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Implementation of a Smartphone as a Wearable and Wireless Accelerometer and Gyroscope Platform for Ascertaining Deep Brain Stimulation Treatment Efficacy of Parkinson's Disease through Machine Learning Classification

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Abstract

Parkinson's disease manifests in movement disorder symptoms, such as hand tremor. There exists an assortment of therapy interventions. In particular deep brain stimulation offers considerable efficacy for the treatment of Parkinson's disease. However, a considerable challenge is the convergence toward an optimal configuration of tuning parameters. Quantified feedback from a wearable and wireless system consisting of an accelerometer and gyroscope can be enabled through a novel software application on a smartphone. The smartphone with its internal accelerometer and gyroscope can record the quantified attributes of Parkinson's disease and tremor through mounting the smartphone about the dorsum of the hand. The recorded data can be then wirelessly transmitted as an email attachment to an Internet derived resource for subsequent post-processing. The inertial sensor data can be consolidated into a feature set for machine learning classification. A multilayer perceptron neural network has been successfully applied to attain considerable classification accuracy between deep brain stimulation "On" and "Off" scenarios for a subject with Parkinson's disease. The findings establish the foundation for the broad objective of applying wearable and wireless systems for the development of closed-loop optimization of deep brain stimulation parameters in the context of cloud computing with machine learning classification.

Keywords

Parkinson's Disease, Deep Brain Stimulation, Wearable and Wireless Systems, Smartphone, Machine Learning, Wireless Accelerometer, Wireless Gyroscope, Hand Tremor

1. Introduction

There exists an assortment of treatment interventions for the amelioration of Parkinson's disease neuro-motor symptoms, such as tremor. Traditional approaches advocate the application of a medication strategy or even the ablation of neurological structures [1] [2]. Within the bounds of the recent quarter of a century, the application of deep brain stimulation has been established as a considerably efficacious strategy for resolving Parkinson's disease tremor [3]. The proper implementation of a deep brain stimulation device requires the amalgamation of multiple endeavors, such as the stereotactic surgery for inserting the electrodes to the targeted neural structures deeply encased in the brain and the selection of an optimal set of deep brain stimulation device tuning parameters [4] [5].

The convergence of an optimal set of deep brain stimulation tuning parameters can present an arduous and daunting task even for a highly skilled and specialized neurologist. Intuitively, a quantified feedback would be advantageous throughout the tuning process for improved and objective acuity. Current approaches employ the Unified Parkinson's Disease Rating Scale (UPDRS), for which a skilled specialist applies expert, yet subjective interpretation of a prescribed ordinal scale [6]. However, the reliability of such ordinal scales is a subject of contention [6]-[11]. Furthermore, light of the limited number of skilled specialists, rampant neurodegenerative diseases may further impart strain on limited medical resources.

LeMoyne *et al.* applied the inertial sensor of a smartphone to measure Parkinson's disease tremor. The application enabled the smartphone to function as a wearable and wireless accelerometer platform with the wireless conveyance of the trial sample recordings as email attachments through the Internet. A notable advantage of this capability is the observation that the experimental location and post-processing resources can be remotely situated anywhere in the world [9]-[14]. Further permeation of the smartphone and portable media device as wearable and wireless inertial sensor platforms have been successfully demonstrated for an assortment of domains, such as quantification of gait, reflex, and exercise/therapy scenarios, for which machine learning has augmented the capability of wearable and wireless systems with considerable classification accuracy [9] [10] [11] [12] [13].

The objective of the research endeavor is to demonstrate machine learning classification accuracy for distinguishing between deep brain stimulation "On" and "Off" status for a subject with Parkinson's disease from an engineering proof of concept perspective through the quantified feedback of a smartphone functioning as a wireless and wearable inertial sensor system. Quantified feedback is provided through the accelerometer and gyroscope of the smartphone and conveyed by wireless transmission to the Internet as an email attachment for remote post-processing. The smartphone functioning as a wearable and wireless platform is mounted to the dorsum of the hand and secured by a latex glove. The signal data from the accelerometer and gyroscope internal to the smartphone are consolidated into a feature set for the classification of deep brain stimulation "On" and "Off" status for a subject with Parkinson's disease tremor for machine learning classification using a multilayer perceptron neural network.

2. Background

2.1. Fundamentals of Parkinson's Disease

Parkinson's disease affects on the order of one million people in the United States of America [1]. The onset of Parkinson's disease generally occurs for people exceeding the age threshold of 55 years [15]. Intuitively as the population progressively becomes older, Parkinson's disease becomes an increasing topic of concern.

