



Perceptual learning of motion discrimination: Location specificity and behavioral role of dorsal and ventral areas

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ABSTRACT

One interesting observation of perceptual learning is the asymmetric benefit seen in a differential neural noise level: learning a weak/noise can affect significantly the same stimulus a high noise background. The mechanism underlying this asymmetric benefit has been investigated by behavioral, neurophysiological, brain imaging, and computational modeling studies. One study (PNAS 113 (2016) 5724–5729) reported that TMS stimulation of dorsal and ventral areas impaired motion discrimination of moving dots in a 40% coherence (“noise”) and 100% coherence (zero-noise) level, respectively. However, after discrimination training a 100% coherence, only TMS stimulation had an effect on the performance of motion discrimination both coherence levels. The results revealed a learning-induced change of functional specialization of visual areas. We have conducted a behavioral study of high resolution functional magnetic resonance imaging (fMRI) to investigate the behavioral role of dorsal and ventral areas in perceptual learning-induced changes. First, with a task of high location-specific motion discrimination, we observed behavioral improvements in learning (e.g., an effect/learning ratio = 81.9% ± 14.8% at 100% coherence). Second and more importantly, we found complementary effects of motion learning from 40% to 100% coherence, a critical balance in learning in high resolution. The asymmetric effects have similar behavioral mechanisms underlying motion discrimination, occurring at a coherence level. The effects of high resolution conclusion regarding the role of dorsal and ventral areas in motion discrimination, occurring at a coherence level, reveal the effects of perceptual learning, a novel observation of behavioral evidence. I remain grateful to the funding agencies of dorsal and ventral TMS stimulation on motion discrimination observation.

1. Introduction

Perceptual learning leads to behavioral discrimination of fine stimulus differences. As first observed, initial perceptual learning is site-specific on the trained stimulus condition (e.g., Ball & Sekuler, 1982; Kanai & Sagi, 1991; Schoenfeld, Vogel, & O’Ban, 1995; Ciaramita, Kaadira, Wehmeier, & Gilbey, 1997; Yu, Klein, & Levi, 2004). Among a variety of learning specificities, the one originally reported by Doherty and Levi (2005) is noise. The finding has shown that learning with a Gabo stimulus a zero-noise can affect a high level of neural noise. However, the same orientation learning a high level of neural noise can affect little or zero-noise. This asymmetric learning can have been replicated in other tasks including motion discrimination, direction discrimination, and Vernier alignment (Liu, Chen, & Doherty, 2006; Chang, Koehn, & Welchman, 2013; Chang, Meoach, Koehn, & Welchman, 2014; Xie & Yu, 2019).

Several effects have been made on the neural mechanisms underlying this asymmetric learning (Chodha & DeAngelis,

2008; Liu, Li, & Doherty, 2010; Chang et al., 2014; Chen, Cai, Zhou, Thomson, & Fang, 2016; Xie & Yu, 2019). Computationally, Levi et al. (2010) suggested that training a high noise, a zero-noise, impairs the width of the neural channel, but in a level of the neural channel. Additionally, training a zero-noise is required to achieve the optimal channel width. As a result, only learning a zero-noise, in which the optimal width of the neural channel has been achieved, can affect a high noise.

As for the behavioral mechanisms, Chodha and DeAngelis (2008) reported that training of fine direction discrimination, which relies on ventral areas like V4 and IT, also impairs a monkey’s coarse discrimination. Moreover, coarse discrimination is no longer affected by removal of chemical inactivation of MT. Because the direction tuning in MT neurons is unchanged, Chodha and DeAngelis (2008) attributed the change of the width in the neuronal decision space.

