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Smart Camera-Based Patient-Specific Seizure Detection

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Abstract—**Detection of seizures using smart cameras has potential benefits since it does not require contact with the patient and can be easily deployed. Timely seizure alerts are crucial to prevent potential complications from seizures such as secondary injuries, and to initiate treatment to stop a seizure. In our small, preliminary study, we demonstrated that camera-based patient-specific seizure detection can provide reliable detection of convulsive seizures and in some cases, even outperform the EEG-based seizure detector. We therefore see a need for the development of user-friendly, trainable, smart camera system which can be easily re-trained for each patient by a caregiver or at home by a family member.**

Keywords—seizure detection, deep learning, smart camera, motion analysis.

I. Introduction

Epilepsy affects 1-2% of the total population. Anti-epileptic drugs have shown some effectiveness in treating the disorder, however nearly 30% of people with epilepsy suffer from seizures that are refractory to medication, or surgery does not offer sufficient seizure control [1, 2]. People suffering from intractable epilepsy have increased rates of morbidity and are more susceptible to sudden unexpected death in epilepsy (SUDEP) [3]. Thus, there is an urgent need for a seizure monitoring device that can immediately alert caregivers (and/or emergency medical personnel) when a person is having a seizure and at risk for SUDEP, which often happens after Generalized Tonic-Clonic Seizures (GTCS). GTCS is characterized by both stiffness and jerky motions and is the most common type seen in patients with epilepsy. GTCS is considered a medical emergency. If it lasts more than five minutes then it can be life-threatening for the patient. Alerting about GTCS events may have a protective effect in preventing SUDEP. Many SUDEPs occur during sleep when a person is not supervised [4]. To reduce the risk of injury or death, doctors frequently recommend that caregivers constantly monitor patients, resulting in a significant loss of independence. There is also the need for a highly specific and sensitive device with the ability to continuously monitor and automatically detect seizures and provide seizure alerts for the prevention of seizure induced complications.

Typically, EEG-based systems are used to detect seizures in clinical settings but they are not currently suitable for continuous use in home settings. EEG-based seizure detection is well-studied and achieved impressive sensitivity and specificity [5-10]. However, trained EEG technicians are needed for reliable EEG acquisition. In an attempt to reduce caregiver burden and improve patient outcomes, researchers have developed several non-EEG based wearable devices and motion detection sensors to detect seizures. Seizure alarms on the market use signals from sources such as EKG, limb acceleration/movement, motion sensors, EMG sensors, audio/video combinations and even multimodal sensor array platforms [11-18]. Most of these seizure detectors require sensors to be worn by patients. This can cause discomfort and some patients may not tolerate wearable sensors.

Cameras with artificial intelligence (AI) capabilities, sometimes called “smart cameras”, offer the promise of increased automation. Smart camera-based seizure detection is a non-contact, inexpensive and easy deployable method. Advantages of camera-based methods include contactless monitoring, ease of use, and the ability to watch in real-time or play back an event for review. Camera-based seizure detection has been extensively researched for more than a decade [19-22]. Early research has been mainly focused on extracting features based on patient’s motion analysis in video recordings in order to develop automated seizure detectors [23]. However, the performance of feature-based methods is determined by the quality of the selected parameters, and finding the good features is always a challenge. This problem can be solved by using deep learning neural networks (DLNNs). Compared to traditional machine learning, deep learning can provide improved accuracy and better utilization of data with less required domain expertise. Deep learning techniques have emerged as a powerful strategy for learning feature representations directly from data and have led to remarkable breakthroughs in the field of generic object recognition [24-27].

Convolutional neural networks (CNNs) have previously been applied to seizure detection using single frame-based and video sequence approaches [20]. Combination of infrared and depth image based CNNs was used in [28] to identify unnatural postures of patients during convulsive seizures. Video sequences have also been used for motion analysis in epileptic patients [29, 30]. Deep learning-based techniques are therefore a promising approach for detecting GTCS from video recordings. However performance of these methods as generic seizure detectors was low in comparison to the EEG-based seizure detectors. Currently available seizure detection devices report over 90%, or even 100% sensitivity for GTCS detection but the specificity or the false positive rate still needs to be improved.

