

Small Movements Detection In Video Using Video-EEG Data

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Abstract— Long-term video-EEG monitoring with sleep recording is the gold standard for diagnosing epilepsy. Automated methods for video-EEG analysis primarily focus on EEG, neglecting the video modality. This paper addresses the underexplored problem of detecting small motions, such as eye blinks and eyelid fluttering, from video recordings. We propose a novel pipeline that uses EEG eye movement and myographic artifacts as a source of ground-truth labels to train a video-based classifier. Our video-based classifier achieves 94.4% test accuracy and 87.4% accuracy when tested on a different subject.

Keywords—CNN, EEG, video, video-EEG.

I. INTRODUCTION

Epilepsy is one of the most common brain diseases, characterized by an enduring predisposition to generate epileptic seizures [1]. An epileptic seizure occurs due to a sudden imbalance between the brain's excitatory and inhibitory systems, leading to hypersynchronization of neural activity in individual brain regions or across multiple neural networks. Scalp electroencephalogram (EEG) is a method for studying cerebral activity using electrodes placed on the scalp. Long-term video-EEG monitoring with sleep recording is currently the primary method for diagnosing epilepsy. Throughout the night, EEG and ECG sensors, as well as cameras, record the patient's condition. The doctor then analyzes the recordings for epileptiform activity and seizures, using data from the EEG, cameras, and microphones. The value of this method lies in the ability to synchronize the bioelectric brain activity recording (EEG) with the video image of the subject, thus allowing accurate comparison of changes in EEG with any movements or unnatural states, and interpretation of those correlates. In recent years, efforts have been made to automate the search for events of interest in such data. A review article [2] lists the works devoted to the search for epileptiform activity and epileptic seizures from EEG recordings, video, as well as multimodal models using video and EEG together.

Numerous studies are devoted to detecting abnormal activity in EEG; less attention has been paid to video processing in video-EEG recordings. To our knowledge, no studies have focused on detecting small patient movements that are difficult to detect by the human eye, although they are potentially significant. In particular, abnormal activity that may indicate an epileptic seizure includes various eye

movements: rhythmic blinking, fluttering of the eyelids (for example, in juvenile myoclonic epilepsy or Jeavons syndrome), fixed gaze (in absence epilepsy), and aversion of the eyes to the side [3-5].

In this paper, we present a new approach to video-based small motion detection, which can find applications in epilepsy studies and other domains. We train a machine learning model to recognize blinking in video recordings obtained during video-EEG monitoring. Ground-truth labels for the patient's movements in videos are constructed using the EEG modality, since even subtle movements in patient's muscles are reflected in EEG recordings as certain artifacts. We make our model publicly available, along with a unique dataset obtained during video-EEG monitoring of three healthy volunteers, and a web-based viewer for this data. The dataset includes recordings from three night vision cameras, a thermal imaging signal, a 21-channel EEG, an ECG, and actigraphy data (parameters measured by wrist-worn fitness trackers, such as sleep stage and blood oxygen saturation).

II. RELATED WORK

A. EEG Artifacts Detection

EEG sensors record potential differences between points on the patient's scalp. The goal is to identify potential differences associated with the electrical activity of neurons in the brain. However, the patient's body movements are accompanied by electrical muscle activity and interferences at the interface between the electrode and skin, which is reflected in the EEG recording as bursts, sometimes many times greater in amplitude than neuronal activity. Such bursts are called myographic artifacts (in case of muscular activity) and electrode artifacts (in case of interferences due to the electrode movement) [6, 7]. Another type is eye movement artifacts: the eyeball acts as a dipole, and its rotation produces characteristic waveforms in the EEG.

