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ESTIMATION OF THE DEPTH OF ANESTHESIA BY ELECTROENCEPHALOGRAM USING NEURAL NETWORKS

Abstract.
Introduction. *Monitoring of the depth of anesthesia (DA) during surgery is a complex task. Since electroencephalogram (EEG) signals contain valuable information about processes in the brain, EEG analysis is considered to be one of the most useful methods for the study and assessment of anesthetic depth in clinical applications. While the EEG of conscious subjects, as a rule, contains mixed alpha and beta rhythms, the frequency composition of the EEG is affected by anesthesia. Changes in EEG signals caused by the transition from a conscious state to that of deep anesthesia manifest as a shift of the spectral components of the signal to the lower part of the frequency range. However, anesthesia causes a whole range of neurophysiological changes, which cannot be correctly assessed using a single indicator.*
Objective. *In order to adequately describe complex processes during the transition from a conscious state to that of deep anesthesia, a method for assessing DA is proposed that uses a comprehensive set of parameters reflecting changes in the EEG signal. The article presents the results of the study into the possibility of building a regression model based on artificial neural networks (ANN) to determine depth of anesthesia using a set of parameters calculated by EEG.*
Materials and methods. *The authors of the article propose a method for assessing DA based on the use of neural networks, whose input parameters are time and frequency, as well as EEG parameters comprising spectral entropy (SE), burst-suppression ratio (BSR), spectral edge frequency (SEF95) and relative beta ratio (RBR) for three pairs of frequency ranges.*
Results. *The optimal ANN parameters were determined, at which the highest level of regression is achieved between the calculated and the verified DA index values.*
Conclusion. *In order to create a more practically applicable version of the algorithm, it is necessary to further investigate the noise stability of the proposed method and develop a set of algorithmic solutions that ensure the reliable operation of the algorithm in the presence of noise.*

Key words: EEG, Depth of anesthesia estimation, Artificial neural networks, Spectral entropy, BIS-index

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ОЦЕНКА ГЛУБИНЫ АНЕСТЕЗИИ ПО ЭЛЕКТРОЭНЦЕФАЛОГРАММЕ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННЫХ СЕТЕЙ

Аннотация
Введение. *Мониторинг глубины анестезии при проведении хирургических операций является сложной задачей. Поскольку сигналы электроэнцефалограммы (ЭЭГ) содержат ценную информацию о процессах в головном мозге, анализ ЭЭГ рассматривается как один из наиболее полезных методов в исследовании и оценке глубины анестезии в клинических применениях. Анестезирующие средства влияют на частотный состав ЭЭГ. ЭЭГ бодрствующих субъектов, как правило, содержит смешанные альфа- и бета-ритмы. Изменения в ЭЭГ, вызванные переходом от состояния бодрствования к состоянию глубокой анестезии, проявляются в виде смещения спектральных составляющих сигнала к нижней части диапазона частот. Однако анестезирующие средства вызывают целый комплекс нейрофизиологических изменений, который невозможно правильно оценить только одним показателем.*
Цель работы. *Для адекватного описания сложных процессов в период перехода от бодрствования к глубокой анестезии необходим метод оценки глубины анестезии, использующий комплексный набор параметров, отражающих изменения в сигнале ЭЭГ. В настоящей статье представлены результаты исследования возможности построения регрессионной модели на основе искусственных нейронных сетей (ИНС) для определения уровней анестезии с использованием набора рассчитываемых по ЭЭГ параметров.*
Материалы и методы. *Предложен метод оценки уровня анестезии, основанный на применении ИНС, входными параметрами которых являются временны́е и частотные показатели ЭЭГ, а именно: спектральная энтропия; отношение "вспышки/подавление"; спектральная краевая частота и логарифм отношения мощностей спектра для трех пар частотных диапазонов.*
Результаты. *Были определены оптимальные параметры ИНС, при которых достигается наивысший уровень регрессии между рассчитанными и верифицированными значениями показателя глубины анестезии.*
Заключение. *Для создания практического варианта алгоритма необходимо дополнительно исследовать помехоустойчивость рассматриваемого метода и разработать комплекс алгоритмических решений, обеспечивающих надежную работу алгоритма при наличии шумов.*