The predominant neuro-anatomical basis for Parkinson's disease is derived from the degeneration of dopaminergic neurons located in the substantia nigra [1]. Parkinson's disease manifests in the observably characteristic movement disorders [16]. Distinctive resting tremor, such as about the hand, can develop with a typical frequency on the order of four to five per second [1] [17].

2.2. Treatment Alternatives for Parkinson's Disease

Parkinson's disease movement disorder symptoms can be attenuated through three interventions:

1) Medication;
2) Pallidotomy [1] [2];
3) Deep brain stimulation [3] [4] [5].

Medical intervention can involve the prescription of L-dopa as a conventional therapy for ameliorating Parkinson's disease symptoms [1]. The pallidotomy is reserved for scenarios for which other therapy alternatives are considered intractable. The pallidotomy consists of brain surgery that induces a lesion about the internal aspect of the globus pallidus [1] [2].

2.3. Deep Brain Stimulation Fundamentals

On the order of a quarter of a century ago deep brain stimulation was introduced as an efficacious means to treat movement disorder, such as Parkinson's disease. The procedure for implanting deep brain stimulation electrodes requires stereotactic surgery that targets neurological structures, such as the VIM (ventralis intermedius) nucleus of the thalamus [3]. The targeted electrodes are controlled by an implantable pulse generator (IPG). The IPG generates that electric stimulation to the targeted neurological structure and is comprised of the battery representing the energy source and regulating electronic circuitry. Stimulation configurations can be developed by the careful determination of parameters, such as polarity, stimulation amplitude, pulse width, and stimulation rate. The programmer transmits through wireless connectivity the selected parameter configuration to the IPG [5]. Intuitively, the inherent challenge to successfully implementing deep brain stimulation is the acquisition of an optimal configuration of stimulation parameters within the scope of the efficient application of expert clinical resources.

2.4. Challenges with Tuning a Deep Brain Stimulation System

The proper implementation of a deep brain stimulation system necessitates a multi-faceted perspective for optimal efficacy. For example, the deep brain stimulation lead could be expertly implanted from a skilled neurosurgeon. However, other techniques are instrumental for the best operation of a deep brain stimulation system for ameliorating the movement disorder symptoms, such ascertaining an optimal set of tuning parameters [18].

Programming the pulse generator for a deep brain stimulation device can represent a daunting task, even for a highly skilled neurologist. There exists a considerable assortment of parameter combinations. Logically, a systemic approach is highly desirable to converge upon an optimal parameter setting [18].

2.5. Quantification of Parkinson's Disease Tremor

The quantification of Parkinson's disease tremor may serve as an instrumental role for converging to an optimal set of deep brain stimulation system tuning parameters. Traditionally the UPDRS serves as an ordinal scale strategy for quantifying the severity of Parkinson's disease tremor [6]. However, such ordinal scales inherently require the subjective interpretation of an expert clinician, for which the reliability of these scales is a subject of contention [6]-[11].

An alternative to the ordinal scale approach is the application of inertial sensors in the context of wearable and wireless systems [9] [10] [11] [12] [13]. For example, accelerometers have been applied to quantify Parkinson's disease tremor with considerable success [7] [9]-[14] [19] [20]. With the advent of wireless technology tethered configurations for inertial sensors have become obsolete [21].

During 2010 LeMoyne *et al.* applied a smartphone in the context of a wearable and wireless accelerometer platform for the successful quantification of Parkinson's disease hand tremor. The trial data was conveyed by wireless transmission to the Internet as an email attachment. Furthermore, the experimental site and post-processing resources were located on effectively opposite sides of the continental United States [14]. The research endeavor applies a simultaneous recording of the accelerometer and gyroscope signal to provide a more comprehensive feature set for machine learning classification differentiation for a subject with Parkinson's disease hand tremor respective of deep brain stimulation device "On" and "Off" status.

2.6. Machine Learning for Differentiating between Deep Brain Stimulation Device "On" and "Off" Status

With quantified measurement through a smartphone functioning as a wearable and wireless accelerometer and gyroscope platform a feature set can be developed for the classification of disparate states, such as a deep brain stimulation device in "On" and "Off" modes [11] [22]. Classification accuracy can be achieved through the application of a suitable machine learning algorithm. The Waikato Environment for Knowledge Analysis (WEKA) consists of an array of machine learning alternatives, such as the multilayer perceptron neural network [23] [24] [25]. In particular the multilayer perceptron neural network emulates a semblance of neurologically derived perceptivity, since the fundamentals of the algorithm are derived from a computational representation of the neuron, which represents the foundational basis of the brain [26].