Finding (and possibly eliminating) artifacts usually precedes any automated EEG analysis, so many methods have been developed for this task [8]. Commonly used approaches include:

- 1) Independent component analysis (ICA) and other techniques based on the assumption that artifacts and brain signals are independent (uncorrelated)
- 2) Wavelet transform (artifacts are removed by applying a threshold to wavelet coefficients)
- 3) Machine learning (ML), including deep learning (DL),

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methods

4) Hybrid methods

In recent years, deep learning (DL) methods – such as recurrent neural networks, transformer-like architectures, and state-space models – have achieved state-of-the-art results in artifact detection and removal when trained on large datasets such as TUAR (Temple University Hospital Artifacts Dataset) [9] and EEGDenoiseNet [10]. In 2024, Chen et al. introduced Denoisformer [11] – an artifact removal transformer for single-channel EEG. The next year, Chuang et al. introduced another transformer – ART [12], which works natively with multichannel signal. Researchers have devoted significant attention to so-called foundation models that learn in an unsupervised manner from large amounts of unlabeled data before being fine-tuned to downstream tasks. Prominent examples include LaBraM (2023) [13], EEGPT (2024) [14], and FEMBA (2025) [15].

B. Movements Detection From Video and Video-EEG

Numerous studies have focused on the automatic recognition of abnormal patient movements from video, primarily in the context of seizures and fall detection. Many methods have been developed, ranging from relatively simple object tracking algorithms to complex convolutional neural networks [16, 17]. Most of them are aimed at recognizing movements that are easily detected by the naked eye. Some are devoted to signal analysis during video-EEG monitoring.

In 2002, Li et al. [18] attached markers to the patient's body during video-EEG monitoring and detected their trajectories using image processing techniques. In 2024, Cao et al. [19] extracted features from video to enhance their EEG-based epileptic seizure detector but concluded that the video modality did not significantly improve performance. In 2025, Morozov and Sushkova [20] developed an algorithm for motion detection using a video-EEG signal based on optical flow.

Manifestations of epileptic seizures may include turning the eyes to the side, rhythmic eye blinking, eyelid fluttering, and staring [21, 22]. In 2021, Mitsuhashi et al. developed a seizure detection tool based on eye tracking [23]. In 2024, Barquan et al. presented their device for early seizure monitoring, which combines eye tracking with EEG and ECG sensors [24]. However, in both studies, eye movements were detected using specialized devices, not conventional cameras. More detailed overview of computer vision, machine learning, and deep learning algorithms developed for video seizure detection is provided in [16] and [25].

C. Eyeblink detection

Eyeblink detection from video has been studied in multiple works outside the epilepsy domain. Researchers have used a variety of approaches, ranging from classic computer vision methods such as frame-by-frame differences and Haar features [26], to sophisticated machine learning models such as Vision Transformer, which has been adapted for this task [27]. Some algorithms are capable of performing detection in real time [28]. A review [29] provides more details on how modern deep learning models are used to detect blinks.

Some studies have been devoted to detecting patient blinks in clinical settings using specialized sensors [30, 31]. However, to the authors' knowledge, specialized algorithms for

analyzing patient blinks from video, and especially for video-EEG, have not been proposed.

D. Motion Magnification

In the 2000s, MIT developed the Motion Magnification technology [32], which was used, among other things, to analyze biometric indicators such as heart rate and breathing patterns from video [33, 34]. Many modifications of the method have been developed [35], including those based on machine learning [36]. Motion magnification is particularly useful for detecting repetitive, small (sub-pixel) movements.

III. METHODS

In this work, we developed and implemented a pipeline for classifying video segments into those that contain blinking episodes and those that do not. The general pipeline diagram is shown in Figure 1.

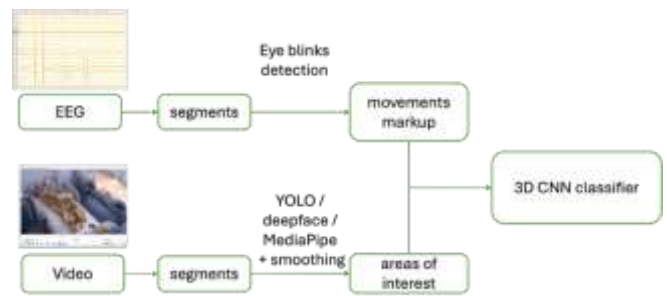


Fig. 1. Classification model training pipeline

The camera video is cut into 1-second fragments, and the corresponding EEG fragments are extracted. We have chosen a 1-second window as a heuristic based on the typical blink duration, which is between 150 and 400 ms [37]; however, we did not perform systematic optimization of the window length, and therefore larger or smaller window length might yield better performance.

