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HYBRID CONVOLUTIONAL-MULTILAYER PERCEPTRON ARTIFICIAL NEURAL NETWORK FOR PERSON RECOGNITION BY HIGH GAMMA EEG FEATURES

Selitsky S.

University of Bedfordshire, United Kingdom

ГИБРИДНАЯ ИСКУССТВЕННАЯ НЕЙРОННАЯ СЕТЬ CNN-MLP ДЛЯ РАСПОЗНАВАНИЯ ЛЮДЕЙ С ИСПОЛЬЗОВАНИЕМ СТРУКТУР ЧАСТОТ ВЫСОКОГО ГАММА-СПЕКТРА ЭЭГ

С. Селицкий

Школа компьютерных наук и технологий, Университет Бедфордшира, Великобритания

We propose to use a hybrid Convolutional-Multilayer Perceptron Neural Network (CNN-MLP) architecture to learn high gamma EEG features for person recognition. An original EEG data set was collected featuring recordings during various physical and mental activities for this study. Experiments with high and low gamma and beta scale Convolutional filters were conducted. Particular usefulness of the EEG bands was observed, and high gamma scale CNN features were recognized as efficient for the person recognition task.

Keywords: person recognition, EEG, high gamma, CNN-MLP, Machine Learning, Artificial Intelligent

В работе использована гибридная искусственная нейронная сеть типа сверточно-многослойного перцептрона для изучения структур из верхнего гамма-спектра электроэнцефалографии (ЭЭГ) для распознавания людей. В связи с этим был собран исходный набор данных ЭЭГ у различных людей, включавший записи во время различных физических действий и умственной деятельности. Выполнены исследования с высокими и низкими, гамма- и бета-масштабными свёрточными фильтрами. В результате работы отмечалась выборочная эффективность полос ЭЭГ, а функции сверточного многослойного персептрона с высоким гамма-масштабированием были признаны эффективными в персональном распознавании индивидуума.

Ключевые слова: ЭЭГ, персональное распознавание, высокий гамма-спектр, нейронные сети, многослойный персептрон, машинное обучение, искусственный интеллект

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Для цитирования: Селицкий С. ГИБРИДНАЯ ИСКУССТВЕННАЯ НЕЙРОННАЯ СЕТЬ CNN-MLP ДЛЯ РАСПОЗНАВАНИЯ ЛЮДЕЙ С ИСПОЛЬЗОВАНИЕМ СТРУКТУР ЧАСТОТ ВЫСОКОГО ГАММА-СПЕКТРА ЭЭГ. *Медицинский вестник Северного Кавказа*. 2022;17(2):192-196. DOI – https://doi.org/10.14300/mnnc.2022.17046

ANN – artificial neural networks
CNN – convolutional neural networks
EEG – electroencephalograms
LSTM – long-short term memory
ML – machine learning
MLP – multilayer perceptron

Application of machine learning (ML) to the analysis of electroencephalography (EEG) was successfully applied, first, for anomaly or pathology detection, such as seizure [1], depression [2], schizophrenia [3], hearing deficiency [4], consciousness level [5] detection. More recently, for less obvious ways of human biometrics classification, such as emotion [6–8], motor movement [9–11], intent [12–14], sleep stages [15], newborn age detection [16–19], and, finally, person recognition [20] and identification [21–24]. In this pilot study, we concentrate on person detection using EEG. However, the data set is collected for the study, which is still gathering data, hosts records of subjects occupied with different physical, emotional, and mental activities and suitable for various classification tasks, which are planned to be conducted in the future. «To go to» artificial neural networks (ANN) ML models for EEG data analysis [25–27] are Long-short term memory (LSTM) ANN, due to their design goal of handling sequential data of arbitrary length.

