RESEARCH ARTICLE

Neural surprise in somatosensory Bayesian learning

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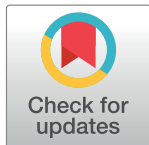
Abstract

Tracking statistical regularities of the environment is important for shaping human behavior and perception. Evidence suggests that the brain learns environmental dependencies using Bayesian principles. However, much remains unknown about the employed algorithms, for somesthesis in particular. Here, we describe the cortical dynamics of the somatosensory learning system to investigate both the form of the generative model as well as its neural surprise signatures. Specifically, we recorded EEG data from 40 participants subjected to a somatosensory roving-stimulus paradigm and performed single-trial modeling across peristimulus time in both sensor and source space. Our Bayesian model selection procedure indicates that evoked potentials are best described by a non-hierarchical learning model that tracks transitions between observations using leaky integration. From around 70ms post-stimulus onset, secondary somatosensory cortices are found to represent confidence-corrected surprise as a measure of model inadequacy. Indications of Bayesian surprise encoding, reflecting model updating, are found in primary somatosensory cortex from around 140ms. This dissociation is compatible with the idea that early surprise signals may control subsequent model update rates. In sum, our findings support the hypothesis that early somatosensory processing reflects Bayesian perceptual learning and contribute to an understanding of its underlying mechanisms.