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EEG-Based Neurohaptics Research: A Literature Review

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ABSTRACT Neurohaptics is the field of study that strives to understand the complex neural representation provoked in response to tactile and/or kinesthetic stimuli. This field has garnered a noticeable attention over the past decade not only in neuro-scientific research but also in medical, marketing and engineering fields. In this paper, we review existing literature on Electroencephalography (EEG)-based neurohaptic studies charting out the main themes and significant findings. Furthermore, we provide a brief review of the EEG analytical methods commonly utilized in the neurohaptic domain. Also, we present a case study with the complete flow of conducting neurohaptic research studies. Lastly, we discuss limitations and provide directions for future neurohaptic research, such as: modeling quality of haptic experience, improving neurohaptic systems and neurohatpics in virtual reality.

INDEX TERMS Neurohaptics, EEG, touch, haptics, neuroscience.

I. INTRODUCTION

A. HAPTICS

We perceive the world around us through the different sensors we are equipped with such as our eyes, ears and skin. Our biological sensors probe the environment, each in its own modality, forming a corresponding perception in our brains about the surrounding environment. However, the human brain's capacity goes beyond perception; after analyzing the perceived information, a state of cognition is formed producing mental understanding and knowledge. Scientists are keen to decode the working principles of our senses and how they affect our cognition and emotion. It is know that haptic sensations are connected by neural networks that are widespread in our bodies and neural pathways, including the somatosensory system. The skin has an area of around 1.8 m^2 and a weight of 5 kg for an adult human [1]. Haptic perception is of great use and importance in our daily lives and plays both discriminative and affective roles [2], [3]. Humans use haptic sensation to hold objects and discriminate between them in terms of shape, size, weight and texture. Haptic sensation also allows us to feel temperature, pressure, pain and pleasure. Haptic perception is even of greater importance for individuals who lose their vision. Interestingly, haptic sensation is the first sense to develop in a human fetus, making it the origin of where awareness begins to form [4], [5]. Both visual and auditory modalities have been extensively studied from perceptual and cognitive perspectives. Haptic modality in particular, however, has recently been the target of intensive research and scrutiny. Understanding haptic perception has become an exciting area in the technological, industrial, medical, gaming and scientific research [6]. The motivations for this area of inquiry are as follows: 1) To better understand and quantify haptic perception and cognition on a fundamental level 2) To enable the novel technology of haptic interfaces such as tactile displays [7]–[9], and 3) To develop other applications including assistive haptic rehabilitation [10]–[12], haptic gaming [13] and social media [14]. In any multimodal system, the haptic modality can be considered as a separate independent channel of information for the user, or as a complementary channel to the visual and auditory modalities [15].

Due to the aforementioned reasons, detailed studies on the characteristics of the sense of touch and its affective and cognitive components have been actively investigated in past years [16]. In traditional research, haptic modality is studied through self-reporting and/or behavioral observations. However, the self-reporting method is subjective, difficult to reproduce and sometimes affected by social pressure [17]. Additionally, behavioral observation cannot give access to the subjects' mental states and it cannot provide

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real-time feedback. Instead, it relies on participants' memories [18], [19]. Thus neither method is ideal.

B. NEUROSCIENCE

More than half the human brain is devoted to processing sensory experiences (i.e. visual, auditory, haptic, olfactory and gustatory experiences). Touch, in particular, is an important part of the communication with the physical world. How things feel drives our thoughts and behaviour, influences our comprehension and retention of information, and profoundly shapes our emotional responses.

In recent years, novel methodologies to explore the neurobiological bases of mind and behavior have inspired the field of haptics [20]. Neurophysiological methods such as functional magnetic resonance imaging (fMRI) and Electroencephalography (EEG) provide a more robust and reliable alternative than self-reporting or performance evaluation. Additionally, they provide a quantitative measure for the participants' neural processing of perception and cognition in real time [21].

fMRI is a neuroimaging technique that measures brain activity by detecting the blood-oxygen-level-dependency (BOLD) in the whole brain [22]. Its working principle relies on the fact that BOLD is coupled with neural activation. fMRI has a high spatial resolution and is capable of imaging deep brain activities, such as the limbic system. However, fMRI is costly and is very limiting in terms of the possible experimental setups to be used and the type of electronics incorporated in the experiment. It also has a limitation of low temporal resolution. Whole-brain scanning generally takes two or three seconds [23].

In contrast to fMRI, EEG is a lower cost apparatus capable of recording the cortical neural activation. It does not require a Magnet Room (MR) shield room. Unlike in fMRI, the participants can sit or move, unlike with fMRI, which allows a more natural environment. EEG also has a high temporal resolution, and thus it allows a real-time activity analysis for the neural mechanisms of touch.

C. NEUROHAPTICS

The term ''neurohaptics'' has been used previously to refer to the discipline which deals with the convergence of neuroscience and engineering in haptics [24]. The term is also used to refer to the understanding of how the human sense of touch and its underlying brain functions work [25].

In this paper, we define neurohaptics as: *the science and technology that investigates the neural representation and cognitive modulations associated with tactile and/or kinesthetic haptic interactions.*

D. CONTRIBUTIONS OF THIS SURVEY ARTICLE

Driven by the several advantages of the EEG approach, this article surveys the literature of EEG-based neurohaptic research over the last decade. The article examines EEG-based neurohaptic studies that are most pertinent to the analysis of the underlying neural mechanisms of touch and its effect on perception, cognition and emotion. To highlight the importance of this study, we surveyed the number of publications in the past decade using (EEG OR Electroencephalography) AND (haptic* OR tactile* OR neurohaptics) keywords in the following digital libraries: IEEE, Springer, Science Direct, and ACM. The result of this search, shown in Figure 1, indicates a noticeable increasing trend of research activities in this field.

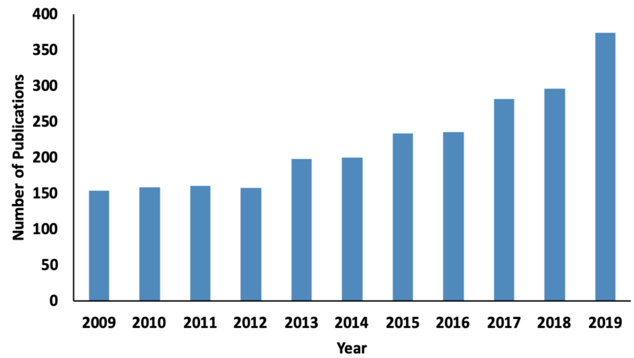

FIGURE 1. Publications during the past decade on EEG-based neurohaptics. Keywords: (EEG OR Electroencephalography) AND (haptic* OR tactile* OR neurohaptics) in IEEE, Springer, Science Direct and ACM.

The major contributions of this article are outlined as follows:

- A holistic survey and taxonomy of EEG data analysis methods for neurohaptics. The developed taxonomy is based on an exhaustive research of recent publications in the field.
- A comprehensive summary and visualization of the findings in neurohaptics (shown in Figure 9).
- A detailed discussion on future interesting open research challenges regarding neurohaptics from both science and technology perspectives.
- A case study demonstrating the methodology of conducting EEG-based neurohaptic research studies, including forming a research question, designing an experimental setup and protocol, conducting data analysis and showing sample results.

