Brain-Computer Interface Technology for Speech Recognition: A Review

Mashael M. AlSaleh* Mahnaz Arvaneh* Heidi Christensen* and Roger K. Moore*
* University of Sheffield, Sheffield, United Kingdom
E-mail: mmalsaleh1,m.arvaneh,heidi.christensen,r.k.moore@sheffield.ac.uk

***Abstract*—This paper presents an overview of the studies that have been conducted with the purpose of understanding the use of brain signals as input to a speech recogniser. The studies have been categorised based on the type of the technology used with a summary of the methodologies used and achieved results. In addition, the paper gives an insight into some studies that examined the effect of the chosen stimuli on brain activities as an important factor in the recognition process. The remaining part of this paper lists the limitations of the available studies and the challenges for future work in this area.**

I. Introduction

Brain Computer Interface (BCI) is one of the promising technologies that has been examined as an alternative communication technology [1], [2], [3]. Neuromuscular impairments prevent users from using most of the available communication aids, since they require some degree of muscle movement. This makes them unsuitable for people with severe disabilities who have limited movement in their muscles, such as people with locked-in syndrome [4], [5]. In more general circumstances it would be desirable to communicate only using brain activities, e.g., due to security issues.

In the literature, brain activity has been used for communication in two different ways: controlling spellers [6], [7] and capturing speech information [8], [3]. This review paper focuses on BCI studies related to speech. These studies mainly focus on the following objectives: a) understanding the mechanism of spoken (i.e. overt) and unspoken (i.e. covert) speech production in the brain, b) recognising speech from covert speech using brain signals.

Both invasive and non-invasive BCI have been used for speech studies. For invasive BCI, Electrocorticography (ECoG) has been used in several studies in order to have better insights into the brain areas related to speech [9], [10], [11]. ECoG can retrieve accurate information in terms of time and spatial resolution, which is promising for the direct translation of brain activities into text or speech without the need for averaging brain signals. For non-invasive BCI, the Electroencephalogram (EEG) was utilized in preliminary studies to recognise a limited number of words, syllables, or vowels [12], [13], [14]. Moreover, functional Magnetic Resonance (fMRI) was used to determine changes in the activation of brain areas during speech tasks [15], [16]. During the speech imagination task, the subjects are asked to imagine the pronunciation of speech stimuli. In some studies, subjects are asked to imagine the movement of articulators as in [13] while in other studies the subjects are asked not to imagine any movement as in [17].

This paper sheds light on studies that used BCI technologies for speech recognition and understanding. The methodology followed to conduct these studies are explained, and the achieved results in this area are reported. The studies are categorised based on the sensors used to measure brain activities as well as different types of performed imagined speech. The limitations of the current studies are discussed in detail. Furthermore, we discuss the possible effects of a word's meaning on brain signals and whether it can help achieve better speech detection.

II. Studying Speech using Electrocorticography(ECoG)

ECoG electrodes are directly placed on the brain surface. The use of ECoG began in the 1950s when it was used to localise epileptic seizures accurately before surgery [9]. The resulting signals are high quality in terms of their spatial and temporal details. In [9], the researchers tried to address whether or not it is possible to determine the vowels and consonants of spoken and imagined words following visual and audio stimuli using ECoG signals. In order to answer this question, four experimental conditions (visual stimuli/actual spoken, audio/actual, visual/imagined, and audio/imagined) were examined, with four possible vowels sounds (/ë/, /æ/, /i:/, or /u:/) and consonant pairs (/b,t/, /c,n/, /h,d/, /l,d/, /m,n/, /p_p/, /r,d/, /s,t/, or /t,n/) in thirty-six words. The findings showed that the brain areas activated during actual speech are the primary motor cortex, Broca's area, and posterior superior temporal gyrus. In contrast, in the imagined speech, two small foci in the temporal and frontal regions were activated. The results were promising, with classification accuracy in some cases of 55% between the four above mentioned classes.

A recent study conducted by [10] explored the brain regions that are involved in all the phases of speech production: preparation, execution and monitoring by using ECoG BCI technology. They described the uniqueness of this study as it examined the neural representations of speech features in cases of continuous speech, rather than taking each sound separately. In the experiment, subjects were asked to speak loudly while their speech was recorded using a microphone. The texts were between 109 and 411 words long taken from political speeches or nursery rhymes. In the analysis part, the comparison between vowels and consonants was used as the main phonological discrimination dimension. Other dimensions included place (labial, coronal and dorsal) and manner of articulation (obstruent and sonorant), and voicing status (voiced and voiceless). Based on the results obtained, the authors identified the brain network areas that were involved in the speech production process.

