Speech Imagery BCI Training Using Game with a Purpose

Abdulrahman Mohamed Selim
Maurice Rekrut
abdulrahman.mohamed@dfki.de
Maurice.Rekrut@dfki.de
German Research Center for Artificial Intelligence (DFKI)
Saarbrücken, Germany

Michael Barz
Daniel Sonntag
michael.barz@dfki.de
daniel.sonntag@dfki.de
German Research Center for Artificial Intelligence (DFKI)
Saarbrücken, Germany
University of Oldenburg
Oldenburg, Germany

ABSTRACT

Games are used in multiple fields of brain–computer interface (BCI) research and applications to improve participants' engagement and enjoyment during electroencephalogram (EEG) data collection. However, despite potential benefits, no current studies have reported on implemented games for Speech Imagery BCI. Imagined speech is speech produced without audible sounds or active movement of the articulatory muscles. Collecting imagined speech EEG data is a time-consuming, mentally exhausting, and cumbersome process, which requires participants to read words off a computer screen and produce them as imagined speech. To improve this process for study participants, we implemented a maze-like game where a participant navigated a virtual robot capable of performing five actions that represented our words of interest while we recorded their EEG data. The study setup was evaluated with 15 participants. Based on their feedback, the game improved their engagement and enjoyment while resulting in a 69.10% average classification accuracy using a random forest classifier.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; *Interaction devices.*

KEYWORDS

BCI, EEG, Imagined speech, Game with a purpose (GWAP), User study

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1 INTRODUCTION

A Brain-Computer Interface (BCI) attempts to decode a person's brain activity in order to understand their intentions and to interact with external devices [7]. One active area in the BCI domain is Speech Imagery BCI; speech imagery is the ability to produce speech internally in the absence of any muscle movements and audible sounds [13]. Speech Imagery BCI is an active area of research and is regarded as a possible solution for multiple use cases across various domains where normal (overt) speech is not suitable; for example, in the industrial domain, where workers might not be able to communicate efficiently using overt speech due to loud or noisy environments, and in the medical domain to restore the communication pathways of patients with certain maladies which affect their ability to produce overt speech, like Amyotrophic lateral sclerosis (ALS) or certain forms of paralysis. One method of monitoring a person's brain activity for BCIs is using electroencephalography (EEG) devices, which record the electrical activity of a person's brain using electrodes placed on the scalp [15]. EEG devices are non-invasive and relatively cheap in comparison to other brain imaging modalities [1]. In addition, the number of portable and simple-to-use EEG equipment offered to the research community has increased in recent years [1]. These factors contributed to a rise in EEG-based BCI research.

Imagined speech EEG data collection studies are troublesome in multiple ways. They are quite time-consuming; the time it takes to set up the EEG headset with the participant depends on the number of electrodes and the type of headset, but it usually exceeds 30 minutes [9]. Data processing is often conducted in a within-participant manner, which necessitates collecting a large amount of data from each participant [10, 14, 16, 20, 22]. This leads to a data collection study being sometimes split over the course of multiple sessions [14, 16, 22], resulting in the overall study lasting multiple hours; for example, the study in Mohanchandra and Saha [14] lasted almost two hours for just the data collection. During those long data collection studies, participants were almost always told the same set of rules: to sit still by not moving any muscles, to minimise blinking, not to produce any audible sounds, and to fully concentrate on the word of interest [10, 14, 20, 24]. Most often, the target words are presented to the participants in written form on a computer screen for them to read and repeat silently when a cue is shown. One variation which can be found in the literature is to ask participants questions regarding the word of interest instead of showing them the words to read [16, 20, 22].

