Within-subject vs. Multi-Subject Eye Movement Classification: A Comparative Study

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Abstract. People with speech disabilities face significant communication challenges, especially those with motor impairments that prevent them from using sign language. To address this issue, eye movement-based communication systems like Blink to Speak (BTS) have been developed, allowing users to convey messages through eight eye movement alphabets. This study evaluates the classification of BTS alphabets using electrooculography (EOG) signals, comparing two approaches: within-subject (WS) and between-subject (BS). A dataset of EOG signals from 38 subjects was used to train and test a Random Forest model, selected for its superior performance in BS classification. Results show that WS classification generally outperforms BS, with F1-score improvements in 33 out of 38 subjects and across all alphabets. Alphabets with lower inter-subject similarity, such as “Wink”, “Roll” and “Left” achieved the most significant improvements in WS, while those with high similarity, like "Down" and "Blink," showed less enhancement. Despite the superior performance of the WS approach, it requires an extensive data collection and calibration process, which may hinder practical implementation. Future work should consider balancing quick adaptability (favoring BS classification) and model accuracy (favoring WS classification), depending on user needs and application context.

Keywords: Blink to Speak, Electrooculography, Machine Learning Algoritms, Multi-Subject, Speech disability, Within-subject.

1 Introduction

1.1 Speech disability

Communication is a fundamental process for human interaction that allows transmission of information, thoughts and emotions. Although non-verbal communication through gestures, symbols or elements may exist, verbal communication through speech facilitates direct expression and immediate feedback [1].

Unfortunately, there are some conditions, such as phonological disorders, in which speech can be affected, thereby impacting the quality of life of those who suffer from

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them. In 2020 alone, National Institute of Statistics and Geography reported that 945,000 Mexicans are affected by these conditions, presenting speech disabilities [2]. While sign language may be an option for communication for these individuals, it is not for those suffering from amyotrophic lateral sclerosis, motor neuron disease, severe motor disabilities or neurodegenerative disorders, as they cannot use this language due to limitations in upper limb movement that characterize these types of diseases [3].

1.2 Devices for people with communication difficulties

In recent years, technological advances have enabled development of devices that help meet communication needs of people with speech disabilities. Among these, Human-Computer Interfaces (HCIs) stand out, as they allow interaction between humans and devices through bioelectrical signals captured from different parts of body [4]. HCIs focused on communication typically capture brain activity [5], subvocal signals [6] and ocular signals [7], serving as effective alternatives for individuals with limited mobility.

In addition to these technological developments, communication languages based on ocular activity have been created: “Blink to Speak” (BTS) and “Blink to Live”, the latter being inspired by the former [8]. BTS represents an innovative ocular language intended for universal application, featuring fifty everyday messages that support communication between patients and their caregivers or family members. This language is based on eight alphabets characterized by execution of relatively simple ocular movements such as closing eyes, blinking, moving eyes to left, moving eyes to right, moving eyes up, moving eyes down, winking and executing an ocular rotation with both eyes, that is an ocular turn in three quadrants. For simplicity, these eight alphabets are known respectively by following names: 1) Close, 2) Blink, 3) Left, 4) Right, 5) Up, 6) Down, 7) Wink and 8) Rotate (see Fig. 1). The combination of one or several of these alphabets gives rise to ocular movement patterns that represent messages. Some of messages are: “I feel like eating”, which is communicated with Up and Down alphabets; “Call the doctor”, expressed with a blink and a movement to left; and “I’m proud of you”, represented by two consecutive blinks followed by closing eyes [9].

Interpreting BTS language can be a tedious process that requires significant attention from receiver, which makes it prone to errors. In this context, augmentative and alternative communication systems offer great assistance by proposing various solutions based on monitoring of ocular movements [10, 11].

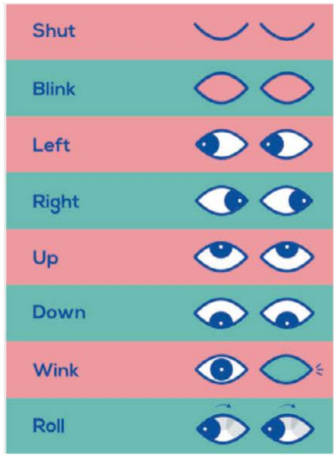

Fig. 1. Alphabets of Blink to Speak [9].

