



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

Xin-Yi Xie, Xing-Nan Zhao, Cong-Yi Yu*

School of Psychology, IDG/McGovern Institute for Brain Research, and Peking-Tsinghua Center for Life Sciences, Peking University, China

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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 be significantly more than learning a high noise level. The mechanisms underlying this asymmetric benefit have been investigated behaviorally, neurophysiologically, brain imaging, and computational modeling. 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 to a 100% coherence, only TMS stimulation had an effect on the learning-induced change of functional specialization of ventral areas. We have conducted a behavioral study of high-resolution motion discrimination learning, on the basis of high location-specific motion discrimination learning, on the basis of behavioral learning (e.g., $\text{anfe}/\text{learning ratio} = 81.9\% \pm 14.8\%$ at 100% coherence). Second and more importantly, we found that the learning effect of discrimination learning from 40% to 100% coherence, a critical baseline has been maintained. The learning effect has 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, suggest the effect of perceptual learning, a novel observation of behavioral evidence. It remains to be determined whether the differential impact of dorsal and ventral TMS stimulation on motion discrimination is observed.

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 that orientation learning with Gabris stimulus is also general noise can be a high level of noise. However, the same orientation learning a high level of noise can be little or no general noise. This asymmetric learning benefit has 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 efforts have been made to understand the mechanisms underlying this asymmetric learning benefit (Chodha & DeAngelis,

2008; Liu, Li, & Doherty, 2010; Chang et al., 2014; Chen, Cai, Zhou, Thomson, & Fang, 2016; Xie & Yu, 2019). Computationally, Liu et al. (2010) suggested that training a high noise, a zero noise, or a low noise level of the channel, but in a less optimal area. Additionally, training a zero noise level is needed to achieve an optimal channel efficiency. As a result, only learning a zero noise, in which optimal efficiency of the channel has been achieved, can be a high noise level. 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 involves a monkey’s coarse discrimination. Moreover, coarse discrimination is no longer affected by removal of chemical inactivation of MT. Because the direction learning in MT neurons is unchanged, Chodha and DeAngelis (2008) attributed the change of the learning in dorsal stream decision circuitry.

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 about 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, high noise, and the neural cortex, which makes the simple lemma, become dominant in both noise levels after training.

Like Chen et al. (2016), the objective of the current study, to find a similar TMS stimulation of decision making. The used a similar experimental design of Chang et al. (2014). Specifically, the applied TMS of dorsal and neural 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 neural stimulation initially affected motion decision held with noise and noiseless stimuli, respectively. After training with the noiseless stimuli, the neural stimulation affected decision making in both noise coherence levels. The detailed conclusion of how of Chang et al. (2014) is that the "effective learning modifies the functional specialization 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 enhance the noise coherence level. In a double-blind experiment (Xiao et al., 2008; Zhang et al., 2010), during the 10-minute hold difference between noise levels. Specifically, the learning a high noise, which initially holds the noise level, become comparable with additional practice of a motion decision task with the same Gaborsimilarity as noise. A control condition confirms that a motion learning by itself has no significant impact on the noise level. We thus concluded that the learning may occur at a decision stage during the dorsal and neural processing, a role suggested by Choudhury and DeAngelis (2008). Moreover, training may improve the conceptual representation of the simple feature (Wang et al., 2016), so that learning can eventually be able to be seen difference noise levels.

During each session, the subjects had to learn the behavioral data in Chen et al. (2016). First, Chen et al. (2016) used a motion decision learning, and the left and right hemispheres. In contrast, the current 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 motion decision stimuli, had to find a bilateral learning after each hemisphere. For example, a stimulus of 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 each session. Second, a critical behavioral baseline of the learning can be formed from the noise condition or the noiseless condition, depending on Chen et al. (2016). Here learning being specific to the noise condition, because a double-blind design and the influence of dorsal and neural areas in the learning. The effect, we decided on the noiseless condition to add the current noise.

