Transfer of object learning across distinct visual learning paradigms

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Perception of visual stimuli improves with experience. For objects, learning is specific for the stimuli used during training. This is shown in perceptual learning paradigms in which visual perception is challenged by degrading the stimuli, e.g. by backward masking or adding simultaneous noise. We present the first study designed to investigate whether visual object learning is specific to the type of stimulus degradation used. Sixteen participants were trained to recognize common objects. Half of them was trained in a backward masking paradigm, the other half in a simultaneous noise addition paradigm. After five days, performance was measured in four tests: (1) the trained paradigm with the trained objects, (2) the trained paradigm with new objects, (3) the untrained paradigm with the trained objects and (4) the untrained paradigm with new objects. Training effects were specific for the trained objects. In addition, an object-specific transfer to the untrained paradigm was found. The group trained in the simultaneous noise addition paradigm showed a complete transfer of performance to the backward masking task. The transfer was only partial when reversed. This pattern of results indicates that both general processes and processes specific for the type of stimulus degradation are involved in perceptual learning.

Keywords: learning, object recognition, masking, simultaneous noise addition, specificity


Introduction

Performance in a wide range of perceptual tasks improves as a result of extensive exposure or training (Fine & Jacobs, 2002; Goldstone, 1998). When trained with a limited set of stimuli, detection, discrimination and identification show increased accuracy, particularly when the stimuli are hard to perceive or discriminate to begin with. These changes are long-lasting (Karni & Sagi, 1993; Schoups, Vogels, & Orban, 1995).

Unlike cognitive learning, perceptual learning is often remarkably specific for the exact trained stimulus and task attributes, with little or no transfer to untrained conditions. With stimuli varying on simple dimensions such as oriented gratings, specificity has been found for a range of stimulus attributes: orientation (e.g., Fiorentini & Berardi, 1981; Schoups et al., 1995), visual field location (e.g., Crist, Kadia, Westheimer, & Gilbert, 1997; Fahle, 2004; Karni & Sagi, 1991; Shiu & Pashler, 1992), direction of movement (e.g., Ball & Sekuler, 1982, 1987), spatial frequency (e.g., Fiorentini & Berardi, 1981; Yu, Klein, & Levi, 2004), hyperacuity (Poggio, Fahle, & Edelman, 1992), contrast (Yu et al., 2004) and primitive shape (Sigman & Gilbert, 2000).

Next to simple stimuli, a few studies looked at the specificity of perceptual learning of complex objects (e.g., Furmanski & Engel, 2000; Grill-Spector, Kushnir, Hendler, & Malach, 2000; McCarley, Kramer, Wickens, Vidoni, & Boot, 2004). These studies also reported a learning specificity for the trained objects, but this specificity was most often only partial. In addition, generalization of perceptual learning is found for some aspects of the complex objects. Furmanski and Engel (2000) found that after training, learning did transfer across changes in the size of the presented object.

Perceptual learning phenomena have been interpreted at a more abstract level, in terms of an enhanced signal-to-noise ratio (SNR) in a signal detection framework. Different theories assume the enhanced SNR is the consequence of either decreasing the internal noise (McLaren, Kaye, & Mackintosh, 1989), enhancing the signal (Gold, Bennett, & Sekuler, 1999) or a combination of both (Dosher & Lu, 1998).

A common feature of the previous studies is that each study applied one specific perceptual learning paradigm. In general, such a paradigm involves a manipulation to make the task hard for subjects by degrading the relevant stimulus differences. This degradation can be done in several ways: making the relevant stimulus differences very small (e.g., Schoups et al., 1995); adding simultaneous noise to the stimulus (e.g., Gold et al., 1999; Rainer & Miller, 2000); or restricting the time that the stimulus is...
visible by presenting it very shortly followed by a masking pattern (backward masking, e.g., Furmanski & Engel, 2000; Op de Beeck, Wagemans, & Vogels, 2007). A few studies have manipulated aspects of the noise used to degrade the stimuli (Dosher & Lu, 2005; Lu, Chu, & Dosher, 2006; Petrov, Dosher, & Lu, 2005), but this occurred within one type of degradation. But no study has ever considered the possibility that effects might be specific for the exact type of stimulus degradation that is used.

However, as suggested by Op de Beeck et al. (2007), different paradigms might pose other challenges to the visual processing system. The difficulty in a backward masking paradigm is related to temporal speed: the relevant signal needs to be processed in the very small time window the stimulus is presented, since after presentation of the mask no relevant information is left on the screen. In contrast, temporal speed is less a factor in the simultaneous noise addition paradigm.