Ключевые слова: ЭЭГ, оценка глубины анестезии, искусственные нейронные сети, спектральная энтропия, BIS-индекс

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Introduction. During general anesthesia, a patient experiences a complete loss of consciousness achieved through a combination of injectable and inhaled drugs. This type of anesthesia is often used for highly invasive surgical interventions or when a complete relaxation of the patient is needed. The most important task of the anesthesiologist is to ensure optimal dosages that prevent episodes of intraoperative consciousness, which can cause dangerous psychological effects in patients [1]. Therefore, an anesthesiologist should be able to accurately control the depth of anesthesia (DA) and ensure its adequacy. Thus, the development of methods and algorithms for the accurate assessment of the depth of anesthesia during surgical operations is particularly important.

Over the past two decades, new DA assessment approaches based on electroencephalogram (EEG) signal processing have been adopted, replacing traditional haemodynamic monitoring methods. Since anesthesia has a direct effect on the synaptic activity of brain neurons [2], it is possible to use EEG analysis to permit a quantitative DA assessment [3], [4].

Due to the complexity of an EEG visual interpretation, it is necessary to use automatic computer-aided signal processing techniques to assess anesthetic depth. A number of studies report on the use of non-linear analysis to assess DA using EEG. In particular, in [5], the use of spectral entropy and approximate entropy to quantify the regularity of an EEG signal was investigated. The results demonstrate the high sensitivity of these parameters to signal frequency content and dose of anesthetic drug. The DA parameter, namely a spectral edge frequency (SEF), is studied in [6]. The sensitivity and specificity for predicting a movements occurrence during anesthesia are 72 and 82%, respectively, when a frequency threshold value is SEF=14 Hz.

The bispectral index (BIS) is a widely used algorithm for DA assessment [3], [7]. The BIS algorithm comprises a complex time-frequency parameter having several sub-parameters whose values change according to a patient's DA. BIS indices near zero values correspond to a very low brain activity state, and values in the interval from 20 to 80 denote different levels of surgical anesthesia, while their values close to 100 mean a patient wakefulness. Two BIS-index sub-parameters are burst-suppression ratio (BSR) and relative beta ratio (RBR) [7].

Anesthesia causes a complex of neurophysiological changes, which determines the EEG complexity [3]. An entire set of EEG parameters describing all factors of transition from wakefulness to deep anesthesia is required in order to be able to quantify these changes. After the required set of EEG parameters has been formed, it can be used to calculate numerical indicators that characterise various stages of anesthesia.

The rapid technology evolution contributes to the emergence of new recognition and classification methods, among which those based on neural networks are among the most promising. Artificial neural networks (ANN) are computational algorithms consisting of a series of interconnected elementary processors (cells or neurons). Since the most important feature of ANNs is the ability to learn, they are suitable for tasks related to pattern recognition, prediction, optimisation and classification. Technically, learning implies the ability to find coefficients of connections between neurons. In the process of learning, a neural network is able to detect complex dependencies between input and output data, as well as perform a generalisation. Each cell is characterised by a transfer function that processes its input information, while its weighted output is sent to other cells that are associated with it [8], [9].

In the present study, which aims to investigate the possibility of building an ANN-based regression model to determine levels of anesthesia using a set of parameters calculated by EEG, the following parameters are used as inputs:

– spectral entropy (SE);
– burst-suppression ratio (BSR);
– spectral edge frequency (SEF95);
– logarithm of the relative beta ratio (RBR) for three pairs of frequency bands.

Materials and methods. The data consist of EEG records obtained during surgery via electrodes located on a patient's forehead. The anesthetic used is Propofol. In parallel with the signal recording, control device (anesthesia monitor) readings are recorded once every 30 seconds, which allow a quantitative estimation of anesthesia via BIS-index. The study uses a set of 319 EEG fragments of 30 seconds each; these are selected to allow presentation of the entire range of BIS-index values as evenly as possible. The algorithm and experiments implementations are performed by using the MATLAB software.