2 Related works

Studies found in state-of-art focused on interpreting BTS language messages are few and limited to recognizing only two alphabets [12, 13], in addition to fact that ocular movement patterns are not always interpreted as described in the BTS language manual [9]. Therefore, a search is conducted for works focused on activity of interest: monitoring of ocular activity.

2.1 Systems for eye movement monitoring

There are two main approaches to detecting ocular patterns: computer vision-based systems and sensor-based systems. Regarding computer vision-based systems, simple and affordable solutions have been presented, such as in [8], where a language of 64 messages is proposed using only 4 key alphabets based on BTS. This acquisition method is viable for classifying alphabets included in that language, but it is not suitable for BTS language since it cannot differentiate between moving eyes down and blinking. Another related work uses video frames, in which, by detecting 6 reference points around eye area, blinks are identified and counted, assigning interpretations to 4 patterns according to BTS language. The disadvantage of this work is that messages to be interpreted are limited, as only blinks can be counted [14].

Alternatively, there are sensor-based eye pattern recognition systems: in [15] an infrared sensor is used to count blinks and represent seven messages, two of these corresponding to BTS language. In addition, use of infrared reflectometry in an eye tracking system [16] stands out, where pupils are detected to identify eye movements. Another way to detect them is through magnetic field sensors, where the position of eye is detected by means of a special contact lens placed on eyeball [17]. Although these systems offer advantages, such as detection of specific patterns, some of them are limited by need to control external factors such as lighting and position of detection device, as well as complication in detection of some movements related to alphabets of BTS language when position of pupil remains in the same position, as in the case of blinking since only eyelid moves and when at rest pupil remains looking towards center. Another sensor-based system is electrooculography (EOG), which has shown promising results for identifying users of BTS language alphabets, without posing a risk [7]. Work has been developed in which eye movement patterns composed of up to 4 movements considered as alphabets (left, right, up and down) are classified [18–20], with performances around 75% accuracy. Its reported good performance and practicality of its implementation, without need to control external conditions such as lighting, highlights it as a viable alternative.

However, the need for an EOG-based system that interprets BTS language messages is present, which is why research focused on interpretation of this language has been developed in recent years.

2.2 Systems for interpreting the alphabets of the Blink to Speak language

Advanced works currently in state-of-art focused on interpretation of BTS language are based on EOG signals. First of them works with 10 messages of BTS language selected according to complexity of message and its communicative intention. EOG activity corresponding to each message is recorded in 20 subjects, from which features are extracted to train a decision tree model. 83.4% of accuracy of multiclass classification is reported. However, classification is dependent on length of record, which makes classification difficult when all messages of BTS language are to be classified [21].

Another study examines the classification of messages of BTS language from a general perspective, classifying 8 alphabets that make up the language [22]. This work records in 38 subjects EOG activity coming from 3 channels in bipolar configuration (horizontal channel, right channel and left channel). Each subject performs a series of 5 eye movements corresponding to each of alphabets of BTS language. EOG records are segmented to extract repetitions individually and they are featured in order to form dataset with which machine learning classifier models are trained. Random Forest (RF), Multi-Layer Perceptron Classifier and Decision Tree are tested, obtaining highest F1-score of 82% with RF model. This multiclass classification is performed considering records of all subjects, which makes it a between-subjects classification, however, there are also works that perform within-subject EOG signal classification.

2.3 Within-subject and between-subject classification of electrooculographic signals

EOG signal classification can be approached from two main approaches: within-subject (WS) and between-subject (BS). In the WS approach, model is trained and tested using data from same subject, which allows capturing individual characteristics of signals. However, BS classification involves use of records from multiple subjects, which presents challenge of interindividual variability, but offers a more generalizable system to new users [23]. This distinction is crucial for development of personalized or universal interfaces oriented to communication. Selection between these approaches depends on application and balance between desired precision and generalization in EOG eye movement recognition system.

Table 1 presents some of works found for classification of EOG signals corresponding to individual eye movements that in this context are considered alphabets of BTS language, regardless of their implementation. It is highlighted whether their classification is WS or BS.

Table 1. Within-subject and between-subject electrooculography activity classification work.

