

Cross-task perceptual learning of object recognition in simulated retinal implant perception

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The perception gained by retina implants (RI) is limited, which asks for a learning regime to improve patients' visual perception. Here we simulated RI vision and investigated if object recognition in RI patients can be improved and maintained through training. Importantly, we asked if the trained object recognition can be generalized to a new task context, and to new viewpoints of the trained objects. For this purpose, we adopted two training tasks, a labelling task where participants had to choose the correct label out of other distracting labels for the presented object, and a reverse labelling task where participants had to choose the correct object out of other distracting objects to match the presented label. Our results showed that, despite of the task order, recognition performance was improved in both tasks and lasted at least for a week. The improved object recognition, however, can be transferred only from the labelling task to the reverse labelling task but not vice versa. Additionally, the trained object recognition can be transferred to new viewpoints of the trained objects only in the labelling task but not in the reverse labelling task. Training with the labelling task is therefore recommended for RI

patients to achieve persistent and flexible visual perception.

Introduction

A growing number of people worldwide are suffering from photoreceptor degeneration in the retina, which characterizes diseases such as retinitis pigmentosa (RP) and age-related macular degeneration (AMD), and causes gradual vision loss (Bourne et al., 2017; Congdon et al., 2004). In an effort to restore vision to patients who suffer from photoreceptor diseases, great progress has been made in the development of visual prostheses (Fine & Boynton, 2015). One of these technologies is the retinal implant (RI), a photoelectric device which stimulates the remaining neurons in the retina to evoke action potentials that can be transmitted to the visual cortex to form visual percepts (Chader, Weiland, & Humayun, 2009; Shepherd, Shivdasani, Nayagam, Williams, & Blamey, 2013; Zrenner, 2002).

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Clinical trials with RI systems that have obtained regulatory approval for clinical treatment (Argus II system, Ho et al., 2015; and Alpha IMS system, Zrenner et al., 2011) report that the patients were able to detect the number and location of stimuli (Stingl et al., 2017), discriminate orientation and motion direction (Ho et al., 2015), and even read large letters (Zrenner et al., 2011). Despite these promising results, the perception gained by RI is still limited (Shepherd et al., 2013), and there is a large variation of the gained perception according to the few clinical reports (Beyeler, Rokem, Boynton, & Fine, 2017b). For instance, with the Argus II system, whereas some patients did not show improvement in discriminating motion direction after the implantation (Castaldi et al., 2016), other patients showed enhanced performance after prolonged experience with the system (Dorn et al., 2013; Ho et al., 2015). Of importance for the current study, reports of shape recognition have been variable (Stingl et al., 2017, Zrenner et al., 2011). Such limitations and variation raise the question whether, and to what extent, RI perception can be improved through training.

It is well documented that training on a visual task can significantly improve visual perception (see Goldstone, 1998; Watanabe & Sasaki, 2015, for reviews). These improvements, due to visual perceptual plasticity, can persist for months or even years (Goldstone, 1998). Training on a visual task can significantly strengthen visual perception in both healthy subjects and patients with visual deficits (Ooi, Su, Natale, & He, 2013; Polat, Ma-Naim, Belkin, & Sagi, 2004). Visual perceptual plasticity can be gained from the familiarity of a particular task (task-dependent), or from boosted representation of the trained feature irrelevant of the task (task-independent, Watanabe & Sasaki, 2015). The task-dependent plasticity constrains the improved visual performance to a particular task. Therefore, it is important to achieve task-independent perceptual plasticity for RI users such that the improved visual perception can generalize to other contexts.

The goal of our study was to develop a training paradigm that can help RI patients to make optimal use of their newfound vision. To reduce unnecessary testing burden for patients, we conducted simulation experiments mimicking the limited vision of the patients with a subretinal implant (Perez Fornos, Sommerhalder, Pittard, Safran, & Pelizzone, 2008). Such simulated RI-vision was realized by reducing spatial resolution, field of view, and implementing specific distortions in pictures shown to observers with intact vision (Beyeler et al., 2017a; Chen, Suaning, Morley, & Lovell, 2009). Specifically, we focused on the visual ability of recognizing everyday objects. With the large amounts of variants for each object and

the different retinal representations of the same individual object given by different viewpoints, we were able to test the flexibility of the trained visual ability.

Here we investigated if a perceptual learning regime can improve object recognition in simulated RI-vision, and if the improved object recognition can be transferred to a different task. For this purpose, we included two different tasks, a labelling task where participants have to choose the correct label out of other distracting labels for the presented object, and a reverse labelling task where participants have to choose the correct object out of other distracting objects to match the presented label (Figure 1B). Both tasks required the discrimination of the correct object representation from a set of competing object representations. They differed in that either one visually presented object needed to be compared to memory traces of visual objects (in the labelling task) or one visual object memory trace needed to be compared to a set of object pictures (in the reverse labelling task). In principle, we expected to observe improvement in object recognition irrespective of the particular training type. However, the reverse labelling task lends itself to a feature-based comparison of object pictures, whereas the labelling task emphasizes a more holistic comparison of the stimulus with object memory traces (Song, Hu, Li, Li, & Liu, 2010). Given the reduction of distinctive features in RI vision, a holistic strategy might be more successful than a feature-based strategy.

We hypothesized that if object recognition training can transfer across tasks, the improved performance in one task would persist, or could be even further boosted, in the other task. Taking advantage of the different viewpoints of everyday objects, we also asked whether the object recognition of trained viewpoints can transfer to new, untrained viewpoints. Moreover, it has been shown that learning fine visual discriminations can be speeded up by insertion of easy trials into the training (Ahissar & Hochstein, 1997; Maertens & Pollmann, 2005; Rubin, Nakayama, & Shapley, 1997). Once a feature difference has been detected, it will lower the discrimination threshold for this feature in the future. Based on these findings, while controlling the task difficulty in terms of the alternative choices in Experiment 1, we manipulated the task difficulty in Experiment 2 by varying the number of alternative choices in the hope that the easier trials at the beginning of the task could boost the learning process. Additionally, the persistence of the improved object recognition was also tested in Experiment 1 by including a posttest which took place one week after the training session.

