Informatics and Technology in Clinical Care and Public Health
J. Mantas et al. (Eds.)

doi:10.3233/SHTI210852

Prediction of Postoperative Speech Dysfunction Based on Cortico-Cortical Evoked Potentials and Machine Learning

Timur ISHANKULOV[a,1], Gleb DANILOV[a], David PITSKHELAURI[a], Oleg TITOV[a], Anna OGURTSOVA[a], Svetlana BUKLINA[a], Evgeniy GULAEV[b], Tatyana KONAKOVA[a] and Andrey BYKANOV[a]

[a] *Laboratory of Biomedical Informatics and Artificial Intelligence, National Medical Research Center for Neurosurgery named after N.N. Burdenko, Moscow, Russian Federation*

[b] *National Medical Research Center of Traumatology and Orthopedics named after N.N. Priorov, Moscow, Russian Federation*

Abstract. The possibility of postoperative speech dysfunction prediction in neurosurgery based on intraoperative cortico-cortical evoked potentials (CCEP) might provide a new basis to refine the criteria for the extent of intracerebral tumor resection and preserve patients' quality of life. In this study, we aimed to test the quality of predicting postoperative speech dysfunction with machine learning based on the initial intraoperative CCEP before tumor removal. CCEP data were reported for 26 patients. We used several machine learning models to predict speech deterioration following neurosurgery: a random forest of decision trees, logistic regression, support vector machine with different types of the kernel (linear, radial, and polynomial). The best result with F1-score = 0.638 was obtained by a support vector machine with a polynomial kernel. Most models showed low specificity and high sensitivity (reached 0.993 for the best model). Our pilot study demonstrated the insufficient quality of speech dysfunction prediction by solely intraoperative CCEP recorded before glial tumor resection, grounding our further research of CCEP postresectional dynamics.

Keywords. CCEP, cortico-cortical evoked potentials, machine learning, artificial intelligence, neuro-oncology, glial tumors, speech function

1. Introduction

Structural and functional neural networks underlying such human brain functions as speech are a permanent research subject for modern brain connectomics [1]. Intraoperative preservation of speech function is one of the most important goals in neurosurgery of intracerebral tumors located near eloquent areas [2]. The monitoring of the effective connections through language pathways during brain tumor surgery can be achieved by recording cortico-cortical evoked potentials (CCEPs) [3–5]. Nowadays the number of such studies is very limited.

[1] Corresponding Author, Timur Ishankulov, N.N. Burdenko Neurosurgery Center, 4th Tverskaya-Yamskaya str. 16, Moscow 125047, Russian Federation; E-mail: tishankulov@nsi.ru.

This pilot study aimed to predict speech function deterioration in the early postoperative period based on intraoperative cortico-cortical evoked potentials [6] recorded before glial tumor removal. The hypothesis we tested was that the baseline CCEPs might contain predictors of postoperative speech disorders. The exploration of CCEPs patterns might contribute to refine the criteria for the extent of intracerebral tumor resection and preserve patients' quality of life.

2. Methods

Intraoperative registration of CCEPs [7] was performed using a 32-channel intraoperative monitoring system "Neuro-IOM" (Neurosoft LLC, Russia) and a pair of subdural electrode strips. One electrode was placed in the frontal speech region (Broca's area); the second electrode was located on the surface of the upper temporal gyrus in its posterior parts and the supramarginal gyrus. The CCEPs were registered before and after resection of the tumor.

The dataset obtained contained recordings of 26 patients with brain gliomas in eloquent areas. The number of CCEP recordings for each patient was not set in this pilot study (varied from 1 to 8). The dataset included a set of files (n = 105, 1 file for each recording) with intraoperative CCEPs records before tumor removal. Each record contained 8 or 16 signal channels with high correlation between them.