The remainder of the article is organized as follows: section 2 discusses the two types of analysis performed on EEG signals, namely intra-regional and inter-regional analysis. Additionally, EEG artifacts will be discussed and their methods of removal will be elaborated. In section 3, a thorough literature review is presented along with classification of neurohaptic studies into five relevant sub-topics: emotions and touch, observed touch, haptic memory,, and discriminative touch. Section 4 presents a case study to demonstrate EEG-based neurohaptics research study, including a research question, experimental setup and protocol, data analysis and results. Section 5 summarizes the findings in the neurohaptics research field and outlines research challenges and future prospects for EEG-based neurohaptic research such as: modeling quality of haptic experience, improving neurohaptic systems and neurohatpics in virtual reality.

II. EEG-BASED ANALYTICAL METHODS

A. ARTIFACTS REMOVAL

A perfect EEG signal originates only from the cerebral cortex. In reality, EEG signals are contaminated with electrical activities from sources other than the brain. Any signal that is not originating from the brain is called an artifact. EEG artifacts can be categorized as internal (physiological) and external (non-physiological). Physiological artifacts arise from the subject's body parts other than the brain whereas non-physiological artifacts are typically produced by devices in the surrounding environment [26]. Physiological artifacts include movement artifacts, oculogyric potentials (due to eye movement and blinking), myogenic potentials (due to muscle movement such as jaw or facial movements) and cardiac potentials (due to the pulsating heart) [27]. Non-physiological artifacts include the common 50Hz/60Hz components of the utility frequency and the electric field produced by the surrounding electronics and apparatuses [28].

As artifacts can mimic or distort EEG signals, it is of much importance to distinguish the genuine brain activity from artifacts to avoid misinterpretation. There are three general ways to deal with EEG artifacts: prevention [29], rejection or cancellation [30]. The goal is to develop mathematical methods capable of artifact identification and removal without compromising the EEG signal quality. As the artifact sources are quite different, most researchers aim to detect and cancel a specific type of noise per algorithm. Below are the techniques commonly employed in de-noising the EEG signals [31]:

- Simple filtering: Notch filters are commonly used to reject 50Hz/60Hz components. However, simple filters such as band pass, low pass, or high pass are not an option for other artifacts because the frequency bands of the artifact and the EEG signal can overlap.
- Regression algorithms: These represent the most commonly used correction methods up until the mid-1990s, due to their simple algorithm and modest computational cost. Regression algorithms operate on the premise that one or more reference channels comprise all the artifacts, so other channels are corrected by subtracting the contaminated EEG channels from the reference channels [32]. Regression can be implemented equally in the time domain or the frequency domain by estimating the influence of the noisy reference channels on the targeted channel. Due to the required premise in having reference channels, a limitation of this technique, this method was replaced by other advanced algorithms such as blind source separation (BSS) methods [31]. However, regression algorithms are still considered to be the standard technique that other methods' performances are compared to.
- Blind source separation (BSS): BSS methods such as independent component analysis (ICA) and principle component analysis (PCA) [33] are widespread and common in eliminating Electrooculography (EOG) and Electrocardiogram (ECG) artifacts [29], [34]. For each BSS method, several algorithms have proven successful in tackling most of the physiological artifacts.

In their comprehensive review on EEG artifacts removal, J. A. Urigüen and B. Garcia-Zapirain [31] surveyed tens of papers and found that 45% of the reviewed literature used ICA for artifacts removal, whereas regression methods represented 11%. Among the different ICA algorithms, InfoMax [35], second order blind identification (SOBI), [36] and constrained ICA (cICA) [37] are most commonly employed. An adaptive mixture of independent component analyzers (AMICA), [38] which is also an algorithm based on ICA, has been proposed as an alternative for the aforementioned algorithms; it has a slightly better accuracy on the cost of processing time. After thorough experimentation by the same authors on recorded EEG signals, they found that revised aligned artifact averaging (RAAA, a regression method) or SOBI perform best to eliminate EOG artifacts. SOBI or AMICA perform best in removing both Electromyography (EMG) and ECG artifacts, and AMICA, InfoMax or SoBI are all suitable choices for removing all artifacts at once.

B. INTRA-REGIONAL ANALYSIS

We refer to EEG analytical methods that are based on detecting features from regions on the cortex as intra-regional analyses. Features can vary depending on the type of task given to the participants in a neurohaptic study and on the type of analysis intended by the researcher. Herein, we will discuss four main EEG features commonly tackled under regional analyses in neurohaptics: event related potentials (ERP), somatosensory evoked potentials (SEP), steady state somatosensory evoked potential (SSSEP), and power spectral density (PSD).

1) EVENT RELATED POTENTIALS (ERP)

ERP was first used in correlating the recorded potentials to a specific event [39]. ERPs are microvolt voltages that are generated in the brain in response to specific stimuli [40]. ERP signals can be generated in response to either a sensory, motor or cognitive event in a time-locked manner. ERPs are thought to be formed due to an additive post-synaptic activity of the similarly-oriented cortical pyramidal neurons during information processing [41]. An ERP is typically small and hardly observable. Thus, it is usually formed by averaging over many instances of the signal for a particular event [42]. ERPs can be divided into two categories with respect to the types of processes they represent. The early components, which peak in the first 100ms, are called "exogenous" or "sensory" as they largely depend on the type of stimulus and its physical characteristics. The later components that peak after 100ms are called "indigenous" or "cognitive" as they reflect the evaluation and cognition processes in the subject [43]. ERP peaks are identified by their amplitude and latency. ERP components are often given names with respect to their polarity (positive/negative) and their order or latency. Notable components include: P50, N100, P200, N200, N300,

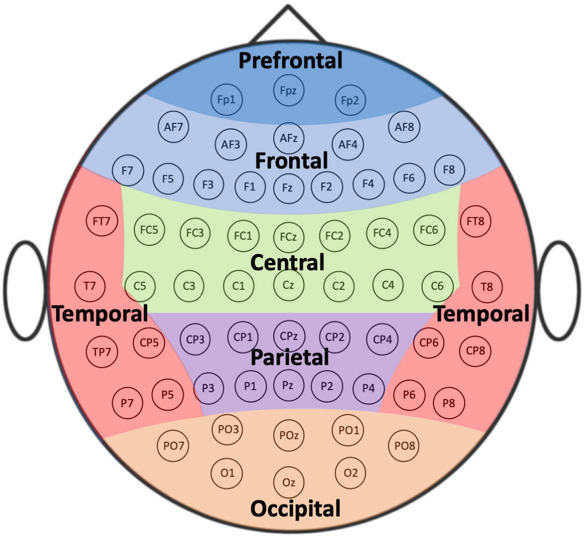

FIGURE 2. Electrodes locations and brain cortical regions.

P300, N400 and P600, where P and N refer to positive and negative peaks respectively. It should be noted, however, that these components are usually not modality-independent. In other words, components elicited due to events in different modalities are not necessarily related to the same underlying functional brain activity. Additionally, within a single modality, ERP components having the same labels in different experiments might be interpreted differently [44]. ERPs are often measured from Fz, Cz and Pz electrodes; locations are indicated in Figure 2.