However, the tiring and demanding nature of EEG data collection studies is common among other BCI applications. Lotte et al. [12] argued that the solution to this can be seen as either improving the processing elements, e.g. García-Salinas et al. [6] tried to use fewer data from the participants to shorten the data collection duration, or improving the human aspect of the procedure to make it less cumbersome and more enjoyable from the participants' perspective. de Castro-Cros et al. [5], Rexwinkle et al. [21], Škola et al. [26] all agreed that games help increase participants' engagement and enjoyment while mediating the repetitive nature of conventional BCI studies, which in turn improved the participants' overall user experience. This falls under the concept of a game with a purpose (GWAP) where participants play a game while important data about a specific problem is collected from them in the background [21, 23].

However, the majority of BCI literature reported on GWAPs implemented for Motor Imagery (MI) BCI studies [5, 21, 26], and there are no current publications that reported on implemented GWAPs for Speech Imagery BCI studies, despite their possible benefits. In this work, we show that GWAPs can have a promising effect on Speech Imagery BCI studies. We created a computer-based maze-like game in which the participants interacted with an industrial robot to produce words of interest in the form of command words to control the robot in a teleoperation scenario. The setup was tested in an actual EEG data collection study with 15 participants. Their qualitative feedback, in the form of unstructured interviews, showed us that we were on the right track to improve the enjoyment and engagement factors of the study. In addition, we were able to produce accuracies significantly above chance level for imagined speech classification, which meant that the game did not negatively affect the EEG data quality[1].

2 METHODS

Our objective was to create a game where the words of interest for the training of the Speech Imagery BCI were presented as in-game actions for a robot. We wanted to build the game based on a possible real-world Speech Imagery BCI use case. We decided on a teleoperation industrial setting where the participant would control a robot to move it between two factories. A participant would be able to play, and when they figured out which action to perform, they would indicate that they were ready to repeat the word of interest on cue. Simultaneously, we would be recording their EEG data. However, caution is needed in designing GWAPs for BCI studies because some mental states, e.g. stress and fatigue, have a noticeable effect on EEG signals [5, 21]. Lotte et al. [12] discussed other specific key points for designing games to improve BCI data collection studies. The game should be relevant to the study. It should show participants feedback regarding their actions during the study, as this could help motivate them for longer periods of time. It should provide pre-training to show the participants what to expect during the actual study and to make them more comfortable with the actions they would perform afterwards. Lastly, self-paced studies, i.e. allowing the participants to proceed at their own pace, improved their overall experience. All the upcoming requirements and elements were chosen to cater to the regulations and requirements of EEG studies while implementing our idea.

[1]Our other publication [19], focused on the EEG processing side of this study

2.1 Word Selection

This research was conducted at the German Research Centre for Artificial Intelligence (DFKI) at Saarland University in Germany, which has a large number of English-speaking staff and students; therefore, English was chosen as the main language for the study. We had certain requirements for the words of interest: the words had to be either known and easy to pronounce or easily understandable by non-native English speakers who had adequate language proficiency; the words had to be suitable for robot commands; and they needed to be from at least two different word categories to enable suitable game dynamics. A suitable choice that fit all these requirements was to use directions *Up*, *Left*, and *Right*, and actions *Pick*, and *Push*. The words had to be presented shuffled *Up, Left, Pick* to avoid block-wise presentation *Up, Up, Up*, which can cause label leakage due to classifying arbitrary brain states, e.g. fatigue, rather than valuable information from cognitive processing [11].

2.2 Game Implementation

The game needed to be fairly straightforward to avoid causing any stress or confusion. Each command must be very clear to the participant. Otherwise, the EEG signals of interest might get contaminated by brain activity related to confusion. The game needed many distinct levels because each participant had to provide multiple samples of each word. We wanted to show a variety of word combinations across multiple levels to avoid repetition while ensuring that each word was evenly represented at each level. We used GDevelop[2] for developing our game. It is an open-source game development software built on the concept of event-based programming. We built a 2D maze-like game in which a participant controlled a robot to navigate from one factory to another while pushing away boxes and picking up gears.

