Intelligent Service for Hybrid Analysis of Continuous Mental Processes Based on EEG and Video Data

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***Abstract*—In the paper we present our developed service for analyzing the continuous mental processes of the human brain. We developed the service to support electroencephalogram data analysis specialist. The service allows to implement a hybrid analysis of continuous processes using electroencephalogram and video recording data. Electroencephalogram data analysis is performed on the basis of static and dynamic signal characteristics in different frequency ranges. The video is analyzed using the models developed earlier by the authors, which allow tracking such physiological parameters as respiration rate, blood pressure, heart rate, blood oxygen saturation, and different motion parameters of human body & head. Hybrid analysis of these two data sources allows for partial automation of signal filtering, speeds up electroencephalogram analysis by a specialist, and training automatic models for recognizing continuous mental processes. Our service provides a practical implementation of such hybrid analysis using a set of signal processing modules adaptable to the needs of the study. The article describes the functionality of individual modules of the service and provides some practical examples of their use in analyzing the meditation process.**

I. INTRODUCTION

Electroencephalogram (EEG) analysis is one of the most widely used ways to study continuous mental processes (hereafter continuous processes) such as sleep [1], [2], meditation [3] and cognitive activity (including logical problem solving [4], [5]). Brain bioelectrical signals available for measurement from the surface of the human head are rather weak, noisy, and may contain various types of artifacts (e.g., related to muscle activity: blinking, swallowing, head movements, vascular pulsation, cardiogram, etc.), therefore, their preliminary cleaning or filtering is necessary [6]. Usually, artefactual signals exceed the EEG signal in amplitude/power (blinks, slow waves when shaking the head, etc.) or frequency (muscle artifacts). In the first case, these are easily distinguishable and eye-visible artifacts with their own characteristic pattern. In the second case, the frequency of muscle artifacts (mimic or from jaw clenching and cheekbone movement) fits into the spectrum of the beta range (18-30 Hz) and may exceed the signal in amplitude [6].

EEG signal artifact removal often does not involve the active use of synchronized video recording (although its very presence is mentioned in a number of studies [7], [8], [9]), which may be due to the lack of integration mechanisms for extracting human physiological characteristics based on the intelligent analysis of its video. Such mechanisms in combination with standard EEG presentation tools will significantly speed up the analysis and reduce the influence of the human factor.

We propose to analyze the participant's video recording based on our previous papers. We extract the following information: respiration rate [10], heart rate [11], blood pressure [12], blood oxygen saturation [13], eyes and mouth states (open/closed) [14]. We use this information to automate the search and removal of artifacts, and to analyze the EEG signal as part of the continuous process. Synchronized video and EEG data provide additional information about muscle artifacts that significantly decrease probability of specialist error during the data analysis.

Every participant of experiment receives instructions that he/she should implement during the experiment. However, sometimes he/she does not follow these instructions precisely. We called such a sequence of observed actions performed by the participant a continuous process (see Fig. 1). We propose to analyze continuous process since EEG data and video analysis does not provide possibilities to exactly determine a human state.

Any continuous process can be split into time intervals (hereafter fragments). Each fragment is characterized by a set of certain features that can be computed from EEG and video data. We assume that the set of these features is not sufficient for meaningful classification of fragments [6]. However, analyzing the dynamics of their changes may yield different results. For example, by comparing different fragments during the human meditation session, one could try to assess the significance of changes between the maximal meditation intensity and the background state.

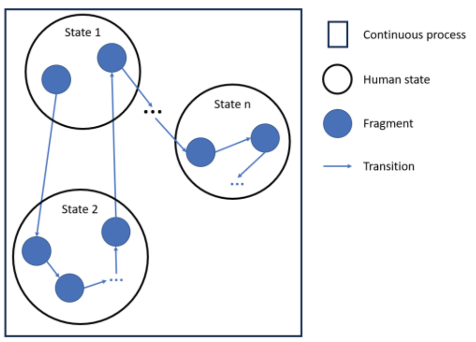

Fig. 1. The scheme of the continuous process

We cannot know in advance what characterizes this intensity for a particular participant or what part of the recording it occurred in, but the fact of change may be a more general indication of successful meditation. In addition, we try to estimate the stability of the meditation peak based on the dynamics of the fragment features. To facilitate the analysis of these dynamics, it is worthwhile to use some generalizations. Let us call a cluster of fragments similar to each other a human state. The human state may not be fully interpretable, but this kind of generalization will allow us to statistically assess the dynamics of transitions between them. Such statistical estimates may be more universal in classifying continuous processes than classifying individual fragments. However, there is no reason not to use both of these approaches in the analysis.