Several neurohaptics studies employed ERPs to infer information and answer questions about the sense of touch. In a passive touch experiment aiming to understand the neural differences between healthy and blind people during a haptic object recognition task, Alonso *et al.* found that blind subjects have a shorter reaction time when recognizing objects, and their P100 has a shorter latency and smaller peak [45]. Shorter latencies and smaller peaks are attributed to less effort/attention required to perform the task because the sense of touch is more developed in blind subjects. In another study by Hoefer *et al.* on fabric qualities, it was found the P300 component has a higher peak amplitude for the most favorable fabric suggesting less distraction and better cognitive resources during the favorable fabric/skin interaction [46]. Reuter *et al.* studied ERP changes in tactile discrimination tasks with relation to age and expertise. Enlarged somatosensory N70 amplitudes were detected in experts due to specific excitability of the somatosensory cortex, whereas a smaller P300 amplitude was detected in both older adults and experts; the latter result indicates fewer available resources and a reduced cognitive effort for the experts [47].

2) SOMATOSENSORY EVOKED POTENTIALS (SEP)

SEPs are generated in response to a stimulus of touch; they are measured from scalp locations under the somatosensory cortex. Additionally, SEPs consist of a series of positive and negative peaks that reflect neural sequential activation correlated with touch [48]. Generally, SEP consists of an early cortical component provoked in the contralateral primary somatosensory cortex correlated with the physical characteristics of the touched stimulus, such as N20, P27, and P50 [49]. Later components, such as N140 and P200, are typically larger in amplitude and more distributed over the scalp, mainly above the secondary somatosensory cortex and frontal cortex, indicating a higher cognitive processing [50], [51].

Several haptic studies showed that the modulation of one or more SEP components can be based on the characteristic of the touch experience, whether endogenous or exogenous. For example, some of the SEP components, both early and late, demonstrated correlation with tactile attention [52]. Early SEP components such as the P50 have been shown to be modulated when the spatial location of the touch is attended [53]. Another study examined postural sway while standing with and without a light fingertip touch; the study found that P50, N140 and P200 were enhanced by touching a stable surface. However, P50 and N140 were also present while touching a non-stable surface; thus, P200 is the task-related potential [49]. A study by Genna *et al.* aiming to examine the temporal features of late-latency SEPs and their cortical distribution in a prolonged passive touch identified P100-N140-P240 peaks. The study found that both P100 and N140 peaks were bilateral potentials with greater amplitude in the contralateral hemisphere and delayed latency in the ipsilateral hemisphere [54].

3) STEADY STATE SOMATOSENSORY EVOKED POTENTIAL (SSSEP)

In the past two decades, several studies showed that applying vibrations on the skin in a sinusoidal repetitive manner elicits cortical activities at the same frequency of stimulation and its harmonics; these EEG signals are called SSSEP [55]. For example, a vibration applied to the hand elicits SSSEPs that are prominent in the contralateral parietal region located at the primary somatosensory cortex S1 [56]. In experiments where there is competing or parallel stimulation, SSSEP can be used through frequency tagging to distinguish between the different cortical activities provoked by the different stimuli. Other EEG signals such as ERP or SEP elicited in the cortex are indistinguishable in the case of two or more simultaneous stimulations [57].

SSSEPs gained special interest in BCI applications aiming to replace systems that were dependent on visual attention or steady state visually evoked potentials (SSVEP), especially for patients suffering from loss of control over their eye muscles [58]–[60]. SSSEP was also employed in other, non-BCI neurohaptic studies. A study by Pang *et al.* used the neural frequency tagging concept to study competitive neural interactions, processing resources, and cortical distribution during controlled somatosensory attention [57]. Moungou *et al.* developed a novel means of characterizing the cortical response related to various textured stimuli in passive touch using SSSEP [60]. In a follow-up study, they compared the cortical activity of passive and active textured stimuli using SSSEPs [61]. Other applications where SSSEP proved useful include the study of neural activations during fine texture exploration. Fine natural textures elicit high frequency vibrotactile sensations, thus the provoked high frequency correlated EEG is hard to measure because the cortex acts as a low-pass filter. Modulating fine textures frequencies with a mechanical low-tactile frequency can be used to tag specific textures to areas in the brain exhibited as SSSEPs; this facilitates easy measuring from the cortex [62].

4) POWER SPECTRAL DENSITY (PSD)

PSD is one of the most commonly used forms of EEG data analysis in neurohaptics. In PSD analysis, the average power of the EEG signal is computed in a specific frequency range. This is usually accomplished by fast Fourier transformation expressed in microvolts squared per Hertz. The PSD of the different EEG waveforms can be calculated with respect to their corresponding frequency ranges. EEG waveforms, referred to as rhythmic activity, are generally classified with respect to their frequency ranges: delta (0.1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz) [63]. Each frequency range is noted to have a specific distribution over the scalp or to be correlated with some biological phenomenon. An alpha waves has rhythmic activity that lies in the frequency range of alpha waves. However, its suppression in the sensorimotor cortex is associated with motor actions or the imagination thereof. The wave suppression is called event-related desynchronization (ERD).

Most of the neurohaptic studies used the rhythmic activity analysis to better understand the sense of touch. For example, in a study aiming to investigate how the rhythmic activity is distributed over different regions in the scalp during a tactile discrimination task, a feedforward 15 Hz beta band oscillatory network was identified from somatosensory to parietal to prefrontal regions and a recurrent 80 Hz gamma network was identified from prefrontal to posterior parietal to somatosensory and back to prefrontal regions. The identified networks are thought to reflect accumulation of sensory information and attentional selection of task-relevant details, respectively [64]. In other studies, rhythmic activities are used to study impaired individuals while performing a haptic task. For example, a study by M. Grunwald showed that it is possible to discriminate between subjects suffering from mild cognitive impairment and mild dementia from healthy subjects using rhythmic activity during the performance of a haptic task (i.e. theta waves distribution over the scalp) [65].

C. INTER-REGIONAL ANALYSIS

In contrast to intra-regional analysis, inter-regional analytical methods are based on analyzing brain signals from different regions on the scalp simultaneously and finding correlated brain networks. Functionally-related brain regions that are spatially separated are related by what is known as functional connectivity. There are several methods that are based on inter-regional analysis used to study functional connectivity in the neurohaptic domains, such as phase locking value (PLV) [66], Granger causality [67] and graph theory [68]. These methods were introduced in other domains and were successfully applied in the field of EEG data analysis. We will discuss the three aforementioned methods below.

1) PHASE LOCKING VALUE (PLV)

PLV is one way of assessing the functional connectivity between two brain regions first introduced in 1999 [69]. The assumption behind this method is that if two brain regions are connected functionally, then the difference between the instantaneous phase of their EEG signals is almost constant. PLV takes values between 0 and 1, where 0 implies that there is no synchrony between the two signals, and a value of 1 implies a constant phase difference between the two signals. PLV should be applied carefully because a false connectivity might be realized in the case of volume conduction; a single source in the brain might manifest its activity on two electrode sites resulting in spurious PLV [66].

An example neurohaptic study was carried out by Park *et al.* Therein, PLV was used to assess functional connectivity during an active touch task to a surface haptic device capable of providing tactile feedback. The study aimed to extract PLVs from alpha, beta, and gamma frequency bands and compare the results in the absence and presence of tactile feedback from a touchscreen device. The study showed different functional beta connectivity in interhemispheric areas [70].

