Exploring Spatio-Spectral Electroencephalogram Modulations of Imbuing Emotional Intent During Active Piano Playing

Jachin Edward Pousson, Yi-Wei Shen, Yuan-Pin Lin, *Member, IEEE*, Aleksandras Voicikas, Evaldas Pipinis, Valdis Bernhofs, Lana Burmistrova, and Inga Griškova-Bulanova

***Abstract*—Imbuing emotional intent serves as a crucial modulator of music improvisation during active musical instrument playing. However, most improvisation-related neural endeavors have been gained without considering the emotional context. This study attempts to exploit reproducible spatio-spectral electroencephalogram (EEG) oscillations of emotional intent using a data-driven independent component analysis framework in an ecological multiday piano playing experiment. Through the four-day 32-ch EEG dataset of 10 professional players, we showed that EEG patterns were substantially affected by both intra- and inter-individual variability underlying the emotional intent of the dichotomized valence (positive vs. negative) and arousal (high vs. low) categories. Less than half (3–4) of the 10 participants analogously exhibited day-reproducible (≥ three days) spectral modulations at the right frontal beta in response to the valence contrast as well as the frontal central gamma and the superior parietal alpha to the arousal counterpart. In particular, the frontal engagement facilitates a better understanding of the frontal cortex (*e.g.*, dorsolateral prefrontal cortex and anterior cingulate cortex) and its role in intervening emotional processes and expressing spectral signatures that are relatively resistant to natural EEG variability. Such ecologically vivid EEG findings may lead to better understanding of the development of a brain-computer music interface infrastructure capable of guiding the training, performance, and appreciation for emotional improvisatory status or actuating music interaction via emotional context.**

***Index Terms*—Music improvisation, emotional intent, electroencephalogram, independent component analysis, electroencephalogram variability, brain-computer music interface.**

Manuscript received 19 April 2023; revised 12 August 2023 and 2 October 2023; accepted 23 October 2023. Date of publication 26 October 2023; date of current version 8 November 2023. This work was supported in part by the National Science and Technology Council of Taiwan under NSTC 108-2923-E-110-001-MY3; in part by the Research Council of Lithuania under Agreement S-LLT-19-3; and in part by the State Education Development Agency, Republic of Latvia under Agreement LV-LT-TW/2021/1. *(Jachin Edward Pousson and Yi-Wei Shen contributed equally to this work.) (Corresponding author: Yuan-Pin Lin.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Rīga Stradiņš University Research Ethics Committee.

Jachin Edward Pousson, Valdis Bernhofs, and Lana Burmistrova are with the Jāzeps Vītols Latvian Academy of Music, 1050 Riga, Latvia (e-mail: jachin.edward.pousson@jvlma.lv; valdis.bernhofs@jvlma.lv; lana.burmistrova@jvlma.lv).

Yi-Wei Shen was with the Institute of Medical Science and Technology, National Sun Yat-sen University, Kaohsiung 804201, Taiwan (e-mail: syiwei1211@gmail.com).

Yuan-Pin Lin is with the Institute of Medical Science and Technology and the Department of Electrical Engineering, National Sun Yat-sen University, Kaohsiung 804201, Taiwan (e-mail: yplin@mail.nsysu.edu.tw).

Aleksandras Voicikas, Evaldas Pipinis, and Inga Griškova-Bulanova are with the Department of Neurobiology and Biophysics, Vilnius University, 10257 Vilnius, Lithuania (e-mail: avoicikas@gmail.com; evaldas.pipinis@gmail.com; inga.griskova-bulanova@gf.vu.lt).

Digital Object Identifier 10.1109/TNSRE.2023.3327740

I. Introduction

MUSIC improvisation is regarded as a highly complex form of creative human behavior. Musicians are required to simultaneously generate and evaluate melody, harmony, and rhythm in real time, and keep track of the overarching structure of past events that unfolded up to the present moment, while executing precisely coordinated and nuanced motor movements to physically play a musical instrument. At a professional level, music improvisation has been considered a separately acquired musical skill that requires deliberate practice to develop [1]. Given the challenges of managing multiple sensory inputs and motor control, music improvisation indicates a high fluency of access between perceptual, emotional, or cognitive processes such as feedback and error correction and a domain-specific (music) knowledge base consisting of hierarchal structures retrieved from long-term memory [1]. Thus, improvisation neuroscience may shed light on the neural underpinnings of cognitive and motor control in creative thought and music production. Particularly, exploring the neurophysiological evidence for musical intent during music improvisation facilitates the development of brain-computer music interfaces (BCMIs) plausibly for realistic training, performance, or other musically interactive contexts beneficial to people regardless of musical expertise. Most of the first BCMI systems were designed for persons with limited ability to move their bodies, enabling them to interact and communicate in real time with others by manipulating changes in their online brain activity [2]. BCMI systems have also been developed as standalone or collaborative musical instruments that have opened up a growing number of novel and unique modes of music interaction for musicians and non-musicians alike [3].

Functional magnetic resonance imaging (fMRI) studies have observed the modulation of activity and functional connectivity in the premotor and prefrontal areas during music improvisation, such as the dorsolateral prefrontal cortex (DLPFC). Bengtsson et al. [4] recruited classical concert pianists and found increased DLPFC activity in free improvisation conditions compared to reproducing improvisation from memory. Limb and Braun [5] investigated spontaneous jazz improvisation conditions compared to either scale playing or playing from memory conditions in professional jazz pianists and found deactivation of the DLPFC during the spontaneous improvisation task. Some studies have explored the aspect of emotional intent in active improvisation. Pinho et al. [6] found decreased DLPFC activity in professional pianists improvising based on specific emotional cues, such as happy/fearful, but increased activity in the same region when the improvisation was based on specific pitch sets. McPherson et al. [7] recruited professional jazz pianists and similarly found deactivation in the DLPFC during improvisation with emotional intent, notably observing more widespread deactivation during positive conditions compared to ambiguous or negative conditions. The aforementioned fMRI studies suggest that DLPFC modulation may indicate immersion in the creative task of music improvisation with or without emotional intent.

Recent wearable electroencephalogram (EEG) sensing technology may provide an ecologically valid capability to study the neural correlates of music contexts [8], [9], [10], [11]. Musical improvisation and its associations with brain networks presumably do not compromise, as an fMRI scanner requires a restricted body posture and movement as well as noticeable acoustic noise accompanying measurement (*i.e.*, remaining supine in a noisy scanner). Exploited music improvisation-driven EEG signatures may facilitate the deployment of BCMI applications in real life settings. Analogous to many fMRI studies, several EEG studies have revealed the relevant spectral oscillations of distinct frequency bands in the frontal region. Dolan et al. [12] found alpha and beta spectral power noticeably differed over the regions near to DLPFC and anterior cingulate cortex (ACC), respectively, in the engagement of prepared versus improvised performance modes. Another measure of brain entropy and signal complexity by Dolan et al. [13] later showed that the prepared performance was associated with more power at low frequencies (delta, theta, and alpha bands), whereas the improvised mode raised more active high-frequency activation (beta and gamma bands). While considering the factor of musical/training experience, Dikaya and Skirtach [14] reported that experienced musicians exhibited higher right frontal alpha activity during improvisation as compared to amateurs. Lopata et al. [15] analogously reported that skilled musicians with formal musical improvisation training had more right frontal alpha activity versus those with informal training. Rosen et al. [16] examined EEG spectral power differences for jazz guitarists improvising to novel chord sequences. High-frequency activity within the beta and gamma ranges was observed in a comparison of low- and high-quality improvisation. Taking into consideration the sensor-level analysis that was concerned with the volume conduction issue [17], Sasaki et al. [18] employed a source-level analysis, *e.g.* as independent component analysis (ICA), and revealed spatio-spectral EEG oscillations in guitarists during an improvisation condition when compared to a scale playing condition. They observed greater activity in theta, alpha, and beta frequency bands in a host of locations, including the medial frontal cortex (MFC), middle frontal gyrus anterior cingulate, polar medial prefrontal cortex, premotor cortex, pre- and postcentral gyrus, superior temporal gyrus, inferior parietal lobule, and temporal-parietal junction, which are suggested to be involved in coordinating planned sequences of movement through monitoring and feedback of sensory states in relation to internal plans and goals. These improvision-induced EEG signatures further facilitated the construction of a machine learning classification technique for a BCMI applicable neurofeedback training to improve creativity. Complementary to the sole experimental design of music improvisation, Pousson et al. [19] recently addressed the neural oscillations of imbuing emotional intent during piano playing. The sensor-level EEG spectral dynamics exhibited a widespread spectral distinction in several frequency bands between distressed/excited and neutral/depressed/relaxed playing predominantly over the frontal and parieto-occipital channels.