Work	WS or BS	Number of records and/or subjects used	Eye movements recognized	Results
[24]	BS	3 subjects, each performed 6 sequences of 12 movements	Left, right, up and down	94.11% correct
[25]	BS	3 subjects, each performed 5 times each movement	Left, right, up and down	Statistically significant features by ANNOVA
[26]	WS	4 subjects, each performed 56 movements	Left and right	96.9% Accuracy (classifier not reported)
[27]	WS	5 subjects, 10 repetitions of each movement	Left, right, up and down	100% separable features
[28]	BS	10 subjects, 5 movement sequences	Shut, up and wink	SVM classifier with 78% Accuracy
[29]	BS	12 subjects, each performed 10 movement sequences	Left and right	KNN classifier with 99% F1-score
[19]	WS	30 repetitions between the 4 movements	Left, right, up and down	MLP classifier with 75% Precision
[20]	WS	Sequence of the 4 movements during 10 seconds	Left, right, up and down	SVM classifier with 76.9% Jacard index

Although classification of EOG records corresponding to eye movements considered as alphabets of BTS language shows good performance, it is desired to know if for classification of all alphabets that make up BTS language it is convenient to perform a BS classification as reported in [22] or a WS classification.

3 Methodology

In order to make comparison between BS and WS classification, it is proposed to use dataset used in [22]. Next, we explain how it is composed and the analysis of similarities found in EOG records, which is why we decided to carry out this work.

Regarding WS classification, Random Forest model is used, which is machine learning model that obtains the best F1-score in BS classification.

3.1 Data Used

Dataset used to train classifier model is made up of features extracted from recorded EOG signals. Ocular activity was recorded using 7 gold cup electrodes in a bipolar configuration around eye area (see Fig. 2). It should be noted that recording was carried out under the approval of research protocol of University of Guadalajara, CUCS campus, with folio 24-16.

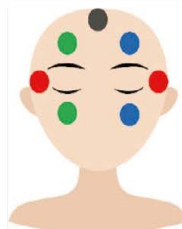

Fig. 2. Placement of gold cup electrodes for bilateral EOG recording (red electrodes for horizontal channel recording, green for right channel, blue for left channel and black for reference) [22].

Features were extracted from separate EOG channels: horizontal, right and left channels, and from signals resulting from combination of separate channels, such as subtraction of horizontal channel minus right channel, horizontal channel minus left channel and subtraction of right channel minus left channel, as well as sum of 3 separate channels. Arithmetic mean, variance, kurtosis, skewness, area under the curve, difference between maximum and minimum values and coefficients of a degree 5 polynomial of separate channels are calculated. As for characterization of signals resulting from combination of channels, they are characterized with arithmetic mean, variance, kurtosis, skewness, area under the curve and difference between maximum values (this last feature is not extracted from the sum signal of 3 channels). It should be noted that before extracting features, each record is added to its minimum value in order to ensure that all its values are positive and thus avoid arithmetic means close to zero.

Pearson correlation is calculated for 59 features calculated from EOG records and one of features with a correlation greater than ±0.9 is eliminated. In total, 21 attributes were eliminated, corresponding to arithmetic means and attributes from sum signal of 3 channels, except for area under the curve. Resulting data set with which the classifier models are trained and tested is composed of 38 attributes corresponding to the features obtained from EOG records and 1498 instances, belonging to repetitions of alphabets of BTS language that could be extracted from the 38 test subjects.

3.2 Similarity in electrooculographic recordings

In studies focused on BS classification, a comparison is conducted by analyzing average repetitions of each subject across different BTS alphabets (see Fig. 3).

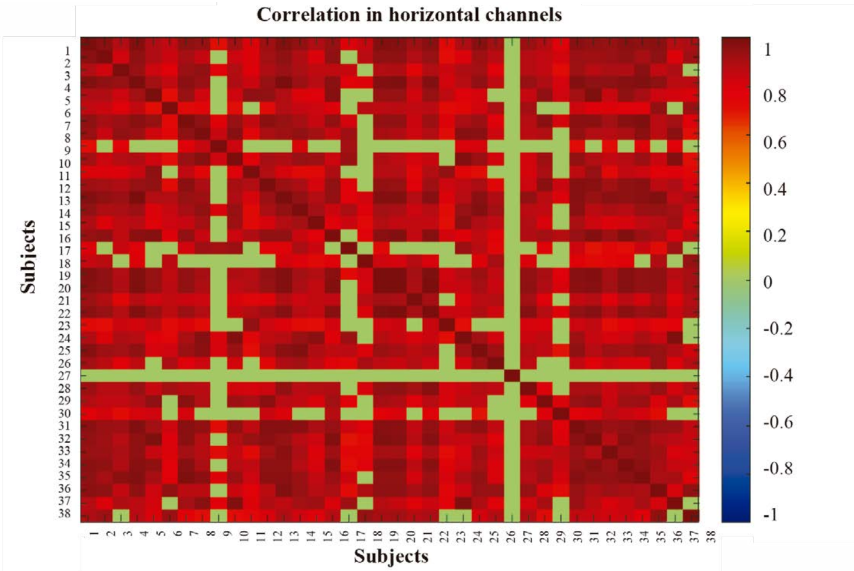

Fig. 3. Correlation matrix between the "Blink" alphabets in its horizontal channel. Modified from [22].