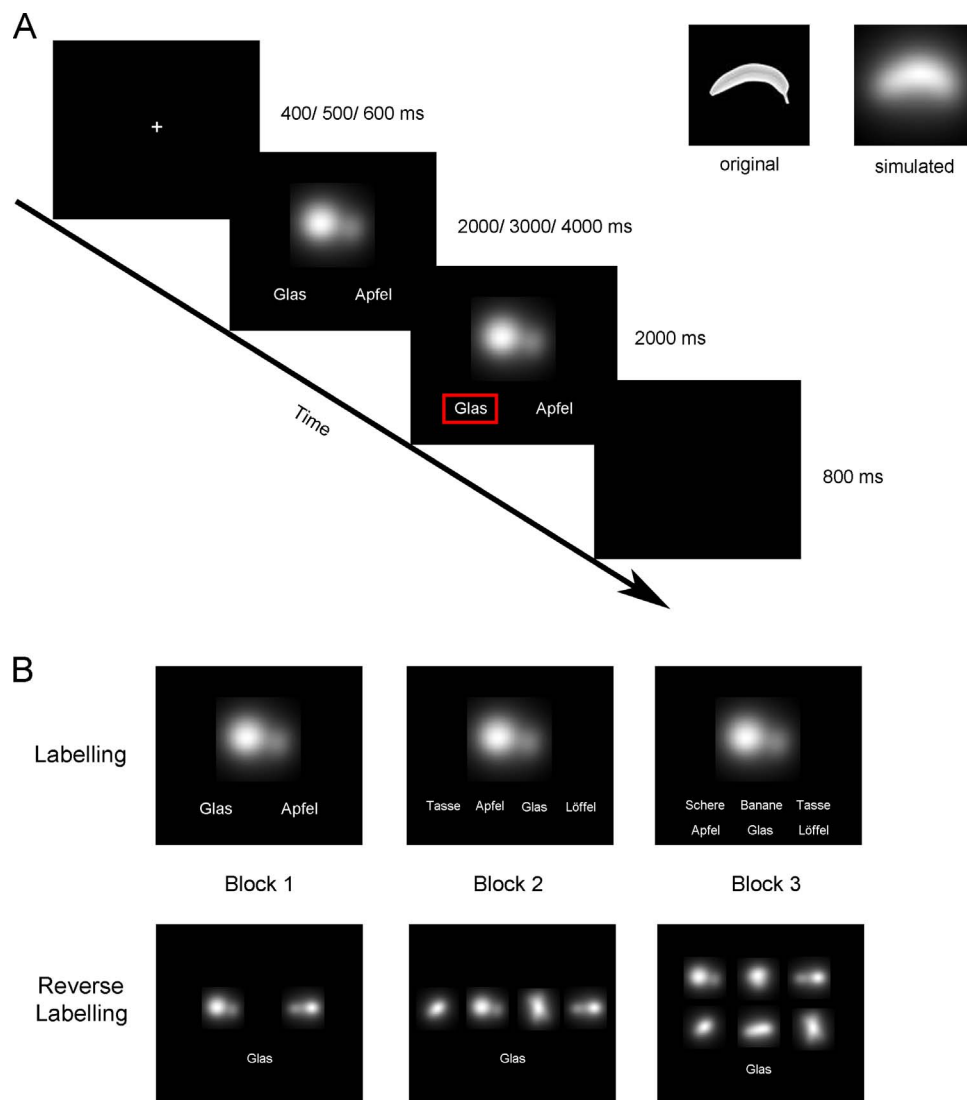


Figure 1. (A) An example trial in the labeling task (left), the original and the simulated picture of a banana (right). (B) The labeling task (upper) and the reverse labelling task (lower) in Experiment 2 where the number of the alternative choices increased over the three blocks. In Experiment 1, the number of alternative choices was always four. The target object shown in both (A) and (B) is a horizontally localized glass. The true labels of the objects in the reverse labelling task in B are glass, spoon (Block 1, from left to right); banana, glass, scissors, spoon (Block 2, from left to right); glass, apple, spoon, banana, toothpaste, scissors (Block 3, upper row from left to right and lower row from left to right).

Experiment 1

In Experiment 1, we recruited two groups of participants in the training session, with one group accomplishing the reverse labelling task after the labelling task (Experiment 1A) and the other group accomplishing the labelling task after the reverse labelling task (Experiment 1B). With this manipulation, we were able to investigate whether the trained object recognition can transfer from one task to the other task. To test the persistence of the trained object recognition, both groups of participants accomplished a posttest one week after the training, the task of

which was the same as the second task in the training session.

Methods

Participants

Thirty-two healthy students who had never been exposed to the simulated pictures participated in Experiment 1, with half of them randomly assigned to Experiment 1A (10 females, 19–29 years old) and the other half assigned to Experiment 1B (10 females, 19–28 years old). All participants had normal or corrected-to-normal vision, and all of them were German native

speakers. This experiment was conducted in accordance with the Declaration of Helsinki and was approved by the local ethics review board. A written consent form was obtained from each of the participants prior to the experiment. Two participants from each group did not show up in the posttest, and the analysis on the persistency of the training effect was hereby conducted on the remaining 14 participants (Experiment 1A: nine females, 19–29 years old; Experiment 1B: eight females, 19–28 years old).

Stimuli and design

In both experiments, stimuli were simulated object pictures using Pulse2percept software (Beyeler, Boynton, Fine, & Rokem, 2017a). The simulation is based on a validated model of retinal axonal pathways, which modelled the spatial and temporal properties of the retinal tissues by a series of linear filtering and nonlinear processing (Horsager et al., 2009; Nanduri et al., 2012). This model has been shown to describe spatial distortions, temporal nonlinearities, and spatiotemporal interactions across RI devices, patients, and different behavioral experiments (see Beyeler et al., 2017a for details and a direct comparison between the percept predicted by the model and the percept drawn by patients). The technical parameters were set according to the subretinal Alpha IMS system (Retina Implant AG, Tübingen; Zrenner et al., 2011); that is, each picture had a resolution of 1369 stimulating electrodes in an area covering a visual field of 8° visual angle. The likelihood of axonal stimulation was set $\lambda = 0.1$, because of the subretinal stimulation of the bipolar cell layer. With the simulation, the objects appeared as “round spots of light” (Figures 1 and 2), which matched the reported percepts of patients with the subretinal Alpha IMS (Wilke et al., 2011). Eight different objects (apple, banana, Bottle, cup, glass, spoon, scissors, and toothpaste) from different viewpoints were simulated, rendering 64 pictures in total (see Figure 2 for the whole set of the simulated pictures).

There were two tasks in each of the two experiments: a labelling task (Figure 1B, upper) and a reverse labelling task (Figure 1B, lower). In the labelling task, one object picture was presented at the center of the screen, below which four German words referring to four different object labels were presented. Participants were asked to choose the correct label for the object picture by clicking the left button of the mouse. In the reverse labelling task, one object label was presented at the lower visual field of the screen, above which four object pictures were presented. Participants were asked to choose the correct picture matching the label by clicking the left button of the mouse. In Experiment 1A, the labelling task was followed by the reverse

labelling task; in Experiment 1B, the order of the two tasks was reversed.

There was an additional block of posttest, which took place one week after the training. The task in the posttest was the same as the second task during training, to avoid contamination from the other task.

Procedures

Participants were tested in a soundproof and dimly lighted room. They were seated in front of a monitor screen and were required to fixate at the central cross throughout each trial. They were also required to avoid any head movements such that the eye-to-monitor distance was fixed at 65 cm.

Each trial began with a white fixation cross at the center of a black screen for a duration randomly selected from 400/500/600 ms (Figure 1A, left). Then the task frame, which contained the picture(s) and label(s), was presented up to 3 s until the first mouse click or the 3 s-time limit was reached. Mouse click beyond this time limit was identified as a response omission for the current trial. After the task frame, a feedback frame was presented for 2 s. The feedback frame was the same as the task frame except that the correct picture or label was marked by a red box. The intertrial-interval was a blank screen of 800 ms. Participants were asked to respond as accurately and fast as possible.