So, it is needed to develop a service designed for static and dynamic, hybrid analysis of continuous processes (sequences of human states) based on EEG data and synchronized video recording. By hybrid analysis we mean a set of analysis methods based on the use of multiple data sources that allow mutual verification of each other. In addition, the service should provide tools for the necessary filtering and transformations of the data, as well as integration of classification models. The novelty of the service is to apply the computer vision methods to automate EEG data analysis.

The rest of the paper is structured as follows: Section II gives an overview of existing works of EEG signal filtering, analysis of continuous processes based on various physiological characteristics, and EEG signal recording tools. The results of this review prove the relevance of the service development. Section III describes the architecture of the developed service and the purpose of its individual modules, as well as the general scenario of working with data. Section IV shows practical cases of working with the service on the example of analyzing the meditation process and describes partially automated scenarios of data processing.

II. RELATED WORK

Different methods of EEG signal processing and filtering are discussed in the book [6]. There are two main approaches to artifact removal: correction of the original signal as a whole (e.g., using the independent component analysis (ICA) method that excludes the signal components corresponded mostly to artifacts) or removal of artifact fragments. In some cases, if the signal of a particular channel is persistently incorrect, the signal of this channel may be replaced by the averaged data of neighboring channels (if there are enough of them), or it may be excluded from further consideration.

Some types of EEG signal artifacts caused by external sources, such as head movement or single jaw movements, cannot be corrected automatically. Fig. 2 shows an example of such artifact, probably caused by a jaw movement by a participant, affecting all EEG channels over a long-time interval.

Correction of such artifact by the ICA method is impossible due to the uniqueness of its pattern. In general, the book [6] emphasizes the importance of filtering data by ICA or other methods before analyzing it directly.

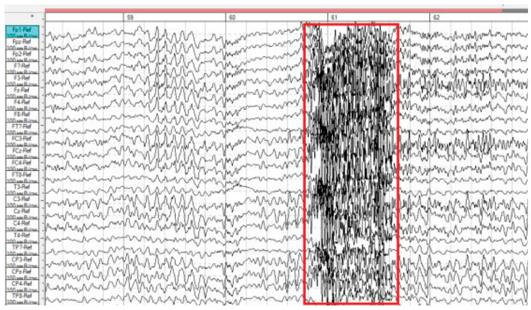

Fig. 2. An example of a single artifact

In our work we call this process data pre-filtering stage. The book highlights the key role of analyzing signal power in different frequency ranges for interpreting human brain processes. Various methods based on the Fourier transform, such as the Welch method, are proposed for power calculation.

Authors of the paper [15] compare the EEG signal power in different frequency ranges in experienced meditators during meditation with the background state. The last 6 minutes of 21-minute meditation recordings are used for comparison. This approach is probably based on the assumption that meditation intensity increases with time, which is not supported either in the paper or in our own surveys of meditators. However, the authors themselves note that their “future planned analysis will focus on the temporal evolution of brain dynamics in the meditation vs. control state so as to assess the onset vs. maintenance of meditation state effects and the relative stability of the spectral power dynamics across the two states”. This direction of works fully corresponds to our proposed approach to the analysis of the dynamics of continuous processes. The authors use the ICA method to filter artifacts before analysis. The results (expressed as changes in the EEG signal power values in the α, θ and γ bands of the frontal scalp area for the meditative state compared to the background state) are statistically significant, but they cannot be directly applied to the classification of continuous processes.

Authors of the paper [16] developed a model for automatic recognition of the meditative state using spectral analysis of the EEG signal as well as synchronized data on the current respiration rate. They used the ICA method to remove artifacts. A special piezoelectric belt was used to measure respiratory rate. The results show that the accuracy of a recognition model trained on both EEG and respiration rate data is significantly higher than the accuracy of models trained on these data separately. However, the changes in EEG signal power in almost all frequency ranges (except θ), contradict the results of paper [15]. Differences in results can be explained by differences in methodology. In the paper [16], only inexperienced meditators participated, and listening to the radio was used as a background state.