Thus, it is possible that perceptual learning in these different paradigms is based on different, paradigm-specific processes to optimize the processing of relevant information, thereby improving performance. The aforementioned signal detection models do not make any predictions about transfer across paradigms, because they ignore the possible existence of these paradigm-specific processes. If a prediction would be made from these models, it would be related to the implicit assumption that it is warranted to make an abstraction of paradigm-specific processes. If this is true, then one would predict a complete transfer of learning effects across paradigms. However, as far as paradigm-specific processes are involved in perceptual learning, we expect no transfer or only a partial transfer of learning effects across paradigms.

The present study was designed to investigate whether a transfer of performance occurs between distinct visual learning paradigms. Participants were trained to recognize common objects in either a backward masking paradigm or a simultaneous noise addition paradigm. After training, performance was measured in four tests: (1) the trained paradigm with the trained stimulus set, (2) the trained paradigm with a new stimulus set, (3) the untrained paradigm with the trained stimuli and (4) the untrained paradigm with new stimuli.

Based on the aforementioned previous research, we expected an object-specific improvement of performance during training. This means that when participants are tested with a stimulus set other than the trained one, performance will decrease in comparison to performance on a test with the trained stimulus set. Regarding performance on the last day in the untrained paradigm, two alternatives are possible, dependent on the kind of learning processes involved. If no paradigm-specific processes are involved, performance on both tests with the trained stimulus set would be the same for all participants, regardless of the paradigm they were trained in. In case performance in a particular paradigm is based on specific learning processes, we expected only a partial or no transfer to the untrained paradigm.

The results showed a general learning effect, which was specific for the trained stimulus set. When trained in the simultaneous noise addition paradigm, participants showed a complete transfer of performance to the backward masking paradigm. The other group of participants showed only a partial transfer when tested in the simultaneous noise addition paradigm. This pattern of results indicates that in addition to general learning processes, processes specific to a particular paradigm might be involved in the learning process.

### Method

#### Participants

Sixteen students of the Catholic University of Leuven (K.U. Leuven) with normal or corrected-to-normal vision participated in this study as paid volunteers (ages between 19 and 22 years, two males). All participants were naïve with respect to both paradigms. The experiments were approved by the ethical committee of the Faculty of Psychology and Educational Sciences (K.U. Leuven) and participants signed an informed consent at the start of the first session.

#### Apparatus

Stimuli were presented with a Toshiba laptop running Windows XP on a 85 Hz 17 inch screen using the Psychophysics toolbox (Brainard, 1997) for MATLAB (Mathworks, Inc.). The screen was gamma-corrected. Viewing distance was approximately 50 cm. The room was darkened.

#### Stimuli

Two stimulus sets comprising 20 pictures of common objects were used in the experiment. Objects were initially assigned randomly to the two sets, but a few objects were shifted in order to equate difficulty of the two sets as much as possible (based on the performance of the two authors in the two learning paradigms). The pictures were adjusted to 450 by 450 pixels (approximately 17 visual degrees) and converted to grayscale. The contrast of the grayscale stimuli was reduced to 62.5% of the original contrast. The stimuli were equalized for the Fourier amplitude spectrum (Figure 1).

Forty noise images were created with the same average Fourier amplitude spectrum, but a random phase spectrum, and randomly assigned to two noise stimulus sets.
The noise images were used as masking patterns as well as for adding noise to the object images by morphing linearly between objects and noise images (Figure 1). We used this method because we wanted to use noise and masking patterns that were as similar as possible in the two tasks. Backward masking studies typically use structured patterns as masks, but structured patterns would not be appropriate as noise patterns in the simultaneous noise patterns. Studies applying simultaneous noise typically use white noise, but white noise would not properly mask the object images. So we decided to use noise/masking patterns with a Fourier amplitude spectrum that is unstructured (so very useful for simultaneous noise) and matched to the spectrum of the object images (so better at masking these images). The screen background luminance on which the stimuli were presented was set at the mean luminance of the object images.