For both experiments, there were 64 trials in each block. Each picture appeared as the target picture only once in each block. In each block, the 64 trials were presented in a pseudorandom order in the way that eight objects from four different viewpoints were followed by the same eight objects from four additional different viewpoints, rendering two miniblocks in each block and 12 miniblocks in total. This arrangement was chosen to investigate if the training on the first four viewpoints could be transferred to the untrained new viewpoints, particularly in Block 1 where all of the pictures were presented for the first time. Thus, each picture appeared as the target picture three times in total in each task. Within each miniblock, the distracting picture(s) or label(s) in each trial was randomly selected from other object pictures or labels. Each picture/label appeared as one of the distractors with equal probability. There was a 1 min break after each block, and a 3 min break between the two tasks. Prior to each task, six example trials were provided. In these example trials, the original picture (without simulation) of different objects (Clock, Shoe, Cherry, Headphone, Brush, and Blob) was presented, to prevent participants' exposure to the simulated pictures.

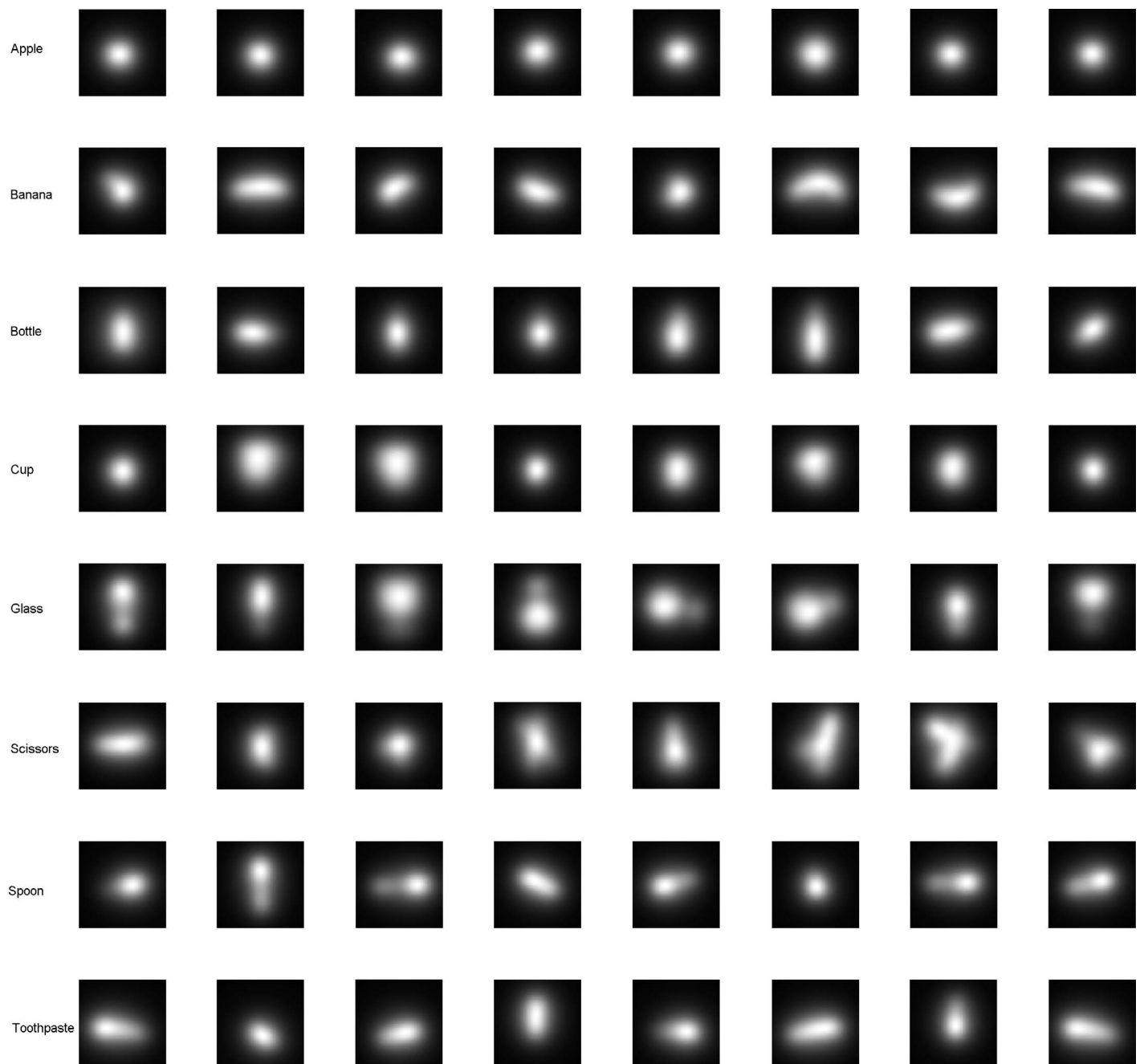


Figure 2. The eight simulated objects (by row) from eight viewpoints (by column) in both experiments. Note here each column does not indicate the same viewpoint for different objects.

Statistical analysis of data

For each participant, the accuracy was calculated as the percentage of trials with a correct response. To show the initial performance in recognizing the simulated pictures, the accuracy in Block 1 of the first task, where each of the simulated pictures was presented for the first time, was calculated for each object (Table 1). The initial accuracies for each of the eight objects were collapsed across the two tasks (to ensure statistical power given only eight pictures for each object in each task) and compared with the

theoretical chance-level (25% given the four-alternative-choice task) using a one-sample t test (one-sided).

In both Experiments 1A and 1B, a 2 (task: labelling vs. reverse labelling) \times 3 (block order: 1, 2, vs. 3) repeated-measures ANOVA was then conducted on the accuracy to show if there was improvement in object recognition from the first task to the second task, and if there was a training effect within each task.

To show the learning curve over the repetition of the pictures across two tasks, the accuracy was calculated

Experiment	Apple	Banana	Bottle	Cup	Glass	Scissors	Spoon	Toothpaste
Experiment 1A	82.0 (5.6)	39.8 (5.6)	38.3 (5.3)	43.8 (6.1)	31.3 (6.0)	48.4 (4.1)	46.1 (7.0)	34.4 (6.6)
Experiment 1B	70.3 (6.3)	42.2 (4.5)	34.4 (3.2)	43.8 (4.4)	45.3 (5.1)	45.3 (5.0)	46.9 (4.2)	43.8 (3.7)
Experiment 2A	89.1 (3.7)	61.7 (3.6)	53.9 (3.9)	69.5 (4.2)	51.7 (5.6)	63.3 (4.9)	68.0 (4.9)	61.7 (4.6)
Experiment 2B	80.2 (3.1)	64.7 (3.5)	61.0 (2.9)	59.6 (4.5)	63.2 (4.6)	69.1 (3.7)	75.7 (3.6)	72.8 (4.6)

Table 1. Mean accuracy with standard errors (%) in recognizing the eight objects for Block 1 in the labelling task (Experiments 1A and 2A) and reverse labelling task (Experiments 1B and 2B).

for each miniblock and shown as a function of the 12 miniblocks.

