INNATE: Intelligent Non-invasive Nocturnal epilepsy Assistive TEchnology

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Abstract—Epilepsy is a neurological disease that affects the brain and is characterised by repeated seizures. Generalised, focal and unknown are three major types of seizures. Each type has several subgroups. For this reason, seizure detection and classification are expensive and erroneous. Other factors can also affect the detection. For example, patients can have a combination of different seizures or start with one type and finish with another. Nocturnal epilepsy can be prominent in many sufferers of this disease. This displays seizures that occur during the sleep cycle. The nature of such seizures makes the gathering of data and the subsequent detection and classification complex and costly. The current standard for seizure detection is the invasive use of electroencephalogram (EEG) monitoring. Both medical and research communities have expressed a large interest in the detection and classification of seizures automatically and non-invasively. This project proposes the use of 3D computer vision and pattern recognition techniques to detect seizures non-invasively.

Keywords: Epilepsy, Seizure, Kinect 2, Surface normals, PCL

1. Introduction

There are many applications of computer vision and pattern recognition in biomedical engineering. Some related examples are fall detection [1], Parkinson’s analysis [2] and the smart bedroom [3], [4]. In these cases, the video system is based on the use of 2D/3D cameras. Within seizure detection, there are also a number of research cases that use RGB-D data. For seizure detection, there are some good examples such as [5], [6]. In some of the aforementioned examples, RGB-D data is obtained using a Microsoft Kinect 1. In [5], the focus is on the rhythmic movements of the patients limbs in a particular seizure phase. The training algorithms in [5], [6] are based on support vector machines and neural nets. The introduced system in [5] utilises coloured pyjamas for patients. The segmentation and tracking of the limbs are much easier but far from a real world scenario. As most individuals sleep covered with a duvet or sheet, nocturnal seizures will not occur in this manner outside of a laboratory setup. In [6], authors used maximum-likelihood detection for low cost and wireless seizure detection. This system is based on the assumption that clonic seizures have periodic movements.

In [7], accelerometers are attached to the patients wrist and ankle and video data are used to detect two types of seizure in children. Movement patterns are classified using spatiotemporal features across point of interests. A very good review on vision-based motion detection, analysis and recognition of seizures can be found in [8]. Using infra-red and depth data has improved the results of night activity recognition as shown in [9]. A Microsoft Kinect 1 sensor detects children movements that fall into the defined seizure patterns which leads to an alarm to parents/carers.

Using 3D cameras to capture seizure information has some difficulties in areas such as setting up the correct viewpoint, occlusion or where there is insufficient data during nocturnal seizure due to a duvet or a sheet. For this purpose, we will adopt a sensor fusion approach by incorporating audio signals. In [10], an open source based seizure detector has been introduced with the help of a Microsoft Kinect 1, a smartwatch and audio signals. There are some important factors in the hardware set-up for detecting seizures. The main issue is that the acquisition devices are very sensitive to ambient noise. Other issues can include the field of view or room geometry. A good example of tackling the field of view with the help of two sensors can be found in [4]. Another important factor in dealing with patients video data is privacy. There are some off the shelf candidates for capturing 3D data such as the Microsoft Kinect 1 and 2. In this paper, we employ the Microsoft Kinect 2. In the next section, we describe our methodology and experimental set-up. In Section 3, we conclude this paper and discuss future plans.

2. Method and Experimental Set-Up

In this paper, we use the Microsoft Kinect 2 to collect infra-red and point cloud data. The Microsoft Kinect 2 has a higher resolution for both colour and depth. It also has a bigger horizontal and vertical field of view. The Microsoft Kinect 2 location is above the patient’s bed. The data gathered is in a very low light environment to imitate night conditions. The current frame rate to capture data is approximately 7 frames per second (fps). We use the robot operating system (ROS) [11] and Libfreenect2 [12] libraries in an open source environment to record the data. We record ambient sound with the 4 microphones via the Microsoft
Kinect 2. For this purpose, we use the HARK libraries [13] in an open source platform. Point cloud data are fed into the processing stage as shown in Figure 1. A primary step is to pre-process the data before it is moved to the classification of any non-normative behaviour of the individual. The first step of this process is to segment the 3D data into different body parts. This data is then fed into a simple pass-through filter to remove the remaining background. This stage is repeated for each frame. Features are then extracted from keypoints of the point cloud data and from surface normal properties. Finally, we extract dynamic features from motion characteristics of consecutive frames in a time interval. These features are suitable to extract key frames of the whole scene. This part is accomplished using PCL libraries [14]. Additional features include extracting periodic movements in the users limbs. Following feature extraction, we will employ a classification algorithm to the gathered data. A good approach for this stage is a Bag-Of-Visual-Words to classify the seizures To generate a test set of data, we have used a set of volunteers within a laboratory environment. The project will be expanded to incorporate volunteers with nocturnal epilepsy within real world environments. We recorded data in two conditions: 1) uncovered patient body movements and 2) covered patient body movements which are more realistic as nocturnal seizures happen at night while patients are asleep and covered with a duvet or a sheet. The second problem is one of the most interesting topics among computer vision researchers. Technically, it refers to a rigid body (human body) movements under a deformable dynamic surface (duvet, sheet).

3. Discussion and Future Plans

In this paper, we give an introduction to the project INNATE. The goal of this project is to detect and classify epileptic seizures with the help of 3D computer vision and pattern recognition methods. We described experimental set-up to record user data. This initial data is fed into a feature extraction algorithm. In this stage, first, we discard the background and go on to label the limbs using clustering. For each part, we compute features based on surface normals and keypoint features. Moreover, time varying properties are considered as another set of features to be fed into a learning algorithm. We are currently working on a learning algorithm and expanding the dataset. Future plans include gathering data across two scenarios, 1) uncovered body and 2) covered body. We are also producing ground truth data for each scenario through the addition of accelerometers.

References