Behavior Classification from Repetitive Finger Movements

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***Abstract*—Repetitive movement patterns are an indication for many psychological and neurological conditions. The current measurement method for repetitive behavior consists of placing accelerometers on the patient. However, this restricts the movements, especially when it concerns the measurement of fingers. The aim of this paper is to classify repetitive finger motion in a non-invasive way by using sEMG where the motion of the fingers is not restricted. A deep learning model is successfully trained to classify three types of finger motion. The model has extraordinary performance on the person it is trained for and a performance of 73% - 100% for other persons where the model is not trained for.**

Keywords—Stereotypic behavior, movement detection, classification, electromyography, sEMG, deep learning, MATLAB

I. INTRODUCTION

Repetition in human behavior is a valuable source of information for detecting abnormalities. Stereotypic behavior is seen in autistic spectrum disorder, developmental coordination disorder, obsessive–compulsive behavior and stereotypic movement disorder [1-3]. Stereotypic behavior is an indicator on aberrant behavior checklists and is one of the defining factors of autism [4]. In fact, it correlates well with the severity of autism [5]. Repetitive movements are also seen with a similar frequency of occurrence in obsessive compulsive behavior [6], especially in combination with the insistence of sameness and rituals [7]. Most studies of repetitive behavior outside autism originate from animal behavior studies, because there, besides observed with impaired animals, frustration in captivity results in such behavior [8].

Repetitive movement of the body can be measured quite easily using accelerometers on the chest or extremities [9]. Nevertheless, it is hard to find studies in which the repetitive behavior is studied as a signal: meaning logging it as a frequency and amplitude. In Table 1, an attempt is made to classify several repetitive movements based on their frequency. The estimates and conditions come from common sense and from the literature mentioned above.

Especially the body rocking and finger-fiddling appear to be interesting measures that will be strongly indicative for mental conditions when monitored. Systems are reported that can measure repetitive motion of the hands in order to evaluate stress on the wrist during manual work [10]. Although these systems have a different aim to study cumulative trauma disorders, the method used to derive intensity and the degree of repetitiveness from simple inclinometers is useful. The numerical definition of postural load goes back to 1974 [11]. While body rocking can be measured using accelerometers, for example with the acceleration sensors in mobile phones, the finger fiddling is not trivial to measure. The reason is that the hand is not a convenient place to place sensors on, especially not with the intended target groups. Sensors on the finger and the hand will limit the freedom of motion immediately.

TABLE I. REPETITIVE BEHAVIOR CLASSIFIED BY FREQUENCY

Behavior	Mental condition	Frequency	Where on body?
Sleep-wake rhythm	Sleep disorder, general stress	24hrs ≈ 11-12μHz	Whole body
Repetitive actions, fidgeting	Obsessive Compulsive Disorder (OCD), nervousness	minutes ≈ 10mHz	Whole body
Body rocking	Autism, Stereotypic Movement Disorder	tens of sec ≈ 1-5Hz	Chest
Periodic limb movement	Anxiety muscle twitching, stress	tens of sec ≈ 1-5Hz	Legs, arms
Finger fiddling	Stress, depression	tens of sec ≈ 1-5Hz	Fingers

II. GOAL

We aim to detect and classify repetitive finger motion with surface-electromyography (sEMG) on the lower arm with deep learning. The question is whether it is possible to classify the index-finger and thumb movements from a single channel sEMG signal. The research question is whether the non-specific sEMG signal can be used with deep learning to classify at least two types of finger twitching.

III. THEORY

Surface electromyography (sEMG) is a clinical method to measure the activity of muscles. It is technically relatively easy to implement because muscles generate a signal of tens of millivolts and the bandwidth is not significantly higher than 500Hz [12]. Therefore, simple portable applications are found, for example to measure tension in muscles originating from mental stress [13].

