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Automated video analysis of emotion and dystonia in epileptic seizures

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Abstract

Objective

To investigate the accuracy of deep learning methods applied to seizure video data, in discriminating individual semiologic features of dystonia and emotion in epileptic seizures.

Methods

A dataset of epileptic seizure videos was used from patients explored with stereo-EEG for focal pharmacoresistant epilepsy. All patients had hyperkinetic (HKN) seizures according to ILAE definition. Presence or absence of (1) dystonia and (2) emotional features in each seizure was documented by an experienced clinician. A deep learning multi-stream model with appearance and skeletal keypoints, face and body information, using graph

convolutional neural networks, was used to test discrimination of dystonia and emotion. Classification accuracy was assessed using a leave-one-subject-out analysis.

Results

We studied 38 HKN seizure videos in 19 patients. By visual analysis based on ILAE criteria, 9/19 patients were considered to have dystonia and 9/19 patients were considered to have emotional signs. Two patients had both dystonia and emotional signs. Applying the deep learning multistream model, spatiotemporal features of facial appearance showed best accuracy for emotion detection (F1 score 0.84), while skeletal keypoint detection performed best for dystonia (F1 score 0.83).

Significance

Here, we investigated deep learning of video data for analyzing individual semiologic features of dystonia and emotion in hyperkinetic seizures. Automated classification of individual semiologic features is possible and merits further study.

Key words

Semiology, neural network, artificial intelligence, hyperkinetic, dystonia, emotion

1. Introduction

Hyperkinetic (HKN) seizures(Fisher et al., 2017) are amongst the most challenging seizure patterns for clinicians to characterize, as they are heterogeneous and may arise from various cortical localizations(Fayerstein et al., 2020). Specific associated semiologic features of HKN seizures, notably dystonia and emotion, are associated with different cortical localizations at group level(Fayerstein et al., 2020).

Video-based human action recognition has emerged as a main research area in the field of computer vision and pattern recognition, and rapid technical advances have allowed increasingly fine-grained analysis of action, gestures and facial expression(Wu et al., 2017). Potential advantages of deep-learning approaches in the context of video-recording of seizures could include analysis of complex seizure semiologies, to better detect and characterize subtle patterns at group level(McGonigal et al., 2021). However to date, deep learning methods have been relatively little applied to video recording of seizures(Ahmedt-

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Aristizabal et al., 2017). Early application of convolutional neural networks to epileptic seizure video data was based on the idea that neural networks would be able to learn discriminative features from video frames that could distinguish normal patient poses and appearances from those occurring during seizures(Achilles et al., 2015) . This was a key methodological change from prior methods based on quantifying motion data and then applying hand-picked video features for neural networks to learn.

Neural network approaches have previously been applied to video data for distinguishing epileptic seizure type, e.g. mesial temporal versus extra-temporal(Ahmedt-Aristizabal et al., 2018), temporal versus frontal(Karácsony et al., 2020), and focal versus focal to bilateral tonic-clonic seizures(Pérez-García et al., 2021). However, no work to date has focused on deep learning approaches to investigate individual semiologic features. Here, we examined hyperkinetic seizures using deep learning methodology, to assess presence of emotional and dystonic signs.

2. Methods

2.1. Patient and video selection

This study was approved by the Institutional Review Board (IRB): all patients provided written informed consent. All patients underwent stereoelectroencephalography (SEEG) for presurgical evaluation of pharmacoresistant focal epilepsy at Timone Hospital between 2000 and 2020. All had focal epileptic seizures involving hyperkinetic motor behavior, defined according to International League Against Epilepsy (ILAE) criteria (i.e., involving predominantly proximal limb or axial muscles producing irregular sequential ballistic movements, such as pedaling, pelvic thrusting, thrashing, rocking movements; increased rate of ongoing movements or inappropriately rapid performance of a movement)(Blume et al., 2001). Each patient's seizures were visually analyzed by expert clinicians (FB, AMcG) for presence or absence of (1) limb dystonia and (2) emotional expression, defined according to ILAE criteria(Beniczky et al., 2022; Blume et al., 2001) and as previously described (Fayerstein et al., 2020). Emotional expression was particularly based on the facial expression (e.g., fear, rage, smiling); bodily behavior with an emotional aspect was also present in some (e.g., defense or attack behavior). At least 1 representative seizure was used per patient.