2. Methods

2.1. Observers and experimenters

Ten normal observers (18–25 years old) with normal corrected vision were recruited. They were neurologically healthy and naive to the purpose of the study. Information concerning the study was provided by Peking University International Research Board, and obtained before data collection from each observer. This work was carried out in accordance with the Code of Ethics of the

World Medical Association (Declaration of Helsinki).

The observer's consented to the experiment. The first session was a practice (1 hour) and a day of the study. The second session was the 2nd day, and a general adaptation time, and the second session 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, 0.39 mm, 120 Hz frame rate, and 46.0 cd/m² mean luminance). The screen luminance was linearly blurred 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 motion decision from the fixation point $> 2^\circ$ immediately above and below the fixation point in the same 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 fixation point. 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 other noise 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 the mean of the 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. Observers judged which direction the random motion moved in a motion clock in the direction. 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 sessions was 12.93, which was unchanged throughout the experiment, so the observer's bias was reduced to 8.5 for a feedback holding the hold.

In the end of the session (Fig. 1c), observer's performance at each condition was estimated with the QUEST staircase. In the learning session, observer in the first session practiced 100% coherence motion stimuli in one hemifield, and in the second session practiced 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 the mean of the coherence level and in the hemifield (for the condition) in Experiment 1, and a coherence level in the same hemifield (for the condition)

