Representational Similarity Analysis for Tracking Neural Correlates of Haptic Learning on a Multimodal Device

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***Abstract*—A goal of wearable haptic devices has been to enable haptic communication, where individuals learn to map information typically processed visually or aurally to haptic cues via a process of cross-modal associative learning. Neural correlates have been used to evaluate haptic perception and may provide a more objective approach to assess association performance than more commonly used behavioral measures of performance. In this article, we examine Representational Similarity Analysis (RSA) of electroencephalography (EEG) as a framework to evaluate how the neural representation of multifeatured haptic cues changes with association training. We focus on the first phase of cross-modal associative learning, perception of multimodal cues. A participant learned to map phonemes to multimodal haptic cues, and EEG data were acquired before and after training to create neural representational spaces that were compared to theoretical models. Our perceptual model showed better correlations to the neural representational space before training, while the feature-based model showed better correlations with the post-training data. These results suggest that training may lead to a sharpening of the sensory response to haptic cues. Our results show promise that an EEG-RSA approach can capture a shift in the representational space of cues, as a means to track haptic learning.**

***Index Terms*—Wearable haptics, multimodal haptics, haptic learning, EEG, Representational Similarity Analysis, neural correlates.**

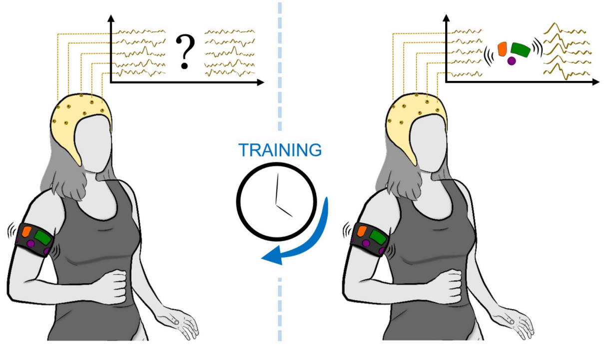

Fig. 1. We examine EEG-RSA as a framework to evaluate how the neural representation of multifeatured, haptic cues changes with association training. By developing two hypothetical models, first we evaluate if the neural representation of haptic cues before training is more correlated to perceptual confusion between the cues. Then, we evaluate if the neural representation of haptic cues after training is more reflective of the unique haptic features of the cues themselves.

I. Introduction

WEARABLE haptic devices show promise for enabling novel haptic communication methods, giving a user the ability to receive information through the sense of touch [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. A central objective of designers of wearable haptic communication systems is to encode information, which is typically processed visually or aurally, as tactile stimulation patterns presented to the skin [1], [7], [12], [13]. Wearable haptic systems have been used to transmit guidance and instructions from virtual agents that convey navigation information [14], [15], performance feedback to trainees using surgical simulators [13], motion guidance for individuals undergoing physical therapy [12], [16], as well as discrete forms of language [1], [3], [4], [5], [6], [7], [17]. Two aspects are critical to successfully transmit information to a user with tactile displays. Individuals must reliably perceive the tactile cues themselves, as well as learn and retain the mappings between information typically processed by the visual or auditory senses to that of tactile cues. This relies on a process known as cross-modal association (or cross-modal associative learning) [18], [19]. In this article, we focus on the first phase of successful cross-modal associative learning, accurate haptic perception of the multimodal cues.

A major challenge when developing these devices is how the learning of haptic cues is assessed. Typically, protocols for associative learning on haptic-communication devices include testing phases where subjects respond via closed-set (i.e. multiple choice) or open-set responses (i.e. free response) [1], [2], [5], [7],

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[20]. Notably, the majority of these testing protocols reported in the literature are limited to closed-set options [1]. Association results are then summarized as recognition rates or percent accuracies, often presented in confusion matrices [1], [7]. However, behavioral observations such as multiple-choice responses can be relatively subjective, hard to reproduce, confounded by experimental environments such as social pressure [21], and confounded by strategic guesses [22]. Therefore, these kinds of behavioral results may only provide limited insights into *what* individuals are actually learning throughout haptic training. Careful investigation of how haptic training changes the neural correlates of the response to haptic cues may provide deeper insights into what has been learned [21], [23], [24], [25], [26], [27], [28], [29], [30]. Therefore, our ultimate goal is to develop quantitative methods for analyzing neural correlates to help track, and promote, the learning of haptic cue sets that are used to encode information.

This article explores one quantitative approach to investigating the neural changes that occur in response to haptic learning, an analysis framework known as Representational Similarity Analysis (RSA). RSA provides insight into the structure of neural representations through investigation of the similarity structure of a set of neural responses [31], [32], [33], [34], [35]. These techniques can be used with a variety of brain imaging techniques, including non-invasive recordings such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). In brief, pair-wise distances of the brain's response to unique stimuli are computed in order to estimate a representational space of how dissimilar each stimulus is from every other one [31], [32], [34], [35], [36], [37], what is referred to as a Representational Dissimilarity Matrix (RDM) [34], [35]. The structure of these RDMs can then be interrogated, for example by comparing the empirical RDMs calculated from neural recordings to different theoretical models of what information is being processed about the stimuli [36] or to data collected with the same stimuli in a different task [38], which can also be structured as RDMs. Using this approach, we can form hypotheses of what individuals are learning, or becoming sensitive to, during the course of haptic learning, which should be reflected as a change in how the RDMs are structured after training. This may be a particularly useful technique to better understand how haptic cue sets are represented in the brain, and how they are changed by the learning environment.

RSA has recently been applied to studies of haptic perception [39], [40], [41], [42], [43]. For example, Perini et al. used an fMRI-RSA approach to better understand how haptic object size is represented in the brain [39]. They had individuals grasp objects of various sizes and found specific brain regions where more similar neural activity patterns corresponded to the grasping of more similar object sizes [39]. Tame et al. used fMRI-RSA to investigate the representation of tactile space on the hand [40], showing that the neural representation of the skin space matched a perceptual model derived from behavioral results where individuals were tasked to respond to air puff stimulation in the form of a 3 × 3 grid [40]. Malone et al. used an fMRI-RSA approach to investigate the neural mechanisms of vibrotactile categorization after individuals were trained to sort vibrotactile cues into different groups [42]. They showed that different neural representations of cues, specifically reflecting perceptual or categorical selectivity, occur in different regions of the brain [42].

