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Smartphone-Based Natural Environment Electroencephalogram Experimentation- Opportunities and Challenges

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Abstract— **Using a smartphone for Electroencephalogram (EEG) based research in the natural environment is a growing field of study. It brings attention to device portability, participant mobility, and system specifications. This article discusses the most recent developments in the field of EEG investigations using smartphones in natural environments, for healthy and clinical applications. We integrate the current trends in smartphone-based EEG studies, namely experimental paradigms, electrode/hardware compatibility, preprocessing frameworks, classifiers, and software apps. However, smartphone devices have inherent limitations like computational time and algorithm performance. Implementing artifact reduction and classification algorithms together in an android smartphone app is still speculative, and possible solutions are proposed. This review presents a holistic insight into our current understanding and challenges of the smartphone's role in natural environment electroencephalogram trials.**

Clinical Relevance— **These portable smartphone-based EEG systems will be useful in monitoring individuals with psychiatric diseases, in addition to human brain applications in a natural setting. With ubiquitous availability of internet on smartphones, telemedicine is another possible application.**

I. Introduction

Electroencephalogram or EEG is a high temporal resolution technique used to analyse neurocognitive processes[1]. Traditional EEG experiments included wired electrodes mounted on the participants' scalp, connected to a large amplifier with a computer monitor placed in front. This kind of experimental setup is only possible in a confined environment such as a laboratory. With time wired electrodes transformed into wireless, wearables, and beyond wearables while reduced amplifier size enabled better movement possibilities for the participants and allowed the flexible design of experiments[2]. EEG-based experimentation in a natural environment using a smartphone is currently an active area of research. However, such experiments attract several challenges from the perspectives of a smartphone BCI app developer. Smartphone-based mobile electroencephalography (mobile EEG) is a non-invasive, portable, and very affordable next-generation neuroscientific technique for studying real-time brain activity. Reducing the number of electrodes as much as possible helps participants behave naturally. A massive amount of artifacts often come along with the EEG signals of interest. These include biological artefacts like heartbeats, eye and muscle movements, and electrical artefacts such as wire, electrode movement and line noise[3]. Smartphone-based mobile EEG will enable the whole-body movement of participants, thereby giving rise to additional sources of artifacts. Implementing a suitable and robust pre-processing algorithm will obtain our signal of interest. Then integrating with a classifier may provide information about aspects of brain function. Our review paper aims to focus on the smartphone for natural environment EEG experiments. To the best of our knowledge, no such review work has been reported as of now. Fig. 1 represents the graphical abstract of our review work.

II. Current Trends In Smartphone-Based EEG

A. Paradigms/Experiments

Designing an EEG-based BCI framework for a particular application requires selecting a protocol and paradigm for all the experimental stages. At the first stage, the subject executes an experimental task (e.g., visual, auditory, or imagery) upon which the brain activity is recorded through the EEG signals. Utilizing these EEG signals, a neural decoder is developed for the paradigm. The generated neural decoder is then used for BCI control during subsequent performing of the tasks. Abiri et al.[4] discusses the broad idea of paradigm types and their applications. The auditory oddball paradigm has been used recently in several EEG-based real-life environment studies[5], [6]. Apart from that, paradigms such as the competing-speaker paradigm[7], high-pressure learning task[8], walking task[9], mixed-bridges knowledge paradigm[10] are also used to study behavioural changes within EEG in naturalistic environmental studies.

B. Smartphone Software Apps

BCI aims at using brain waves to control various auxiliary devices. Stopczynski et al. presented the Smartphone Brain Scanner as a portable smartphone-based 3D EEG imaging system[11] that captured the brain activity during a finger-tapping experiment. NeuroPhone, a BCI application on iPhone[12], used P300 signals to dial numbers through the Dial Tim application. The first Nokia phone-based BCI[13] consisted of a visual stimulator, a wireless EEG headband, and a Bluetooth-enabled module. It used an external visual stimulator to realize the SSVEP (Steady State Visually Evoked Potential) paradigm by showing a virtual telephone keypad to dial a number. The integrated signal processing on a single