Calculation of parameters. The BSR sub-parameter is used to evaluate the burst-suppression ratio during deep anesthesia. In this case, signal segments having very low amplitude alternate with high amplitude segments. To calculate this parameter, "suppression" segments are identified as periods having a duration of at least 0.5 s when the EEG voltage does not exceed ±5.0 μV [7]. Following a calculation of the total time in a "suppression" state, the BSR parameter is determined as a fraction of the segment's total length where EEG meets the "suppression" criteria.

In order to determine the spectral entropy value, a calculation of power spectral density (PSD) is performed using the fast Fourier transform method. Then the obtained PSD is normalised so that the result of multiplying the total signal power in a certain frequency band $f_1 \le f \le f_2$ by normalisation constant is equal to one:

$$\sum_{f_i=f_1}^{f_2} P_{\mathrm{n}}(f_i) = C_{\mathrm{n}} \sum_{f_i=f_1}^{f_2} P_0(f_i) = 1,$$

where $P_n(f_i)$ is the normalised PSD value; C_n is the normalisation constant; $P_0(f_i)$ is a PSD value of EEG signal at the *i*-th frequency value in a studied range.

Next, spectral entropy values are calculated [10]:

$$\mathrm{SE} = \sum_{f_i = f_1}^{f_2} P_n(f_i) \lg \frac{1}{P_n(f_i)}.$$

To calculate the normalised $\mathrm{SE_n}$ value, the obtained result is divided by the lg*N* value, where *N* is a number of frequency components:

$$\mathrm{SE_n} = \mathrm{SE}/\lg N.$$

The spectral edge frequency (SEF95) is a frequency within which 95% of spectrum power is concentrated. SEF95 usually decreases during anesthesia [7]. The RBR parameter is a logarithm of the total power ratio P_0 in an empirically-defined, low-frequency band (from 0 to 1.5 Hz) to the sum of this quantity and a total power P_i in the *i*-th frequency range:

$$\mathrm{RBR}_i = \lg \frac{P_0}{P_0 + P_i},$$

where $i = 1$, 2, 3, and P_1, P_2, P_3 are calculated for frequency ranges of 7–16, 4–6 and 16–30 Hz, respectively. These ranges are chosen empirically according to the best separation between different anesthetic state criteria [11], [12].

Thus, a set of six EEG indicators is formed, namely SE, BSR, SEF95, RBR_1, RBR_2 and RBR_3 for all verified levels of anesthesia.

Selection of ANN structure. These parameters are used as ANN input variables for all levels of anaesthesia. For the ANN training and testing, samples are first randomly mixed and then divided into the following databases: a training database made up of 60% of the total sample size, a validation database composed of 20% of the total sample size and a test database comprising 20% of the total sample size.

In order to assess anesthesia levels, the most appropriate approach for modelling the ANN structure is the multilayer perceptron (MLP) model [13], since it can be used to solve the regression problem for one output parameter. The ANN effectiveness is estimated by using the regression coefficient *R*. Structures with one, two, three and four hidden layers are investigated. The number of neurons in each hidden layer varies from 10 to 100 with a step of 5 neurons. Hyperbolic tangent and linear functions are selected as activation functions of the hidden and output layers, respectively [14], [15].