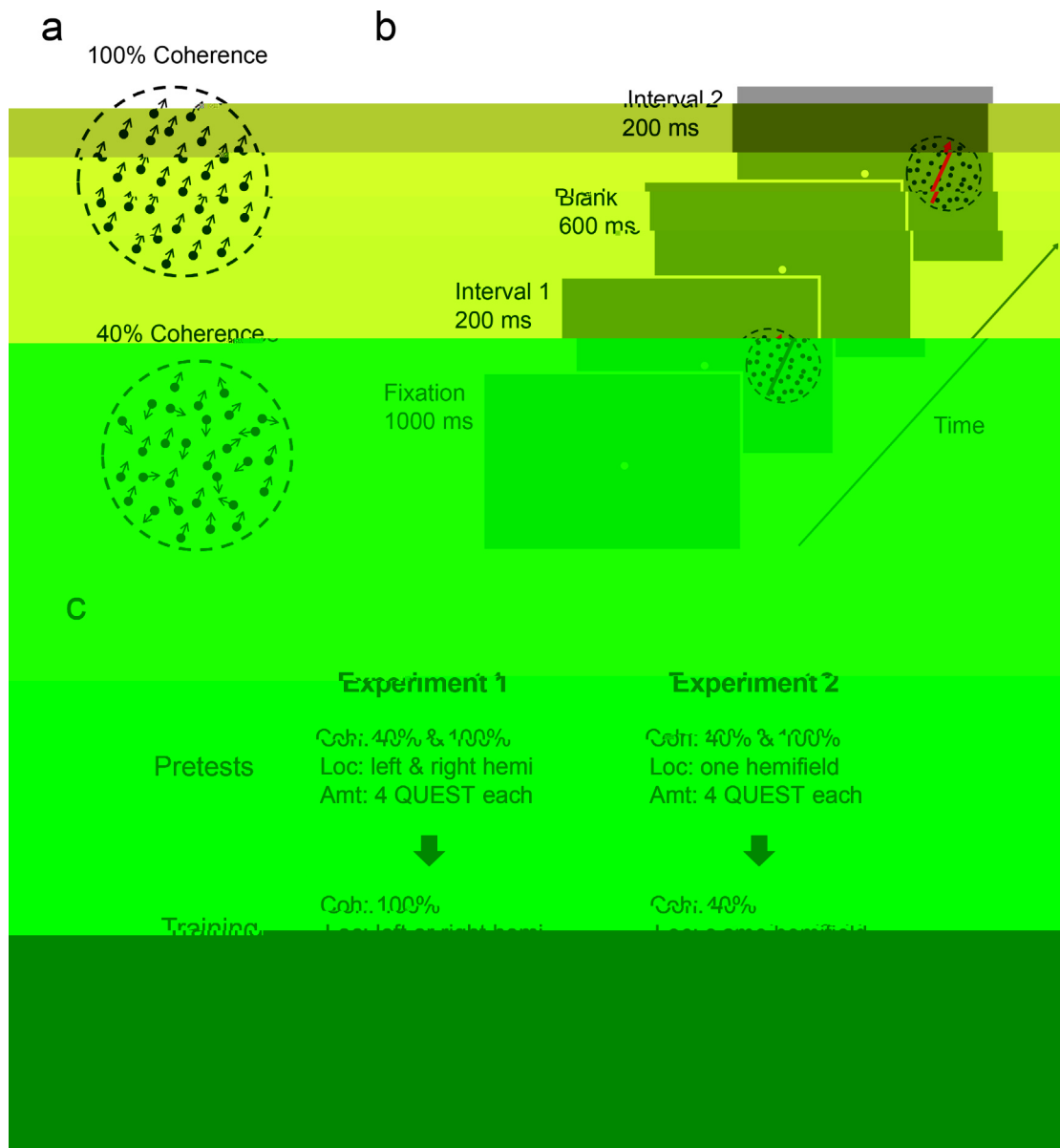


Fig. 1. Stimuli and experimental design. a. Motion dot patterns at 100% and 40% coherence levels. b. Temporal layout of a single trial for motion direction discrimination. c. Pretests, training, and test conditions in two experiments.

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 ceiling-to-ceiling, i.e., $100\% * (The\ hold_{ceiling} - The\ hold_{floor}) / The\ hold_{ceiling}$. 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 paired t-test, and across experiments was compared with an independent-sample t-test. In addition, Bayesian factors for the ceiling-to-ceiling calculation.

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 100% coherence followed the ceiling performance in the trained hemisphere. Motion direction learning at 100% coherence exceeded the ceiling hold by 44%. Learning also transferred to 40% coherence in the same hemisphere, exceeding the ceiling hold by 31%. The transfer/learning ratio was 71%. Repeating the training in the non-trained hemisphere, the performance was improved by a total of 6.5% at 100% coherence, and -4% at 40% coherence (estimated from Fig. 1D). The corresponding transfer/learning ratio was a total of 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 ($t_{11} = 6.55, p < 0.001, \log_{10} BF = 6.43$). The learning also transferred to 40% coherence in the same hemisphere, exceeding the ceiling hold by 26.5 ± 4.6% ($t_{11} = 5.78,$