The accuracy for the last miniblock in the first task (sixth miniblock in total) and the accuracy for the first miniblock in the second task (seventh miniblock in total) were compared with a paired t test. If the accuracy was significantly lower in the seventh miniblock, the transfer hypothesis was rejected. Alternatively, transfer from the first task to the second task was inferred from one of two outcomes: (a) the accuracy in the seventh miniblock was higher than the accuracy in the sixth miniblock; (b) the accuracy in the seventh miniblock was equivalent to the accuracy in the sixth miniblock. Therefore, in case of a nonsignificant t test, we calculated a directional Bayes factor BF_{0-} (Rouder, Morey, Speckman, & Province, 2012; Wagenmakers et al., 2018a) using JASP (Wagenmakers et al., 2018b) to quantify the extent to which the null hypothesis was supported. The B_{0-} is the variant of Bayesian null hypothesis testing (often denoted as B_{01}) where the “-” sign denotes the direction of the alternative hypothesis, given a one-sided test; see Supplementary Figure S1 for an example of this type of BF analysis. Here, the BF_{0-} describes the relative probability of the data under the null hypothesis that the accuracy in miniblock seven was equal or higher than the accuracy in miniblock six, relative to the alternative hypothesis that the accuracy in miniblock seven was lower than in miniblock six. Per convention, a $BF > 3$ is taken as moderate evidence for the tested hypothesis (Wagenmakers et al., 2018b).

Moreover, the accuracy in the first miniblock in the first task (first miniblock in total) and the first miniblock in the second task (seventh miniblock in total) were also compared with a paired t test. A significant accuracy increase in this comparison was taken as an additional indicator of transfer from the first to the second task, in addition to an accuracy increase or a null effect between the sixth miniblock and the seventh miniblock. By contrast, no increase from the first miniblock to the seventh miniblock would speak against transfer. The accuracies for the two miniblocks within Block 1 were further compared using a paired t test, to show if the trained object recognition could be transferred to untrained viewpoints.

To investigate whether and to which extent the training effect persists after one week, a repeated measures ANOVA with posthoc comparisons was

conducted on the accuracies in the first training block, the last training block, and the posttest. Similar to the one-sided t tests on task transfer, the null hypothesis for the persistence was “the accuracy in the posttest was equal to or higher than the accuracy in the last training block” while the alternative hypothesis was “the accuracy in the posttest was lower than the accuracy in the last training block.” In case a nonsignificant p value was observed, B_{0-} was accordingly calculated to determine the extent to which the null hypothesis is reliable when a nonsignificant p value was observed.

Results

Initial performance in recognizing each object

As shown in Table 1, the initial performance, i.e., the accuracy for Block 1, in recognizing each of the eight objects was above the theoretical chance-level (25%), all $p < 0.008$ (one-sided, with Bonferroni corrections for the eight comparisons). The accuracy for the apple was higher than the accuracies for the other objects, probably due to the lower variation of appearance from different viewpoints (Figure 2).

Experiment 1A: Labelling followed by reverse labelling

The overall accuracy collapsed over the three blocks was $49.5\% \pm 3.2\%$ (mean \pm SD) in the labelling task, and was $60.5\% \pm 2.4\%$ in the reverse labelling task. The accuracies collapsed over the two tasks in each of the three blocks were $53.2\% \pm 2.9\%$, $54.3\% \pm 2.6\%$, and $57.7\% \pm 3.2\%$. The increase in accuracy from the labelling task to the reverse labelling task was confirmed by the main effect of task type according to the 2×3 ANOVA, $F(1, 15) = 27.55$, $p < 0.001$, $\eta^2 = 0.647$ (Figure 3A, upper). However, the main effect of block, $F(2, 30) = 2.34$, $p = 0.113$, and the interaction, $F(2, 30) = 2.45$, $p = 0.104$, did not reach significance. Although the main effect of block and the interaction were too weak to reach statistical significance, a separate ANOVA showed a main effect of block only for the labelling task, $F(2, 30) = 3.47$, $p = 0.044$, $\eta^2 = 0.188$, which was due to a linear increasing trend over blocks (45.5%, 49.6%, 53.4%), $F(1, 15) = 6.22$, $p = 0.025$, $\eta^2 = 0.293$, but not for the reverse labelling task, $F < 1$.

