

A Mathematical Account of Dynamic Texture Synthesis for Probing Visual Perception

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Perception is often described as a predictive process based on an optimal inference with respect to a generative model. Under such an assumption, we study here the principled construction of a generative model of movies specifically crafted for visual perception. In addition, we present a psychophysical study of speed perception in a Bayesian context that takes advantage of the generative model.

Dynamic Texture Stimulation Model: Motion Clouds We first provide an axiomatic derivation of the Motion Clouds model introduced in [1]. In particular, we show that the original definition as a spatiotemporal stationary Gaussian field could be approximated by the random aggregation of warped patterns providing a generative model. We define a dynamic texture as

$$I_\lambda(x, t) = \frac{1}{\sqrt{\lambda}} \sum_{p \in \mathbb{N}} g(\rho_p R_{\theta_p}(x - X_p - V_p t)) \quad (1)$$

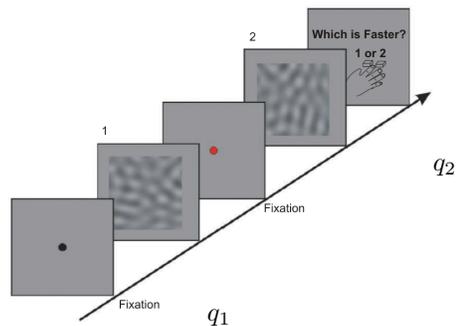
where $(X_p)_{p \in \mathbb{N}}$ is a 2D Poisson process of intensity λ and $(\rho_p, \theta_p, V_p)_{p \in \mathbb{N}}$ are iid random variables each with a given density. When λ grows to infinity and g is close to a pure wave, I_λ converges to a dynamic texture I which is a stationary Gaussian field of mean 0 and a power spectrum that only depends on densities of (ρ_0, θ_0, V_0) . This texture formulation fully parametrises the possible dynamic transformations that observers viewing a world scene can be subjected to, for example zooms, rotations, vibrations (noise) and others. We prove under some brief assumption that this model is equivalent to the linear stochastic partial differential equation below

$$\frac{\partial^2 I}{\partial t^2} + \alpha \star \frac{\partial I}{\partial t} + \beta \star I = \frac{\partial W}{\partial t}. \quad (2)$$

This description of the generative model in the form of Equation (2) critically allows us to implement a real time generative numerical scheme. Importantly, the formulation can then rapidly and conveniently be implemented into experiments probing the visual system.

Bayesian Modeling of a Psychophysic Experiment The aim of the experiment was to synthesise observer zooming transformations using the frequency parameters of the dynamic stimuli and to systematically test the effect these have on perceived speed. The experiment consists in a two-alternative forced choice task wherein we ask the participants which of the two presented stimuli, over several trials with a range of parameters, which of the two presented stimuli is moving faster.

Inspired by [2], we build a simple model that allows us to write a theoretical expression for the psychometric curves. In this context we apply the well known Bayes rule that models the decision task performed by the observer. Assuming that the latter uses the same generative model as for the stimulation makes it possible to use the densities that define the stimuli as a likelihood. As a result we determine a prior on the tested parameters that could explain the experimental psychometric curves by solving a constrained linear problem.



References

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- [2] A. Stocker, E. Simoncelli. Noise characteristics and prior expectations in human visual speed perception, *Nature Neuroscience* 9 (4) pp. 578–585, 2006.