Consistent with Chodha and DeAngelis (2008), Chang et al. (2014) reported that TMS stimulation of superior parietal cortex (PPC) and lateral occipital area (LO) impaired direction discrimination

high and low noise levels, respectively. Before deciding on training a high noise, TMS stimulation of LO impaired decision making in both noise levels, and stimulation of PPC become ineffective. However, Chang et al. (2014) concluded that learning changes the weight of the neural and dorsal areas in decision making, and the hand dominance decision circuitry. Thus, learning reduced the weight of the dorsal cortex in decision making, and the neural cortex, which mainly controls the simple movement, become dominant in both noise levels after training.

Like Chen et al. (2016), the objective of the current study was to find a similar TMS stimulation protocol for decision making. The used a similar experimental design of Chang et al. (2014). Specifically, the applied TMS to dorsal and ventral areas, and compared the impact of TMS on motion decision held with 100% coherence (no noise) and 40% coherence ("noise") motion decision before and after training a high noise. The results obtained were also similar. Thus, dorsal and ventral stimulation initially affected motion decision held with noise and noiseless stimuli, respectively. After training with the noiseless stimuli, overall stimulation affected decision making in both noise conditions. The dorsal stimulation conclusion of Chang et al. (2014) brings a "central learning modifies the functional specialisation of dorsal cortical areas", eventually suggesting learning-induced change of dorsal areas in motion decision making.

Finally, a new development from our lab (Xie & Yang, 2019) shows that learning a high noise can actually improve noiseless performance. This has been mainly reported (Xiao et al., 2008; Zhang et al., 2010), despite the 10-time held difference at noiseless level. Specifically, Verne learning a high noise, which initially holds performance noiseless, becomes comparable with additional practice of an online decision making with the same Gaborsimilarity as noiseless. A control condition confirms that online training by itself has no significant impact on Verne held. We thus concluded that Verne learning may occur at a decision age during training and online occurrence is a result of generalised by Chodh and DeAngeli (2008). Moreover, training mainly on the conceptual representation of the similarity feature (Wang et al., 2016), so that learning can eventually be comparable between different noise levels.

During each session, a subject had to concentrate on the behavioural data in Chen et al. (2016). First, Chen et al. (2016) reported that motion decision learning affects the online trained hemifield. In contrast, the data from our lab (Wang, Zhang, Klein, Xie, & Yang, 2014; Xiong, Xie, & Yang, 2016) and other lab (Rokem & Silbert, 2010; Zhang & Li, 2010), which also studied motion decision learning with moving dots stimuli, had to find a bilateral learning advantage on hemifield. For example, a 67% of decision learning in Zhang and Li (2010) (see Fig. 1), more than 100% in Rokem and Silbert (2010) (see Fig. 1a) and 75% in Wang et al. (2014) (see Fig. 1a) after the second, a critical behavioural baseline of the learning can be derived from the noise condition or the noiseless condition training in Chen et al. (2016). Here learning being specific to the noiseless condition necessitates a double-dissociation of the influence of dorsal and ventral areas in central learning. The effect was decided on noiseless condition to add the effect concentration.

2. Methods

2.1. Observers and experimenters

Ten naïve observers (18–25 years old) with normal corrected vision were recruited. They were not financially motivated and were naive to the purpose of the study. Information concerning their background was obtained from Peking University International Research Board, which was obtained before a collection of each observer. This work was carried out in accordance with the Code of Ethics of the

World Medical Association (Declaration of Helsinki).

The observer informed consented before the experiment. The first experiment (1st session) was a pre-test of the design. The second experiment (2nd session), a pre-graduate student named Anna. The second experiment collected more than half of the data (see Results).

2.2. Apparatus and stimuli

The stimuli were generated with Psychtoolbox-3 (Brainard, 1997; Pelli, 1997) and presented on a 21-in SONY G520 CRT monitor (1024 pixel, 768 lines, 0.39 mm horizontal pixel, 120 Hertz frame rate, and 46.0 cd/m² mean luminance). The screen luminance was linearly distributed by an 8-bit look-up table. Viewing a binocular distance of 60 cm with a chin-and-head rest. An Eelink-1000 eyetracker (SR Research, Kanata, Ontario, Canada) monitored eye movements. A visual feedback of the position derived from the fixation point $> 2^\circ$ immediately above and below occurred in the same trial block, which accounted for $< 2\%$ of total trials.