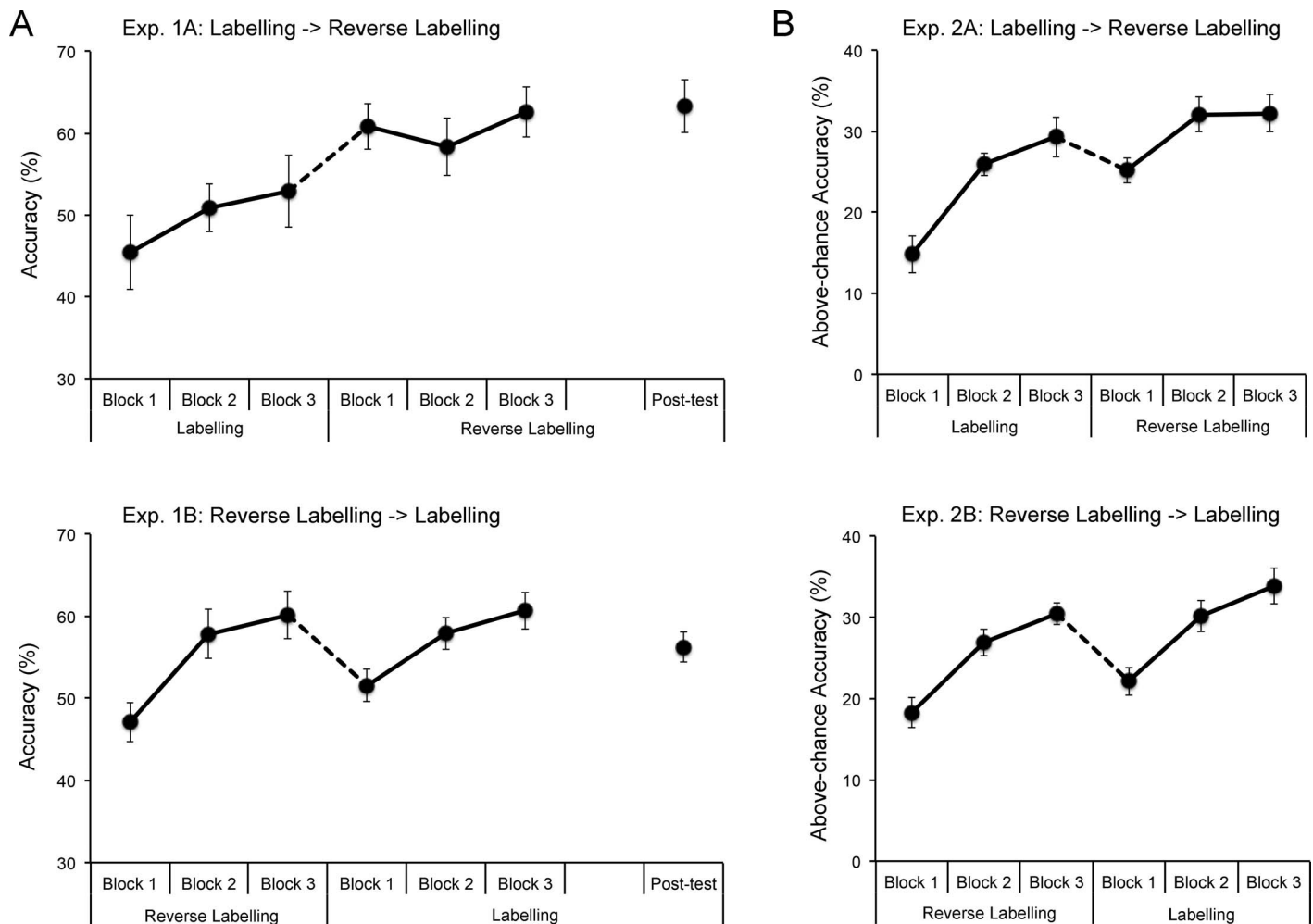


Figure 3. (A) Accuracies with standard errors are shown as a function of block order and task type in Experiment 1A (upper) and Experiment 1B (lower). For the posttest which was completed one week after the training, the task was the same as the second task during training. (B) Above-chance accuracies with standard errors are shown as a function of block order and task type in Experiment 2A (upper) and Experiment 2B (lower). The dashed line indicates a change in task type.

The accuracy did not drop from the sixth miniblock (53.3%) to the seventh miniblock (59.8%), $t(15) = 1.73$, $p = 0.948$ (one-sided). The BF analysis showed that $B_{0-} = 9.218$, indicating that the null hypothesis (“the accuracy in the seventh miniblock was equal to or higher than the accuracy in the sixth miniblock”) was 9.218 times more likely to be true than the alternative hypothesis (“the accuracy in the seventh miniblock was lower than the accuracy in the sixth miniblock”). Moreover, the accuracy in the seventh miniblock was higher than the accuracy in the first miniblock (42.8%), $t(15) = 3.65$, $p = 0.002$. These results indicated a transfer between the two tasks (Figure 4A, upper). There was also a transfer from trained viewpoints to untrained viewpoints, as shown by the increased accuracy from the first miniblock (42.8%) to the second miniblock of the labelling task (48.2%), $t(15) = 2.41$, $p = 0.029$.

For the persistency of the training effect, the ANOVA showed a significant main effect, $F(2, 26) = 18.31$, $p < 0.001$, $\eta^2 = 0.585$, with the accuracies in the last training block (62.6%) and the posttest (63.3%) both higher than the accuracy in the first training block (45.4%), $p = 0.003$ and $p < 0.001$, respectively (with Bonferroni corrections), whereas the accuracy in the last training block did not differ from the accuracy in the posttest, $p > 0.9$. The BF analysis comparing the accuracy in the training block and the accuracy in the posttest showed that $B_{0-} = 4.739$, indicating that the null hypothesis (“the accuracy in the posttest was equal to or higher than the accuracy in the last training block”) was 4.739 times more likely to be true than the alternative hypothesis (“the accuracy in the posttest was lower than the accuracy in the last training block”; Figure 3A, upper). These results suggested that the improved object recognition by training can last at least for a week.

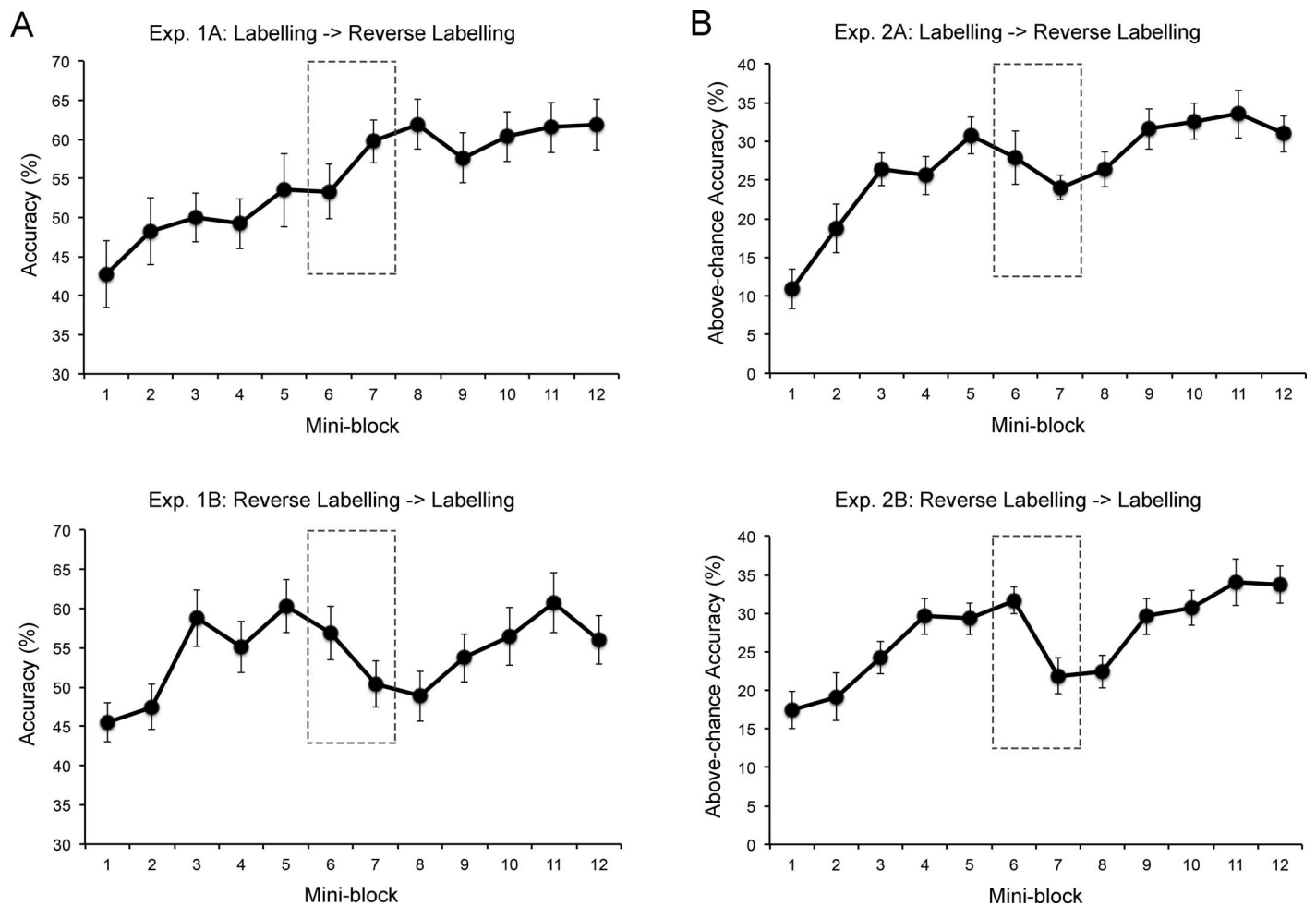


Figure 4. (A) Accuracies with standard errors are shown as a function of the 12 miniblocks in Experiment 1A (upper) and Experiment 1B (lower). (B) Above-chance accuracies with standard errors are shown as a function of the 12 miniblocks in Experiment 2A (upper) and Experiment 2B (lower). The dashed square indicates the above-chance accuracy/accuracy in the last miniblock of the first task, and that in the first miniblock of the second task, from which a transfer between tasks can be inferred.

