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Telemedicine Perspectives for Wearable and Wireless Applications Serving the Domain of Neurorehabilitation and Movement Disorder Treatment

Robert LeMoyne[1]* and Timothy Mastroianni[2]

[1] Post-Doctorate of the Department of Biological Sciences and Center for Bioengineering Innovation, Northern Arizona University, USA

[2] T. Mastroianni is Independent, Pittsburgh, USA

***Corresponding author**: Robert LeMoyne, Post-Doctorate of the Department of Biological Sciences and Center for Bioengineering Innovation, Northern Arizona University, USA, Email: rlemoyne07@gmail.com

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ABSTRACT

The application of wearable and wireless systems in the context of telemedicine represents a quantum leap in the acuity of biomedical engineering for patient specific healthcare. As an alternative to traditional clinical evaluation, a patient can be evaluated for an extended duration at the convenience of an autonomous and personalized setting. The experimental data collection site and post-processing resources can be remotely situated, even on opposite sides of the world. The evolutionary pathway emphasizes transition from wireless accelerometer nodes to the role of smartphones and portable media devices capable as functioning as wireless accelerometer and gyroscope platforms. Future extrapolation anticipates wearable and wireless sensor nodes with localized wireless access to more powerful devices, such as a tablet, for connectivity to the Internet and cloud computing resources. Post-processing resources, such as machine learning, can be applied to differentiate between classes of the derived feature set, such as graduated levels of recovery. The scope of the application of wearable and wireless systems for telemedicine emphasizes the considerable domain of neurorehabilitation regarding gait and tendon reflex quantification and movement disorder assessment, such as Parkinson's disease and essential tremor.

INTRODUCTION

Over the course of the past few decades the synthesis of telecommunications have radically evolved enabling highly novel and game changing applications for the biomedical community. For example wearable and wireless devices have developed into systems with considerable miniaturization, sensing, and telecommunication capability [1,2]. Even twenty years ago during the 1990's the advent of wearable and wireless devices for monitoring patients regarding their specific state of neurorehabilitation and neurodegenerative movement disorder progression in the context of a home bound setting with access to international post-processing resources and expertise may have been considered to be science fiction. Now these wearable and wireless applications are an inevitable aspect of reality. LeMoyne and Mastroianni have provided substantial contributions to the research, development, testing, and evaluation of wearable and wireless systems for the domains of neurorehabilitation, such as hemiplegic motor quality for persons with traumatic brain injury or stroke, and neurodegenerative movement disorder, such as Parkinson's disease and essential tremor. Foundational to the wearable and wireless device is the inertial sensor, which applies an accelerometer and/or a gyroscope [1-25].

Inertial sensors, such as the accelerometer, which measure acceleration, have been proposed for the monitoring of human motion during the 1950's. However, these devices were considered too cumbersome and even unreliable for the monitoring and recording of human motion. Other industries, such as the automotive industry, facilitated the miniaturization and reliability for broader commercial application of inertial sensors, such as the accelerometer [1,2,26]. Accelerometers using tethering and data logging approaches have progressed to wireless and wearable systems [1,2,27]. The wireless accelerometer has been a subject of considerable research, development, testing, and evaluation for the evaluation of human movement with subsequent application of wireless gyroscope platforms [1-27]. Another aspect of the inertial sensor is the gyroscope, which measures angular rate of change [11-13,25]. Wireless accelerometer and gyroscope platforms have been demonstrated through the progressive research, development, testing, and evaluation of smartphones, such as iPhones, and portable media devices, such as iPods. These devices have demonstrated the potential for wirelessly transmitting data samples as email attachments through connectivity to the Internet separating experimentation sites from post-processing resources by thousands of miles and even effectively opposite sides of the world, which establishes perspective of the powerful utility of cloud computing [1,3-6,11-13,16,17,22-25].