The motion stimuli (Fig. 1a) were generated with the same Matlab code obtained from the lab of the laboratory of Chen et al. (2016), originally for a different purpose. It consisted of 400 black random dots (0.1–0.1 each at the minimal luminance) moving at a speed of 37 pixels in an invisible 9-cm diameter circular window. This window was centered on the horizontal meridian 9° above the left edge of the central fixation. In the 100% coherence condition, all dots moved in the same direction (22.5° or 337.5°). In the 40% coherence condition, 40% of the dots, which were randomly chosen, moved in the same direction (22.5° or 337.5°), and the rest of the dots moved in random direction.

2.3. Procedure

The experimental procedure followed that of Chen et al. (2016) closely and was similar. Specifically, motion decision decision making held were measured with a formal 2AFC QUEST staircase method using the same Matlab code from Chen et al. (2016). In each trial, the coherence and speed (coherence direction, Δdirection) were set as a level, presented in a 200 ms stimulus in a random mode, which were set as a 600 ms in the simple condition (Fig. 1b). A small high fixation point preceded each trial by 1000 ms and a red horizontal bar. Observer judged which hemifield the random motion moved in a mouse click in the decision. A digital feedback was given on incorrect responses. Each QUEST staircase consisted of 40 trials, so the decision decision making held a 75% coherence. The learning decision difference of the QUEST staircase in both experiments was 12.93, which was unchanged throughout the experiment for most observers, but reduced to 8.5 for a few high learning held.

In the endogenous session (Fig. 1c), observer performance at each condition was estimated with the QUEST staircase. In the training session, observer in the first experiment achieved 100% coherence motion stimuli in one hemifield, and in the second experiment achieved 40% coherence motion stimuli in one hemifield. Training lasted for five sessions, with each session consisting of 20 QUEST staircase.

To measure the amount of learning and transfer, the decision decision making held were measured at coherence level and in one hemifield (for endogenous condition) in Experiment 1, and at coherence level in the same hemifield. A held 6

