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A NEW ALGORITHM FOR DETECTING MOTION ARTIFACTS IN VIDEO-EEG MONITORING DATA

D.M. Murashov ¹, Yu.V. Obukhov ², I.A. Kershner ²,
M.V. Sinkin ³, I.V. Okuneva ³

¹ Federal Research Center “Computer Science and Control” of RAS,
119333, Russia, Moscow, 42 Vavilov str.

² Kotelnikov IRE RAS, 125009, Russia, Moscow, Mokhovaya str., 11, b.7

³ Sklifosovsky Research Institute for Emergency Medicine,
129090, Russia, Moscow, Bolshaya Suharevskaya Square, 3.

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Abstract. The article proposes a new algorithm for detecting artifacts in video recordings of long-term video-EEG monitoring data in the context of the problem of diagnosing delayed cerebral ischemia after subarachnoid hemorrhage. The main idea of the new algorithm is as follows. First, to ensure the invariance of the algorithm with respect to illumination variations, we calculate the motion measures from the edge map of the region of interest. Secondly, to expand the set of motion measures by including variation of information between the blurred edge maps of two consecutive frames. Third, to combine detectors that use different measures of scene motion. An experiment on clinical video-EEG monitoring data showed that the proposed algorithm provides sensitivity of 0.94, specificity of 0.94, accuracy of 0.94, and F1 score of 0.91. The obtained characteristics correspond to the level of known motion detectors in video-EEG data.

Key words: video-electroencephalographic monitoring; optical flow; variation of information; edge map; artifacts; cerebral ischemia; motion measure.

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Corresponding author: Kershner Ivan Andreevich, ivan_kershner@mail.ru

Introduction

One of the tasks associated with the problem of diagnosing vascular spasm and cerebral ischemia in patients with subarachnoid hemorrhage using video-EEG monitoring data is the detection of EEG signal distortions caused by patient movement and the work of medical personnel in the intensive care unit [1]. Such distortions may impair diagnostic and event prediction results. To detect and remove artifacts of patient vital activity and artifacts caused by the work of medical personnel, video recordings synchronous with EEG are analyzed.

The problem of motion detection in video data, which arises in various subject areas, has been addressed in a large number of publications (see, for example, the review [2]). In the field of medical diagnostics, there are known works in which the authors, using the analysis of video recordings, solve the problems of measuring the intensity of movement and motor activity of newborns, detecting clonic and myoclonic seizures in newborns, and recognizing apneas after an epileptic seizure [3–5]. The features needed for event recognition are computed from the optical flow.

In [1], the authors proposed an algorithm for detecting motor activity in video frames based on a classifier, in which the value of the optical flow calculated in the region of interest was also used as a feature. Optical flow was calculated using the Lucas-Canade method [6]. The algorithm provided reliable detection of motion artifacts in long-term video-EEG monitoring data. However, many patient videos show periodic fluctuations in illumination levels caused by medical equipment in the intensive care units. Fluctuations in illumination levels caused changes in the magnitude of optical flow that were comparable to changes caused by intense movement in the frame. Such interference in video recordings leads to an increase in false alarms of the detector and a decrease in the accuracy of artifact detection. Therefore, the task arises of modifying the motion artifact detector to ensure robustness against the above-mentioned interference. In addition, to increase the reliability of motion artifact detection, it seems appropriate to expand the set of features (indicators of motion) used in the algorithm.

A number of publications are known that have considered methods for calculating optical flow that are invariant with respect to changes in illumination. One group of methods uses neural network technologies. For example, [7] proposed a weakly supervised neural network framework to estimate illumination-invariant optical flows between image pairs. The difficulties in applying neural networks to medical videos are related to the lack of suitable image databases for training. Another group of methods uses operators that compute invariant local descriptors used to obtain the optical flow value. In [8], an analysis was made of a number of well-known descriptors based on rank transforms [9], census transform [10], LDP (Local Directional Pattern) transform [11] and modified LDP transform (MLDP) [12], correlation transform [13], normalized neighborhood descriptor (NND) [14], as well as two descriptors based on pixel brightness differences in 8 directions. The analysis showed that the above edge descriptors are effective on various test image databases.