The domain of wearable and wireless systems spans myriad of possible applications for the biomedical community. The context of wearable and wireless applications is highly relevant for hemiplegic gait and evaluation of patellar tendon reflex [1,2,20-25]. The nature of the patellar tendon reflex is highly correlated to quality of gait [1,2,21,28]. Another subject for wearable and wireless systems is movement disorder, such as resulting from Parkinson's disease and essential tremor [1,2,16,17]. Foundational to the understanding of the role of wireless and wearable sensing devices for hemiplegic dysfunction regarding gait and movement disorders is the neurological basis for these conditions.

GAIT AND ASSOCIATED TENDON REFLEXES

Gait incorporates the fluid, rhythmic, and synchronous transition of both legs in locomotion through the support of sophisticated neurological structures, such as cortical control, interneuronal integration, and proprioceptive feedback. Particular scenarios of traumatic brain injury and stroke can manifest into hemiplegia, for which the affected side is characterized by decremented motor control and spasticity [7-10,29]. These characteristics of brain injury can lead to hemiplegic gait, which is asymmetric in nature [7-10,24]. The tendon reflex is also a highly associated aspect of gait, and hemiplegic reflex, such as the patellar tendon reflex, is characterized as amplified in nature [21,28].

A quantified feedback strategy can augment the efficacy of the therapy strategy [29]. Ordinal scale strategies for assessing the rehabilitation status are implemented through the observation and expert interpretation of a clinician, such as for gait the Rivermead Mobility Index and the Functional Independence Measure [10,30,31]. Ordinal scale approaches are used to also quantify the patellar tendon reflex response, such as through the NINDS scale and Mayo Clinic scale [20,21,28,32,33]. These scales have been known to be controversial regarding their reliability [20,21,28,33]. The application of the ordinal scale is generally reserved for a clinical environment, which only provides a brief snapshot of the true nature of the subject's neurorehabilitation status. Intuitively, the application of the ordinal scale technique requires the expertise of a skilled clinician, which is a highly limited resource.

Another technique involves the application of conventional gait analysis systems, which can determine kinetic and kinematic features of gait. A force plate evaluates the force profile as a function of time regarding the stance phase of gait. The force plate can provide valuable information regarding the quantified characteristics of stance subphases. Optical analysis can provide valuable kinematic data for deriving joint relationships during gait. Electromyogram elucidates the efferent activity of muscle contractions [34,35]. The primary issue with these conventional gait analysis systems is they are generally confined to a clinical gait analysis laboratory. Also a particular skill set is generally required for the appropriate operation of experimental apparatus.

By contrast, modern wearable and wireless devices can be easily applied to a readily identifiable anatomical mounting position. Post-processing can be later conducted remotely [1]. Wireless and wearable accelerometer nodes have been applied to quantify disparity of hemiplegic gait in terms of both the temporal and frequency domains [7,36]. Subsequent extensions of wireless and wearable accelerometer platforms have lead to the research, development, testing, and evaluation of smartphones and portable media devices. These devices are equipped with robust telecommunications systems that readily connect them to the Internet through approaches, such as email [1].

LeMoyne and Mastroianni have pioneered the application of smartphones and portable media devices for the quantification of gait. During 2010 LeMoyne and Mastroianni applied the iPhone, which is a broadly used smartphone, as a wireless accelerometer platform through a software application to quantify gait. The software application enables the smartphone to function as a wireless accelerometer platform by recording a trial sample as an attachment for email that can be wirelessly transmitted by connectivity to the Internet [4-6]. Since the iPhone and iPod have similar software architectures the application can be also applied to a portable media device, such as an iPod. During 2011 LeMoyne and Mastroianni quantified gait through a portable media device functioning as a wireless accelerometer platform [3]. With the inclusion of a gyroscope sensor, the smartphone has been recently demonstrated for the quantification and machine learning classification of a gait related therapy concept and identification of reduced arm swing, which is an aspect of hemiplegic gait [13,37].

Further research, development, testing, and evaluation demonstrated the ability of tandem mounted portable media devices to quantify disparity of hemiplegic gait [38]. Functioning as a wireless gyroscope platform the smartphone quantified a feature set that distinguished reduced arm swing for an affected and healthy hemiplegic arm pair using machine learning [37]. The primary disparity between a smartphone and portable media devices pertains to the telecommunication capacity [1].