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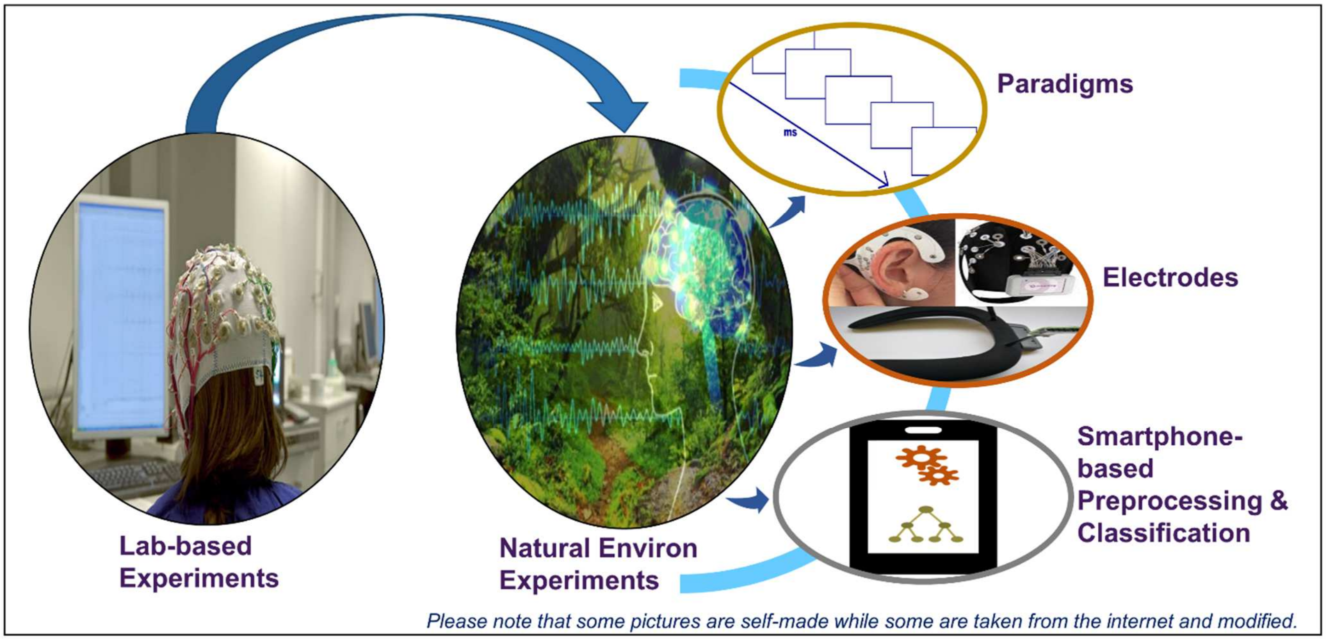

Figure 1. Current Challenges in Natural Environ EEG Experiments

device resulted in a fully smartphone-operated BCI in the following year[14]. Due to its single paradigm and proprietary communication protocol, its application remained limited. In the following years, Blum et al. put forward an EEG-BCI multi-app framework[15], which integrated data acquisition(smarting app), BCI processing on SCALA(Signal Processing and CLassification on Android), and stimulus presentation(Stimulus Android app) on an android smartphone. Although the framework was flexible in terms of paradigm and sensors used, it had one limitation of running multiple apps simultaneously at the same time for data acquisition. An app named TinnituSense is reported to integrate all the previous applications into a single one, thus resulting in the first smartphone app to record and visualize data in real-time[16], which permits real-world EEG experiments. To comprehend how sounds are perceived in real-world situations, Hölle et al. created two Android apps (AFEx and Record-a) that, when combined with a commercially available smarting app on an Android smartphone, enabled simultaneous acquisition of EEG data and audio features, such as sound onsets, average signal power (RMS), and power spectral density (PSD)[17]. A recent Android app called CameraEEG, created by Madhavan et al., allowed synchronised collection of EEG and video data[18] In contrast to natural recording applications that seem to utilise numerous apps or intricate arrangements to present/record them, the CameraEEG android app records electroencephalogram and external stimuli using a single android application with EEG device-specific libraries.