Some researchers have used measures of chaos and information measures to detect events in various types of signals. For example, in [15], an approximate estimate of the Kolmogorov entropy (K-entropy) was used to detect dynamic irregularities associated with nonlinear properties of biomedical signals. In [16], in the motion detector for calculating the threshold, the authors proposed to use the Kullback-Leibler divergence when comparing the histograms of the background and the neighborhood of the analyzed pixels in the video frames. An alternative information-theoretical measure is the variation of information [17], which characterizes the information difference between two frames. The variation of information is calculated directly from the joint distribution of pixel brightness of two consecutive frames. Unlike the Kullback-Leibler divergence, the variation of information is a true metric. The greater the value of variation of information, the greater the difference in the content of the two frames. Thus, this metric can be considered as a measure of the intensity of movement in the frame.

In this paper, based on the analysis of methods for ensuring the robustness of optical flow with respect to changes in scene illumination in the frame, a new algorithm for detecting motion artifacts in video recordings of long-term video-EEG monitoring

data is proposed. The main idea of the new algorithm is as follows. First, we propose to calculate scene motion measures from the region of interest (ROI) edge maps (or contour maps), which represent the contours of scene objects. Second, to expand the feature set for motion detection by including variation of information between blurred edge maps of two consecutive frames. Third, to combine detectors that use different measures of scene activity.

1. Materials and Methods

In the study, we use twelve-hour video recordings from long-term video EEG monitoring data from three adult patients. For video recording of the patient's condition during the day and night, a FullHD video camera Hikvision DS-2CD2443G0-IW is used. The camera is equipped with a built-in IR illumination, allowing shooting in the dark. The video recording consists of MPEG4 files containing a ten-minute fragment. The frame size is 1920 by 1080 pixels. In the frame we select a rectangular region of interest of size W by N pixels, $W \leq 1920$, $N \leq 1080$. The region of interest is the part of the frame in which the head of a patient lying on a hospital bed is visible (see Fig. 1). Video shooting can be performed from different angles. It is necessary to detect movement in the area of interest caused by the patient's vital activity (e.g. head and limb movements) and patient care by medical personnel. Even slight movements of the patient's head and limbs should be detected.

In the following subsections, we propose an algorithm for detecting motor activity in video frames. When detecting motion artifacts, we will use two measures of motion in the region of interest: the optical flow value and the variation of information between successive frames. To ensure robustness, motion measures will be calculated from the edge maps of the region of interest. To make a decision about detecting an artifact, we will use a classifier with a quadratic discriminant function, described in [18].

2. Improving the robustness of the motion detector relative to the scene illumination level

In [1], artifacts are detected by the value of an indicator characterizing the degree of activity in the ROI. The motion measure in the region of interest is the value of the smoothed optical flow calculated in the region of interest of the frames of the video sequence:

$$\hat{J}(k) = \phi(\theta(U_k)), \quad (1)$$

where $\hat{J}(k)$ is the motion measure in the region of interest for frame number k ; $\phi()$ is the Kalman filter operator; $\theta()$ is an operator for calculating optical flow; U_k is the brightness function of the region of interest of the frame number k .

As noted in the Introduction, fluctuations in illumination levels distort the magnitude of the optical flow, which leads to a decrease in the accuracy of artifact detection. We propose to modify the algorithm to improve the accuracy. The following model is considered. We assume that the image of the region of interest in frame number of the video is described by the function [19]:

$$U_k(x, y) = F_1(x, y, k) + F_2(x, y, k), \quad (2)$$

where $U_k(x, y)$ is the image function in the region of interest of frame number k [19], $k = 1, 2, \dots, K$; $F_1(x, y, k)$ and $F_2(x, y, k)$ are the brightness functions from different light sources; x, y are spatial coordinates, $0 \leq x \leq W$, $0 \leq y \leq H$; W and N are the width and height of the frame's ROI (in pixels), respectively. It is assumed that the component $F_2(x, y, k)$ describes the fluctuations of illumination. This function is constant in some neighborhood $\Omega(x, y)$ of the point with coordinates (x, y) in frame number k and changes between frames $k-1$ and k (it depends on time):

$$\begin{aligned} F_2(x, y, k) &= c(k), (x, y) \in \Omega, c(k) = \text{const}, \\ |F_2(x, y, k) - F_2(x, y, k-1)| &> 0. \end{aligned} \quad (3)$$