Patient-by-patient variability of seizure manifestations makes development of reliable, generic seizure detectors difficult. To improve the reliability and performance of seizure detection, patient-specific

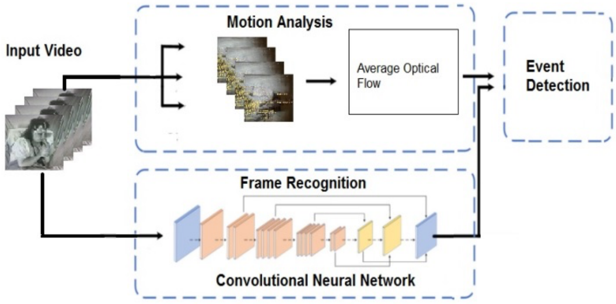

Fig. 1. Input video frames from the camera are sent to the pre-trained DLNN and to the Motion analysis module. Event detection module combines the information from these two modules and declares a seizure detection if the thresholds are met.

approaches have been employed [7, 9, 31]. Patient-specific systems have better performance due to the rather consistent intra-patient seizure onset patterns. The disadvantage of a patient-specific approach is the fact that the detector has limited data to perform training and validation. In order to overcome those difficulties, we propose a smart-camera-based, patient-specific approach to detect seizures with usage of transfer learning and data augmentation techniques.

II. METHODS

The conceptual diagram of the components and data flow for the proposed seizure detector (SzD) is shown in Fig. 1. There are three modules: DLNN, Motion analysis and Event detection. The pre-trained DLNN classifies each input video frame as seizure or non-seizure and passes the certainty of recognition (CR) of seizure to the Event detection module. Motion analysis module works in parallel; it computes the average optical flow and assigns the "amount of motion" to each video frame. The main purpose of the Event detection module is to declare the seizure event when the CR exceeds the predetermined threshold. To remove the CR fluctuations, it runs moving average over K frames. It also uses the motion information to reject the frames with low motion values. The thresholds to reject the false positive frames and to declare a seizure event are patient-specific and determined during the training phase.

A. *Seizure detection approach*

Video can naturally be decomposed into image and motion components. The image component carries information about scenes and objects depicted in the video. The temporal part, in the form of motion across the frames, conveys the movement of the objects. Our proposed seizure detection approach, SzD, is based on a frame-based classification using AlexNet, pre-trained convolutional DLNN [24] and motion analysis using the classical Horn-Schunck algorithm to estimate the average

The DLNN is individually trained to remember the specific seizure manifestations for each patient. Two of the DLNN output nodes have been devoted to recognize the seizure and non-seizure activity.

The moving average interval and the CR threshold to declare the seizure detection have been determined individually for each patient using training seizure and non-seizure video segments. The CR thresholds were in the range 0.65-0.9, and K, the number of frames to average, was in the range of 10-15.

Seizure video segments were labeled by two expert scorers. Non-seizure video clips have been collected from seizure-free recording of the same patient and represent a variety of patient activities such eating, reading books or watching TV, sleeping, interaction with caregivers and family members.

B. *Training with small dataset*

Our approach to seizure detection is patient-specific when detection algorithms are trained using data from the first seizure. While we can collect enough examples of non-seizure activity using seizure-free recordings, the seizure video recording length is from 15 seconds to 1-2 minutes. Also, even seizure manifestations are usually similar for the same patients, other conditions such as lighting, background and camera position in the room can be changed.

Re-training a large DLNN such as AlexNet with only few training samples of a patient's seizure activity can lead to overfitting and does not guarantee good performance if the patient is observed under different lighting conditions or has a different video background.

