Capturing the Structure of Electrodermal Activity with Deep Neural Networks

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Abstract— **Deep neural networks (DNN) have recently gained a lot of interest because of their ability to learn representations and high-level abstractions directly from data. Their use is particularly applicable in biomedical signal processing because of the characteristic structure of the corresponding signals. We use an autoassociative DNN to model the Electrodermal Activity (EDA), a physiological signal that depicts typical shape fluctuations over time and responds to the sympathetic nervous system (SNS) activation. The analysis of EDA signals was motivated by the sensory difficulties of children with Autism Spectrum Disorder during dental cleaning by monitoring physiological stress and anxiety in two dental environments. Compared to traditionally-used skin conductance level and response measures, EDA features automatically derived by DNN capture signal patterns in a more reliable way. These results provide a foundation towards accurate automatically-derived measures of stress and anxiety from biomedical signals.**

I. Introduction

Deep Neural Networks (DNN) are deep architectures with the ability to learn features from complex signals. They have provided significant contributions to speech and image processing, while their use in biomedical applications remains limited [1]. Electrodermal Activity (EDA) is a biomedical signal related to stress, emotion and cognition, and is measured from psychophysiologically-induced eccrine sweat gland activity of the skin [2]. It depicts a characteristic structure making DNN is a compelling modeling technique.

We propose the use of an autoencoder to automatically create EDA features because of its ability to preserve a large amount of information in a low-dimensional space [3]. Our experimental data comes from EDA signals of children undergoing dental prophylaxis in two different dental environments designed to elicit distinct physiological responses. Classification was performed between the two environments using the DNN features.

II. Data Description

There has been considerable effort to make the dental prophylaxis less stressful for children with special health care needs [4]. One approach is to utilize a new sensory adapted dental environment (SADE) by modifying the dental room with respect to the visual, tactile, and auditory stimuli encountered [4]. Our data was collected from forty-four children, ages from 6 -12 (n = 22 Autism Spectrum Disorder (ASD), n = 22 typical), each undergoing a dental cleaning in both the regular dental environment (RDE) and the SADE. EDA was recorded (F_s=32Hz) with pre-gelled electrodes placed on the fingertips of the index and middle finger of the participant's less-dominant hand.

III. Methodologies and Results

We performed low pass filter (32 samples) and segmentation of the EDA signals into analysis frames of 50, 100, and 150 samples. These were used as an input to the DNN with an autoassociative architecture ("autoencoder") [3] performing identity mapping between the input and output layers (Fig. 1). The features of interest found in the middle layer are called "bottleneck" features. The intermediate layer consisted of 10, 20, 30, and 40 nodes, while the bottleneck layer included 1, 2, and 3 nodes.

The bottleneck features are fed in a K-nearest neighbor (K-NN) classifier with and without the use of linear discriminant analysis (LDA) (Fig. 1) to classify the input signals between the two environments. Our baseline includes the Skin Conductance Level (SCL) and Skin Conductance Response (SCR) features [2] being the input of the K-NN.

Results indicate significant differences in the signals obtained from the two environments. While SCL and SCR measures depict unweighted accuracy (UA) of 52.3 and 47.2%, respectively, DNN-derived features reach UA up to 58 and 63.6% (Fig. 2), with the ones transformed through LDA providing best results. The sources of error resulted from various subject-dependent factors such as ASD severity, gender distribution, and a limited sample size.

IV. Conclusions

We present a novel technique using DNN to analyze EDA for differentiating between distinct physiological responses of children. Results indicate the DNN's ability to capture the signal structure through its hidden layers. For future reference, more analysis on the system architecture and feature interpretation are needed.

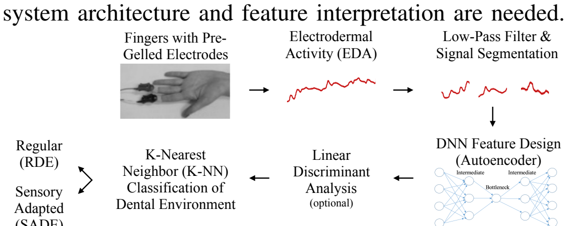

Fig. 1. Schematic representation of the proposed method.

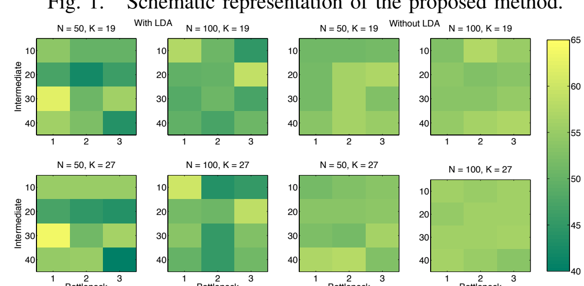

Fig. 2. Unweighted accuracy (UA%) for classifying between regular and sensory adapted dental environments using the DNN features with different analysis window (N), size of intermediate and bottleneck layers, and number of neighbors (K). Colorbars represent UA (%).

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