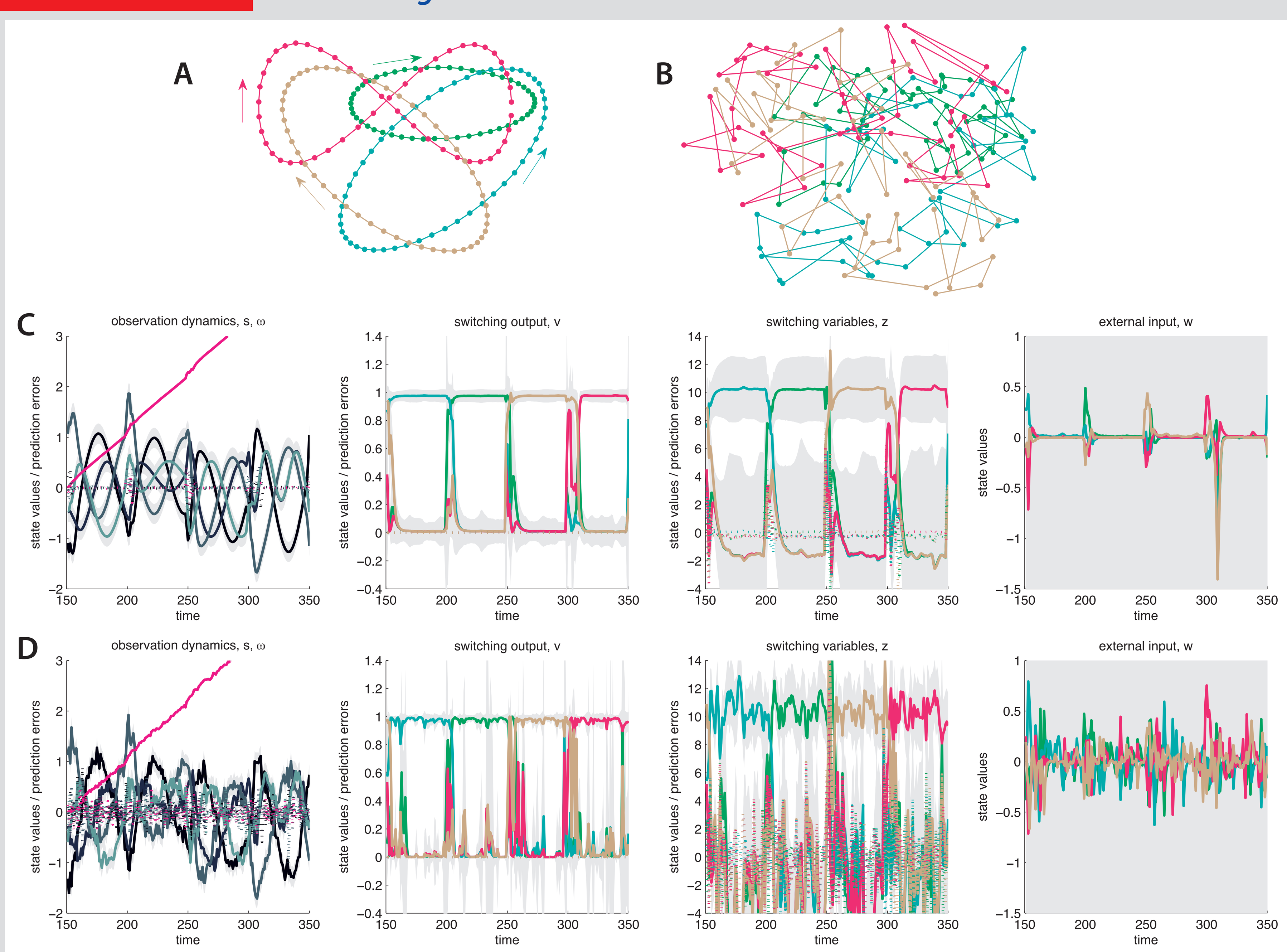
$$\mathbf{y} = \mathbf{A}\mathbf{s} + \mathbf{b} + \boldsymbol{\epsilon}_y$$

By adding Wiener-process noise to the differential equations defined by the model we obtain a probabilistic formulation in terms of a multidimensional stochastic differential equation. External input to the Hopfield network is modelled as an Ornstein-Uhlenbeck process which drives switching between different percepts in the model. We infer the switching variables from noisy observations y using a standard nonlinear filtering method (the unscented Kalman filter [5]) which implements approximate online Bayesian inference for nonlinear time-series models with hidden (unobserved) variables.

A Hopfield network [3] implements the dynamics between switching variables (the "switching dynamics"). The Hopfield dynamics implements a winner-take-all mechanism between switching variables such that only one of these is active in each stable fixed point of the dynamics. We associate each switching variable with different parameters of a parametric differential equation implemented by a dynamic movement primitive (DMP) [4]. The parameters are interpolated based on the values of the switching variables and the resulting differential equation (the observation dynamics) is used to generate observations.

