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Machine Learning Evaluation of Passive Wireless Neurosensing Recorder for Biopotentials Recognition

Melany Gutierrez-Hernandez, Carolina Moncion, Satheesh Bojja-Venkatakrishnan, and John L. Volakis
College of Engineering and Computing, Florida International University, Miami, FL, USA

Abstract— **Neuropotentials monitoring can help individuals to significantly enhance their physical and mental well-being. We present an evaluation of a multichannel, passive and fully implantable wireless neurosensing system (WiNS). WiNS employs radiofrequency and optical communications to address the need for non-battery-operated systems. In this study, we will present a new automated technique to identify signal segments eliminating the difficulty of manual classification of evoked biopotentials. In addition, machine learning algorithms are adopted to evaluate signal quality from WiNS and compare it with a commercially available wired system. Somatosensory evoked potential data measured from wired and our wireless systems shows < 6% deviation in machine learning testing accuracy, indicating successful detection of biopotential signal as low as 15 μV_{pp}. These results support the concept that real-time machine interface for wireless and passive acquisition of biopotentials is indeed feasible translating to several uses for future clinical research.**

I. Introduction

Neuropotential recording provides essential information to better understand the brain's functionality and to diagnose neurological diseases early. To sense certain brain signals, implantable technologies are employed. However, wires are still required to connect the electrodes located on the brain to external equipment restricting movement and possible causing infections. In addition, current wireless implanted neural recording systems require use of batteries that may lead to heat in the brain which can cause tissue damage. To overcome these issues a multichannel passive wireless neurosensing system (WiNS) has been proposed with very minor heating to the brain. Therefore, WiNS minimizes injury and preserves the natural lifestyle of the patient [1].

Several benchtop and *in vivo* measurements have been performed to demonstrate the potential of WiNS which can significantly impact the future neuroscience research [2]. The recorded data could be employed to analyze the patient's well-being in real-time as well as offer a diagnosis and treatment for several neurological disorders such as epilepsy, Parkinson's, Alzheimer's, tremor, etc. However, an automated brain-machine interface system is still required to collect and process the recorded neural data in real time. Such automated process serves to eliminate the need for manual classification of biopotentials. Therefore, by introducing artificial intelligence (AI) and implementing machine learning (ML) algorithms, automatic recognition of the recorded signals can be achieved.

In this paper, we present an analysis of ML techniques to process recorded biopotentials. Further, we demonstrate that the WiNS system quality signal is comparable to existing wired recorders.

II. Neurosensing System

Wireless Neurosensing System (WiNS) is the result of several years of collaborative research that led to a fully implantable, minimally invasive, wireless and passive alternative that does not require a battery. WiNS is composed of two principal components, the implant, and the interrogator. The operation principle of the proposed technology relies on radiofrequency and optical communications, as shown in Fig. 1. A carrier signal is generated at the interrogator and transmitted to the implant where it is mixed with the neural signals from the brain. Subsequently, this modulated signal is transmitted back to the interrogator for demodulation and processing. Recent versions of this system have incorporated multichannel recording and an impedance matching network to minimize the mismatches between the neural electrodes and the recording circuits [3,4].

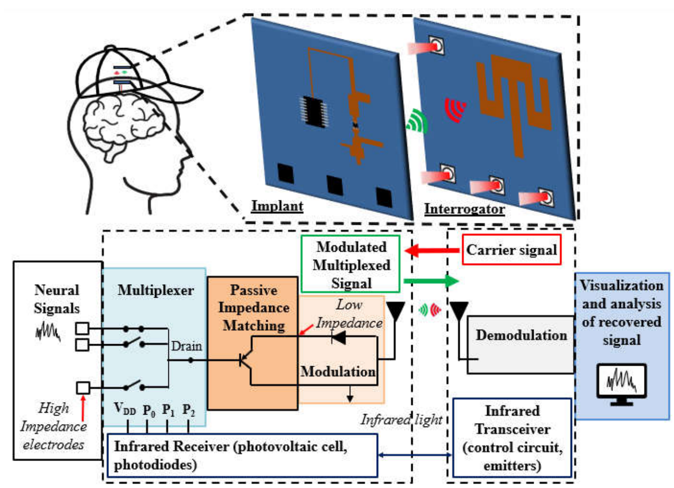

Fig. 1: Block diagram of the neurosensing system able to detect neural signals as low as 15 μV_{pp}.

III. Experimental Set-Up and Measurements

In vivo recordings in rats were performed in compliance with the Institutional Animal Care and Use Committee (IACUC) at Florida International University (Approval No. 20-040). Somatosensory evoked potentials (SSEPs) were recorded in these experiments by eliciting activity in the somatosensory cortex, specifically in the hind limb (HL) region, as shown in Fig. 2 (a). Evoked brain signals were detected using an electrocorticographic 32 channels grid. A typical recording sampling rate of 500 Hz per channel was used for recording. In addition, a commercially available wired system Open Ephys was employed as a reference system.