For investigation of such continuous processes as sleep or routine work, it would be desirable to bring the recording conditions closer to those of everyday life. And while the extraction of physiological characteristics from video allows us to achieve this, there may be problems with EEG recording using professional EEG helmets, which are expensive and difficult to handle.

Authors of the paper [17] compare the quality of recordings obtained with different types of devices: the classical device with gel electrodes - NVX and two relatively new devices with dry electrodes - Neiry Headband from Neiry LLC, Russia, and Muse Headband from InterAxon LLC, Canada. The paper shows that the Neiry device has no significant disadvantages when registering the relaxed state of a person, as it shows comparable results with NVX in delta-, theta- and alpha-bands. At the same time, the authors separately note that it is still better to use gel electrodes to analyze beta- and gamma-bands. However, as it follows from the previous reviewed works, these bands are not so important for analyzing the meditative state, unlike the theta band. Although we are currently using gel electrodes in our work, these results suggest that the availability of the service we are developing may be increased in the future. Devices with dry electrodes are typically conventional headbands that can be placed on the head in a short period of time without the involvement of a specialist, allowing monitoring of brain activity at home.

So, the book [6] provides a description of EEG signal artifact removal methods, such as the ICA method, which we use in the data pre-filtering stage. At the same time, the book mentions the existence of single artifacts that cannot be removed automatically, and for this reason we have developed additional tools for their removal. In the paper [15] authors say that there are statistically significant differences in EEG signal power values in different frequency ranges and for this reason we also use them to analyze continuous processes. In addition, the authors note the prospect of assessing the dynamics and stability of the meditative state and for its realization we have developed tools for analyzing the dynamics of continuous processes. Authors of the paper [16] were able to significantly increase the accuracy of the meditation recognition model by adding breathing rate data to EEG data. They used a special belt to record these data, while we propose to use video for this purpose (as well as for recording other physiological parameters). This will simplify the recording procedure and make it more accessible to non-specialists. The results of the paper [17] will allow us to increase accessibility even more, since they present new dry-electrode devices for EEG recording. Such devices are faster to use and do not require the help of a specialist during installation. Although we currently use a standard gel-electrode device for EEG recording, in the future we will be able to record new types of continuous processes in domestic conditions.

III. SERVICE ARCHITECTURE

Fig. 3 shows the general architecture of the developed service. It should be mentioned that the bulk of the data transformations are performed in a single layer of data processing modules. Architecture includes data processing modules that integrated into the data reader module in the secondary processing stage are directly adapted to compute the fragment features required for subsequent classification. The specific set of modules is adaptive and based on the goal. We propose video tracking module to determine human physiological parameters and feature extraction module for topographic maps of fragments. The modules call each other in an arbitrary order and they add new feature layers. The specialist decides which layer should be involved in the final model.

Data processing modules interact with each other, as they are all based on a common scheme of dividing the original EEG signal into equal fragments. Modules do not pre-calculate signal characteristics and do not store them, but at any moment, at the request of the user or another module, are able to dynamically calculate all necessary characteristics for a certain fragment, having the original signal data and a certain time interval corresponding to the fragment.

A. Data Reading Module

Data Reading module reads input EEG files and breaks them into fragments of the same specified length. These fragments are the basic abstraction for working in almost all other modules as the most compatible with the used classification methods. Each fragment is characterized by its length, offset, and reference to the original data.

B. PSD Module

PSD (Power Spectral Density) module computes the spatial characteristics of EEG signal power distribution in different frequency ranges that are important for many subsequent stages as the most suitable for human interpretation. The calculation is based on the computation of the power spectral density of the signal, which is performed using the Welch method based on the Fourier transform [6] with the following parameters (window length - 2 s; overlap - 50%).

C. Artifact Filtering Module

Artifacts Filtering module provides to specialist additional functionality of data filtering that usually cannot be automized. The module provides decision support to specialist for removing single artifacts based on the attributes of the corresponding fragment (see Section IV.A) that cannot be corrected at the Data Pre-filtering Stage [6]. When the specialist removes such fragments he/she should check the EEG data before these artifacts removal.

D. Video Module

The Video module is used by the service both to facilitate the artifacts removal and recognize continuous processes. To remove artifacts, we propose automatic monitor the facial muscles activity (for example, blinking, jaw movement, etc.), as well as the movement (change in tilt) of the head, because they are most evident on the EEG signal and interfere with its analysis. However, such body movements are not very indicative from the point of view of recognition of continuous human states, and therefore at the next stage (after the removal of artifacts), more complex quantitative signs are recognized, such as respiratory rate and heart rate.