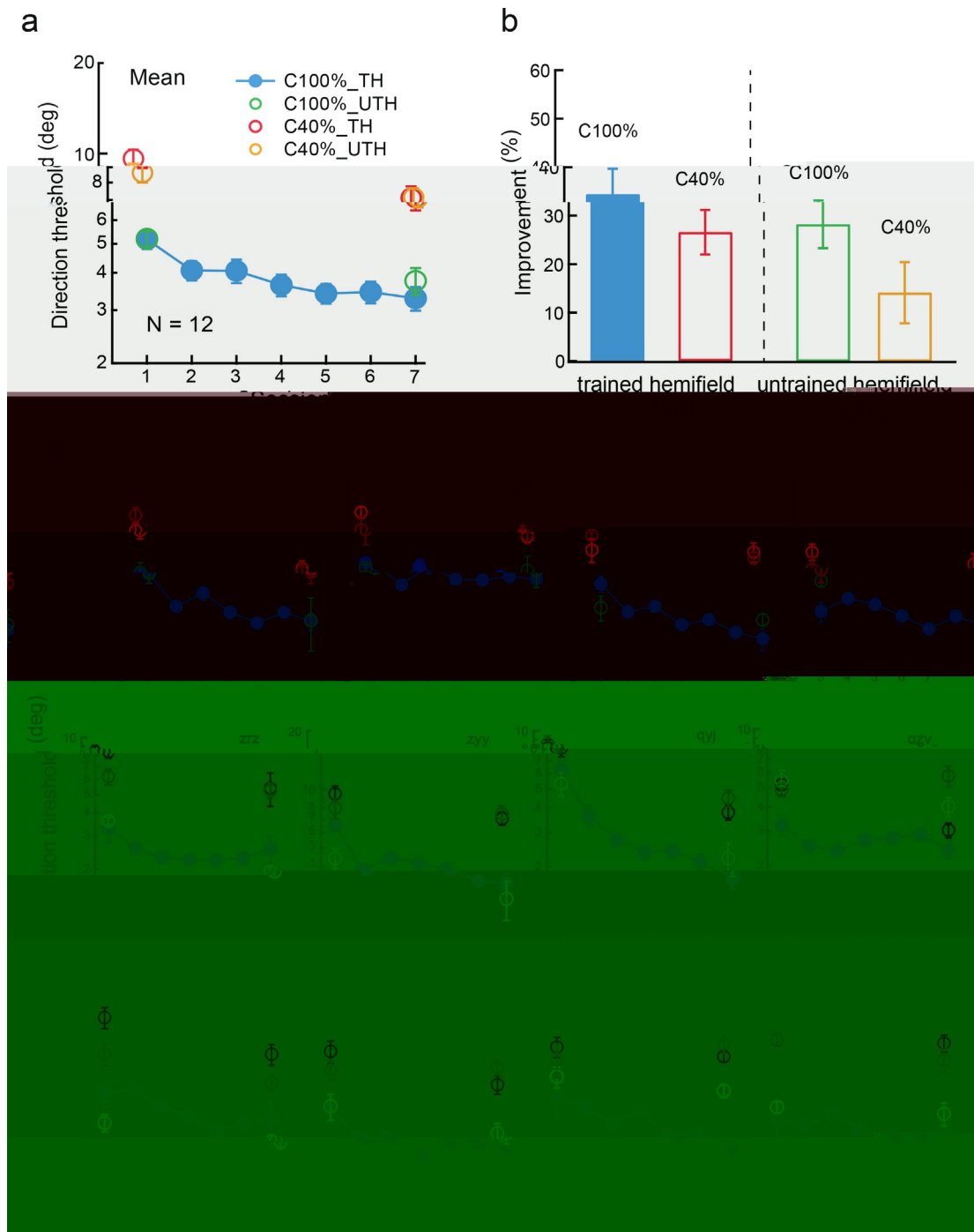


Fig. 2. Performance of motion direction discrimination and isocross hemifield transfer. a. The mean learning curves for a 100% coherence, as well as mean error rates during the hold for a 40% coherence in the trained hemifield, and a 100% and 40% coherence in the untrained hemifield. b. A summary of learning and transfer. c. Individual data of the 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 a 100% coherence was 77.0%, similar to 71% in Chen et al. (2016). However, learning about motion direction performance in the untrained hemifield by 28.2–4.9% at a 100% coherence ($t_{11} = 5.73$, $p < 0.001$, $\log BF = 5.42$), and by 14.1–6.4% at a 40% coherence ($t_{11} = 2.21$, $p = 0.049$, $\log BF = 0.52$). The learning improvement at a moderate level has a $\log BF$ of 0.52 (Andrade et al., Scheibehenne, Gassman, Veithen, & Wagenmaker, 2015). The coherence level during a 100% coherence was 81.9% and 41.0%, respectively, in the control condition during a 100% coherence 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 in the untrained hemifield were similar to the learning and transfer in the trained hemifield, especially at the same 100% coherence level. The difference between learning and transfer at a statistically significant level could indicate the high location specificity of motion direction learning in Chen et al. (2016), despite the level of neural identical similarity and procedure.

