Unsupervised learning in human activity recognition using wrist-sensing data

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I. Motivation

In recent years, with the proliferation of wearable and mobile sensing technologies, there has been a significant effort in developing human activity recognition systems using mobile sensing [1]. Ranging from tracking typical mobility patterns (walking, running, etc.) to more complex activities (cooking, social interaction), systems have been developed to passively capture sensor data related to human activities, and accurately identify the activity performed. Traditional methods in HAR typically involve the collection of accurately labelled datasets, where participants are required to manually identify the activity they performed, in order for such labelled data to then be used in the development of appropriate machine learning classifiers. This traditional approach suffers from significant scalability issues. The process of self-reporting can put a significant burden on users, which may discourage them from using such technologies. Furthermore, activities that people perform during their daily lives can change, with new activities appearing at different times in their lives. In this work we explore the development of an unsupervised technique for human activity recognition, without the need for accurately labelling data to produce a training dataset.

In this work we take advantage of a large dataset of wrist-worn sensor data captured as part of the Innovate UK funded Epilepsy Networks. In this project, a number of patients suffering from epilepsy were asked to wear a smart wrist-band (Microsoft Band 2) for the most part of their day, for periods of months. The objective of the project was to use wrist-band sensing to capture physiological signals that can help detect epileptic seizures. As a by-product of the deployment, a large dataset of wearable data was produced that contain sensor readings as participants were going about their lives. Specifically, we have collected data from 58 patients, which include accelerometer, gyroscope, heart rate, and skin temperature from a wrist worn device. The full set includes data for approximately 6,500 days (about 112 days for each participant). Being able to detect the daily activities of these users can add significant value to the overall project. Indeed, there are indications that particular physical activity patterns can have an effect on the progress of conditions like epilepsy, and the mental well-being of a patient suffering from a long-term health condition.

II. Approach

In this work we intent is to explore the feasibility of detecting high-level daily activities using wrist-mounted sensor data without the need for self-reported ground truth by the users. Our approach is to employ a deep-learning model to help identify similar activity patterns across the whole dataset. With an appropriate clustering of activities that are similar, we can then employ appropriate heuristics to identify the possible activities that these clusters represent.

Our approach is influenced by techniques that apply deep learning to model sketch drawings by analysing drawing gestures that may represent similar images [2]. In a similar manner we hypothesise that wrist-sensing movement data captured by the same user, when performing similar activities will be relatively similar across multiple occurrences of the same activity, and quite distinct from other daily activities.

Specifically, we utilise the accelerometer and gyroscope data captured from the dominant hand of participants. These datasets, are then transformed to produce the 3D relative change of position and direction of the hand of the participant with respect to the previous time frame. Such 3D gesture patterns are then fed into an auto encoder. The auto encoder combines an encoder and decoder neural network to produce an intermediate vector representation of the input data (See Figure 1). We consider that for similar activities, the encoded vector representation should be similar. Preliminary results have been produced using labelled activities from a small set of healthy volunteers including running, walking, typing et al. Additional results were produced using public activity datasets – HHAR [3]. The results shows that different activities are clustered in different groups in an embedded n-dimensional space (n is the length of the encoded vector). The Euclidean distance between the data block can help identify activities that are similar. Future work will focus on the development of unsupervised or semi-supervised techniques to label such activity clusters with the type of activities performed.

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Figure 1. Flow chart of the proposed variational auto encoder deeping learning model