In each case, these studies show the effectiveness of RSA in developing theories of the nature of haptic processing. These approaches have all been based on fMRI analyses. Restricting RSA to fMRI may limit adoption of this method in the haptics community due to the inherent cost and accessibility of scanners, and fMRI scanner compatibility with haptic devices [21], [44]. EEG data, which is less expensive to collect and more compatible with haptic devices, might be a preferred imaging modality. Furthermore, few of these studies have focused on how haptic learning changes haptic representation. One group has extended the RSA approach to both haptic learning and to EEG data, investigating the neural basis of vibrotactile speech learning on a sensory substitution vocoder device using both fMRI and EEG data [45]; however, their investigations, like most others that employ RSA [39], [40], [41], are limited to perception and learning of haptic cues based only on a single modality, such as vibration. Haptic researchers are increasingly employing multimodal wearable haptic devices to transmit haptic information to users [1], [46], [47], [48], [49], [50], [51], as discrete haptic cues generated by unimodal devices can be particularly difficult to learn [1].

In this article, we present methods for using an EEG-RSA approach to quantify changes in perceptual sensitivity of cues conveyed via a wearable, multimodal haptic device. We use an EEG-RSA framework to evaluate changes in the neural representation of haptic cues after association training, where the subject learned to map discrete phonemes to multimodal haptic cues. We introduce the general methodology and demonstrate the feasibility of our approach in a use-case scenario to evaluate how the sensitivity to haptic cues may change after association training. Our EEG-RSA approach provides a framework and foundation for applying these techniques to better understand the neural mechanisms of haptic association learning.

II. METHODS

Generally speaking, Representational Similarity Analysis (RSA) is a method that enables researchers to relate brain-activity measurements, behavioral measurements, and/or theoretical models. It reduces neural activity patterns to representational dissimilarity matrices (RDMs), such that we can represent the extent to which neural activity patterns of one condition or stimulus are correlated to every other one in an experiment. We can also compare these neural matrices to conceptual models of haptic cue representation, also structured as RDMs.

We apply RSA to a haptic association task where a single subject first learned to identify multimodal haptic cues, and then learned to associate those haptic cues to phonemes. Our analysis is focused on the first component of successful cross-modal association, accurate perception of the haptic cues. We first developed two theoretical models of the haptic cues, constructed to capture how the cues may be represented at the cortical level both before *and* after training. Then we used these models in an EEG-RSA framework to evaluate how the sensitivity to

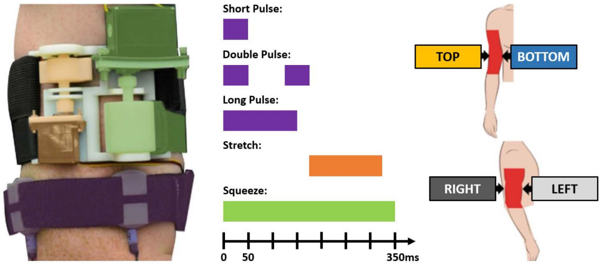

Fig. 2. (Left) The MISSIVE with actuation components that correspond to unique MISSIVE features, shown in the middle, highlighted. (Middle) MISSIVE cue features and corresponding timings. (Right) The four locations on the arm where vibration can occur.

multimodal haptic cues changes with training, as depicted in Fig. 1.

In the following sub-sections we lay out the methods and framework for our RSA approach. First, we present the multimodal haptic cues that can be generated by our wearable haptic device. Then, we describe how the two theoretical models, the Perceptual and Feature-Based Model, were determined. Third, we present our use-case experiment where a single participant learned to map these multimodal cues to phonemes while EEG data were acquired. Finally, we describe the correlation analyses and significance testing that we use to evaluate the models when applying RSA to our EEG data set.

A. *Haptic Cue Delivery Via a Wearable Device*

A wearable haptic device, the MISSIVE (Multi-sensory Interface of Squeeze, Stretch, and Integrated Vibration Elements) [1], [46], was the multimodal haptic device considered in our use-case analysis (see Fig. 2 (left)). The MISSIVE is worn on the upper arm and is comprised of three actuation mechanisms: radial squeeze, lateral skin stretch, and vibration [1]. The vibration element of the MISSIVE is comprised of four vibrotactors, such that vibration can occur at one of four locations, presented at the top, left, bottom, or right of the user's arm. One of three vibration patterns can be rendered, a short pulse (50 ms), long pulse (150 ms), or double pulse (one 50 ms pulse, 75 ms pause, and another 50 ms pulse). The lateral skin stretch cue has a duration of 150 ms. The radial squeeze cue has a duration of 350 ms. These unique modes of actuation combine to make up unique haptic cues, transmitting the different actuation modes simultaneously and/or in succession [1]. Nine haptic cues delivered on this device, shown in Fig. 3, were considered for our use-case analysis (see Section II-D for more details).

B. *Perceptual Model*

The first model we developed was designed to estimate the expected similarity structure of MISSIVE cues prior to training. We estimated this model empirically, relying on behavioral data from a previous study conducted in our lab by Sullivan et al. [46]. In this study, 13 participants who had never used the MISSIVE device before were presented with a randomized sequence of 32 MISSIVE cues repeated 5 times each and were asked to report on the 32 cues that were presented. These data allow for the construction of a confusion matrix of the percentage of times each cue is confused for every other cue. The confusion matrix is a type of RDM, under the assumption that items that are more dissimilar are less likely to be confused, and serves as the basis for our first model, the Perceptual Model. We hypothesized that the neural representation of cues before training should reflect a model capturing perceptual confusion between cues that is experienced by a naïve population.

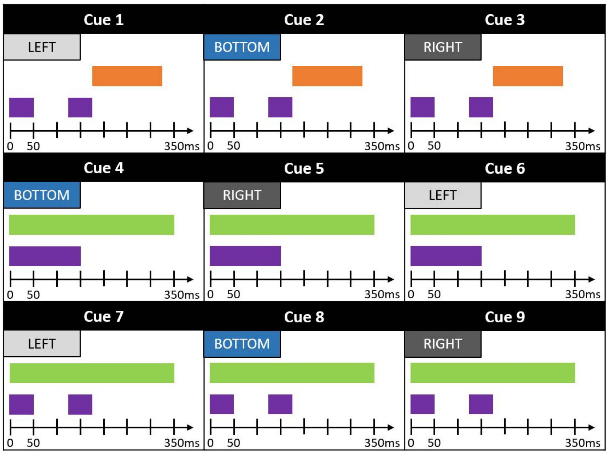

Fig. 3. Nine haptic cues, delivered via the MISSIVE, considered throughout the use-case experimental analysis. Corresponding features and timing profiles are shown for each cue.