Learning paradigms

Backward masking paradigm: In each trial, first a fixation cross was presented. Then the stimulus was shown for a variable time. Stimuli were presented at slightly different locations with a maximum deviation of 1.8° from the center of the screen. Two interleaved two-down, one-up staircase procedures were used to determine the exposure duration. Starting value was 118 ms and the size of each step was approximately 12 ms (step size of 1 frame at an 85 Hz refresh rate). A noise image was presented as a mask for 250 ms immediately after the stimulus, to prevent further visual processing. To increase task difficulty and avoid ceiling effects, the contrast of the object images was further reduced by 80%. The order of both stimuli and masks were randomized independently. Participants responded by typing the first three letters of the object name. After each response feedback was provided for 500 ms: the participants received a ‘true’ or ‘false’ message on the screen. In case of an error, the correct object name was also presented.

Simultaneous noise addition paradigm: In each trial, first a fixation cross was presented for 400 ms. Then a morph image between object and noise was shown for 118 ms around the center (maximum deviation of 1.8°). No masking pattern was shown in this paradigm. Morphs were created on a trial-by-trial basis and consisted of a pixel-wise linear combination of a randomly chosen object and noise image. The regulation of the difficulty level of the trial (percentage of the object image presented), the response and the feedback were arranged in the same way as during the backward masking paradigm. During the first trial the morph image was composed of 40% of the object image and 60% of the noise image. Step size was 4%.

Procedure

Half of the participants were trained on the backward masking paradigm, the other half on the simultaneous noise addition paradigm. Within each paradigm an equal amount of participants was trained with stimulus set 1 and with stimulus set 2. Training lasted for five days. Each training session started with a preview of the used stimulus set. Stimuli were presented for 2 s along with the name of the object. Each session comprised eight blocks of 80 stimuli (two staircases of 40 trials each), 640 trials in total. Daily sessions lasted approximately 1 h.

On the last day of the experiment we measured participants’ thresholds on all four combinations of paradigms (backward masking and simultaneous noise addition) and stimulus sets (trained and new set). First a preview of both stimulus sets was presented. The order of the four tests was counterbalanced across participants. This series of four tests was repeated twice. Each test contained one block of 80 stimuli (two staircases of 40 trials each). Before the start of each block, participants received information on which paradigm and stimulus set they would be tested on.
Data analysis

Individual performance thresholds were estimated for each training day and each test at the last day of the experiment. Thresholds were defined as the exposure duration or the percentage of the object image present in the morph image at which a 70.7% correct performance was obtained. Individual data were pooled together for each training day and each test. The primary analyses are based on the average endpoints at the end of the staircases. Due to the use of the adaptive staircase method, trials at the end of a block will approximate the exposure duration and the percentage of the object image present in the morph image at which a 70.7% correct performance is reached (Levitt, 1971). For each day and test, the values of the exposure duration or the percentage of the object image on the last trial of each staircase were averaged. Estimates are presented in Figures 2 and 3.

In addition, we verified whether similar findings were obtained after fitting a psychometric function to all trials of the staircases. Using the Psignifit Software Package implemented in MATLAB (Wichmann & Hill, 2001), psychometric functions were fitted to the data by plotting the average percentage correct as a function of exposure duration or percentage of the object image. Three commonly used sigmoid functions, the Weibull, logistic and cumulative Gaussian distribution function, were used. Goodness of fit was calculated with the Deviance statistic. This statistic was compared against sampling distributions created by 2000 Monte Carlo simulations. The fit was evaluated on the basis of the cumulative probability estimate (criteria: $p < 0.95$). Using this criterion, the percentages of data where no good fit was reached were compared for the different distribution functions used previously. This resulted in a removal of 5.6%, 6.3% and 11.8% of the data for respectively the cumulative Gaussian, the logistic and the Weibull function. Further analyses were done using the threshold estimates based on the fits with the cumulative Gaussian distribution. Estimates are graphically presented in Appendix A.

Statistical Analysis System (SAS) and Statistical Package for the Social Sciences (SPSS) software were used to analyze the results. Results obtained with both threshold estimates were very similar. Using alpha-level 0.05 as the threshold of significance, all reported effects significant with one method were also significant with the other method. Statistical significance levels reported are obtained by using the performance thresholds estimated with the endpoints method.

Results

Training effect

The thresholds for both paradigms showed a gradual decline, i.e. task performance gradually improved (Figures 2 and 3). Performance thresholds improved from 67 ms ($SEM = 5$ ms) exposure duration to 49 ms ($SEM = 4$ ms) in the backward masking paradigm and from 37.6% ($SEM = 0.5$%) of the object image to 30.1% ($SEM = 0.8$%) for the simultaneous noise addition paradigm. In both paradigms, the main effect of the sessions was highly significant.
(backward masking paradigm: $F(5,35) = 10.815, p < 0.001$; simultaneous noise addition paradigm: $F(5,35) = 23.507, p < 0.001$, repeated measures ANOVA).