In [1], optical flow was calculated by the Lucas-Canade algorithm [6], which uses the partial derivative with respect to time of the pixel brightness in the image window. In this case, the component $F_2(x, y, k)$, depending on time (on the frame number), will distort the derivative of brightness with respect to time and, accordingly,

the optical flow. For example, if there is no movement in the video, the optical flow will have a non-zero value due to the variation in illumination. In the new motion artifact detection algorithm, we propose to use the Canny algorithm [20] to generate the edge map. The Canny algorithm uses differential operators that calculate the differences in pixel brightness in the neighborhood $\Omega(x,y)$ of a pixel with coordinates (x,y) in frame k , and thresholding operation. In this case, the component $F_2(x,y,k)$, which takes into account in (2) the interference in the form of illumination fluctuations, will not distort the edge maps in frames $k-1$ and k and, accordingly, the value of the optical flow. When implementing the Canny detector, edges shorter than $L_{\min}$ pixels are removed as noise. The minimum edge length $L_{\min}$ is selected depending on the size of the ROI.

Figure 1 shows three frames of video recording of video-EEG monitoring data, which depict the resting state and movement of the patient's hand, and the corresponding edge maps. Frames (a) and (b) and contour maps (d) and (e) illustrate the patient's resting state (contour maps differ slightly), while figures (c) and (f) correspond to hand movement (contour maps (e) and (f) differ significantly).

Table 1 shows the mean values and standard deviations of the optical flow $\hat{J}$ calculated from the region of interest images and the contour maps of the frames of video recordings of the patient's resting state and low-intensity movements (slow low-amplitude head movements and slow hand movements). From the data in Table 1, it follows that in the video recordings of the resting state with fluctuating illumination levels, the mean value of optical flow is 0.679 and the standard deviation is 0.077, which exceeds the mean value of flow equal to 0.559 and the standard deviation equal to 0.064 in the recordings with movement in the frame with constant scene illumination. The data in Table 1 also show that the use of edge maps made it possible to reduce the influence of illumination fluctuations on the value of optical flow. In particular, the mean optical flow value in video recordings of the resting state with fluctuating illumination levels is 0.945 and the standard deviation is 0.02, while in recordings with low-intensity movement (weak head and hand movements, facial

expressions) with constant scene illumination, the mean optical flow value was 1.063 and the standard deviation was 0.0528.

Table 1. Characteristics of the motion measure calculated from images of different types.

Image type	Content of video	Characteristics of the motion measure $\hat{J}(k)$	
		Mean	Standard deviation
Images of the region of interest	Rest, illumination fluctuations	0.679	0.077
	Movement	0.559	0.064
Contour maps of the region of interest	Rest, illumination fluctuations	0.945	0.02
	Movement	1.063	0.053