2) GRANGER CAUSALITY

Granger causality is a mathematical technique introduced first in the economics field by the Noble Prize laureate Clive Granger in 1969 [71]. This is a statistical approach that is based on prediction. The theory states that if signal A1 causes signal A2, then taking A1 past values into account should improve the prediction A2 as compared to considering A2 past values only. Thus, Granger causality is directional by nature. Mathematically, this is modeled with a linear autoregressive model and by comparing the prediction error with and without past values of A1. Recently, several studies tried to extend Granger causality to non-linear cases [72] and non-parametric methods instead of autoregression [73].

In a neurohaptic study by Adhikari *et al.*, which aims to identify oscillatory networks during a tactile discrimination task, a parametric Granger causality method was used on single trial EEG-source signals to evaluate patterns of causality in beta and gamma bands. A 15 Hz beta network (feedforward) and an 80 Hz gamma network (recurrent) were identified in which the strength of their activities is correlated with the accuracy of the tactile discrimination task [64].

3) GRAPH THEORY

Graph theory is a field in mathematics that is used to model relationships between objects. A graph in graph theory is a mathematical representation of a network, which consists of nodes and connections between them; connections can be

TABLE 1. Advantages and disadvantages of the EEG analytical methods.

Technique	Description	Observations	Key Reference
PSD	- Frequency domain analysis that measures the energy of the cortical activity of the main EEG frequency bands.	- Frequency bands: Theta, Alpha, Beta, Gamma. - Beta activity is associated with attention, alpha and beta are both associated with motor execution and gamma activity is associated with mental activity and cognition.	[76] [77]
ERP	- Time domain analysis that relies on observing positive and negative peaks (waveforms) correlated to a particular sensory, cognitive or perceptual event.	- Measure the mean amplitude and latency of the peaks at (Cz, Fz and Pz) electrodes. - N100 waveform is correlated with the detection/perception of the stimulus event while P300 waveform is correlated with attention.	[43] [78] [42]
SEP	- Time domain analysis that relies on observing EEG waveforms associated with touch. It is used to evaluate the somatosensory pathway for haptic input	- Measure the mean amplitude and latency of the peaks at (C3, CP3, C4, CP4) electrodes.	[78]
SSSEP	- Frequency domain analysis that deals with the neural response of an external steady-state sinusoidal Stimulus that is modulated by the subject interaction.	- Measured over the somatosensory cortex (C3, CP3, C4, CP4).	[62] [79]
PLV	- Measures of EEG connectivity (phase synchrony between EEG signals)	- Does not provide information about the direction of connectivity.	[80] [69]
Granger Causality	- Statistical method that investigate causality between two signals	- Provides quantitative information on directional connectivity	[81] [80] [82] [83]
Graph Theory	- Graphical representation of inter-brain connectivity including directed/non-directed, binary/weighted graphs	- Robustness of the graph is affected by the choice of the number of electrodes (spatial resolution of the EEG recordings)	[81] [84]

either directed or directionless. Recently, a couple of neurohaptics studies were implemented based on graph theory methods to assess functional connectivity between different brain cortical parts using the acquired EEG signals [74]. Each brain site is considered a node, and the connections strength and direction are both assessed to develop a valid network representation. A study by Hua *et al.* investigated brain functional networks related to affective touch using graph theory [75]. It was found that not only a highly distributed functional network exists for affective touch, but also such a network is modulated by the type of emotion the affective touch induces (pleasant, neutral, unpleasant).

In summary, this section introduced several EEG features and analytical methods. A summary of the EEG analytical methods is presented in Figure 3. The usage of these methods was surveyed in the neurohaptics literature; the distribution of the methods is illustrated in Figure 4. Inter-regional analytical methods are under-explored by the neurohaptics community, which suggests there is a much room for future contributions using these methods. Prior to deciding on the best methods for EEG analysis, awareness about the main features and limitations is needed. We list some of the key advantages and limitations of the discussed methods in Table 1.

III. EEG-BASED NEUROHAPTICS STUDIES

More than 70 neurohaptics studies have been surveyed most of which used EEG as a tool. Around 75% of the studies investigated the neural responses of hand, palm or fingers touch as can be seen in Figure 5. Also, around 55% of the studies handled passive touch while 45% studied active touch. In this section, we highlight the main findings of the neurohaptics studies in the literature. Finding patterns among the surveyed literature work, it was decided to categorize the studies as follows: emotions and touch, observed touch, haptic memory, discriminative touch, and tactile perception with age.

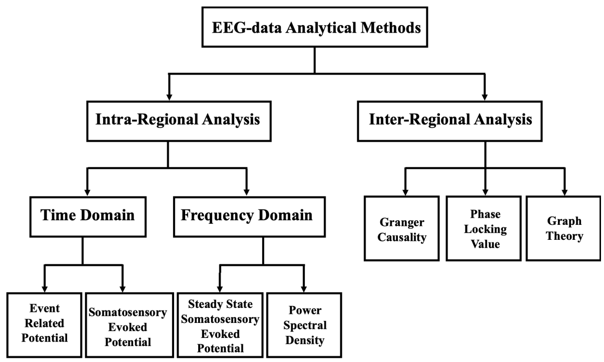

FIGURE 3. Taxonomy of EEG data analysis methods in Neurohaptics.

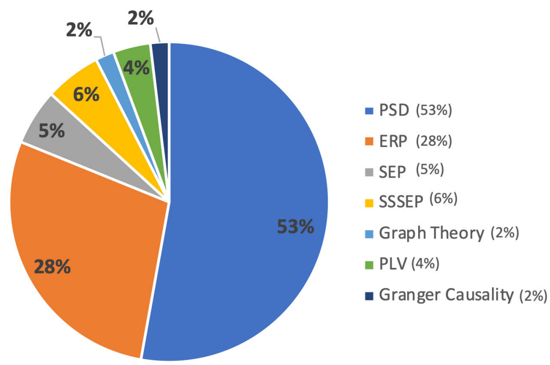

FIGURE 4. Distribution of EEG analytical methods in the neurohaptics literature.

A. EMOTIONS AND TOUCH

Affective touch is the field that studies the ability of a haptic stimulus to provoke or elicit emotions in the subject [85], [86]. It is of great importance to objectively understand the type of emotions elicited by specific haptic stimuli to build systems that provoke specific emotional responses (e.g. pleasant or unpleasant). Previous studies

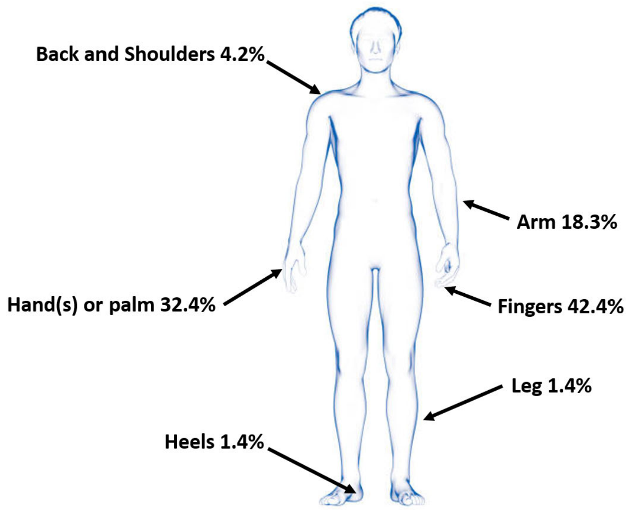

FIGURE 5. Body parts involved in neurohaptics experiments.