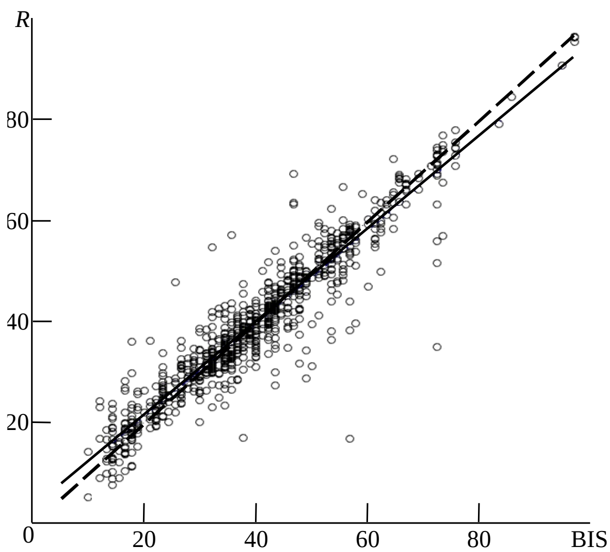
Results analysis. The table shows regression coefficients R_{av} for ANN different structures that are averaged over test sample values. The highest value of the coefficient $R_{av} = 0.94$ is achieved for an ANN structure having hidden layers containing 60, 35, 35 and 60 neurons in the first, second, third and fourth layers, respectively. Studies have shown that a further increase in the number of layers does not lead to an increase in the average coefficient value.

Regression coefficient values averaged over the test sample

Number of ANN hidden layers	R_{av}
1	0.87
2	0.88
3	0.89
4	0.94

The testing results of the developed ANN are presented in the figure, which compares the ANN predicted values of anesthesia depth D with the BIS-index values obtained on the test sample. The circles denote results obtained from the sample elements, the solid line shows a comparison of the BIS-index and ANN results, while the dashed line reflects the indices complete matching.

The figure shows that the depth of anesthesia estimates formed by ANN are in a good agreement with the results obtained by the traditional methodology of the anesthesia depth estimation.



Results comparison of anesthesia depth predictions given by the artificial neural network and BIS-index values

Conclusion. In the presented study, an ANN-based method for assessing the level of anesthesia, whose input parameters are EEG parameters of time and frequency, namely: spectral entropy (SE); burst-suppression ratio (BSR); spectral edge frequency (SEF95) and logarithm of the relative band ratio (RBR) for three pairs of frequency bands is proposed. The optimal ANN parameters take the form of a multilayer perceptron, in which the highest level of regression is achieved between the calculated and the verified values of the anaesthesia depth indices, are determined. The proposed method can be used in anesthesia monitors used to control the depth of anaesthesia in order to select an adequate dose of anesthesia during surgical procedures, allowing both intraoperative consciousness episodes and excessively deep anesthesia to be avoided. In order to create a practical version of the algorithm, it will be necessary to further investigate the noise immunity of the proposed method and develop a set of algorithmic solutions that ensure a reliable execution of the algorithm in the presence of sources of noise.

REFERENCES

1. Rampil IJ. A primer for EEG signal processing in anaesthesia. Anesthesiology. 1998, vol. 89, pp. 980–1002.

2. Welling P. G. Pharmacokinetics: Processes, Mathematics, and Applications. 2nd ed. Washington DC: American Chemical Society. 1997, 393 p.

3. Glass P. S., Bloom M., Kearse L., Rosow C., Sebel P., Manberg P. Bispectral analysis measures sedation and memory effects of propofol, midazolam, isoflurane, and alfentanil in normal volunteers. Anesthesiology, 1997, vol. 86(4), pp. 836–847.

4. Traast H. S., Kalkman C. J. Electroencephalographic characteristics of emergence from propofol/sufentanil total intervenouse anesthesia. Anesthesia & Analgesia. 1995, vol. 81(2), pp. 366–371. doi: 10.1097/00000539-199508000-00027

5. Ferenets R., Vanluchene A., Lipping T., Heyse B., Struys M. Behavior of Entropy/Complexity Measures of the Electroencephalogram during Propofol-induced Sedation. Anesthesiology, 2007, vol. 106(4), pp. 696–706. doi:10.1097/01.anes.0000264790.07231.2d

6. Schwender D., Daunderer M., Mulzer S., Klasing S., Finsterer U., Peter K. Spectral edge frequency of the electroencephalogram to monitor 'depth' of anaesthesia with isoflurane or propofol. British Journal of Anaesthesia, 1996, vol. 77(2), pp. 179–184. doi: 10.1093/bja/77.2.179

7. Tong S., Thakor N. V. Quantitative EEG Analysis Methods and Clinical Applications. Norwood: Artech House, 2009, 421 p.