The aforementioned improvisation neuroscience endeavors have considerably evidenced brain region-specific (*e.g.*, frontal regions) and spectral band-specific (*e.g.*, alpha and beta) activity intervened in highly complex music improvisation. However, imbuing emotional intent is considered as an ecologically crucial modulator in creative music production [7], [20]. Only a few studies [6], [7], [19] further elucidate its interplay in brain modulation during active improvisation. Most critically, emotional experience is well acknowledged to behave distinctively for an individual across time and between individuals. Such salient intra- and inter-individual variability in brain activity considerably impede the deployment of a real-world application [9], [21], [22]. Towards a BCMI-deployable infrastructure, this study attempts to exploit spatio-spectral EEG modulations of emotional intents using a data-driven source-level ICA given a multiday dataset collected by an active piano-playing task. To the best of our knowledge, most EEG studies contribute to the design without the aspect of emotional intent [12], [13], [14], [15], [16] or without multiday data collection [18]. This study is the first attempt to appraise a representative set of relatively day-/individual-reproducible and emotion-relevant EEG signatures with an active setting of musical instrument playing. By considering both intra- and inter-individual EEG variability, this study may lead to better understanding of emotion-driven BCMI modeling in real-world deployment.

II. Materials and Methods

A. EEG Dataset

This study employed the EEG dataset collected by [19] to explore reliable spatio-spectral EEG oscillations of emotional intent during music improvisation. The following paragraphs

Fig. 1. Setting of EEG recording during piano playing at the Jazeps Vitols Latvian Music Academy in Riga.

briefly describe the experimental protocol and EEG recording settings used to collect the dataset. Ten healthy right-handed participants (8 female and 2 male; age: 24.7 $\pm$ 6.5 years (mean $\pm$ standard deviation (STD)) participated in emotional piano playing for a total of four days paced over approximately two months. The participants played the piano regularly either as part of their profession or academic training for 18.4 $\pm$ 6.2 years (min: 5 years). None of them received academic jazz training or was known to improvise regularly on the piano. The experimental protocol was approved by the Rīga Stradiņš University Research Ethics Committee.

In the piano-playing task, participants were instructed to play the same musical score while intentionally expressing one of five emotional intents, including excited, distressed, depressed, relaxed, and neutral states, based on the valence-arousal emotion model [23]. The score was self-composed by the author to be sufficiently simple for an experienced piano player to pick up quickly and create expressive variations. An extended pentatonic scale was chosen to evade the tendency of Western classical music to gravitate towards the tonic through subdominant and dominant tensions as a means to convey intent [24]. Each participant underwent 10 blocks of 5-trial runs for every day's session (*i.e.*, 50 trials per day), and each trial was randomly assigned to one of the five target emotion intents. Following an initial 15-sec resting state in each trial, the participant was required to play mechanically (regarded as baseline) for 30 s and then play expressively for another 30 s with an intended emotion that was instructed at the beginning. For emotional performance, participants were allowed to use tempo, rhythm, articulation, embellishment, and other expressive cues to express the target intent. Finally, they rated their performance on a nine-point scale for both emotional valence and arousal categories (from negative/low to positive/high) regarding how well they felt their performance reflected the intended target emotion.

The data collection took place in a room within the Jazeps Vitols Latvian Music Academy in Riga, Latvia (see Fig. 1), where the participants regularly practiced and rehearsed. A 32-channel Enobio system was used to record EEG signals. The electrode placement adhered to the International 10–20 system and used common mode sense (CMS) and driven right leg (DRL) electrodes connected to the right earlobe for electrical grounding. The system sampled the EEG signals at 500 Hz and at a bandwidth of 0 – 125 Hz with a 50 Hz notch filter to remove power line noise.

Accordingly, each participant collected 50 75-sec trial segments composed of a 15-sec resting state, a 30-sec mechanical play, and a 30-sec emotional play for each day session. The four-day dataset contained 2,000 piano playing trials (*i.e.*, 10 participants $\times$ 4 days $\times$ 50 trials) and offered this study to investigate realistic cross-day and cross-participant spatio-spectral EEG oscillations of emotional intent during piano improvisation.

B. Exploring Day-Stationary Spatio-Spectral EEG Oscillations

To derive representative EEG modulations, this study first explored day-stationary spatio-spectral EEG oscillations in each individual given four-day sessions and then summarized the consistency of personalized outcomes among 10 subjects for appraising their neurophysiological validity. The following analytical framework was adopted for the objective, including artifact suppression, EEG source decomposition and clustering, and inter-participant commonality. EEG data analysis and visualization were performed using the EEGLab toolbox/scripts (Delorme and Makeig [25]) and MATLAB functions/scripts (The Mathworks, Inc., Natick, MA, USA). The details of the processing procedures and their implementation are as follows.

In this study, we initially applied a band-pass filter (1–50 Hz) to suppress the artifacts. Artifact subspace reconstruction (ASR) [26], [27] was then employed to compensate high-variance artifacts plausibly accompanied by naturalistic piano playing (the user-defined threshold of the standard deviation was set to 20), which preserved the signal quality for the subsequent ICA procedure. An extended infomax ICA algorithm was run on each ASR-processed single-day session and was assumed to separate EEG signals into spatially static and temporally independent components (ICs) [17]. Through the DIPFIT routine [28], a best-fitting single equivalent current dipole was calculated to estimate the source location of each IC using a boundary element head model co-registered to the MNI brain template (Montreal Neurological Institute, MNI, Quebec, Canada). Only the IC associated with the dipoles located within the brain that explained more than 85% of the variance in their scalp maps (*i.e.*, residual variance $<$ 15%) were further considered. Note that 85% is a popular setting to ensure the physiological plausibility of an IC as referred to [29]. The remaining ICs were visually inspected in terms of a scalp map and power spectrum to isolate interpretable cortical sources. Given 30 ICs (excluding two reference channels), this procedure returned 41.9 $\pm$ 8.5 ICs (mean $\pm$ STD) for the four-day session of each individual (*i.e.*, 10.5 $\pm$ 2.1 ICs per single-day session).