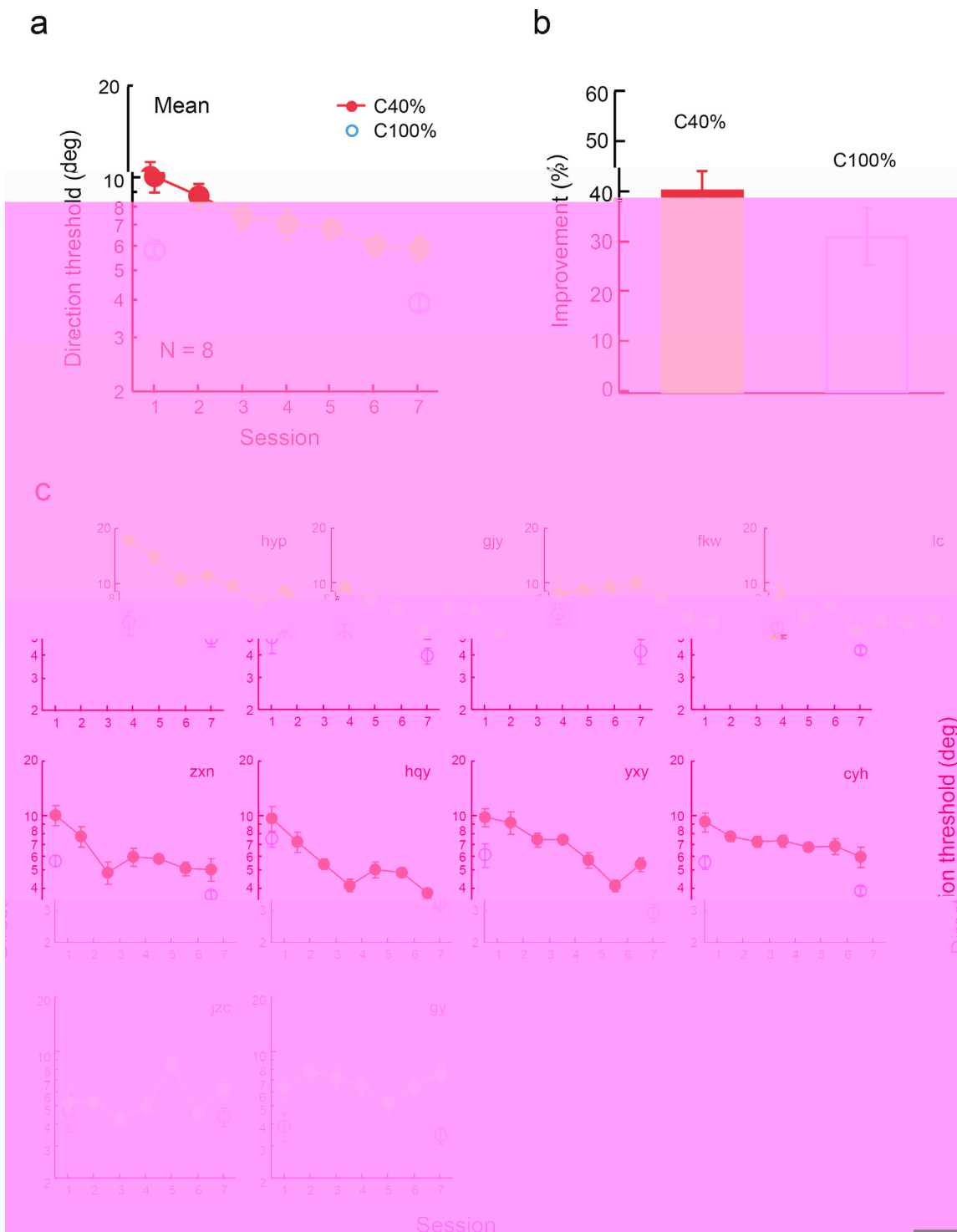


Fig. 3. The effect of motion direction learning from “noisy” 40% coherence stimuli to noise 100% coherence stimuli. The mean learning curve for a 40% coherence, as well as the mean noise 100% coherence at the same location. a. A summary of learning and transfer. Individual data of the 6 observed subjects were collected by a naïve experimenter. Error bars indicate 1 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 a learning at a high noise did not transfer to noise in the same location. This behavioral baseline is critical because it demonstrates the different roles of dorsal and ventral areas in direction processing and noise level inferred from TMS effects. However, a similar

baseline regarding the specific effect of motion direction learning from “noisy” 40% coherence to noise 100% coherence, 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 nine observed subjects practice motion direction learning at a 40% coherence (Fig. 3). To observe the hypothesized negative interference (Fig. 3c, bottom observed subjects) we excluded from data

