Hidden Markov model decoding of retinal responses with estimation of eye path

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We perceive visual stimuli even in the presence of incessant image motion due to fixational eye movements. We would like to better understand how these movements affect the perception of visual stimuli, without any assumed knowledge of trajectory of the eye during a given fixation [1, 5]. The challenge lies in the estimation of the image given noisy, spatiotemporally-filtered retinal ganglion cell responses, without detailed knowledge of the true eye path on any given trial.

To approach the problem, we construct an extended hidden Markov model (HMM), with eye position included as a hidden Markovian state variable. Retinal responses are modeled using a generalized linear model approach [2, 4] which is sufficiently general to incorporate realistic spatiotemporal filtering as well as auto- and cross-correlations between spike trains. We develop an expectation-maximization (EM) approach to infer the eye path and underlying image simultaneously: in this setting the expectation (E) step corresponds to the inference of the eye path, given a fixed estimated image, and the maximization (M) step corresponds to the inference of the image, given a fixed estimated eye path. We use a sequential Monte Carlo ("particle filtering") method to carry out the E step, and employ a computationally-efficient concave optimization approach [3] to compute the maximum a posterior (MAP) estimate of the image in the M step. This EM method turns out to be significantly more stable and accurate than the computationally-intensive mixture-of-Gaussian filter approach developed in [4], and may also be applied to correct eye-movement artifacts in the estimation of receptive fields in visual sensory neurophysiology experiments.

References

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