The duration of the signal recording after stimulation was 300 ms. Each signal record included 7,500 discrete values in 8 or 16 channels. A vector of 7500 values was averaged and smoothed by the moving average method, transforming into a new vector consisting of 300 average values. Stimulation artifacts were automatically removed by comparing with the amplitude of the remaining signal part multiplied by 1.25. If this value was exceeded, then the starting index was shifted up to 10 ms to the right. In addition, the starting index of the signal was always shifted by 1 ms, even if the artifact was not observed, in order to exclude the influence of the first millisecond of the signal.

The basic set of signal features included signal amplitude, wave type, latency up to a peak (positive or negative) value [7]. Neurophysiologists typically used them to describe the CCEPs records. A medical expert indicated the characteristics of speech dysfunctions before and after surgery for each patient.

The average value across the entire signal was calculated and used as an additional feature. The peak values (local extremums) were calculated with a minimum distance between the peaks equal to 20 ms and a minimum peak height of 5 μV.

We formed the target variable based on the changes in the cumulative assessment of the patient's speech dysfunctions after surgery ranging from 0 to 45 (0 is the norm). The binary target variable took a value of 1 if the speech dysfunctions estimate increased after surgery (speech worsened) and a value of 0 otherwise (speech preserved).

Several machine learning models were used to predict the deterioration of speech functions in the postoperative period: a random forest of decision trees (RF), logistic regression (LR), support vector machine (SVM) with different types of kernel – linear (Lin), radial basis function (RBF) and polynomial (Poly). Each test was performed after the data were randomly sampled into training (80%) and testing (20%) subsets with stratification. The model was trained on a training subset; 5-fold cross-validation (CV) was applied to evaluate the model's quality before the final testing. Each machine learning model was tested 300 times with stratified resampling (1500 tests in total). This approach allowed to do the calculations with low margin of error (<0.005).

We used standard metrics to evaluate the test results: accuracy on validation samples within the cross-validation (CV), specificity (Spec), sensitivity (Sens), the proportion of correct classifier responses (Acc), precision (Prec), recall (Rec), F1-score (F1) and the area under the receiver operating characteristic curve (AUC). The results for particular machine learning model were averaged across all metrics to exclude the influence of the "by chance" data split and to reduce the margin of error. We separated data by patients — all the recordings of each patient were included into the only one subset: train or test.

3. Results

The results of our classification experiments are presented in Table 1.

Table 1. Classification of CCEPs data by binary outcome with 5 machine learning models.

Model	CV	Spec	Sens	Prec	Rec	Acc	F1	AUC
RF	0.680	0.319	0.809	0.569	0.564	0.606	0.530	0.564
LR	0.687	0.168	0.965	0.555	0.566	0.649	0.500	0.566
SVM (Lin)	0.674	0.098	0.944	0.411	0.521	0.612	0.432	0.521
SVM (RBF)	0.730	0.324	0.973	0.649	0.649	0.716	0.604	0.649
SVM (Poly)	**0.747**	**0.370**	**0.993**	**0.683**	**0.681**	**0.747**	**0.638**	**0.681**

The results of cross-validation were expectedly higher (equal in case of SVM (Poly) model) compared to the accuracy of test results. The difference between mentioned metrics varied from 0 to 0.074 (up to 12% decrease).

The best result for the F1-score metric was 0.638 using the SVM (Poly) model. A high sensitivity index was observed in most tests, reaching 0.993 in the best model. The specificity of the best solution was 0.370 — the model correctly identified only 37% of patients with improved/preserved speech functions.

4. Discussion

Our pilot research considered methods for predicting the deterioration or improvement/preservation of speech functions in the postoperative period using machine learning algorithms. This is the pioneering study to apply machine learning for predicting speech dysfunctions based on CCEP data to the best of our literature knowledge.

Researchers rely on such parameters as the amplitude of value fluctuation and the latency to the signal peak in the analysis of CCEP data (7–11). We utilized the average for all signal values, the latency to the signals' peak states (local extremums), and their values in µV in addition to common parameters.