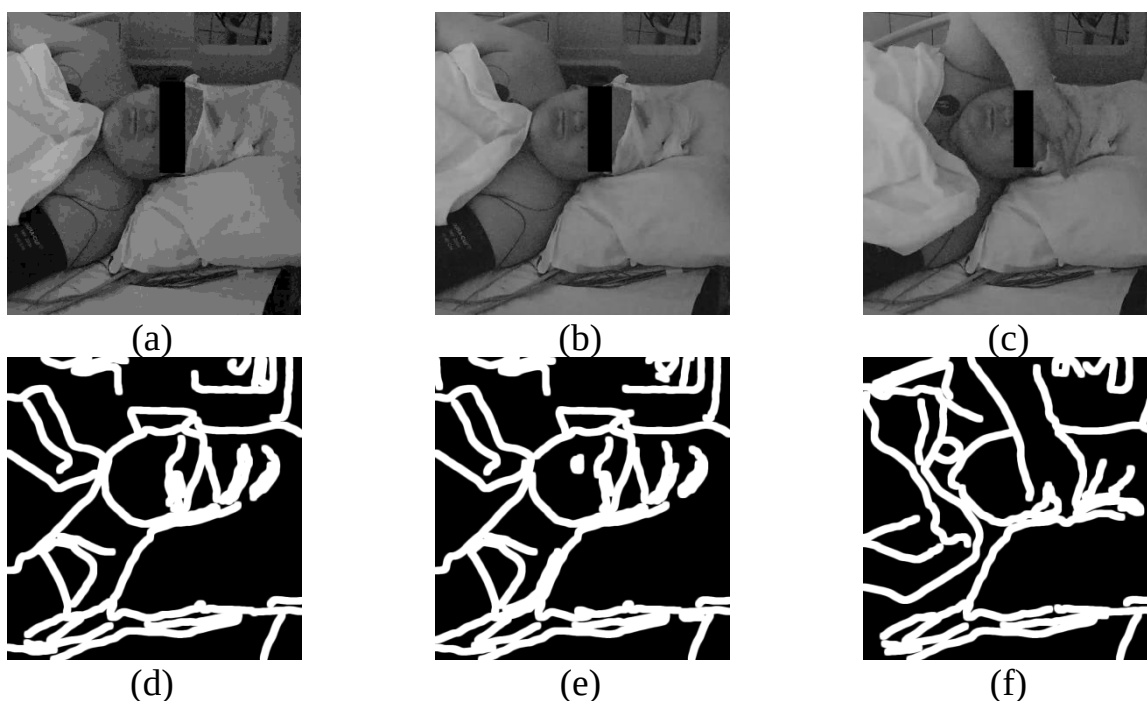


Fig. 1. Three frames of video recording from video-EEG monitoring data (a), (b), (c) and contour maps of these frames (d), (e) (f), illustrating the patient's resting state and hand movement.

3. Optical flow based motion measure

Let the ROI edge map $E_k^{emap}(x,y)$ in the frame $U_k(x,y)$ be obtained using the edge detector and Gaussian filter:

$$E_k^{emap}(x,y) = G\{\psi(U_k(x,y))\}, \quad (4)$$

where $\psi()$ is the edge detector operator, $G\{\}$ is the Gaussian blur operator.

The model for computing the motion measure is represented by the following relationship:

$$J(k) = \frac{1}{WH} \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \sqrt{V_x^2(x,y,k) + V_y^2(x,y,k)} + \delta(k), \quad (5)$$

where $J(k)$ is the value of the measure calculated from the edge map E_k^{emap} of the frame number k ; W, H are the width and height of the ROI; $V_x(x,y,k)$ and $V_y(x,y,k)$ are the optical flow values along the X and Y axes in a pixel with coordinates (x,y) ; $\delta(k)$ is noise. To calculate $V_x(x,y,k)$ and $V_y(x,y,k)$ we use the Lucas-Kanade algorithm [6]. Since the $J(k)$ function contains a noise component, we use a smoothed value of the motion measure $\hat{J}(k)$ when detecting events. For smoothing, a discrete version of the Kalman-Bucy filtering algorithm is used, since it ensures obtaining an optimal estimate in the sense of minimum error variance.

4. Information-theoretical measure of scene activity

To improve the reliability of motion detection in a frame, we propose to use as a second measure of motion an information-theoretic measure of the difference between video frames, namely, the variation of information [17]. As with the optical flow-based activity measure, we will analyze ROI edge maps. Let the edge maps of the frame ROI be described by random variables $E_k^{emap}(x,y)$ and $E_{k-1}^{emap}(x,y)$ with values $e_k(x,y)$ and $e_{k-1}(x,y)$, respectively. We will consider successive frames of video recording as the input and output of some information channel:

$$E_k^{emap} = f(E_{k-1}^{emap}) + \eta_{k-1} \quad (6)$$

where E_{k-1}^{emap} is the channel input, E_k^{emap} is the channel output; f is the transformation function; η_{k-1} is the channel noise, variables E_{k-1}^{emap} and η_{k-1} are independent. The variation of information according to the definition [17] is calculated by the formula:

$$VI(E_k^{emap}, E_{k-1}^{emap}) = H(E_k^{emap} | E_{k-1}^{emap}) + H(E_{k-1}^{emap} | E_k^{emap}), \quad (7)$$

where $VI(E_k^{emap}, E_{k-1}^{emap})$ is the variation of information between edge maps E_{k-1}^{emap} and E_k^{emap} , $H(E_{k-1}^{emap} | E_k^{emap})$ is the conditional entropy of the channel input given that E_k^{emap} is observed at the output; $H(E_k^{emap} | E_{k-1}^{emap})$ is the conditional entropy of the channel output given E_{k-1}^{emap} . As in the case of the first activity measure, we will use the value of the smoothed by the Kalman-Bucy filter variation of information $\hat{VI}(E_k^{emap}, E_{k-1}^{emap})$.