LSTM units have saturable sigmoid gates that allow for updating or forgetting weights of the transformation matrix based on the history of one-by-one observation training. The drawback of LSTM architecture is its difficult parallelization of multiple computing processes. If the length of the sequences in a study can be set fixed, convolutional neural networks (CNN) are more efficient in capturing sequence length because they can be easily trained parallelly [28–30]. Analyzing EGG records in such fixed-length fragments using CNN and hybrid architectures is another popular ML approach [4, 9, 19, 20, 32, 36]. Input in CNN is expected as a pseudo-image, in which the duration of the EEG record is considered as a height of the «image,» and EEG channels are considered either as the «width» or pseudo-color channels. The functioning of the Convolution layer can be viewed as a set of learnable filters-matrices scanning the image and being applied to it via element-wise multiplication and summation (dot product in simple implementation).

In our study, we concentrate on using short CNN masks designed to capture high gamma wave structures, trying to verify the hypothesis that such waves bare useful person-specific information that could be used for classification.

Data set. The data set is a pilot data collection from the more considerable planned experimental study. So far, EEG data were collected from 11 subjects during multiple sessions with intervals of several weeks for some subjects. The EEG sessions were of various lengths and recorded during numerous activities, such as idleness, lying table game, dance, motor skills acquisition, and emotion impersonation. For EEG recording, a minimally invasive MindRove Arc device (https://mindrove.com/arc) was used (Fig. 1). This device is a wireless wearable device with semi-dry electrodes and a Wi-Fi connection to the data collection station. It has six electrodes located at the top of the skull in the arc fashion, in the order C5, C3, C1, C2, C4, and C6 from left to right, a bias electrode located behind the left, and a reference electrode – behind the right ear. The sampling rate is 500 Hz, and the measurement resolution is 0.045 μV. The measurements were done with a 50 Hz filter enabled. Although strictly not necessary, electrode gel «Spectra 360» was used for connectivity reliability.

Fig. 1. Mind Rove Arc with electrode enumeration.
Photo retrieved from https://mindrove.com/wp-content/uploads/2021/11/UserManual_v2_0_0.pdf

Proposed solution. It was observed that imagery information generates more person-specific signatures than motor-related signatures [37]. It has also been suggested that gamma waves are associated with visual awareness and consciousness [7]. Having an EEG recording equipment sampling at a higher rate (500 HZ) than equipment used in other research (circa 200–100 Hz), we decided to investigate the potentially person-specific high gamma wave features that the CNN filters could learn. The following (Table 1) hybrid CNN-MLP (Multilayer Perceptron) architecture was used. Interest in MLP models, as rivals to CNN and using wider than deeper architectures [31], have been rising in the last years [33]; therefore, we utilized the best parts of these «two worlds.» ANN parameters are filtered length H, filter width M (equal to the number of EEG channels), several filters N, average pooling size, and stride K. Sizes of the two Fully-connected layers following the Flatten layer were set to match the preceding Convolutional, Average Pooling and Flatten layers. The last Fully-connected layer size was set to the number of subject classes C. The width of the convolution filters is equal to the pseudo-image width; despite the use of 2-dimensional Convolution layer implementation, effectively, they were performing multi-channel 1-dimensional convolution. The Average Pooling layer was used to reduce the dimensionality of the Convolutional features input to the rest of the fully-connected MLP layers to meet the hardware limitations.

Table 1

CNN-MLP hybrid ANN architecture

Layers
Pseudo-image Input (L × M), L – EEG fragment length, M – number of channels
Pseudo2D Convolution (H × M filter, N filters, 1 stride), H – filter height
Average Pooling (K × 1 size and stride)
Flatten (F=(L – H + 1)N/K size)
Fully-connected (F size)
ReLU
Fully-connected (2F + 1 size)
ReLU
Fully-connected (C size), C – number of classes
Softmax
Classification

ANN parameters are filtered length H, filter width M (equal to the number of EEG channels), several filters N, average pooling size, and stride K. Sizes of the two Fully-connected layers following the Flatten layer were set to match the preceding Convolutional, Average Pooling and Flatten layers. The last Fully-connected layer size was set to the number of subject classes C. The width of the convolution filters is equal to the pseudo-image width, despite the use of 2-dimensional Convolution layer implementation; effectively, they were performing multi-channel 1-dimensional convolution. The Average Pooling layer was used to reduce the dimensionality of the Convolutional features input to the rest of the fully-connected MLP layers to meet the hardware limitations.