Before we outline the formulation of the Perceptual Model, it is important to remark on several differences between the cues used in Sullivan et al.'s study and those used in this study. First, Sullivan et al. included a larger set of 32 MISSIVE cues, while our study focuses only on nine cues. This difference is accounted for in the generation of our model space, described below. Second, Sullivan et al. used slightly different cues with only short and long pulse vibrations, and not the double pulse vibrations that we consider. To accommodate this second difference, we assume that the short pulse vibration is comparable to the double pulse feature considered in our haptic cue set. With this assumption, the nine cues considered for our use-case scenario were a subset of the 32 cues used in the behavioral experiment previously conducted by Sullivan et al. [46].

To generate the RDM of the Perceptual Model space for our nine cues, we applied a normalization procedure to Sullivan et al.'s perceptual results. Specifically, each cell in our resulting 9x9 RDM was calculated to be the proportion of times each cue in Sullivan et al.'s study was perceived as every other cue, out of behavioral responses that were one of our nine cues of interest, resulting in a normalized version of the confusion matrix previously explained. Fig. 4 illustrates this normalization process for the perceived responses to Cue 1. The distribution on the top left shows the number of times the cue was perceived as one of the 32 cues in Sullivan's study, where the total number of responses add up to 65 (13 participants x 5 presentations of each cue). The distribution to the right shows the normalized distribution used for our model, where perceived responses were only considered if they were one of the nine haptic cues of interest. In this way, only 25 total perceptual responses were used

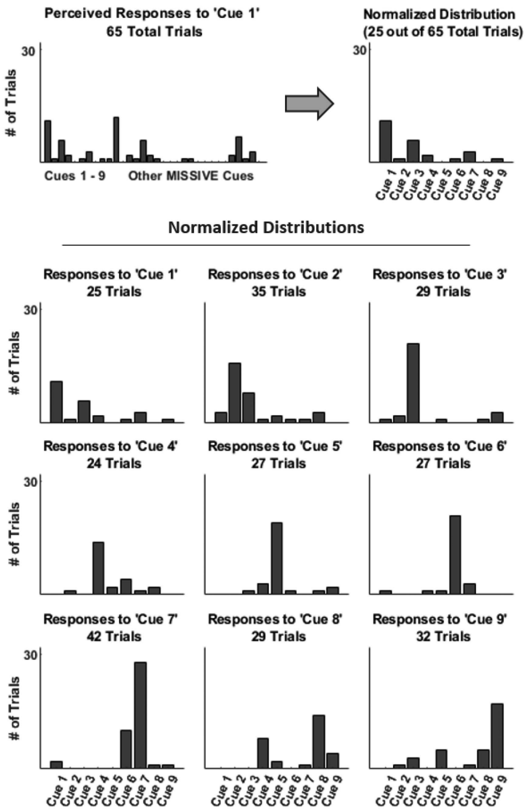

Fig. 4. Normalized distributions of perceptual responses to the nine haptic cues of interest, based on results from a previous behavioral study considering 32 MISSIVE cues. (Top) The left shows the distribution of perceived responses to Cue 1, where subjects could respond out of 32 cues, and the right shows the normalized distribution where perceived responses were only included in the distribution if they were out of one of the nine cues of interest. (Bottom) Normalized distributions of perceived responses to each of the nine haptic cues.

to determine the confusion ratios for Cue 1. Fig. 4 also shows the normalized distributions for each of the nine cues, including the total number of responses from which the confusion ratios were determined.

The resulting RDM was asymmetric, as the ratio that a rendered cue, e.g., Cue 1, is perceived as another cue, e.g., Cue 2, may not be equal to the ratio Cue 2 is perceived as Cue 1. However, we assumed a ground truth where over a significant number of trials these ratios would eventually even out. After determining the normalized confusion ratios, the resulting matrix was averaged across the diagonal to give an ideal, symmetric matrix, as shown in Fig. 5. We predict that the neural representation of the haptic cues before association training should be more correlated with this Perceptual Model than the neural representation of the cues after training. This rationale is based on evidence that novice users are likely to make perceptual errors when discerning between haptic stimulus cues [46], [52], [53], [54], [55], [56]. Furthermore, non-invasive neural measurements have been shown to reflect behavioral error and perceptual uncertainty [57], [58], [59]. Therefore, we would expect the neural representation of haptic cues, prior to any training, to reflect a model space representative of perceptual confusion between cues that is based on behavioral responses from an inexperienced population.

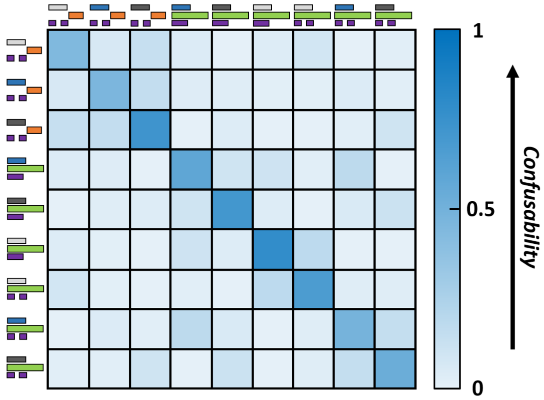

Fig. 5. Perceptual Model. Each cell holds the proportion (e.g. confusion ratio) that the presentation of each of the nine cues is perceived as every other cue of interest.

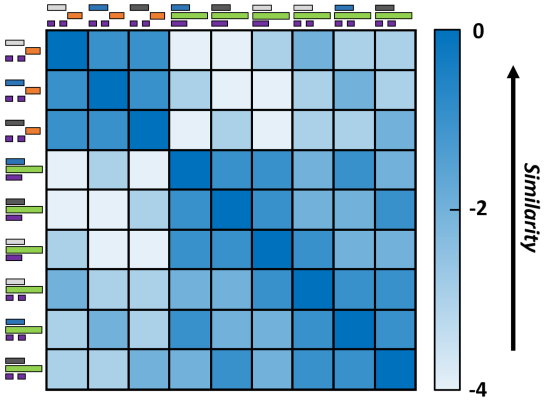

Fig. 6. Feature-Based Model. Each cell holds the number of different features between each cue pair, giving a value for how similar each haptic cue is from every other one.

C. Feature-Based Model

The goal of our second model was to capture how sensitivity to MISSIVE cues may be represented in the brain after training. This theoretical model was developed with the idea that exposure on the MISSIVE device should lead to individuals becoming more sensitive to the unique features of cues presented on the multimodal display. We hypothesized that the neural representation after training should reflect how similar each of the nine haptic cues are to each other in terms of the features of the cues themselves.