2.2. Seizure video dataset

Seizure video clips were segmented from the untrimmed video recordings obtained during the video-SEEG or video-EEG monitoring procedure, to assess the main phase of the seizure event. All were recorded in the usual conditions of the videotelemetry unit with no specific devices, settings or additional procedures. Seizures lasted in general 30-90 seconds, rarely up to 120 seconds. The main phase of the seizure was determined by analysing changes in behaviour including abnormal movements and altered facial expression. Since these seizures were pre-selected for the presence of hyperkinetic behaviour, the clinical seizure onset was typically abrupt, and the seizure-related movements were rapid and of high amplitude and thus clearly looked different from the patient's baseline state. In the case of any question concerning choice of segment, this was discussed with expert clinicians. After segmenting each seizure, the new video clip was saved in its original format, including MPG, MP4, AVI, and ASF. We then converted the trimmed clips into image sequences for each clip at a frame rate of 25 frames per second, while keeping the resolution unchanged, including 352 x 576, 352 x 288, 704 x 576, 720 x 576, and 1280 x 720. We resized the aspect ratio until the frames were fed into the developed models. The methodology used here is completely automatic for facial detection, using existing open-source algorithms. For skeletal detection, we also used existing open-source algorithms; this process required only minor manual checking in 10% of frames, to refine detection for the learning step in our patient cohort. Skeletal detection was then completely automatic for the analysis step. Learning and analysis steps used the same video dataset through a leave-one-subject-out methodology. We adopted a fast SSD network(Liu et al., 2016) with MobileNet(Howard et al., 2017) backbone for region of interest (ROI) detection, i.e., detecting patients and their faces. The SSD model was pretrained on the Imagenet dataset(Deng et al., 2009) and fine-tuned on our dataset. For body joint localization, we detected the 2D keypoints of upper-limb on the detected patient with Keypoint-RCNN(He et al., 2017) which is pretrained on MS COCO(Lin et al., 2014) and fine-tuned on our dataset. The 11 detected points include head, neck, left/right shoulders, left/right elbows, left/right wrists, left/right hips, and bottom of the spine. The detected 2D keypoints were fed into a 3D estimator(Lin et al., 2014) for 3D pose estimation. For face stream, we used a toolbox for extracting 2D facial landmarks with the detected face. There are 23 keypoints detected for each face, focusing on eyebrows,

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eyes, nose, and mouth. For facial feature extraction, we used the last layer output before classification layer of a VGG-19 model(Simonyan and Zisserman, 2014) pretrained on a public facial expression recognition dataset(Goodfellow et al., 2013). Please see Supplementary Material, and also(Hou et al., 2021) for further detail.

2.3. Multi-Stream Framework for Seizure Classification

After converting the seizure video into an image sequence, we detected and cropped the region of the patient's body and face, followed by keypoint detectors for facial and joint landmark localization (Fig 1A and 1B). The pose can be represented as the detected joints and the connections between them: as such we can view the pose as a 'graph', where joints and connections are seen as vertices and edges respectively, and then analyzed by a model called graph convolutional networks (GCN) for pose-based action recognition.

Detected keypoints were fed into separated adaptive graph convolutional network (AGCN) for classification, which are viewed as Keypoint Streams. AGCN allows use of the adjacency matrix, which represents the topology of the keypoints and is trainable and learnable for a better performance, while GCN instead uses a pre-defined, fixed one.

The cropped detected region of patient and face were fed into their corresponding feature extractor and adopted temporal convolutional networks (TCNs) for temporal reasoning. We used knowledge distillation (the process of transferring the knowledge from a pre-trained model to another model) to transfer the learned knowledge to the Keypoint Streams. The predictions by AGCN from the pose and face streams were further combined for better performance, as shown in Fig 2A and 2B. Details for each stream are described in a recent work(Hou et al., 2021).

3. Results

The dataset comprised 38 HKN seizure videos from 19 patients (7 females, 12 males; age at seizure onset 1-44 years; median 7 years). The number of seizures included per patient ranged from 1-6 (mean 2, median 1). Nine of the 19 patients had ictal dystonia and 9/19 had ictal emotional signs. Two patients displayed both dystonia and emotional signs in their seizures. The EZ lobar localization as defined by SEEG was frontal in 9 patients; temporo-

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frontal in 2 patients; temporal in 1 patient; parietal in 3 patients; operculo-insular in 3 patients; and multi-focal in 1 patient.