Experiments. The experiments were run on the Linux (Ubuntu 20.04.3 LTS) operating system with two dual Tesla K80 GPUs (with 2 × 12GB GDDR5 memory each) and one QuadroPro K6000 (with 12GB GDDR5 memory, as well), X299 chipset motherboard, 256 GB DDR4 RAM, and i9-10900X CPU. The Experiments were run on MATLAB 2022a with Deep Learning Toolbox. ANN models were trained using the «Adam» learning algorithm with 0.01 initial learning coefficient, mini-batch size circa 16000, and 40 epochs. From the sets of EEG recordings for each subject, randomly selected records for training and records for testing. Fragments of 4 seconds duration (or L=2000 data points) were cut from all records. The step between cuts was 1 data point. Cuttings of the long records were limited to 20000 first data points, thus making no more than 18001 training fragments to ensure balanced training. No other prior processing of the training or test data was performed on the raw data. Input data normalization, Max Pooling instead of Average Pooling, adding Batch Normalization, and Dropout layers have also been experimented with. In addition to the short-wave CNN filter dimensions (3–13) associated with gamma waves, for contrast, we ran experiments with more extended filters associated with betta waves. Accuracy was calculated as a ratio of correctly classified test data points to the whole number of test data points.

Results and Discussion. Initial min-max per-channel data normalization applied to each 4-seconds EEG fragment resulted in a random accuracy of circa 0.09; therefore, all subsequent experiments were run without normalization. ANN architecture used for experiments did not have saturable sigmoid activation functions, and input channels had the same measurement unit data; therefore, input data normalization was not strictly needed. Adding Batch Normalization and Dropout layers to first test architectures has smoothed the training process; however, it produced marginally worse accuracy results and slowed down training. Therefore, those layers were not used for the majority of experiments. Using the Max Pooling layer instead of Average Pooling in the first runs produced worse results and was retired for further investigations. The pooling size and stride parameters K of 2 and 5 were experimented with and provided inferior results to the parameter value of 3, or training did not even converge for the former parameters. Therefore, subsequent experiments were conducted with the latter parameter of 3. The primary Convolutional filter height parameter H=5 corresponds to wave features at 100 Hz, as compared with other values (Table 2).

Table 2

Accuracy for various Convolution layer filter height (width is set to number of channels 6), number of filters 16, and pooling size and stride 3

CNN filter size	Frequency [Hz]	Accuracy
3	167	0.3478
5	100	0.4752
7	71	0.1870
13	38	0.4721
17	29	0.3442
31	16	0.4752
37	13	0.3478

The number of filters N was pushed to the maximal value allowed by the GPU for the given ANN architecture – of 16. Examples of the filters learnt for H=5, K=3, N=16 can be seen on Figure 2, and for the beta frequency filter height H=31 – on Figure 3. The latter, longer CNN filters capture repetition of the higher frequency features.