The Feature-Based Model was generated by counting the number of features (up to 4) that distinguished two cues from each other, such that comparison between each stimulus pair was given a rank from 0 to -4 in terms of how many different features each cue had compared to every other one (e.g. haptic cue differed by a vibration component or differed by squeeze). A value of 0 meant cues were identical to each other, and a value of -4 meant all 4 features were different, as illustrated in Fig. 6. We predict that the neural representation of the haptic cues after association training should be more correlated with this Feature-Based Model than the neural representation of the cues before training. The rationale behind this is the idea that training leads to a sharpening of the sensory response to haptic cues, such that after training the neural representation of haptic cues starts to reflect the features of the cues themselves [42]. Therefore, if learning on the MISSIVE device makes the individual more sensitive to the differences between the mulitmodal haptics cues, where this detection between cue differences may be picked up with neural recordings, then the individual should start to better disambiguate the patterns of the multimodal haptic cues themselves, such that EEG captures similarities and dissimilarities that correlate to that of the MISSIVE feature space.

D. Use-Case Experiment

1) Participant: A single subject (N = 1) was considered for this use-case analysis. The participant was male, left-handed, age 24 and did not report any cognitive or sensory impairments that would inhibit their ability to complete the experimental tasks. The participant gave informed consent, and the protocol was approved by the Rice University Institutional Review Board (IRB-FY2020-169).

2) Association (Exposure) Training: The participant completed 4 days of association training based on an established protocol [1]. In this protocol, the participant was tasked to map 23 phonemes to unique haptic cues, and subsequently learn a set of 50 words made up of those phonemes [1]. On the first day only, the participant was exposed to how the haptic cues felt and asked to identify their components. In this 10 minute cue familiarization phase, the participant could click on a spatial representation of any multimodal haptic cue and its assigned phoneme, such that the cue was felt on their arm. Although the participant was instructed to focus on the multimodal haptic cues, the phoneme text representation was shown on the screen and an audio clip corresponding to that phoneme was played into headphones. Once the participant felt comfortable with the cues, they could move on to a self-test exercise, where random multimodal cues were presented to the participant and he was then tasked to identify which features were present. Correct feedback was provided. The remainder of training focused on the participant familiarizing himself with four sets of phonemes and subsequent words made from them. Depending on the day, the training protocol could include Pre-Tests, phases where the participant learned sets of new phonemes, phases where the participant was introduced to words, Review Phases, Cumulative Assessments, and Post-Tests. Day 1 involved 23 minutes of training, Day 2 involved 37 minutes of training, Day 3 involved 30 minutes of training, and Day 4 included 10 minutes of training. Training time did not include the time it took for the Pre- and Post-Tests, which added overall exposure to the haptic cues.

3) EEG Sessions: An EEG study was designed in order to elicit neural responses to MISSIVE haptic cues. Using the classic oddball paradigm, frequently presented 'standard' cues are infrequently interrupted by 'deviant' cues that differ from the standard by some distinct characteristic [60], [61]. Four sets of oddball runs, of 1000 trials each, were used to present haptic cues to the participant. In each block, deviant cues made up 15% of the trials and varied from standard cues by one degree of freedom in terms of where on the arm the vibration component of the MISSIVE cue was felt (Fig. 2 (Right)). Deviant cues in each block were split evenly into two prototypes, such that each set made up half of the total deviant cues in a given block. Each cue of the first deviant prototype was mapped to a phoneme after training (as were the standard cues), however the second deviant prototype remained unmapped.

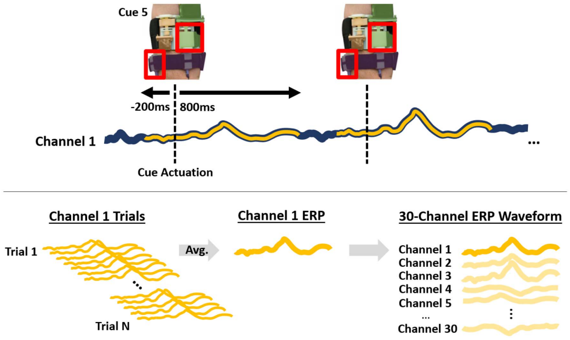

Fig. 7. (Top) Example trial showing response epoch 200 ms before and 800 ms after the presentation of Cue 5, on Channel 1 of a 30-channel EEG recording. (Bottom) Each trial response recorded is averaged together to compute the overall Channel ERP, for each channel separately. These channel ERPs are then combined to form a 30-channel ERP waveform response, in this case in response to Cue 5.

Only data from three blocks, therefore neural recordings in response to a total of nine haptic cues, were considered for this use case analysis, to evaluate how the participant's sensitivity to these cues changed after training. This set of cues can be seen in Fig. 3, where row 1 of the figure corresponds to the cues presented in Block 1, row 2 corresponds to Block 2, and row 3 corresponds to Block 3. This set of cues was strategic to consider, as the cues between blocks were characteristically more different from one another and cues within blocks were more similar, providing a dynamic set for RSA. Cues between the experimental blocks varied by at least a stretch, squeeze, vibration type and/or vibration location, whereas cues within groups only varied by one degree of freedom, the location on the arm the vibration was felt. Data from the fourth block were not considered because cues in this block only comprised a single vibrational component, and we were specifically interested in the study of multimodal cues.

EEG sessions occurred both before and after association training, making up the pre- and post-conditions in our use-case analysis. The subject received passive exposure to the haptic cues throughout the oddball blocks, and EEG data were recorded with a 32 channel actiCAP (Brain Products GmbH, Germany), collected at a sampling rate of 500 hz. 30 electrodes served as the full-scalp recording channels and two channels, the Left and Right Mastoid, served as reference electrodes.