Figure 1 shows an overview of what a level looked like from a zoomed-out view. We zoomed the camera on the robot while the participant was playing to allow the participant to focus on the upcoming step and not further on. We added black borders around each step to make it easy for a participant to recognise which word to produce by always moving from one square to another. In the left panel in Figure 2, we show what the actual view looked like to the player in the end. We chose this robot asset because it had an industrial look, which fit our scenario, and it was front-facing, which made it easier for participants to remember the directions. We chose the box asset for *Push* and the gear asset for *Pick* because they fit the aesthetics of the game and, more importantly, because they were distinct from one another to prevent any confusion. All three assets had movement animations implemented to make the game visually pleasing; the robot had an idle state movement of moving its arms and wheels, and both the box and gear assets had a rotational movement around their axes.

To allow the participants to navigate the game at their own pace, we used the spacebar as the game controller. Pressing it caused a black screen to appear for two seconds, during which the participant focused on which command they had to say, and when a white cross appeared in the middle of the screen for two additional seconds, as a cue, the participant would produce the imagined speech. Figure 2 shows an example of a sequence where a participant would say

[2]https://gdevelop-app.com/

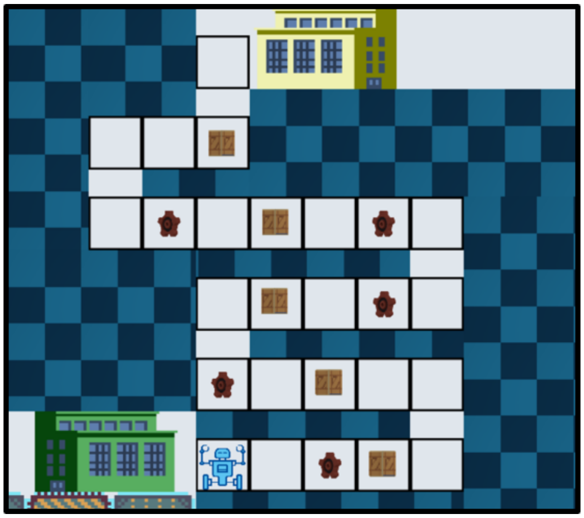

Figure 1: Level Overview

Right during the last two seconds. The choice of using the spacebar to control the game came to mind because a lot of games utilise the spacebar in their controls, and it might feel normal to the participants; for example, Google's Dino Game [3], and Nintendo's Super Mario[4]. Each word interaction lasted approximately six seconds, where roughly two seconds were spent figuring out which word to say, two seconds for preparation after the space press, and two seconds to produce imagined speech. We chose 25 words per level, so each level would take roughly two and a half minutes to complete. After four levels, the participant would have been collecting data for 10 minutes. Afterwards, they would take a small break, adhering to the general recommendations for conducting BCI studies [25]. To fit the game perspective, we added an end-of-level screen to inform the participants that they had successfully finished the level by reaching the factory.

An important point to highlight is that the robot always performed the correct command, meaning it was not controlled using the EEG signals. The game was a medium to present the words more interactively than just reading them off the screen. The participants were informed of this beforehand because the study was not based on their thinking otherwise. In the end, the game consisted of each participant performing 400 imagined speech repetitions, where each of the five words *Up*, *Left*, *Right*, *Pick*, and *Push* was repeated 80 times. An additional tutorial level was created so the participants would become accustomed to the command words and the game mechanics.

2.3 EEG Processing

We processed each user's imagined speech EEG data using a Random Forest classifier with four-fold cross-validation and Common Spatial Patterns [8] as features. We used accuracy as our main evaluation metric. In our previous publication [19], we discuss in depth our EEG data processing methods.