Experiment 1B: Reverse labelling followed by labelling

The overall accuracy collapsed over the three blocks was $54.0\% \pm 2.6\%$ in the reverse labelling task, and was $54.4\% \pm 2.8\%$ in the labelling task. The accuracies collapsed over the two tasks in each of the three blocks were $48.0\% \pm 2.3\%$, $56.0\% \pm 2.8\%$, and $58.5\% \pm 3.0\%$. The overall accuracy in the reverse labelling task did not significantly differ from the overall accuracy in the labelling task, $F < 1$. However, there was a significant main effect of block, $F(2, 30) = 28.33$, $p < 0.001$, $\eta^2 = 0.654$, indicating increased accuracy from Block 1 (48.0%) to Block 2 (56.0%), and from Block 2 to Block 3 (58.5%), both $p < 0.001$ (with Bonferroni correction; Figure 3A, lower). The interaction between task and block did not reach significance, $F(2, 30) = 2.40$, $p = 0.108$.

The paired t test showed a drop in accuracy from the sixth miniblock (56.8%) to seventh miniblock (50.4%), $t(15) = 2.11$, $p = 0.026$ (one-sided). Moreover, the

difference in accuracy between the first miniblock (45.5%) and the seventh miniblock was not reliable, $t(15) = 1.86$, $p = 0.083$ (Figure 4A, lower). The drop of performance to the initial level of the training session suggested that the improved performance in the labelling task was not transferred to the reverse labelling task. In addition, there was no difference in accuracy between the two miniblocks within Block 1, $t < 1$, suggesting the lack of transfer from trained viewpoints to untrained viewpoints.

For the persistence of the training effect, the ANOVA showed a significant main effect, $F(2, 26) = 15.96$, $p < 0.001$, $\eta^2 = 0.551$, with the accuracies in the last training block (60.7%) and the posttest (56.3%) both higher than the accuracy in the first training block (47.1%), $p < 0.001$ and $p = 0.015$, respectively (with Bonferroni corrections) whereas the accuracy difference between the last training block and the posttest did not reach significance, $p = 0.127$. The BF analysis showed that $B_{0-} = 0.288$, which equals to $B_{-0} = 3.469$,

indicating that the alternative hypothesis (“the accuracy in the posttest was lower than the accuracy in the last training block”) was 3.469 times more likely to be true than the null hypothesis (“the accuracy in the posttest was equal to or higher than the accuracy in the last training block”; Figure 3A, lower). These results suggested a reduction of recognition performance after one week, but not to the initial pretraining level.

Experiment 2

We have shown in Experiment 1 that the object recognition in simulated RI vision can be trained and can transfer from the labelling task to the reverse labelling task. In Experiment 2, we further investigated whether including easy trials could boost the learning process, as shown in previous studies (Ahissar & Hochstein, 1997; Maertens & Pollmann, 2005; Rubin et al., 1997). For this purpose, in contrast to the four-alternative-choices task throughout the training session in Experiment 1, we manipulated the task difficulty in Experiment 2 by varying the number of the alternative choices in each task.

Methods

Participants

Another 33 healthy students who had never been exposed to the simulated pictures participated in Experiment 2, with 16 of them (eight females, age: 18–31 years old) randomly assigned to Experiment 2A, and the other 17 (12 females, age: 18–26 years old) assigned to Experiment 2B. All participants had normal or corrected-to-normal vision, and all of them were German native speakers. This experiment was conducted in accordance with the Declaration of Helsinki and was approved by the local ethics review board. Written informed consent form was obtained from each of the participants prior to the experiment.

Stimuli and design

Stimuli and design in Experiment 2 were the same as in Experiment 1 except that each task had an increasing difficulty over three consecutive blocks. Specifically, there were two alternative choices in Block 1, four in Block 2, and six in Block 3 (Figure 1B). The time limit for accepting response was 2 s when there were two alternative choices (Block 1), 3 s when there were four alternative choices (Block 2) and 4 s when there were six alternative choices (Block 3).

Statistical analysis of data

Similar statistical analysis was conducted in Experiment 2 except the following exceptions.

To accommodate to the different levels of difficulty in different blocks, the theoretical chance-level accuracy (50% in Block 1, 25% in Block 2, and 16.7% in Block 3) was subtracted from the raw accuracy, rendering the above-chance accuracy (ACA) in each block. The analyses concerning the comparisons across different blocks in Experiment 2 were thus conducted on the ACAs rather than the raw accuracies.

To verify the results based on the ACAs, we also calculated Z scores, which normalized the accuracy by taking into account the probability density of the accuracy. In each block/miniblock, the Z score of a binomial distribution was calculated with the equation

$$z = \frac{X - np}{\sqrt{np(1 - p)}},$$

where X was the amount of correct responses in each block/miniblock, n was the amount of trials in each block/miniblock, and p was the theoretical chance-level accuracy (1/2 in Block one, 1/4 in Block two and 1/6 in Block three) in each block/miniblock. The analyses concerning the comparisons across different blocks in Experiment 2 were also conducted on the Z scores.

Results

Initial performance in recognizing each object

As in Experiment 1, the initial accuracies (Table 1) in recognizing the objects were all above the theoretical chance-level (50%), $p < 0.016$, except the accuracy for the glass, $t(32) = 2.10$, $p = 0.176$ (one-sided, with Bonferroni corrections for the eight comparisons).