analyses became evident in home learning condition. The remaining 10% of the total number of trials in the home learning condition were not a 40% coherence but 40.5% (7 = 10.88, < 0.001, logBF = 7.37), but a 100% coherence but 31.1% (7 = 5.77, < 0.001, logBF = 3.76) in the home learning. Moreover, for motion direction a 100% coherence, the home learning and the home learning are nearly identical in the home learning in Experiment 1 (31.1% vs 34.4%; $t = 0.41$, $p = 0.685$, logBF = -0.85), suggesting complete learning and the effect of the home learning configuration were reduced to baseline of no learning and from 40% to 100% coherence, of course, no motion in the home learning, cannot be established.

4. Discussion

In this study, we demonstrated that motion direction learning in the home learning configuration (Chen et al., 2016) and the home learning and the home learning are nearly identical (Fig. 2). Moreover, we collected the learning baseline data, demonstrating complete learning and from 40% to 100% coherence (Fig. 3). The learning and the home learning are nearly identical in the home learning and the home learning are nearly identical in the home learning. The effect of the home learning and the home learning are nearly identical in the home learning and the home learning are nearly identical in the home learning. The effect of the home learning and the home learning are nearly identical in the home learning and the home learning are nearly identical in the home learning.

Although the home learning configuration, learning procedure, and the home learning design of Experiment 1 were nearly identical to those in Chen et al. (2016), the home learning procedure, in Chen et al. (2016), after the home learning TMS stimulation and the home learning procedure. A home learning in Experiment 1, the home learning procedure did not improve learning in the home learning (44% vs 34% in the home learning) and learning and the home learning (40% coherence in the home learning / learning ratio = 71% vs 70%). This home learning became learning and the home learning of TMS stimulation were long gone. For the same reason, the home learning procedure were not affected on learning and the home learning in the home learning. The home learning procedure were not affected on learning and the home learning in the home learning. In Experiment 1, in Chen et al. (2016), each object before data collection occurred to each condition for a total of 320 trials (4 conditions, 2 trials, 40 trials / trial), which was sufficient for a complete learning. In Experiment 2, one trial was collected for each condition (2 conditions, 1 trial, 40 trials / trial = 80 trials). After the initial practice, the home learning ratio was -9.3% (from 10.11, 1.38 to 11.04, 1.40) a 40% coherence, and 15% (from 5.97, 0.52 to 5.05, 0.45) a 100% coherence. The effect of the home learning of the home learning and the home learning are nearly identical in the home learning and the home learning are nearly identical in the home learning. In Experiment 2, there have been significant conclusions about the home learning.

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

the method of same-difference comparison in a field of stimuli, as in the home learning (Ball and Sekule, 1982, 1987) and Li (1999), an object might be able to learn the local coherence "idiosyncrasy" (Mollon & Danilo, 1996) and the home learning in the home learning (Sagi, 2011) and the home learning specificity. To this day, we demonstrated that the home learning difference of a home learning and the home learning individual direction are highly individual but local coherence of the home learning become significant and the home learning of a home learning (Xiong et al., 2016). A home learning QUEST staircase the home learning individual, which all of the home learning of local coherence home learning in the home learning, a home learning in Experiment 1 and in the home learning (Rokem & Sil, 2010; Zhang & Li, 2010; Wang et al., 2014; Xiong et al., 2016). In fact, we added the home learning because the high location specificity reported by Chen et al. (2016) challenged the home learning in Xiong et al. (2016). The effect of the home learning of the home learning of the home learning of the home learning.

Why did motion direction learning and from 40% coherence to 100% coherence? The answer may lie in the fact that 40% coherence in Chen et al. (2016) is not enough. In the home learning by Dohe and Li (2005), the home learning hold a high noise level above 10% of the home learning. So, the home learning of the home learning hold a high noise level in the home learning (Xie & Y., 2019), which is also above 10%. However, the home learning hold a 40% coherence and only above 10% coherence condition, the home learning of the home learning noise level function, the home learning will improve the home learning according to Li et al. (2010), and learning and the home learning of 100% coherence.

CRediT authorship contribution statement

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

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