Learning to classify new categories based on a small number of examples is a long-standing challenge in modern computer vision [33]. There are several approaches to few-shot training such as semi-supervised approaches using additional unlabeled data, fine tuning from pre-trained models, rendering synthetic examples and augmenting the training examples. The capability of recognizing objects in challenging environments is a key component for many computer vision and robotics tasks. Many methods have been proposed to address a particular recognition challenge, such as occlusion [34], variation in aspect ratio or changes of viewpoint [35].

Our proposed solution consists of a combination of transfer learning technique and training data augmentation with automatically generated surrogate seizure samples.

The main idea of the transfer learning is to use a CNN model trained on a large image dataset and transfer its knowledge to a new smaller dataset. One obvious advantage is that a model can learn more efficiently since it starts with a pre-initialized weight matrix. CNNs used in computer vision tasks for transfer learning are usually trained on the large image datasets such as ImageNet for a couple of weeks using very powerful GPUs. By using transfer learning, it is possible to train the DLNN using much less data and in much less time. It has been shown that intermediate representations learned from ImageNet also provided substantial gains over hand-engineered features when transferred to other tasks [36, 37].

Synthetic data has been widely used in the training of DLNN for various tasks, including object detection, pose estimation, robotic control, autonomous driving, etc., and proved to be a useful source for data augmentation. Mixing real and synthetic data to improve object recognition detection performance have shown usefulness when real data is limited. A successful example can be found in the person image analysis method that uses the image dataset with synthetic human models for various uses such as person pose estimation [38].

The surrogate sample is defined as the original video frame or image acquired by a video camera pointed at the object of interest but modified using various image processing and computer vision techniques. For example, we can detect the patient in the frame and rotate for a range of angles. We can resize the patient, detect edges, apply different color mapping, and move the patient position in the frame to simulate different percentages of occlusion. This can be accomplished automatically using the OpenCV software framework [39].

We developed algorithms and software to augment the small training dataset by automatically generating surrogate training samples. Using just a short video clip (15-20 seconds) of the patient's seizure, it is possible to generate hundreds or even thousands of training samples. It is also a good technique to make the model invariant to changes in size, translation, viewpoint, illumination etc.

Overfitting was also handled by limiting the number of layers of the DLNN, in conjunction with the use of techniques such as dropouts and regularization [40].

III. RESULTS

In our small, preliminary study, we used the MATLAB implementation of AlexNet and opticalFlowHS object for estimating optical flow using the Horn-Schunck method. AlexNet is trained on more than one million images and can classify images into 1000 object categories. As a result, the model has learned rich feature representations for a wide range of objects. For transfer learning, we used a new classification layer with only two classes (seizure and non-seizure). We used a learning rate equal to 0.0001 and 0.5 dropout, other parameters were MATLAB defaults. The number of training samples for each patient was in the range of 600-700; about half of them were surrogates. Input video frames have been resized to 227x227 to fit the AlexNet's input layer.

A. Video-EEG Database

The patient/seizure database consisted of 12 epilepsy patients hospitalized for long-term EEG monitoring as part of pre-surgical evaluation of seizure pattern and localization. Patients ranged from 7–65 years and the database contained 6 females and 6 males. Total of 42 seizures (27 daytime and 15 nighttime) were included. Videos were recorded with 640x480 resolution using a Sony camera with low light capability. All patient recordings were anonymized at the original recording sites prior to inclusion in the patient/seizure database. Studies included in the validation study were specified to meet the following criteria:

- Minimum of two seizures,
- Convulsive seizures such as GTCS,
- Continuous video-EEG recording with minimum 24 hours.

All seizures in the patient/seizure database were reviewed by at least two scorers to identify seizure onset time(s), specifically: EEG onset (EO) and clinical/behavioral onset time (CO). EO is defined as the earliest evidence of ictal EEG change that proceeds inexorably to the seizure. CO is defined as the earliest indication of seizure as manifested by EEG or non-EEG activity in the video-EEG recording. The scorers were blinded to the results of the system's performance.