Next, this study employed a semi-automatic IC clustering procedure [9], [10], [22] to explore relatively time-stationary ICs across four days in an individual. A k-means clustering algorithm was first used to aggregate the available ICs into different clusters according to the attributes of their power spectral density, scalp maps, and dipole locations. Outlier ICs were then re-assigned to another suitable cluster or a separate cluster if their distances to the cluster centroids exceeded three STDs. Based on the derived IC clusters, this study further summarized inter-day reproducibility [9] and dipolarity [30]. The reproducibility defines the percentage of day sessions consistently contributing an analogous IC to a target cluster in an individual (D/4, D= the number of day sessions with the IC). The dipolarity refers to the mean percentage of the DIPFIT data variance corresponding to the recruited ICs, reflecting the single-dipole fitting efficacy per cluster. That is, an IC cluster with 100% inter-day reproducibility and 100% dipolarity indicates its perfect presence for all four days as well as its capability of neuropsychological assessment. Particularly, we empirically treated the IC reproducibility as a threshold to further quantify the percentage of participants consistently exhibiting a preferable day-reproducible IC, forming a term of inter-participant IC commonality. This procedure allows us to focus on a representative set of relatively reproducible ICs across days and participants and to elucidate their roles in emotional modulations sequentially.

C. Statistical Assessment of Spatio-Spectral EEG and Emotional Intent

To assess the spatio-spectral EEG correlates of emotional intent upon the explored day-reproducible ICs, a short-time Fourier transform with a 50% overlapped 2-s Hamming window was applied to calculate the logarithmic power spectra of each of the derived ICs in five frequency bands: delta (1 – 3 Hz), theta (4 – 7 Hz), alpha (8 – 13 Hz), beta (14 – 30 Hz), and gamma (31 – 50 Hz). For a trial segment, the preceding 30-sec mechanical play period was treated as a baseline to normalize the 30-sec emotional play segment; that is, subtracting the baseline mean power and dividing by its standard deviation. Noteworthily, instead of a resting baseline commonly used for data normalization, the selection of the mechanical play is intended to suppress the spectral oscillations resulting from piano playing but emphasizes the alterations associated with distinctive emotional intents. Such the task normalization based on a non-resting pre-task period can also be found in [31] and [32]. Some BCI studies have also demonstrated the effectiveness of a preferred baseline normalization or alignment pipeline to obviate data discrepancies between sessions or subjects and thereby enhance predictive model generalizability given substantial EEG variability [33], [34]. The normalized 30-sec spectral time series was then averaged to represent EEG fluctuations in band power for an emotional play. In addition, the self-reported valence and arousal ratings were dichotomized for each trial, given the threshold at the nine-point scale (*i.e.*, $<$ 5 for negative valence/low arousal labels and $>$ 5 for positive valence/high arousal labels). The dichotomization yielded 18.5 $\pm$ 2.7 (mean $\pm$ STD) and 20.9 $\pm$ 2.2 trials for positive and negative valence, respectively, and 26.6 $\pm$ 3.8 and 19.7 $\pm$ 3.9 trials for high and low arousal, respectively, per day session for each participant. As such, the cross-day emotion-annotated EEG samples of an individual facilitated the statistical assessment of spatio-spectral EEG

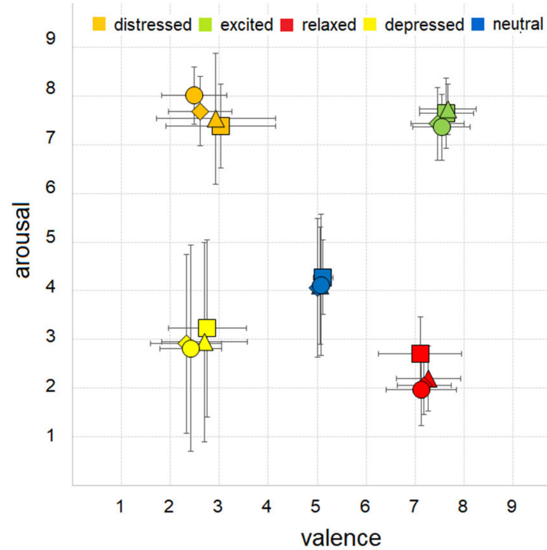

Fig. 2. Self-evaluated valence and arousal responses for each of the five target emotion descriptors over four days. Geometric shapes represent days: square – 1st day, triangle – 2nd day, rhombus – 3rd day, circle – 4th day.

and emotion intent for each day-reproducible IC. Owing to a label imbalance over four days, an unpaired t-test was used to test the statistical significance of EEG differences in the dichotomized valence and arousal categories for each individual. The Benjamini–Hochberg procedure [35] was further applied to correct the resultant p-values by controlling the false discovery rate (FDR) due to multiple comparisons among day-reproducible ICs, frequency bands, and subjects. The FDR-corrected p-values are named as p_{fdr} hereafter. After repeating the statistical assessment for each participant, this study defined the inter-participant emotion commonality to summarize how consistently day-reproducible EEG correlates of emotional intent existed across participants. That is, the percentage of participants with analogous spatio-spectral oscillations was statistically distinctive ($p_{\mathrm{fdr}} < 0.05$) between positive vs. negative valence or between high vs. low arousal.

III. Results

A. Behavioral Ratings of Emotional Intent

The behavioral valence and arousal ratings of the 10 participants were first demonstrated to indicate the feasibility of exploring day-stationary EEG correlates of emotional intent using the adopted four-day dataset. Fig. 2 provides the means and standard deviation of the self-assessed valence and arousal ratings for each of the five target emotion intents in each day session. Generally, the valence scores of 7.4 $\pm$ 1.0 (mean $\pm$ STD) for positive intent (*e.g.*, excited and relaxed) were significantly higher than the scores (2.7 $\pm$ 1.3) for negative intent (*e.g.*, distressed and depressed, $p < 0.01$). The high arousal state (*e.g.*, excited and distressed) led to higher ($p < 0.01$) arousal scores (7.6 $\pm$ 1.3) than the low arousal state (*e.g.*, relaxed and depressed, 2.6 $\pm$ 1.8). Furthermore, valence and arousal ratings did not change substantially across days. Accordingly, the dichotomization (= 5) on the nine-point scale of valence and arousal states allowed this study to explore

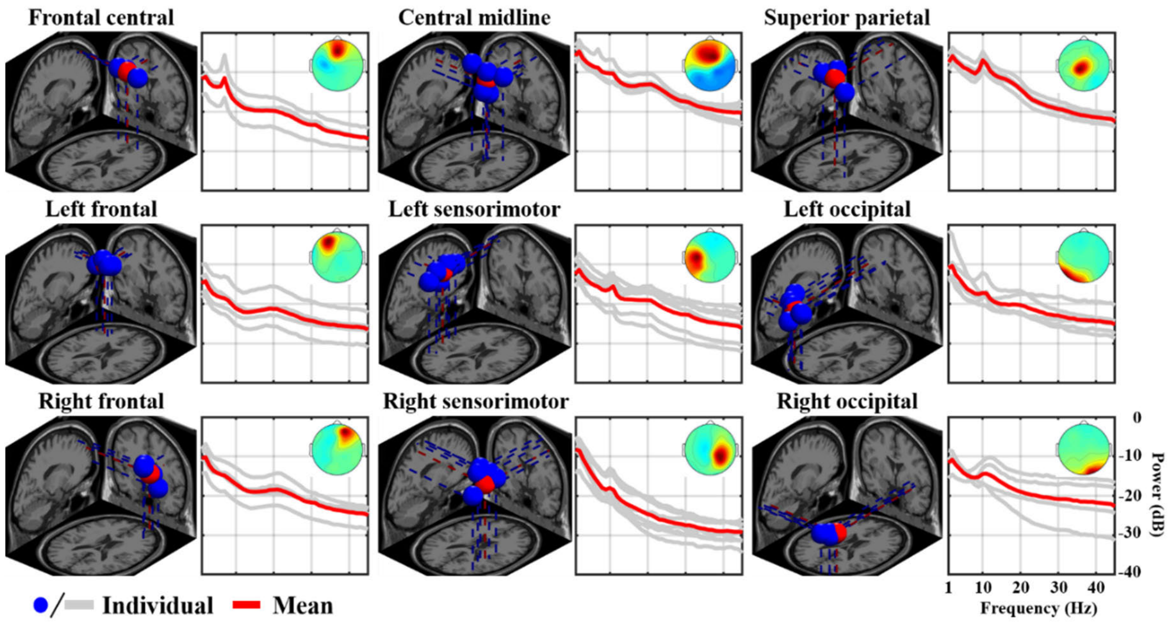

Fig. 3. Nine neurophysiologically day-reproducible IC clusters aggregated from one representative participant along four days. The cluster characteristics in terms of spectral profiles, scalp maps, and 3D dipole locations projected onto the MNI brain template are presented.