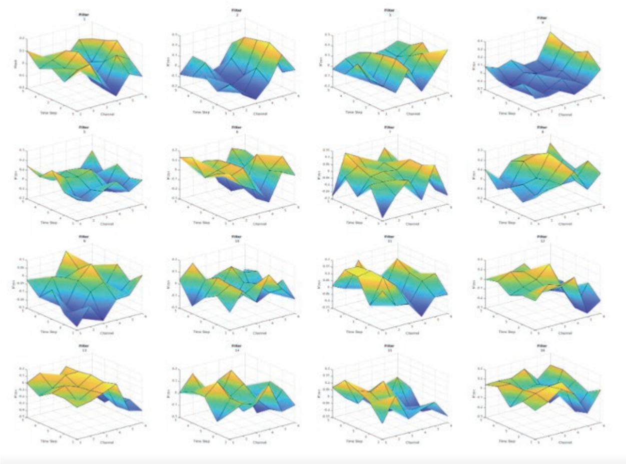

Fig. 2. Convolution filter examples, 16 filters of height 5 and 6 channels

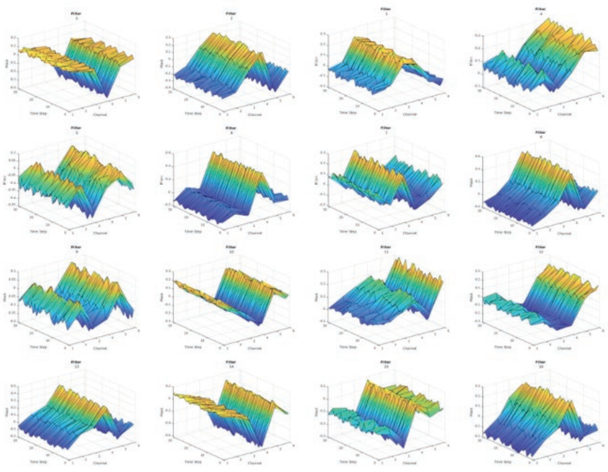

Fig. 3. Convolution filter examples, 16 filters of height 31 and 6 channels

Examples of the activation values on the Convolution layer output, which could be viewed as intensity maps of the features represented by the learned filters, can be seen for correctly identified test example (data point 140 000) in Figure 4 and for incorrectly identified test example (data point 120 000) on Figure 5. The latter case likely demonstrates recording artifacts.

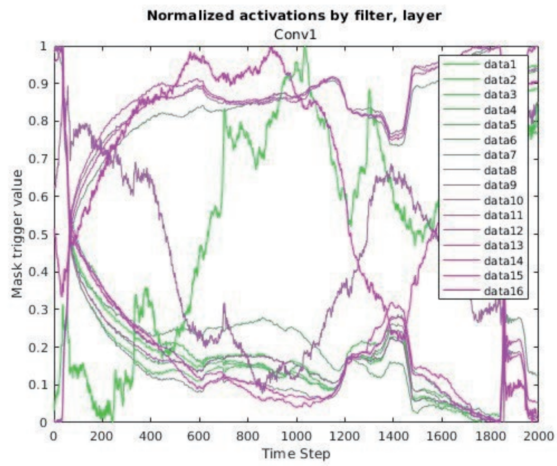

Fig. 4. Convolution layer activation values for each of 16 5×6 filters. Correctly classified data point 140 000

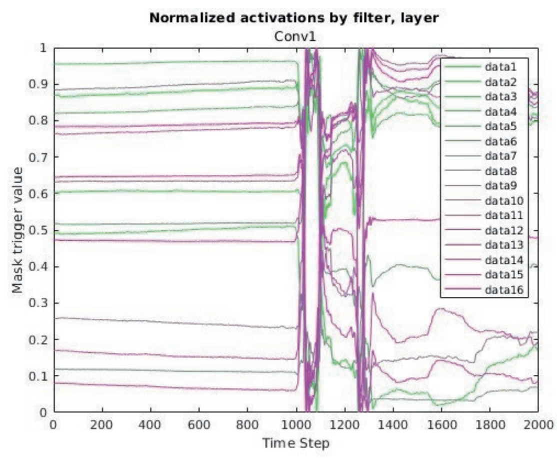

Fig. 5. Convolution layer activation values for each of 16 5×6 filters. Incorrectly classified data point 120 000

In such a way, areas in the image similar to the filter mask will produce a higher output than non-similar areas. The filters are randomly initialized and trained via standard back-propagation learning algorithms to create masks that would minimize the objective classification function. Another ANN architecture proven to be effective in the case of the small EGG and other medical imaging sets is evolutionary polynomial GMDH-type (Group Method of Data Handling) [28, 23, 38]. Yet another popular ML branch of Decision Trees (DT) has also been applied to EEG problems [13, 25, 29].

