Convulsive Movement Detection using Low-Resolution Thermopile Sensor Array

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Abstract

Sudden Unexplained Death in Epilepsy (SUDEP) is a fatal threat to patients who suffer from convulsive seizures. The causes of the SUDEP are still ambiguous, and the patients who suffer from epileptic seizures may face death during sleep, likely after an unwitnessed convulsive seizure. An important step towards SUDEP prevention is reliable seizure detection during sleep that is inexpensive and unobtrusive. In this work, we developed a non-contact, non-intrusive, privacy-preserving system that can detect convulsive movements experienced by human subjects. Detection is accomplished by a combination of uncooled low-cost, low-power, low-resolution (8×8) *IR array sensor, and a deep learning algorithm implemented with a Convolutional Neural Network (CNN). The thermopile sensor array is placed 1m from subjects who are reclining in bed. The CNN training set consists of thermal video streams from 40 healthy subjects mimicking convulsive movements or lying in bed without making convulsive movements. After training, the CNN was tested on thermal video streams not included in the training set and had a 99.2% accuracy in classifying convulsive movements and non-convulsive episodes, with no false negatives to distinguish between the occurrence and non-occurrence of convulsive movements. The performance results show that the thermopile sensor array has the potential to detect convulsive seizures while maintaining patient privacy and not requiring direct patient contact.*

1. Introduction

More than 65 million people world-wide, with 3.4 million in the United States, suffer from epilepsy [28]. Unfortunately, they carry a higher risk for death than the general population. Every year 1 out of 1000 people with epilepsy dies from Sudden Unexpected Death in Epilepsy (SUDEP) [24], [14]. The cause of SUDEP is still unknown, but in most cases death occurs in sleep and victims are found face down in bed [13]. Early detection of seizures and simple interventions could reduce the risk of SUDEP [13]. We seek to design a low-cost, contact-free, and privacy-preserving system to detect epileptic seizures during sleep.

Many methods are used to detect seizures [17, 6, 4, 19, 23, 22, 15, 18, 20, 21, 27, 16, 25, 26, 12, 1, 10], but most are not well-suited for in-home seizure monitoring that would be required for SUDEP prevention. The electroencephalogram (EEG) is the gold-standard method for seizure detection, and measures the electrical activity of the brain. However, EEG electrodes are not suitable for routine home use since they are uncomfortable and it is potentially harmful to have them attached to the scalp for a long period of time. Another approach is to indirectly detect seizures by monitoring a subject's heart rate with electrocardiography (ECG) [6]. Because the heart rate usually increases during an epileptic seizure, ECG is used as indicator of seizures in newborns and with implanted devices like the vagal nerve stimulator [6]. As with the EEG though, it is very difficult for a patient to wear the ECG electrodes for a long period of time.

Recently, non-electrode based wearable devices have been introduced to detect convulsive seizures. Most of the technologies rely on sensors attached to the body to detect body movements and/or heartbeat, such as microelectromechanical sensors or pulse oximeters [17]. These sensors are typically coupled to a wireless communication channel to transmit the signal for processing. Although such wearable sensor devices are small, the body contact needed for these devices may bother a patient during sleep or patients may not remember to wear the devices.

Systems based on accelerometer devices are also used

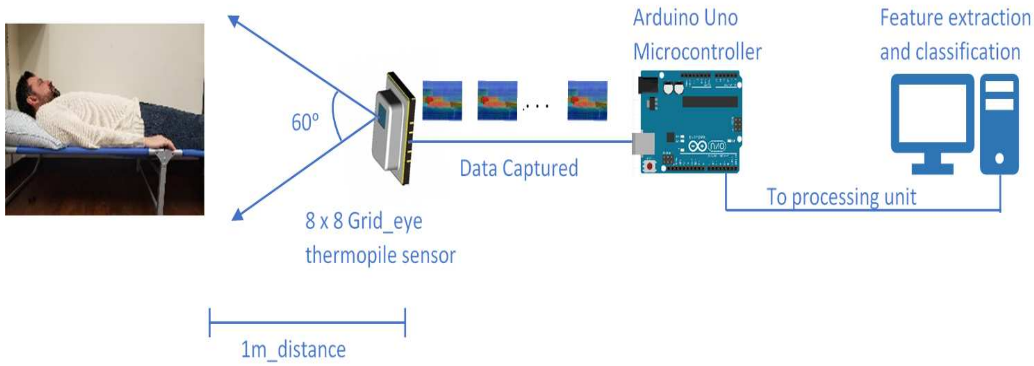

Figure 1. The proposed system consists of a thermopile sensor array, Arduino Uno micro controller, and a processing unit for extracting and classifying data.