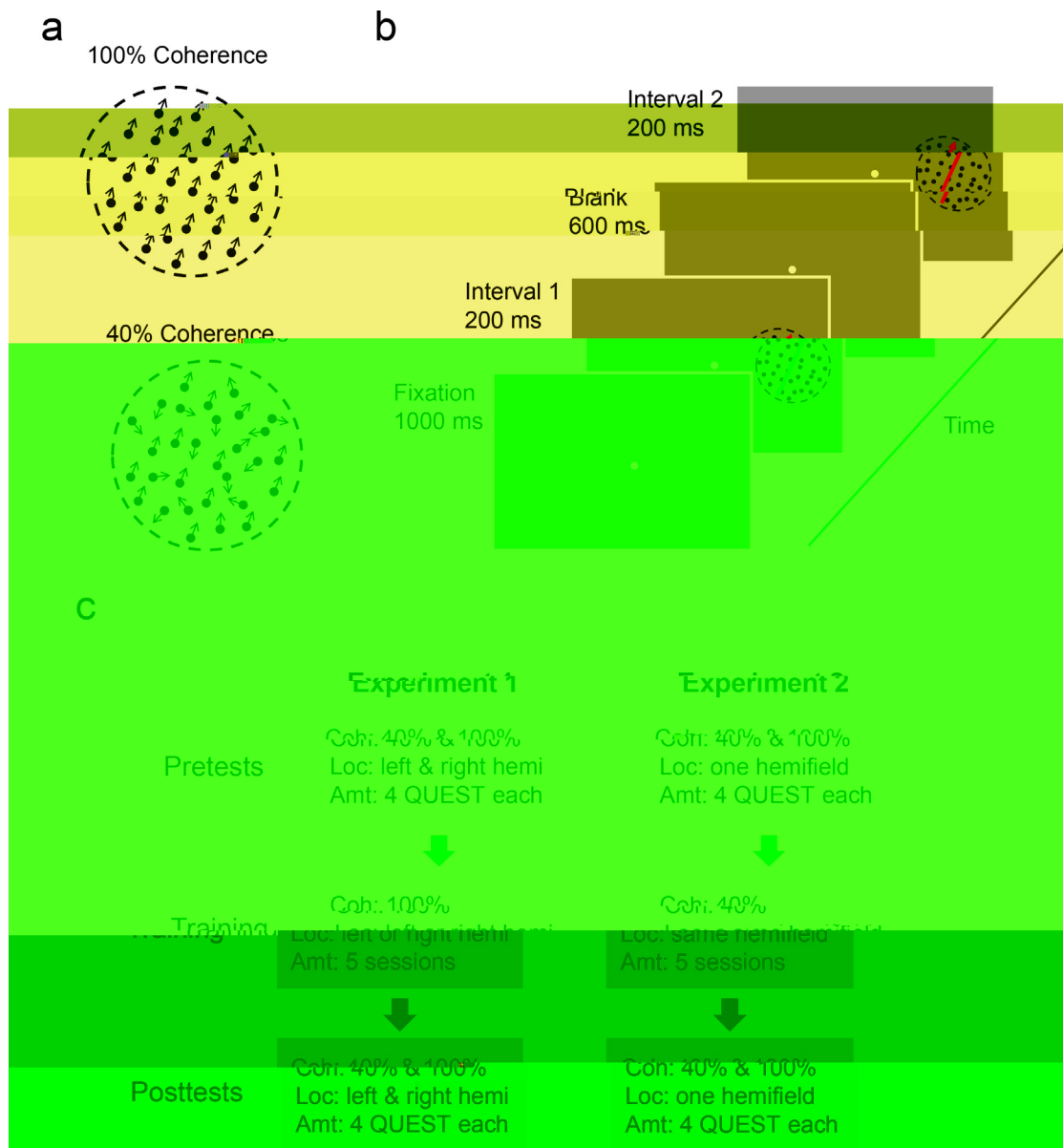


Fig. 1. Stimuli and experimental design. a. Moving dots at a given coherence level. b. Temporal layout of a single trial for motion direction discrimination. c. Pretest, training, and posttest conditions in two experiments.

before data collection on the same day.

2.4. Statistical analysis

Data were analyzed using JASP 0.12.1. The learning and transfer effects were measured by the ceiling hold improvement from each coherence level, i.e., $100\% * (Threshold_e - Threshold_o) / Threshold_e$. Individual improvements were calculated and then averaged to produce the mean improvement and SEM. The hold improvement was compared again, here at 0, with a one-sample t-test. The hold improvement between training and transfer conditions in the same experiment was compared with a two-tailed paired t-test, and across experiments was compared with an independent-sample t-test. In addition, Bayesian factors for the reverse effect were also calculated.

3. Results

3.1. Experiment I: Transfer of motion direction learning across hemispheres

Chen et al. (2016) reported that the ceiling learning of motion direction discrimination at a 100% coherence level led to the transfer to the non-trained hemisphere. Motion direction learning at a 100% coherence level did not lead to a 44% learning also transferred to 40% coherence in the same hemisphere, indicating direction held by 31%. The transfer/learning ratio was 71%. In the non-trained hemisphere, the performance was improved by a small amount (6.5% at 100% coherence, and -4% at 40% coherence (estimated from Fig. 1D)). The corresponding transfer/learning ratio was a small amount (14.8% and -9.1%, respectively).