TABLE I
MEAN DIPOLARITY (%) AND INTER-DAY IC REPRODUCIBILITY (%) PER IC CLUSTER FROM A REPRESENTATIVE SUBJECT

IC source	Dipolarity (%)	Inter-day reproducibility (%)
Frontal central	94.1	75
Left frontal	92.7	100
Right frontal	89.9	100
Central midline	93.8	100
Left sensorimotor	93.1	100
Right sensorimotor	91.1	75
Superior parietal	91.7	75
Left occipital	92.3	100
Right occipital	92.1	75

relatively day-stationary, emotion-relevant EEG oscillations. Neutral trials were not excluded from the dichotomization procedure.

B. Day-Stationary Spatio-Spectral EEG Oscillations

To illustrate the capability of relatively day-stationary EEG sources using ICA, Fig. 3 shows neurophysiologically interpretable IC clusters from a representative participant in terms of scalp maps, spectral profiles, and diploe locations. Their corresponding dipolarity and inter-day reproducibility are also listed in Table I. Nine well-dipolar ICs (mean dipolarity: 89.9 – 94.1%) appeared reproducibly for at least three days (>75%) with the locations at left frontal, frontal central, right frontal, left sensorimotor, central midline, right sensorimotor, left occipital, superior parietal, and right occipital brain regions. The three frontal IC sources exhibited theta and beta peaks in their spectral profiles. The remaining sources typically exhibited an alpha peak with distinct amplitudes.

Fig. 4 further summarizes the grand mean dipolarity and inter-day reproducibility of the IC clusters from 10 participants and their resultant inter-participant IC commonality. There were nine IC clusters often aggregating for four days, including frontal central, left/right frontal, central midline, left/right sensorimotor, superior parietal, and left/right occipital ICs. As shown in Fig. 4A, the clusters resulted in a mean dipolarity of 92.3% (STD: 1.5%; range: 90.1 – 94.9%) and a mean inter-day reproducibility of 71.2% (STD: 12.7%; range: 50.0 – 90.0%). The dipolar ICs located at the parieto-occipital regions tended to be highly reproducible across days (75.0 – 90.0%), followed by sensorimotor sources (75 and 77.8%) and frontal sources (55.6 – 69.4%). The worst case was found with the central midline source (50.0%). The spectral profiles of the nine IC clusters generally assembled the outcomes explored from the representative participant (Fig. 3). That is, the frontal sources typically accompanied a minor peak in both theta and beta bands, while the other sources were associated with an alpha peak. However, as can be seen, their mean peak amplitudes (in red) were more or less smeared due to the obvious intra- or/and inter-individual variability (in gray) in the collected four-day dataset of 10 participants.

To evaluate the inter-participant IC commonality for day-stationary ICs, this study only considered the participants having the IC with the inter-day reproducibility $\geq$ 75% with respect to the aforementioned grand mean inter-day reproducibility of 71.2% (STD: 12.7%). As such, the nine clusters returned a mean IC commonality of 63.3% (STD: 21.2%; range: 30.0 – 90.0%), as shown in Fig. 4B. The sensorimotor, parietal, and occipital sources tended to often be reproducible over time and among participants, leading to an IC commonality of $\geq$ 70.0%. Contrastingly, the frontal and central sources exhibited greater disparity among participants ($\leq$ 50%), with the frontal central counterpart being the worst

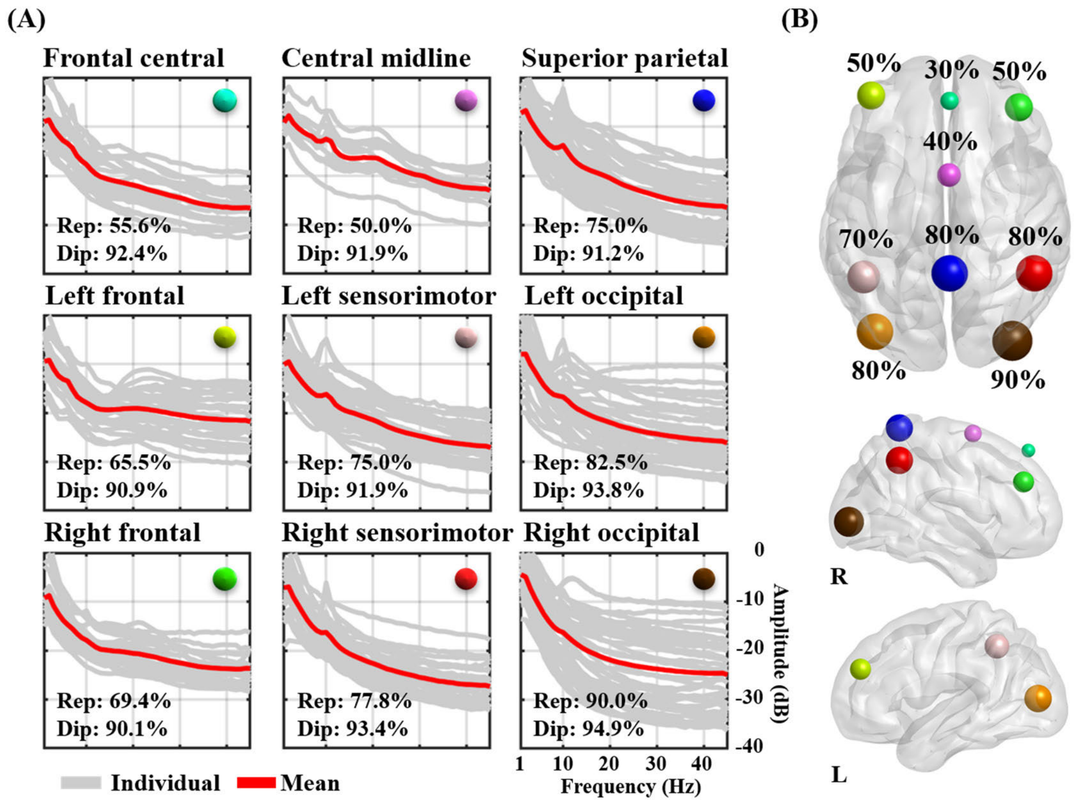

Fig. 4. Nine neurophysiologically day-reproducible IC clusters summarized from 10 participants and the corresponding inter-participant IC commonality. (A) shows the cluster characteristics and the corresponding dipolarity (Dip) and inter-day reproducibility (Rep). (B) projects the dipole centroids of the IC cluster to the brain. The dipole size is scaled by the inter-participant IC commonality for analogous ICs with inter-day reproducibility $\geq$ 75% (*i.e.*, at least three of four days).

case (30%). Accordingly, complying with an empirical criterion of three-day reproducibility, the discernibly distinct IC commonality reflected realistic EEG variability in active piano improvisation.