E. EEG Features Module

The EEG Features module is used to extract features from the processed EEG signal or its characteristics. Typically, these characteristics include power distribution, statistical & frequency parameters, and others.

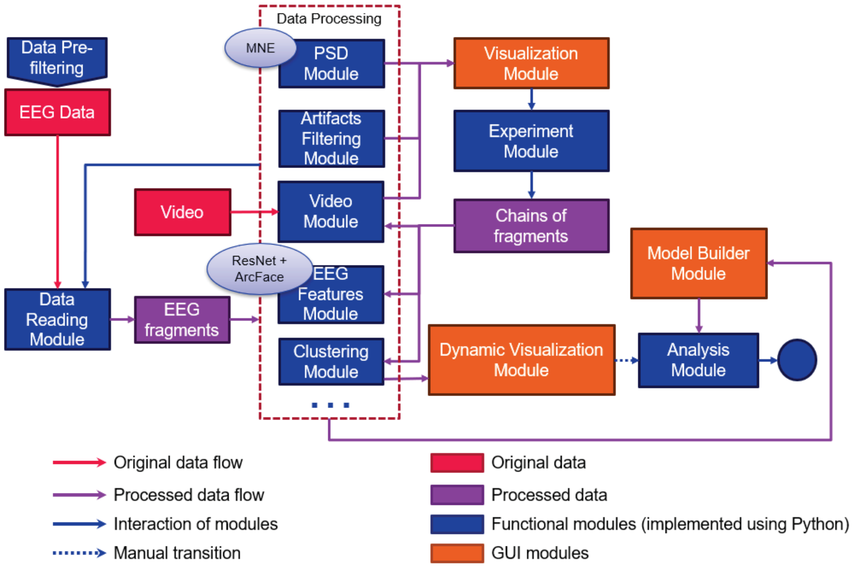

Fig. 3. Architecture of the developed service

We proposed abstract feature vectors of fragments are extracted based on the corresponding topographic maps of the spatial power distribution obtained using the PSD module. A detailed description of the applied transformations is given below.

F. Visualization Module

The Visualization module displays the spatial distribution of EEG signal power for signal fragments in the form of a sequence of topographic maps, as well as recommendations of the EEG Artifact Filtering Module. In case of uncertainty, the specialist can view a certain fragment to go to more detailed characteristics of the fragment provided by other modules in order to make a final decision on its removal. The Visualization Module is the graphical interface that allows the specialist to work with functionality implemented by the Experiment module.

G. Experiment Module

To increase the adaptability of the service, we proposed the abstraction Experiment, which is a user-generated subset of processed fragments for further analytics and consists of chains (which in turn are composed of fragments). The chains are sequences of fragments following each other in time, which may well refer to different continuous processes and/or to different records. The functionality of the module allows creating these chains, synchronizing EEG fragments with arbitrary video fragments, assigning different continuous process index to them, etc.

Chains of fragments usage increases the convenience and adaptability of the service. Particular study determines different data recording scheme. In some studies, each human state corresponds to a separate EEG recording, while in others, transitions between different states may be important. In this case the recording (both EEG and video) is carried out without stopping. So, the entity "experiment" allows us to abstract from the specifics of the recording and focus on analyzing chains of fragments. Chains of fragments are, in fact, a new markup used by data processing modules in further analysis (with labels of time, continuous process index, video offset and others).

H. Clustering Module

The Clustering module distinguish groups of fragments of the selected chain. Depending on the studied continuous process the specialist selects the number of clusters and the characteristics of the fragments. The resulting sequence of clusters allows us to compute a sequence of transition matrices between clusters. The value of each element of the transition matrix is determined by the number of transitions from cluster i to cluster j on a given sliding window within the chain.

J. Dynamic Visualization Module

The Dynamic Visualization Module allows to visualize the results of clustering, as well as the dynamics of changes in transitions between clusters. It includes a representation of the sequence of transition matrices and clustering results. This can be useful for a preliminary assessment of the quality of the analyzed chain by a specialist before proceeding directly to classification.