However, the variation of information is not uniquely related to the magnitude of the optical flow. Using data from 10 video fragments, we calculated the correlation coefficients between the values of optical flow $\hat{J}(k)$ and smoothed variation of information $\hat{VI}(E_k^{emap}, E_{k-1}^{emap})$. The values of the correlation coefficient range from 0.427 to 0.95, which corresponds to gradations from “moderate degree of association” to “very high degree of dependence” between the measures under consideration according to the Chaddock scale [21].

To verify the possibility of constructing a motion detector, we calculated the value of variation of information in a video recording of the patient's resting state and low-intensity movement. Table 2 shows the mean values and standard deviations of the smoothed variation of information $\hat{VI}$ in the contour maps of the region of interest. At rest, the average value of variation of information between frames is 0.816 with the standard deviation being 0.015. In the video with the patient's movement, the average value of variation of information is 0.953, and the standard deviation increases more than twice and is equal to 0.032. The data in Table 2 confirm that the variation of information values differ depending on the content of the records, and this functional can be used as a measure of activity in the motion detector under conditions of fluctuating illumination levels.

Table 2. Characteristics of the theoretical-informational measure of activity.

Content of video	Mean	Standard deviation
Rest, illumination fluctuations	0.8160	0.0150
Movement	0.9529	0.0322

5. Making decisions about detecting artifacts

The specificity of the disease under study is that the presence of a certain number of false-positive decisions on the detection of motion artifacts has an insignificant effect on the accuracy of the diagnosis of delayed cerebral ischemia. In this work, we will make a decision about the detection of an artifact (event) independently for each of the activity measures, and then combine the obtained decisions. This approach simplifies the tuning of classifiers and the interpretation of the results obtained. We will combine the classifiers' decisions using the logical operator “OR”. The event will be considered detected if at least one of the classifiers gives a positive decision. With this method of combining, an increase in false positive decisions is possible, but at the same time, the sensitivity of the detector increases and the probability of missing artifacts decreases.

The decision to detect an event is made by a classifier with a quadratic discriminant function [18]:

$$Event_1 = \begin{cases} 1, & \text{if } g_i(\varphi_i(k)) > 0 \text{ and } k - k^* \geq M; \\ 0, & \text{if } g_i(\varphi_i(k)) \leq 0 \text{ and } k - k^* < M; \end{cases} \quad (8)$$

$$g_i(\varphi_i(k)) = -\left(\frac{1}{2\sigma_{i1}^2} - \frac{1}{2\sigma_{i2}^2}\right)\varphi_i^2(k) + \left(\frac{\mu_{i1}}{2\sigma_{i1}^2} - \frac{\mu_{i2}}{2\sigma_{i2}^2}\right)\varphi_i(k) - \left(\frac{\mu_{i1}^2}{2\sigma_{i1}^2} - \frac{\mu_{i2}^2}{2\sigma_{i2}^2}\right), \quad (9)$$

where $Event_1$ is an event indicator; g_i is a separating function that depends on the activity measures $\varphi_i \in \{\hat{J}, \hat{V}T\}$; μ_{i1} , σ_{i1} and μ_{i2} , σ_{i2} are the mean values and standard deviations of the motion measure $\varphi_i(k)$ for video fragments with low and high scene dynamics, respectively; k^* is the frame number starting from which the inequality $g_i(\varphi_i(k)) > 0$ is satisfied; M is the length of the frame sequence required to make a decision about the detection of an artifact. The combined decision is defined as:

$$Event = Event_1 \vee Event_2 \quad (10)$$

where the symbol $\vee$ denotes the logical “OR” operation. Classifier parameters Eq. (8) – (9) are calculated when tuning classifiers for video fragments with low and high scene dynamics.