In our replication experiment (Fig. 2), motion direction learning at 100% coherence improved the performance by 34.4 ± 5.3% at 100% coherence ($t_{11} = 6.55, p < 0.001, \log Bayes\ factor [logBF] = 6.43$). The learning also transferred to 40% coherence in the same hemisphere, indicating the held by 26.5 ± 4.6% ($t_{11} = 5.78,$

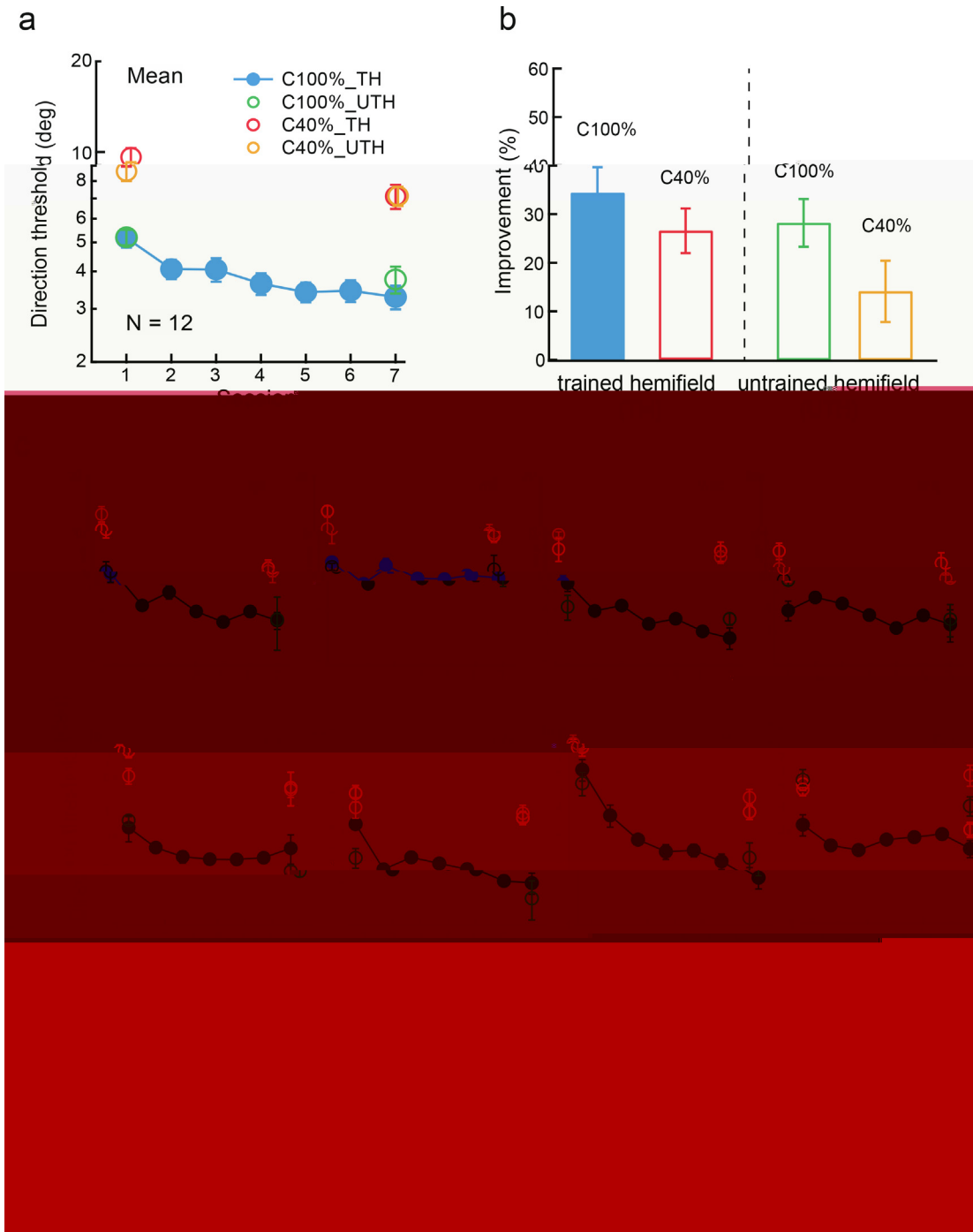


Fig. 2. Performance of learning of motion direction discrimination and its cross-hemispheric transfer. **a**, The mean learning curve at 100% coherence, as well as mean error rates during the hold at 40% coherence in the trained hemifield, and a 100% and 40% coherence in the untrained hemifield. **b**, A summary of learning and transfer. **c**, Individual learning data of last 7 observations were collected by a naïve observer. Error bars indicate 1 standard error of the mean.