2.7. Smartphone as a Wearable and Wireless System for Quantifying Parkinson's Disease Hand Tremor and Machine Learning Classification for Deep Brain Stimulation in "On" and "Off" Mode

The smartphone constitutes a wearable and wireless system equipped with an accelerometer and gyroscope for quantifying and recording hand tremor for Parkinson's disease, which can be applied about the dorsum of the hand. Machine learning can be applied to distinguish between two deep brain stimulation scenarios, such as "On" and "Off" mode. The objective of the research endeavor is to apply the multilayer perceptron neural network to attain considerable machine learning classification accuracy for deep brain stimulation device in "On" and "Off" modes regarding a subject with Parkinson's disease through a smartphone as a wireless and wearable system. The machine learning feature set is comprised of quantification of Parkinson's disease hand tremor through a smartphone recording an accelerometer and gyroscope signal in the context of a wearable and wireless system with the trial data wirelessly conveyed as an email attachment through connectivity to the Internet.

3. Material and Methods

The demonstration of machine learning classification to distinguish between deep brain stimulation "On" and "Off" status for treating Parkinson's disease tremor was from the perspective of engineering proof of concept. One subject with bilateral subthalamic nucleusdeep brain stimulation to ameliorate Parkinson's disease tremor was selected for the experiment. Informed consent was performed, and the study was performed at Allegheny General Hospital. The smartphone was equipped with a software application that enabled the simultaneous recording of the accelerometer and gyroscope signal. The recorded inertial sensor data was conveyed as an email attachment through wireless connectivity to the Internet, for which the smartphone was representative as a wearable and wireless system.

The mounting strategy involved securing the smartphone about the dorsum of the hand through a latex glove. Similar approaches have been applied for using the smartphone and associated wireless inertial sensors for measuring Parkinson's disease tremor symptoms [14] [19] [20] [22]. A representative illustration of the smartphone mounting strategy is represented in **Figure 1**. **Figure 2** provides a representation of the deep brain stimulation patient programmer that enables the modification of status to "On" and "Off" mode.

Figure 1. Smartphone mounted to the dorsum of the hand by a latex glove.

Figure 2. Deep brain stimulation patient programmer for setting status to "On" and "Off" mode.

The Waikato Environment for Knowledge Analysis (WEKA) was selected for applying machine learning classification, for which the multilayer perceptron neural network was determined as the most appropriate algorithm. Ten-fold cross validation was applied to the machine learning classification. In order to conduct machine learning classification through WEKA, an Attribute-Relation File Format (ARFF) was developed comprising the attributes of feature set [23] [24] [25]. The ARFF was derived by consolidating the magnitude of the accelerometer signal and pitch, roll, and yaw aspects of the gyroscope signal through software automation provided by Matlab. The feature set consist of the maximum, minimum, mean, standard deviation, and coefficient of variation the respective inertial signal data, which is based on the success of previously successful machine learning classification endeavors involving wearable and wireless inertial sensors [27] [28] [29] [30].

The experimental protocol pertained to 10 repetitions with the deep brain stimulation system in "On" status and 10 repetitions using "Off" status. The trials were conducted with the subject's wrist suspended beyond the edge of an arm support. The smartphone application for acquiring the accelerometer and gyroscope signal was set to a sampling rate of approximately 100 Hz for a recording duration of approximately 10 seconds. The following protocol was applied:

1) Secure the smartphone about the dorsum of the hand through a latex glove.

2) Arrange the subjects arm, such that the wrist is oriented in a suspended manner over the arm support.

3) Activate the recording sequence of the smartphone for acquisition of the accelerometer and gyroscope signal.

4) Upon completion of the accelerometer and gyroscope signal recording convey the trial sample data as an email attachment through wireless connectivity to the Internet.

Repeat steps 1 - 4 for both scenarios with the deep brain stimulation system in "On" status for 10 repetitions and 10 repetitions using "Off" status.

4. Results and Discussion

4.1. Results

From an observational perspective, the subject demonstrated attenuation in tremor severity with the deep brain stimulation device in the "On" mode relative to the "Off" mode. **Figure 3** provides a representation of the acceleration magnitude signal of the subject's hand tremor measured by the smartphone operating as a wireless and wearable system with the deep brain stimulation system in "On" mode. **Figure 4** demonstrate the amplified hand tremor of the acceleration magnitude signal for the subject with the deep brain stimulation system set to "Off" mode.