C. *Electrodes/Hardware compatible with Smartphone-based EEG*

The first and foremost step for natural environment EEG experimentation is selecting appropriate hardware and electrodes for the study. The data acquisition system should be chosen based on the task, participants' nature, and the research question. The selection of the electrodes can be decided based on factors such as the type of the electrode (wired or wireless), cost, data quality, and the setup time to put the electrodes. Table I. represents some commercially available EEG amplifiers/electrodes which have been used in many studies. Apart from these, task design and data storage play a significant role in a smartphone-based EEG study. Scanlon et al. compared active and passive electrode configurations during standing and walking conditions[19]. Their main takeaway was that regardless of whether the electrode type is active or passive, the signal quality for both experiments remained the same. Hence use of passive electrodes would provide the participant a hassle-free investigation with much freedom of movement for outdoor experiments. Bleichner et al. developed cEEGrid electrodes to capture EEG signals around the ear used for auditory attention studies[2]. These were lightweight, comfortable to wear anywhere, easy to set up, and concealable. Hölle et al.[5] also used cEEGrid electrodes along with smarting and presentation apps to study auditory perception in an everyday context. With the development of mobile EEG hardware, Bleichner and Emkes[20] developed a nEEGlace, a modified version of the Smarting amplifier for beyond-the-lab trials. They tested it with the previously developed smarting and presentation app. Further, Hölle et al. also used the smarting app and cEEGrid electrodes to study auditory perception in daily life situations[5]. Lin et al.[21] developed a cost-efficient custom-made electrode holder assembly with replaceable montage using a 3D printer tested using dry electrodes. When comparing ear-EEG with scalp-EEG data for auditory attention tasks, Meiser et al.)[22] came to the conclusion that ear-EEG captured equivalent signal quality with strong event-related potentials (ERPs). Aside from the LiveAmp and SmartingMobi amplifiers utilised in the preceding investigations, Smarting Pro and Smarting Pro X are the most recent additions to the mobileEEG amplifiers that provide high density EEG recordings. Smarting Pro was reportedly used recently in a spatial navigation study[23].

TABLE I. COMMERCIALLY AVAILABLE WIRELESS EEG HARDWARE/ELECTRODES

Company	**Product Name**	**Channels**	**Bluetooth enabled?**	**Battery Life (if applicable)**	**Compatible with Smartphones?**	**Smartphone Compatible App**
Brain Products	LiveAmp	8, 16, 24, 32	Yes	>3 hrs wireless, >4.5 hrs on memory card	No	-
Emotiv	EPOC X	14	Yes	Upto 9 hrs	No	EMOTIV App
	EPOC+	14	Yes	Upto 6 hrs	Yes	
	INSIGHT	5	Yes	Upto 4 hrs	Yes	
NeuroSky	MindWave Mobile 2	1	Yes	8 hrs	Yes	Mindwave Mobile 2 App
Advanced Brain Monitoring	B-Alert X Series	Upto 20	Yes	Upto 8 hrs	No	-
	Stat X Series	Upto 20	Yes	Upto 8 hrs	No	-
g.tec	g.Nautilus PRO	8, 16, 32	Yes	Upto 10 hrs	Yes	-
	g.Nautilus RESEARCH	8, 16, 32, 64	Yes	Upto 10 hrs		
	g.Nautilus Multi-Purpose	8, 16, 32, 64	Yes	6 hrs (64 ch), 10 hrs (8, 16, 32 ch)		
	g.Nautilus PRO FLEXIBLE	8, 16, 32	Yes	>6hrs (64 ch), >10 hrs (8, 16, 32 ch)		
Neuroelectrics	Enobio®	8, 20, 32	Yes	Upto 20 hrs	No	-
InteraXon	Muse S	1	Yes	Upto 10 hrs	Yes	Muse App
	Muse 2	1	Yes	Upto 5 hrs		
Cognionics	Quick-20m	20	Yes	6 hrs	No	-
	Quick-20rv2	21	Yes	8 hrs		
	Quick-32r	32	Yes	8 hrs wireless		
	Mobile Series	72, 128	Yes	4 hrs wireless, 10 hrs with micro-SD card		
mBrainTrain	SMARTING mobi	24, 20	Yes	Upto 5 hrs	Yes	SMARTING App, CameraEEG App
	Smarting PRO	32	Yes	>10 hrs		SMARTING App
	Smarting PRO X	64	Yes	>10 hrs		SMARTING App
	SMARTING SLEEP	24	Yes	Upto 15 hrs		SMARTING App
	Smartfones	11	Yes	-		SMARTING App
Wearable Sensing	DSI 24	24	Yes	Continuous (hot-swappable batteries)	No	-
	DSI 7	7	Yes	>12 hrs		
	DSI 7 Flex	7	Yes	>12 hrs		
	VR 300	7	Yes	>12 hrs		
	NeuSenW	8-64	Yes	4 hrs		
	NeuroCube	8	Yes	Upto 2 hrs		
TMSi	cEEGrid	10	Yes	Upto 5 hrs	Yes	SMARTING App, CameraEEG App
imec	EEG Headset	8	Yes	8 hrs	No	-