The EEG fragments are classified as containing or not containing eye movements using an algorithm implemented in the MNE-Python library [38]. A search for eye movement artifacts was performed in the frontal channels FP1-A1 and FP2-A2 (a monopolar montage is used). Fragments containing the recognized artifact in both channels are then selected, as well as those that do not contain any artifacts within a 3-second window (i.e. fragments that contain no artifacts in themselves and in two neighboring 1-second windows).

The subject's face is extracted from the corresponding video fragments using the YOLOv5 neural network [39] (we tried using YOLO, as well as different pose detection models from the DeepFace and MediaPipe libraries, and only YOLO demonstrated decent accuracy on our data). The YOLO model is applied to each frame, after which the center of the head is determined as the average of the coordinates of the eyes and nose. The position of the center of the head is smoothed over time using coordinate-wise Nadaraya-Watson regression, and a square with a side equal to 0.7 of the distance between the subject's shoulders, calculated as the average value of the distance over the entire 1-second fragment, is cut out around the time-smoothed center. Further manual filtering of the resulting video fragments is then performed to remove those that do not contain the subject's face (for example, the subject turned away) or those for which

the blink recognition algorithm incorrectly identified the presence or absence of eye movements.

The resulting fragments constitute the training set, which is used to train a classifier. We tested several widely used classification architectures:

1. A simple three-dimensional convolutional network (3D CNN) [40]
2. A multi-scale temporal convolution network [41] combined with 3D convolutional layers
3. A 3D convolutional network with additional residual connections and a convolutional block attention module (ResNet + CBAM) [42, 43]

IV. DATASET

To evaluate our approach, we used a novel dataset of video-EEG recordings collected at Medical Center "XXI Century" in 2025. The dataset contains 8-hour-long recordings of three healthy individuals throughout the night.

For each subject, the following modalities were recorded:

- 1) 21-channel clinical grade EEG with reference ear electrodes and an additional ECG channel
- 2) Video synchronized with EEG: two Ultra HD night vision cameras (one for the face and another for the general view)
- 3) A standalone HD night vision camera (aiming at the face from a different angle than the one mentioned above) (an example frame is shown in Fig. 2).
- 4) A thermal camera aiming at the upper part of the subject's body
- 5) Audio from a studio-grade microphone near the subject's mouth
- 6) Data from two wrist-worn fitness trackers (Apple Watch, Fitbit), including heart rate and sleep stage

Each subject signed a written consent form to participate in the study and completed a questionnaire regarding their health condition.

The videos are saved as fragments of 5 minutes (or less).



Fig. 2. An example of a frame from a standalone camera. The subject is wearing an EEG cap and two fitness trackers. A microphone is located at the top, used to record the subject's breathing. The subject is asleep, and a nurse is adjusting the amount of conductive gel in the cap

Figure 3 illustrates a data feature that affects its usability: during recording, pauses sometimes occur (for example, during periodic autocalibration of the encephalograph), resulting in gaps in the EEG recording (and in the corresponding recordings of the two video cameras

synchronized with the EEG apparatus). The recording consists of several spliced fragments; as a result, the time in the recording gradually lags further and further behind real astronomical time (after just an hour of recording, the lag can reach tens of seconds), while other modalities (video, audio, actigraphy, and thermal imaging signal) are recorded in astronomical time. This requires additional alignment between modalities (which can be accomplished, e.g., by inspecting timestamps on video recordings from cameras synchronized with the EEG since they show real astronomical time) before using some combinations of modalities.