investigated neural response to affective touch using fabric based caressing devices passively placed on the subjects forearms using EEG data analysis [23], [46], [87]. An observed early prominent feature is the alpha rhythm suppression in the contralateral somatosensory cortex, which reflects the endogenous aspect of the tactile processing [23]. An increased beta oscillation in the parietal-frontal regions [23] and gamma oscillation in somatosensory cortex and the frontal regions are found to be correlated with the pleasant fabric touch [87]. In another study investigating interpersonal touch, beta oscillation in the middle frontal cortex was also found to be correlated with pleasant interpersonal touch (embracing, massaging, rubbing) [88]. Haptic preference is also important in consumer electronics; EEG is used as an objective tool for measuring the haptic preference of items during the process of examination or manipulation. For example, in a study evaluating the haptic preference of a washing machine knob, the valence score was found to be highly correlated with the middle frontal gamma oscillation [89].

B. OBSERVED TOUCH

The primary somatosensory cortex does not only respond to felt touch but also gets activated by a seen or observed touch; this is due to the mirror neurons in the S1 cortex [90], [91]. Touch observation provokes somatosensory cortex below the threshold of perception; an observed touch does not actually provoke any conscious tactile experience or sensation. However, the mirroring somatic system is suggested to be responsible for the unconscious simulation of other somatic states; thus, it is the system behind the empathic interpersonal sharing of the haptic and tactile experiences [92]. Alpha rhythm suppression in the primary somatosensory cortex is found to be one of the most prominent EEG features elicited by observed touch [93].

A comprehensive study on observed touch and the mirroring effect saw an investigation of the neural response of observed touch. In particular, it was investigated whether this response is modulated by the task or the subject's gender [94]. Participants observed images of touch/no-touch cases and were asked to categorize each image as touch vs. no touch (explicit task) or same vs. opposite gender interaction (implicit task). An early alpha rhythm suppression (a sensorimotor mirroring) and a late positive potential (LPP, socio-affective mirroring), were both observed during the display of touch images. Alpha rhythms, being an early endogenous effects, were not modulated by the categorization task. However, late positive potentials were modulated such that the LPPs declined when comparing the explicit task to the implicit task in women; the LPP even disappeared in men. Many other studies reported the alpha rhythm suppression while observing touch [95]–[97]; however, a question is posed whether the alpha rhythm suppression is due to the motor part of the active touch or due to the tactile sensation. A cross-modal repetition method was employed; it was found that the alpha suppression is sensitive to modulation in tactile and not motor properties. This suggests the existence of a tactile mirroring system [98]. In another study, the neural representation due to observing an interpersonal touch and experiencing a real human touch were compared [99]. Beta oscillations in the primary somatosensory cortex was observed as a common activity in both cases associated to unconscious tactile processing. However, an alpha oscillation in the frontal and parietal pathways was identified as a marker underpinning actual touch sensation.

C. HAPTIC MEMORY

Haptic memory is a sensory memory that is related to touch stimuli. Haptic memory is necessary in assessing and retrieving characteristics of familiar objects such as their weights, shapes and texture to apply, for example, appropriate gripping forces [100]. Several studies in the literature investigated the neural activation during haptic memory retrieval exercises under different conditions and tasks while solely depending on the touch sensation. A study by Grunwald *et al.* investigated the relationship between the complexity of haptic stimuli (geometric shapes) and the theta power oscillation. The mean exploration time was used as an objective measure of complexity for the objects. It was found that theta power at the central and parietal cortex is linearly correlated with the shape complexity towards the end of the exploration session. However, theta power was found to be independent of the shape complexity at the beginning of the exploration session. This is explained by the minimal working memory load at the beginning of the exploration task regardless of the object; working memory load reaches its peak towards the end of the exploration time when the perceptual model of the shape is almost completed [101]. Other studies also confirmed theta power enhancement in the central parietal cortex at the end of the exploration session of complex haptic stimuli [102], [103]. Another neural effect prominent during haptic memory experiments is the old-new ERP peaking between 550 ms to 750 ms. Old-new ERP peaks are detected when a familiar haptic stimulus is recognized by the subject. Haptic recognition tasks relying on the haptic sensation solely reported the identification of old-new ERP when a familiar object is recognized haptically [103], [104].

D. DISCRIMINATIVE TOUCH

A touch can be either affective or discriminative. Discriminative touch allows humans to perceive pressure, heat, texture and vibration. All these characteristics provide vital haptic information about the objects dealt with in everyday life. Additionally, discriminative touch is used to identify external haptic stimuli and thus reacts with a subsequent action accordingly [2]. Neural activations during the process of discriminating rough surfaces have been especially investigated extensively in the literature; reported neural characteristics include ERP and PSD features. Using an oddball paradigm in tasks that require to distinguish varied roughness surfaces showed a relationship between the degree of roughness and the P300 peak characteristics. A study investigated the neural activations while passively touching three fabrics (cotton, linen and silk) and three papers (photo paper, craft paper and normal paper) of different levels of roughness. The amplitude of the P300 was found to be higher for fabric as compared to paper samples. The latency of the P300 peak identifies the different textures [105]. Another study confirmed the correlation of the P300 peak characteristics in an oddball paradigm with the discrimination between surfaces of different roughness. The study went further and explored the effect of the presentation method of the stimuli on the discrimination task. It was found that the more difficult the discrimination task is, the smaller is the amplitude of the P300 [16]. Other studies relied on finding PSD related features linked to the explored surfaces. For example, in a study by C. Genna in which varied coarseness levels of surfaces passively applied to the fingertips of the subjects, contralateral alpha power is found to be inversely proportional to the roughness of the stimulus [106]. This result is confirmed by the study conducted by Zhang *et al.* which aimed to explore the neural response to active tactile investigation of different fabric qualities with varying softness [107]. Fabrics were graded subjectively by the participants and evaluated by physical indicators; neural activations are thus compared with the softness grade. Alpha power was found to be proportional to the softness of the fabric.

Moving to functional connectivity analysis, one target question is to find the functionally related brain regions during a discriminative tactile task. One study attempted to address this question by asking subjects to perform a passive touch task with the index finger to varying braille display patterns and discriminate between them [64]. Garner causality was used to find the related brain regions. A feedforward 15 Hz beta network from the somatosensory to parietal to the prefrontal regions was observed, indicating an accumulation of the collected sensory information during the task. On the other hand, a recurrent 80 Hz gamma network was observed from the prefrontal to posterior parietal to the somatosensory regions and then back to the prefrontal region, probably indicating attentional selection of task-relevant sensory information. The accuracy in the discrimination task was correlated to the activity strength of the aforementioned networks. Further studies confirmed the involvement of beta and gamma bands during discriminative touch [108]. The study shows that differences in beta and gamma oscillations in the middle frontal and parietal areas at the late period of the active touch task are found. Furthermore, strong beta event-related desynchronization (ERD) and rebound in the presence of tactile stimulation in the contralateral parietal area are observed.