K. Model Builder Module

The Model Builder module allows to specify a set of fragments features (including the results of clustering) used by the final classification model, taking into account the scheme of the studied state. The resulting set of features is used by the Analysis module. The specific model used for classification is developed manually by a specialist.

L. Analysis Module

The Analysis module is used to classify chains of fragments, both on the basis of static features of fragments corresponding to certain states, and on the basis of the evaluation of dynamics obtained as a result of clustering. In addition, the stability of certain clusters and their distinguishability allow us to assess the quality of the achieved state.

M. Data Processing Sequence

The Data Reader Module splits the original EEG signal into fragments and transmits them to the data processing modules. These modules may call each other while working with fragments. After a series of mutual calls of modules (in any order) some of them transmit the results for further processing (specialist determines the module sequence based on the scenario). At the initial (primary) stage of data processing, the PSD, artifact filtering, and video processing modules are mainly involved, and their data are passed to the data visualization module for building appropriate representations. This module is a graphical interface for working with the experiment creation module, which is completed by creating a corresponding set of fragment chains. The resulting chains are used by the data processing modules, which may request a second read from the data reading module, taking advantage of the fragment metadata stored in the chains. At this (secondary) stage of data processing, video processing, fragment feature extraction, clustering, and other modules are directly involved. Before classifying the records, the dynamic visualization module displays the results of the clustering module, which allows a specialist to evaluate their acceptability. In case of a positive assessment, they are passed to the analysis module, which performs their classification with the help of a model created by the specialist by working with the model creation module.

N. Data processing stages

The breakdown into stages allows the specialist to abstract away from working with the original recordings and prepare an abstract data set that is most suitable for further analysis.

Work with the raw EEG recordings is performed only at the primary stage, where only basic data processing modules such as PSD, artifact removal and video processing are used, which are mainly needed for filtering the raw data and general quality assessment of the recordings set. Through the interface provided to the user at this stage, it is possible to perform data partitioning, remove obviously incorrect data, and combine fragments of the original records into chains.

Data manipulation at the secondary stage is based on previously saved chains and involves more sophisticated data processing modules (such as fragment feature extraction and clustering modules, as well as secondary video processing). The user has the option of filtering the desired chains based on the previously defined partitioning, and, after a preliminary visual assessment of their processing quality, passing them on for training or testing the classification model. Somewhat separately in this scheme there is a module of model creation, which allows to specify a specific set of features on the basis of which classification will be performed.

IV. CASE STUDY

In this section we show practical use cases, descriptions of the modules, and scenarios mentioned above.

A. Artifacts Removal Scenario

The specialist works with the topographic visualization and removes (excludes for further analysis) processed representations of fragments that correspond to artifact-containing fragments of the original signal.

1) We propose a function for preliminary evaluation of the signal quality of all records of the set: it is possible that the artifact will appear on the power spectral density function for the whole record (see Fig.4).

2) If some function looks abnormal the specialist should carefully consider the relevant topographic maps. If the alleged artifact is significant then the corresponding topographic map should visually stand out (abnormal fragment) from the general series.

3) In case the specialist finds an abnormal fragment he/she has possibility to click to the corresponding topographic map and open a panel with detailed information about it. Here they pay attention to the numerical power values in the frequency range. If there is a disproportionate short-term power peak in a separate frequency range, it is probably caused by the presence of an artifact in this fragment.

4) Specialist has possibility to delete the whole fragment or its individual channel.

Sometimes, in case of incorrect placement of electrodes in the EEG helmet, loss of contact with the subject's head surface, or other reasons, one of the recording channels may be partially or completely unusable. In case the corresponding signal is not processed, it may significantly damage the analysis of the entire recording (e.g. for topographic maps). That allows to delete this EEG channel from several recordings at once in case they have been recorded sequentially.

If the recording channel is deleted the service will offer the EEG analysis specialist to replace the data of this channel when building topographic maps with the averaged data of the nearest three neighboring channels by coordinates (see Fig. 5).