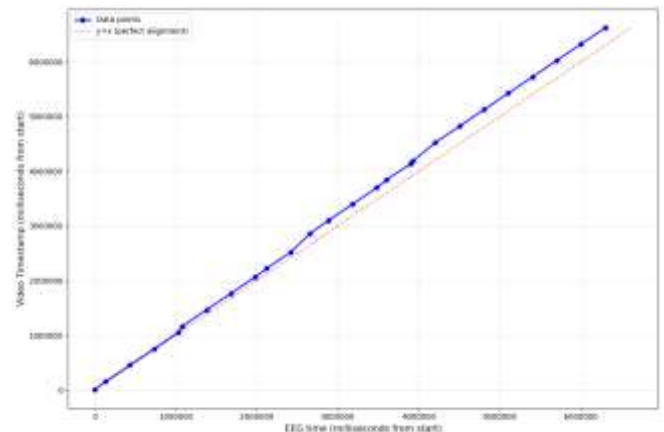


Fig. 3. Discrepancy between clock time and EEG time. The starting points of the fragments in the coordinates (EEG time, video/clock time) are shown in blue (the first 27 video fragments from the beginning of the recording).

V. EXPERIMENTS

The eye movement recognition algorithm applied to the EEG recordings in question detected an average of approximately 1,200 blinks per subject over 8 hours. In the data from one of the subjects used to train the classifier, the number of segments in which the algorithm recognized blinks in both EEG channels that we considered was 773, and the number of segments in which no blinks were recognized in either channel within a 3-second window was 310. After manual filtering of the relevant video segments, 337 segments with blinks and 204 without blinks were included in the final sample. Of them, 60% were included in the training subset and 40% in the test subset; the train/test split was performed randomly. We did not use any balancing techniques because the dataset is already balanced.

For training, we used the Adam [44] optimizer with learning rate set to 0.001 and learning rate reduction on plateau (ReduceLROnPlateau scheduler from PyTorch [45]). We used a batch size of 4 to ensure that videos fit into memory.

The multi-scale temporal CNN classifier trained on this data demonstrated an average accuracy of 94.4% on the test set (more metrics are provided in Table 1). When the classifier was trained on a set of fragments that have not undergone manual filtering (also divided into training and testing subsets), the average accuracy on the test set was 87.4%. A simple 3D CNN demonstrated slightly inferior results, and ResNet + CBAM performed even worse.

Video fragments of another subject, both containing and not containing blinks, were selected in a similar manner. When tested on this data as a test set, the multiscale temporal 3D CNN classifier achieved an average accuracy of 87.4% (more

metrics are given in Table 2). Other architectures demonstrated inferior results.

Table 1. Metrics on the test dataset (heldout samples from the same subject's data that is used for training), mean values and standard deviations over 20 random train/test splits. Best results highlighted in bold

Model	Accuracy		Precision		Recall		F1	
	mean	SD	mean	SD	mean	SD	mean	SD
3D CNN	91.6	4.5	93.0	4.4	93.7	3.3	93.3	3.5
multiscale	94.4	3.1	95.5	3.4	95.7	1.9	95.6	2.3
ResNet	86.1	6.3	88.7	5.6	89.1	5.3	88.9	5.0

Table 2. Metrics on the dataset of blinks of a subject unseen during training, mean values and standard deviation (calculated for 20 different versions of the model trained on 20 randomly selected training subsets of the same subject's data). Best results highlighted in bold

Model	Accuracy		Precision		Recall		F1	
	mean	SD	mean	SD	mean	SD	mean	SD
3D CNN	83.0	6.3	84.8	6.3	96.4	3.9	90.1	3.6
multiscale	87.4	7.0	89.6	6.6	95.9	3.3	92.5	3.9
ResNet	68	25	77	28	72	34	73	31

The achieved accuracy for single-subject data is comparable to that of the blink detection methods described in the review [26] (the accuracy values reported there are 97.5% or lower). However, it is incorrect to make a direct comparison, since the algorithms are tested under different conditions on different datasets.