Experiment 2A: Labelling followed by reverse labelling

The overall ACA collapsed over the three blocks was $23.4\% \pm 1.3\%$ in the labelling task, and was $29.9\% \pm 1.6\%$ in the reverse labelling task. The ACAs collapsed over the two tasks in the three blocks were $20.0\% \pm 1.2\%$, $29.1\% \pm 1.4\%$, and $30.8\% \pm 2.1\%$. The 2×3 ANOVA showed a main effect of task, $F(1, 15) = 23.68$, $p < 0.001$, $\eta^2 = 0.612$, indicating higher ACA in the reverse labelling task than in the labelling task, and a main effect of block, $F(2, 30) = 20.83$, $p < 0.001$, $\eta^2 = 0.581$. This main effect was due to increasing accuracy over the three blocks, as revealed by a linear trend, $F(1, 15) = 23.39$, $p < 0.001$, $\eta^2 = 0.609$ (Figure 3B, upper). However, the interaction between task and block order was not significant, $F(2, 30) = 2.52$, $p = 0.097$, $\eta^2 = 0.144$. The 2×3 ANOVA on the Z scores showed the same pattern. There was a significant main effect of task, $F(1, 15) = 22.5$, $p < 0.001$, $\eta^2 = 0.600$, indicating

better performance in the reverse labelling task ($Z = 5.63$) than in the labelling task ($Z = 4.49$). The main effect of block was also significant, $F(1, 15) = 45.38$, $p < 0.001$, $\eta^2 = 0.752$ (Block one: $Z = 3.20$, Block two: $Z = 5.37$, Block three: $Z = 6.61$). The interaction was not significant, $F(2, 30) = 1.50$, $p = 0.239$, $\eta^2 = 0.091$.

A paired t test yielded no evidence that the ACA for the last miniblock of the labelling task (sixth miniblock in total, 27.9%) was higher than the ACA for the first miniblock of the reverse labelling task (seventh miniblock in total, 24.0%), $t(15) = 1.20$, $p = 0.124$ (one-sided). The BF analysis showed that $B_{0-} = 1.231$, indicating that the null hypothesis (“the ACA in the seventh miniblock was equal to or higher than the ACA in the sixth miniblock”) was 1.231 times more likely to be true than the alternative hypothesis (“the ACA in the seventh miniblock was lower than the ACA in the sixth miniblock”). The B_{0-} here may not be taken as strong evidence (e.g., > 3) to accept either the null hypothesis or the alternative hypothesis. However, the ACA in the seventh miniblock was higher than the ACA in the first miniblock (10.9%), $t(15) = 3.92$, $p = 0.001$ (Figure 4B, upper). The analysis on the Z scores showed a decrease in Z score from the sixth miniblock ($Z = 4.23$) to the seventh miniblock ($Z = 2.72$), $t(15) = 3.14$, $p = 0.003$ (one-sided), whereas the Z score in the seventh miniblock was still higher than the Z score in the first miniblock ($Z = 1.24$), $t(15) = 3.92$, $p = 0.001$. These results indicated that the improved object recognition in the labelling task to some extent, if not fully, transferred to the reverse labelling task.

Moreover, the paired t test on the ACAs within Block 1 showed that the ACAs for the second miniblock (18.8%) was higher than the ACAs for the first miniblock (10.9%), $t(15) = 2.32$, $p = 0.035$, suggesting that the object recognition of the trained viewpoints transferred to untrained, new viewpoints.

Experiment 2B: Reverse labelling followed by labelling

The overall ACA collapsed over the three blocks was $25.2\% \pm 1.2\%$ in the reverse labelling task, and was $28.7\% \pm 1.4\%$ in the labelling task. The ACAs collapsed over the two tasks in the three blocks were $20.2\% \pm 1.2\%$, $28.5\% \pm 1.2\%$, and $32.2\% \pm 1.5\%$. The 2×3 ANOVA showed a main effect of task, $F(1,16) = 4.85$, $p = 0.043$, $\eta^2 = 0.233$, indicating higher ACA in the labelling task than in the reverse labelling task, and a main effect of block order, $F(2, 32) = 36.04$, $p < 0.001$, $\eta^2 = 0.693$. This main effect was due to increasing accuracy over the three blocks, as shown by a linear trend, $F(1, 16) = 47.39$, $p < 0.001$, $\eta^2 = 0.748$ (Figure 3B, lower). However, the interaction between task and block order did not reach significance, $F < 1$. The 2×3 ANOVA on the Z scores showed the same pattern. There was a significant main effect of task, $F(1, 16) =$

4.79 , $p = 0.044$, $\eta^2 = 0.230$, indicating better performance in the labelling task ($Z = 5.46$) than in the reverse labelling task ($Z = 4.82$), a main effect of block order, $F(2, 32) = 88.12$, $p < 0.001$, $\eta^2 = 0.846$ (Block one: $Z = 3.24$, Block two: $Z = 5.27$, Block three: $Z = 6.91$), but no interaction, $F < 1$.

There was a drop of ACA from the sixth miniblock (31.7%) to the seventh miniblock (21.9%), $t(16) = 3.55$, $p = 0.001$ (one-sided). Moreover, the ACA in the first miniblock (17.5%) did not differ from the ACA in the seventh miniblock (21.9%), $t(16) = 1.22$, $p = 0.241$ (Figure 4B, lower). The paired t test showed a decrease in Z score from the sixth miniblock ($Z = 4.81$) to seventh miniblock ($Z = 2.47$), $t(16) = 6.57$, $p < 0.001$ (one-sided), while the Z score in the seventh miniblock did not differ from the Z score in the first miniblock ($Z = 1.98$), $t(16) = 1.22$, $p = 0.241$ (Figure 4B, lower). The drop of performance to the initial level of the training session indicated the absence of the transfer from the reverse labelling task to the labelling task.

The transfer from trained viewpoints to untrained viewpoints was also absent, as revealed by the null effect between the first two miniblocks of the reverse labelling task (17.5% vs. 19.1%), $t < 1$.

Comparisons across the four experiments

The above analysis showed consistent different patterns of training effect when the labelling task was followed by the reverse labelling task (Experiments 1A and 2A) and when the task order was reversed (Experiments 1B and 2B), irrespective of whether the alternative choices increased over the three blocks (Experiment 1 vs. 2). To investigate whether the different patterns were due to different choice difficulties of the four experiments, we conducted a 2 (task type: labelling vs. reverse labelling) \times 2 (choice difficulty: 2 alternative choices vs. 4 alternative choices) ANOVA on the ACAs in the first miniblock. Only the ACAs in the first miniblock were included in the analysis in order to avoid any contamination from the improvement by training. As a result, neither the two main effects nor the interaction between the task type and choice difficulty reached significance, all $p > 0.1$, suggesting comparable starting capabilities in recognizing the simulated pictures regardless of the task type (labelling vs. reverse labelling), and regardless of the alternative choices (2 vs. 4). As such, the observed different patterns cannot be reduced to be a by-product of the different tasks or different number of alternative choices.

To reveal which training procedure produced the best improvement in object recognition, we calculated the improvement by subtracting the ACAs in the first miniblock from the ACAs in the last miniblock, and conducted a 2 (task order: labelling followed by reverse

labelling vs. reverse labelling followed by labelling) \times 2 (choice difficulty: increasing alternative choices from 2 to 6 vs. constant 4-alternative choices) ANOVA on the ACAs difference. The results showed a trend of task order, $F(1, 61) = 3.54$, $p = 0.065$, $\eta^2 = 0.054$, whereas the main effect of choice difficulty, $F(1, 61) = 1.00$, $p = 0.321$, and the interaction, $F < 1$, were not significant. These results suggested a better overall improvement with the training procedure where the labelling task was followed by the reverse labelling task than the reverse order (18.2% vs. 14.8% in ACA). However, including easy trials at the beginning of the training did not lead to better improvement than when the task difficulty was controlled.