Conclusions. High frequency «hyper gamma» EEG features can be detected by the CNN architecture and successfully used by the following MLP layers for person identification. There are closely intertwined frequency bands (circa 100, 40, 15 Hz) that are more suitable and less suitable (circa 170, 70, 40, 13 Hz) for personal identification. Features learned by the Convolution filters sized for lower frequencies do not represent unique structures but rather a repetition of higher frequency features, which indicates the latter's importance for person recognition. Parallel Convolution cascade cells covering ranges of frequency bands, which should be capable of capturing more complex wave structures, would be a natural area for further research. Activation outputs cluster together for some filters, indicating redundancy and the potential to reduce them to free resources for more complex cascade architectures. Cases of inaccurate classification in the proposed solutions may be associated with unfiltered artifacts; therefore, more tight data pre-processing would be another area of methodology improvement.

Disclosures: The authors declare no conflict of interest.

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References

1. Acharya U. R., Oh S. L., Hagiwara Y., Tan J. H., Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in biology and medicine*. 2018;100:270-278. https://doi.org/10.1016/j.compbiomed.2017.09.017
2. Greco C., Matarazzo O., Cordasco G., Vinciarelli A., Callejas Z. [et al.] Discriminative power of EEG-based biomarkers in major depressive disorder: A systematic review. IEEE Access. 2021;PP:1-1. https://doi.org/10.1109/ACCESS.2021.3103047
3. Khare S. K., Bajaj V., Siuly S., Sinha G. Classification of schizophrenia pa- tients through empirical wavelet transformation using electroencephalogram signals. *Modelling and Analysis of Active Biopotential Signals in Healthcare.* 2020;1:1-26. https://doi.org/10.1088/978-0-7503-3279-8ch1
4. Islam M. N., Sulaiman N., Al Farid F., Uddin J., Alyami S. A. [et al.] Diagnosis of hearing deficiency using EEG based AEP signals: Cwt and improved-vgg16 pipeline. *Peer J. Computer Science.* 2021;7,e638. https://doi.org/10.7717/peerj-cs.638
5. Liu Q., Cai J., Fan S. Z., Abbod M. F., Shieh J. S. [et al.] Spectrum analysis of EEG signals using cnn to model patient's consciousness level based on anesthesiologists' experience. *IEEE.* 2019;7:53731-53742. https://doi.org/10.1109/ACCESS.2019.2912273
6. Alhagry S., Fahmy A. A., El-Khoribi R. A. Emotion recognition based on eeg using lstm recurrent neural network. *Emotion*. 2017;8(10):355-358.
7. Du X., Ma C., Zhang G., Li J., Lai Y. K. [et al.] An efficient lSTM network for emotion recognition from multichannel EEG signals. *IEEE Trans. Affect. Comput.* 2020. https://doi.org/10.1109/TAFFC.2020.3013711
8. Xing X., Li Z., Xu T., Shu L., Hu B. [et al.] SAE+ LSTM: A new framework for emotion recognition from multi-channel EEG. *Frontiers in neurorobotics.* 2019;13(37):1-14. https://doi.org/10.3389/fnbot.2019.00037
9. Sheykhivand S., Mousavi Z., Rezaii T. Y., Farzamnia A. Recognizing emotions evoked by music using cnn-lstm networks on EEG signals. *IEEE.* 2020:139332-139345 https://doi.org/10.1088/1742-6596/2024/1/012044
10. Alarcao S. M., Fonseca M. J. Emotions recognition using EEG signals: A survey. *IEEE Transactions on Affective Computing*. 2017;10(3):374-393. https://doi.org/10.1109/TAFFC.2017.2714671
11. Zhang G., Davoodnia V., Sepas-Moghaddam A., Zhang Y., Etemad A. Classification of hand movements from EEG using a deep attention-based lstm network. *IEEE Sensors Journal*. 2019;20(6):3113-3122. https://doi.org/10.1109/JSEN.2019.2956998
12. Zhou H., Zhao X., Zhang H., Kuang S. The mechanism of a multi-branch structure for EEG-based motor imagery classification. In: 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO). *IEEE.* 2019:2473-2477. https://doi.org/10.3390/diagnostics12040995
13. Kurkin S. A., Pitsik E. N., Musatov V. Y., Runnova A. E., Hramov A. E. Artificial neural networks as a tool for recognition of movements by electroencephalograms. *In: ICINCO*. 2018;1:176-181. Available at: https://www.scitepress.org/papers/2018/68602/68602.pdf
14. Vega C. F., Quevedo J., Escandón E., Kiani M., Ding W. [et al.] Fuzzy temporal convolutional neural networks in p300-based brain – computer interface for smart home interaction. *Applied Soft Computing.* 2022;117:108359. https://doi.org/10.1016/j.asoc.2021.108359
15. Kang J. S., Park U., Gonuguntla V., Veluvolu K. C., Lee M. Human implicit intent recognition based on the phase synchrony of EEG signals. *Pattern Recognition Letters*. 2015;66:144-152. https://doi.org/10.1016/j.patrec.2015.06.013
16. Schetinin V., Jakaite L., Schult J. Informativeness of sleep cycle features in bayesian assessment of newborn electroencephalographic maturation. *DBLP.* 2011:1-6. https://doi.org/10.1109/CBMS.2011.5999111
17. Jakaite L., Schetinin V., Maple C. Bayesian assessment of newborn brain maturity from two-channel sleep electroencephalograms. *Computational and Mathematical Methods in Medicine.* 2012:629654. https://doi.org/10.1155/2012/629654
18. Schetinin V., Jakaite L. Classification of newborn EEG maturity with Bayesian averaging over decision trees. *Expert Systems with Applications.* 2012;39(10):9340-9347. https://doi.org/10.1016/j.eswa.2012.02.184
19. Selitsky S., Selitskaya N., Schult J. Machine learning approach to classification of sleep electroencephalograms from newborns at risk of brain pathologies. *Medical News of North Caucasus*. 2021;16(2):140-143. https://doi.org/10.14300/mnnc.2021.16031
20. Schetinin V., Jakaite L., Nyah N., Novakovic D., Krzanowski W. Feature extraction with GMDH-type neural networks for EEG-based person identification. *International Journal of Neural Systems*. 2018;28(06):1750064. https://doi.org/10.1142/S0129065717500642
21. Jakaite L., Schetinin V., Schult J. Feature extraction from electroencephalograms for Bayesian assessment of newborn brain maturity. In: Proceedings of the 24th IEEE International Symposium on Computer-Based Medical Systems. 2011 https://doi.org/10.1109/CBMS.2011.5999109
22. La Rocca D., Campisi P., Scarano G. EEG biometrics for individual recognition in resting state with closed eyes. In: 2012 BIOSIG-Proceedings of the International Conference of Biometrics Special Interest Group (BIOSIG). IEEE. 2012:1-12.
23. Hammad M., Pławiak P., Wang K., Acharya U. R. Resnet-attention model for human authentication using EEG signals. *Expert Systems.* 2021;38(6):e12547. https://doi.org/10.1111/exsy.12547
24. Michielli N., Acharya U. R., Molinari F. Cascaded lstm recurrent neural network for automated sleep stage classification using single-channel EEG signals.