C. Spatio-Spectral EEG Correlates of Emotional Intent

Among the derived nine IC clusters (*i.e.*, inter-participant IC commonality range: 30.0-90.0%), only three ICs were located in the right frontal (Talairach coordinates x = 41, y = 42, z = 30; BA = 9), frontal central (x = 2, y = 39, z = 11; BA = 32), and superior parietal (x = 3, y = −48, z = 60; BA = 7) regions, exhibiting spectral modulations underlying the dichotomized emotional intent with an inter-participant emotion commonality of 30–40% (see Fig. 5). This indicates that only three or four participants showed analogous day-reproducible spatio-spectral tendency toward the same emotional intent during piano playing. For the valence category (Fig. 5A), the right frontal beta returned the emotion commonality of 40%. Emotional play with positive intent tended to promote beta enhancement when compared to negative ones, which was consistently seen in four participants. For the arousal category, the high arousal play manifested significant augmentation in the frontal central gamma and the superior parietal alpha compared to the low arousal play with 30% emotion commonality (see Fig. 5B). The remaining six day-reproducible IC sources were statistically irrelevant to emotional intent for most participants (*i.e.*, emotion commonality $\leq$ 20%). Therefore, the derived inferior inter-participant emotion commonality may be attributed in part to the ecologically introduced inter-day EEG variability in piano playing with the target emotional intent. As can be seen, the spectral profiles of the dichotomized states differed across days and thereby led to noticeable overlapping distributions (see the right panel) for each participant. This could impede the exploration of the day-reproducible spatio-spectral gap of emotional contrast.

IV. Discussion

This study employed a data-driven ICA approach to explore the relatively day-stationary EEG spatio-spectral modulations of imbuing emotional intent in active piano playing. Our results showed that EEG patterns were substantially affected by intra- and inter-individual variability when intentionally expressing emotional intent. Among the nine day-stationary IC clusters, only three ICs located near the frontal and parietal brain regions manifested distinctive spectral modulations to the dichotomized emotional valence and arousal categories, yet only led to an inter-participant emotion commonality of 30 – 40%. While previous studies mostly contributed to the design without the aspect of emotional intent, as well as a single-day analysis scenario [6], [7], [13], [14], [15], [16], [18], this study advances the neuroscientific endeavors of music improvisation and affective computing by appraising the EEG (non)stationarity of emotional intent in a multiday active piano-playing setting.

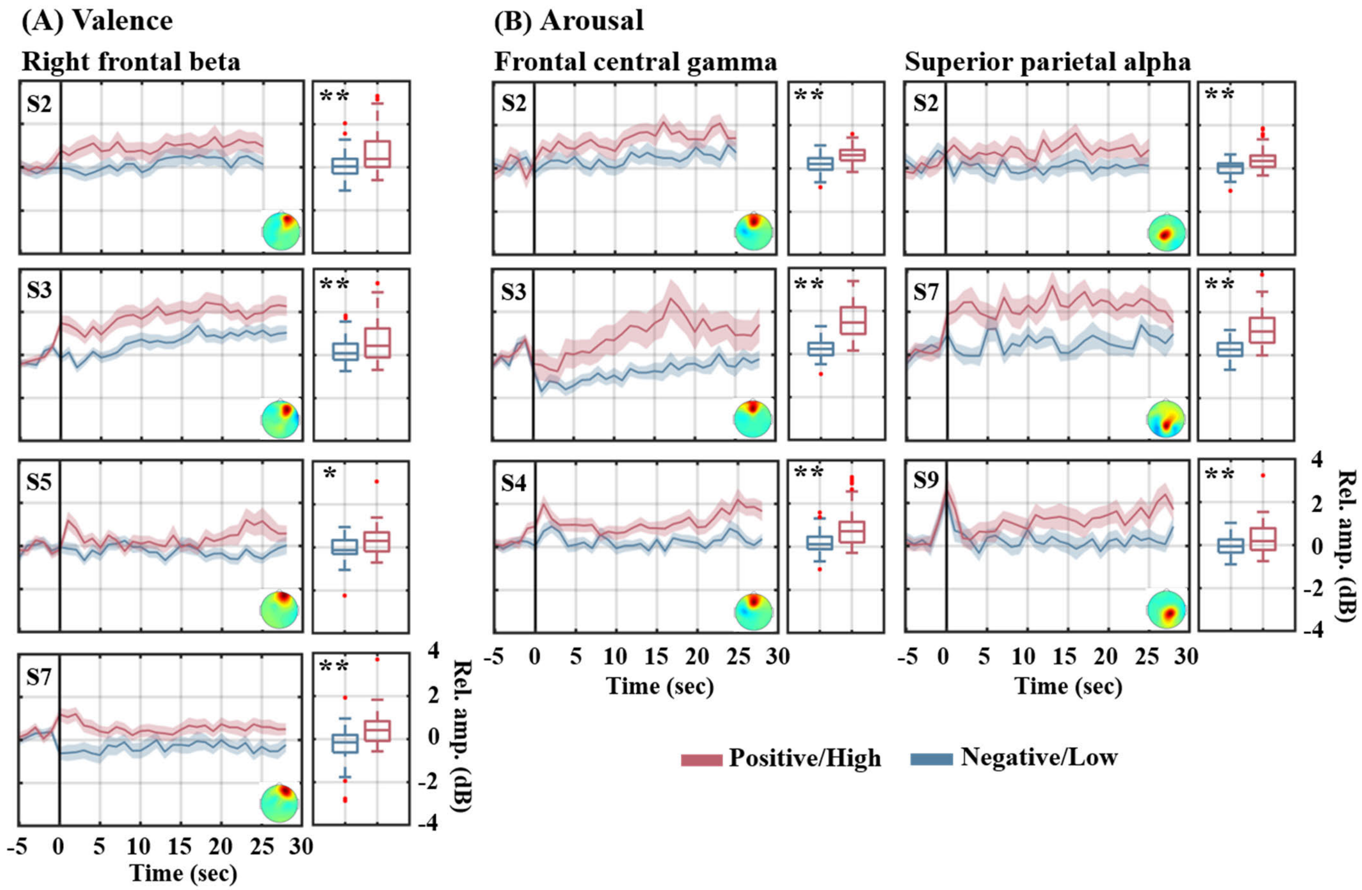

Fig. 5. Relatively day-reproducible, participant-consistent spatio-spectral EEG modulations underlying emotional intent of the dichotomized valence and arousal categories. Each subplot represents a resultant participant. The left panel shows the spectral time course of emotional play with respect to the last five seconds of mechanical play as the baseline. The right panel of the subplot shows the spectral average of the emotion play. The bands represent the corresponding standard error. $**$ and $*$ indicate the statistically significance with $p_{\mathrm{fdr}} < 0.01$ and $p_{\mathrm{fdr}} < 0.05$, respectively.