[3]https://dino-chrome.com/en
[4]https://en.wikipedia.org/wiki/Super_Mario

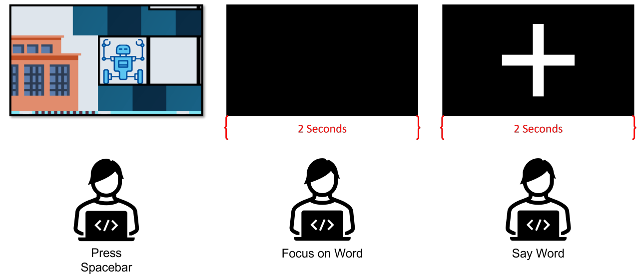

Figure 2: Game control sequence for the word *Right*.

3 EXPERIMENT

We received the approval of the Ethical Review Board of the Faculty of Mathematics and Computer Science at Saarland University[5] to conduct the study. At the beginning of each study, the participant was greeted, and the study purpose and procedure were explained in detail to them. After signing a consent form allowing us to collect and use their EEG signals, we fixed a 64-channel LiveAmp EEG headset[6] on the participant's head. Afterwards, the participant played the tutorial level until they felt accustomed and comfortable with the words and the game mechanics. After finishing the study, an informal spoken interview was conducted with each participant to evaluate how they perceived the study and the game. We specifically asked them what they liked and disliked about the game and if they had any feedback regarding how to improve the game setup. We structured the data collection pipeline in a client-server architecture to allow real-time data processing. The setup was running on two separate PCs, and the server was able to classify the data in real-time. However, the classification accuracies in the results were calculated offline after the study[7].

4 RESULTS

4.1 Resulting Dataset

The dataset included four female and eleven male participants who were all right-handed. The participants' ages ranged from 20 years old to 35 years old, with an average age of 26.8. The participants were non-native English speakers of four different nationalities, but they all had adequate English knowledge due to their studies and professions. All of the participants provided written consent to collect and use their EEG data for scientific purposes.

4.2 Study Feedback

After each data collection session, we conducted an informal spoken interview with each participant to obtain feedback on the study. Five participants had previously participated in other imagined speech EEG data collection studies, and all five stated that the game provided a more interactive and interesting study environment. It did get boring after a while due to the game's simplicity, but they said it made them concentrate more frequently over the course of the study than in the other studies. The remaining participants

[5]https://erb.cs.uni-saarland.de/
[6]From Brain Products GmbH: https://www.brainproducts.com/
[7]Our codebase and game are available on GitHub https://github.com/AMSelim/Master_Thesis

stated that the game became slightly boring in the long run because it was a bit predictable. However, when we described how standard imagined speech studies were typically conducted, as reported in the literature, they felt that the game was heading in the right direction in terms of making the study engaging.

One participant noted that the robot's forward movement was an oversimplification that they might wish to change from a purely game perspective. Another participant said they liked how the robot looked because it helped them remember the phrases, especially *Up* because they were scared they might say *Forwards* instead, but the game perspective with the top view of the robot, helped them avoid making any mistakes. Another participant enjoyed the animation of the assets because it drew their attention to the game and study rather than allowing their thoughts to wander. All 15 participants agreed that producing imagined speech required intense concentration to focus on producing it correctly while minimising their thoughts. The notion that the robot always performed the correct command made them feel more relaxed because they were afraid of making mistakes which might have derailed the study.

4.3 Classification Results

Speech Imagery BCI studies usually compare their accuracies against the chance level. However, the standard method for calculating the chance level, i.e., dividing 100% by the total number of classes, was criticised because it could only be achieved if we had an infinite number of samples [4]. Based on the work of Combrisson and Jerbi [4], we computed an adjusted chance level of 28% instead of 20% as the significance threshold for our evaluation. We were able to achieve a maximum accuracy of 96%, a minimum accuracy of 50.25%, and an average accuracy of 69.10%, which was computed by summing the participants' accuracies and dividing by the total number of participants. The prediction was correct, i.e. true positive, when the classifier's prediction equalled the true label and was wrong when it equalled any of the other four labels.