Computers in biology and medicine. 2019;106:71-81. https://doi.org/10.1016/j.compbiomed.2019.01.013
25. Lawhern V. J., Solon A. J., Waytowich N. R., Gordon S. M., Hung C. P., Lance B. J. EEGnet: a compact convolutional neural network for EEG-based brain – computer interfaces. *Journal of Neural Engineering*. 2018;15(5):056013. https://doi.org/10.1088/1741-2552/aace8c
26. Amin S. U., Muhammad G., Abdul W., Bencherif M., Alsulaiman M. Multi-CNN feature fusion for efficient EEG classification. In: 2020 IEEE International Conference on Multimedia & Expo Workshops (ICMEW). 2020:1-6. https://doi.org/10.1109/icmew46912.2020.9106021
27. Sheykhivand S., Mousavi Z., Rezaii T. Y., Farzamnia A. Recognizing emotions evoked by music using CNN-LSTM networks on EEG signals. *IEEE*. 2020:139332-139345. https://doi.org/10.3390/s22062346
28. Schetinin V., Schult J. Learning polynomial networks for classification of clinical electroencephalograms. *Soft Computing*. 2006;10(4):397-403. https://doi.org/10.1007/s00500-005-0499-3
29. Nyah N., Jakaite L., Schetinin V., Sant P., Aggoun A. Evolving polynomial neural networks for detecting abnormal patterns. 8th IEEE International Conference on Intelligent Systems. *IEEE*. 2016:74-80. https://doi.org/10.1109/IS.2016.7737403
30. Nguyen P., Tran D., Huang X., Sharma D. A proposed feature extraction method for EEG-based person identification. In: Proceedings on the International Conference on Artificial Intelligence. 2012.
31. Chang W., Wang H., Yan G., Liu C. An EEG based familiar and unfamiliar person identification and classification system using feature extraction and directed functional brain network. *Expert Systems with Applications*. 2020:113448. https://doi.org/10.3390/brainsci11111424
32. Gold I. Does 40-hz oscillation play a role in visual consciousness? *Consciousness and Cognition*. 1999;8(2): 186-195. Available at: https://www.sciencedirect.com/science/article/pii/S1053810099903999
33. Nguyen P., Tran D., Huang X., Sharma D. A proposed feature extraction method for EEG-based person identification. In: Proceedings on the International Conference on Artificial Intelligence (ICAI). 2012.
34. Schetinin V., Jakaite L. Classification of newborn EEG maturity with bayesian averaging over decision trees. *Expert Syst*. 2012;39(10):9340-9347. https://doi.org/10.1016/j.eswa.2012.02.184
35. Selitskiy S. Kolmogorov's gate non-linearity as a step toward much smaller artificial neural networks. In: Proceedings of the 24th International Conference on Enterprise Information Systems. *ICEIS*. 2022:492-499. https://doi.org/10.5220/0011060700003179
36. Tolstikhin I. O., Houlsby N., Kolesnikov A., Beyer L., Zhai X. [et al.] MLP-mixer: An all-MLP architecture for vision. Advances in Neural Information Processing Systems. 2021. Available at: https://papers.nips.cc/paper/2021/file/cba0a4ee5ccd02fda0fe3f9a3e7b89fe-Paper.pdf
37. Yang H., Han J., Min K. A multi-column CNN model for emotion recognition from EEG signals. *Sensors*. 2019;19(21):4736. https://doi.org/10.3390/s19214736
38. Yang S., Deravi F. On the effectiveness of EEG signals as a source of biometric information. In: 2012 Third International Conference on Emerging Security Technologies. *IEEE*. 2012:49-52. https://doi.org/10.1109/EST.2012.8