Correlations greater than 0.7 are counted and shown as a descending percentage in Table 2, where alphabets that appear at beginning of table are more replicable between different subjects, that is, they are more similar between different people and last ones are those that are made with greater differences between different people.

Table 2. Similarity between within-subject models of alphabets by channel. Modified from [22].

Alphabets	Horizontal Channel	Right Channel	Left Channel	Percentage of similarity between different subjects
Down	90.33 %	93.03 %	93.31 %	92.22 %
Blink	83.93 %	90.18 %	90.04 %	88.05 %
Up	46.23 %	72.40 %	70.55 %	63.06 %
Right	95.59 %	60.46 %	30.87 %	62.30 %
Shut	52.49 %	54.34 %	54.62 %	53.82 %
Left	79.66 %	54.20 %	18.78 %	50.88 %
Roll	41.11 %	45.09 %	30.01 %	38.74 %
Wink	13.51 %	20.91 %	13.51 %	15.98 %

Originally, comparison of each alphabet by channel is used to determine whether or not it is feasible to eliminate a recording channel. In context of this work, it is used to define alphabets that are most similar between different subjects. As observed in Table 2, "Down" and "Blink" are quite similar between different people, so in WS classification is not expected to improve for these particular alphabets. However, it is observed that "Wink", "Roll" and "Left" are very different between different subjects, so classification performance is expected to improve.

3.3 Training and testing of Random Forest

Since a comparison with BS classification results is desired, it is decided to use algorithm with the best reported F1-score, which is Random Forest. It is decided to take F1-score metric as a reference for performance of classification model since it is metric that encompasses precision and recall.

It is desired to obtain performance of WS models, that is, for each of 38 subjects that make up dataset, a Random Forest algorithm will be trained and tested, all with the same configuration. For each of subjects, only instances of dataset that belong to it are selected (around 40 instances) and data is divided randomly and stratified in order to ensure balance in number of instances per class both in training and testing. 60% of data is used for training and 40% for testing, and it is validated with cross-correlation. For each subject, model is trained and tested 20 times, using different training and testing data in each iteration, and average performance is reported at the end of 20 iterations.

4 Results and Discusión

Table 3 shows F1-score metric obtained from average of 20 iterations of Random Forest model, for each of subjects. Average performance of model and performances for each BTS alphabet are reported.

Table 3. F1-score performances for within-subject models.