The next section will describe the algorithm for detecting motion artifacts in the region of interest of video frames.

6. Algorithm for detecting motion artifacts

The algorithm for recording motion artifacts in the video channel of video-EEG monitoring data includes the following operations.

- 1) Set $k^* = \infty$.
- 2) Read frame number k from the video sequence.
- 3) Obtain edge map E_k^{emap} (see eq. (4)) from region of interest image U_k .
- 4) Calculate the values of optical flow $J(k)$ using eq. (5) and variation of information $VI(E_k^{emap}, E_{k-1}^{emap})$ in the region of interest using eq. (7).
- 5) Calculate the smoothed motion measures $\hat{J}(k)$ and $\hat{VI}(E_k^{emap}, E_{k+1}^{emap})$.
- 6) Check conditions eq. (8, 9). If condition $g_i(\varphi_i(k)) > 0$ is met and $k^* < 0$, then the current frame number is stored $k^* = k$. If conditions eq. (8, 9) are met, then a decision is made to detect the artifact $Event_i$; compute $Event$ using eq. (10). If $g_i(\varphi_i(k)) \leq 0$ and $k - k^* \geq M$ then $k = k+1$ and go to step 1.
- 7) $k = k+1$; repeat steps 2 – 6.

The algorithm is implemented in the MATLAB environment. The value of the parameter was found empirically and is equal to 2. To ensure acceptable speed of the algorithm, we analyze every tenth frame of the recording.

The next section will describe the computational experiment and present the testing results of the developed motion artifact detector.

7. Results

A computational experiment was conducted to evaluate the effectiveness of the proposed algorithm for detecting motion artifacts in video data. The calculations were performed on a computer with an Intel CORE i7-9750H processor with a clock frequency of 2.60 GHz and 32 GB of RAM. In the experiment, using the F1 measure we evaluated the efficiency of motion artifact detection. We used long-term video recordings of three patients obtained in clinical settings. The video recordings show daily changes in the illumination of the ward and fluctuations in illumination caused by the equipment. Patients were in a state of sleep and wakefulness. We analyzed 193 video fragments, each 25 seconds long, that corresponded to epileptiform discharges recorded on the EEG and associated with an increased risk of delayed cerebral ischemia. The following events related to the patients' life activities and the work of the personnel were recorded on video: movements of the patient's limbs, head movements, movements of the patient's body (change of posture), breathing, examination of the patient, application of a bandage, and other operations related to patient care. It was necessary to detect movements of low, medium and high intensity. The selected algorithm parameters should ensure detection of the above events, excluding movements caused by the patient's breathing.

The motion artifact detection results are shown in Table 3. The table shows the results of separate operation of detectors using the optical flow value and variation of information, as well as the algorithm combining these detectors in accordance with eq. (10).

Table 3. Results of detection of motion artifacts.

Detector	True positive	True negative	False positive	False negative
Optical Flow-based	50	125	3	15
VI-based	42	123	5	23
Combined	61	120	8	4

Based on the data in Table 3, the quality measures of motion artifact detection were calculated separately for each of the considered measures of the motion of the region of interest, as well as for the combined detector. The values of the measures are presented in Table 4.

Table 4. Values of quality measures for motion artifact detection.

Algorithm	Precision	Sensitivity	Specificity	Accuracy	F1 score
Optical Flow-based	0.95	0.77	0.98	0.91	0.85
VI-based	0.89	0.65	0.96	0.85	0.75
Combined	0.88	0.94	0.94	0.94	0.91

8. Discussion

The results of the experiment, presented in Tables 3 and 4, show that combining the detectors made it possible to increase the number of true positives with a slight decrease in true negatives and a slight increase in false positives, and also to significantly reduce the number of false negatives. This resulted in an increase in sensitivity to 94 %, accuracy to 94 % and F1 score to 91 %, and a slight decrease in precision (to 88 %) as well as specificity (to 94 %).

