Does Training on Broad Band Tactile Stimulation Promote the Generalization of Learning?

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***Abstract*— Given the clear role of sensory feedback in successful motor control, there is a growing interest in integrating substitutionary tactile feedback into robotic limb devices. To enhance the utility of such feedback, here we investigate how to best improve the limited generalization of tactile learning across body parts and stimulus properties. Specifically, we sought to understand how perceptual learning with different types of tactile stimuli may give rise to different patterns of learning generalization. To address this, we utilized vibro-tactile effectors to present patterns of stimulation in a match-to-sample paradigm. One group of participants trained on narrow-band stimulation consisting of simple sinusoidal vibrations, and the other on broad-band stimulation generated from music. We hypothesized that training on broad-band tactile stimulation would promote greater generalization of learning outcomes. We found training with broad-band stimuli generalized to underlying stimulus features of frequency discrimination but showed weaker generalization to un-trained digits. This study provides a first step towards devising perceptual learning paradigms that will generalize broadly to the untrained perceptual contexts.**

Keywords*— perceptual learning, tactile perception, specificity and generalization of learning, broad-band stimulation, learning transfer

I. Introduction

Movements are produced by a combination of motor outflow and sensory inflow. Movements for object manipulation, such as grasping a cup or playing a musical instrument, require rapid integration of motor control and sensory feedback. It is the assimilation of these two processes that leads to the intuitive execution of movements [1]. Patients experiencing sensory loss from the body demonstrate how even simple tasks, like lifting a cup, are devastated by the absence of somatosensory feedback [2]. As such, it is being increasingly recognised that the functionality of artificial limbs is severely restricted by the absence of this essential source of action information [3]. Artificial tactile feedback is realised through the delivery of direct somatosensory stimulation through targeted reinnervation [4], direct [5] and transcutaneous electrical nerve stimulation [6], as well as cutaneous stimulation – most commonly using vibro-tactors [7]. A key challenge for successful tactile integration across these approaches is the ability of the perceptual systems to successfully interpret the artificial stimulation.

The field of Perceptual Learning provides a window into the ways that sensory experiences shape current perceptions of the world. Perceptual learning studies typically train participants on simple stimuli that resemble basic dimensions of neural coding (e.g. pure frequencies, durations, and intensities). The extent to which learning is specific to these basic stimulus-features has been taken as evidence of low-level sensory learning [8, 9, 10, 11, 12]. For example, tactile perceptual learning studies have shown that the primary somatosensory cortex is selectively tuned to simple frequencies of mechanical sinusoids delivered to the fingertips [13, 14, 15, 16]. Other studies have found that tactile PL can generalize from trained to un-trained digits [15] and that generalization of learning may reflect topography of their representation in the somatosensory cortex with greater learning generalization to overlapping representations [16, 17, 18], however see also [19, 20] for complete generalization across fingers.

However, recent theories suggest that perceptual learning is best understood through a model where multiple components, including low-level sensory representations, as well as higher order read-out weights, decision rules, and attention are combined together to generate the observed changes in performance [21]. This model suggests that to achieve generalization of learning one should find stimuli that would activate a broader range of neural and cognitive processes during learning. For example, [22] found that auditory cortical responses for broad-band "complex" stimulation were more robust than for narrow-band stimuli "pure" stimulation. Moreover, event related potential (ERP) recordings in humans find that broad-band frequencies are better perceived and are easier to recall than narrow-band frequencies [23, 24, 25]. Additionally, a number of studies suggest musical structures facilitate neural encoding [26, 27] and generalization of learning [28, 29].

Here, we sought to address the extent to which the generalization of tactile perceptual is mediated by the complexity of the training stimuli. Participants discriminated either sequences of narrow-band tones or broad-band "tactile music" (described below), presented on vibro-tactile effectors. We investigated how resultant learning generalized to untrained stimuli. We hypothesized that broad-band stimulation training would produce generalization to underlying stimulus dimensions such as frequency and duration discrimination. To our knowledge, no studies in the tactile domain have examined how broad-band stimuli, which may be considered to be more ecological, might yield different patterns of generalization from training.