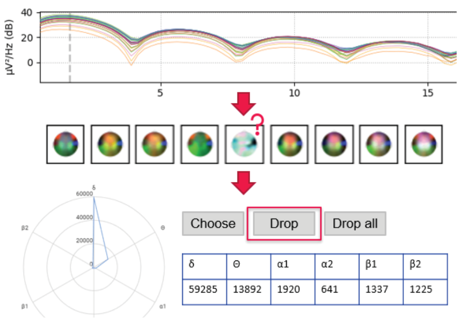

Fig. 4. An example of removing a single EEG signal artifact

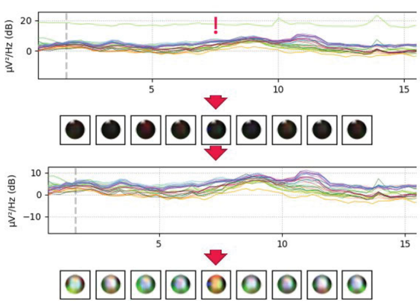

Fig. 5. An example of removing an incorrect EEG signal channel

In some cases the cause of an error in data analysis may not be a technical problem, but rather a participant's behavior that does not comply with the instructions. These types of errors are the most difficult to detect. We propose a function that provides a convenient presentation of the corresponding video data for manual search. Fig. 6 shows two rows of topographic maps for the meditator's recordings with eyes closed and open, respectively. It can be noticed that the power distribution shape in occipital region of the element in red frame differs from other ones in "Closed Eyes" row. However, it is similar to one of the elements of the "Open Eyes" row. Clicking on this element will allow us to view the synchronized fragment of the video, which will make sure that the assumption is correct. The figure shows that the meditator opened his eyes contrary to the instructions and therefore the fragment should be excluded from further analysis.

These visualization tools allowed us not only to significantly reduce the number of artifacts in the original recordings, but also to make some observations about their properties. Visual detection of some of these properties required a comparative analysis of several high-quality participant's recordings at once, with the functionality of parallel tracking of the dynamics of power distribution changes in the frequency ranges of interest, which would have been difficult to accomplish without using our service.

B. Clustering

It is often impossible to unambiguously map various human states to continuous processes. The characteristics of EEG fragments are usually more indicative of the participant's brain features rather than features of any particular human state. However, the dynamics of changes in distinguishable human states may be more indicative in this respect. For example, in case when there is a chaotic change of states throughout a meditation recording, it is obvious that the person has failed to achieve a stable meditative state, whatever the individual features of his/her individual fragments of the recording may be. The specifics of the dynamics of the various states are currently being clarified. To visualize the dynamics of changes we use interface (see Fig. 7). This interface is essentially an implementation of the concept of continuous processes dynamics analysis described in the Introduction. The table in the left part is the matrix of transitions between human states within the continuous process.

C. Feature extraction

Before the feature extraction module can start processing data the following data transformations should be implemented. The following sequence of actions (performed by different modules) leads to feature extraction of fragment images.

1) Filtering of artifacts of the original EEG recordings by the ICA method [6] (performed using third-party software).
2) Splitting records into *8*-second fragments, the length of which is empirically chosen and is a parameter.
3) Computation of the power spectral density of each fragment (computation is performed using the Welch method [19] based on the Fourier transform; window length - *2s*; overlap - *50%*).
4) Calculation of power in 6 frequency bands (δ: *[1,5; 3,75]*, θ: *[4; 7.75]*, $\alpha1$: *[8, 10.25]*, $\alpha2$: *[10.5; 13.25]*, $\beta1$: *[13.5, 18]*, $\beta2$: *[18.5; 30]*).

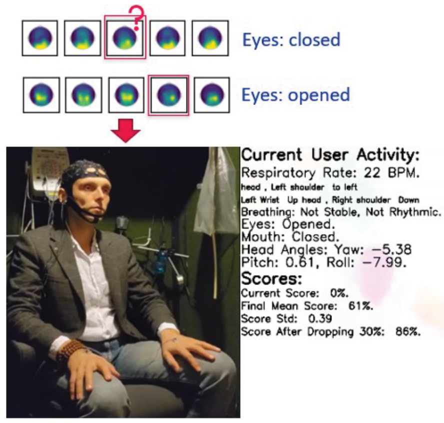

Fig. 6. An example of identifying an incorrect state of the meditator

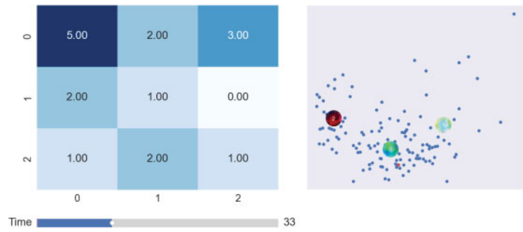

Fig. 7. The interface of the Dynamic Visualization Module

5) Removal of incorrect EEG recording channels (signal recovery is performed using data from three neighboring channels).
6) Removal of singular (see Section IV.A) incorrect fragments of EEG recordings.
7) Conversion of spectral data of fragments into RGB image.
8) Feature extraction from fragment images.