When looking at the beginning of the training, a significant difference in performance between the first and the second training day was found for both the backward masking paradigm ($t(7) = 3.283, p = 0.013$, paired $t$-test) and the simultaneous noise addition paradigm ($t(7) = 4.839, p = 0.002$, paired $t$-test). As can be noticed in Figures 2 and 3, perceptual learning did not stop after the first two sessions, but persisted throughout at least part of the rest of the training. Both groups of participants showed a significant learning effect between the second and the fifth day of training (backward masking paradigm: $t(7) = 2.480, p = 0.042$; simultaneous noise addition paradigm: $t(7) = 3.502, p = 0.010$, paired $t$-tests).

**Object specificity**

We investigated whether the learning effect did generalize to the new stimulus set or whether it was specific to the trained set. We compared the performance at the test with the new stimuli with the performance on the trained set during the first day of training and during the test at the last day. For the backward masking paradigm, performance on the last day was better for the trained (49 ms, $SEM = 4$ ms) than for the new (60 ms, $SEM = 4$ ms) stimuli ($t(7) = 3.444, p = 0.011$, paired $t$-test, Figure 2). The difference between the first day (67 ms, $SEM = 5$ ms) and the test on the last day with the new stimulus set did not reach significance ($t(7) = 1.374$, ns, paired $t$-test). The same pattern was found for the simultaneous noise addition paradigm: a significant decrease in performance on the last day was found when comparing the new (38.4%, $SEM = 0.9\%$) to the trained (30.1%, $SEM = 0.8\%$) stimulus set ($t(7) = 5.555, p = 0.001$, paired $t$-test, Figure 3), while the difference between the first day (37.6%, $SEM = 0.5\%$) and the test on the last day with the new stimuli was not significant ($t(7) = 0.638$, ns, paired $t$-test). Thus, in both paradigms, improvement was specific for the trained objects without any generalization occurring.

**Transfer to the untrained paradigm**

The hypotheses tested in this experiment made specific predictions about the transfer of training effects to the untrained paradigm. The results show that at least part of the object-specific training effect as described for the trained paradigm transferred to the untrained paradigm. For the group trained in the simultaneous noise addition paradigm, the performance on the test in the backward masking paradigm was significantly better for the trained stimuli (46 ms, $SEM = 1$ ms) than for the untrained stimuli (61 ms, $SEM = 2$ ms) ($t(7) = 5.602, p = 0.001$, paired $t$-test). The same result applied to the performance from the other group (trained in the backward masking paradigm) on the simultaneous noise addition paradigm tests on the last day (34.6% ($SEM = 1.2\%$) for the trained stimuli and 38.8% ($SEM = 1.4\%$) for the untrained stimuli, $t(7) = 2.480, p = 0.042$, paired $t$-test).

Thus, considering the stimulus specificity in the untrained paradigm, at least part of the learning effect transferred when participants were tested with the new paradigm. However, these results do not determine whether this transfer was complete. To look further into this transfer, performance of the trained and untrained group (between-subject comparison) was compared. First we assessed Levene’s test of equality of error variances to check if the assumption of equal variances between groups was not violated. For performance in the simultaneous noise addition paradigm the variances did not differ significantly ($W(1,14) = 1.105$, ns), but for performance in the backward masking paradigm a significant difference was found ($W(1,14) = 11.255, p = 0.005$). Therefore we controlled for this by using the Welch test (Welch, 1947) when comparing the performances on the backward masking test.

Participants trained on the simultaneous noise addition paradigm showed a complete transfer of learning to the backward masking paradigm. These subjects reached a threshold (46 ms, $SEM = 1$ ms) in the backward masking paradigm test with the trained stimulus set that was not significantly different from the threshold (49 ms, $SEM = 4$ ms) obtained by the subjects trained in the backward masking paradigm ($t(7.959) = 0.462$, ns, Welch’s $t$-test, Figure 2). Thus, training in the simultaneous noise addition paradigm is as good for improving performance in the backward masking paradigm as training in the backward masking paradigm itself.