The quantification of the tendon reflex response, such as for the patellar tendon, is a correlated to the domain of locomotion. The synchronous modulation of the reflex circuitry facilitates the control of gait. Dysfunction to the quality of the tendon reflex response can lead to impairment of gait and potential for the development of compensatory mechanisms [10,28,29]. For example, hyperactive patellar tendon reflex response as a consequence of hemiplegia associates with asymmetry during gait [7-10,28,29].

In a similar theme to the clinical ordinal approach for gait analysis, an ordinal strategy technique is generally applied to quantify the observed characteristics of reflex response. A clinician is first tasked with eliciting the tendon reflex through a brisk hammer strike, and then applies expertise to align the observation with an ordinal value that best described the reflex response. However, the ordinal approach is a subject of controversy as its reliability is debatable [20,21,28].

LeMoyne *et al.* have developed an alternative methodology that incorporates discrete levels of potential energy and wireless accelerometers that are essentially wearable throughout the evaluation. The alternative incorporates the use of an impact pendulum attached to a reflex hammer for precise, targeted, and predetermined levels of potential energy for eliciting the patellar tendon reflex. A wireless accelerometer is worn between the lateral malleolus and an elastic band, such as a sock. This technique has been demonstrated for reliably quantifying the patellar tendon reflex response and also even the associated neural latency [18-20,28].

This technique for quantifying the patellar tendon reflex response through a wireless quantified reflex system has been extended to smartphones and portable media devices [1,22,23]. Portable media devices, such as the iPod, serve as convenient wireless accelerometer platforms, which can be readily connected to a local wireless Internet region [22]. Smartphones, such as the iPhone, are enabled with broader telecommunication packages, which can extend beyond a local wireless Internet region to more remote and isolated regions [23]. Similar software can be applied for the smartphone and portable media device, enabling them to function as wireless accelerometer platforms. Their trial samples can be conveyed as email attachments with wireless connectivity to the Internet. The technique of applying smartphones and portable media devices in the context of the wireless reflex quantification strategy has been demonstrated to reliably quantify the patellar tendon reflex response [1,22-24]. The capacity for classifying a feature set through the application of a portable media device functioning as a wireless accelerometer platform has been successfully demonstrated through machine learning [24].

With the progressive evolution of smartphones and portable media devices the sensor package eventually incorporated the gyroscope determining the angular rate of rotation. Using a portable media device as a wireless gyroscope platform the patellar tendon reflex was accurately and reliably quantified [25]. The trial data was conveyed as an email attachment through wireless connectivity to the Internet, which essentially enabled a cloud computing architecture. Locations for experimental data collection and post-processing can be situated remote. For example, LeMoyne and Mastroianni demonstrated this capability by conducting the acquisition of the patellar tendon reflex response through a portable media device functioning as a wireless gyroscope platform in Lhasa, Tibet. The trial data package was later post-processed in Flagstaff, Arizona of the United States of America [39].

MOVEMENT DISORDERS

Another domain highly relevant for smartphones and portable media devices is the quantification of movement disorders [1]. Two of prevalent types of movement disorder are Parkinson's disease and essential tremor. They are both characterized as neurodegenerative in nature, which manifest with symptomatic tremor. However, Parkinson's disease involves a resting tremor, and by contrast essential tremor consists of a kinetic tremor, such as while attempting to reach and grab an object. The neurological basis of Parkinson's disease is due to the inability of the substantia nigra to produce dopamine, but the cause of essential tremor is unknown. Both Parkinson's disease and essential tremor involve treatment strategies, such as drug therapy and deep brain stimulation [1,2,14-17].

