State-of-the-art of Imagined Speech: Analysis in Basic Needs, Syllables and Commands for Brain-Computer Interfaces

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Abstract. Imagined Speech decoding through brain-computer interfaces has emerged as a promising approach for assisting people with severe communication challenges. Imagined speech refers to brain activity generated when a person internally simulates Speech without vocalizing, enabling communication through non-invasive methods like electroencephalography. This work comprehensively reviews Imagined Speech research, categorizing studies into three strands: syllable imagination, command imagination and basic needs. Comparative tables highlight the methodologies, languages, classifiers, and performance metrics used across studies. Results show significant variability in accuracy due to differences in data acquisition, signal processing, and classification algorithms. Despite notable advances, challenges remain in generalizing models to real-world applications and improving usability outside laboratory settings. Future research should focus on standardized methodologies, larger datasets, and hybrid systems to enhance accuracy and applicability. Development of Imagined Speech based BCIs holds significant potential for restoring communication and autonomy for individuals with speech impairments.

Keywords: Basic Needs, Brain-Computer Interface, Commands, Electroencephalography, Imagined Speech, Review, Syllables.

1 Introduction

1.1 Communication

Communication is an essential process in human life that enables the transmission of ideas, thoughts, emotions, and needs between people. Through communication, individuals can interact with their environment, establish relationships, learn, and actively participate in society [1].

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There are various forms of communication, with verbal and non-verbal being the most common. Verbal communication is carried out through spoken or written language, while nonverbal communication encompasses gestures, facial expressions, body postures, and other methods that either complement or replace spoken language.

Disabilities in Human Communication. Difficulties in human communication can limit a person's ability to express their thoughts, needs, and emotions, negatively impacting their quality of life. These difficulties might be due to a range of factors, including neurodegenerative diseases, brain injuries, developmental disorders, or paralysis [2].

According to 2020 Population and Housing Census conducted by Mexico's National Institute of Statistics, Geography, and Information (INEGI, by its Spanish acronym), around 6.18 million individuals, roughly 4.9% of the country's population, live with some form of disability. Within this group, around 15% experience difficulties in speaking or communicating, affecting more than 945,000 people. This sector includes individuals who struggle to articulate speech comprehensibly as well as those who cannot communicate verbally [2]. Main causes of communication disabilities include stroke, amyotrophic lateral sclerosis (ALS), and cerebral palsy.

1.2 Bioelectronics Interfaces for Communication

Bioelectronic interfaces for communication are systems designed to establish direct interaction between human body and electronic devices, enabling transmission of information without relying on verbal or written communication methods. These interfaces are particularly beneficial for individuals with severe disabilities that prevent them from speaking, writing, or performing voluntary motor movements, such as those with neurodegenerative diseases or speech impairments [3].

Relevance of these interfaces on the lives of individuals with speech difficulties is significant, as they provide the possibility of regaining communication abilities and control over their environment. Their implementation contributes to improving quality of life by promoting autonomy in daily activities and fostering social and emotional integration for patients. In this regard, these technologies are not only a technical advancement but also a key tool in the rehabilitation and inclusion processes of individuals with speech disabilities [4].

Brain Computer Interfaces (BCI). Among advanced technologies in bioelectronics interfaces for communication are Brain-Computer Interfaces. They establish a direct link between the brain and an external device without the need for muscular activity. They function by recording electrophysiological signals, usually through Electroencephalograms (EEG), to interpret the user's intentions in real time [5]. These innovations allow individuals with locked-in syndrome or conditions like amyotrophic lateral sclerosis (ALS) to communicate by using their neural activity to operate devices [6].

BCIs come in various forms, depending on the signals they employ and the objectives they are designed to achieve. Common BCIs rely on electrophysiological sources such as EEG, which detects the electrical activity generated by large populations of neurons.

1.3 Imagined Speech

Imagined Speech (IS) refers to the brain activity that occurs when a person mentally simulates the act of speaking without performing the physical movements necessary to produce sound. Recent research has shown that imagining the pronunciation of words activates brain regions like those involved in actual speech, such as Broca's area and other regions related to motor control of language [7]. This neural activity generates specific patterns that can be detected using techniques such as EEG, enabling the decoding of imagined speech through BCIs.

BCIs based on imagined speech represent a significant advancement in the development of assistive communication systems for individuals with severe disabilities that prevent them from speaking or moving, such as those with locked-in syndrome or severe brain injuries. However, decoding imagined speech remains a challenge due to the complexity of brain signals, which are subtle and vary significantly between individuals.

These BCI systems can be used to facilitate communication by generating commands based on imagined words or syllables. For example, a user could imagine a specific word or command, and the BCI system would interpret those signals to translate them into instructions that allow controlling a device or typing on a screen.