The application of deep learning to recognize stereotypic behaviour is reported, but mainly on accelerometer signals [9]. Therefore, the feasibility of the combination of sEMG with deep learning to classify hand gestures is still worth to be investigated. Some primitive classification using sEMG was found for the use of controlling prosthetic hands [14]. However, in that application, the final goal is not to estimate stress and the features used are not based on repetitiveness.

The measured potential from the muscle has to be processed to extract features that are useful to train a deep learning model. We have chosen 19 features that are generated from the signal. The mean, median and root mean squared values are the first three features. These features contain information about the dimension of the signal.

The skewness and kurtosis are two features that hold information about the distribution of values in the signal.

Autocorrelation contains information about the repetitiveness of the signal itself. The position and height of the three highest peaks of the produced result are taken as 5 features (the first peak is always at the same location). Finally, the location and height of 5 peaks of a power spectral analysis are taken for the remaining 9 features. FFT is utilized to determine the frequency of the motion.

Data acquisition and processing is done inside MATLAB, as well as the training of the deep learning model. Therefore, three classifications are created based on repetitive motions. Classification one, the hand is relaxed, second, flapping of the hand and third, forced rubbing of the thumb and index finger. The best results were obtained to classify these 3 types of movements, by using a deep learning model built on 5 layers. First a sequence input layer for the 19 features and second a layer with 10 hidden nodes. The remaining three are the essential fully connected, softmax and a classification layer. The model is trained with 90% of the available data where 10% is used as validation data after the training process.

IV. Experiment

A MATLAB GUI is programmed to handle the data acquisition, processing, visualization, classification and training. Raw sEMG data is acquired and stored with this tool. The acquisition is performed with a National Instruments USB-6009 module. One of the four differential analog inputs was utilized to measure the amplified sEMG signal. Amplification is performed by a bio-amplifier from PHYWE. The knobs are set to the EMG filter settings and a 1000x amplification.

To keep the sEMG electrode placement simple and non-invasive, we have chosen to use three Ag/AgCl gel electrodes (Ambu White Sensor, type WS-00-S) above the flexor digitorum superficialis muscle. Two electrodes are used to measure the potential difference and the third is used as a reference. An essential part of the measurement is to place the electrodes correctly on the underarm of the test person. The positions are schematically depicted in Figure 1. The distance of the differential (+, -) electrodes varies to 4 to 6 cm per person where the reference electrode (R) is placed at the inner side of the under arm near the elbow.

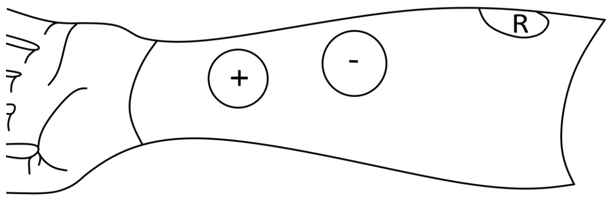

Figure 1: Placement of the electrodes on the left underarm.

V. Results

The number of datasets for one person used is 150, for every classification 50, containing each 5 seconds of measurement data. The time needed to train the model, on a GPU, is less than a minute with 100% accuracy on the validation data (NVIDIA GeForce GTX 1050 GPU, Intel i7-7700HQ CPU, 2.80GHz, 16GB RAM).

To validate the accuracy of the trained model, tests have been performed on a person where the model is trained for. 100% of the movements were classified correctly and the frequency of the movements is calculated correctly.

The model is also tested with persons new to the trained model. The movements have been performed 5 times in a random order for the 3 classifications. The accuracy of the model for the first classification is 83%, second 73% and the last 89%. Worth noting is that for one of the five persons the model had an accuracy of 100% for all movements.

VI. Conclusion and Recommendations

The trained deep learning model in combination with the 19 features is capable of classifying movements of a person known by the model. It is a non-invasive way to classify hand and finger motions in combination with the frequency of the movement. The model performs best on a person that is familiar to the model.

It is recommended to create a personalized model per person when this proof of concept is used. Movement data of the subject in question must be gathered and the deep learning model must be retrained, resulting in the best performance.

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