to detect the change in direction and velocity of movements, which are distinguishable in the case of convulsive seizures from those observed due to ordinary body motion or lack of motion [4], [23], [9]. The disadvantage of this method is a high rate of false positives since accelerometer responses may be triggered not only with a seizure but also with movements of normal daily activity. Micro-Electromechanical systems (MEMS) have been used to detect convulsive seizures and have a lower rate of false positive alarms than accelerometer devices, but the false positive rate is still high [8].

Continuous image-based-monitoring systems such as night-vision camera and video monitoring can be used to detect epileptic seizure during sleep [18]. However, image-based-monitoring systems can be an uncomfortable invasion of privacy for patients, and complex video systems may not be affordable. Furthermore, because of the high rate of false negative detections reported with such systems, video-based-monitoring systems are often unreliable for detecting epileptic seizures [20].

This work is designed to be the first to detect convulsive movements using contact-free, non-intrusive, passive sensors that can detect the infrared signals that radiate from the human body during sleep. A low-resolution Panasonic Grid-Eye (8×8) IR thermal sensors array is used to detect the change in temperature due to body movements from about one meter away. A customized deep learning convolutional neural network (CNN) algorithm is designed to detect the occurrence or non-occurrence of convulsions. The rest of the paper is organized as follows. Section II describes the proposed system. Feature extraction and classification using a customized deep learning CNN network are discussed in Section III. The performance metrics of the classification method are explained in Section IV. The performance results of the proposed system are discussed in Section V. Finally, Section VI provides the conclusion of our study.

2. System design

The seizure-detection system consists of a low-resolution (8×8) Grid-eye thermopile sensor to capture the thermal images due to body movements within its field of view, an Arduino uno microcontroller with 10 Hz sampling rate, 10-bit quantization level, and a processing unit for feature extraction and classification, as seen in figure (1).

2.1. Data Acquisition using the Thermopile Sensor Array

A thermopile sensor array consists of low-cost, highly sensitive, uncooled sensors that generate an electrical signal proportional to the detected infrared radiation when infrared radiation is incident on their active area. Individual thermoelements are made of two different thermal activity materials and can detect light with a wavelength between 8 and 13μm, which is not perceivable by the human eye. Their operation is based on the Seeback effect phenomena in which the heat difference between two different thermal activity materials generates an electrical signal between the two ends of the thermoelement[11]. The thermopile sensors generate a thermal image from the infrared radiation displayed as a matrix (Figure 2) [5]. We used an 8×8 Panasonic Grid-EYE sensor array that captures a thermal 64-pixel images every 100msec, with a power consumption of $\simeq$ 15 mW. The low resolution of the sensor array is advantageous in preserving the privacy of the observed subjects.

Data for this study were collected from normal recruited subjects under a protocol approved by an Institutional Review Board of the University of Illinois at Chicago. Before the start of the data acquisition, we presented to the subjects, two different YouTube videos of patients experiencing a convulsive epileptic seizure. In each session, each subject was asked to lie down on a couch, located one meter away from the thermopile sensor array, and perform a set of different activities consisting of 1) pretending to sleep without