Initial preprocessing, including eye-blink and artifact removal, was completed using the EEGLAB 14.1.2b toolbox [62]. Then, 30-channel event-related potential (ERP) activity patterns were computed in response to each of the haptic cues. This was done by averaging the EEG-activity recorded over all the trials at each channel, using an epoch that ranged from 200 ms before to 800 ms after the initial MISSIVE cue onset. This process was completed in MATLAB and is illustrated in Fig. 7. Each

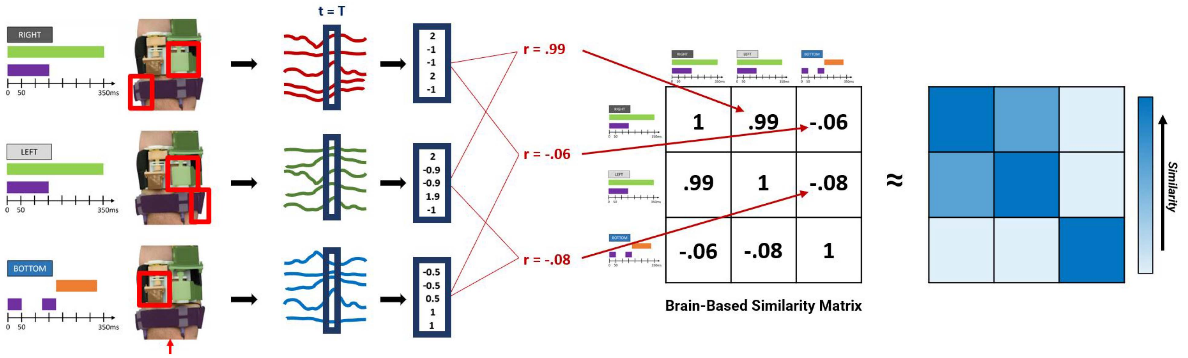

Fig. 8. RSA enables us to reduce high dimensional neural signals of unique stimuli into a 2D representational space, the brain-based similarity matrix. Brain-based similarity matrices represent how similar the brain response to a particular stimulus is to every other stimulus considered. Populating the representational similarity matrix at each time point allows us to determine how this space changes with time.

30-channel ERP activity pattern was stored in MATLAB as the overall neural response to each haptic cue considered, separately for the pre- and post-conditions.

E. Representational Similarity Analysis Framework

The following subsections outline how the brain representational spaces for the pre- and post-conditions were computed. We also describe how these similarity spaces were compared to each theoretical model, the Perceptual and Feature-Based models, to assess our hypotheses.

1) Brain-Based Similarity Space: Each 30-channel ERP activity pattern holds information regarding the similarities between each pair of haptic cues. Cues that are more similar, as in the first two MISSIVE cues displayed on the leftmost side of Fig. 8, should result in more similar neural activity over time. High dimensional ERP waveforms make it difficult to compare the overall neural response to each unique haptic cue. Representational Similarity Analysis (RSA) gives us a way to actually quantify this. RSA enables us to quantify *how similar* the neural activity pattern across all channels recorded may be, at *each* time point considered. Fig. 8 shows a conceptual representation of this methodology, considering three example MISSIVE cues.

As shown in Fig. 8, the presentation of each unique haptic cue results in different overall neural activity patterns. The mock ERP waveforms, displayed in red, green, and blue, across five demonstrative channels, illustrate this. If we consider the neural response pattern to each cue at a particular time point, t = T, we can represent the activity captured across the channels as vectors of voltage values. Then, for each time point, we can determine how similar these vector channel activity patterns are by correlating each of the vectors for all pairs of stimuli. Patterns that are more similar will have a correlation value closer to 1. Using the resulting correlation values, we can build the fundamental RDM for the current time point, which gives a 2D representational space of how the brain represents a unique set of stimuli at that time. This is shown on the rightmost side of Fig. 8 by the brain-based similarity matrix. In this way, we can reduce a high dimensional neural response space to a visual and comprehensible 2D space (i.e., the brain-based similarity matrix) that represents *how* similar the brain response to a particular stimulus is to every other stimulus considered. Doing this at each time point allows us to interpret how this representational space changes dynamically over time.

This general methodology follows analysis presented in Wang et al. [37], and was applied to our framework to determine the brain-based representational space of the nine MISSIVE cues, both before and after training. First, to reduce signal noise, the 30-channel ERP waveforms were binned into 20 ms time bins. This reduced the 30-channel ERP activity patterns for each haptic cue to 50 time bins instead of 500 time points. Next, brain-based similarity matrices were computed for both the pre- and post-training conditions. The brain-based similarity of each haptic cue to every other haptic cue was computed at each time bin by correlating the distributed patterns across the scalp between each pair of cues (see Fig. 8). At each time bin, we quantified the similarity between the pattern of neural activity for all possible pairs of the nine haptic cues by calculating Pearson's r value between the channel vectors. These correlation values were then used to construct the brain-based similarity matrices, resulting in 9x9 RDMs at each time bin. This entire framework was implemented in MATLAB.

2) Correlation Analysis: We performed separate correlation analyses to evaluate how the neural representation, or brain-based similarity space, of haptic cues in each training condition was related to 1) the Perceptual Model and 2) the Feature-Based Model. For each analysis, the model space was related to the brain-based representational spaces using non-parametric Spearman's correlation of the off-diagonal. Specifically, for both pre- and post-training conditions, the off-diagonal of the brain-based similarity matrix (RDM) at every time bin was Spearman rank correlated to the off-diagonal of the model space. Each analysis resulted in two time series of Spearman correlation values ($\mathbf{r}_{pre}$ and $\mathbf{r}_{post}$) and the corresponding p-values, indicating how similar the neural representation of each training condition was to the model in question, over time. To complete the analysis, we also compared the two model spaces via Spearman's rank correlation of the off-diagonal.

3) Significance Testing: Our approach to significance testing took part in two stages. First, we determined, for the pre- and post-training EEG signals separately, whether there was a