$p < 0.001$, $\log BF = 5.49$). The coherence level during learning was 77.0%, similar to 71% in Chen et al. (2016). However, learning also improved the performance in the untrained hemifield by 28.2–4.9% at 100% coherence ($t_{11} = 5.73$, $p < 0.001$, $\log BF = 5.42$), and by 14.1–6.4% at 40% coherence ($t_{11} = 2.21$, $p = 0.049$, $\log BF = 0.52$). The learning improvement in a mode also had a $\log BF$ of 0.52 (Andrade et al., Scheibehenne, Gorman, Wagenmakers & Wagenmakers, 2015). The coherence level during learning was 81.9% and 41.0%, respectively, in the condition of the coherence level of 14.8% and -9.1% in Chen et al. (2016). Moreover, there was no significant statistical difference between learning and transfer at the

same 100% coherence level ($t_{11} = 1.22$, $p = 0.247$, $\log BF = -0.64$) between learning and transfer in the untrained hemifield. Overall, the learning and transfer were similar. On the other hand, the learning and transfer were also similar in the untrained hemifield at the same 100% coherence level. The difference between learning and transfer was also statistically significant. The results also indicate the high location specificity of motion direction learning in Chen et al. (2016), despite the use of nearly identical stimuli and procedures.

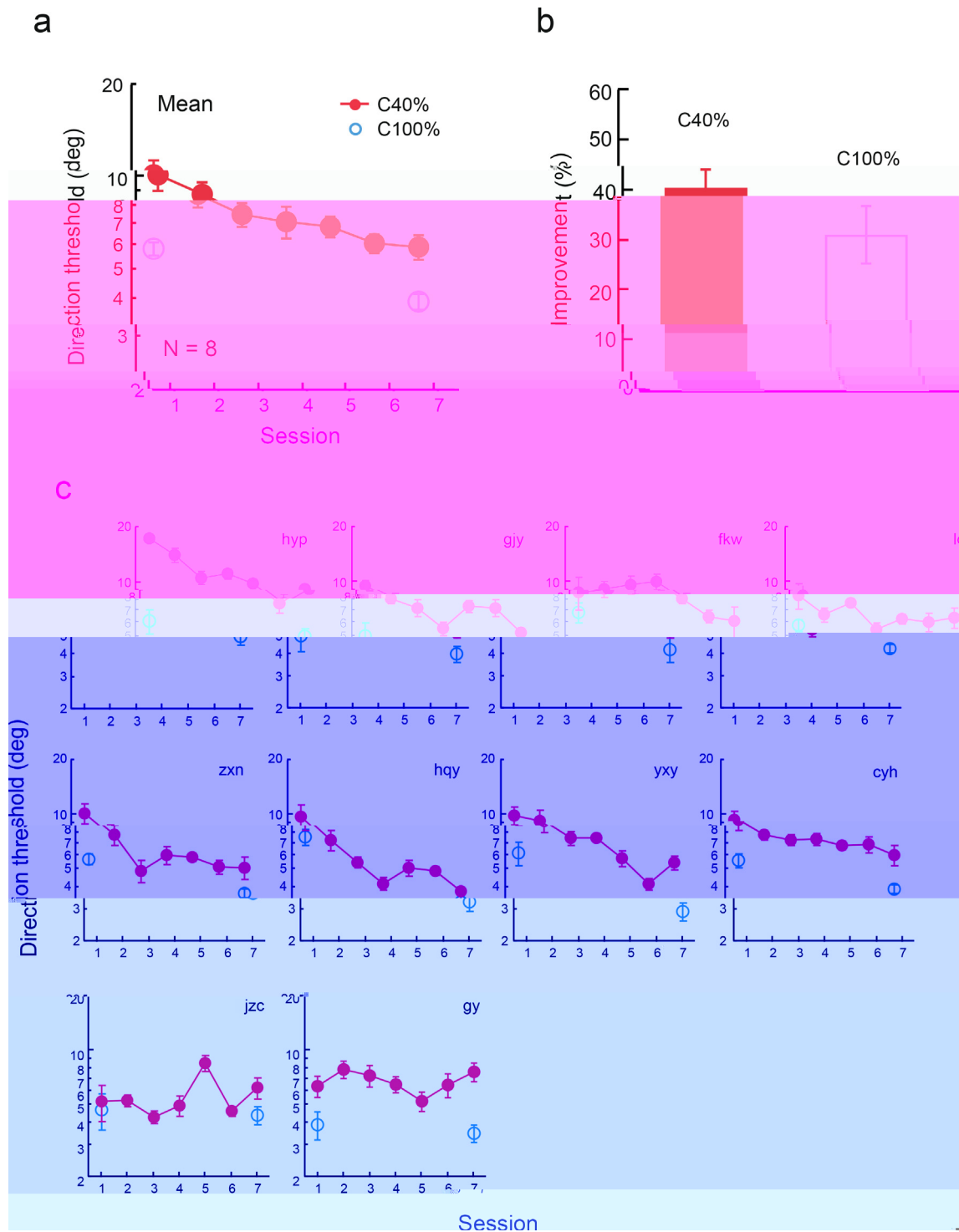


Fig. 3. Transfer of motion direction learning from “noisy” 40% coherence stimuli to noise-free 100% coherence stimuli. a. The mean learning curve for a 40% coherence, as well as the mean noise-free holding performance at the same location. b. A summary of learning and transfer. Individual elements of the data of the 16 observed subjects are collected below and are indicated by the standard error of the mean.

3.2. Experiment II: Transfer of motion direction learning from noisy to zero-noise stimuli

In an earlier TMS study, Chang et al. (2014) showed that subjects learned a high noise did not transfer to noise-free stimuli. This behavioral baseline is critical because it demonstrates the difference of dorsal and ventral areas in direction processing and noise level inferred from TMS effects. However, a similar