The closest to the problem of detecting motion artifacts in video recordings of video-EEG monitoring data is the problem of epileptic seizures segmentation. In publications on the topic of video-EEG monitoring data analysis, a number of algorithms for detecting patient movement are known [22]. We compare the accuracy characteristics of motion artifact detection by the algorithm proposed in this paper with the characteristics of known algorithms. However, it should be noted that, unlike the task of detecting seizures characterized by fairly intense limb movements, in our task it is necessary to detect even low-intensity movements of the patient's head and limbs. This feature of the task caused some increase in the number of false positive and false negative detections. In [23], the acceptable sensitivity level of systems for automatic recognition of epileptic seizures based on video recordings from video-EEG monitoring data is considered to be no lower than 70 %. According to estimates given in the articles [23, 24], the sensitivity of various epileptic seizure detectors (for three

types of seizures) based on video is from 75 to 100 % and specificity between 53–93 %. The authors of the review [25] report on the sensitivity of markerless motion detectors in the task of recognizing epileptic seizures of about 94 % and specificity of 87 %, achieved on clinical recordings. In [26], the sensitivity of the motion detector for the optical flow value was 75–100 % with a corresponding change in precision from 100 to 85 %. In [27] the sensitivity of the method for segmentation of clonic seizures was 95 %. The seizure detection algorithm in [5] yielded an overall sensitivity value of 94 %. These data show that the characteristics of the proposed in this work motion artifact detector (see Table 4) correspond to the characteristics of known motion detectors in systems for analyzing video recordings from video-EEG monitoring data.

Conclusion

A new algorithm for detecting motion artifacts in video recordings of long-term video-EEG monitoring data is proposed in the context of the problem of diagnosing delayed cerebral ischemia after subarachnoid hemorrhage. The algorithm uses two integral measures of motion. The first is based on the optical flow calculated in the region of interest of the video frames. The second is the variation of information between images of the region of interest in successive frames. To reduce the impact of illumination level fluctuations in the intensive care unit on the accuracy of artifact detection, we proposed to calculate motion measures from ROI blurred edge maps. Detectors built on the basis of two motion measures are combined using the logical “OR” rule. The computational experiment showed that the proposed algorithm provides sensitivity of 0.94, specificity of 0.94, accuracy of 0.94 and F1 score of 0.91. The characteristics of the proposed motion artifact detection algorithm correspond to the characteristics of known motion detectors in video-EEG monitoring data analysis systems. In further studies, we will apply the proposed algorithm together with the EEG signal analysis algorithm for the diagnosis of delayed cerebral ischemia after subarachnoid hemorrhage.

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References

1. Murashov D. et al. An algorithm for detecting artifacts in video recordings of long-term video-EEG monitoring data for the diagnostics of delayed cerebral ischemia // 2023 IX International Conference on Information Technology and Nanotechnology (ITNT). – IEEE, 2023. – C. 1-5. <https://doi.org/10.1109/itnt57377.2023.10139085>
2. Zhu H. et al. A review of video object detection: Datasets, metrics and methods // Applied Sciences. – 2020. – T. 10. – №. 21. – C. 7834. <https://doi.org/10.3390/app10217834>
3. Cattani L. et al. Monitoring infants by automatic video processing: A unified approach to motion analysis // Computers in biology and Medicine. – 2017. – T. 80. – C. 158-165. <https://doi.org/10.1016/j.compbiomed.2016.11.010>
4. Geertsema E.E. et al. Automated non-contact detection of central apneas using video // Biomedical Signal Processing and Control. – 2020. – T. 55. – C. 101658. <https://doi.org/10.1016/j.bspc.2019.101658>
5. van Westrhenen A. et al. Automated video-based detection of nocturnal motor seizures in children // Epilepsia. – 2020. – T. 61. – C. S36-S40. <https://doi.org/10.1111/epi.16504>
6. Lucas B.D., Kanade T. An iterative image registration technique with an application to stereo vision // IJCAI'81: 7th international joint conference on Artificial intelligence. – 1981. – T. 2. – C. 674-679.
7. Huang Z. et al. Life: Lighting invariant flow estimation // arXiv preprint arXiv:2104.03097. – 2021.
8. Trinh D.H., Daul C. On illumination-invariant variational optical flow for weakly textured scenes // Computer Vision and Image Understanding. – 2019. – T. 179. – C. 1-18.