A. Inter-Day Reproducible EEG Sources Using ICA

Previous EEG studies mostly demonstrated the efficacy of ICA in finding a consensus of neurophysiological source activity from a group of individuals regarding music perception and emotional experience [8], [10], [11], [22], [36], while a recent study exclusively attempted to explore relatively day-reproducible sources across individuals [9]. However, the number of ICs to be resolved by ICA is mathematically confined by the number of scalp channels used for recording. A sparse or limited channel montage may affect the applicability of the ICA (*i.e.*, IC source availability). Onton and Makeig [37] documented that a 31-channel setting typically yields 5 – 15 neurophysiologically interpretable ICs. Later studies confirmed such a practical guide, *e.g.*, 32 channels for 8 – 5 ICs (mean: 11.2) in a motor imagery task [38], 30 channels for 11.2 $\pm$ 1.9 ICs (mean $\pm$ STD) in a music listening task [9], and 30 channels for 10.8 $\pm$ 0.5 ICs in a music listening task using a multiple-day ICA framework [22]. Unlike in a stationary setting (*e.g.*, sitting still), the piano playing task conducted in this study plausibly raised more natural artifacts, including eye movement, neck muscle tension, scalp muscle activities, and headset motion. It is reasonable to expect that these distinctive, non-stationary artifact behaviors may impede ICA from reconstructing meaningful cortical ICs per recording day session. A recent guitar-playing study [18] reported a suboptimal availability of ICs (2 – 7 ICs) owing to the motion interference, even with a 64-ch recording. Thus, our 30-ch EEG setting which returned 10.5 $\pm$ 2.1 meaningful ICs per day session should be both explainable and acceptable.

Aggregated day-reproducible IC clusters were found in the frontal, central, sensorimotor, parietal, and occipital regions of the cortex, which resembled the findings commonly reported in music and emotion studies [9], [10], [22], [36]. While most EEG-ICA studies summarized participant group-wise IC reproducibility, less effort was invested in IC reproducibility over time for each individual. A recent music-listening study [9] reported 76.03 $\pm$ 10.40% (mean $\pm$ STD) inter-day IC reproducibility (min: 60.89 $\pm$ 28.36%, max: 88.57 $\pm$ 10.98%) over eight recording days. Our resultant inter-day IC reproducibility of 71.2 $\pm$ 12.7% among the nine clusters explored in an active piano playing task should be explainable. It is likely that naturalistic artifact sources that contribute to stronger signal variance to the scalp could spread widely during certain day sessions and then compete with underlying brain sources that are either weak or indistinctive signals to be reconstructed [37]. Therefore, we believe that such relatively day-reproducible IC clusters summarized across 10 participants were valid for exploring their links to emotional intent.

B. Inter-Participant Common Spectral Modulations to Emotional Intent

A threshold of 75% inter-day reproducibility (*i.e.,* appearing for at least three days) was imposed to define the day-reproducible cluster and quantify the IC commonality across participants, leading to 63.3 ± 21.2% (mean ± STD) inter-participant IC commonality (range: 30.0-90.0%; see Fig. 4B). However, the IC commonality was considerably enhanced to a certain extent by loosening the threshold, for example, to 50% (two days only). In this case, the commonality was 82.2 ± 13.0% within a range of 60.0 – 100.0% (not presented in Results). This setting subjectively boosted the number of participants recruited to assess whether each IC of interest possessed emotional links. However, the resultant findings will inevitably be made with less demand for cross-day reproducibility. To address the posed scope of exploring day-reproducible modulations, this study conducted a sequential analysis of emotional intent with a stringent threshold, *e.g.*, 75%. On the other hand, a music-listening study [9] with an 8-day recording setting reported a better IC commonality (mean ± STD: 71.11 ± 18.33%; range: 50–100%) using the same threshold of 75% (at least six days). Given analogously resolved ICs per single-day session (theirs: 11.20 ± 1.96, ours: 10.5 ± 2.1), both our inferior mean commonality and larger commonality range could be attributed to active music playing presumably being accompanied by stronger non-stationarity of cortical sources along days and across individuals compared to passive music-listening.

To the best of our knowledge, this study is the first attempt to exploit day-reproducible spatio-spectral EEG modulations of emotional intent during active piano playing. It is challenging to justify the neurophysiological validity of our findings exclusively due to the lack of comparable longitudinal studies. Here, we intended to link our cross-day outcomes to existing emotion-related endeavors, mostly conducted using single-day and/or stationary recording scenarios. Our findings showed that less than half (3 – 4) of the 10 participants analogously exhibited day-reproducible spectral modulations at the right frontal (BA9) beta in response to the valence contrast as well as the frontal central (BA32) gamma and the superior parietal (BA7) alpha to the arousal counterpart (see Fig. 5). The predominant engagement of the frontal and parietal activities may be, in part, supported by a longitudinal music-listening study [9], [22]. They documented the links of the frontal (BA9 and BA10) and central midline (BA6) sources to the valence category with the same inter-participant commonality (30 – 40%), and the involvement of the superior parietal (BA5) source to the arousal counterpart with less commonality (25%) [9]. However, most of them projected high-frequency spectral modulations in the beta and gamma bands over the neighboring brain regions of interest, while our findings exhibited a noticeable frontal vs. parietal distinction; that is, the frontal area tended to reflect the beta and gamma modulations and the parietal area was associated with the alpha alteration. Even though the spectral disparity may be attributed to different experimental tasks (stationary music-listening vs. active piano-playing), the consensus between the studies by means of the ICA-driven, multiple-day analytical scenario facilitated a better understanding of the role of the frontal cortex (*e.g.*, DLPFC (BA9), ACC (BA 24, 32, and 33) [8], [39], [40], [41], [42]) in intervening in emotional processes and expressing spectral signatures that are relatively resistant to ecological intra- and inter-individual EEG variability. Additionally, our cross-day findings and existing single-day outcomes regarding emotional responses may support or complement each other, *e.g.*, posterior alpha relevant to emotional affect and intensity [36], [43], [44] and prefrontal beta and gamma asymmetry in valence [45].

Referring to existing single-day music improvisation findings, the resultant day-reproducible frontal sources (*e.g.*, right frontal sources) evidently replicated previous fMRI studies with professional musicians. DLPFC activation was found to be diversely driven by music improvisation [4], [5] and considerably altered in response to the emotional intent of the valence aspect [6], [7]. Previous single-day EEG studies have shed light on the validity of spectral engagement with frontal brain sources. Under different study settings investigating music improvisation, several spectral signatures have been revealed at distinct frequency bands accordingly, *e.g.*, improvised performance mode associated with alpha, beta, and gamma power near the DLPFC, ACC, and MFC compared to prepared or scale playing modes [12], [13], [18], while improvisation by skilled or formally trained musicians exhibiting higher right frontal alpha [14], [15], [16], and high-quality improvisation leading to high-frequency beta and gamma activation against low-quality counterparts [16]. Taken together, the frontal beta and gamma modulations explored by the dichotomized valence and arousal contrasts in our study were more plausibly attributed to music improvisation quality, since emotion expression is acknowledged as a crucial modulator of the creative process [7], [20]. Finally, this study did not yield any sensorimotor intervention for emotional intent, despite corresponding to a relatively high inter-day reproducibility across participants (*i.e.*, inter-participant IC commonality: 70 – 80%, see Fig. 4B). The absence of sensorimotor outcomes may be attributed to the fact that piano fingering strategies and their corresponding motoric spectral patterns did not substantially alter the expression of different target emotional intent for the recruited participants in this study. Additionally, the inconsistent motoric signature compared to the previous EEG music improvisation study [18] is likely due to the difference in study focus; that is, they focused on the exclusive neural distinction between improvisation and scale playing.

Music offers a unique capability to evoke a wide range of emotional responses across cultures and has led to ever-growing functional neuroimaging studies to elucidate the interplay between emotion and brain networks [41], [42]. It is evident that music-evoked emotions raise a diverse interactive engagement of cortical and subcortical structures relevant to sensory, motor, memory, and reward processes [41], [42], [46]. Additionally, the brain may switch between different strategies to execute or respond to the same task in an ecologically realistic setting [47]. The engaged brain sources and their communication coupling are unlikely to persist on a daily basis in terms of location and spectral characteristics.

