Dynamic Texture Synthesis for Probing Visual Perception

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The study of visual perception is often based on the understanding of experimental data corresponding to responses to a stimulus. Therefore, it is as important to have well-defined and conveniently generated stimuli as to realize and model an experiment. To this purpose, we have extended a class of Gaussian stimuli called Motion Clouds with a generative model and a real-time implementation. We also introduce a mathematical framework for psychophysical data analysis that can benefit from this generative model. This is a joint work with Andrew Meso, Laurent Perrinet and Gabriel Peyré.

Dynamic Texture Stimulation Model A Motion Clouds, introduced in [**?**], is a synthetic and randomly generated movie. We show that the original definition as a spatiotemporal stationary Gaussian field can be approximated by the random aggregation of warped patterns providing a generative model. We define a dynamic texture as

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

where R_θ is the rotation of angle θ, $(X_p)_{p\in\mathbb{N}}$ 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 a sine function, 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). We prove that, for an appropriate choice of the Fourier transform of α, β and the spatial covariance of the Gaussian process $\partial W/\partial t$ which is a white noise in time, this model is equivalent to the linear stochastic partial differential equation below

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

where $\star$ denotes the spatial convolution. This description of the generative model in the form of Equation (**??**) allows us to implement a real-time generative numerical scheme.

Bayesian Modeling of a Psychophysic Experiment The experiment consists in a two-alternative forced choice task wherein we ask the participants, over several trials with a range of parameters, which of the two presented stimuli is moving faster. The parameters of interest are the modes of the distribution of ρ_0 and V_0 defined by the generative model and we test the influence of the first over the discrimination of the second. The results are modelled using a Bayesian decision process. Denoting $v = (v_1, v_2) \in {\mathbb{R}_+}^2$ the speed modes of the two stimuli, the participants have to determine whether v belongs to $E = \{(v_1, v_2) | v_1 \geq v_2\}$ or not. Therefore we are able to explicit the psychometric function as follows

$$\varphi_E(v) = \iint_{\mathcal{I}^2} \mathbf{1}_E(\hat{v}(i)) \mathbb{P}_{I|V}(i|v) \mathrm{d}i \tag{3}$$

where $\hat{v}(i)$ is the internal estimation of v made by the observer from the movies $i \in \mathcal{I}^2$ and $\mathbb{P}_{I|V}$ is the distribution of the movies knowing the parameter v. Using a MAP estimator for $\hat{v}(i)$ allows to locally estimate the prior about v using a method inspired by [**?**]. Moreover, we show that this approach can be seen as a particular case of a general framework.

Références

[1] P. Sanz-Leon, I. Vanzetta, G. Masson, L. Perrinet, *Motion clouds: model-based stimulus synthesis of natural-like random textures for the study of motion perception*, Journal of Neurophysiology, pp. 3217–3226, 2012.

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

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