Subjects	Average F1-score	Shut	Blink	Left	Right	Up	Down	Wink	Roll
Subject 1	88.04%	100.00%	69.00%	76.17%	100.00%	86.67%	73.50%	100.00%	99.00%
Subject 2	86.27%	94.67%	62.17%	100.00%	92.33%	72.67%	89.00%	91.67%	87.67%
Subject 3	76.94%	69.17%	76.02%	100.00%	85.67%	95.33%	95.33%	0.00%	94.00%
Subject 4	93.44%	97.00%	88.33%	100.00%	100.00%	76.33%	100.00%	100.00%	85.83%
Subject 5	97.67%	98.00%	100.00%	96.00%	91.67%	100.00%	99.00%	96.67%	100.00%
Subject 6	90.75%	93.33%	69.86%	100.00%	96.33%	70.83%	95.67%	100.00%	100.00%
Subject 7	89.58%	78.17%	83.50%	99.00%	94.00%	68.33%	100.00%	93.67%	100.00%
Subject 8	77.33%	90.67%	89.00%	97.33%	49.50%	53.33%	49.50%	92.33%	97.00%
Subject 9	98.33%	91.67%	95.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Subject 10	89.71%	87.67%	88.33%	85.33%	100.00%	97.00%	93.33%	83.67%	82.33%
Subject 11	68.56%	25.76%	30.05%	100.00%	74.00%	56.52%	89.67%	100.00%	72.50%
Subject 12	93.44%	90.67%	76.50%	100.00%	98.00%	93.67%	95.00%	98.00%	95.67%
Subject 13	88.69%	83.33%	85.33%	95.00%	99.00%	90.00%	87.33%	69.50%	100.00%
Subject 14	96.67%	100.00%	98.00%	96.67%	91.67%	98.33%	91.33%	99.00%	98.33%
Subject 15	95.46%	92.00%	80.00%	100.00%	96.67%	100.00%	95.00%	100.00%	100.00%
Subject 16	84.69%	90.33%	88.67%	100.00%	62.17%	51.67%	84.67%	100.00%	100.00%
Subject 17	94.46%	97.00%	99.00%	98.33%	95.67%	83.33%	95.33%	96.67%	90.33%
Subject 18	84.77%	90.00%	51.83%	97.00%	93.33%	63.00%	92.00%	100.00%	91.00%
Subject 19	82.13%	86.67%	62.17%	99.00%	95.86%	91.33%	86.67%	43.33%	92.00%
Subject 20	89.35%	87.00%	76.33%	100.00%	95.67%	74.83%	93.00%	93.33%	94.67%
Subject 21	67.56%	50.50%	34.95%	96.00%	78.52%	84.02%	75.67%	22.83%	98.00%
Subject 22	88.77%	79.17%	63.67%	100.00%	100.00%	75.36%	95.00%	97.00%	100.00%
Subject 23	84.77%	87.67%	80.67%	99.00%	82.83%	61.33%	66.67%	100.00%	100.00%
Subject 24	82.61%	51.33%	72.19%	100.00%	96.67%	62.33%	98.33%	90.33%	89.67%
Subject 25	82.29%	61.17%	48.83%	83.33%	95.83%	82.17%	97.00%	96.33%	93.67%
Subject 26	79.15%	75.00%	67.33%	95.00%	53.83%	77.50%	82.00%	90.00%	92.57%
Subject 27	88.56%	88.00%	76.50%	99.00%	83.33%	80.67%	83.00%	99.00%	99.00%
Subject 28	89.23%	85.17%	87.33%	99.00%	99.00%	82.00%	76.33%	85.00%	100.00%
Subject 29	88.33%	46.67%	75.50%	99.00%	100.00%	90.50%	100.00%	100.00%	95.00%
Subject 30	93.67%	95.67%	96.33%	94.00%	87.33%	100.00%	80.00%	99.00%	97.00%
Subject 31	98.00%	98.00%	98.33%	96.67%	96.67%	98.33%	100.00%	99.00%	97.00%
Subject 32	94.46%	94.67%	88.33%	100.00%	98.33%	100.00%	100.00%	77.33%	97.00%
Subject 33	84.98%	74.83%	55.67%	91.33%	100.00%	69.33%	95.33%	100.00%	93.33%
Subject 34	86.30%	99.00%	100.00%	100.00%	91.67%	81.33%	100.00%	48.83%	69.57%
Subject 35	92.06%	96.33%	87.50%	89.67%	98.00%	96.33%	87.33%	94.33%	87.00%
Subject 36	94.67%	92.00%	86.67%	100.00%	99.00%	100.00%	86.67%	100.00%	93.00%
Subject 37	82.92%	90.33%	93.00%	99.00%	92.19%	80.50%	60.86%	60.17%	87.33%
Subject 38	91.17%	95.33%	83.67%	96.33%	99.00%	81.67%	96.33%	87.33%	89.67%

Performance of Random Forest model in BS classification is compared with WS classification results obtained in this study, as shown in Table 4. First row of Table 4 presents the previously reported performance for BS classification, which serves as benchmark to surpass in WS classification. Second row indicates number of cases where performance improves, highlighted in green in Table 3. Conversely, third row displays number of cases where performance decreases by 60%, marked in red in Table 3.

Table 4. Performance evaluation for within-subject models.

	F1-score	Shut	Blink	Left	Right	Up	Down	Wink	Roll
Reported performance in between-subject classification [22]	82%	81.65%	72.11%	88.07%	93.74%	70.46%	90.41%	68.28%	84.34%
Number of subjects in which the F1-score improves	33	28	27	35	23	30	22	33	35
Number of subjects with an F1-score below 60%	0	4	5	0	2	3	1	4	0

When considering only performances of Random Forest model, WS classification generally outperforms BS classification. As shown in second row of Table 4, performance improves in 33 out of 38 subjects, with enhancements observed across all alphabets. However, it must be considered that this does not apply to all subjects, since in case of subjects 8 and 21 average performance of model does not improve and 3 of alphabets lower their performance to less than 60%.