5 DISCUSSION

According to the participants' feedback, using the game in the data collection study proved to be promising for increasing their engagement. In addition, it improved their overall experience because the study lasted for an average of 90 minutes[8], which was quite long, but the game made it tolerable. However, the game was too simple; we made it simple on purpose to eliminate any external influence that might have affected the EEG signals of interest, but we might have caused an oversimplification. The fact that we could not find any prior work for GWAPs used in Speech Imagery BCI studies meant that we did not have any work to base our design on, and we had to be extra cautious not to make the game difficult as it might have produced other EEG signals that would have contaminated our signals of interest.

Making the game move at each participant's pace turned out to be important. It made the participants feel more at ease and allowed us to account for each participant's individual needs because some participants got tired more often than others, requiring more frequent and longer breaks. Being straightforward about the game mechanics proved to be very beneficial. All participants expressed concern that making any mistakes would derail the entire study, and they were anxious about it. Therefore, when we assured them that the robot would always perform the correct action, they became more relaxed, which is required in BCI studies.

The game itself did not negatively affect the classification results. Our 69.10% average accuracy is above the 28% adjusted chance level. This result is comparable to those of other studies. Qureshi et al. [18] achieved a 40.3% maximum classification accuracy and a 32.9% average accuracy for five words and eight participants, while Pawar and Dhage [17] achieved a 63.67% average accuracy also for five words and eight participants. Our previous publication [19] discussed the full EEG processing and results in detail.

However, further testing is needed to determine whether GWAPs can potentially improve EEG data quality. We would have been able to better evaluate the effects of the game on the system if we had a control group which did not use the game. Further studies are needed for an in-depth evaluation of the effects of GWAPs on Speech Imagery BCI. We believe our approach was a step in the right direction because, despite the oversimplification, the participants commented on being more attentive and focused in the long run. Future studies should focus on finding the line where the game is considered relevant, interesting, and simple, yet not boring. In addition, using modalities such as eye tracking could help correctly evaluate a participant's visual attention and focus during a study [2, 3] and determine which game elements might be distracting.

6 CONCLUSION

In this paper, we described our GWAP-based Speech Imagery BCI EEG data collection method. We tested our game in a study where 15 participants wore a 64-channel EEG headset and produced imagined speech while playing our teleoperation maze-like game to control an industrial robot using five commands *Up*, *Left*, *Right*, *Pick*, and *Push*. The game was a medium to present the words of interest but was not EEG-controlled. We evaluated our newly developed approach using an informal interview. The game proved to be useful by increasing participants' enjoyment and engagement. However, the game design and mechanics might have been oversimplified. The game did not negatively affect the imagined speech classification as we were able to achieve an average accuracy of 69.10%, which is comparable to other imagined speech EEG studies. Based on the participants' feedback, we discussed the different game aspects and how each affected the study. Implementing GWAPs for Speech Imagery BCI studies requires more research to determine whether games could actually improve the EEG signal quality and to further study when a game is considered simple yet still engaging enough without contaminating the EEG signal. With this work, we provided useful insights and a first step into this promising field of GWAP-based Speech Imagery BCI training.

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[8]The imagined speech EEG data was only one-half of the EEG data recorded, with the other half being for overt speech EEG data, which is why the full study lasted 90 minutes

REFERENCES

[1] Teresa Bailey. 2014. Diagnosing and Treating Developmental Disorders with qEEG and Neurotherapy. In *Clinical Neurotherapy*. Elsevier, 321–355. https://doi.org/10.1016/B978-0-12-396988-0.00013-1

[2] Michael Barz, Sebastian Kapp, Jochen Kuhn, and Daniel Sonntag. 2021. Automatic Recognition and Augmentation of Attended Objects in Real-Time Using Eye Tracking and a Head-Mounted Display. In *ACM Symposium on Eye Tracking Research and Applications (ETRA '21 Adjunct)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3450341.3458766 event-place: Virtual Event, Germany.