Humans engage in internal dialogue most of the time. Unlike engaging in an actual conversation with another person, this discourse is entirely imagined, meaning that we voluntarily simulate speaking without making intentional movements of speech articulators. Therefore, even in cases where a person has muscle paralysis and cannot move their articulators, they are still capable of imagining speech or actively thinking in words [8].

In these circumstances, it is essential to have systems that enable spoken communication without the need to produce a comprehensible acoustic signal [9]. Since speech facilitates the most direct interaction among humans, there has been growing interest in the decoding of imagined speech. A system designed to interpret imagined speech has various applications, including the ability to facilitate communication for patients with speech limitations, as well as devices operation such as computers through mental control [2, 8].

In the last decade, numerous researchers have developed various implementations of systems to decode imagined speech from EEG signals. However, progress in this field has been slower compared to other areas within brain-computer interfaces, such as BCI spellers, Blink-to-speak, or subvocal speech [9,11-13]

This slowdown is largely due to the heterogeneity of studies in various aspects, ranging from data collection methods to the machine learning algorithms used for decoding, as well as the criteria employed for evaluation. These differences make direct comparisons between studies difficult, posing a challenge for the standardization of the field [2].

Despite these difficulties, the study of imagined speech and its decoding continues to evolve through the implementation of new approaches and tools, aiming to improve its accuracy and applicability [2].

In the field of research on IS, multiple types of IS have been identified based on what is intended to be expressed. The classification into different categories and the development of a comparative table facilitate the identification of recurring patterns, effective methodologies, and underexplored areas of research. Keeping this classification updated helps reflect the latest advancements, fostering collaborative efforts and the sharing of knowledge within the scientific community. Moreover, by including the dimension of basic needs, this study expands the scope of imagined speech toward more practical applications, with the goal of enhancing the quality of life for individuals with severe disabilities.

3 Methodology and Results

A comparative table is developed that compiles the main characteristics of studies on IS. This table facilitates the analysis of methodologies, results, and trends in each study, providing a dynamic and useful tool for researchers in this field.

3.1 Imagination of Syllables

The syllable imagination strand focuses on decoding basic units of language, such as vowels, consonants, and syllables. This approach aims to identify specific patterns associated with imagining individual sounds. Commonly used stimuli in this strand are auditory or visual, presenting subjects with tasks such as imagining a specific vowel or syllable (see Table 1).

Table 1. Imagination of Syllables: Compendium of Research

References	Imagined Taks	Language and Country	Classifier and Performance
DaSalla, C.S., (2009) [12]	Vowel articulation involving /a/ and /u/, along with a baseline condition where no action is taken	USA - English	SVM with 78% accuracy
Sharon, R.A., (2020) [13]	Three tasks: Perception, Imagination and Speaking of 25 and 54 syllables such as "a", "am" and "give", and others	USA - English	GMM-HMM with 37.2% accuracy
Kara One Database, (2015) [14]	Seven phonemic or syllabic prompts combined with four words taken from the Kent list of phonetically similar pairs	USA - English	DBN and SVM with 87% accuracy in binary classification and 53% in multi-class classification
Jahangiri, A., (2019) [15]	"BA", "FO", "LE" and "RY"	United Kingdom - English	Davies-Bouldin index Pseudo-Linear

Brigham, K., (2010) [16]	Syllabes "ba" and "ku"	USA - English	Linear SVM classifier with 99.76% accuracy
Brigham, K., (2010) [17]	Syllables "ba" and "ku"	USA - English	k-NN with 61% accuracy
Min, B., (2016) [18]	Vowel classification	Korea - Korean	ELM, SVM and LDA, using binary classification and 69.68% accuracy on average across the three classifiers
Cooney, C., (2018) [19]	Seven phonemic or syllabic prompts combined with four words	United Kingdom – English	SVM and ANN and the best performance SVM (~21%), while the worst SVM (~11%)
Tottrup, L., (2019) [20]	Seven distinct actions: producing three words, executing two arm movements and a resting state	Denmark – English	Random Forest with 61% accuracy
Saha, P., (2019) [21]	Seven phonemic or syllabic prompts combined with four words	Canada - English	CNN with accuracy of 83.42%, six binary classification.
D'Zmura, M., (2009) [22]	Binary classification /ba/ and /ku/ syllables	USA - English	Matched-Filter Classification using binary classification with 75% accuracy
Deng, S., (2010) [23]	Binary classification /ba/ and /ku/ syllables	USA - English	SOBI and Hilbert-Huang Transform (HHT) with the highest classification accuracy was 26% (S6)
Chi, X., (2011) [24]	Imagined pronouncing ten phonemes, categorized by articulation: jaw movement (/aa/, /ae/), tongue movement (/l/, /r/), nasals (/m/, /n/), lip movement (/uu/, /ow/), and fricatives (/s/, /z/).	USA – English	Naïve Bayes and LDA with the overall classification performance was 67.31% on overage