Based on BTS alphabet similarities presented in Table 2, it was expected that "Down" and "Blink" would not improve their performances because they are very similar between different subjects. This is confirmed, as these alphabets are among the three with the least improvement, showing gains in only 22 and 27 out of 38 subjects, respectively. In contrast, "Wink", "Roll" and "Left" which exhibit the least similarity between subjects, benefit more from WS classification. This is validated by substantial improvements, with performance gains in 33, 35 and 33 subjects, respectively.

5 Conclusions and Future Work

Considering only performance of Random Forest classifier, WS classification, where the model is trained and tested with data from same subject, as done in this study, generally yields better results. However, applying this approach in real-life scenarios could present challenges, particularly regarding time required to record EOG patterns and train and test classification models. This process can be time-consuming, as it involves calibrating device that interprets BTS alphabets and performing multiple recordings of each alphabet.

WS classification can be especially beneficial for individuals who involuntarily perform movements outside the guidelines of BTS language. Examples include raising eyebrows when looking upward ("Up" alphabet), blinking when looking to "Left" or "Right" being unable to "Wink" with one eye, or struggling to perform "Roll" movement in specified direction.

For future work, to select what type of classification is desired to be performed for identification of BTS alphabets by means of EOG signals, it is essential to identify what priorities there are in research, if it is design of classifier models, it is suggested to train and test model with data from a single subject (WS classification), or for those cases in which subjects cannot correctly perform eye movements. On the other hand, if what is desired is to adapt the system that interprets BTS alphabets to different subjects more quickly, a classification that considers all subjects can be used (classification BS), sacrificing a little of the model's designs, but still obtaining acceptable results.

References

1. Hernández Rosado, M., Lluesma Rojas, M. de la C., De Veras Olivera, B.: Hacia una comunicación eficaz. Revista Cubana de Educación Superior. 38, (2019).
2. INEGI: Estadísticas a propósito del día internacional de las personas con discapacidad (datos nacionales). (2021).
3. Rico Ivorra, A.: Comunicación Aumentativa y Alternativa en personas con Esclerosis Lateral Amiotrófica y su impacto en la calidad de vida. (2021).
4. Zhang, J., Wang, B., Zhang, C., Xiao, Y., Wang, M.Y.: An EEG/EMG/EOG-based multimodal human-machine interface to real-time control of a soft robot hand. Front Neurorobot. 13, 420002 (2019).
5. Gutiérrez-Zermeño, M., Aguilera-Rodríguez, E., Barajas-González, E., Román-Godínez, I., Torres-Ramos, S., Salido-Ruiz, R.A.: Decoding Imagined Speech of Daily Use Words from EEG Signals Using Binary Classification. IFMBE Proc. 86, 293–301 (2023).
6. Silva-Acosta, V., Alfaro-Cortés, H.H., García-Manzo, R.E., Ruiz, R.A.S., Godínez, I.R., Ramos, S.T.: Clasificación inter-sujeto e intra-sujeto de señales SVEMG utilizando redes neuronales para la intención del habla. Miscelánea Científica en México. 575 (2020).
7. Belkhiria, C., Boudir, A., Hurter, C., Peysakhovich, V.: EOG-Based Human–Computer Interface: 2000–2020 Review. Sensors. 22, 4914 (2022).
8. Ezzat, M., Maged, M., Gamal, Y., Adel, M., Alrahmawy, M., El-Metwally, S.: Blink-To-Live eye-based communication system for users with speech impairments. Sci Rep. 13, 7961 (2023).
9. Sane, H., Nivins, S.: Blink to speak, https://www.blinktospeak.com/blink-to-speak-book, last accessed 2023/06/19.
10. Pinto, S., Quintarelli, S., Silani, V.: New technologies and Amyotrophic Lateral Sclerosis – Which step forward rushed by the COVID-19 pandemic? J Neurol Sci. 418, 117081 (2020).
11. Pugliese, R., Sala, R., Regondi, S., Beltrami, B., Lunetta, C.: Emerging technologies for management of patients with amyotrophic lateral sclerosis: from telehealth to assistive robotics and neural interfaces. J Neurol. 269, 2910–2921 (2022).
12. Jebakani, S., Divya, J., Megha, S., Santhosh, H.: Eye blink to voice for paralyzed patients. International Journal of Information Technology (IJIT). 6, (2020).
13. Tyagi, S., Gupta, A., Maurya, A., Garg, A., Vats, K., Kumar, A.: Design of Blink to Speak System for Paralysed People. i-Manager's Journal on Embedded Systems. 8, 14 (2020).