II. Methods

A. Participants

We recruited 46 undergraduate students from the University of California, Riverside (13 male, mean age=20.3, SD=2.18), who were paid $10-15 an hour based on performance. They were randomly assigned to either of 2 training groups and completed 10 sessions over a period of 2 weeks. 4 participants were excluded for poor performance during training. All participants signed an informed consent, as approved by the UCR Human Subject Review Board, reported normal hearing and vision, and no history of psychiatric or neurological disorders.

B. Materials

All experiments were controlled using a Mac Mini (Apple, Inc., Cupertino, CA) running OSX 10.5.6. Tactile stimulation was delivered using vibro-tactile electromagnetic solenoid-type stimulators and a Dancer Design vibro-tactile amplifier tactamp 4.2 (Dancer Design, 2017). Stimulation patterns were generated in Matlab (Mathworks Inc., Natick MA), with the use of Psychophysics Toolbox [30].

C. Stimuli

Training Sessions - Participants trained on a match-to-sample task discrimination task using one of two types of stimulation (see fig. 2).

- The *Narrow-Band Group* experienced stimulus sequences made up of 8 frequencies (16, 32, 64, 128, 256, 512, 1024 and 2048 Hz) with 0.25 seconds of duration each, presented in pseudorandom order with no repeats for a total sequence duration of 2 sec.
- The *Broad-band Group* experienced vibratory 'music' patterns composed by a British music studio for the specific use with vibro-tactile stimulators. These sequences were made up of spectrally broad-band sounds laid out in time with musical rhythm.

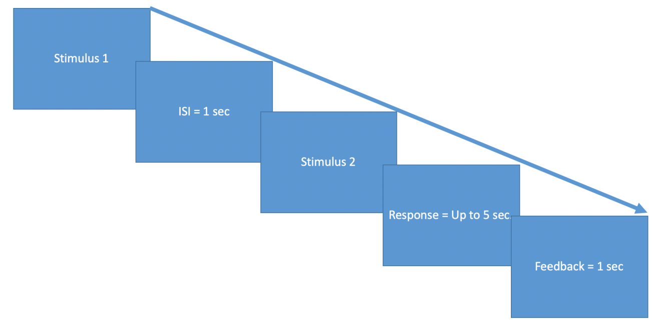

Diagram of a single trial. Stimulus 1 (sample) was followed by an inter-stimulus-interval (ISI) of 1 second. This was followed by the presentation of stimulus 2 (match or non-match). Participants had 5 seconds to make a response. Immediately following the participant's response feedback was presented for 1 second.

Test Sessions - We evaluated generalization of tactile discrimination, by testing discrimination of 4 (untrained) types of vibro-tactile stimuli:

- *Frequency Test* – narrow-band vibration stimuli of 0.5s duration that adaptively varied above a baseline of 128Hz.
- *Duration Test* - narrow-band vibration stimuli of 128Hz frequency, adaptively varying in duration above a 0.5s baseline.
- *Didgeridoo Test* - an untrained broad-band sequence of vibrations made by an Australian traditional instrument with stimulus differences manipulated in the same manner as used in trained (see below for details). The didgeridoo was chosen for the purpose of including a type of broad-band stimulation as different as possible from the utilized stimulation for training, but which was also musical. Since the didgeridoo has an unusual spectra with instances of "missing fundamental" frequencies, it was a suitable candidate for our test of broad-band perception with a novel stimuli set.
- *Untrained-Fingers Test* - trained broad-band stimuli (described above) was used to test untrained fingers (homologous to the trained fingers).

D. Procedure

In each session, participants laid their hands on a piece of foam (to dampen spread of vibrations) and placed the middle finger of one hand on one stimulator and the index finger of the other hand on the other stimulator. Headphones playing white noise were worn to prevent auditory feedback of the tactile stimulation. In each trial, a sequence of two mechanical vibro-tactile stimuli were delivered to the fingertips: a first stimulus, a 1s inter-stimulus interval (ISI), then a second stimulus. The task was to report (within 5 seconds) if the second stimulus matched the first (yes or no) via foot-pedals ('left' or 'right'). Visual response feedback was provided (see fig. 1). On Day 1, a practice was given of 15 trials of each task first with the left-index and right-middle fingers) and again with the right-index and left-middle fingers.