[3] Michael Barz and Daniel Sonntag. 2021. Automatic Visual Attention Detection for Mobile Eye Tracking Using Pre-Trained Computer Vision Models and Human Gaze. *Sensors* 21, 12 (June 2021), 4143. https://doi.org/10.3390/s21124143

[4] Etienne Combrisson and Karim Jerbi. 2015. Exceeding chance level by chance: The caveat of theoretical chance levels in brain signal classification and statistical assessment of decoding accuracy. *Journal of Neuroscience Methods* 250 (July 2015), 126–136. https://doi.org/10.1016/j.jneumeth.2015.01.010

[5] Martí de Castro-Cros, Marc Sebastian-Romagosa, Javier Rodríguez-Serrano, Eloy Opisso, Manuel Ochoa, Rupert Ortner, Christoph Guger, and Dani Tost. 2020. Effects of Gamification in BCI Functional Rehabilitation. *Frontiers in Neuroscience* 14 (Aug. 2020), 882. https://doi.org/10.3389/fnins.2020.00882

[6] Jesús S. García-Salinas, Luis Villaseñor-Pineda, Carlos A. Reyes-García, and Alejandro A. Torres-García. 2019. Transfer learning in imagined speech EEG-based BCIs. *Biomedical Signal Processing and Control* 50 (April 2019), 151–157. https://doi.org/10.1016/j.bspc.2019.01.006

[7] Bin He. 2018. Introduction. In *Neuromodulation*. Elsevier, 339. https://doi.org/10.1016/B978-0-12-805353-9.02005-2

[8] Z.J. Koles. 1991. The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG. *Electroencephalography and Clinical Neurophysiology* 79, 6 (Dec. 1991), 440–447. https://doi.org/10.1016/0013-4694(91)90163-X

[9] Patrick Ledwidge, Jeremy Foust, and Adam Ramsey. 2018. Recommendations for Developing an EEG Laboratory at a Primarily Undergraduate Institution. *Journal of undergraduate neuroscience education: JUNE: a publication of FUN, Faculty for Undergraduate Neuroscience* 17, 1 (2018), A10–A19.

[10] Seo-Hyun Lee, Minji Lee, and Seong-Whan Lee. 2020. EEG Representations of Spatial and Temporal Features in Imagined Speech and Overt Speech. In *Pattern Recognition*, Shivakumara Palaiahnakote, Gabriella Sanniti di Baja, Liang Wang, and Wei Qi Yan (Eds.). Vol. 12047. Springer International Publishing, Cham, 387–400. https://doi.org/10.1007/978-3-030-41299-9_30 Series Title: Lecture Notes in Computer Science.

[11] Ren Li, Jared S. Johansen, Hamad Ahmed, Thomas V. Ilyevsky, Ronnie B Wilbur, Hari M Bharadwaj, and Jeffrey Mark Siskind. 2018. Training on the test set? An analysis of Spampinato et al. [31]. (2018). https://doi.org/10.48550/ARXIV.1812.07697 Publisher: arXiv Version Number: 1.

[12] Fabien Lotte, Florian Larrue, and Christian Mühl. 2013. Flaws in current human training protocols for spontaneous Brain-Computer Interfaces: lessons learned from instructional design. *Frontiers in Human Neuroscience* 7 (2013). https://doi.org/10.3389/fnhum.2013.00568

[13] Stéphanie Martin, Peter Brunner, Chris Holdgraf, Hans-Jochen Heinze, Nathan E. Crone, Jochem Rieger, Gerwin Schalk, Robert T. Knight, and Brian N. Pasley. 2014. Decoding spectrotemporal features of overt and covert speech from the human cortex. *Frontiers in Neuroengineering* 7 (2014). https://www.frontiersin.org/articles/10.3389/fneng.2014.00014

[14] Kusuma Mohanchandra and Snehanshu Saha. 2016. A Communication Paradigm Using Subvocalized Speech: Translating Brain Signals into Speech. *Augmented Human Research* 1, 1 (Dec. 2016), 3. https://doi.org/10.1007/s41133-016-0001-z