To extract the feature vector from the RGB image of fragments we use a feature extractor presented in the form of a ResNet-34 model (using the ArcFace loss function [18], which allows maximizing the distance between elements of different classes in the feature space). This model is widely used in combination with the random forest method to solve the classification problem with a limited set of data and a relatively large number of features [19] and often demonstrates better accuracy in comparison with using exclusively CNN models.

D. Hybrid analysis

Hybrid analysis can be useful at various stages of data processing, such as the primary stage of data analysis. Fig. 8 shows the interface implemented by the data visualization module. Its left part displays a sequence of topographic maps of the spatial distribution of signal fragments. The right part displays a synchronized video fragment (corresponding to the topographic map on which the mouse cursor is hovered), which additionally displays such basic parameters of the meditator as breathing rate, eye and mouth state (open/closed), head and body tilt, as well as the current assessment of meditation quality. The topographic map sequence shows the recommendations of the artifact filtering module (red boxes), which are based on the application of the LOF (local outlier factor) method to the characteristics of the fragments (obtained from both the EEG signal and the video).

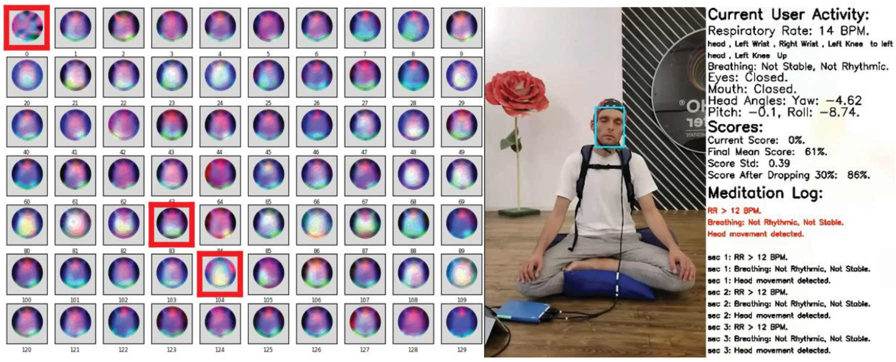

Fig. 8. Hybrid EEG analysis: specialist simultaneously watch processed video and EEG data

Application of the LOF method makes it possible not to exclude small clusters of fragments that may be important for analysis (e.g., the peak of a meditation state). However, manual analysis of fragments may still be required, and the hybrid representation allows us to do this. If necessary, the specialist can switch to a more detailed hybrid view by clicking the mouse on the fragment (see Section IV.A). The parameters shown in the figure are used in the primary stage of the analysis. In the secondary stage, parameters such as blood pressure, heart rate and oxygen saturation are also extracted from the video (see Section I). These parameters can also be used in the hybrid analysis, but this time directly for human state recognition.

V. Conclusion

In this paper, we presented our developed service for classification and analysis of continuous mental processes of the human brain. The service allows hybrid analysis of EEG and video data with corresponding feature extraction mechanisms from these both data sources. The paper demonstrates the high adaptability of the service for different research needs (using a wide range of EEG and video features that can be selected for a specific continuous process) as well as for data collection & analysis methodologies (using the developed data partitioning scheme). The mechanism of record fragment chains presented in the paper allows flexible partitioning and filtering of the source data, after which it is possible to start analyzing and recognizing complex dynamic continuous processes at a higher level of abstraction. The paper describes the composition and purpose of various functional modules of the service, the specifics of their interaction and data conversion as well as the general scenario of working with them. In addition, the paper demonstrates practical examples of working with the service with special attention paid to the description of partly automated parts. Future work will focus on expanding our dataset by recording different types of continuous processes other than meditation. At the moment, the service can be used by a specialist only, but the paper shows the potential for its application at home using dry-electrode EEG recording devices.

References

[1] R. Cox, J. Fell, “Analyzing human sleep EEG: A methodological primer with code implementation”, *Sleep Medicine Reviews*, vol. 54, Dec. 2020.