Both aspects may demonstrate that emotion-evoked brain networks exhibit salient intra- and inter-individual differences in spatio-spectral EEG patterns, as previously reported [9], [21], [22], [48], [49]. Most critically, EEG correlates of emotional responses ecologically exhibit diverse profiles across individuals plausibly ascribed to dominant factors of personality [50] and gender [51]. This may explain in part the manifested inferior inter-participant emotion commonality found in this study. Instead of solving a generic model for all individuals, machine learning-basis personalized modeling [52] can be a potential breakthrough to deploy a BCMI infrastructure in the real world.

C. Limitations

Scalp EEG signals are known to encapsulate less electrical amplitudes from deep brain regions. Thus, in this study, it was barely possible to pinpoint some subcortical regions that have been reported previously to be relevant in fMRI studies [41], [42]. The interpretation of day-stationary emotional intent EEG findings must consider the limited accessibility of deep EEG sources derived by ICA. Additionally, this study parsed EEG sources using one of the most commonly used ICA algorithms, *e.g.*, extended infomax ICA. Different algorithms have been documented to return distinctive effectiveness for source decomposition. Particularly, adaptive mixture ICA (AMICA) has been reported to be superior in component separation [30] and has been empirically demonstrated in effective modeling of EEG correlating with brain state changes, *e.g.,* step adaptation [31] and emotion imagination [53]. Considering the ecological music improvisation experiment, the multiple-model AMICA framework may be a contemporary alternative for exploring EEG modulations of imbuing emotional intent during active music playing in future studies.

Finally, there may be a tradeoff between emotion intent-embedded music improvisation tasks with and without a pre-composed music score. To avoid over-complicating the experimental variables, the dataset used in this study used pre-composed music scores for the active playing task. However, considering that the resulting knowledge is aimed at informing the BCMI design and its deployment challenges, future follow-up efforts should adopt a score-free design and explore how the day-stationary EEG spatio-spectral modulations behave against the current study settings.

V. Conclusion

This study attempted to exploit reliable spatio-spectral EEG oscillations of emotional intent during active piano playing using a data-driven ICA framework. Given the four-day dataset of 10 participants, we demonstrated substantial intra- and inter-individual EEG variability that inevitably impeded the finding of common emotion-relevant EEG patterns. Three ICs located near the frontal and parietal brain regions manifested relatively day-stationary ($\geq$ three days) distinctive spectral modulations to the dichotomized emotional valence and arousal categories, but only led to an inter-participant emotion commonality of 30 – 40%. Particularly, the frontal engagement facilitated better understanding of the frontal cortex (*e.g.*, DLPFC and ACC) in terms of its role in intervening in emotional processes and expression of spectral signatures that are relatively resistant to natural EEG variability. As such, the empirical findings on an ecological multiday protocol contribute to the complementary evidence of affective computing in an active mode rather than a passive mode often addressed in the literature.

References

[1] J. Pressing, "Psychological constraints on improvisational expertise and communication," in *In the Course of Performance: Studies in the World of Musical Improvisation*. Chicago, IL, USA: Univ. of Chicago Press, 1998, pp. 47–68.

[2] J. Castet and E. R. Miranda, *Guide to Brain-Computer Music Interfacing*. London, U.K.: Springer, 2014, p. 1.

[3] H. Gürkök and A. Nijholt, "Affective brain–computer interfaces for arts," in *Proc. Humaine Assoc. Conf. Affect. Comput. Intell. Interact.*, 2013, pp. 827–831.

[4] S. L. Bengtsson, M. Csíkszentmihályi, and F. Ullén, "Cortical regions involved in the generation of musical structures during improvisation in pianists," *J. Cognit. Neurosci.*, vol. 19, no. 5, pp. 830–842, May 2007.

[5] C. J. Limb and A. R. Braun, "Neural substrates of spontaneous musical performance: An fMRI study of jazz improvisation," *PLoS ONE*, vol. 3, no. 2, p. e1679, Feb. 2008.

[6] A. L. Pinho, F. Ullen, M. Castelo-Branco, P. Fransson, and O. de Manzano, "Addressing a paradox: Dual strategies for creative performance in introspective and extrospective networks," *Cereb Cortex*, vol. 26, no. 7, pp. 3052–3063, Jul. 2016.

[7] M. J. McPherson, F. S. Barrett, M. Lopez-Gonzalez, P. Jiradejvong, and C. J. Limb, "Emotional intent modulates the neural substrates of creativity: An fMRI study of emotionally targeted improvisation in jazz musicians," *Sci. Rep.*, vol. 6, no. 1, p. 18460, Jan. 2016.

[8] Y.-P. Lin, J.-R. Duann, J.-H. Chen, and T.-P. Jung, "Electroencephalographic dynamics of musical emotion perception revealed by independent spectral components," *NeuroReport*, vol. 21, no. 6, pp. 410–415, Apr. 2010.

[9] Y.-W. Shen and Y.-P. Lin, "Challenge for affective brain–computer interfaces: Non-stationary spatio-spectral EEG oscillations of emotional responses," *Frontiers Human Neurosci.*, vol. 13, p. 366, Oct. 2019.

[10] Y.-P. Lin, J.-R. Duann, W. Feng, J.-H. Chen, and T.-P. Jung, "Revealing spatio-spectral electroencephalographic dynamics of musical mode and tempo perception by independent component analysis," *J. NeuroEngineering Rehabil.*, vol. 11, no. 1, p. 18, Feb. 2014.

[11] F. Cong et al., "Linking brain responses to naturalistic music through analysis of ongoing EEG and stimulus features," *IEEE Trans. Multimedia*, vol. 15, no. 5, pp. 1060–1069, Aug. 2013.

[12] D. Dolan, J. Sloboda, H. Jensen, B. Crüts, and E. Feygelson, "The improvisatory approach to classical music performance: An empirical investigation into its characteristics and impact," *Music Perform. Res.*, vol. 6, pp. 1–38, Jan. 2013.

[13] D. Dolan et al., "The improvisational state of mind: A multidisciplinary study of an improvisatory approach to classical music repertoire performance," *Frontiers Psychol.*, vol. 9, p. 1341, Sep. 2018.

[14] L. A. Dikaya and I. A. Skirtach, "Neurophysiological correlates of musical creativity: The example of improvisation," *Psychol. Russia, State Art*, vol. 8, no. 3, pp. 84–97, 2015.

[15] J. A. Lopata, E. A. Nowicki, and M. F. Joanisse, "Creativity as a distinct trainable mental state: An EEG study of musical improvisation," *Neuropsychologia*, vol. 99, pp. 246–258, May 2017.

[16] D. S. Rosen, Y. Oh, B. Erickson, F. Zhang, Y. E. Kim, and J. Kounios, "Dual-process contributions to creativity in jazz improvisations: An SPM-EEG study," *NeuroImage*, vol. 213, Jun. 2020, Art. no. 116632.

[17] T. P. Jung et al., "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology*, vol. 37, no. 2, pp. 78–163, Mar. 2000.

[18] M. Sasaki, J. Iversen, and D. E. Callan, "Music improvisation is characterized by increase EEG spectral power in prefrontal and perceptual motor cortical sources and can be reliably classified from non-improvisatory performance," *Frontiers Human Neurosci.*, vol. 13, p. 435, Dec. 2019.

[19] J. E. Pousson et al., "Spectral characteristics of EEG during active emotional musical performance," *Sensors*, vol. 21, no. 22, p. 7466, Nov. 2021.

[20] P. Verhaeghen, J. Joormann, and R. Khan, "Why we sing the blues: The relation between self-reflective rumination, mood, and creativity," *Emotion*, vol. 5, no. 2, pp. 226–232, Jun. 2005.