Unlike many EEG-based brain-to-text systems that require averaging brain signals from multiple trials in order to have an accurate silent speech translation, the ECoG-based systems work using single-trial classification. The high signal to noise ratio of ECoG signals helps better understand the mechanism of the speech production in brain. It is noted that most of the participants in ECoG studies were patients with seizure who used ECoG electrodes mainly for localising their epileptic seizures. Typically, the use of ECoG for unspoken speech recognition is limited due to its invasiveness.

III. Studying Speech using Functional Magnetic Resonance Imaging (fMRI)

fRMI was discovered by [15]. It measures the changes in the local blood oxygenation level during neural activation. fMRI has been used in communication and speech studies. In [16], researchers investigated whether fMRI can be used to decode binary answers (”Yes”/”No”). An experiment was conducted on 15 participants with no neurological disorders. They were asked, ”Do you have sisters or brothers?”, and 90 percent of the answers were decoded correctly within three minutes of scanning. This demonstrated that fMRI is an accurate and reasonably timely communication tool.

A recent study has been conducted by [18] to create a map of words in the brain based on their semantics. Seven English native subjects have been asked to listen to hours of narrative stories consisting of 10,470 words while fMRI scanning took place. The words have been clustered into twelve groups using K-means clustering where each category was inspected and labelled manually. The results showed consistency in the organization of words among users.

In general, due to bulkiness, immobility and the slow time response, the use of fMRI as a communication system may not be feasible in the daily life. However, its good spatial resolution helps understand the brain activities associated with covert and overt speech production.

IV. Studying Speech using Electroencephalogram (EEG)

Several studies used EEG to explore the possibility of reading what people are thinking about. Experiments with speech imagination can be divided into three types based on the imagined part (i.e. word imagination, syllable imagination, and vowel imagination.)

In their use of imagined speech as a user authentication technique, [19] has argued that speech imagery is more convenient and intuitive for users than motor imagery or any other types of mental activity. However, more research and practice on speech imagery are required to establish the most appropriate methods of use to generate discriminative EEG signals without any overt actions.

Due to portability and inexpensiveness, EEG has the highest potential among other modalities in order to be used as a communication system for daily life. In particular, advances in sensor technology are likely to lead to wireless, dry and less expensive EEG sensors. However, the low signal-to-noise ratio and the inherent non-stationarity in EEG signals make speech recognition a challenge. Thus, advances are needed in signal processing algorithms to have more robust and accurate communication systems working based on EEG.

Table I summarises the important studies that used EEG for speech recognition. These studies are further discussed in the following subsection.

A. Word imagination

In [20], researchers have built a speaker-dependent silent speech recognition system using both EMG to help in determining the onset of these signals and EEG to identify the intended speech. The system was built in two phases: the learning phase and the decoding phase. The two phases have been applied in two experiments, where subjects spoke loudly in the first phase and silently in the second phase. The first experiment was to record janken (that is, the Japanese equivalent of the “Rock, Paper,Scissors” game), and the second was to record the four different words for seasons in Japanese. In the learning phase, the brain areas related to speech were identified by applying Independent Component Analysis (ICA) to map them to the related equivalent current dipole source localisation (ECDL). The researchers compared the results of ICA with previous studies exploring neuroimaging during speech production. In addition, this mapping was compared with the Directions into Velocities of Articulators model (DIVA). DIVA indicated that the intended speech sounds are shown by neurons in the left ventral premotor cortex as formant frequency trajectories that will be sent to the primary motor cortex, where they are then transformed into motor commands to speech articulators. The last stage in this learning phase was to create a relationship between ICAs and speech spectrograms using a Kalman filter. In the decoding phase, a Kalman filter was used to estimate the silent speech spectrograms based on the learning phase results. The first experiment showed that speech recognition was based on vowels transitions, which are not applicable in some Japanese words. This resulted in the use of HMM and Gaussian mixture densities to decipher the differences between vowels and consonants in the learning phase of the second experiment. Then in the decoding phase HMM takes the spectrogram estimated by Kalman filter to distinguish between consonant and vowel transitions in the second experiment.