baseline regarding the specific transfer of motion direction learning from “noisy” 40% coherence to noise-free 100% coherence stimuli is missing in Chen et al. (2016). Because of its importance on the interpretation of the TMS data in Chen et al. (2016), we decided to collect data for this baseline condition.

We had no observed specific motion direction learning at a 40% coherence (Fig. 3). To observe the hypothesized negative interference (Fig. 3c, bottom observation) we excluded from data

analysed because they were included in homochromic learning could be. The remaining elements had a learning improvement of 40% coherence b (7 = 10.88, < 0.001, logBF = 7.37), but a 100% coherence b 31.1 ± 5.7% (7 = 5.46, < 0.001, logBF = 3.76) at the same location. Moreover, for motion direction a 100% coherence, the improvement was high learning and the elements were nearly identical to the homologous elements in Experiment 1 (31.1% ± 3.44%; t = 0.41, p = 0.685, logBF = -0.85), suggesting complete learning and performance. Therefore, the hemifield configuration he affected baseline of no learning and performance of 40% coherence, of form noise or no-noise motion stimuli, cannot be established.

4. Discussion

In his study, we demonstrated a motion direction learning in the hemifield configuration of Chen et al. (2016) and a bilateral acco hemifield effect especially at the 100% coherence level. The learning and performance in the identical (Fig. 2). Moreover, we collected the learning baseline data, demonstrating complete learning and performance from 40% to 100% coherence (Fig. 3). The learning and performance in the motion direction a no-noise coherence level are likely associated with similar brain mechanisms. Therefore, the inference of dorsal and ventral areas in motion direction processing is all an effect of cerebral learning and the role, may not be related to the direction behavior evidence in Chen et al. (2016). I remain neutral in the direction of dorsal and ventral TMS stimulation on motion direction discrimination a coherence level of 40% coherence.