To adjust difficulty, the difference between stimuli was modified adaptively via a 2-down 1-up staged staircase [31]. That is, after 2 correct responses, the difference between stimuli was reduced (making the judgment harder). After 1 incorrect response, the difference would increase (making the judgment easier). The size of the difference adjustment (step sizes) decreased progressively: 20% change for the first two reversals, 15% for the third, 10% for the fourth, and 5% from the fifth and on. In the *Frequency Test* and *Duration Test*, adaptive adjustments were made to the frequency or duration differences between the first and second stimuli, respectively.

For the *Broad-band Training; Narrow-band Training; Untrained-Fingers Test; and Didgeridoo Test,* we used a re-sampling procedure to determine the difference between first and second stimuli. For any one trial, the stimuli were divided into 8 equal segments. Each section was pseudo-randomly allocated to either be stretched or compressed (by changing the sampling rate of each segment). Half of the segments were stretched and half compressed, keeping the total duration of the stimulus unchanged. The magnitude of this re-sampling procedure was the adaptive parameter for these tasks. That is, the extent of stretch/ compression for each segment was larger in easy trials (bigger difference between stimuli one and two), and smaller in harder trials.

Test sessions consisted of 60 trials for each of the four tasks (order randomized) and were conducted on the second and tenth day. Each testing session lasted around 10 minutes.

Training sessions consisted of 200 trials each and were conducted on days 3-9. These were divided into 5 blocks. Feedback (correct/ incorrect) was presented after each trial, and a score on a ten-point scale was presented after each block based on staircase. This score was used to assign monetary bonus. In each block, participants with scores of 9 received an extra \$0.5, and scores of 10 received an extra \$1. Participants were always trained on a middle and index finger concurrently (whether the index/ middle was left/ right was pseudo-randomly assigned). Each training session took about 40 minutes to finish.

E. Data Analysis

The threshold used for analyses was the median of the last 6 reversals of each test, or the last 24 reversals of training. Threshold values beyond +/-2 SD were considered outliers and were removed from group level analyses. We first looked at the training data to evaluate learning effects over days (A). To do so, we conducted two mixed-model ANOVAs (one for thresholds and reaction times, separately). We used the within-subject factor Session (Pre vs Post), and the between-subject factor Group (Narrow vs Broad-Band). We next looked at test performance, to evaluate generalization of learning to different stimulus features or different (untrained fingers) (B). This was achieved by conducting four (one per test type) 2 X 2 mixed-model ANOVAs also with within-subject factor: Time (Pre vs Post); and between-subject factor: Group (Narrow-band vs Broad-band). Significant main effects and interactions were followed-up with post-hoc tests, namely related-samples t-tests with Bonferroni corrections for multiple comparisons.

III. Results

A. Training Results

To address learning on the training tasks, we contrasted performance of the first vs last training days. Thresholds improved on both tasks (Fig. 2; main effects of Session; $F_{(1,40)}=23.06$, $p<.001$, $\eta^2=.345$) as did reaction times ($F_{(1,40)}=25.73$, $p<.001$, $\eta^2=.38$). We found no group differences (thresholds, $F_{(1,40)}=0.16$, $p=.689$, $\eta^2=.005$; reaction times, $F_{(1,40)}=2.608$, $p=.114$, $\eta^2=.061$), nor interactions with group that were statistically significant. Post hoc tests showed significant improvements in threshold (broad-band, $t_{(20)}=2.77$, $p=.024$, Cohen's $d=.61$; narrow-band , $t_{(20)}=3.93$, $p=.001$, Cohen's $d=.86$) and reaction times (broad-band, $t_{(18)}=2.77$, $p=.024$, Cohen's $d=.606$); narrow-band, $t_{(20)}=4.54$, $p<.001$, Cohen's $d=.991$) for both groups.