[21] Y.-P. Lin, "Constructing a personalized cross-day EEG-based emotion-classification model using transfer learning," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 5, pp. 1255–1264, May 2020.

[22] Y.-W. Shen and Y.-P. Lin, "Cross-day data diversity improves inter-individual emotion commonality of spatio-spectral EEG signatures using independent component analysis," *IEEE Trans. Affect. Comput.*, early access, doi: 10.1109/TAFFC.2023.3261867.

[23] J. A. Russell, "A circumplex model of affect," *J. Personality Social Psychol.*, vol. 39, no. 6, pp. 1161–1178, Dec. 1980.

[24] E. Bigand et al., "Empirical evidence for musical syntax processing? Computer simulations reveal the contribution of auditory short-term memory," *Frontiers Syst. Neurosci.*, vol. 8, p. 94, Jun. 2014.

[25] A. Delorme and S. Makeig, "Eeglab: An open source toolbox for analysis of single-trial eeg dynamics including independent component analysis," *J. Neurosci. Methods*, vol. 134, no. 1, pp. 9–21, 2004.

[26] C.-Y. Chang, S.-H. Hsu, L. Pion-Tonachini, and T.-P. Jung, "Evaluation of artifact subspace reconstruction for automatic artifact components removal in multi-channel EEG recordings," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 4, pp. 1114–1121, Apr. 2020.

[27] T. R. Mullen et al., "Real-time neuroimaging and cognitive monitoring using wearable dry EEG," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 11, pp. 2553–2567, Nov. 2015.

[28] R. Oostenveld and T. F. Oostendorp, "Validating the boundary element method for forward and inverse EEG computations in the presence of a hole in the skull," *Hum. Brain Mapping*, vol. 17, no. 3, pp. 92–179, Nov. 2002.

[29] F. Artoni, D. Menicucci, A. Delorme, S. Makeig, and S. Micera, "RELICA: A method for estimating the reliability of independent components," *NeuroImage*, vol. 103, pp. 391–400, Dec. 2014.

[30] A. Delorme, J. Palmer, J. Onton, R. Oostenveld, and S. Makeig, "Independent EEG sources are dipolar," *PLoS ONE*, vol. 7, no. 2, Feb. 2012, Art. no. e30135.

[31] J. Wagner, R. Martínez-Cancino, and S. Makeig, "Trial-by-trial source-resolved EEG responses to gait task challenges predict subsequent step adaptation," *NeuroImage*, vol. 199, pp. 691–703, Oct. 2019.

[32] Y.-C. Chen et al., "Spatial and temporal EEG dynamics of motion sickness," *NeuroImage*, vol. 49, no. 3, pp. 2862–2870, Feb. 2010.

[33] H. He and D. Wu, "Transfer learning for brain–computer interfaces: A Euclidean space data alignment approach," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 2, pp. 399–410, Feb. 2020.

[34] P. Zanini, M. Congedo, C. Jutten, S. Said, and Y. Berthoumieu, "Transfer learning: A Riemannian geometry framework with applications to brain–computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 5, pp. 1107–1116, May 2018.

[35] Y. Benjamini and Y. Hochberg, "Controlling the false discovery rate: A practical and powerful approach to multiple testing," *J. Roy. Stat. Society, Ser. B Methodol.*, vol. 57, no. 1, pp. 289–300, Jan. 1995.

[36] L. Rogenmoser, N. Zollinger, S. Elmer, and L. Jäncke, "Independent component processes underlying emotions during natural music listening," *Social Cogn. Affect. Neurosci.*, vol. 11, no. 9, pp. 1428–1439, Sep. 2016.

[37] J. Onton and S. Makeig, "Information-based modeling of event-related brain dynamics," *Prog. Brain Res.*, vol. 159, pp. 99–120, 2006.

[38] Y. Wang, Y.-T. Wang, and T.-P. Jung, "Translation of EEG spatial filters from resting to motor imagery using independent component analysis," *PLoS ONE*, vol. 7, no. 5, May 2012, Art. no. e37665.

[39] K. L. Phan, T. Wager, S. F. Taylor, and I. Liberzon, "Functional neuroanatomy of emotion: A meta-analysis of emotion activation studies in PET and fMRI," *NeuroImage*, vol. 16, no. 2, pp. 331–348, Jun. 2002.

[40] M. T. Mitterschiffthaler, C. H. Fu, J. A. Dalton, C. M. Andrew, and S. C. Williams, "A functional MRI study of happy and sad affective states induced by classical music," *Hum. Brain Mapping*, vol. 28, no. 11, pp. 1150–1162, Nov. 2007.

[41] S. Koelsch, "Brain correlates of music-evoked emotions," *Nature Rev. Neurosci.*, vol. 15, no. 3, pp. 170–180, Mar. 2014.

[42] S. Koelsch, "A coordinate-based meta-analysis of music-evoked emotions," *NeuroImage*, vol. 223, Dec. 2020, Art. no. 117350.

[43] W. Heller, "Neuropsychological mechanisms of individual differences in emotion, personality, and arousal," *Neuropsychology*, vol. 7, no. 4, pp. 476–489, Oct. 1993.

[44] V. J. Schmithorst, "Separate cortical networks involved in music perception: Preliminary functional MRI evidence for modularity of music processing," *NeuroImage*, vol. 25, no. 2, pp. 444–451, Apr. 2005.

[45] I. Daly et al., "Neural correlates of emotional responses to music: An EEG study," *Neurosci. Lett.*, vol. 573, pp. 52–57, Jun. 2014.

[46] W. Trost, S. Frühholz, T. Cochrane, Y. Cojan, and P. Vuilleumier, "Temporal dynamics of musical emotions examined through intersubject synchrony of brain activity," *Social Cognit. Affect. Neurosci.*, vol. 10, no. 12, pp. 1705–1721, Dec. 2015.

[47] B. Lance et al., "Towards serious games for improved BCI," in *Handbook of Digital Games and Entertainment Technologies*. Singapore: Springer, 2015, pp. 1–28.

[48] Y.-P. Lin and T.-P. Jung, "Improving EEG-based emotion classification using conditional transfer learning," *Frontiers Human Neurosci.*, vol. 11, p. 334, Jun. 2017.

[49] Y.-P. Lin, P.-K. Jao, and Y.-H. Yang, "Improving cross-day EEG-based emotion classification using robust principal component analysis," *Frontiers Comput. Neurosci.*, vol. 11, p. 64, Jul. 2017.

[50] J. I. Schmidtke and W. Heller, "Personality, affect and EEG: Predicting patterns of regional brain activity related to extraversion and neuroticism," *Personality Individual Differences*, vol. 36, no. 3, pp. 717–732, Feb. 2004.

[51] S. A. Lee, C.-Y. Kim, M. Shim, and S.-H. Lee, "Gender differences in neural responses to perceptually invisible fearful face—An ERP study," *Frontiers Behav. Neurosci.*, vol. 11, p. 6, Jan. 2017.

[52] O. G. Sani, Y. Yang, M. B. Lee, H. E. Dawes, E. F. Chang, and M. M. Shanechi, "Mood variations decoded from multi-site intracranial human brain activity," *Nature Biotechnol.*, vol. 36, no. 10, pp. 954–961, Nov. 2018.

[53] S.-H. Hsu, Y. Lin, J. Onton, T.-P. Jung, and S. Makeig, "Unsupervised learning of brain state dynamics during emotion imagination using high-density EEG," *NeuroImage*, vol. 249, Apr. 2022, Art. no. 118873.