In [17], the author and her colleagues attempted to prove that imagination of speech can be recognised effectively if the spoken words are in blocks (i.e. a sequence of words). This work showed that there is a relationship between word order and the recognition rate. More specifically, recording unspoken

TABLE I
BCI RESEARCH STUDIES THAT USED EEG FOR SPEECH RECOGNITION

Article	Task Specification	Types of signals	Brain area targeted	Recognition technique	Performance
[20]	To discriminate between: 1) rock, paper or scissors, 2) spring, summer, autumn, winter	EMG to determine the onset of speech production and EEG to identify the intended speech .	Premotor cortex, supplementary motor area and/or Brocas area.	Hidden Markov Model and Gaussian Mixture Model	29%-100% different between words.
[13]	To discriminate between: open(/a/,/o/), mid (/e/), closed (/i/, /u/) vowels	EEG	Left hemisphere over Wernicke and Broca	Support Vector Machine	84%- 94%
[17]	To discriminate between: alpha, bravo, charlie, delta, echo	EEG & EOG (i.e. for word separation)	The area around oral and facial motor cortex	Linear Discriminant Analysis	45.50%
[19]	To discriminate between: syllables /ba/ & /ku/ in different rhythms	EEG	Not mentioned	Linear Support Vector Machine compared with k-Neighbours classifier.	61%
[21]	To discriminate between: syllables /ba/ and /ku/ and three rhythms	EEG	all areas (128 channels)	Matched filter classification	Not mentioned
[22]	To discriminate between: two vowels /a/, /u/ and a no imagery state as control	EEG and fMRI	Bradman areas 1, 2, 3, 4, 6, 9, 22, 39, 40, 41, 42, 44 and 45	Sparse Logistic Regression method with Variational Approximation (SLR-VAR)	61.2%
[23]	To discriminate between: /a/, /i/, /u/, /e/, & /o/	EEG	The whole brain	Relevance Vector Machine and Support Vector Machine	SVM :77% RVM: 79%
[24]	To discriminate between: 5 Spanish words to be used in controlling computer	EEG and mouse marker to show the start and end of word imagination.	F7, FC5, T7 and P7 (i.e. the nearest to Geschwind -Wernickes mode areas	Naive Bayesian, Random Forests(RF), Support Vector Machine , and Bagging-RF.	Above chance level
[14]	Different vocabularies groups, different modalities: i.e. whispering, silent speech, silent mumbling and unspoken speech	EEG	Primary motor cortex together, the Brocas and Wernickes area	Linear Discriminant Analysis	4 to 5 times higher than chance with up to 10 words

speech could in blocks allow the users to concentrate more (as they reported this) and give signals with less noise and consequently better recognition rate.

In [24], the researchers aimed to create an application that allows users to control a computer screen cursor through unspoken speech. The system was designed to recognise five Spanish words to control the cursor. They examined five different types of classifiers in order to get highly accurate results in comparison with other works in the literature, and they found the results consistent with similar works in terms of classification accuracy.

B. *Syllable imagination*

In [12], the main aim of this work was to use imagined speech for subject identification to be used in authentication. In addition to testing their signal analysis method on EGG signals related to the imagined speech, the researchers examined a database of EEG signals related to Visual Evoked Potential for use in subject identification. During the imagined speech part, the subjects were asked to imagine the speech of two syllables /ba/ and /ku/ at different rhythms. Moreover, the researchers claimed that the use of syllables in imagination instead of full words avoids the effect of semantic on brain signals. Their signal processing method showed a high level of subject identification accuracy. However, they noted that this accuracy decreased when further sessions were recorded that might be due to participants fatigue.

In [21], the researchers investigated whether the linguistic content could be distinguished from brainwaves by finding the brain signature for different linguistic content. The signatures are shown as the difference between alpha, beta, and theta brain rhythms. During the experiment, the subjects were asked to imagine the speech of two syllables /bu/ and /ka/ in three different rhythms without any effort or muscle movement. However, the researchers did not mention any classification accuracy or model training.

A recent study has been conducted by [25] combining EEG signals with audio and facial features in order to use them in the classification for phonological categories during the imagination and pronunciation of phonemic and single words. This multi-modal study provided an accuracy over 90%.