8. Hossein R., Alireza M. D., Mehrab G. Estimation the Depth of Anesthesia by the Use of Artificial Neural Network // Artificial Neural Networks. Methodological Advances and Biomedical Applications. Ed. by Kenji Suzuki. 2011. P. 283–302. doi: 10.5772/15139

9. Viertiö-Oja H., Maja V., Särkelä M., Talja P., Tenkanen N., Tolvanen-Laakso H., Paloheimo M., Vakkuri A., Yli-Hankala A., Meriläinen P. Description of the Entropy algorithm as applied in the Datex-Ohmeda S/5 Entropy Module. Acta Anaesthesiol. Scand. 2004, vol. 48(2), pp. 154–161. doi: 10.1111/j.0001-5172.2004.00322.x

10. Al-Ghaili M. A., Kalinichenko A. N. Evaluation of Depth of Anesthesia Based on Joint Analysis of EEG Frequency and Time Parameters. Isvestiya SPBGETU "LETI" [Proceedings of Saint Petersburg Electrotechnical University], 2018, no. 3, pp. 80–85. (In Russian)

11. Amin H. U., Mumtaz W., Subhani A. R., Saad M. N. M., Malik A. S. Classification of EEG Signals Based on Pattern Recogni-tion Approach. Frontiers in Computational Neuroscience, 2017, vol. 11, art.103. P. 1–12.

12. Lee B., Won D., Seo K., Kim H. J., Lee S. Classification of Wakefulness and Anesthetic Sedation Using Combination Feature of EEG and ECG. Proc. of 2017 5th Intern. Winter Conf. on Brain-Computer Interface (BCI). Sabuk, South Korea, 9–11 Jan. 2017. Piscataway: IEEE, 2017, pp. 88–90. doi: 10.1109/IWW-BCI.2017.7858168

13. Shalbaf R., Behnam H., Sleigh J. W., Steyn-Ross A., Voss L. J. Monitoring the Depth of Anesthesia Using Entropy Features and an Artificial Neural Network. J. of Neuroscience Methods, 2013, vol. 218, iss. 1, pp. 17–24.

14. Benzy V. K., Jasmin E. A., Koshy R. C., Amal F. Wavelet Entropy Based Classification of Depth of Anesthesia. 2016 Intern. Conf. on Computational Techniques in Information and Communication Technologies (ICCTICT), New Delhi, India, 11–13 March 2016. Piscataway, IEEE, 2016, pp. 521–524. doi: 10.1109/ICCTICT.2016.7514635

15. Arslan A., Şen B., Çelebi F. V., Peker M., But A. A Comparison of Different Classification Algorithms for Determining the Depth of Anesthesia Level on a New Set of Attributes. 2015 Intern. Symp. on Innovations in Intelligent Systems and Applications (INISTA), Madrid, Spain, 2–4 Sept. 2015. Piscataway, IEEE, 2015, pp. 1–7. doi: 10.1109/INISTA.2015.7276738

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СПИСОК ЛИТЕРАТУРЫ

1. Rampil IJ. A Primer for EEG Signal Processing in Anaesthesia // Anesthesiology. 1998. Vol. 89. P. 980–1002.

2. Welling P. G. Pharmacokinetics: Processes, Mathematics and Applications. 2nd ed. Washington DC: American Chemical Society. 1997. 393 p.

3. Bispectral Analysis Measures Sedation and Memory Effects of Propofol, Midazolam, Isoflurane and Alfentanil In Normal Volunteers / P. S. Glass, M. Bloom, L. Kearse, C. Rosow, P. Sebel, P. Manberg // Anesthesiology. 1997. Vol. 86(4). P. 836–847.