The obvious limitations of this study are a relatively small number of patients (n = 26), several recordings per patient in one sample and the insufficient number of CCEP recordings after tumor removal. Increasing the amount of data may lead to a higher classification quality.

In our classification approach, we used a binary target variable. Thus, the dataset was split with a smaller possible imbalance compared to using the target variable broke down into several categories according to speech disorders degree (in the latter case, there was a significant imbalance between classes). It will be possible to test CCEPs classification by speech dysfunctions severity with the increased number of patients.

This pilot study demonstrated the insufficient quality of speech dysfunction prediction by solely intraoperative CCEP recorded before glial tumor resection. Our future work will be related to testing new methods for predicting speech disorders, focusing on postresectional CCEP dynamics, adding new features to existing models, and developing new machine learning models, including ensembles.

5. Conclusion

In this pilot study, the quality of speech dysfunction prediction after the neurosurgical interventions in the eloquent area was demonstrated using traditional machine learning methods based on the CCEP data registered before the main stage of surgery. Early detection of the speech dysfunction precursors, according to the CCEP data, can significantly affect the results of such neurosurgery. Thus, it is necessary to continue the research of CCEPs that contributes to a better understanding of speech dysfunctions resulting from surgical interventions and greater surgery safety.

The research was supported by the Russian Foundation for Basic Research grant 19-29-01231.

References

[1] Sporns O. The human connectome: A complex network. Annals of the New York Academy of Sciences. 2011:109–25.

[2] Yamao Y, Matsumoto R, Kikuchi T, Yoshida K, Kunieda T, Miyamoto S. Intraoperative Brain Mapping by Cortico-Cortical Evoked Potential. Vol. 15, Frontiers in Human Neuroscience. 2021.

[3] Leisman G, Moustafa A, Shafir T. Thinking, Walking, Talking: Integratory Motor and Cognitive Brain Function. Front Public Heal. 2016;4.

[4] Kunieda T, Yamao Y, Kikuchi T, Matsumoto R. New approach for exploring cerebral functional connectivity: Review of cortico-cortical evoked potential. Neurologia Medico-Chirurgica. 2015;55:374–82.

[5] Huang C-C, Chang C-S, Hsin Y-L. Time–frequency spectral analysis of cortico-cortical evoked potentials by means of Hilbert–Huang transform. Brain Stimul. 2015;8(2):388.

[6] Matsumoto R, Nair DR, LaPresto E, Bingaman W, Shibasaki H, Lüders HO. Functional connectivity in human cortical motor system: A cortico-cortical evoked potential study. Brain. 2007;130(1):181–97.

[7] Bykanov AE, Pitskhelauri DI, Titov OY, Lin MC, Gulaev E V., Ogurtsova AA, et al. Broca's area intraoperative mapping with cortico-cortical evoked potentials. Zhurnal Vopr Nejrokhirurgii Im NN Burdenko. 2020;84(6):49–56.

[8] Conner CR, Ellmore TM, DiSano MA, Pieters TA, Potter AW, Tandon N. Anatomic and electrophysiologic connectivity of the language system: A combined DTI-CCEP study. Comput Biol Med. 2011;41(12):1100–9.

[9] Silverstein BH, Asano E, Sugiura A, Sonoda M, Lee MH, Jeong JW. Dynamic tractography: Integrating cortico-cortical evoked potentials and diffusion imaging. Neuroimage. 2020;215.

[10] Saito T, Tamura M, Muragaki Y, Maruyama T, Kubota Y, Fukuchi S, et al. Intraoperative cortico-cortical evoked potentials for the evaluation of language function during brain tumor resection: Initial experience with 13 cases. J Neurosurg. 2014;121(4):827–38.

[11] Kubota Y, Enatsu R, Gonzalez-Martinez J, Bulacio J, Mosher J, Burgess RC, et al. In vivo human hippocampal cingulate connectivity: A corticocortical evoked potentials (CCEPs) study. Clin Neurophysiol. 2013;124(8):1547–56.