C. *Vowel imagination*

The study presented in [23] focused on vowels /a/, /i/, /u/, /e/ and /o/ because it was targeting the Japanese language where the structure of the syllables consists of one vowel and one consonant. They examined the differences between two classification algorithms, namely the Relevance Vector Machine with the Gaussian Kernel (RVM-G), and compared the results with those generated by Support Vector Machine with Gaussian Kernel (SVM-G) from [26]. The purpose was to reduce the calculation cost while using 19 channels, Common

Spatial Patterns (CSPs) filtering, and Adaptive Collection (AC). However, the findings showed that there are no differences between RVM and SVM in terms of classification accuracy (i.e. 77% to 79%). Moreover, the calculation cost of RVM is higher and it requires more training data to provide strong results.

In [13], the authors focused on distinguishing between mental state imaginary of open, mid and closed vowels without the imagination of the articulator movements. Twenty-one electrodes were placed over the area Wernicke and Broca's, as they are the areas that are related to speech. In the preprocessing stage, the differences between articulation mode were based on time domain analysis and applying the periodogram by using two fixed factors: the stimulus applied to the subject and the position of the 21 electrodes. Power Spectral Analysis was applied to detect signals that are immersed in noise by considering only the signals between the ranges of 2 to 16 Hz. Finally, the classification process was done with a non-linear Support Vector Machine resulting in the recognition rate between 84% and 94%.

V. Effect of Word Meaning on Brain Activity

In the literature there are several studies that tried to examine the effect of emotional content on the cognitive process. In [27] a study was conducted to understand the influence of emotional stimuli on source memory. In total 64 words in two sets were presented. One set contains neutral words (e.g.: "chair") and the other one contains emotional words (e.g: "emergency"). During the study, the participants were asked to read each word silently and remember the colour in which it was presented. Generally the results suggested an enhancement in the source memory for the emotional words because the participants better remembered the colours in which the emotional words were typed.

Another study by [28] used fMRI scanning to determine the neural regions involved in the emotional valence of the stimulus. Thirteen lists of ten personality-trait adjectives were constructed from Andersons list of personality-trait words [29]. This list included 555 personality-trait words rated by 100 subjects based on likeableness as a personality characteristic. The scanning process was conducted three times. First, in the self-referential processing condition, subjects determined whether they thought each trait described them. Second, in the other referential processing condition, subjects evaluated whether the stimulus represented a generally desirable trait. The third task was letter recognition as control task. In general the results showed that a widely distributed network of brain areas contributes to emotional processing. Moreover, among these regions the right dorsomedial prefrontal cortex is one main area in the self-referential task where its more subjective, perspective- taking aspects involved in emotional evaluation.

In [30], the objective was to measure to what extent emotional connotation influences cortical potentials during reading. In order to achieve this, event-related potentials (ERPs) were recorded during the reading of high-arousal pleasant and unpleasant and low arousal neutral adjectives that were presented at rates of 1 Hz and 3 Hz. The words were selected according to previous independent ratings of 45 subjects on a total of about 500 adjectives. In sum, the study demonstrated effects of emotional word content on a sequence of relatively early (EPN) and late (N400, LPP) cortical indices during uninstructed reading of words: initially, the brain responds to the emotional significant of a word, regardless of its valence. Similar approach was followed by [31] to understand the effect of emotional words on ERP brain activities.

Considering these studies, we can hypothesise that including words with emotional and semantic meanings in the BCI system may improve the speech recognition system, since different emotions influence the brain patterns differently. To the best of our knowledge, such a study has not yet been done.

VI. Limitations of Available Studies

From the literature, it can be clearly understood that the studies done so far for speech recognition using BCI were only conducted on a small number of speech stimuli and a limited number of subjects. Consequently, it is difficult to draw solid conclusions about obtaining the same results in wide range stimuli and subjects. Therefore, these studies have been presented as a proof of concept for speech recognition only. Even to date the results of these studies have not been utilized in a complete communication application. Only limited usage of these results were applied. For example, in [32] the recognition of unspoken speech was used to control a computer mouse. Also, in [19] the results were examined for the use in system authentication.