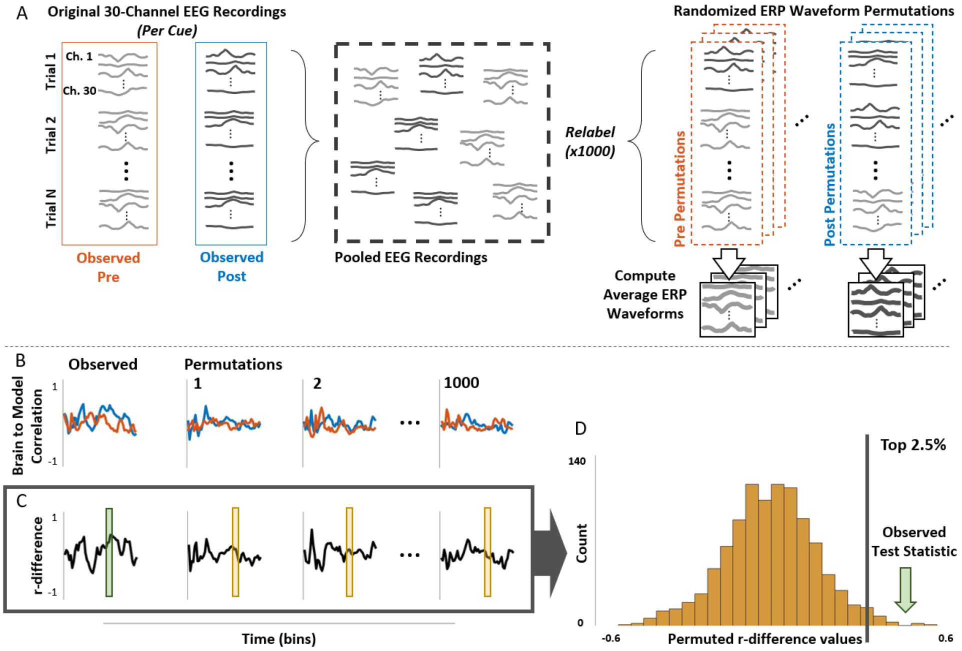

Fig. 9. Bootstrap permutation analysis schematic. (a) For each haptic cue, the original 30-channel EEG recordings from both conditions are pooled into one group and then relabeled as coming from the pre- or post- condition. This is completed 1000 times, and for each permuted data set, the average ERP waveform response is computed. (b) Brain to model correlation results versus time. This shows the observed correlation results between the Feature-Based Model and brain-based representational space of cues before and after training, as well as a few example permutations of this result. These are determined by correlating the Feature-Based Model to each permuted brain-based representational space. (c) Permutation test statistic (r-difference) versus time. For each brain to model correlation, the difference between the post- and pre- correlation time series was calculated to determine the test statistic at every time bin. This was completed for the observed and permuted data sets. Because the Feature-Based Model was considered for the comparisons shown in 9B, the r-difference value was calculated as (r_{post} - r_{pre}). (d) Histogram distribution of permuted r-difference values and significance testing. This shows the distribution of the permuted test statistics, at an example time bin. At this time bin, the observed test statistic falls within the top 2.5% of the distribution, so results are considered to be significant with correction.

significant positive relationship between the similarity structure in the EEG signal and the predicted similarity structure from each model representation. This was determined at each time bin, using a one-tailed significance test ($\alpha = 0.05$) of whether the correlation between the two similarity matrices was greater than 0. Second, for those time points in which at least one of the pre- or post-conditions was significantly greater than zero, we evaluated whether there was a significant difference between the two conditions. This was done with a bootstrap permutation analysis without replacement, which is described in detail in the following paragraphs. A schematic representing this analysis can also be seen in Fig. 9.

The following steps outline how each data permutation was determined. First, the 30-channel EEG recordings from the original trial repeats were pooled into one group, as illustrated in Fig. 9(a). This was completed for the data of each haptic cue separately. Second, the EEG recordings from each trial were randomly assigned (relabeled) as coming from the pre- or post- condition. For the third step, this process was carried out 1000 times to generate 1000 permutations of the original EEG data. Fourth, for each permutation, the average ERP waveforms were computed, as previously explained in Section II-D3 and illustrated in Fig. 7. At the end of this step, each haptic cue had 1000 permutations of its 30-channel ERP waveform response for both the pre- and post- conditions, as shown in Fig. 9(a). The fifth step, not shown in the Fig. 9 schematic, generated the permuted brain-based representational spaces by following the procedure outlined in II-E1 and further illustrated in Fig. 8. Here, the respective permutations of the 30-channel ERP waveforms, for each of the nine haptic cues, were used to construct the associated 9x9 brain-based similarity matrices, at every time bin considered. Finally, the Correlation Analysis described in Section II-E2 was carried out for each permutation, using the original Perceptual and Feature-Based models. Each brain to model comparison resulted in 1000 correlation time series for both the pre- and post- conditions. Fig. 9(b) shows the observed and a few permuted results of correlations between one of the models, in this case the Feature-Based Model, and the brain-based representational space of cues before and after training.

The following paragraphs outline how the test statistic and significance were determined. At each time bin, the test statistic of the permutation analysis was considered to be the difference between the pre- and post-correlation results (r_{pre} - r_{post}), when considering correlations with the Perceptual Model space, and the inverted difference between the post- and pre-correlation results (r_{post} - r_{pre}), when considering correlations with the Feature-Based Model space. In both cases, the test statistic was referred to as the r-difference value. The order of subtraction was determined based on our previous hypotheses, where we expected the pre-training condition to have greater correlation with the Perceptual Model ($r_{pre} > 0$) and we expected the post-training condition to have greater correlation with the Feature-Based Model ($r_{post} > 0$).

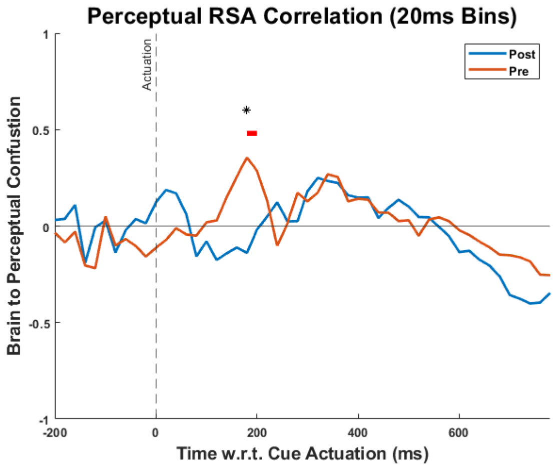

Fig. 10. Perceptual Model correlation results showing correlations between the Perceptual Model and brain-based representational space of cues before and after training. The orange time series shows the pre-training correlation results ($\mathbf{r}_{pre}$) between the brain-based RDMs of the pre-condition and the Perceptual Model space, and the blue time series shows the post-training correlation results ($\mathbf{r}_{post}$) between the brain-based RDMs of the post-condition and the Perceptual Model space. Significant correlation between the pre-training RDMs and Perceptual Model, before correction, is marked by the red significance bar. Significance after correction is marked by an asterisk.

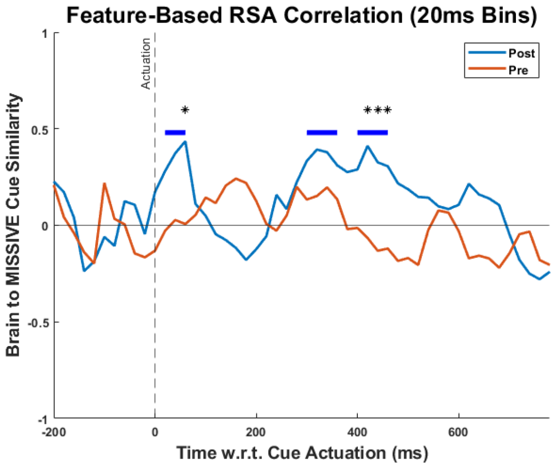

Fig. 11. Feature-Based Model correlation results showing correlations between the Feature-Based Model and brain-based representational space of cues before and after training. The pre-training correlation results ($\mathbf{r}_{pre}$) between the brain-based RDMs of the pre-condition and the Feature-Based Model (orange) and the post-training correlation results ($\mathbf{r}_{post}$) between the brain-based RDMs of the post-condition and the Feature-Based Model (blue) are presented. Significant correlations between the post-training RDMs and Feature-Based Model, before correction, are marked by blue significance bars. Periods of significance with correction are marked by asterisks.