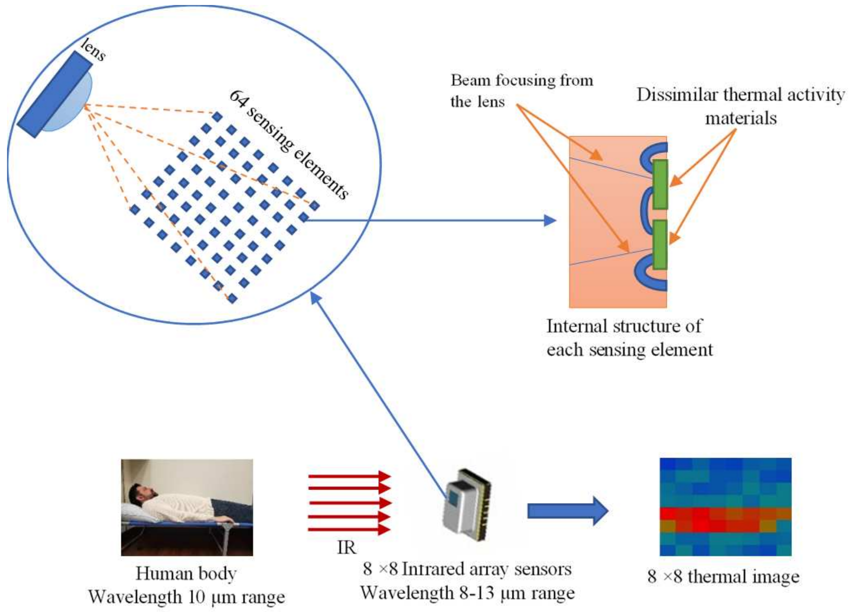

Figure 2. The thermopile sensors that generate a thermal image from the infrared radiation displayed as a matrix.

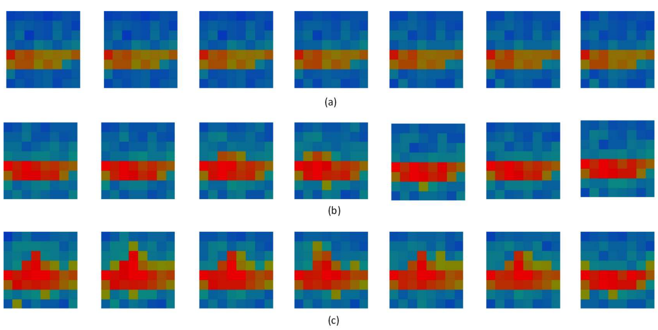

Figure 3. a) A sequence of frames captured by an (8×8) sensor array due to no movement (sleep mode). b) A sequence of frames captured by an (8×8) sensor array due to normal movements. c) A sequence of frames captured by an (8×8) sensor array due to convulsive movements.

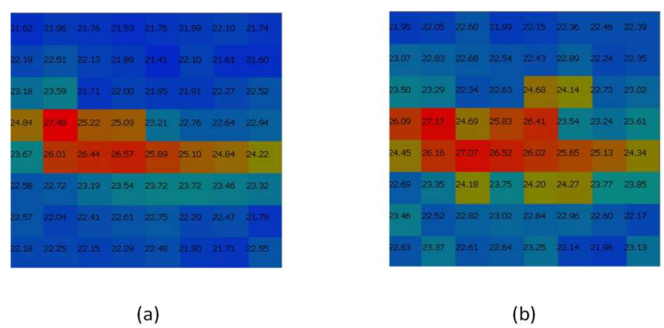

Figure 4. a) A thermal image with corresponding temperature values captured by an (8×8) sensor array due to no movement (sleep mode).b) A thermal image with corresponding temperature values captured by an (8×8) sensor array due to convulsive movement.

moving; 2) mimicking normal incidental body movements by changing the position during sleep; 3) mimicking the convulsive epileptic seizure movements while pretending to be asleep (Figure 3 and Figure 4).

2.2. Input Data Preprocessing

Image preprocessing consisted of calculating the absolute difference between two consecutive frames before feeding the information to the neural network as seen in equation (1).

$$I_{diff}[n] = |I[n] - I[n-1]| \tag{1}$$

where $I[n]$ and $I[n-1]$ represent two consecutive frames captured at time n and $n-1$ respectively by thermopile sensor array and $I_{diff}[n]$ represents the input frame to the neural network. In the absence of motion, the difference is zero and a stationary subject is not detectable. Since we seek to detect the motion not the presence of the subject, the absence of the subject in a difference image used as neural network input is not a concern (Figure 5).