E. TACTILE PERCEPTION WITH AGE

Aging is known to impact our senses and the cognitive processing of sensory information. While much of the research tackles the age-related impairment in the visual and auditory modalities, fewer studies tackle the degradation in somatosensorial modality of older adults. We report here the findings of a couple of neurohaptics studies investigating neural changes during tactile perception tasks in older adults. In a study by Reuter *et al.*, neural activation was measured in young and late middle-aged subjects while conducting tactile pattern and frequency discrimination tasks in an oddball paradigm [47]. P300 peak amplitude at Fz, Cz and Pz electrodes was reduced in late middle-aged adults as compared to the younger adults; a smaller amplitude might indicate a smaller number of resources available for the sensory information processing. An age-related decrease in the P300 amplitude is reported to be more obvious in the parietal electrodes [109]. In another study by Bolton *et al.*, a vibrotactile frequency stimulation was delivered passively to young and older adult index fingers. An oddball paradigm was employed and subjects were asked to attend a specific vibrotactile frequency. The P300 peak was found to be both lower in amplitude with a longer latency in older adults [110]. This prolongation in the P300 peak indicated a slower cognitive processing of the tactile stimuli [111]. In another tactile discrimination task conducted by younger and older adults, a P300 pattern shift from the parietal to the frontal cortex was observed in older adults. Activity in the frontal cortex is reportedly known for cognitive processing; an increased activity in the frontal region can be thought of as a compensation mechanism for the slower cognitive processing in older adults [112].

Table 2 summarizes the surveyed studies including the analytical techniques used and the activated cortical parts, highlighting the main findings.

IV. CASE STUDY: BRAIN ACTIVATION OF TACTILE FEEDBACK ON TOUCHSCREEN DEVICES

A common practice in neuohaptics research involves utilizing interfacing technologies to stimulate participants with desirable touch sensations, and to monitor brain activities associated with such stimulation. The experimental procedure comprises forming a hypothesis, then designing a haptic interaction scheme, conducting an experiment

TABLE 2. Summary of the main findings of the neurohaptic studies.

Topic	Ref	Analysis Technique	Brain Part (Cortex)	Findings
Emotions and Touch	[23], [87], [88], [89] , [120]	PSD	Loc.1:Primary Contralateral Somatosensory Loc.2: Primary Ipsilateral Somatosensory Loc.3: Ipsilateral Temporal and Parietal Loc.4: Middle Frontal Cortex	- Alpha suppression (Loc.1), due to the onset of the contact, is largest for the un-pleasant fabric. - Alpha Suppression (Loc.2) correlates with toucher empathy. - Beta oscillation correlates with pleasant fabric in (Loc.3) and (Loc.4) - Higher gamma oscillation for more pleasant touch in (Loc.1) and (Loc.4)
Observed Touch	[93], [94], [98], [99], [121]	PSD	Loc.1: Primary Somatosensory Loc.2: Frontal and Parietal areas	- Beta band connectivity (Loc.1) shared in seen and felt touch. - Alpha connectivity (Loc.2) is only for the felt touch, distinguishing self and other's tactile representation (supported by MEG and TMS studies) - Attenuation of the central alpha rhythm (Loc.1) is an index of mirror processes (supported by fMRI studies)
Haptic Memory	[101], [102], [103], [104]	PSD/ERP	Loc.1: Central and Parietal Cortex	- Increase in theta oscillation during haptic object exploration - A linear correlation with shape complexity indicating high memory load. - Old/new ERP for recognition of old stimuli around 550ms
Discrimi- native touch	[64], [70], [89], [105], [106], [107], [108]	PSD/ERP PLV/SEP	Loc.1: Parietal and Occipital Cortex Loc.2: Frontal Cortex Loc.3: Primary Somatosensory	- Delay and amplitude of P300 (Loc.1) in an oddball paradigm is correlated with tactile roughness. - Positive correlation between the alpha power (across the scalp) and the soft sensation of the fabrics. - Gamma power is strongly correlated with haptic preference (Loc.2) - Feedforward beta oscillatory network from (Loc.3) to (Loc.1) to (Loc.2) regions, reflecting accumulation and maintenance of sensory information. - A recurrent closed loop of 80 Hz gamma network oscillations occurred from (Loc.2) to (Loc.1) to (Loc.3) and back to (Loc.2) regions, implying involvement of this loop in attentional selection - Beta power in (Loc.4) is correlated with the presence of tactile feedback - Alpha connectivity between contra. motor and somatosensory cortex and ipsi. parietal with the presence of tactile feedback
tactile perception with age	[47], [109], [122], [110]	ERP	Loc.1: Frontal (Fz), Central (Cz) and Parietal (Pz) cortex	- Reduced P300 amplitudes for older adults can indicate fewer available resources in older adults. - Prolonged P300 latencies for older adults indicates slower information processing of tactile information. - Parietal-to-frontal shift in P300 for older adults indicating a compensatory mechanism employing additional cognitive resources.

with participants while recording EEG data, analyzing the recorded data using appropriate EEG analysis techniques, and finally examining the proposed hypothesis. This section presents a case study to demonstrate the methodology of neurohaptic research. The study, thoroughly presented in our previous work [108], involves studying brain activation associated with tactile feedback on a touchscreen device. A link to the complete dataset is also provided in supplementary material.

A. BACKGROUND AND RESEARCH AIM

Recently, various tactile display technologies have become a reality in both academia and industry [113], [114]. With the driving force of Tactile Internet [115], [116], it is crucial to investigate the role of touchscreen-based tactile feedback on the user experience. Previous studies have shown that tactile feedback in touchscreen devices can improve user performance on different tasks [117]. The added value of tactile feedback in touchscreen devices is typically evaluated using self-reporting such as questionnaires after the experiment and/or behavioral data such as task completion time, accuracy, or error rate. While both methods have been used with some success for decades, they suffer from several important limitations. Self-reporting can be inconsistent, unreliable, and difficult to reproduce. In other words, there are ambiguities in expressing the feeling of touch [118]; sometimes reporting is affected by social pressure [119], and sometimes it is difficult to get real-time feedback without disrupting the experiment. Behavioral data also have limitations in providing information about users' mental states such as satisfaction or preference.

Meanwhile, few studies are conducted to explore the neural mechanisms associated with active touch interaction with touchscreen devices. An early study demonstrated that cortical potentials in the contemporary brain is continuously shaped by the use of touchscreen devices [119]. However, no tactile stimulation is incorporated in this study. The aim of the current study under consideration was to provide quantitative and objective data about the neural activation associated with tactile stimulation as the user actively interacts with a touchscreen device capable of providing tactile feedback. The proposed hypothesis here was that tactile feedback on a touchscreen device would produce levels of brain activation statistically different from the case of a touchscreen device without tactile feedback.