Electrodes are the primary part of a data acquisition system; selecting the appropriate electrodes matters significantly. For smartphone-based EEG experiments, selecting the optimal electrode setup for data acquisition is crucial, depending on the type of application and compatibility with smartphone.

D. Pre-processing/Feature Extraction implemented on Smartphone

Natural environment experimentation attracts multiple biological and non-biological artefacts that can often mislead the BCI objective. Selecting a suitable smartphone pre-processing algorithm is another challenging task. Riemannian Artifact Subspace Reconstruction (rASR) developed by Blum et al.[24] was compared with original ASR(Artifact Subspace Reconstruction) for reducing eye and muscle artifacts, which proved to perform better than ASR (Artifact Subspace Reconstruction) in the online and offline analysis[25]. They used MATLAB and EEGLAB for the comparison and analysis. However, ASR is present on the Smarting application. Jacobsen et al.[26] put forward gait-related artifact footprints that can suppress gait-related artifacts while keeping the neurological signals of interest. Bleichner et al.[27] put forward an ICA-based automatized artifact detection technique to study the artefacts' nature and distribution in cEEGrid data. However, its implementation in a smartphone app is yet to be realized. Mehdi et al. put forward a pre-processing pipeline for the TinnituSense app[28]. The pipeline offered a 3rd order Butterworth filter for high pass filtering, a Bandstop filter for line noise removal, and PREP's re-referencing algorithm[29] to detect bad channels. AFEx(Audio Feature Extraction app) was developed for calculating acoustic features such as audio capture, PSD, RMS, acoustic onset detection, etc., to study real-world sound perception[17]. The app ran together with the Record-a app (for LSL data streaming) and smarting app. The feasible option available at this time is to select a pre-processing algorithm that would be suitable with the hardware, power, and battery of a smartphone.

E. Classifiers on Smartphone

Blum et al.[15] presented a simple classifier in the SCALA app named template matching procedure inspired from Choi et al.[30] and Bleichner et al.[2]. The classifier was able to classify between the left attended, and right attended trials. Classification algorithms such as Random Forest (RF) have been implemented in a voice-activity detection app for Android and iOS for real-time on-device noise classification[31], which turned out to give better results than Gaussian Mixture Model(GMM). Later on, Sehgal and Kehtarnavaz[32] compared the previous work with a deep learning algorithm called CNN(Convolutional Neural Network), which intended to act as a switch for noise reduction in signal processing pipelines of hearing devices. Majumder et al.[33] also used deep neural networks for real-time detection of diabetic retinopathy. Long Short-Term Memory (LSTM), an artificial recurrent neural network, has also been reported to better classify different patterns in the same cognitive task[34]. Due to its slower computational time and requirement of high-end GPUs, its implementation on smartphone apps for EEG classification is possibly questionable. Pre-trained models such as BERT(Bidirectional Encoder Representations from Transformers) have shown promising results for EEG-based NLP(Natural Language Processing) tasks[35]. However, these kinds of architectures tend to be very complex and are difficult to implement on a smartphone. A compact version of BERT designed explicitly for mobile devices, called MobileBERT, has shown to be task agnostic and showed better results when compared to the $\text{BERT}_{\text{BASE}}$ algorithm for NLP tasks[36]. Hence, we suggest that these classification algorithms may be implemented and could give good results for a smartphone-based EEG system.

