Challenges in Detecting Epileptic Seizures through Wrist-Worn Sensing Devices

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I. Introduction

Epilepsy is a condition that affects one in every 100 people in the UK alone [1]. This neurological disorder causes abnormal bursts of electrical impulses in the brain, causing neurons to fire in an uncontrolled way that result in the brain and body behaving strangely. There is a range of types of epileptic seizures, ranging from loss of consciousness for a few seconds (Absence seizure), to sever incidents involving convulsions of the whole body that can last for 3-5 minutes (Tonic-Clonic (TC) seizure) and bare a high risk of leading to death. Current practice in long term monitoring of epileptic seizures requires patients to keep a seizure diary recording seizure incidents and discuss the progression of their condition during their outpatient's appointment with the medical team [2]. However, in practice such logs are very inaccurate, with patients forgetting to log all seizures or misplacing their diaries. The result is that the medical team often has inaccurate information about the progression of the condition, which can affect the correct assessment and adjustment of treatment that may be required.

As part of an on-going collaboration between the University of Kent, Poole Hospital, Shearwater Systems Ltd and Graphnet Health (the Epilepsy Care Alliance), we aim to develop a system for the continuous monitoring of epileptic seizures using off-the-shelf wristworn sensing devices (e.g. Microsoft Band 2). The main aim is to utilise physiological data obtained from the wearable, in order to track the occurrence of TC seizures (the most severe seizure type). The data captured by the wristband include accelerometer, gyroscope, heart rate, skin temperature and galvanic skin response. Currently we have embarked in an extensive deployment of a data collection system, where patients are asked to wear the band for the most part of the day, and through a mobile app, to report the occurrence of epileptic seizures. To date, 54 epileptic patients have been enrolled, and have been feeding data for an average 9 months per patient. The dataset includes 1,037 reported seizures, with 478 (46%) being classified as TC seizures. Wearable data have been capture for approximately 17% of those seizures.

II. Challenges

Epileptic seizures are unpredictable and can be very infrequent for most patients. This means that data collection in a controlled environment is unfeasible. Applying an "in-the-wild" approach in data capture, we need to deal with a range of challenges:

Unreliable ground-truth: Using a mobile application where patients can report seizures, has improved the level of compliance of participants submitting seizure information. However, the actual time that a seizure took place is often inaccurate, occasionally being off by more than 30mins from the actual time of the seizure (See Figure 1).

Sparse dataset: The sensor dataset is not continuous. Participants may forget to wear the band at all times, and limited battery life can cause long gaps where no data is collected.

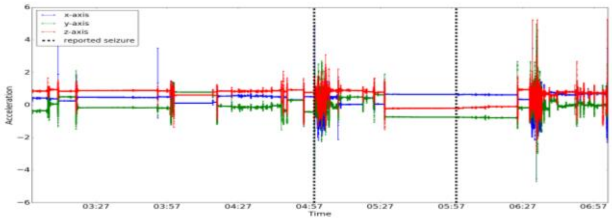

Figure 1: Accelerometer data collected on day where two seizures where reported (04:59 & 05:59). The time reported by the participant (dotted lines) does not always match the actual seizure time.

Cross-patient variation of seizure patterns: Typically, each patient will experience a similar type of convulsions or body movement during a TC seizure. However, these patterns can vary significantly across patients.

III. Methodology

Currently our primary aim is to extract a dataset where collected data can be accurately labelled as being part of a seizure or not. Our overall approach is to employ an "anomaly detection" algorithm over the collected sensor data, targeting a period around the time of the reported seizure. In essence, the self-report is treated as a "hint" on when a seizure took place and not as the exact ground-truth.

More specifically, based on a self-report timestamp, for each seizure a slice of ±1hr of sensor data is extracted for analysis. The data sample is sliced into data bins of 5 secs and a set of time-domain features are calculated. Applying a clustering algorithm (k-means) over the bins, groups them into periods with similar activity patterns. A range of 'k' values are tested and using the silhouette coefficient over the results, we identify the k that best clusters the data in distinctive groups. This approach typically breaks the ±1hr window where a seizure occurred into a small number of clusters, where one of them represents the actual seizure.

In order to accurately identify the data cluster that represents a seizure, we consider that data clusters from multiple reported seizures would demonstrate a similar pattern. We estimate a similarity metric (Euclidean distance) across data clusters from multiple seizures reported by the same patient. We consider that clusters representing a seizure will be similar to each other across multiple seizures from the same patient. Based on the similarities across clusters we are then able to accurately identify the period where a seizure took place, and reliably label the dataset for further analysis. The production of reliable labels, enables the development of a machine learning classifier for the detection of seizures without the need for patent self-reports.

[1] Epilepsy facts and terminology https://www.epilepsy.org.uk/press/facts June 2017

[2] Elger C and Hoppe C "Diagnostic challenges in epilepsy: seizure under-reporting and seizure detection" *The Lancet Neurology* 2018 vol: 17 (3) pp: 279-288