Discussion

In the present study, we simulated RI vision and investigated if object recognition in RI patients can be improved and maintained through training. Our results from two different tasks consistently showed improved recognition performance over two repetitions of the object pictures in both tasks, and the recognition performance persisted at least for a week. These results accord well with the literature on object perceptual learning (Bi & Fang, 2013; Fine & Jacobs, 2002) and provide important new evidence that the visual abilities of RI patients can be strengthened and maintained. Notably, the overall improvement (18.4% when the labelling task was followed by the reverse labelling task) of familiar object recognition in RI vision through such a short period of training was already comparable to the improvement (around 20%) that healthy adults achieved over 5 days of training (Furmanski & Engel, 2000).

An important issue we focused in the present study was the generalization of the training effect. In particular, we investigated the transfer of object recognition to different task contexts, and to new viewpoints of the trained objects. As a result, we found that the improved recognition performance in the labelling task persisted in the following reverse labelling task, suggesting true object recognition, independent of task demands. Specifically, performance in the first miniblock of the reverse labelling task was higher than in the first miniblock of the labelling task in Experiments 1A and 2A. In addition, performance in the first miniblock of the reverse labelling task was not lower than in the last block of the labelling task, though this finding in Experiment 2A ($B_{0-} = 1.231$) was not as conclusive as in Experiment 1A. By contrast, the recognition performance improved by the reverse labelling task dropped in the following labelling task to the level of the first miniblock of the reverse labelling

task in both experiments, suggesting a lesser extent, if not the absence, of task transfer. In addition, the improved object recognition transferred to the untrained viewpoints of the trained objects in the labelling task but not in the reverse labelling task. One plausible explanation might be that the labelling task was easier than the reverse labelling task, thereby producing larger transfer (Ahissar & Hochstein, 1997). This account, however, can be ruled out because the initial performance in both tasks was comparable, and the transfer patterns were consistent in both experiments regardless of task difficulty.

It has been suggested that task-independent plasticity reflects the changed representation of a feature or object in the visual cortex, in contrast to task-dependent plasticity that is associated with changes in the mechanism specific for the trained task, such as the attentional system (Watanabe & Sasaki, 2015). Previous perceptual learning studies with healthy adults do not always show task-independent plasticity, as there were failures in transferring the trained perceptual performance to a different task (Huang, Lu, Tjan, Zhou, & Liu, 2007; Westheimer, Crist, Gorski, & Gilbert, 2001). For example, Huang and colleagues (2007) trained one group of healthy adults to detect a coherent motion signal (detection task) and the other group to discriminate the direction of the coherent motion signal (discrimination task). They found that the group trained with the detection task showed improvement in only detecting but not in discriminating the motion signal, whereas the group trained with the reverse labelling task showed improvement in both tasks. The asymmetry was explained as a result of task-relevancy in the way that detecting motion signal was necessary for discriminating the particular direction whereas the precise direction was unnecessary for detection and could be actively inhibited (Huang et al., 2007; Tsushima, Sasaki, & Watanabe, 2006). This finding suggested that the transfer of perceptual learning was dependent on the top-down attentional set in the training task. From this perspective, although there were improved performances in both tasks in the present study, the improvement in the labelling task may be contributed mainly by the change in representations of the trained objects, whereas the improvement in the reverse labelling task may be due to the processing strategy at hand.

It is well established that top-down information, such as task context, plays a critical role in object recognition (Bar, 2004; Trapp & Bar, 2015). Different task contexts engage different processing strategies, which in turn recruit distinct neural substrates to construct object representations in the brain (Op de Beeck & Becker 2010; Song et al., 2010; Wong, Palmeri, & Gauthier, 2009; Wong, Palmeri, Rogers, Gore, & Gauthier, 2009). Two processing strategies in object

recognition have been documented: a holistic processing strategy which treat the object as an undifferentiated representation, and a parts-based processing strategy which decompose the object into parts and the relations among parts (Farah, 1990). The holistic strategy was found to be dominant in an associative learning task of object recognition where subjects were trained to construct associations between the presented novel object and a particular word, whereas the part-based strategy was dominant in a discrimination learning task where subjects were trained to choose a target object out of other distracting objects (Song et al., 2010).

The labelling task and the reverse labelling task in the present study were similar to the associative learning task and the discrimination task in Song et al. (2010), respectively. Specifically in the labelling task, one object was learned in each trial by the association between the object and the label. By contrast in the reverse labelling task, the differences of multiple objects were learned in each trial. Accordingly, a holistic strategy was supposed to be engaged in the labelling task whereas a parts-based strategy was supposed to be engaged in the reverse labelling task, which in turn should have caused changes in the corresponding representation areas in the brain. However, unlike the unambiguous sensory inputs of the objects in the previous studies (Song et al., 2010; Wong, Palmeri, Rogers, et al., 2009b), the coarse sensory inputs of the object in the present study limited the parts-based processing and may encourage a holistic strategy in both tasks instead (Trapp & Bar, 2015). Therefore, only the labelling task, but not the reverse labelling task, could benefit from the processing strategy and caused representation changes in the brain so as to produce transfer across tasks and viewpoints.

Previous studies showed that RI patients have very limited capability of discriminating low-level features, and the discrimination on low-level features can be improved only after extensive training over months or years (Castaldi et al., 2016; Dorn et al., 2013; Ho et al., 2015). For instance, the RP patients showed comparable chance-level accuracies in motion discrimination before and after the implantation (Castaldi et al., 2016). Another study reported that the improvement in motion discrimination emerged after one year experience with the RI system (Ho et al., 2015). By contrast, the high-level vision such as recognizing letters or daily objects was regained without a training period (Zrenner et al., 2011; but see Beyeler et al., 2017b for a review on the low- vs. high-level vision of RI patients). Similarly in the present study, the initial performance in recognizing the objects was already above chance-level, and can be improved by ~18.4% through a short period of training. Our results of simulated high-level object recognition were consistent with the results from

RI patients, suggesting that the high-level vision of RI patients can be gained and significantly improved without the improvement in low-level vision. Top-down processing, such as the holistic strategy in object recognition, may play a critical role in training the high-level vision of RI patients, and should be taken into account for developing the training regimen for the patients.

In summary, we recommend the labelling task as the training regime for RI patients to achieve persistent and flexible object recognition for the following four reasons: (a) the labelling task produces higher overall improvement than the reverse labelling task in object recognition given the same amount of trainings; (b) the improvement in object recognition through the labelling task can be generalized to discriminate different objects (i.e., the reverse labelling task); (c) the improvement in object recognition through the labelling task can be generalized to new viewpoints of the trained objects; and (d) the improved object recognition through the labelling task fully persisted after one week. Our findings not only provide insights to the development of training protocols for RI patients, but also can help patients and their families to evaluate the expected effects before making the decision for or against implantation.

Keywords: retinal implants, perceptual learning, object recognition, simulated prosthetic vision

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