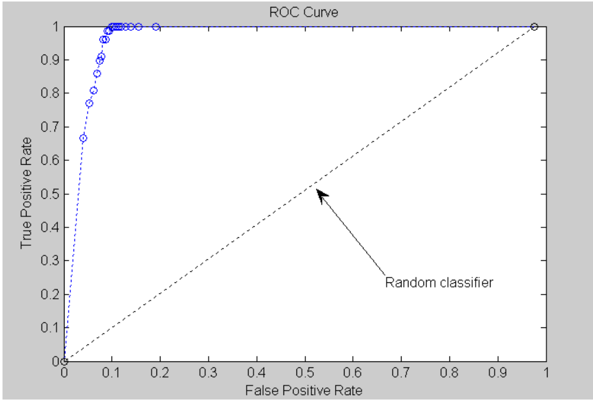

Fig.2. Example of ROC curve for our seizure detection algorithm and comparison with Random detector.

The performance of the seizure detection was evaluated by comparing the detections with this human scoring, using EO (as agreed upon by at least two scorers) as the primary measure of seizure onset time. All tests were conducted on long continuous video recordings of the same patients. For example, if the patient had first seizure during Day 1, then this seizure and other non-seizure video recordings during this day were used for the algorithm training. Testing was done for Day 2 or Day 3 (if available). Data used for the algorithm training and optimization have been excluded when evaluating the performance of the seizure detection algorithm.

B. Performance evaluation

The performance of the seizure detection was evaluated using standard measures such as sensitivity, false positive rate and Receiver Operating Curve (ROC). The sensitivity is defined as follows:

$$Sensitivity = TP/(TP+FN) * 100\%$$

where the *TP* is the number of true positives, i.e., the seizure detector correctly identifies a video segment as it was labeled by the expert. The *FP* is the number of false positives or incorrect seizure detections; and the *FN* is the number of false negatives or the number of undetected (missed by seizure detector) seizure segments which were labeled by the expert. False positive rate is reported as the number of false seizure detections per hour.

The evaluation of a seizure detection algorithm involves numerous caveats that need to be considered and the superiority of a seizure detection algorithm over the random detector must be established [41]. The performance of seizure detection was analyzed using ROC graphs. The ROC of a detector measures its performance as a trade-off between specificity or false positive rate and sensitivity. ROC curves provide a means to compare individual models and select the optimal threshold among all possible test thresholds. For comparison, a random seizure detector was used as well. The random detector we used generated detections following a Gaussian process in time without using any information from video or EEG. The example of the ROC graph is shown in Fig. 2.

Each point on the curve corresponds to a different threshold. The Y-axis of this graph represents the sensitivity of seizure detection (true positive rate) and the X-axis corresponds to 1 – specificity (false positive rate) at that specific threshold value. The points at the bottom left corner of the ROC represent performance for thresholds at which there are no false positives, and none of the seizures can be detected. The top right corner represents thresholds at which all seizures can be detected, but all non-seizure video segments are false positives as well. We can quantify how quickly the ROC curve rises to the upper left hand corner by measuring the area under the curve (AUC). If the area is equal to 1, we have an ideal detector, because it achieves both 100% sensitivity and 100% specificity. If the area is 0.5 (as it is for the random detector), then we have a test which has effectively 50% sensitivity and 50% specificity. This is a system that detects a seizure at random, i.e. its performance is no better than flipping a coin.

The ROC for our seizure detection algorithm was very steep and shows good separation between seizure and non-seizure classes. The AUC values were patient specific and were lied within 0.82-0.98.

C. Comparison with EEG-based seizure detection

For comparison purposes, we also used the commercial, EEG-based seizure detection program SzAC™ (Grass-Telefactor SzAC™ seizure and spike detector [5]). We have also optimized the SzAC™ seizure detection parameters using training EEG data for each patient. The seizure detection results are shown in Table I below.