14. Tyagi, S., Gupta, A., Maurya, A., Garg, A., Vats, K., Kumar, A.: Design of Blink to Speak System for Paralysed People. i-Manager's Journal on Embedded Systems. 8, 14–19 (2020).
15. Malini, V., Jeevanandham, S., Gokul, P., Prathibanandhi, K., Kurinjimalar, L.: Blink To Speak an assistive device for Paralyzed people. In: 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS). pp. 1–3 (2022).
16. Buitrago Jiménez, R.: Sistema de medida de movimientos oculares basado en reflectometría infrarroja, (2017).
17. Gila, L., Villanueva, A., Cabeza, R.: Fisiopatología y técnicas de registro de los movimientos oculares. In: Anales del sistema sanitario de Navarra. pp. 9–26. SciELO Espana (2009).
18. Nathan, D.S., Vinod, A.P., Thomas, K.P.: An electrooculogram based assistive communication system with improved speed and accuracy using multi-directional eye movements. 2012 35th International Conference on Telecommunications and Signal Processing, TSP 2012 - Proceedings. 554–558 (2012).
19. Pérez-Reynoso, F.D., Rodríguez-Guerrero, L., Salgado-Ramírez, J.C., Ortega-Palacios, R.: Human–Machine Interface: Multiclass Classification by Machine Learning on 1D EOG Signals for the Control of an Omnidirectional Robot. Sensors (Basel). 21, 5882 (2021).
20. Hernández Pérez, S.N., Pérez Reynoso, F.D., Gutiérrez, C.A.G., Cosío León, M.D. los Á., Ortega Palacios, R.: EOG Signal Classification with Wavelet and Supervised Learning Algorithms KNN, SVM and DT. Sensors 2023, Vol. 23, Page 4553. 23, 4553 (2023).
21. Padilla-Becerra, M.C., Macias-Castro, D.K., Salido-Ruiz, R.A., Torres-Ramos, S., Román-Godínez, I.: EOG Signal Classification Based on Blink-to-Speak Language. IFMBE Proc. 96, 249–257 (2024).
22. Padilla-Becerra, M.C., Salido-Ruiz, R.A., Román-Godínez, I., Santos-Arce, S.: Caracterización de patrones electrooculográficos relacionados con el lenguaje "Blink to Speak", (2024).
23. Sun, W., Lv, Z., Wu, M., Bi, N., Zhang, S.: A Comparative Experimental Study between Instantaneous and Convolutional BSS Models for Saccadic EOG Signal Separation. IEEE Trans Instrum Meas. 70, (2021).
24. Merino, M., Rivera, O., Gómez, I., Molina, A., Dorronzoro, E.: A method of EOG signal processing to detect the direction of eye movements. In: 2010 First International Conference on Sensor Device Technologies and Applications. pp. 100–105. IEEE (2010).
25. Aungsakul, S., Phinyomark, A., Phukpattaranont, P., Limsakul, C.: Evaluating Feature Extraction Methods of Electrooculography (EOG) Signal for Human-Computer Interface. Procedia Eng. 32, 246–252 (2012).
26. Jiang, J., Zhou, Z., Yin, E., Yu, Y., Hu, D.: Hybrid Brain-Computer Interface (BCI) based on the EEG and EOG signals. Biomed Mater Eng. 24, 2919–2925 (2014).
27. Phukpattaranont, P., Aungsakul, S., Phinyomark, A., Limsakul, C.: Efficient feature for classification of eye movements using electrooculography signals. Thermal Science. 20, 563–572 (2016).
28. Kumar, D., Sharma, A.: Electrooculogram-based virtual reality game control using blink detection and gaze calibration. 2016 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2016. 2358–2362 (2016).

29. Babita, Syal, P., Kumari, P.: Comparative Analysis of KNN, SVM, DT for EOG based Human Computer Interface. International Conference on Current Trends in Computer, Electrical, Electronics and Communication, CTCEEC 2017. 1023–1028 (2018).