Based on the observation of the acceleration magnitude of the accelerometer signal and the roll, pitch, and yaw aspects of the gyroscope signal five attributes were selected to develop a feature set. The feature set consists of the following attributes:

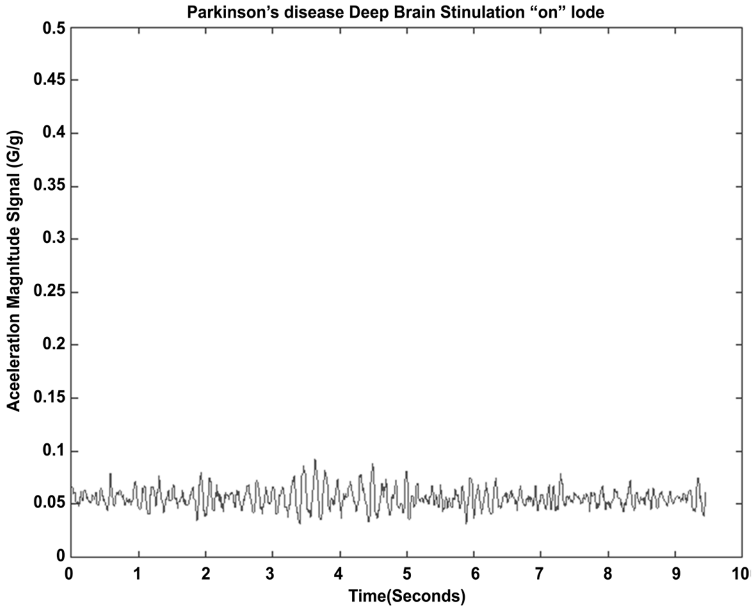

Figure 3. Acceleration magnitude signal of Parkinson's disease hand tremor with deep brain stimulation in "On" mode.

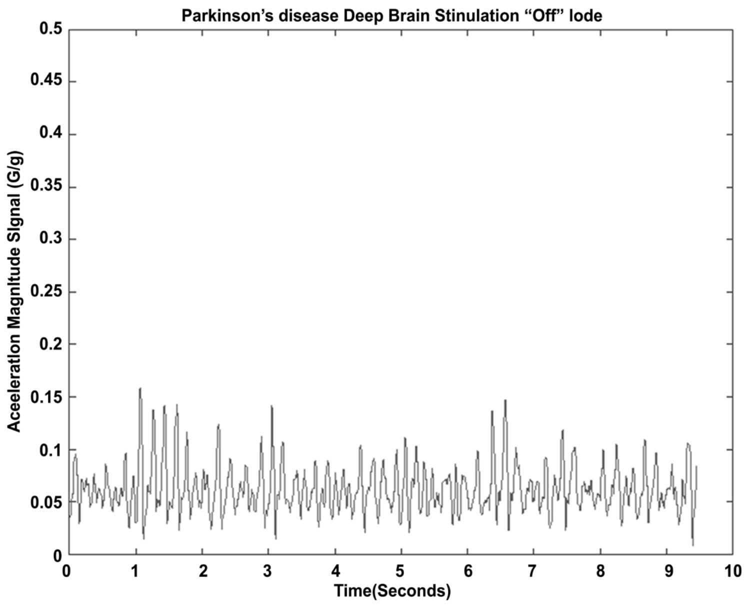

Figure 4. Acceleration magnitude signal of Parkinson's disease hand tremor with deep brain stimulation in "Off" mode.

1) Maximum;
2) Minimum;
3) Mean;
4) Standard deviation;
5) Coefficient of variation.

The 20 trials were consolidated into a feature set through software automated through Matlab, which greatly facilitates the post-processing endeavor for machine learning classification.

Machine learning classification was conducted through the multilayer perceptron neural network provided by WEKA. The multilayer perceptron neural network attains a classification accuracy of 95% for distinguishing between deep brain stimulation device "On" and "Off" status for a subject with Parkinson's disease using the inertial sensor (accelerometer and gyroscope) of the smartphone functioning as a wearable and wireless system. **Figure 5** illustrates a graphic representation of the multilayer perceptron neural network applied for achieving this considerable classification accuracy. The multilayer perceptron neural network consists of 20 input layer nodes, 11 hidden layer nodes, and two output layer nodes. Further analysis of the multilayer perceptron neural network can be applied by addressing the confusion matrix.