B. EXPERIMENTAL SETUP AND PROTOCOL

An experimental setup was developed to evaluate the proposed hypothesis. Figure 6 shows a schematic diagram of the experimental setup (upper diagram) and the designed experimental task (lower part of the figure showing a series of snapshots of the interaction between the user and the touchscreen device). The experimental setup included the TanvasTouch[1] surface haptic device, a secondary screen,

[1] www.tanvas.co

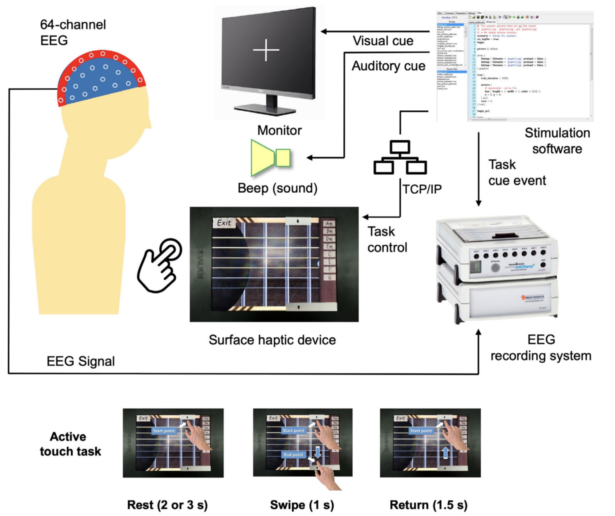

FIGURE 6. Experiment system and motor task on a surface haptic device.

a speaker to provide auditory/visual instructions about the task, a 64-channel EEG device stored in the EEG recording system (BrainAmp by Brain Products, Munich, Germany) and a central processing PC running an application to administer the task. The stimulation software stored the time-stamps of the motor task cues in a file associated with the EEG data. Switching On and off of tactile feedback of the surface haptic device was done through wireless TCP / IP, however it was not affected by communication delays because switching was done during the rest period of the experimental session.

Twenty-six participants with ages ranging from 20 to 39, and of which 14 were males, were recruited for this study. Participants are instructed to perform a task of stroking virtual guitar strings on the surface haptic device in the presence or absence of tactile feedback in a random order. Due to the fact that EEG signals are generally weak and easily contaminated by other signals, the task involves a large number of repetitions to increase the signal-to-noise ratio (SNR). Therefore, a total of 96 trial data are utilized for each condition (the presence/absence of tactile stimulation per participant). The study was carried out with an approved protocol by New York University Abu Dhabi Institutional Review Board (FWA: #073-2017).

EEGLAB toolbox was utilized for EEG signal processing [123]. For pre-processing, the EEG signals were down-sampled from 2500 Hz to 1250 Hz. To remove the effect from the outside locations, EEG signals from locations FT9, FT10, TP9, TP10, PO9, and PO10 were removed from the signal analysis. A zero-phase finite impulse response filter is used for band pass filtering (0.1–55 Hz). A notch filter is applied with a zero-phase digital filter to remove the 50 Hz line noise. The artifact subspace reconstruction method is applied to remove eye movement and muscle artifacts [124]. Then, we epoched the EEG data by the motor task cues and divided them into epochs corresponding to when tactile feedback is applied or not. Finally, EEG signals are re-referenced using the common average reference [125]. After pre-processing, power spectral densities of

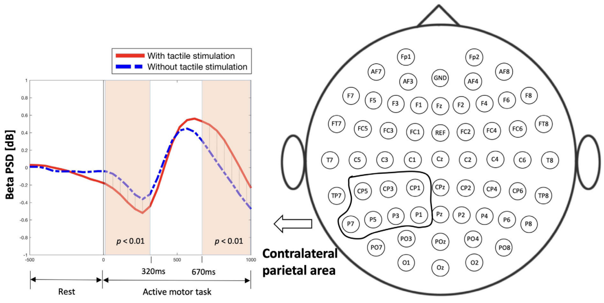

FIGURE 7. Beta PSD difference in the contralateral parietal area.

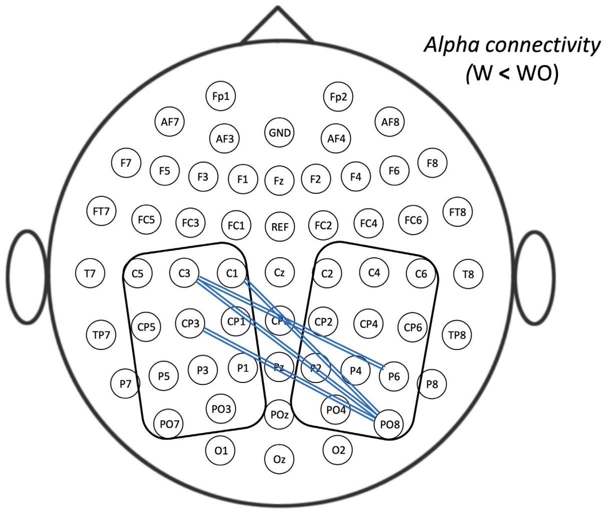

FIGURE 8. PLV differences in interhemispheric functional connectivity. W/WO indicate with/without tactile feedback.

alpha (8–12 Hz), beta (13–30 Hz), and gamma (31–50 Hz) bands for each channel are computed via short-time Fourier transform.

C. INTRA-REGIONAL PSD ANALYSIS

PSD analysis was conducted to investigate the intra-regional activities. When examining the contralateral parietal area, it was found that the beta ERD is statistically stronger in the early stage of the motor task (around 320 ms after motor task cue) when tactile feedback was available compared to the condition of no tactile feedback [126]. Furthermore, the beta rebound [127] was statistically larger with tactile feedback than without, and showed a significant difference after 670 ms (t-test, $p < 0.01$).

D. INTER-REGIONAL PLV ANALYSIS

Inter-regional analysis using PLV (a functional connectivity method) was also considered in this study [70]. PLVs were extracted from electrode pairs in the interhemispheric parietal areas. PLVs of 500 ms period before the motor task cue were used as a base line. Calculated PLVs in the period of one second during the motor task were subjected by the average value of the baseline. Figure 8 shows significant differences of functional connectivity levels in interhemisperic connectivity between with and without tactile-feedback cases. In particular, contralateral motor (C1 and C3) and somatosensory (CP3) areas show stronger alpha connectivity with ipsilateral parietal association (P6) and general interpretation (PO8) areas in the case of the tactile feedback condition compared to the no tactile feedback condition (t-test, $p < 0.0004$). More details about the study and the results can be found in our previous reports [70], [108].

V. SUMMARY, LIMITATIONS AND FUTURE DIRECTIONS

A. SUMMARY OF FINDINGS

In this paper, we have comprehensively reviewed the state-of-the-art neurohaptics studies and shown the increasing attention given to this field through the last 10 years. We have presented the benefits of using EEG data to study the haptic system in humans, and we have highlighted the most robust artifact removal methods. Both inter-regional and intra-regional analytical methods were discussed as well. Studies found in the literature were organized under 5 main categories: emotions and touch, observed touch, haptic memory, discriminative touch and tactile perception with age. Each section was elaborated and sample studies were presented with their findings. In addition to the elaborate summary of Table 1, we highlight the findings of brain activation in the neurohaptics field in a graphical format in Figure 9.