In addition to the limitations in the number of subjects, there is a lack of experimental work concerning of the target population. While the target population of BCI systems in the purpose of communication is locked-in patients, the studies presented in this review were tested on healthy subjects.

One of the general concerns in new research areas is the lack of having general methodology that can guarantee a consistent accuracy in the results. The available studies differ in stimuli presentation (visual or audio), target brain areas, the instructions to subjects (how to conducted the speech imagination task) and analysis technique for the results.

VII. Summary and Conclusion

This review covers two main parts. First, research studies which have been presented how BCI technologies have been used in understanding speech production and speech recognition processes. The stimuli selection in these studies were based on language aspects. For example, the use of syllables because they don't have any semantic meaning in [19] and [33]. Another example is to use different vowels such as in [22] because they are acoustically different and can be easily distinguished. The second part included a sample of studies that tried to examine the effect of emotional words on the cognitive process. This was done using either doing memory tests as in [27], fMRI scanning to determine the regions activated in response to emotional valance of different stimulus, or measuring the differences in ERP activities for different emotional words as in [30].

REFERENCES

[1] G. Pfurtscheller and F. L. Da Silva, "Event-related eeg/meg synchronization and desynchronization: basic principles," *Clinical neurophysiology*, vol. 110, no. 11, pp. 1842–1857, 1999.

[2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.

[3] J. S. Brumberg, A. Nieto-Castanon, P. R. Kennedy, and F. H. Guenther, "Brain–computer interfaces for speech communication," *Speech communication*, vol. 52, no. 4, pp. 367–379, 2010.

[4] A. Kübler, B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer, "Brain–computer communication: Unlocking the locked in." *Psychological bulletin*, vol. 127, no. 3, p. 358, 2001.

[5] N. Birbaumer and L. G. Cohen, "Brain–computer interfaces: communication and restoration of movement in paralysis," *The Journal of physiology*, vol. 579, no. 3, pp. 621–636, 2007.

[6] H. Cecotti, "A self-paced and calibration-less ssvep-based brain–computer interface speller," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 2, pp. 127–133, 2010.

[7] J. Mak, Y. Arbel, J. Minett, L. McCane, B. Yuksel, D. Ryan, D. Thompson, L. Bianchi, and D. Erdogmus, "Optimizing the p300-based brain–computer interface: current status, limitations and future directions," *Journal of neural engineering*, vol. 8, no. 2, p. 025003, 2011.

[8] B. Denby, T. Schultz, K. Honda, T. Hueber, J. M. Gilbert, and J. S. Brumberg, "Silent speech interfaces," *Speech Communication*, vol. 52, no. 4, pp. 270–287, 2010.

[9] X. Pei, J. Hill, and G. Schalk, "Silent communication: toward using brain signals," *IEEE pulse*, vol. 3, no. 1, pp. 43–46, 2012.

[10] F. Lotte, J. S. Brumberg, P. Brunner, A. Gunduz, A. L. Ritaccio, C. Guan, and G. Schalk, "Electrocorticographic representations of segmental features in continuous speech," *Frontiers in human neuroscience*, vol. 9, 2015.

[11] D. Heger, C. Herff, A. d. Pesters, D. Telaar, P. Brunner, G. Schalk, and T. Schultz, "Continuous speech recognition from ecog," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

[12] K. Brigham and B. V. Kumar, "Imagined speech classification with eeg signals for silent communication: a preliminary investigation into synthetic telepathy," in *4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE)*. IEEE, 2010, pp. 1–4.

[13] L. Sarmiento, P. Lorenzana, C. Cortes, W. Arcos, J. Bacca, and A. Tovar, "Brain computer interface (bci) with eeg signals for automatic vowel recognition based on articulation mode," in *5th ISSNIP-IEEE Biosignals and Biorobotics Conference (2014): Biosignals and Robotics for Better and Safer Living (BRC)*. IEEE, 2014, pp. 1–4.

[14] M. Wester and T. Schultz, "Unspoken speech-speech recognition based on electroencephalography," *Master's thesis, Universität Karlsruhe (TH), Karlsruhe, Germany*, 2006.

[15] J. Belliveau, D. Kennedy, R. McKinstry, B. Buchbinder, R. Weisskoff, M. Cohen, J. Vevea, T. Brady, and B. Rosen, "Functional mapping of the human visual cortex by magnetic resonance imaging," *Science*, vol. 254, no. 5032, pp. 716–719, 1991.

