Automatic seizure detection

Seizure detection is a routine process in epilepsy units requiring manual intervention of well-trained specialists. This process could be extensive, inefficient and time-consuming, especially for long term recordings. Gómez et al. proposed an automatic method to detect epileptic seizures using an imaged-EEG representation of brain signals. To accomplish this, we analyzed EEG signals from two different datasets: the CHB-MIT Scalp EEG database and the EPILEPSIAE project that includes scalp and intracranial recordings. We used fully convolutional neural networks to automatically detect seizures. For our best model, we reached average accuracy and specificity values of 99.3% and 99.6%, respectively, for the CHB-MIT dataset, and corresponding values of 98.0% and 98.3% for the EPILEPSIAE patients. For these patients, the inclusion of intracranial electrodes together with scalp ones increased the average accuracy and specificity values to 99.6% and 58.3%, respectively. Regarding the other metrics, our best model reached average precision of 62.7%, recall of 58.3%, F-measure of 59.0% and AP of 54.5% on the CHB-MIT recordings, and comparatively lowers performances for the EPILEPSIAE dataset. For both databases, the number of false alarms per hour reached values less than 0.5/h for 92% of the CHB-MIT patients and less than 1.0/h for 80% of the EPILEPSIAE patients. Compared to recent studies, our lightweight approach does not need any estimation of pre-selected features and demonstrates high performances with promising possibilities for the introduction of such automatic methods in the clinical practice [1)].

The Wearables for Epilepsy And Research (WEAR) International Study Group identified a set of methodology standards to guide research on wearable devices for seizure detection. Bruno et al. formed an international consortium of experts from clinical research, engineering, computer science, and data analytics at the beginning of 2020. The study protocols and practical experience acquired during the development of wearable research studies were discussed and analyzed during bi-weekly virtual meetings to highlight commonalities, strengths, and weaknesses, and to formulate recommendations. Seven major essential components of the experimental design were identified, and recommendations were formulated about: (1) description of study aims, (2) policies and agreements, (3) study population, (4) data collection and technical infrastructure, (5) devices, (6) reporting results, and (7) data sharing. Introducing a framework of methodology standards promotes optimal, accurate, and consistent data collection. It also guarantees that studies are generalizable and comparable, and that results can be replicated, validated, and shared [2)].

The task of seizure detection includes distinguishing different stages of seizures, which are generally divided into inter-ictal, pre-ictal and ictal periods [3)].

In long-term video monitoring, automatic seizure detection holds great promise as a means to reduce the workload of the epileptologist. A convolutional neural network (CNN) designed to process images of EEG plots demonstrated high performance for seizure detection, but still has room for reducing the false-positive alarm rate.

Takahashi et al. combined a CNN that processed images of EEG plots with patient-specific autoencoders (AE) of EEG signals to reduce the false alarms during seizure detection. The AE automatically logged abnormalities, i.e., both seizures and artifacts. Based on seizure logs compiled by expert epileptologists and errors made by AE, they constructed a CNN with 3 output classes: seizure, non-seizure-but-abnormal, and non-seizure. The accumulative measure of number of consecutive seizure labels was used to issue a seizure alarm.

The second-by-second classification performance of AE-CNN was comparable to that of the original CNN. False-positive seizure labels in AE-CNN were more likely interleaved with "non-seizure-but-abnormal" labels than with true-positive seizure labels. Consequently, "non-seizure-but-abnormal" labels interrupted runs of false-positive seizure labels before triggering an alarm. The median false alarm rate with the AE-CNN was reduced to 0.034 h-1, which was one-fifth of that of the original CNN (0.17 h-1).

A label of "non-seizure-but-abnormal" offers practical benefits for seizure detection. The modification of a CNN with an AE is worth considering because AEs can automatically assign "non-seizure-but-abnormal" labels in an unsupervised manner with no additional demands on the time of the epileptologist [4].

1)
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