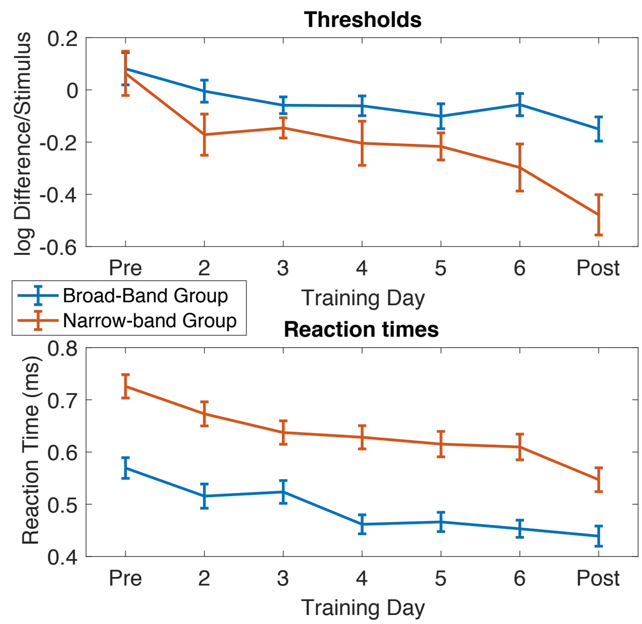

Fig. 2 Performance for each training session for both groups. Top, thresholds for each session (lower numbers mean improved performance). Bottom, reaction-times for the last 100 trials of each training session (higher numbers indicate worse performance). Error bars show within subjects standard error.

B. Generalization of Learning

To understand generalization, we compared changes across test sessions (see fig. 3).

<u>*Frequency Test*</u> – Data from this task addresses the hypothesis that training generalized to component frequencies of the training tasks. Impressively, we found a significant interaction between Time and Group ($F_{(1,35)}=4.73$, $p=.036$, $\eta^2=.119$), suggesting greater generalization to frequency discrimination from broad-band vs narrow-band training. These results suggest an advantage of training with broad-band compared to narrow band stimuli to frequencies discrimination.

Duration Test – Data from this task addresses the hypothesis that training generalized to duration discrimination, another component of both training tasks. Again, while the magnitude of the broad-band effect was greater, the interaction failed to reach significance ($F_{(1,38)}$=2.76, p=.105, η^2=.055), however, a significant main effect of Time ($F_{(1,38)}$=9.41, p=.004, η^2=.188) is suggestive of learning in both groups. This shows that broad-band training transferred as much, or possibly more, to discriminating basic tone durations.

Didgeridoo Test - Data from this task addresses the hypothesis that training generalized to a novel broad-band vibro-tactile stimulus. Here we failed to find an interaction between training groups ($F_{(1,39)}$=1.60, p=.213, η^2=.038), nor a significant effect of Time ($F_{(1,39)}$=1.56, p=.219, η^2=.037). This suggests that neither training led to generalization of learning to a new set of broad-band vibrations.

Untrained-Fingers Test - Data from this task addresses the hypothesis that training generalized to un-trained digits. Here, we found a significant interaction ($F_{(1,35)}$=7.21, p=.011, η^2=.098), this time favoring the narrow-band group. This suggests that broad-band training generalizes to untrained digits to a lesser extent than the narrow-band training.

Table 1. Shows the means and within-subjects standard error in parenthesis for the pre- and post-training threshold measures reported. N-B stands for Narrow-Band and B-B for Broad-Band Groups.

	Group	PRE-	POST-
Training	N-B	0.06 (.08)	-0.47 (.07)
	B-B	0.08 (.06)	-0.14 (.04)
Frequency Test	N-B	-0.45 (.03)	-0.36 (.03)
	B-B	-0.55 (.06)	-0.70 (.06)
Duration Test	N-B	-0.52 (.02)	-0.60 (.02)
	B-B	-0.57 (.04)	-0.78 (.04)
Didgeridoo Test	N-B	0.40 (.03)	0.50 (.03)
	B-B	0.35 (.06)	0.29 (.03)
Untrained-fingers	N-B	0.35 (.08)	-0.15 (.08)
	B-B	0.34 (.06)	0.14 (.06)