The results were different for the group trained in the backward masking paradigm. Concerning the performance on the test in the simultaneous noise addition paradigm with the trained stimulus set at the last day, there is a significant difference between this group of subjects (for who this paradigm is the untrained paradigm, 34.6%, $SEM = 1.2\%$) and the subjects trained in this task (30.1%, $SEM = 0.8\%$) ($t(14) = 2.819, p = 0.014$, two-sample $t$-test, Figure 3). Thus, the transfer to the simultaneous noise addition paradigm was not complete, since participants trained in this paradigm had a better performance than the participants trained in the backward masking paradigm.

**Discussion**

In this study, we examined perceptual learning in a backward masking and simultaneous noise addition
paradigm and the possible transfer of learning between both paradigms. As expected, training in recognizing common objects resulted in an improved performance in both paradigms. These improvements were object-specific. The results with respect to a transfer in performance between the distinct visual learning paradigms were asymmetric. Participants trained in the simultaneous noise addition paradigm showed a complete transfer of performance to the backward masking paradigm. The opposite was not true: when results of both participant groups on the test in the simultaneous noise paradigm on the last day were compared, the group trained in this paradigm showed a better performance than the group trained in the backward masking paradigm. However, part of the learning effect did transfer. Evidence for this is found in the object specificity for the untrained paradigm.

The finding of a transfer in performance between different visual learning paradigms in this study is based on a between-subject design. So the interpretation of the effects involving a between-subject comparison is only valid under the assumption that the random assignment of subjects to the two groups was not by coincidence correlated with any pre-existing inter-individual differences—such as a different pre-training performance in our tasks. One argument that the two subject groups were well balanced in terms of pre-training performance, is that performance on the new stimulus set introduced at the test session was very comparable between the subject groups. Under the assumption that training effects are object-specific, which is confirmed in our study, it seems reasonable to consider this condition as a baseline and a valid measurement of what pre-training performance would have been if it had been tested.

An alternative design is to first measure the participants’ performance in both paradigms in order to provide initial pre-training baseline measures. When tested later in the untrained paradigm, the performance can then be directly compared to participants’ performance before any training has occurred. We did not choose for this alternative design, because in this case participants are no longer naïve to the new paradigm. This has two problematic consequences. First, fast learning effects have been found within one training day (e.g., Fiorentini & Berardi, 1981; Liu & Vaina, 1998) and are found to be long-lasting (Karni & Sagi, 1993). Thus the prior measurement could serve as a training session, through which a transfer of performance to the ‘untrained’ paradigm can no longer be purely measured. Second, participants might immediately be biased to adopt strategies that work for both paradigms, and that would make it trivial to find a transfer of learning effects from one design to the other.

In general, learning follows a negatively accelerated curve (Ritter & Schooler, 2001). This means that an initial rapid improvement is followed by ever decreasing improvements when training is continued. Perceptual learning is no exception (e.g., Dosher & Lu, 2005, 2007). This pattern is also reflected by the data in this study. After a relatively strong increase in performance from the first to the second training session, the learning curve seems to flatten out (Figures 2 and 3). But although learning slowed down, there was still improvement noticeable after the second training session. Thus, participants trained in both paradigms showed the same expected learning pattern.

Our results also agree with previous research showing specificity of learning for the trained stimuli. After training with a specific stimulus set, participants showed a clear degradation of performance when tested on a new stimulus set. Performance even dropped back to pre-training baseline level. The same stimulus specificity was found when participants were tested in the untrained paradigm. But the degree of object specificity is different for our study and other studies using complex objects as stimuli. Other perceptual learning paradigms with human participants found only a partial specificity (Furmanski & Engel, 2000; Grill-Spector et al., 2000; McCarley et al., 2004): performance degraded when tested with a new stimulus set, but part of the learning effect generalized to the new stimuli. The performance did not drop back to the pre-training baseline level. One study using two monkeys as subjects, found (partial) object specificity in only one subject. In the second monkey the learning effect transferred almost completely to the new stimulus set (Op de Beeck et al., 2007). However, in all studies large inter-individual differences with relation to the degree of specificity were found.

In general, we expect an optimization of the processing of relevant information to be the result of perceptual learning—referred to as increased efficiency by Gold et al. (1999). But the relevant aspects can differ between distinct paradigms, as might the processes that are involved in the increase in efficiency. We found a complete transfer of performance to the backward masking paradigm when participants were trained in the simultaneous noise addition paradigm. When looking at this result, it seems that one general learning mechanism is sufficient to explain perceptual learning. However, participants trained in the backward masking paradigm showed only a partial transfer to the simultaneous noise addition paradigm. Additional processes specific to the simultaneous noise addition paradigm seem to be necessary to explain this result. In sum, our results give evidence for the existence of specific processes in addition to general learning processes.