3. Feature Extraction and Classification

Deep learning algorithms are now commonly used to extract and classify features in complex data sets [7]. In this work we used a 2-D Convolutional Neural Network (CNN) as a binary classifier to detect the occurrence and non- occurrence of convulsive motion.

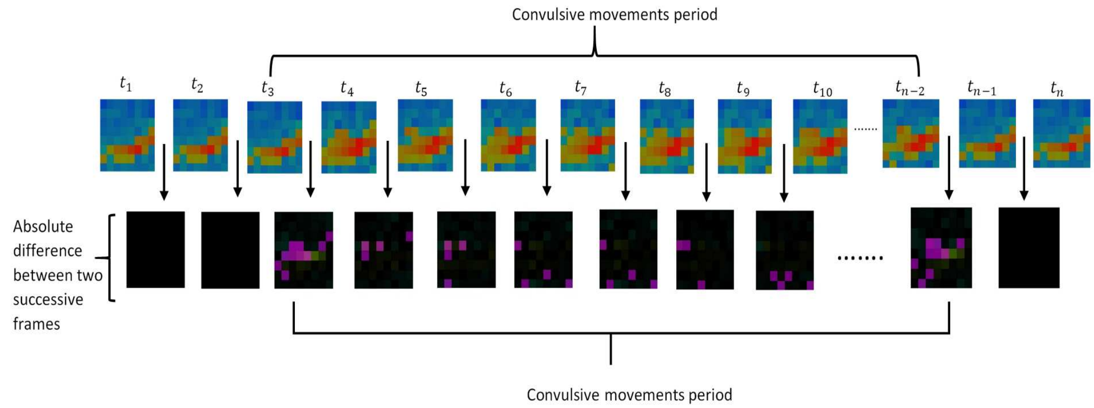

Figure 5. An absolute difference between two consecutive thermal images that captured using an (8×8) thermopile sensor array.

3.1. 2-D CNN Description

The number of parameters that are used in the 2D-CNN depends on the size and depth of the filters, type of filters (kernel filter in our design), and the number of hidden layers and neurons that are used and the way that they connect to each other [3].

Our deep CNN design consists of two convolutional layers, a max pooling layer, and a fully connected layer. Generally, the convolution stage and max pooling stage are responsible of extracting the features from the input images, while the fully connected layer stage classifies the extracted features from the previous stages. The input to the CNN, which represents the set of an (8×8) thermal images, is convolved with 32 kernel filters of size (3×3). An activation map of size $(6 \times 6 \times 32)$ is produced. A batch normalization is used in order to make the learning process more stable, and to reduce the number of epochs that are needed to train the deep network. A Rectified Linear Unit (RELU) activation function is applied to the convolved data to add a non-linearity. A down-sampling or max-pooling filter of size (2×2) is used to reduce the activation map dimensions. The output of the max pooling layer $(3 \times 3 \times 32)$ is convolved with another 16 kernel filters of size (3×3) and down-sampled with a filter of size (2×2). The output of the feature extraction layers $(2 \times 2 \times 16)$ is flattened and fully connected to two hidden layers of size 128 and 64 respectively (see table 1 and Figure 6).

The batch size of this network is 32 with 50 epochs. Excessive training can cause the classifier to memorize the input data. A dropout of 0.2 and a Ridge Regression L_2 regularization with regularization parameter value equal to 0.001 are used to prevent overfitting. In addition to that a K-fold cross validation is applied to the input data images to avoid the poor performance of the classifier [29].

In order to ensure that the sum of the output probabilities is equal to one, the SoftMax function is used to normalize the output vector. An Adam optimizer is used as stochastic gradient descent optimizer with cross-entropy loss to estimate the error of our model and to measure the performance of classification, for which the probability of its output lies between [0,1]. If the predicted probability diverges from the actual label, the loss function increases and vice versa. Equation (2) shows the cross-entropy loss J_{CH} function for multi classes.

$$J_{CH} = -\sum_{c=1}^{C} P_{o,c} \ln \tilde{P}_{o,c} \tag{2}$$

where C represents the number of classes, $P_{o,c}$ is the actual label of observation o, $\tilde{P}_{o,c}$ is the predicted probability of class c, and $\ln$ is the natural log. Since we are dealing with two classes, occurrence and non-occurrence of convulsive movements, the equation of cross entropy loss of our proposed network can be written as follows:

$$J_{CH} = -\left(P \ln\left(\tilde{P}\right) + (1-P)\ln\left(1-\tilde{P}\right)\right) \tag{3}$$

Figure 6 shows the 2-D CNN structural design that is used to classify the captured data of the thermal sensor array.