For each model comparison, we computed our *observed* test statistics, at every time bin, by taking the respective difference between the true correlation results ($\mathbf{r}_{pre}$ - $\mathbf{r}_{post}$ or $\mathbf{r}_{post}$ - $\mathbf{r}_{pre}$). Then, for each permutation, the r-difference values at each time bin were also computed. These computations are illustrated in Fig. 9(c), where the r-difference value at a particular time bin is highlighted. To evaluate points between the true pre- and post-training conditions that were considered to be significantly different from one another, the observed test statistics were compared to the sorted, permuted r-difference values, only at the time bins marked as significant without correction. At each time bin considered, if the observed test statistic fell within the top 2.5% of the distribution of permuted r-difference values for the current time bin, the correlation results between the pre- and post-conditions were justified as being significantly different and the original correlation was considered to be significantly greater than zero, with correction. This process is illustrated in Fig. 9(d), at an example time bin, and culminates the permutation analysis. For the model-to-model comparison, a two-tailed Spearman's rank correlation was used to evaluate if the models were significantly correlated at a significance level of $\alpha = 0.05$. The Spearman's correlation r-value and associated p-value were reported.

III. RESULTS

A. Perceptual Model Correlation

First, we evaluated how the neural representation of haptic cues in the pre- and post-training conditions related to the Perceptual Model. Fig. 10 shows the results for the correlations with the Perceptual Model space, 200 ms before and 800 ms after the time at which onset, or actuation, of every MISSIVE cue occurred (0 ms). Significant correlation between the pre-training RDMs and Perceptual Model, before correction, was found approximately 180 ms to 220 ms following the onset of MISSIVE cues. No significant correlation, before correction, was found between the post-training RDMs and Perceptual Model. Following correction via the permutation analysis, significant correlation between the pre-training RDMs and Perceptual Model was only found at the 9th time bin ($r = 0.355$, $p < 0.05$), approximately 180–200 ms following MISSIVE cue actuation.

B. Feature-Based Model Correlation

Next, we evaluated how the neural representation of haptic cues in the pre- and post-training conditions related to the Feature-Based Model. Fig. 11 shows the results for the correlations with the Feature-Based Model, considered over the same time range as the previous correlation results. Significant correlations between the post-training RDMs and Feature-Based Model, before correction, were found over three different time periods. The first period occurred approximately 20–80 ms after MISSIVE cue actuation. The next two periods of significance occurred approximately between 300 and 480 ms following MISSIVE cue actuation; the first of these intervals spanning 300–380 ms and the second ranging from 400–480 ms. No significant correlation, before correction, was found between the pre-training RDMs and Feature-Based model. Following correction via the permutation analysis, significant correlation between the post-training RDMs and Feature-Based Model were found over two time periods. The first was approximately 60–80 ms following MISSIVE cue actuation, corresponding to the 3rd time bin ($r = 0.436$, $p < 0.01$). The second was found approximately 420–480 ms following MISSIVE cue actuation, from the 21st to 23rd time bin ($r = 0.411$, $p < 0.01$; $r = 0.326$, $p < 0.05$; $r = 0.305$, $p < 0.05$).

C. Perceptual to Feature-Based Model Correlation

The Perceptual and Feature-Based model spaces were found to be significantly correlated with a Spearman's correlation coefficient of $r = 0.65$ ($p < 0.0001$).

IV. DISCUSSION

We evaluated an EEG-RSA framework as a method to quantify how the neural representation of haptic cues changes after cross-modal associative training, on a multimodal, haptic device (The MISSIVE). For a use-case scenario, we developed brain-based representational spaces capturing the similarity space of the multimodal haptic cues both before and after training. Then, to determine if our EEG-RSA framework may be a reliable approach to track changes that occur in the brain, we compared these neural representational spaces to models that were strategically developed to capture how the individual's sensitivity to haptic cues may change after exposure. Since the goal of this use-case analysis was not to track changes specific to haptic-phoneme learning following association training, we do not report on phoneme training performance. For our purposes, the association task was somewhat arbitrary and simply offered prolonged exposure to the haptic cues.

Our first hypothesis investigated if the neural representation of haptic cues *before* training reflected perceptual confusion of the cue space that a naïve population may experience. We compared the Perceptual Model space to the neural representation of haptic cues at every time bin, both before and after training. Results for the Perceptual Model Correlation showed correlation between the Perceptual Model and the neural representation of haptic cues was statistically significant for a small time range *before* training, but there was no significant correlation between the Perceptual Model and neural representational space of cues after training. Specifically, we found a significant correlation between the Perceptual Model and the pre-training RDM at the 9th time bin, which is approximately 180–200 ms after the start of MISSIVE cues. This significant result suggests that prior to training on the MISSIVE device, the neural response reflects perceptual confusion that a novice population may experience with multimodal cues. Individuals interacting with multimodal haptic cues for the first time may make common perceptual errors as to what features are felt and confuse the overall cues [46], [56]. This is even more likely when haptic features may cause masking effects [63], adding complexity to how well subjects can make out the distinct features of a multimodal haptic cue. It is understandable that the neural response to MISSIVE cues in the pre-training condition, before the subject familiarized himself with the haptic cues via association training, reflects common perceptual confusion between MISSIVE haptic cues.

Our second hypothesis investigated if the neural representation of haptic cues *after* training reflected feature differences (e.g., vibration, squeeze, stretch) between the cues. We compared the Feature-Based Model space to the neural representation of haptic cues at every time bin, both before and after training. Results for the Feature-Based Model Correlation showed correlation between the Feature-Based Model and the neural representation of haptic cues was statistically significant for multiple time regions *after* training, but there was no significant correlation between the Feature-Based Model and neural representational space of cues before training. Specifically, we found a significant correlation between the Feature-Based Model and post-training RDMs at the 3rd time bin, approximately 60–80 ms after the start of MISSIVE cues, as well as from the 21st to 23rd time bins, approximately 420–480 ms following MISSIVE cue actuation. This result, that correlations between the brain-based representational space and Feature-Based Model were significant following MISSIVE training, but not prior to training, suggests that training leads to a sharpening of the sensory response to the multimodal haptic cues. This is captured by the brain-based response more precisely tracking the specific features in each haptic cue post training. If the individual was not sensitive to the unique features, response to each cue should reflect neural patterns that are more similar to each other. However, if the individual becomes more sensitive to the MISSIVE cue features, cues that are closer to each other in terms of feature space should be more similar than cues that are farther apart, which our results reflect.

