**Improving the Quality of the TUSZ Corpus**

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The Temple University Hospital Seizure Detection Corpus (TUSZ) [1] has been in distribution since April 2017. It is a subset of the TUH EEG Corpus (TUEG) [2] and the most frequently requested corpus from our 3,000+ subscribers. It was recently featured as the challenge task in the Neureka 2020 Epilepsy Challenge [3]. A summary of the development of the corpus is shown below in Table 1.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Releases** | **Patients** | **Sessions** | **Files** | **Seizure Files** | **Total No. Seizure Events** | **Total Duration (Hours)** | **Seizure Duration (Hours)** |
| **v1.0.0 – 04/17/2017** | 114 | 510 | 2,013 | 291 | 328 | 170 | 4.9 |
| **v1.1.0 – 08/04/2017** | 246 | 686 | 2,489 | 423 | 3,582 | 425 | 28.9 |
| **v1.2.0 – 04/15/2018** | 315 | 822 | 3,064 | 642 | 1,951 | 504 | 36.75 |
| **v1.3.0 – 08/16/2018** | 364 | 970 | 4,023 | 942 | 2,465 | 651 | 52.6 |
| **v1.4.0 – 11/14/2018** | 364 | 969 | 4,020 | 949 | 2,548 | 651 | 53.0 |
| **v1.5.0 – 07/22/2019** | 692 | 1,661 | 6,633 | 1,399 | 3,591 | 1,074 | 74.6 |
| **v1.5.1 – 04/23/2020** | 692 | 1,575 | 6,633 | 1.382 | 3,554 | 1,074 | 73.5 |
| **v1.5.2 – 05/09/2020** | 692 | 2,608 | 6,635 | 1,384 | 3,561 | 1,074 | 73.9 |
| **v1.6.0 – 08/31/2020** | TBD | TBD | TBD | TBD | TBD | TBD | TBD |

**Table 1**. A summary of the TUSZ release history

The TUSZ Corpus is a fully annotated corpus, which means every seizure event that occurs within its files has been annotated. The data is selected from TUEG using a screening process that identifies files most likely to contain seizures [1]. Approximately 7% of the TUEG data contains a seizure event, so it is important we triage TUEG for high yield data. One hour of EEG data requires approximately one hour of human labor to complete annotation using the pipeline described below, so it is important from a financial standpoint that we accurately triage data.

A summary of the labels being used to annotate the data is shown in Table 2. Certain standards are put into place to optimize the annotation process while not sacrificing consistency. Due to the nature of EEG recordings, some records start off with a segment of calibration. This portion of the EEG is instantly recognizable and transitions from what resembles lead artifact to a flat line on all the channels. For the sake of seizure annotation, the calibration is ignored, and no time is wasted on it. During the identification of seizure events, a hard “3 second rule” is used to determine whether two events should be combined into a single larger event. This greatly reduces the time that it takes to annotate a file with multiple events occurring in succession. In addition to the required minimum 3 second gap between seizures, part of our standard dictates that no seizure less than 3 seconds be annotated. Although there is no universally accepted definition for how long a seizure must be, we find that it is difficult to discern with confidence between burst suppression or other morphologically similar impressions when the event is only a couple seconds long. This is due to several reasons, the most notable being the lack of evolution which is oftentimes crucial for the determination of a seizure.

In the first portion of the process, the EEG files are triaged from our TUEG database by an overlapping method of machine learning seizure detection and key word analysis of the respective clinical reports. After the EEG files have been triaged, a team of annotators at NEDC is provided with the files to begin data annotation. An example of an annotation is shown in Figure 1. A summary of the workflow for our annotation process is shown in Figure 2. Several passes are performed over the data to ensure the annotations are accurate. Each file undergoes three passes to ensure that no seizures were missed or misidentified. This is different than the previous versions of the corpus in which there was only a single reviewer for all files. This new workflow results in a greater number of annotators viewing each file and consequently higher quality data. The first pass of TUSZ involves identifying which files contain seizures and annotating them using our annotation tool. The time it takes to fully annotate a file can vary drastically depending on the specific characteristics of each file; however, on average a file containing multiple seizures takes 7 minutes to fully annotate. This includes the time that it takes to read the patient report as well as traverse through the entire file.

Table 2. The labels used to annotate our EEG data are shown.

