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ACQUISITION DESIGN AND OBJECTIVES OF IMAGINED SPEECH RESEARCH BASED ON EEG: REVIEW PAPER

Efy Yosrita[1,2,*], Yaya Heryadi[1], Lili Ayu Wulandhari[3] and Widodo Budiharto[3]

[1]Computer Science Department, BINUS Graduate Program – Doctor of Computer Science
[3]Department of Computer Science, School of Computer Science
Bina Nusantara University
JL. K. H. Syahdan No. 9, Kemanggisan, Palmerah, Jakarta 11480, Indonesia
{ yayaheryadi; wbudiharto }@binus.edu; lwulandhari@binus.ac.id

[2]Faculty of Telematics for Energy
Institut Teknologi PLN
Jl. Lingkar Luar Barat, Duri Kosambi, Cengkareng, Jakarta Barat 11750, Indonesia
*Corresponding author: efy.yosrita@itpln.ac.id

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Abstract. *This paper presents summary of a paper review on EEG signals focusing on signal acquisition design. The discussion is devoted to some prominent research on imagined speech recognition, which is divided into vowel recognition, syllable recognition and word recognition. This explanation provides an overview state of the art from acquisition design to imagined speech recognition research and there is an open opportunity to develop an EEG signal classification model for recognizing some imagined speech with better accuracy and faster recognition process. Hopefully, this presentation can be considered as a reference for new researchers in the field of BCI in designing an acqusition protocol that suits their purpose.*
Keywords: EEG, Acquisition, Word imagination, Syllable imagination, Vowel imagination

1. **Introduction.** Brain computer interface (BCI) is a research area that has been attracting many researchers [1], to explore [2] and develop solution to address problems in various fields. In the past decade a vast number of publications have been available in literature on various methods to build BCI for various purposes such as limited to authentication systems [3], hand assistant system [4], control and communication in non invasive individuals [5,6], and controlling a wheelchair [7-9]. In many of those proposed methods, electroencephalogram (EEG) is the common input signal used in BCI system [10]. In addition, EEG is also widely used to build computer based system to diagnose epilepsy [11-14], detect emotion [15], study of sleep pattern [16], robot control [17,18], for games [19] and for unspoken speech recognition using the K-NN model [20]. The main purpose of developing BCI is to help people with communication limitations due to reduced/not functioning motoric bodies either partially or totally [21] in order to communicate with their environment [22]. This paper sheds light on the studies on BCI technologies particularly for imagined speech recognition that focus on the acquisition design and research objectives. The paper is organized as follows. Section 2 explains about several research doing on BCI field based on EEG signal. Section 3 explains about several research especially the imagined speech based on EEG signal covering vowel, syllable and word recognition. Section 4 suggests the review and opportunity that still open to develop classification model for imagined speech recognition.

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2. **Literature Review.** Several researchers have reviewed EEG and BCI research with different perspectives including Abhang et al. [23], Herff and Schultz [24], AlSaleh et al. [25], Abiri et al. [28], Cooney et al. [26] and Koctúrová and Juhár [27], as shown in Table 1.

Table 1. Review study and point of view

Study	Point of view
Abhang et al. [23]	The recognition of emotion in a person with the help of electroencephalogram (EEG) signals and speech
Herff and Schultz [24]	Analyze the potential of different brain imaging techniques to recognize speech from neural signals by applying automatic speech recognition technology
AlSaleh et al. [25]	The studies were categorized based on the sensors used to measure brain activities as well as different types of performed imagined speech
Cooney et al. [26]	Trends in DS-BCI research, and the current understanding of speech production processes, with an emphasis on imagined speech
Koctúrová and Juhár [27]	Focus on global research and continue the work in BCI technology experimental paradigm
Abiri et al. [28] Rabbani et al. [29]	Focus on the potential utilization of chronic electrocorticography for speech brain computer interface

This paper describes the use of EEG in speech recognition research, especially regarding imagined speech. In general, speech recognition research based on EEG is divided into two parts, i.e., overt speech and covert speech, while covert is further divided into several research derivatives, as shown in Figure 1.