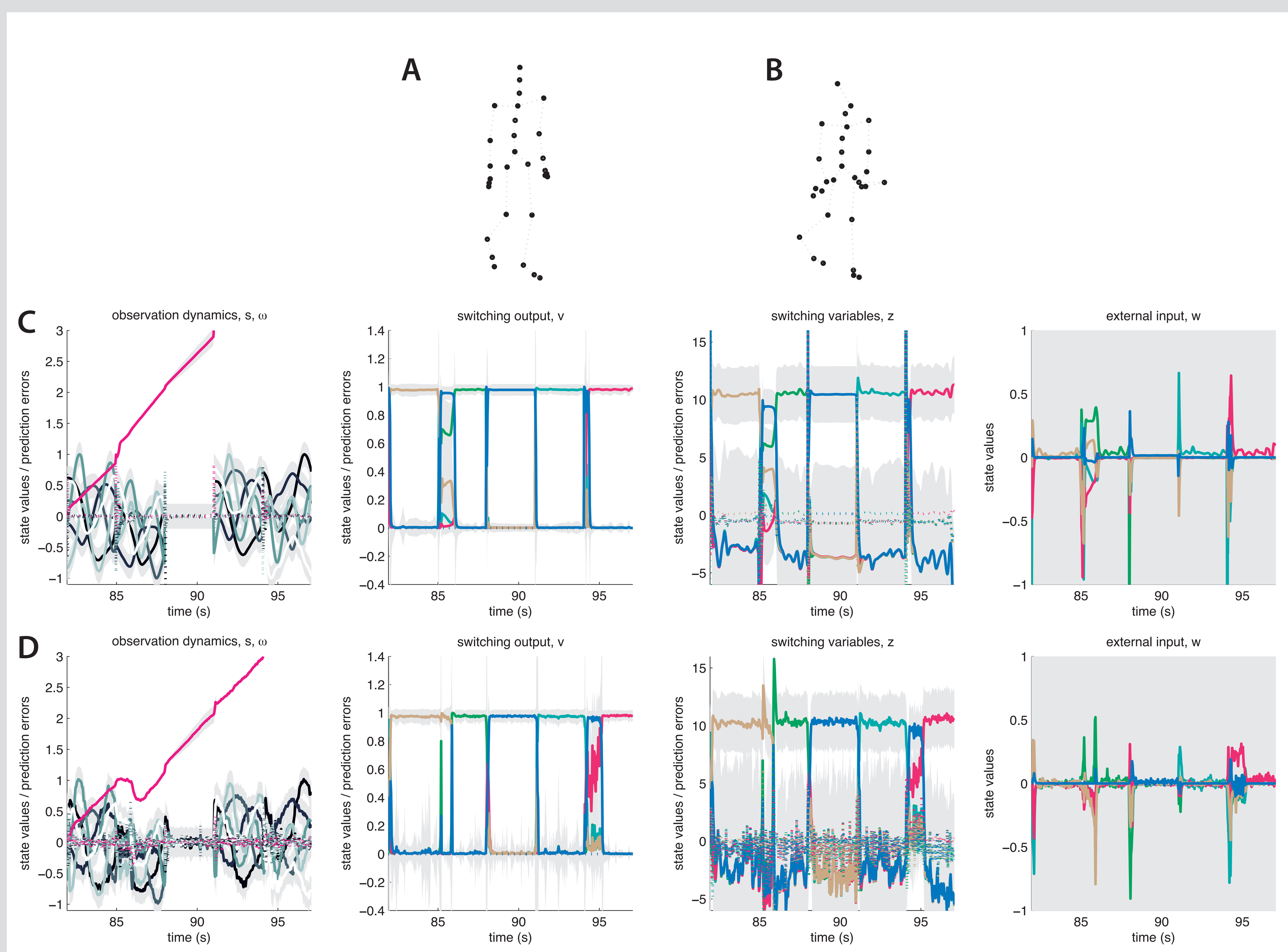
Results

Recognition of nonlinear random dot motion



We illustrate inference in the present model using a simple example of synthetic motions of two dots which followed one of four different trajectories (A). In (C) inference results are shown for when the noise-free dot motion was observed. The decision about which of the four motions is currently observed is read off from the switching variables (the maximum value). The order of motions presented to the model was blue-green-yellow-red which was correctly recognised. Also for moderate amounts of noise (B) the correct motions could be identified (D).

Discrimination of different walks



The switching model can equally be applied to more complicated, real-world motions. We demonstrate this using four different styles of walking as observed via the 3D positions of motion capture markers (DMPs were defined in the first six principle components, observations were directly the 90 x, y and z-values of the 30 markers). We additionally introduced a fifth motion (constant marker positions) to model a still standing walker. We presented the noise-free, original motion capture data (A) frame by frame to the model and inferred the switching variables. Results are shown in (C). The correct order of motions was yellow – green – dark blue – light blue – red. While the green walk was initially incorrectly identified as the blue walk, all other walks were rapidly recognised. For noisy observations (B, D) an additional transient error occurs for the red walk, but otherwise inference was robust against the introduced level of noise.

Summary

We have presented a model to explain rapid perceptual decision making. The model uses switching nonlinear differential equations, where each of these describes specific nonlinear motions in the environment. By inferring the state of the switching variables the model can recognise which motion it currently observes. Our results show that the model rapidly switches to the correct differential equation, i.e., it can rapidly (e.g., within 50ms in the case of the motion capture walks) recognise a dynamic stimulus. We suggest that the combination of the present model with recent models for evidence accumulation in perceptual decision making [1,2] may be used to apply neurobiologically plausible decision making strategies to real-world stimuli like movements generated by humans.

References

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