Cooney, C., (2020) [25]	Vowel classification	United Kingdom – English	CNN with vowels: 35% best accuracy
Tamm, M., (2020) [26]	Vowel classification and six words: "down", "right", "left", "up", "back", and "forward"	Estonia – English	CNN and 24% accuracy
Chengaiyan, et al. (2020) [27]	Vowel classification	India - English	RNN with 72% average accuracy
Matsumoto and Hori (2014) [28]	Japanese vowels classification	Japan – Japanese	RVM with 79% average accuracy

3.2 Imagination of Commands

On the other hand, the command imagination strand focuses on tasks that allow subjects to imagine words or short phrases that can be interpreted as "commands." The stimuli in this approach are usually visual or textual, with the most common classes being, "down", "up", "right", “left” and "select" (also in their Spanish versions: "abajo", "arriba", "derecha", "izquierda" and "seleccionar"), which are associated with specific actions. This approach combines linguistic processing with Motor Imagery, activating both language areas and motor regions of the brain (see Table 2).

Table 2. Imagination of Commands: Compendium of Research

References	Imagined Taks	Language and Country	Classifier and Perfomance
Garcia, J. S., (2018) [29]	These words were selected to represent common directional commands: "arriba", "abajo", "izquierda" and "derecha"	Mexico – Spanish	MT_FD with 65% accuracy
Torres, A.A, (2016) [30]	"arriba", "abajo", "izquierda" and "derecha"	Mexico – Spanish	FIS 3x3 with 68.18% accuracy using 7 channels and 70.33% using all channels
González, E.F., (2017) [31]	"arriba", "abajo", "izquierda", "derecha" and "seleccionar"	Mexico – Spanish	Random Forest with 58.41% accuracy (raw), 63.82% (sonification), and 83.34% (textification).

Torres, A.A., (2012) [32]	Control words for moving a cursor on the computer: "arriba", "abajo", "izquierda", "derecha" and "seleccionar"	Mexico – Spanish	Random Forest, Support Vector Machines and Naïve Bayes and Bagging-RF using multiclass classification and Accuracies above 20%
Torres, A.A., (2013) [33]	Control words for moving a cursor on the computer: "arriba", "abajo", "izquierda", "derecha" and "seleccionar"	Mexico – Spanish	Random Forest, Support Vector Machines and Naïve Bayes. Highest accuracy was 60.11% using 14 channels and 47.93% with 4 channels
Moctezuma, L.F., (2019) [34]	"arriba", "abajo", "izquierda", "derecha" and "seleccionar"	Mexico – Spanish	Random Forest, Support Vector Machines, Naïve Bayes and k-NN. The best accuracy obtained was 92% using linear Support Vector Machine with 10-fold cross-validation.
García, J.S., (2018) [35]	"arriba", "abajo", "izquierda", "derecha" and "seleccionar"	Mexico - Spanish	Tensor decomposition technique, specifically Parallel Factor Analysis (PARAFAC), with 59.7% classification accuracy.
Torres, A.A., (2011) [36]	"arriba" and "abajo"	Mexico – Spanish	Naïve Bayes, MLP, Random Forest and Support Vector Machine, with The average classification accuracy across all classifiers and subjects was 68.75%
Jimenez-Guarneros and Gomez-Gil (2021) [37]	Short and long words classification: "arriba" (up), "abajo" (down), " izquierda" (left), "derecha", (right) and "seleccionar" (select). "cooperate" and "indenpent" for long words classification.	Mexico – Spanish/English	Random Forest, Support Vector Machine, RMDM with 63.42% accuracy for Spanish words and 62.99% accuracy for long words.
Rezazadeh Sereshkeh, A., (2017) [38]	Three mental tasks: Rest, "yes," or "no."	Canada – English	Regularized neural networks and 63.1% accuracy

Balaji. A., (2017) [39]	The tasks featured "Yes" and "No" in English, as well as "Haan" and "Na" in Hindi.	India – English / Hindi	Support Vector Machines, Random Forest, AdaBoost, and a Neural Network reached an accuracy of 85%
Panachakel, A.G., (2020) [40]	Two words: "in" and "cooperate"	USA – English	DNN with 83% accuracy
Rezazadeh, A., (2017) [41]	Two sets of tasks: Mental repetition of the word "no" vs. unrestricted rest. Mental repetition of the word "yes" vs. "no"	Canada – English	Support Vector Machine with 75.9% accuracy for "no" vs rest classification and 69.3% accuracy for "yes" vs "no" classification
Zhang, X., (2020) [42]	Participants imagined pronouncing the syllable /ba/ in the four Mandarin tones	China - Mandarin	Support Vector Machine with 80.1% accuracy using audiovisual condition and 67.7% using only visual condition