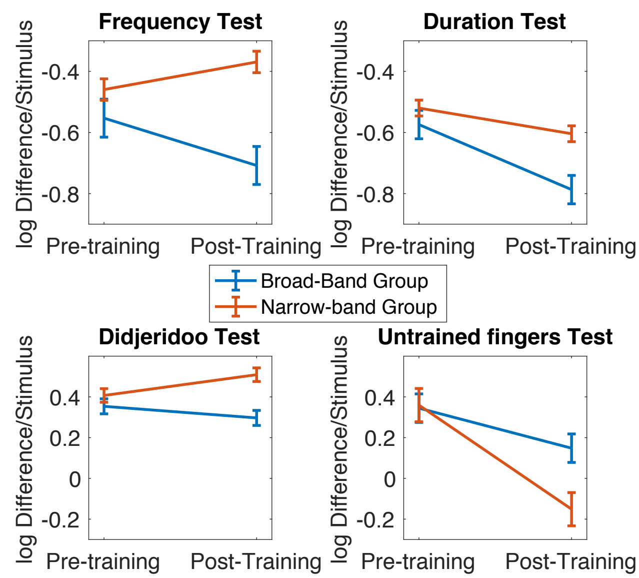

Fig. 3 Generalization of learning to tests. Lower values indicate better performance. Error bars indicate within subjects SEM.

IV. Discussion

Here, we incorporate knowledge from perceptual neuroscience to investigate how to optimise the provision of successful substitutionary sensory feedback. In addition to the invasive nature of brain stimulation required [32], a key challenge for implementing artificial tactile feedback is determining where to provide that feedback. When stimulating a nerve directly, the perceived location on the body is often displaced from the desired location on the artificial hand [33]. With the more common non-invasive interfaces, the stimulation is presented on a nearby skin surface (e.g. the arm [7]). Although participants show an ability to interpret substitutionary feedback to a displaced body part, the contributions to visually guided motor control are minimal [7, 34]. This failure is likely due to the high cognitive and perceptual demand required to translate substitutionary feedback (differing in type and location) onto the artificial hand.

Using training to create new sensori-motor contingencies between the stimulated region and the artificial limb might help address these difficulties. It has been proposed that key to any type of perceptual experience – including the use of technology– depends crucially in the coupling of the sensory inflow and motor outflow as we explore the environment [35]. Research on the sensori-motor integration domain using tasks that afford exploratory behavior including tightly coupled sensory and motor components is needed to address this possibility.

For this study, we focused on the sensory stimulation component of the interaction and hypothesized that training with broad-band vibrations based on music would generalize more broadly to untrained conditions than training on narrow-band stimuli. The results of the *Frequency Test and the Duration tests are largely* consistent with this hypothesis – as we found broad-band training conferred an advantage on a separate (untrained) task assessing frequency perception (with similar trends in the Duration test that failed to reach significance). However, neither training generalized to an untrained complex stimulus (*Didgeridoo test*). Interestingly, generalization of learning was greater for the narrow-band training than for the broad-band training to untrained digits.

The benefits seen from broad-band training may reflect the diversity of frequencies and durations present in the trained stimuli. These could promote a higher-order learning of statistical type of regularities that then transfers to their basic components [36]. This type of facilitation has previously been reported in the auditory domain with musical stimuli [26, 27, 28, 29]. However, the lack of generalization to the *Didgeridoo test* brings to question whether this was due to a difference in the component frequencies that are required for accurate discriminations compared to that in the broad-band training, or that the lack of generalization relies upon higher level components of learning. Future research will be required to differentiate between these possibilities.

Notably, the narrow-band group showed greater generalization of learning to untrained digits. This may suggest some independence between mechanisms that guide stimulus dimensions and ones that are devoted to body maps. While the greater specificity to digits in the broad-band group could represent a lower-level interpretation of learning involving refinement of receptive fields to the trained digits [14, 37], an alternative explanation is that the broadband stimuli led to a more narrow focus of attention to the trained compared to the untrained digits [e.g. see 38]. Further work will be necessary to better understand these mechanisms.

This study is a first step towards understanding factors that influence generalization of tactile perceptual learning. The present results suggest some benefits of training with broad-band stimuli. Future research will be needed to better understand the extent to which this relies upon unshared feature primitives, and/or the extent to which learning is related to higher-level features. Likewise, whether generalization to untrained digits is informative to the level of learning within the system is unclear. Understanding these mechanisms of tactile perceptual learning can have significant consequences to integrating substitutionary tactile feedback.

Acknowledgment

The first author is currently funded by CONACYT and UC Mexus. TRM was supported by the ERC Starting Grant (715022 EmbodiedTech).

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