The confusion matrix further elucidates the nature of the machine learning classification accuracy. For example, the confusion matrix defines specifically which instances of each class were correctly classified and the instances that were incorrectly classified. Regarding this machine learning classification scenario 1 of 20 instances were incorrectly classified. 10 instances were correctly classified as deep brain stimulation in "Off" mode. 9 instances were correctly classified as deep brain stimulation in "On" mode with 1 instance incorrectly classified as deep brain stimulation in "Off" mode.

4.2. Discussion

In the near future, the demonstrated concept can be considerably evolved by developing a Bluetooth wireless inertial sensor node with local connectivity to a smartphone or tablet. This architecture further alleviates mass constraints by enabling a locally wireless inertial sensor node that connects using Bluetooth

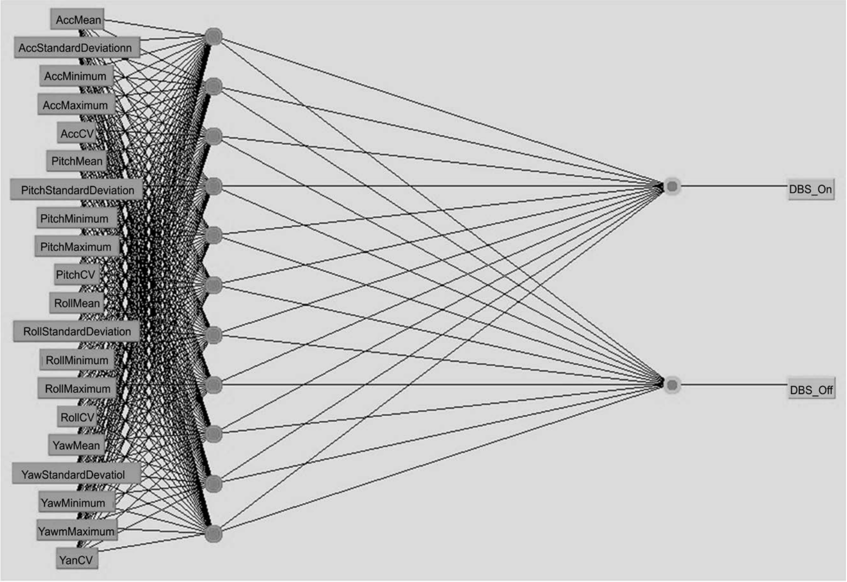

Figure 5. Multilayer perceptron neural network for classifying between deep brain stimulation in "On" and "Off" modes for Parkinson's disease.

wireless to transmit the inertial signal data to a more powerful device, such as a smartphone of tablet. Post-processing could be provided by the smartphone or tablet, and another alternative would be to use the larger wireless footprint of the smartphone or tablet to convey the data package to a Cloud computing resource [9].

Depending of the response time requirements the post-processing resources of the Cloud, smartphone, or tablet could provide a basis for closed loop optimization of the deep brain stimulation system parameters in real-time. Essentially, the subject would benefit from continual optimization of the deep brain stimulation system in a highly quantified and object manner, rather than traveling on a periodic basis to a skilled neurologist, for which the selection of a series of optimal tuning parameters is derived in a manner of subjective interpretation.

5. Conclusions

A smartphone functioning as a wearable and wireless system for quantifying Parkinson's disease hand tremor through its internal accelerometer and gyroscope sensors has been amalgamated with machine learning for the classification of deep brain stimulation in "On" and "Off" mode. The smartphone is mounted to the dorsum of the hand for the recording of the accelerometer and gyroscope signal to quantify the characteristics of Parkinson's disease hand tremor. The accelerometer and gyroscope signal data are conveyed by wireless transmission to the Internet as an email attachment for subsequent machine learning classification. The quantified data is consolidated into a feature set for machine learning classification using a multilayer perceptron neural network. Considerable classification accuracy is attained for distinguishing between deep brain stimulation in "On" and "Off" mode for a subject with Parkinson's disease hand tremor.

The implications of the fundamental research are the advent of wearable and wireless systems for the quantified monitoring health status for people with movement disorder. Furthermore, the acquired inertial sensor signal data can be conveyed by wireless transmission to a cloud computing resource. With machine learning the comprehensive collection of inertial sensor data can contribute to closed-loop optimization of deep brain stimulation tuning configurations and recommendation for improving treatment intervention.

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