I. DISCUSSION

The obtained results demonstrated that computer vision, in particular simple models such as a 3D convolutional network (in combination with YOLO for face position detection), can be used to detect eye movements in patients. A simple 3D CNN demonstrates decent performance on our dataset, and adding architectural complications does not significantly increase the generalization ability; results in Table 2 (metrics on the data from a subject unseen during training) demonstrate that a complicated ResNet + CBAM architecture has poor generalization ability. The resulting 3D-CNN or multi-scale temporal CNN can be used to identify multiple, potentially abnormal (in the context of epilepsy) blinks. However, the authors would like to emphasize that such blinks are abnormal only when occurring simultaneously with epileptiform discharges observed in EEG, and therefore an epileptiform discharge detection algorithm should be used along with our model. This model can be used either separately for a video stream or in combination with models that detect movements from an EEG. It is likely that the use of more sophisticated end-to-end models could improve recognition accuracy; at the same time, our convolutional networks run quickly on a modern computer and can be used for real-time detection. When combined with open/closed eye detection (and epileptiform discharge detection), this model can also be used to identify potentially abnormal fixed-gaze states. The authors believe that, after further training, this model can be successfully used to detect other types of abnormal eye movements (eyelid myoclonus, eye aversion) or limb movements. A promising direction for further research could be the detection of subpixel patient movements from video, with a classifier trained using a

scheme similar to that shown in Fig. 1 (with ground truth labels obtained from EEG), since many such movements are relatively easily identified from EEG.

Manual filtering applied to data after blink detection makes it more difficult to reproduce the procedure on a new dataset and can lead to selection bias. However, as mentioned above in Section V, without filtering the test accuracy is significantly lower. The largest class of incorrect training examples that need to be filtered out are cases in which the person is not looking at the camera. The authors suggest that introducing an additional classifier that determines whether the subject's face is directed towards the camera could help eliminate manual filtering without significant loss of quality. The potential uses of our dataset are not limited to analyzing eye movements in video. It can be used to analyze various movements, breathing, and sleep stages in video, EEG, audio, and thermal images.

II. CONCLUSION

In this paper, we presented a novel approach for detecting small patient movements in video-EEG monitoring data, using EEG signals as a semi-automated source of ground-truth labels. We developed and validated a pipeline that combines EEG artifact detection (eye blinks in frontal channels), face localization with YOLOv5, and a lightweight 3D convolutional network for video classification. Our experiments demonstrate that this method achieves high accuracy on a test set of blink/non-blink fragments from the same patient and lower but still high accuracy on a set of blink/non-blink fragments from another patient.

The key contribution of this paper is the semi-automated creation of a training dataset by automatically searching for blink and non-blink episodes in EEG data, followed by manual selection using corresponding video fragments. This approach allows for the rapid creation of a training dataset (e.g., for a specific patient or under specific filming conditions), after which a classifier can be trained.

Our work can be considered a first step toward building a system for monitoring epilepsy patients, in which the timing

and nature of detected events (e.g., blinks) can (in the case of simultaneous epileptiform discharges in the EEG) indicate the presence of an anomaly (e.g., frequent blinking, fixed gaze, etc., as described in Section 1). In addition to detecting eye movements, the authors believe it is promising to create similar algorithms and pipelines for detecting abnormal limb movements, chewing movements, and other facial muscle movements. Another possible direction for improvement is more fine-grained detection of eye movements: not only blinks, but also eyelid flutters and saccades.

III. DATA AVAILABILITY

Anonymized cropped blink / non-blink fragments of Subject 2 videos used for training are available at Figshare (DOI 10.6084/m9.figshare.32235561). The full dataset is available upon a reasonable request.

IV. CODE AVAILABILITY

The code is available at github.com/STU-EEG/small-movts

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