Using a leave-one-subject out analysis (Table 1), for limb dystonia recognition, AGCNp out-perfomed TCNp, suggesting that the pose keypoint was more informative than the appearance regarding analysis of limb dystonia. With the knowledge distillation from the appearance stream, AGCNp can get a further boost in the performance(F1-score 0.80), showing the effectiveness of knowledge distillation in this task. As for recognizing the presence of emotion in the epileptic seizures, we can observe that TCNf had the best result (F1-score 0.84), indicating that the spatio-temporal appearance features of the face may be more crucial than the facial landmarks for the task.

4. Conclusion

This study is the first to assess accuracy of a neural network in categorizing videos of hyperkinetic epileptic seizures, using automatic detection methods of face and body segments, according to presence or absence of limb dystonia and emotion. The approach of combining streams involving different body segments and facial analysis has previously been employed in a deep learning model of epileptic seizure video analysis(Ahmedt-Aristizabal et al., 2018), but to our knowledge, the present study is the first to utilize these in the context of investigating individual semiologic signs.

While computer vision has existed for decades, particularly rapid evolution has occurred over the last decade due to maturation of deep learning approaches, increased computational power and availability of open source large, labeled data sets for training models(Esteva et al., 2021). Deep learning has been increasingly applied to medical contexts, in part thanks to widely available digital data across many healthcare domains. Harnessing machine learning approaches on video data could allow more objective detection and characterization of semiological patterns and provide a means to study these at larger group level, mitigating some of the observer bias and allowing a degree of quantification of results. However, deep learning has been so far relatively under-explored in epilepsy(Kearney et al., 2019), and has been less investigated for video than for EEG signals(Karácsony et al., 2020; Kearney et al., 2019; Lhatoo et al., 2020).

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An emerging topic within the domain of artificial intelligence applications in medicine is the "explainability" of neural networks: seeking to understand on what basis the algorithms are reaching decisions and achieving categorization of the data. This has become a sub-domain of AI known as "xAI" ("explainable AI")(Tjoa and Guan, 2020). Explainability is especially important in medical applications of AI, since there is a strong need for transparency and accountability of data if clinicians are to be able to trust the results of machine learning(Kundu, 2021; Tjoa and Guan, 2020). The present work is relevant to an xAI framework, in aiming to evaluate the ability of the neural network to distinguish specific pre-defined semiologic features. We chose "emotional expression" and "dystonia" as signs of interest, as these have relevance to cerebral localization in epileptic seizures(Bonini et al., 2014; Fayerstein et al., 2020), and were each represented with similar prevalence in our dataset of hyperkinetic ES. The neural network indeed showed quite good performance in correctly classifying each of these signs as being present or absent: accuracy reached 0.81 for dystonia with the body/pose stream (best detected using 3-D skeletal keypoint detection rather than appearance streams) and accuracy reached 0.78 for facial emotional expression using the face stream (best detected using facial appearance stream rather than keypoints). Thus, skeletal keypoint detection (spatial features) appeared to be key for correct classification of dystonia, while facial appearance stream (temporal features) appeared to produce better accuracy for emotion classification. As well as demonstrating similar accuracy to previous studies automatically classifying overall seizure type(Karácsony et al., 2020), these results hint at underlying mechanisms of automatic detection, for example that detection of facial spatiotemporal features may be more important than facial landmarks in detection of emotional expression.

Thus, the present study shows not only the degree of accuracy of automated detection and classification but also begins to explore the explainability of results."Explainable AI (xAI)"is a key aspect required to build clinician trust in AI approaches: "black-box medicine without a clinical link is not good medicine."(Kundu, 2021) This study, albeit modest in size, is a proof of concept that could be applied to larger datasets, with the expectation that increasing size of dataset over time will improve accuracy of the models. We see this as a pilot study that explores possibility of automated detection of specific semiologic features (dystonia and emotion), which could subsequently be applied to larger datasets with the expectation that increasing size of dataset over time will improve accuracy of the models. For example, in the

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future, an automated video analysis tool could provide clinicians with a probability score of a particular seizure pattern being associated with a specific cortical localisation (similarly to probability scores based on machine learning for detecting subtle MRI abnormalities). Of course, any automated video analysis of semiology would always need to be used as a complementary tool to clinician expertise in analysing the full clinical picture. Further work in automatic detection of individual epileptic seizure semiological patterns requires curation and validation of video datasets by expert clinicians, as done here. Automated detection of specific emotional or motor patterns could be of interest not only in future epilepsy studies but also in other conditions involving altered behavior or motor function, such as movement disorders and neuropsychiatric conditions.