|  |  |  |
| --- | --- | --- |
| **Index** | **Label** | **Description** |
| 0 | null | An undefined annotation. Should not be seen in the data. |
| 1 | spsw | Spike and/or slow wave. A short duration epileptiform event involving an electrographic spike in activity and/or a slow wave (low frequency wave). Usually no more than 1 sec. in duration. |
| 2 | gped | Generalized periodic epileptiform discharge. Periodic diffuse spike/sharp wave discharges across multiple regions or hemispheres. |
| 3 | pled | Periodic lateral epileptiform discharge. A regular, periodically occurring spike/sharp wave seen in a certain locality of the scalp. |
| 4 | eybl | Eyeblink. A specific, sharp, high amplitude eye movement artifact corresponding to blinks. |
| 5 | artf | Artifact. Any non-brain activity electrical signal, such as those due to equipment or environmental factors. |
| 6 | bckg | All other non-seizure cerebral signals. |
| 7 | seiz | Seizure. A basic annotation for seizures. |
| 8 | fnsz | Focal nonspecific seizure. A large category of seizures occurring in a specific focality. |
| 9 | gnsz | Generalized seizure. A large category of seizures occurring in most if not all of the brain. |
| 10 | spsz | Simple partial seizure. Brief seizures that start in one location of the brain (and may spread) where the patient is fully aware and able to interact. |
| 11 | cpsz | Complex partial seizure. Same as simple partial seizure but with impaired awareness. |
| 12 | absz | Absence seizure. Brief, sudden seizure involving lapse in attention. Usually lasts no more than 5 seconds and commonly seen in children. |
| 13 | tnsz | Tonic seizure. A seizure involving the stiffening of the muscles. Usually associated with and annotated as tonic-clonic seizures, but not always (rarely there is no clonic phase). |
| 14 | cnsz | Clonic seizure. A seizure involving sustained, rhythmic jerking. Not seen in our datasets, as it is always associated with tonic clonic seizures and is annotated as such. |
| 15 | tcsz | Tonic-clonic seizure. A seizure involving loss of consciousness and violent muscle contractions. |
| 16 | atsz | Atonic seizure. A seizure involving the loss of tone of muscles in the body. Also never seen as it is always associated with an occasionally occurring phase before a tonic clonic seizure. |
| 17 | mysz | Myoclonic seizure. A seizure associated with brief involuntary twitching or myoclonus. |
| 18 | nesz | Non-epileptic seizure. Any non-epileptic seizure observed. Contains no electrographic signs. |
| 19 | intr | Interesting patterns. Any unusual or interesting patterns observed that don't fit into the above classes. |
| 20 | slow | Slowing. A brief decrease in frequency. |
| 21 | eyem | Eye movement. A very common frontal/prefrontal artifact seen when the eyes move. |
| 22 | chew | Chewing. A specific artifact involving multiple channels that corresponds with patient chewing, “bursty” |
| 23 | shiv | Shivers. A specific, sustained sharp artifact that corresponds with patient shivering. |
| 24 | musc | Muscle artifact. A very common, high frequency, sharp artifact that corresponds with agitation/nervousness in a patient. |
| 25 | elpp | Electrode pop. A short artifact characterized by channels using the same electrode “spiking” with perfect symmetry.  |
| 26 | elst | Electrostatic artifact. Artifact caused by movement or interference on the electrodes, variety of morphologies. |
| 27 | calb | Artifact caused by calibration of the electrodes. Appears as a flattening of the signal in the beginning of files. |
| 28 | hphs | A brief period of high amplitude slow waves. |
| 29 | trip | Large, three-phase waves frequently caused by an underlying metabolic condition. |



**Figure 1**. An example of an annotated EEG signal



**Figure 2**. The data preparation pipeline

Once an event has been identified, the start and stop time for the seizure is stored in our annotation tool. This is done on a channel by channel basis resulting in an accurate representation of the seizure spreading across different parts of the brain. Files that do not contain any seizures take approximately 3 minutes to complete. Even though there is no annotation being made, the file is still carefully examined to make sure that nothing was overlooked. In addition to solely scrolling through a file from start to finish, a file is often examined through different lenses. Depending on the situation, low pass filters are used, as well as increasing the amplitude of certain channels. These techniques are never used in isolation and are meant to further increase our confidence that nothing was missed. Once each file in a given set has been looked at once, the annotators start the review process. The reviewer checks a file and comments any changes that they recommend. This takes about 3 minutes per seizure containing file. After each file has been commented on, the third pass commences. This step takes about 5 minutes per seizure file and requires the reviewer to accept or reject the changes that the second reviewer suggested. Assuming 18% of the files contain seizures, a set of 1,000 files takes roughly 127 work hours to annotate.

Before an annotator contributes to the data interpretation pipeline, they are trained for several weeks on previous datasets. A new annotator is able to be trained using data that resembles what they would see under normal circumstances. An additional benefit of using released data to train is that it serves as a means of constantly checking our work. If a trainee stumbles across an event that was not previously annotated, it is promptly added, and the data release is updated. It takes about three months to train an annotator to a point where their annotations can be trusted. Even though we carefully screen potential annotators during the hiring process, only about 25% of the annotators we hire survive more than one year doing this work. To ensure that the annotators are consistent in their annotations, the team conducts an interrater agreement evaluation periodically to ensure that there is a consensus within the team. The annotation standards are discussed in Ochal et al. [4]. An extended discussion of interrater agreement can be found in Shah et al. [5].

The most recent release of TUSZ, v1.5.2, represents our efforts to review the quality of the annotations for two upcoming challenges we hosted: an internal deep learning challenge at IBM [6] and the Neureka 2020 Epilepsy Challenge [3]. One of the biggest changes that was made to the annotations was the imposition of a stricter standard for determining the start and stop time of a seizure. Although evolution is still included in the annotations, the start times were altered to start when the spike-wave pattern becomes distinct as opposed to merely when the signal starts to shift from background. This cuts down on background that was mislabeled as a seizure. For seizure end times, all post ictal slowing that was included was removed. Only two EEG files were added because, originally, they were corrupted in v1.5.1 but were able to be retrieved for the latest release. The progression from v1.5.0 to v1.5.1 and later to v1.5.2, included the re-annotation of all the EEG files in order to develop a confident dataset regarding seizure identification.

The TUAR Corpus is an open-source database that is currently available for use by any registered member of our consortium. To register and receive access, please follow the instructions provided at this web page: *https://www.isip.piconepress.com/projects/tuh\_eeg/html/downloads.shtml*. The data is located here: *https://www.isip.piconepress.com/projects/tuh\_eeg/downloads/tuh\_eeg\_artifact/v2.0.0/*.

Acknowledgments

Research reported in this publication was most recently supported by the National Science Foundation Partnership for Innovation award number IIP-1827565 and the Pennsylvania Commonwealth Universal Research Enhancement Program (PA CURE). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the official views of any of these organizations.

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