The results show a highly promising ability of the proposed methods to detect the epileptic seizures as anomalies deviating from the normal patient activity. The average sensitivity was 98%, false positive rate 0.05/h and detection delay from -13 sec to + 28 sec with respect to EEG onset. EEG-based SzAC™ had a similar sensitivity but much worse false positive rate of 0.27/h.

Detection delays for seizure detection are presented with respect to EO. Negative numbers mean the detection has occurred before EO and positive numbers mean the detection was declared after EO.

TABLE I. PATIENT-BY-PATIENT SEIZURE DETECTION RESULTS

Patient #	**Hours/Seizures**	**Sensitivity, %**		**False positives per hour**		**Detection Delay Time, s**	
		SzAC	**SzD**	**SzAC**	**SzD**	**SzAC**	**SzD**
Patient 1	24/2	100	100	0.3	0.08	2, 2	**-10, -13**
Patient 2	48/2	100	100	0.8	0.04	1, 13	20, 22
Patient 3	48/2	100	100	0.2	0.05	7, 11	11, 10
Patient 4	30/4	100	100	0.1	0.1	2, 2, 1, 2	**-4, -3,** 5, 3
Patient 5	72/5	100	83	0.4	0.06	1, 2, 5, 4, 3	16, 14, 18, 15, 18
Patient 6	48/3	100	100	0.05	0.08	15, 12, 10	21, 22, 28
Patient 7	96/3	100	100	0.2	0.02	5, 2, 10	**-11, -9, -9**
Patient 8	24/2	100	100	0.2	0.01	2, 2	4, 2
Patient 9	24/2	100	100	0.07	0.02	6, 9	22, 26
Patient 10	24/1	100	100	0.5	0.05	11	19
Patient 11	24/2	50	100	0.02	0.04	2, 4	**-2, -8**
Patient 12	24/2	100	100	0.4	0.06	6, 8	15, 17

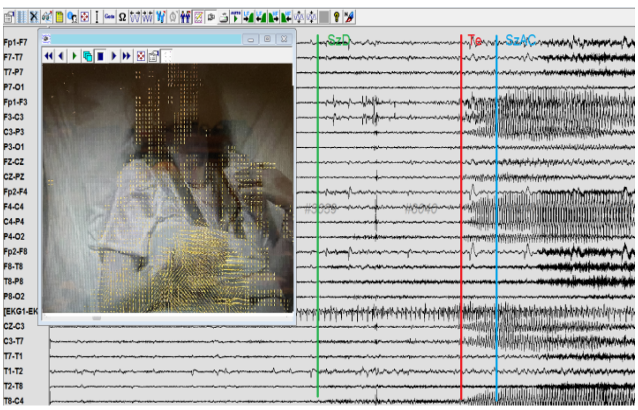

Fig. 3. Patient#1 video-EEG recording for the first testing seizure. Large motion vectors are displayed in video in yellow color during the start of the GTCS. The SzD detection (vertical green line) has been declared 10 sec earlier than EEG onset (Te, red line) and 12.5 sec earlier than EEG-based detector (SzAC™, blue line).

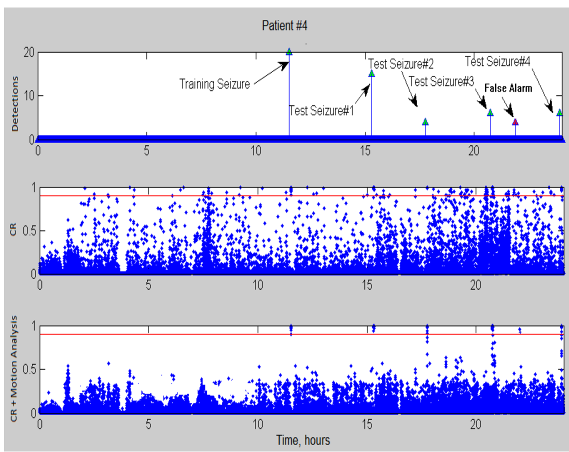

Fig. 4. The upper graph shows seizure detection summary for Patient#4.The middle graph displays the averaged output of the DLNN (certainty of seizure recognition) and the bottom graph is the output of

the Event detection module which combines the motion analysis and DLNN outputs.