B. RESEARCH CHALLENGES

After surveying the literature, we found that there are some challenges that the research community is facing. Each of the challenges represents an opportunity for future work and research development. Below we list some of these challenges:

- Asynchronous EEG Data Analysis: The majority of haptic tasks assigned to subjects in neurohaptics studies follow a synchronous paradigm. However, a more realistic scenario involves an asynchronous interaction where the participants can initiate the interaction whenever they wish. This experimental method is an asynchronous paradigm [128]; there are challenges in analyzing the experimental results.
- EEG Artifacts due to Movement: Experiments involving active touch impose additional challenges during the EEG data analysis. This is because of the movement artifacts produced by the subjects. Novel neuro-imaging techniques must be explored to provide reliable brain scans for participants in realistic activities (eating, dancing, playing sports, playing music, etc.).
- Repetitive Nature: neurohaptics experiments and EEG-based experiments usually require a large number of trials per condition to ensure a good signal quality after averaging. This imposes an unwanted boredom or exhaustion factor for the participant, which is a challenge for the research community. This challenge could be addressed by either improving the quality of EEG data acquisition and/or designing experimental tasks that are more engaging/entertaining. There is also room for machine learning algorithms to improve performance

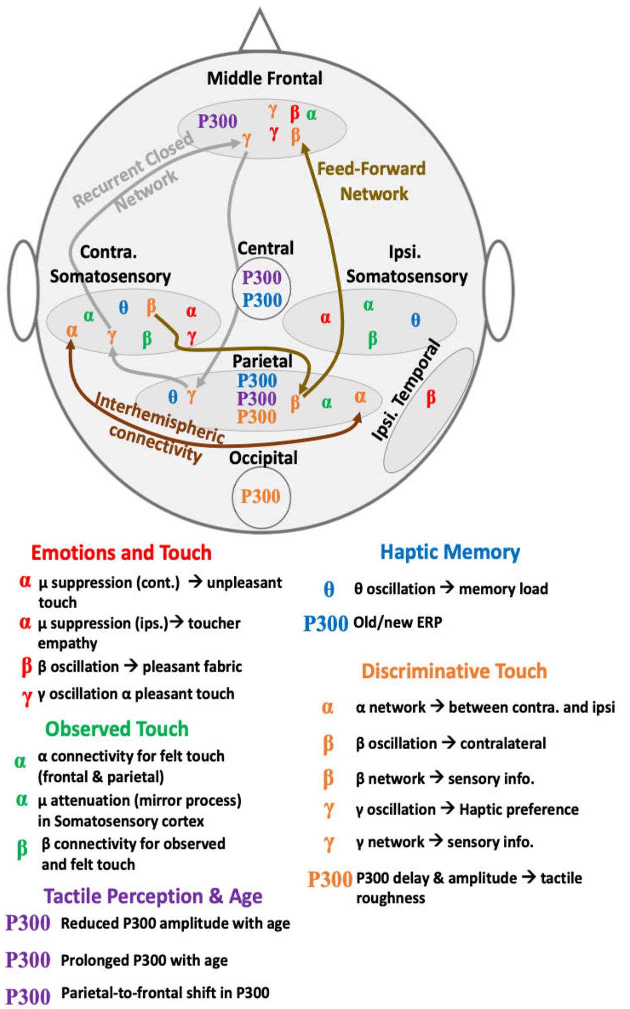

FIGURE 9. Graphical summary of the neural activation correlated with the corresponding haptic field.

based on a single-trial EEG activity. A study showed that it is possible to successfully predict subsequent brain performance (memory performance in this case) based on a single-trial EEG activity before, during and after a cognitive task [129].

- Cumbersome Nature of EEG System Setup: Even though EEG is an important tool for monitoring neurological activities, the required equipment, expertise, and user preparation inhibits its use outside of experimental research labs. Obtaining high-quality EEG requires the use of abrasive/conductive gels to reduce skin-electrode impedance and a large number of electrodes (in the range of 32, 64, 128, or even 256) in order to achieve neural monitoring of suitable quality. It remains a challenge to develop a wearable, low-cost, dry electrode EEG monitoring system without compromising the quality of the EEG signal [130].

C. TRENDS

As can be seen from this review, this field is still young and there is much room for it to be developed. Potential future directions are many, and below we list some of the most interesting ones:

- Neural Representation to Cognitive Modulation Mapping: It would be valuable to see the development of specific EEG experimental platforms for provoking different emotions (pleasure, frustration, disappointment, etc.) and cognitive qualities (attention, memory retention, etc.), relating them to specific brain activation. This step is essential in developing brain activation indexes for the different cognitive processes and emotions; such indexes can act as references for the neurohaptics community to relate the EEG patterns found in their touch experiments with their corresponding cognitive processes and/or emotions.
- Quality of Haptic Experience Modeling: It would be valuable to see the creation of a quality-of-haptic-experience computational model based on a given EEG data set. In other words, this would represent eliminating the need for any subjective reporting of a haptic experience, instead using the recorded EEG data of the subject and quantitatively providing feedback on the user's experience. The above-mentioned direction is a prerequisite for building such a model.
- Novel neuro-imaging technologies: The recent advents of portable technologies that are less sensitive to motion artifacts, such as functional Near-Infra-Red Spectroscopy (fNIRS), have the potential to study brain functions in freely-moving participants [131]. A recent study presented a series of experiments to demonstrate the ability of fNIRS in assessing neural activities in unconstrained environments (playing table tennis, playing piano and playing violin [132]). Results showed the ability of the fNIRS technology to capture brain activities in different real life settings.
- Neurohaptics Systems: A long-term objective of neurohaptics research involves developing neurohaptic systems. Neurohaptics systems include brain-inspired algorithms, computational models of biological neural networks, and actual biological systems that can be embedded in machines with physical sensing and actuation to model and/or simulate the human sense of touch. With neurohaptic systems, novel haptic technologies may be tested against human experience without the need for recruiting human subjects. The neurohaptic system will be able to simulate human experience with haptic interaction.
- Neurohaptics in Virtual Reality: Neurohaptic systems offer a technology that can send and/or receive signals from/to the brain to entirely replicate a physical interaction experience. Advanced neurohaptic VR systems will allow users to transport their consciousness of the physical environment anywhere they want.
- Inter-brain Synchronization During Haptic Interaction: Due to the fact that haptic communication involves the simultaneous exchange of force and movement information, obtaining simultaneous neural recordings from

the communicating brains becomes very interesting. Hyperscanning is a neuroscience technique to obtain simultaneous neural recordings from more than one person in order to study interactive situations. EEG-based hyperscanning is becoming increasingly popular since it allows researchers to explore inter-brain communication in more natural settings, and with high temporal resolution. In hyperscanning experiments, there is a bidirectional haptic communication between two subjects. This can be under scenarios where the nature of the haptic communication is collaborative or competitive.

Finally, this review will serve as a reference for researchers in the field of neurohaptics to help them understand the kind of studies conducted in this field and the reported neural activation correlated with the particular haptic activities; it can also guide researchers to purse next steps in the neurohaptics domain.

VI. CONCLUSION

In this survey article, we reviewed the emerging literature of EEG-based neurohaptics. The article was prefaced by a proper definition of the term, "neurohaptics". We reviewed and categorized the common EEG data analytical methods under two main categories: inter-regional and intra-regional analysis. Then, we performed a holistic survey of the neurohaptics literature and proposed five main fields of interest to the neurohaptics community. We summarized the findings of the most impactful studies under these categories and illustrated the findings in a graphical visualization. A neurohaptics case study was also provided to illustrate the flow of proposing a hypothesis, designing an experimental protocol and analyzing the collected EEG data. Finally, we identified several challenges in the field of neurohaptics and proposed many future directions and trends to be pursued in the field, including such exciting areas as neurohaptics in VR, hyper-scanning in neurophatics and novel neuro-imaging technologies.

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