9. Demetz O., Hafner D., Weickert J. The Complete Rank Transform: A Tool for Accurate and Morphologically Invariant Matching of Structures // BMVC. – 2013. <https://doi.org/10.5244/C.27.50>
10. Zabih R., Woodfill J. Non-parametric local transforms for computing visual correspondence // European conference on computer vision. – Berlin, Heidelberg: Springer Berlin Heidelberg, 1994. – C. 151-158. <https://doi.org/10.1007/BFb0028345>
11. Kabir M.H., Jabid T., Chae O. A local directional pattern variance (LDPv) based face descriptor for human facial expression recognition // 2010 7th IEEE international conference on advanced video and signal based surveillance. – IEEE, 2010. – C. 526-532.
12. Mohamed M.A. et al. Illumination-robust optical flow using a local directional pattern // IEEE Transactions on Circuits and Systems for Video Technology. – 2014. – T. 24. – №. 9. – C. 1499-1508.
13. Molnár J., Chetverikov D., Fazekas S. Illumination-robust variational optical flow using cross-correlation // Computer Vision and Image Understanding. – 2010. – T. 114. – №. 10. – C. 1104-1114.
14. Ali S. et al. Illumination invariant optical flow using neighborhood descriptors // Computer Vision and Image Understanding. – 2016. – T. 145. – C. 95-110. <https://doi.org/10.1016/j.cviu.2015.12.003>
15. Manilo L.A., Nemirko A.P. Recognition of biosignals with nonlinear properties by approximate entropy parameters // Computer Optics. – 2023. – T. 47. – №. 5. – C. 832-840. <https://doi.org/10.18287/2412-6179-CO-1345>
16. Yadav D.K., Singh K. A combined approach of Kullback–Leibler divergence and background subtraction for moving object detection in thermal video // Infrared Physics & Technology. – 2016. – T. 76. – C. 21-31.
17. Meilă M. Comparing clusterings—an information based distance // Journal of multivariate analysis. – 2007. – T. 98. – №. 5. – C. 873-895.
18. Stork D.G. et al. Pattern classification // A Wiley-Interscience Publication. – 2001. – T. 1. – C. 281-297.

19. Pratt W.K. Digital image processing: PIKS Scientific inside. – Hoboken, New Jersey : Wiley-interscience, 2007. – Т. 4. <http://doi.org/10.1002/0471221325>
20. Canny J. A computational approach to edge detection // IEEE Transactions on pattern analysis and machine intelligence. – 2009. – №. 6. – С. 679-698.
21. Chaddock R.E. Principles and methods of statistics. – Houghton Mifflin, 1925.
22. Dmitry M. et al. Application of frequency features of optical flow for event detection in video-EEG monitoring data // Journal of Biomedical Photonics & Engineering. – 2021. – Т. 7. – №. 3. – С. 30301. <http://doi.org/10.18287/JBPE21.07.030301>
23. Rai P. et al. Automated analysis and detection of epileptic seizures in video recordings using artificial intelligence // Frontiers in Neuroinformatics. – 2024. – Т. 18. – С. 1324981.
24. Ulate-Campos A. et al. Automated seizure detection systems and their effectiveness for each type of seizure // Seizure. – 2016. – Т. 40. – С. 88-101. <https://doi.org/10.1016/j.seizure.2016.06.008>
25. Pediaditis M., Tsiknakis M., Leitgeb N. Vision-based motion detection, analysis and recognition of epileptic seizures—a systematic review // Computer methods and programs in biomedicine. – 2012. – Т. 108. – №. 3. – С. 1133-1148.
26. Cuppens K. et al. Automatic video detection of body movement during sleep based on optical flow in pediatric patients with epilepsy // Medical & biological engineering & computing. – 2010. – Т. 48. – №. 9. – С. 923-931.
27. Kalitzin S. et al. Automatic segmentation of episodes containing epileptic clonic seizures in video sequences // IEEE transactions on biomedical engineering. – 2012. – Т. 59. – №. 12. – С. 3379-3385. <https://doi.org/10.1109/TBME.2012.2215609>

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