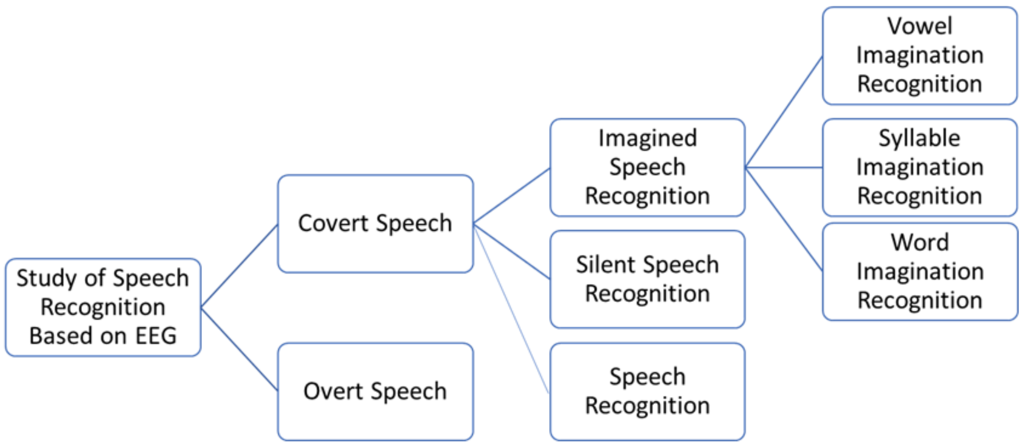

Figure 1. Study of speech recognition based on EEG

Martin et al. divide speech into 2 models, i.e., overt and covert [30], Koctúrová and Juhár divide speech into 3, i.e., speech recognition, silent speech recognition and unspoken speech/imagined speech [27] and for imagined speech AlSaleh et al. divide it into vowels imagination, syllables imagination and word imagination [25].

3. **Study of Speech Imagination Recognition Based on Electroencephalogram (EEG).** Research on speech imagination is divided into three sub-sections, i.e., vowel recognition, syllable recognition and word recognition. Table 2 overviews the signal acquisition design, research objective and proposed method.

Table 2. Speech imagination study

Study	Subsection	Objectives	Proposed method	EEG acquisition
DaSalla et al. [31]	Vowel	Provide a speech rostheses	Control scheme for BCI	3 subjects with 3 mental tasks on a visual cue: 1) imagined mouth opening and imagined vocalization for vowel /a/ 2) imagined lip rounding and imagined vocalization vowel /u/ 3) no action as control
Yoshimura et al. [32]	Vowel	Provide assistive technology	A new approach for speech prostheses	3 subjects with 3 mental tasks on a visual cue: 1) /a/ → imagined mouth opening 2) /u/ → imagined lip rounding 3) /+/ → control task with no imagery
Matsumoto and Hori [33]	Vowel	Provide speech prostheses for impairment person	A classification method for BCI using silent speech.	• 5 subjects and eyes closed when imagining voice production for 1 s while remaining silent and immobilized • /a/, /i/, /u/, /e/, /o/ → imagined • 2 tasks: the fixed order and the random order tasks
Min et al. [34]	Vowel	To classify EEG data on imagined speech in a single trial	The ELM algorithm and friends and variants the ELM algorithm and its variants with kernels	5 subjects and the five vowels and mute sound were randomly presented.
Sarmiento et al. [35]	Vowel	To find the quantity of power of a signal	A novel automatic brain signal recognition protocol based on vowel articulation mode	• 5 subjects with eyes closed • On and off a flasher light 3 s and 30 s • Subject imagined when the flasher on and rest for 3 minutes
D'Zmura et al. [36]	Syllables	To classify single trials offline according to condition	EEG waveform envelopes	• 4 subjects with single experimental and 20 trials for each of the six conditions • Block and randomized order were presented. • Subjects were keeping their eyes open during the 6 s, following the cue speech was imagined without any vocalization whatsoever.
Brigham and Kumar [37]	Syllables	To identify which subject the signals originated from	Method of assessing the degree of subject-to-subject variation and the feasibility of using imagined speech for subject identification	• Secunder dataset • 14 male and 14 female subjects, the subject was seated. • The subjects' task was to decide whether the second picture ($2) was the same as the first stimulus (S1) [38].
Deng et al. [39]	Syllables	To determine the rhythm with which imagined syllables are produced may be decoded from EEG recordings	A modified second-order blind identification (SOBI) algorithm to remove artefact signals and reduce data dimensionality	• 7 subjects with opening their eyes • The task was to imagine speaking one of two syllables, /ba/ or /ku/, in one of three rhythms. • Each subject performed 120 trials and total of 720 trials recorded per subject.
Wester [40]	Word	Investigate possibility to recognize naturally thought unspoken speech	The methods of automatic speech recognition	5 subjects, the subject was sitting and facing the CRT display and the screen showed instructions which the subject had to follow.