About author

Selitsky Stas, postgraduate student at the School of Computer Science and Technology; e-mail: selitsky@yahoo.com

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CHARACTERISTICS OF LUMEN OF THE ANTERIOR INTERVENTRICULAR BRANCH WITH DIFFERENT VARIANTS OF CORONARY BRANCHING IN HEARTS WITH MYOCARDIAL BRIDGING

Korobkeev A. A., Kuzmin I. S., Lezhnina O. Yu.

Stavropol State Medical University, Russian Federation

ХАРАКТЕРИСТИКА ПРОСВЕТА ПЕРЕДНЕЙ МЕЖЖЕЛУДОЧКОВОЙ ВЕТВИ ПРИ РАЗЛИЧНЫХ ВАРИАНТАХ ВЕТВЛЕНИЙ ВЕНЕЧНЫХ АРТЕРИЙ НА СЕРДЦАХ С МИОКАРДИАЛЬНЫМ МОСТИКОМ

А. А. Коробкеев, И. С. Кузмин, О. Ю. Лежнина

Ставропольский государственный медицинский университет, Российская Федерация

The anterior intraventricular branch has been examined in the systole phase on 60 antemortem angiograms with left-anterior and right-vertebral variants of branching of coronal arteries in people of second adult age with a myocardial bridge. Data on a comparative examination of the lumen of the anterior intraventricular branch at the left-vertebral and right-vertebral variants of branching of coronal arteries in the subepicardial and intramural departments of the main highway are presented.

Keywords: myocardial bridge, anterior interventricular branch, systole, left variant of coronary branching, right variant of coronary branching, internal diameter