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Conflict of interest

None to declare

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None

Legends to Table and Figures

Table 1. Results of automated classification of seizures with and without dystonia and emotion, based on our method regarding the body/face stream. The evaluation is based on a leave-one-subject-out (LOSO) method.
AGCN= adaptive graph convolutional network (graph-based model incorporating keypoints and their topology).
TCN= temporal convolutional network (model incorporating temporal reasoning).
KD=knowledge distillation (the process of transferring the knowledge from a pre-trained model to another model for model compression or imposing learning regulation on the latter one).

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The subscript “p’ refers to pose, and the subscript “f” refers to face.

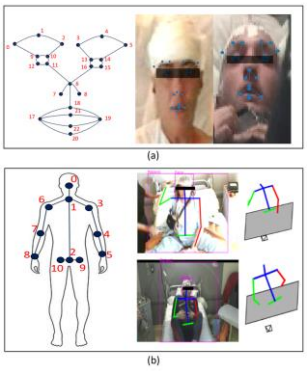

Figure 1. Examples of (a) facial and (b) body skeletal key points detection. On the right, Figure 1(b) also shows samples of ROI detection and (2D/3D) upper limb keypoints detection. The 11 detected points include head, neck, left/right shoulders, left/right elbows, left/right wrists, left/right hips, and bottom of the spine; using predominantly upper body skeletal keypoints was best adapted to the patients’ position in the bed.

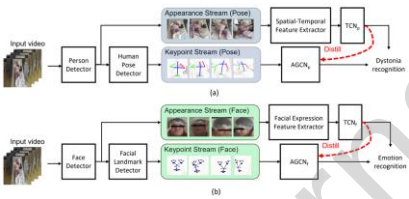

Figure 2. Overview of the proposed multi-stream framework, applied to (a) dystonia recognition and (b) emotion recognition, in which whole body and facial features are detected, respectively. For each, keypoints (detection of anatomical landmarks) and stream (spatiotemporal information) are analyzed. In the training phase, knowledge distillation (the process of transferring the knowledge from a pre-trained model to another model for model compression or imposing learning regulation on the latter one) is applied from a trained temporal convolutional network (TCN) to regulate the learning of the corresponding adaptive graph convolutional network (AGCN), a graph-based model incorporating keypoints and their topology. In the testing phase, only the learned AGCNs are used for final prediction.

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Table 1

Results of automated classification of seizures with and without dystonia and emotion, based on our method regarding the body/face stream. The evaluation is based on a leave-one-subject-out (LOSO) method.

AGCN= adaptive graph convolutional network (graph-based model incorporating keypoints and their topology).

TCN= temporal convolutional network (model incorporating temporal reasoning).

KD=knowledge distillation (the process of transferring the knowledge from a pre-trained model to another model for model compression or imposing learning regulation on the latter one).

The subscript "p' refers to pose, and the subscript "f" refers to face.

Dystonia recognition		
Model	F1-score	Accuracy
$AGCN_p$	0.78	0.76
TCN_p	0.76	0.73
$AGCN_p$ + KD	0.83	0.81
Emotion recognition		
Model	F1-score	Accuracy
$AGCN_f$	0.74	0.71
TCN_f	0.84	0.80
$AGCN_f$ + KD	0.80	0.78

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Highlights

- Deep learning analysis of seizure videos allows automated classification of semiology
- Presence of dystonia and/or emotion in hyperkinetic seizures was assessed
- Dystonia was best detected by skeletal keypoints, and emotional signs by facial appearance
- Spatiotemporal facial features were superior to facial keypoints for emotion detection
- Skeletal keypoints topology was superior to spatiotemporal model for dystonia detection

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