(continued)

Porbadnigk [41]	Word	To recognizing unspoken speech	Recognizing unspoken speech method	• 21 subjects, the subject was seated and facing a CRT display. • Phase 1, the word was shown for two seconds. • Phase 2, the screen turned blue. • After 2 seconds, the subject had to blink with both eyes and then imagine speaking the word then, s/he had to signal the end of the thought with a second blink.
Castañeda et al. [42]	Word	To integrate people with severe motor disabilities to their environment	Applying to EEG signals sonification and textification methods	Secondary dataset • 27 subjects • The data set consists of the imagined pronunciation of five words in Spanish: "arriba" (up), "abajo" (down), "izquierda" (left), "derecha" (right), and "seleccionar" (select). • Imagined pronunciation of each word was repeated 33 times.
Balaji et al. [43]	Word	Bilingual speech classification	A novel model by combining bilingual interpretation and decision making	• 5 subjects were asked to keep their eyes closed and remain still. • Presented with an auditory stimulus via headphones consisted of 10 question with 'Yes' and 'No' answer played out randomly.
Abdallah et al. [44]	Word	Classification for the two English words 'ON' and 'OFF'	Applying an articial neural network with three layers	• The subjects should think of the word displayed in a video and perform a mouse click when the video shows a red screen. • Each subject did 5 sessions of two words 'ON/OFF'.
Sereshkeh et al. [45]	Word	To develop two intuitive online BCIs based solely on covert speech	Real-time classification of EEG signals arising from covert speech	• 12 subjects • Subjects were asked to answer a perceptual yes versus no question by iteratively repeating the answer ("yes" or "no") mentally without any vocalization or motor movement, especially of the lips, tongue or jaw.
Hashim et al. [46]	Word	Improvements of word recognition	Simple word based approach using (MFCC) and (k-NN) towards recognizing two simple words using EEG signals	• 4 subjects • Subjects imagine the shown word ten times for each session, with a break in between. • For one subject, there are 50 trials for each word and total there are 400 trials for four different subjects.
Abdallah et al. [47]	Word	Optimize the BCI system for unspoken speech recognition that focuses on wernick area	Method of an optimized BCI system for unspoken speech recognition	• Subjects are 19 and 25 years old. • Each subject performs between 3 and 5 sessions of recording for each of the 5 Arabic words. • Each session consists of 1m30sec of recordings with 15 and 20 repetition of a same word.
AlSaleh et al. [48]	Word	Discriminate imagined speech and non-speech tasks	Method for discriminating imagined speech and non-speech tasks	• 11 imagined speech stimuli were used as blocks were recorded for each subject, each word was presented in random order eight times.
AlSaleh et al. [49]	Word	Unspoken words recognition using block recording	Optimizing the length and training size of imagined speech	• 9 subjects • Subjects were asked to imagine the pronunciation of each word for a total of 100 trials (repetitions).
Bakhshali et al. [50]	Word	Imagined speech classification	Evaluated with statistical methods for channel selection and frequency band	• Secunder dataset, KARA One database

These are several points that can be derived from Table 2:

1) Study in speech recognition using EEG signals as input has explored a range of sentence structure which are including vowels, syllables, and words level with various duration and number of repetitions in data acquisition process.
2) Imagined speech stimuli (mostly 5 subjects) has been widely used as input for generating EEG signals.
3) Several classification models used in speech imagination research include HMM, RF, NB, SVM, ANN, LDA, Adaboost, K-NN.
4) Several methods achieve a high level for word imagination recognition, the highest level of accuracy is 95% with the ANN classifier, for binary classification (yes/no) with approach of 3 phases: signal acquisition, preprocessing and feature extraction [44].
5) Most of the researchers used the dataset obtained from recording EEG signal using various schemes.
6) The accuracy rate for binary classification is 95% for yes-no word classification and for multiclass classification an average recognition rate is 45.50% for alpha, bravo, charlie, delta, echo words.

4. **Conclusions.** It can be concluded that there is an open opportunity to develop classification model using EEG signal [14] for recognizing some imagined speech recognition with better accuracy and faster recognition to be used to support healthcare professionals. The main challenge in this research area is to reduce the computational cost using another method but Riemannian metrics or an optimized implementation of matrix algebra [50], feature extraction framework for motor imagination [51], to enhance accuracies and reduce trial duration [52].

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