Although the hemifield configuration, learning procedure, and experimental design of Experiment 1 were nearly identical to those in Chen et al. (2016), the results are not comparable. In Chen et al. (2016), after the TMS stimulation of the forehead and the same choral effects were observed. A homin in Experiment 1D, the additional procedure did not improve learning and the learning and performance in the same hemifield (learning and performance = 71% to 70%). This stimulus became learning and performance of the TMS stimulation were long gone. For the same reason, the additional procedure was not expected to affect learning and performance in the learned hemifield. The procedure of learning elements in an affected bilateral learning. In Experiment 1, as in Chen et al. (2016), each object before data collection occurred to each condition for a total of 320 trials (4 conditions × 20 trials/condition), which is sufficient for a complete learning. In Experiment 2, one trial was repeated for each condition (2 conditions × 10 trials/condition = 80 trials). After the initial practice, the performance was -9.3% (from 10.11 ± 1.38 to 11.04 ± 1.40) at 40% coherence, and 15% (from 5.97 ± 0.52 to 5.05 ± 0.45) at 100% coherence. The performance difference for the impact of possible dorsal learning and inconspicuous in the hemisphere of 80 trials of practice. I think safe to conclude that cerebral learning elements in Experiment 2 have not been significantly confirmed by dorsal learning.

High location specificity of motion direction learning has been reported (Ball and Sekule, 1982, 1987; Li, 1999). So why did motion direction learning fail to homochromic specificity here? I might depend on how direction held a measure. Mollon and Danilo (1996) once pointed out that location specificity in cerebral learning may result from an object's "learning about the local feature of his visual image; about the local object of his eye's motion; and about the specificity of individual neurons in his visual area." A learning and generalization (Xiong et al. 2016), when training is formed in the direction held measure by a

method of same-difference comparison in a field of stimuli, as in earlier studies by Ball and Sekule (1982, 1987) and Li (1999), an object might be able to learn the local coherence "idiosyncrasy" (Mollon & Danilo, 1996) and which could result in learning (Sagi, 2011) and high location specificity. To this point, we demonstrated that the direction difference of a stimulus is like contrast, but the individual direction is a high level of bilateral coordination. The effect of ventral local cerebral learning becomes significant and not affected by a hemisphere (Xiong et al. 2016). A standard QUEST staircase method is used to determine the local coherence level of local coherence in motion learning in homochromic learning, a homin in Experiment 1 and in the study (Rokem & Sil, 2010; Zhang & Li, 2010; Wang et al., 2014; Xiong et al., 2016). In fact, we added the control because the high location specificity reported by Chen et al. (2016) challenged the above direction evidence in Xiong et al. (2016). Therefore, the inference is not as good as Chen et al.'s experiment to double check the direction.

Why did motion direction learning and performance from noise 40% coherence or no-noise 100% coherence? The answer may lie in the fact that 40% coherence in Chen et al. (2016) is not noise enough. In the original study by Dohe and Li (2005), the control held a high noise level above 10 times of the held noise level. So the difference of Vernier held a high noise level in our study (Xie & Y, 2019), which is also above 10 times. However, the motion direction held a 40% coherence level only above a high noise level a 100% coherence (Fig. 2 and 3). Therefore, the 40% coherence condition is almost the noise level of the held noise level of function, the learning could still occur in the eighth of the channel according to Li et al. (2010), and learning and performance of 100% coherence.

CRedit authorship contribution statement

Xin-Yu Xie: In experiment, Formal analysis, Writing - original draft. Xing-Nan Zhao: In experiment. Cong Yu: Conceptualization, Formal analysis, Writing - review and editing.

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