III. Challenges and Future Directions

A smartphone-based mobile EEG system using an android app will open gateways to various challenges such as a motion-tolerant system, i.e., the system should be motion tolerable so that EEG recordings can be conducted anywhere (i.e., outdoors or indoors)[2]. The app should be able to detect and classify external artifacts from the acquired signals. Low power artefact removal algorithms and efficient classifiers integrating into smartphone apps are currently an active area of research; however, more work is still required[37]. Progress in these areas will help realize a reliable app to acquire brain signals for applications like mindfulness training[38]. Also, lightweight and wireless acquisition devices will enable hassle-free experiments in any environment[19]. The entire system should be discreet and comfortable so that participants can perform their daily tasks without getting noticed by others[2]. Furthermore, EEG recordings in a natural environment open scope to measure brain activity in a comfortable and less conscious environment. It gives us a way to investigate the impact of the environment on human behaviour[39]. Additionally, such an EEG monitoring system will open gateways to monitor infants showing neurological abnormalities born to cocaine-addicted mothers [40], and in Alzheimer's patients[41]. Extreme smartphone use has been linked to decreased workplace productivity[42]. West et al. revealed smartphone overuse leading to depression and anxious symptoms using a non-portable EEG device[43]. Electrodes with Smarting Pro coupled to a laptop seem to have been utilised for real-time studies to comprehend navigational ambiguity[23]. The effect of various musical genres and the connectivity of the human brain have lately been studied using EEG[44]. From a mobility and user-friendliness perspective, a smartphone-based EEG system will be more beneficial in carrying out such investigations. Depending on the cognitive problem on hand, additional smartphone sensors (such as accelerometer, gyroscope, and GPS) may be combined with the EEG to enable multimodal data analysis. Availability of internet on smartphones enables Telemedicine possibility. Building specific app for cognitive disorders like Parkinson's, or Epilepsy in consultation with clinicians is a future opportunity.

Apart from these challenges, using a minimum number of electrodes based on Region of Interest (ROI) would provide less data, resulting in faster analysis. Also, incorporating prior knowledge and selecting channels that promote higher classification accuracy will provide less error rate for the test data set. Electrodes can be selected according to ease of use since the signal quality remains the same regardless of the amplification system type (active or passive)[19]. Evaluating the pre-processing and classification algorithms using evaluating metrics would also contribute towards getting a better smartphone-based EEG app. Additionally, further research in the areas of LSL (Lab Streaming Layer) and its integration to smartphone apps with user-friendly graphical interfaces are areas for future work.

IV. Conclusion

EEG in a natural environment is currently an active area of research. Incorporating a mobile EEG recording system, a pre-processing algorithm, and a classifier will give us a better smartphone-based EEG system. Artefact reduction algorithms such as ASR or rASR seem to perform reasonably well. Their integration with an efficient classifier on a smartphone app is perhaps the next step forward. In this regard, CNN and MobileBERT on smartphones for natural language processing applications seem motivating. It is necessary to study them and work towards implementation on an app. Given the limited processing capacity of smartphones, it is necessary for future studies to propose efficient ways for a commercially viable portable EEG system. We believe these are some immediate perspectives for a smartphone-based EEG system for natural environment applications.

Author Contributions

CNG and SC proposed the idea. First draft of the entire paper was written by DH. CNG and DH then discussed and refined the paper to arrive at final submitted version.

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