4. Evaluation Metric of System Design

The selection of the evaluation metric is a crucial step in many classification problems to get an optimum classifier, and to measure the quality of the machine learning or deep learning models. One such metric is the confusion matrix,which is an array of size $(m \times m)$ (Predicted labels $\times$ Actual labels), where m represents the number of the classes of the classifier model [2]. Since we have two classes in our model, occurrence and non-occurrence of convulsive movements, m is 2, and the model is a binary classifier. If the predicted label and actual label of the confusion matrix are both false, the class cell of the confusion matrix indicates true positive (TN), while if both are

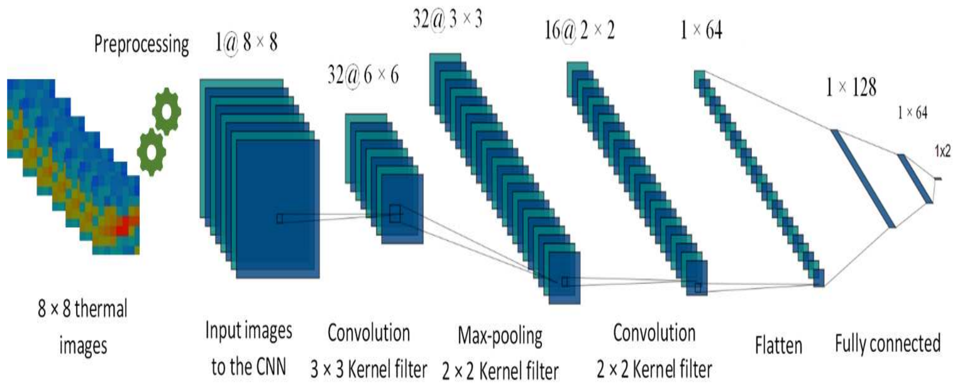

Figure 6. A structural diagram of the proposed 2-D CNN that used to classify captured thermal images into occurrence or non occurrence of convulsive movements.

true, then the class cell refers to true positive (TP). A false positive (FP) is generated when the predicted value is true, and the actual value is false. In our design the (FP) refers to a false alarm generated in response to a non-convulsive state. The converse situation (i.e. a convulsive movement is misclassified as a non-convulsive movement), is a false negative (FN). All the metric parameters can be represented mathematically as:

$$P_R = \frac{TP}{TP + FP}, \tag{4}$$

$$R_C = \frac{TP}{TP + FN}, \tag{5}$$

$$F1_{Score} = 2 \times \frac{P_R \times R_C}{P_R + R_C}, \tag{6}$$

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{7}$$

in which Precision (P_R), or Positive Predicted Value, is the ratio of the number of cases with correctly detected convulsive movements to the total number of cases that the CNN classifies as having convulsive movements. Recall (R_C), or sensitivity, is the ratio of number of cases with convulsive movements that were detected correctly to the number of all cases with convulsive movements. $F1 - Score$ is the harmonic mean of the recall and precision. A_{cc} is the diagnostic accuracy, or the probability that the model's prediction is correct [2].