The results for Patient#1 (see Fig. 3), #4 (see Fig. 4), #7 and #11 are especially interesting since the testing seizures were detected before the EEG onset and earlier than the EEG-based seizure detector. Fig. 4 demonstrates the effect of combining the motion analysis and the DLNN frame classification. The seizure output of the DLNN had many spurious peaks or false positives (the middle graph). Simply setting the threshold for the mean optical flow has eliminated many false classifications (the bottom graph). As we see from Fig. 3, the motion vectors were very large during the GTSC and this information has been incorporated into the decision making logic. The thresholds were patient-specific and have been determined using training data for each patient. To validate these results, we intend to use this same approach, but with a much larger number of patients/seizures.

IV. IMPLEMENTATION ON EMBEDDED PLATFORM

Benefits of in-camera seizure detection are the real-time, automated decision-making, and data privacy. With in-camera seizure detection, video is processed internally and only seizure alerts are transmitted. Implementing smart-camera based seizure detection on the embedded platform requires efficient hardware acceleration, high computational performance, and low power consumption.

These goals can be achieved using embedded systems optimized for computer vision and AI tasks such as NVIDIA Jetson family platform [42]. We selected the NVIDIA Jetson Nano as the embedded platform for our camera-based seizure detection. Jetson Nano is a single board computer powered by NVIDIA GPU with 4 GB of memory which allows real-time image processing and DLNN inference. Implementing real-time deep learning inference and fast transfer learning on the edge (in-camera) is possible with usage of GPU accelerated image/video processing building blocks such as the NVIDIA CUDA framework, Transfer Learning Kit, TensorFlow and TensorRT software libraries [43,44].

We did preliminary experiments to evaluate the performance of re-training AlexNet on the NVIDIA Jetson Nano system. Our tests showed that it can run the inference engine in real-time and it takes about 15-20 minutes to re-train the AlexNet with two extra output nodes for seizure and non-seizure classes. The performance in terms of inference time for Jetson Nano using various DLNN models and frameworks has also been presented and compared with other embedded systems in this work [45].

V. CONCLUSION

We have demonstrated that using a relatively simple approach such as combination of image-based pre-trained CNN and patient-specific motion estimation yielded good results in comparison with commercial EEG-based seizure detection. We should note that the proposed smart camera-based seizure detection algorithm is limited to detect convulsive seizures such as GTCS and it is not intended to be the replacement of the EEG-based seizure detectors. However, it can be used at home as a continuous seizure monitoring and alert system to prevent seizure induced complications, including SUDEP. It also can be used as a replacement of the standard video camera used in long-term video-EEG monitoring in epilepsy centers. Smart cameras can complement the EEG-based seizure detection providing reliable, patient-specific detection of GTCS.

We have also proposed the real-time implementation of seizure detector and in-camera training with usage of GPU accelerated image/video processing building blocks from NVIDIA Jetson Nano platform.

VI. FUTURE WORK

We are planning to use the same approach for our larger validation study with more patients/seizures. The algorithms will also be evaluated under different lighting conditions, camera angles, and surroundings. We are also planning to use other DLNN architectures and techniques specifically designed for human action recognition and video sequence classification. It will include the Recurrent Neural Network and its variant, Long Short-Term Memory network as well as 3D CNN [46]. These DLNN architectures belong to the most successful machine learning approaches when it comes to video sequence modeling.

One of the future tasks is to add the capability to customize the smart camera for other applications with user-friendly software interface. Most advanced patient monitoring cameras use video analytics to detect a single specific, pre-programmed event. The customization of smart cameras is either not possible or is difficult for a non-specialist and requires extensive knowledge of various software development tools and even some programming skills. This problem can be overcome with development of the user-friendly desktop application software or mobile app which enables easy, suitable for non-specialists, re-training of the smart camera.

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