[2] W. Al-Salman, Y. Li, A. Oudah, S. Almaged, “Sleep stage classification in EEG signals using the clustering approach based probability distribution features coupled with classification algorithms”, *Neuroscience Research*, 2023, pp. 51-67.

[3] R. Cahn and J. Polich, *Meditation states and traits: EEG, ERP, and neuroimaging studies*, Psychological Bulletin, 2006.

[4] M.H. Díaz, F.M. Córdova, L. Cañete, F. Palominos, F. Cifuentes, G. Rivas, “Inter-channel Correlation in the EEG Activity During a Cognitive Problem Solving Task with an Increasing Difficulty Questions Progression”, *Procedia Computer Science*, vol. 55, 2015, pp. 1420-1425.

[5] M.H. Díaz, F.M. Córdova, L. Cañete, F. Palominos, F. Cifuentes, C. Sánchez, M. Herrera, “Order and Chaos in the Brain: Fractal Time Series Analysis of the EEG Activity During a Cognitive Problem Solving Task”, *Procedia Comp. Science*, vol. 55, 2015, pp. 1410-1419.

[6] S. Tong and N.V. Thakor *Quantitative EEG Analysis Methods and Clinical Applications,* Artech House, 2009.

[7] M. Erlichman, “Electroencephalographic (EEG) video monitoring”, *Health Technol Assess Rep*, vol. 4, 1990, pp. 1-14.

[8] E.M. Mizrahi, “Electroencephalographic-video monitoring in neonates, infants, and children”, *J Child Neurol*., vol. 1, 1994, pp. 46-56.

[9] E.M. Mizrahi, “Pediatric electroencephalographic video monitoring”, *J Clin Neurophysiol*, vol. 2, 1999, pp. 100-110.

[10] W. Othman, A. Kashevnik, I. Ryabchikov, N. Shilov, “Contactless Camera-Based Approach for Driver Respiratory Rate Evaluation in Vehicle Cabin”, *2022 Intelligent Systems Conference, Amsterdam, The Netherlands.,* vol. 2, Sept. 2022.

[11] W. Othman, A. Kashevnik, “Video-Based Real-Time Heart Rate Detection for Drivers Inside the Cabin Using a Smartphone”, *2022 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS 2022), Bali, Indonesia.*, Nov. 2022, pp. 1-5.

[12] B. Hamoud, A. Kashevnik, W. Othman, N. Shilov, “Neural Network Model Combination for Video-Based Blood Pressure Estimation: New Approach and Evaluation”, *Sensors MDPI AG, Basel, Switzerland.*, vol. 23, Apr. 2023, pp. 1-16.

[13] B. Hamoud, W. Othman, N. Shilov, A. Kashevnik, "Contactless Oxygen Saturation Detection Based on Face Analysis: An Approach and Case Study", 2023 33rd Conference of Open Innovations Association (FRUCT), Zilina, Slovakia, 2023, pp. 54-62.

[14] F. Hasan, A. Kashevnik, “State-of-the-Art Analysis of Modern Drowsiness Detection Algorithms Based on Computer Vision”, Proceedings of the 29th Conference of Open Innovations Association FRUCT, Tampere, Finland., vol. 29, May 2021, pp. 141-149.

[15] B.R. Cahn, A. Delorme, J. Polich, “Occipital gamma activation during Vipassana meditation”, *Cogn Process*, 1999, pp. 39–56.

[16] A. Ahani, H. Wahbeh, H. Nezamfar, “Quantitative change of EEG and respiration signals during mindfulness meditation”, *J Neuro Engineering Rehabil*., 2014, pp. 87.

[17] D. Kleeva, I. Ninenko, M. Lebedev, “Resting-state EEG recorded with gel-based versus consumer dry electrodes: spectral characteristics and across-device correlations”, *Cold Spring Harbor Lab.*, Aug. 2023.

[18] J. Deng, J. Guo, J. Yang, N. Xue, I. Kotsia, S. Zafeiriou “ArcFace: Additive Angular Margin Loss for Deep Face Recognition”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, Oct. 2022, pp. 5962-5979.

[19] M.K. Yaqoob, S.F. Ali, M. Bilal, Hanif M. S., U.M. Al-Saggaf, “ResNet Based Deep Features and Random Forest Classifier for Diabetic Retinopathy Detection”, *Sensors*, 2023, pp. 3883.