

Visual perceptual learning modulates decision network in the human brain: The evidence from psychophysics, modeling, and functional magnetic resonance imaging

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Perceptual learning refers to improved perceptual performance after intensive training and was initially suggested to reflect long-term plasticity in early visual cortex. Recent behavioral and neurophysiological evidence further suggested that the plasticity in brain regions related to decision making could also contribute to the observed training effects. However, how perceptual learning modulates the responses of decision-related regions in the human brain remains largely unknown. In the present study, we combined psychophysics and functional magnetic resonance imaging (fMRI), and adopted a model-based approach to investigate this issue. We trained participants on a motion direction discrimination task and fitted their behavioral data using the linear ballistic accumulator model. The results from model fitting showed that behavioral improvement could be well explained by a specific improvement in sensory information accumulation. A critical model parameter, the drift rate of the information accumulation, was correlated with the fMRI responses derived from three spatial independent components: ventral premotor cortex (PMv), supplementary eye field (SEF), and the frontoparietal network, including intraparietal sulcus (IPS) and frontal eye field (FEF). In this decision network, we found that the behavioral training effects were accompanied by signal enhancement specific to trained direction in PMv and FEF. Further, we also found direction-specific signal reduction in sensory areas (V3A and MT+), as well as the strengthened effective connectivity from V3A to PMv and from IPS to FEF. These findings provide evidence for the learning-induced decision refinement after perceptual learning and the brain regions that are involved in this process.

Introduction

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Materials and methods

Subjects

(10, 12; 17–25) A A

Stimuli

(C) 40–60; 1,024 × 768; (C) 48–60; 1,024 × 768; (B, 1997; A, 1997) A AB (3.0) 75 (B, 1992). A 10° (~0 / 2). A 400 4°.

Procedure

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fMRI data preprocessing

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Learning effects on drift rate

$F(1, 21) = 15.60, p = 0.001, \eta^2 = 0.426;$
 $F(1, 21) = 48.27, p < 0.001, \eta^2 = 0.697;$
 $F(1, 21) = 25.43, p < 0.001, \eta^2 = 0.548.$

$F(1, 21) = 27.22, p < 0.001,$
 $F(1, 21) = 0.08, p = 0.78.$

(C. C. & , 2012;
 2011). (, 2012) (-) - (-)
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 b, (b - a/2).

$F(3, 12) = 15.48, p < 0.001, R^2 = 0.67; \beta = 0.73, p < 0.001,$
 $\beta = 0.214, p = 0.26,$
 $\beta = -0.01, p = 0.97.$

Session effect on decision caution

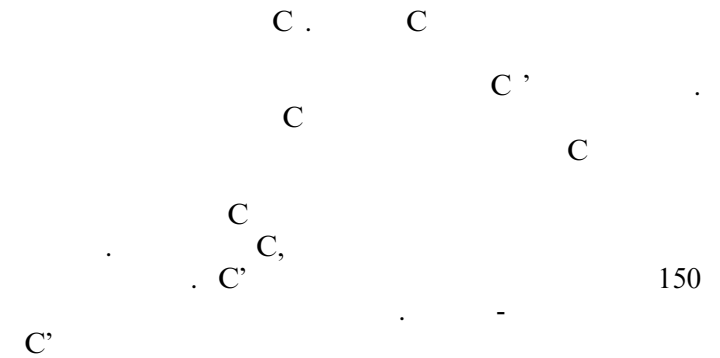
$F(1, 21) = 8.45, p < 0.01, \eta^2 = 0.287$ (2). (=

$= 0.97, p < 0.001,$ (

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Brain network for sensory information accumulation



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 $p < 0.05,$
 $F(21) = 2.697, p < 0.05,$
 $F(21) = 2.192, p = 0.09,$
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Learning effects within decision network

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0.315.),
 +, $F(1, 21) = 9.652$, $p = 0.005$, $\eta^2 =$

Learning modulates feedforward connectivity

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