4. Traast H. S., Kalkman C. J. Electroencephalographic Characteristics of Emergence from Propofol/Sufentanil Total Intervenouse Anesthesia // Anesthesia & Analgesia. 1995. Vol. 81(2). P. 366–371. doi: 10.1097/00000539-199508000-00027

5. Behavior of Entropy/Complexity Measures of the Electroencephalogram during Propofol-induced Sedation / R. Ferenets, A. Vanluchene, T. Lipping, B. Heyse, M. Struys // Anesthesiology. 2007. Vol. 106(4). P. 696–706. doi:10.1097/01.anes.0000264790.07231.2d

6. Spectral Edge Frequency of the Electroencephalogram to Monitor 'Depth' of Anaesthesia with Isoflurane or Propofol / D. Schwender, M. Daunderer, S. Mulzer, S. Klasing, U. Finsterer, K. Peter // Brit. J. of Anaesthesia. 1996. Vol. 77(2). P. 179–184. doi: 10.1093/bja/77.2.179

7. Tong S., Thakor N. V. Quantitative EEG Analysis Methods and Clinical Applications. Norwood: Artech House, 2009. 421 p.

8. Hossein R., Alireza M. D., Mehrab G. Estimation the Depth of Anesthesia by the Use of Artificial Neural Network // Artificial Neural Networks. Methodological Advances and Biomed. Appl. Ed. by K. Suzuki. 2011. P. 283–302. doi: 10.5772/15139

9. Description of the Entropy Algorithm as Applied in the Datex-Ohmeda S/5 Entropy Module / H. Viertiö-Oja, V. Maja, M. Särkelä, P. Talja, N. Tenkanen, H. Tolvanen-Laakso, M. Paloheimo, A. Vakkuri, A. Yli-Hankala, P. Meriläinen // Acta Anaesthesiol. Scand. 2004. Vol 48(2). P. 154–161. doi: 10.1111/j.0001-5172.2004.00322.x

10. Аль-Гаили М. А., Калиниченко А. Н. Оценка глубины анестезии на основе совместного анализа частотных и временны́х параметров ЭЭГ // Изв. СПбГЭТУ "ЛЭТИ". 2018. № 3. С. 80–85.

11. Classification of EEG Signals Based on Pattern Recognition Approach / H. U. Amin, W. Mumtaz, A. R. Subhani, M. N. M. Saad, A. S. Malik // Frontiers in Computational Neuroscience. 2017. Vol. 11, art.103. P. 1–12.

12. Classification of Wakefulness and Anaesthetic Sedation Using Combination Feature of EEG and ECG / B. Lee, D. Won, K. Seo, H. J. Kim, S. Lee // Proc. of 2017 5th Intern. Winter Conf. on Brain-Computer Interface (BCI). Sabuk, South Korea, 9–11 Jan. 2017. Piscataway: IEEE, 2017. P. 88–90. doi: 10.1109/IWW-BCI.2017.7858168

13. Monitoring the Depth of Anesthesia Using Entropy Features and an Artificial Neural Network / R. Shalbaf, H. Behnam, J. W. Sleigh, A. Steyn-Ross, L. J. Voss // J. of Neuroscience Methods. 2013. Vol. 218, iss. 1. P. 17–24.

14. Wavelet Entropy Based Classification of Depth of Anaesthesia / V. K. Benzy, E. A. Jasmin, R. C. Koshy, F. Amal // 2016 Intern. Conf. on Computational Techniques in In-formation and Communication Technologies (ICCTICT), New Delhi, India, 11–13 March 2016. Piscataway: IEEE, 2016. P. 521–524. doi: 10.1109/ICCTICT.2016.7514635

15. A Comparison of Different Classification Algorithms for Determining the Depth of Anesthesia Level on a New Set of Attributes / A. Arslan, B. Şen, F. V. Çelebi, M. Peker, A. But // 2015 Intern. Symp. on Innovations in Intelligent Systems and Applications (INISTA), Madrid, Spain, 2–4 Sept. 2015. Piscataway: IEEE, 2015. P. 1–7. doi: 10.1109/INISTA.2015.7276738

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