The idea of more than only one general learning process is not new. Specificity to the trained objects already rules out the possibility that the learning effect is caused by an improvement of general perceptual abilities, because this would be equal for both trained and new objects (Furmanski & Engel, 2000). Comparing low-noise and high-noise conditions, Dosher and Lu (2005) found an
asymmetric transfer of performance: training in the high-noise condition did not improve performance in the low-noise tests, whereas transfer of performance was found when the conditions were reversed. Furthermore, Petrov et al. (2005) found partial context specificity when manipulating the noise background in which stimuli were embedded. Thus even within the same paradigm, manipulations of the noise can cause the use of multiple processes. Lu et al. (2006) found that different mechanisms of perceptual learning can even be trained independently. However, these proposals refer to different aspects of the stimulus or task than manipulated in this study. Previous studies have looked at only one of the paradigms used in this study, under the (implicit) assumption that the studied learning processes would be equal in both paradigms or that possible differences would not influence the studied processes. But up to now both paradigms had not yet been compared in one study.

Looking at each paradigm separately, different studies have attempted to identify the processes underlying the learning effect. For the backward masking paradigm, Wolford, Marchak, and Hughes (1988) proposed an improvement of the temporal resolution of the processing at a sensory level through enhanced alertness. At a neuronal level, Op de Beeck et al. (2007) found a reduction in responsiveness of inferior temporal neurons to the mask patterns following long-term training. But since a complete transfer from the simultaneous noise addition paradigm to the backward masking paradigm was found, these processes characteristic for the backward masking paradigm are either not necessary or also optimized during training in the simultaneous noise addition paradigm.

Regarding the simultaneous noise addition paradigm, Rainer and Miller (2000) trained monkeys to recognize natural objects degraded with a noise pattern. After training, neurons in the prefrontal cortex showed a more narrow tuning to familiar objects. Neural activity was also more robust with relation to the stimulus degradation. This might be the neural substrate of the effect of enhanced signal strength or increased efficiency found in the simultaneous noise addition paradigm (Dosher & Lu, 1998; Gold et al., 1999). However, it is unclear why this process would be partially specific to the simultaneous noise addition paradigm, giving rise to the only partial transfer from the backward masking paradigm to the simultaneous noise addition paradigm.

Thus, which process might be relevant in the simultaneous noise addition paradigm and not in the backward masking paradigm? One candidate is re-entrant or feedback processing. This type of processing is included in a popular theoretical approach, the reverse hierarchy theory of visual perceptual learning (Ahissar & Hochstein, 2004). According to this theory, perceptual learning is a top-down guided process, which begins at the top of the cortical visual hierarchy and searches backward for the most informative neurons to solve the task. Multiple studies have suggested that masking interrupts or even eliminates such feedback processes (e.g., Di Lollo, Enns, & Rensink, 2000; Lamme, Zipser, & Spekreijse, 2002). One variant of feedback processes might be the covert scanning of a presented noisy image to find its most visible parts, which is only possible if the image is presented on the screen for a sufficiently long period of time. These feedback processes might not be involved in training with the backward masking paradigm. If learning in the simultaneous noise addition paradigm would be related in part to the improvement in these feedback processes, the learning effects would not be induced fully by training in a backward masking situation, which is exactly what we observed.

Conclusion

In conclusion, our results suggest that, following training, an object-specific increase in recognition performance for common objects is found in both the backward masking and the simultaneous noise addition paradigm. The pattern of transfer between the distinct visual learning paradigms suggests that both general and specific learning processes are involved.

Appendix A

Figures A1 and A2.

![Figure A1](https://example.com/figA1.png)

Figure A1. Thresholds for the backward masking paradigm are plotted as a function of the day and the paradigm in which participants were trained. Thresholds are estimated using the method with the psychometric fits. Error bars represent the standard error of the mean (SEM).
Acknowledgments

This work was supported by the Research Council of K.U. Leuven (CREA/07/004), the Fund for Scientific Research—Flanders (1.5.022.08), and by the Human Frontier Science Program (CDA 0040/2008).

Commercial relationships: none.

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