5. Results and Discussion

Twenty eight male and 12 female healthy subjects were recruited to be monitored with the IR array while acting out either 12 seconds of convulsive movements or 12

Layer type	O/P shape	no. of parameters
Conv 2d, 1 stride, 0 Pad	32 ×6 × 6	896
Batch-Normalization	32 ×6 × 6	128
RELU (Activation Function)	32 ×6 × 6	0
Max-Pooling 2d, 1 strides, 0 Pad	32 ×3 × 3	0
Conv 2d, 1 stride, 0 Padding	16 ×2 × 2	2064
Batch-Normalization	16 ×2 × 2	64
RELU (Activation Function)	16 ×2 × 2	0
Flatten	64	0
Dense_Hidden	128	8320
Activation	128	0
Dense_Hidden	64	8256
Activation	64	0
Dropout	64	0
Dense_Output	2	130
Soft-max (Activation Function)	2	0

Table 1. The structural layers and number of parameters of the 2D_CNN.

seconds of simulated rest or normal movements. Altogether 4800 frames were collected for each of the two class $\left(12seconds \times 10\frac{frames}{second} \times 40subjects\right)$. The total of preprocessed 9520 images are fed into the CNN for training. In order to avoid the small data set issues, the data were augmented using an image data generator.

The image data set was split into 10 groups of equal size (476-images) for each group. The first group was used as a test dataset while the remaining groups were used as training dataset. The performance metrics and the classification accuracy were then calculated. The procedure was repeated

	Pre-cision	Re-call	F1-Score	Sup-port
Convulsive movements	1.00	0.98	0.99	800
Non-convulsive movements	0.98	1.00	0.99	800
Avg / total	0.99	0.99	0.99	1600

Table 2. The structural layers and number of parameters of the 2D_CNN.

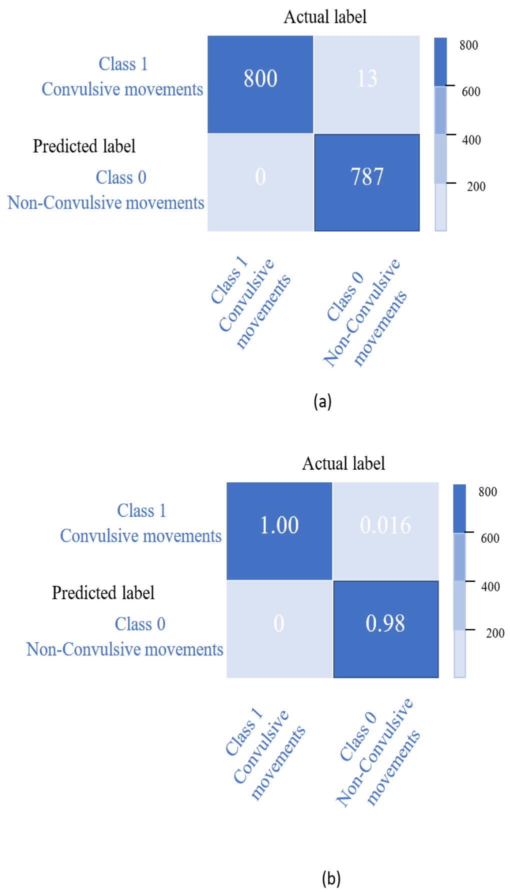

Figure 7. Evaluation metric of the 2D_CNN.

10 times, each time trained with nine groups and tested with the remaining group. The test set contains 1600 images, and the classification accuracy of the network is 99.2% (Table 2).

The 2D-CNN classifier had no false negatives. meaning that it identified all the cases with convulsive movements. Thirteen episodes of normal movement were misclassified as convulsive, giving a false positives rate of 1.6% (Figure 7). A comparison between the original captured thermal images data sets, and absolute difference images data sets $I_{input}[n]$ is shown in Table 3. Absolute difference image based classification is far superior to single image based classification. This is due to the fact that we classify movement information not the thermal images using the CNN.

I/P to CNN	TP	FP	TN	FN	Accuracy
$I_{diff}[n]$	800	13	787	0	99.2%
$I[n]$	669	131	672	128	83.3%

Table 3. A comparison between the captured thermal images data sets, before taking the absolute difference, and after taking the absolute difference.

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6. Conclusion

In this proof-of-concept study, the pairing of a low-resolution IR sensor array with a CNN showed promise as a detecting convulsive movements. Since the thermal sensor array is contact-free and privacy preserving, it might eventually prove to be a practical tool for home monitoring of epileptic subjects at risk for SUDEP. While this study demonstrated the technical feasibility of a low-cost non-invasive system, the next step will require training and testing on patients with epileptic seizures.

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