IV. Neurosensing System Evaluation

In this paper, we aim to evaluate the performance of our wireless recording method by comparing datasets recorded from a wired system and WiNS. The raw data was first filtered using a 60 Hz notch filter and then passed through a band-pass filter across $0.1 - 100\ Hz$. Each recording was five minutes in lenght and were segmented from -50 to $250\ ms$, referenced to the time when HL stimulation occurred. Here, we introduce a machine learning algorithm to remove noisy trials automatically from the WiNS system recording. Further, somatosensory evoked potentials (SSEPs) were extracted by averaging across the identified signal segments.

Notably, several machine learning classification methods are available. These are categorized based on their complexity in ML, deep learning (DL) and transfer learning (TL) modalities. ML algorithms are usually simple to interpret and understand. Some of the popular techniques are the ensemble methods including the random forest (RF) approach that employs several decision trees. RF approach is robust to outliers and nonlinear data, making it more suitable for noisy signals. On the other hand, DL algorithms can incorporate several hidden layers. An efficient DL method for images is the convolutional neural network (CNN) which has little dependence on pre-processing. Transfer learning is employed when already trained networks from one task are reused for another task. Two examples are GoogleNet (22 layers deep) and SqueezeNet (18 layers deep). The latter can classify objects into 1000 categories.

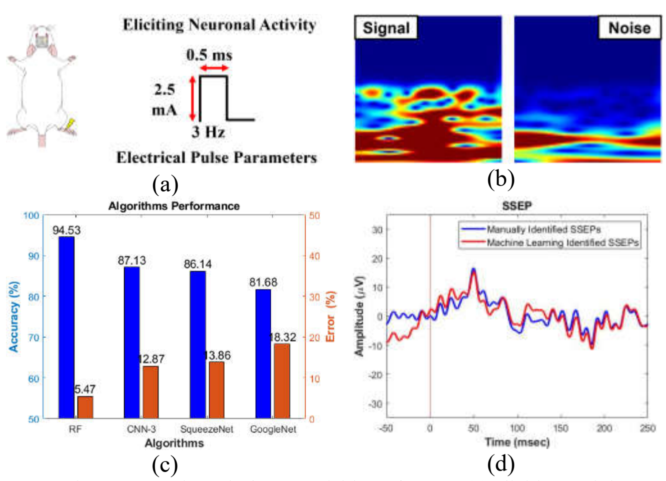

Figure 2. Passive wireless acquisition of SSEP: (a) eliciting activity characteristics, (b) labeled noise/signal segments scalograms, (c) classification performance and (d) manually and machine learning recovered SSEP.

Random Forest, Convolutional Neural Network of three layers (CNN- 3), GoogleNet and SqueezeNet with modifications for our dataset, were employed for classification. For the last three algorithms, a continuous wavelet transform filter bank was precomputed to create the scalograms. The latter are time frequency representations generated from the data, as shown in Fig. 2 (b). Since the recorded data is unbalanced, introducing a negative impact on algorithm accuracy, the amount of signal segments was under sampled for training the algorithm. The models were constructed and trained in MATLAB. The training data set was composed of 807 segments while the testing data set was comprised of 201 segments. The results in Fig. 2 (c) show that RF is the best classifier for the data. Notably, RF training time took 55 seconds. By employing the RF trained model with datasets from a single recording, we can determine the SSEP. This indicates that manual and ML extraction have the same timing and similar amplitude for the maximum peak, Fig. 2 (d). These results demonstrated that we can automatically recognize signal segments, eliminating difficulties of manually identifying noisy segments and thereby reducing processing time.

After SSEP extraction, we proceeded to analyze the datasets recorded from the wired system and WiNS. The same pre-process techniques were again used to generate scalograms. Fig. 3 (a) shows the SSEP scalograms of WiNS vs the wired system. For this classification, the training dataset was composed of 71 segments. The measurement dataset was comprised of 17 segments. From Fig. 3 (b), the measured SSEP data from wired and wireless systems shows $< 6\%$ discrepancy. We remark that measurements indicate a detectable neural signal of amplitude as low as 15 μV_{pp}.

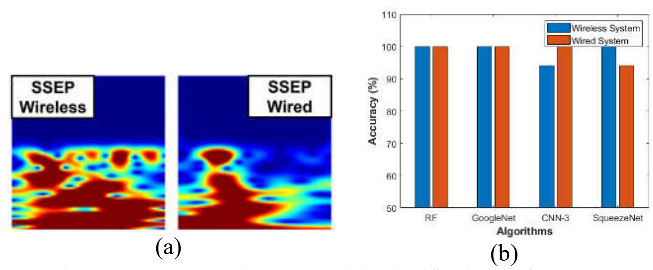

Figure 3. (a) SSEP Scalograms and (b) classification performance.

V. Conclusions

A new data analysis technique with AI/ML algorithms was used to process wired and WiNS received medical datasets. It was demonstrated that the recording of the evoked neuronal activity using a multichannel and passive WiNS is comparable to a wired system. We also introduced a machine learning technique to enable the SSEP signal recognition and avoid the need for manual classification. In the future, we will employ this machine learning algorithm to automatically recognize recordings from various stimulation paradigms in real time.

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