[15] M.R. Nuwer and P. Coutin-Churchman. 2014. Brain Mapping and Quantitative Electroencephalogram. In *Encyclopedia of the Neurological Sciences*. Elsevier, 499–504. https://doi.org/10.1016/B978-0-12-385157-4.00519-4

[16] Dipti Pawar and Sudhir Dhage. 2020. Multiclass covert speech classification using extreme learning machine. *Biomedical Engineering Letters* 10, 2 (May 2020), 217–226. https://doi.org/10.1007/s13534-020-00152-x

[17] Dipti Pawar and Sudhir Dhage. 2023. EEG-based covert speech decoding using random rotation extreme learning machine ensemble for intuitive BCI communication. *Biomedical Signal Processing and Control* 80 (Feb. 2023), 104379. https://doi.org/10.1016/j.bspc.2022.104379

[18] Muhammad Naveed Iqbal Qureshi, Beomjun Min, Hyeong-jun Park, Dongrae Cho, Woosu Choi, and Boreom Lee. 2018. Multiclass Classification of Word Imagination Speech With Hybrid Connectivity Features. *IEEE Transactions on Biomedical Engineering* 65, 10 (Oct. 2018), 2168–2177. https://doi.org/10.1109/TBME.2017.2786251 Conference Name: IEEE Transactions on Biomedical Engineering.

[19] Maurice Rekrut, Abdulrahman Mohamed Selim, and Antonio Krüger. 2022. Improving Silent Speech BCI Training Procedures Through Transfer from Overt to Silent Speech. In *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. 2650–2656. https://doi.org/10.1109/SMC53654.2022.9945447 ISSN: 2577-1655.

[20] Maurice Rekrut, Mansi Sharma, Matthias Schmitt, Jan Alexandersson, and Antonio Kruger. 2021. Decoding Semantic Categories from EEG Activity in Silent Speech Imagination Tasks. In *2021 9th International Winter Conference on Brain-Computer Interface (BCI)*. IEEE, Gangwon, Korea (South), 1–7. https://doi.org/10.1109/BCI51272.2021.9385357

[21] Joe T. Rexwinkle, Gregory Lieberman, Matthew Jaswa, and Brent J. Lance. 2019. Development of a Game with a Purpose for Acquisition of Brain-Computer Interface Data. (2019). https://doi.org/10.48550/ARXIV.1910.00106 Publisher: arXiv Version Number: 1.

[22] Alborz Rezazadeh Sereshkeh, Robert Trott, Aurélien Bricout, and Tom Chau. 2017. Online EEG Classification of Covert Speech for Brain–Computer Interfacing. *International Journal of Neural Systems* 27, 08 (Dec. 2017), 1750033. https://doi.org/10.1142/S0129065717500332

[23] L. von Ahn. 2006. Games with a purpose. *Computer* 39, 6 (June 2006), 92–94. https://doi.org/10.1109/MC.2006.196 Conference Name: Computer.

[24] Hiroki Watanabe, Hiroki Tanaka, Sakriani Sakti, and Satoshi Nakamura. 2020. Synchronization between overt speech envelope and EEG oscillations during imagined speech. *Neuroscience Research* 153 (April 2020), 48–55. https://doi.org/10.1016/j.neures.2019.04.004

[25] Xiaolei Xia and Li Hu. 2019. EEG: Neural Basis and Measurement. In *EEG Signal Processing and Feature Extraction*, Li Hu and Zhiguo Zhang (Eds.). Springer Singapore, Singapore, 7–21. https://doi.org/10.1007/978-981-13-9113-2_2

[26] Filip Škola, Simona Tinková, and Fotis Liarokapis. 2019. Progressive Training for Motor Imagery Brain-Computer Interfaces Using Gamification and Virtual Reality Embodiment. *Frontiers in Human Neuroscience* 13 (Sept. 2019), 329. https://doi.org/10.3389/fnhum.2019.00329