[16] L. Naci, R. Cusack, V. Z. Jia, and A. M. Owen, "The brain's silent messenger: using selective attention to decode human thought for brain-based communication," *The Journal of Neuroscience*, vol. 33, no. 22, pp. 9385–9393, 2013.

[17] A. Porbadnigk, M. Wester, and T. S. Jan-p Calliess, "Eeg-based speech recognition impact of temporal effects," 2009.

[18] A. G. Huth, W. A. D. Heer, T. L. Griffiths, F. E. Theunissen, and L. Jack, "Natural speech reveals the semantic maps that tile human cerebral cortex," *Nature*, vol. 532, no. 7600, pp. 453–458, 2016. [Online]. Available: http://dx.doi.org/10.1038/nature17637

[19] K. Brigham and B. Kumar, "Subject identification from electroencephalogram (eeg) signals during imagined speech," in *Fourth IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS)*, 2010, pp. 1–8.

[20] H. Yamaguchi, T. Yamazaki, K. Yamamoto, S. Ueno, A. Yamaguchi, T. Ito, S. Hirose, K. Kamijo, H. Takayanagi, T. Yamanoi *et al.*, "Decoding silent speech in japanese from single trial eegs: Preliminary results," *Journal of Computer Science & Systems Biology*, vol. 2015, 2015.

[21] M. DZmura, S. Deng, T. Lappas, S. Thorpe, and R. Srinivasan, "Toward eeg sensing of imagined speech," in *International Conference on Human-Computer Interaction*. Springer, 2009, pp. 40–48.

[22] N. Yoshimura, A. Satsuma, C. S. Dasalla, T. Hanakawa, M. A. Sato, and Y. Koike, "Usability of EEG cortical currents in classification of vowel speech imagery," *2011 International Conference on Virtual Rehabilitation, ICVR 2011*, pp. 2–3, 2011.

[23] M. Matsumoto and J. Hori, "Classification of silent speech using support vector machine and relevance vector machine," *Applied Soft Computing*, vol. 20, pp. 95–102, 2014.

[24] A. A. T. García, C. A. R. García, and L. V. Pineda, "Toward a silent speech interface based on unspoken speech." in *BIOSIGNALS*, 2012, pp. 370–373.

[25] S. Zhao and F. Rudzicz, "Classifying phonological categories in imagined and articulated speech," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, vol. 2015-Augus, 2015, pp. 992–996.

[26] M. Matsumoto and J. Hori, "Classification of silent speech using adaptive collection," in *IEEE Symposium on Computational Intelligence in Rehabilitation and Assistive Technologies (CIRAT)*, 2013, pp. 5–12.

[27] S. Doerksen and A. P. Shimamura, "Source memory enhancement for emotional words." *Emotion*, vol. 1, no. 1, p. 5, 2001.

[28] P. Fossati, S. J. Hevenor, S. J. Graham, C. Grady, M. L. Keightley, F. Craik, and H. Mayberg, "In search of the emotional self: an FMRI study using positive and negative emotional words." *The American journal of psychiatry*, vol. 160, no. 11, pp. 1938–1945, 2003.

[29] N. H. Anderson, "Likableness ratings of 555 personality-trait words." *Journal of personality and social psychology*, vol. 9, no. 3, pp. 272–279, 1968.

[30] C. Herbert, M. Junghofer, and J. Kissler, "Event related potentials to emotional adjectives during reading," *Psychophysiology*, vol. 45, no. 3, pp. 487–498, 2008.

[31] A. Schacht and W. Sommer, "Time course and task dependence of emotion effects in word processing," *Cognitive, affective & behavioral neuroscience*, vol. 9, no. 1, pp. 28–43, 2009. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/19246325

[32] A. A. T. García, C. A. García, and L. V. Pineda, "Toward a silent speech interface based on unspoken speech," in *International Conference on Bio-Inspired Systems and Signal Processing (BIOSIGNALS)*, 2012, pp. 370–373.

[33] M. D'Zmura, S. Deng, T. Lappas, S. Thorpe, and R. Srinivasan, "Toward eeg sensing of imagined speech," *Human-Computer Interaction, New Trends Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 5610 LNCS, pp. 40–48, 2009.