Significant correlations between the models and brain RDMs indicate that the model representational structure is reflected in the neural patterns. However, the model may not be significantly correlated to the brain-based RDMs, which make up the brain-based representational space, at every time point considered. Speculatively, this could be due to more significant regions being time-locked to specific Somatosensory Evoked Potentials (SEPs), which can occur due to natural or mechanical stimulation at the surface of the skin [21], [64], [65], [66]. Each MISSIVE cue includes several feature components that perturb the surface of the skin (e.g., vibration, stretch, and squeeze), so SEPs present in the 30-channel ERP waveforms would subsequently influence the 9×9 brain-based RDMs used for the correlation analysis over time, where RDMs at time bins that align with the timing of unique SEP components may hold the most relevant (i.e., significant) neural information. In future work, it may be important to characterize SEPs time-locked to each unique MISSIVE feature, for both the pre- and post-training conditions, such that we can gain more insight into the timings of significant results.

Finally, we completed a model to model comparison, and found that the Perceptual and Feature-Based models were significantly correlated based on a Spearman's Rank correlation. This is an interesting and promising result, as only the pre-training neural similarity space was significantly correlated with the Perceptual Model space and only the post-training neural similarity space was significantly correlated with the Feature-Based Model space. This double dissociation suggests that both models capture the representational structure of the haptic cues, in terms of the cues' similarity to one another, however the EEG is able to reflect small nuances of the models that capture how the neural space may shift with training.

Our results show promise for an EEG-RSA approach to track representational changes at the neural level that occur following haptic association learning. Specifically, our framework showed that we can quantify neural changes in how multimodal haptic cues are represented with respect to other cues. The flexibility of this approach allowed us to test models that were strategically hypothesized and designed to capture how the neural representational space of unique multimodal haptic cues may change after training on the wearable device. The first model represented cues with respect to others based on their perceptual confusability, where perceptually more similar cues should be confused more often, and the second model represented cues based on the similarity of their mechanical features. By testing two different models, we demonstrated the versatility and robustness of an EEG-RSA approach and tracked how the sensitivity to haptic cues changed with extended training on the multimodal device and specifically how the representational space of the cues may be structured. We were even able to capture that the nuanced features of each model were uniquely reflected in the brain-based similarity spaces, as the two models themselves were correlated, but only the Perceptual Model was significantly correlated with the pre-training neural space and only the Feature-Based Model was significantly correlated with the post-training space.

Other groups have used RSA to investigate haptic perception [39], [40], [41]. However, the only other group, to our knowledge, that considered an RSA approach inline with that of tracking neural correlates of haptic learning was Malone et al. [42]. They used an fMRI-RSA approach to investigate the neural mechanisms of vibrotactile categorization on a unimodal haptic device, and claim to be the first group to characterize the neural mechanisms of perceptual categorization of trained vibrotactile stimuli in humans. In their work, subjects trained to categorize vibrotactile cues presented on the arm into two different groups, and then fMRI responses were measured during a categorization task with the trained stimuli. To evaluate the perceptual categorization space of the somatosensory system, Malone et al. compared the neural (dis)similarity space to two models, one that was representative of the perceptual similarity of cues and the other that was representative of the categories which each stimulus was trained to be in. They found that their models captured neural representation of cues and specifically that perceptual and categorical selectivity were represented in different regions of the brain [42]. However, their work, as well as the majority of RSA studies investigating haptic perception [39], [40], [41], is limited to fMRI analysis, and further restricted to unimodal haptic devices, often utilizing continuous-time features to transmit vibrotactile cues. Our results show promise to extend RSA to EEG-based frameworks while considering cue delivery on multimodal haptic devices. This is crucial as EEG is more affordable and accessible to the haptics community, as well as compatible with haptic devices [21]. Furthermore, haptic researchers are moving away from purely unimodal devices as multimodal devices are becoming much more prevalent in haptic applications [1], [46], [47], [48], [49], [50], [51].

Beyond our promising results, our use-case analysis was limited to the first phase of successful cross-modal associative learning, accurate perception of the multimodal cues. In future work, we plan to extend our approach to the second part of cross-modal associative learning, where individuals must successfully learn and retain mappings between visual or auditory modalities and that of tactile cues. Our framework could be used to assess if the brain-based similarity space is shaped by the representational similarity space of what it is being associated with, such as phonemes. Although our current analysis may not provide a comparison to the phonological space, our use-case analysis provides a good assessment of the potential feasibility of EEG-RSA to track haptic learning. In future work, we plan to test our EEG-RSA approach on more participants, to account for individual variability and further verify the versatility and robustness of our methodology. Furthermore, it should be noted that by considering full-scalp EEG, we ignore questions related to the topology of brain activity due to haptic stimulation. Although these should be addressed in future work, already we see evidence that with just four days of practice on the MISSIVE device, there are changes in the overall neural structure. Specifically, we observe changes in the neural representation of how these cues are processed, where the individual becomes better at distinguishing at least the somatosensory features. It was not obvious that RSA with EEG would capture this, so it is an exciting finding for using neural signals to track haptic learning.

V. CONCLUSION

We conducted an exploratory study ($N = 1$) to evaluate RSA as a general method to track neural correlates of haptic learning. We aimed to address if we could track neural changes associated with training on a multifeatured haptic device with our framework, and restricted the scope of our analysis to the first phase of successful cross-modal associative learning, accurate perception of the multimodal cues. We evaluated how the sensitivity to multifeatured cues changed after training. We developed two models that were hypothesized to be representative of the neural space both before *and* after training, and evaluated if the sensory space to haptic cues changed with directed practice. Specifically, we considered if learning on a multifeatured haptic device made individuals more sensitive to the haptic cues. Results suggest that, prior to training, the neural representation of haptic cues reflects perceptual responses to cues experienced in a naïve population. Training leads to a sharpening of the sensory response to haptic cues, such that after training the neural representation of haptic cues starts to reflect the features of the cues themselves. Overall, our analysis supports feasibility of an EEG-RSA approach to investigate training for associative learning on multimodal haptic devices.

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