3.3 Imagination of Basic Needs

Finally, basic needs strand represents an innovative approach that focuses on tasks related to fundamental daily life activities, such as "comer", "dormir", "beber", and "excretar". This approach has a clearly communicative purpose, aimed at improving the quality of life of individuals with severe disabilities by developing systems that enable them to express these essential needs. In this strand, auditory stimuli (such as an audio cue stating the word related to the need), visual stimuli (representative images), and textual stimuli (written words) are used.

The basic needs strand is proposed in our work to give a more communicative and functional approach to the study of Imagined Speech, considering its relationship with Motor Imagery (see Table 3).

Table 3. Imagination of Basic Needs: Compendium of Research

References	Imagined Taks	Language and Country	Classifier and Perfomance
Gutierrez-Zermeno, M., et al. (2022) [7]	Four common words in Spanish: "Comer", "Baño", "Descansar" and "Okay"	Mexico - Spanish	Decision Tree and Support Vector Machine using CSP. One vs Rest models and 93.1% for "Descansar", 81.2% for "Comer", 73.7% for "Baño", and 70% for "Okay".

Barajas Gonzalez, E., (2024) [2]	Four common words in Spanish: "Beber", "Dormir", "Comer" and "Excretar"	Mexico – Spanish	The highest accuracy was achieved with Naïve Bayes at 24% using multiclass classification

4 Discussion, Applications, Trends and Opportunities

The development of BCIs for Imagined Speech decoding has garnered increasing interest in recent years, yet their application in real-world scenarios still faces multiple obstacles. Although various studies have demonstrated the feasibility of classifying words, phonemes, and basic commands from EEG signals, the effective translation of thoughts into comprehensible language remains an open challenge. Beyond speech restoration, integrating these systems into environments such as smart device control or user identification through neural patterns suggests a broad range of potential applications. However, the complexity of imagined speech lies in its highly variable nature across individuals, which limits the generalization of current models and underscores the need for more personalized approaches to neural decoding.

One of main challenges in this field is ability of these systems to function under dynamic and uncontrolled conditions. Most reviewed studies have been conducted in laboratory settings with strictly defined experimental paradigms, which contribute to achieving high accuracy rates in artificial scenarios but do not guarantee success in everyday life. Additionally, the reliance on high-density EEG and the need for multiple training sessions hinder the implementation of these systems outside academic environments. Development of accessible hardware with configurations optimized for daily use is a key requirement for the adoption of these technologies in clinical or personal settings.

Another aspect to consider is the difference in accuracy between brain signal acquisition techniques. Methods such as Electrocorticography (ECoG) and Magnetoencephalography (MEG) have shown significantly higher results compared to EEG, raising the possibility that imagined speech decoding heavily depends on the type of signal used. However, while these techniques offer greater spatial resolution and precision, their implementation is invasive or costly, limiting their applicability to a small group of users. In this regard, future research should focus on improving EEG processing algorithms to bridge the accuracy gap without compromising usability.

Despite current challenges, there are strategies that could accelerate the transition of imagined speech BCI systems toward more functional applications. On the one hand, the use of deep learning models trained on large datasets could enhance the generalization capability of algorithms, reducing reliance on individual calibration sessions. Additionally, the incorporation of hybrid approaches that combine EEG signals with additional biomarkers (such as residual muscle activity or pupillary responses) could increase the reliability of these systems without resorting to invasive methods.

5 Conclusions

Research on imagined speech has advanced significantly over the past decade, although its development has been slower compared to other areas of brain-computer interfaces, owing to complexity and variable nature of EEG signals. Lack of standardization in methodologies and decoding algorithms has made it difficult to compare studies, highlighting need for unified approaches. In this context, proposals to classify imagined speech into different categories based on the intended content represent a key advancement, as it facilitates the identification of recurring patterns, effective methodologies, and research opportunities.

This classification not only improves the systematization of knowledge but also expands practical applications, particularly in assistive communication for individuals with severe disabilities, paving the way for the development of technologies that are more accessible and effective. Despite the challenges, use a new tools and methodological approaches continues to enhance the accuracy of decoding systems, driving the integration of these technologies into real-world scenarios and fostering greater collaboration among researchers. In this regard, state-of-the-art provides a comprehensive overview of the advances and limitations in imagined speech decoding, laying the foundation for future research and encouraging the development of more effective and applicable strategies in the fields of neurotechnology and assistive communication.

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