Treatment strategies for these movement disorders are provided in a clinical setting, for which the expert clinician prescribes a therapy based only on a relatively brief temporal duration. However, in order to provide a more optimized treatment, a more robust and objectively quantified methodology capable of characterizing a more substantial temporal window would be advisable. Wearable and wireless accelerometer systems, such as smartphones and portable media devices, enable substantial potential for advancement of the diagnosis and treatment of neurodegenerative movement disorders [1,2,14-17].

As early as 2007 LeMoyne discussed the utility of wearable and wireless accelerometers for measuring Parkinson's disease status [2,40]. Using simulated tremor LeMoyne *et al.* demonstrated the ability to apply a wireless accelerometer node as a wearable sensor about the dorsum of the hand [15]. Further evaluation of this methodology became apparent with the evolution of the smartphone [17].

During 2010 LeMoyne *et al.* applied a smartphone to quantify the tremor status of a person with Parkinson's disease. The data was successfully contrasted and statistically significant relative to a person without Parkinson's disease. The trial samples were conveyed as email attachments through wireless connectivity to the Internet. The experimental resources were located in Pittsburgh, Pennsylvania, and the post-processing was conducted in greater Los Angeles, California [17]. With the sensor and telecommunication capability of smartphones and portable media devices for diagnosing status of people with movement disorders established, further advance of the methodology has been proposed. For example, a smartphone could provide conclusive and quantified feedback as to the status of deep brain stimulation for people with movement disorders [16].

Deep brain stimulation constitutes an advanced technology for the treatment of movement disorders. However, the optimal tuning of the multiple deep brain stimulator parameters is an endeavor of considerable challenge. An expert clinician is presented with on the order of thousands of permutations, which considerably impacts the patient's quality of life. LeMoyne *et al.* have advocated wearable and wireless systems as highly capable devices for facilitating optimal tuning of deep brain stimulation for movement disorders [1,2,14-17].

LeMoyne *et al.* successfully tested and evaluated the efficacy of a deep brain stimulator during 2015. The process involved quantifying trial samples of the subject through a wireless accelerometer platform provided through using a smartphone secured to the dorsum of the hand by a latex glove. The subject was instructed to grasp a lightweight object across a table with the deep brain stimulator set in 'On' and 'Off' modes. Machine learning using a support vector machine was applied to the feature set derived from the acceleration waveform attaining perfect classification accuracy. Using the telecommunication capability of the smartphone, the trial samples were attached to email using wireless connectivity to the Internet. The experiment was conducted in the local area of Pittsburgh, Pennsylvania, and the post-processing was performed in Flagstaff, Arizona [16]. This methodology demonstrated for establishing the efficacy of deep brain stimulation for essential tremor underscores the utility of telemedical applications and especially future potential. For example, a future goal involves the development of automated tuning and optimization of the deep brain stimulator [1,16].

MACHINE LEARNING

Regarding the domain of post-processing for wearable and wireless systems machine learning provides a considerable advance from the application of descriptive and inferential statistics. The Waikato Environment for Knowledge Analysis **(WEKA)** offers an assortment of machine learning platforms [41-43]. Of course the proper selection of a suitable machine learning platform is unique to the context of the research scope [44].

Two successfully implemented machine learning applications in the context of smartphone and portable media devices are the multilayer perception neural network and support vector machine [13,16,24,37]. The support vector machine transforms the feature set to a hyperspace, which is then consolidated to a hyperplane for delineation by a support vector [41-43,45]. The multilayer neural network is based on the computational representation of the neuron, therefore representing a biomimetic representation of human perception [41-43,46].

The inherent challenge for the application of machine learning involves determining a representative feature set from the available quantified sensor data [24,44]. Regarding **WEKA**, a feature set is then consolidated into an Attribute-Relation File Format **(ARFF)** file [41-43]. Software packages, such as Matlab or Python, can be readily applied to automate the transition of data into a cohesive feature set [13,16,24,37,47].

A future opportunity for machine learning in the context of telemedical applications is the use of very large databases of information to enable advanced diagnostics and prognostics. With the synthesis of telemedical monitoring systems machine learning can provide a foundation for optimizing rehabilitation efficacy.

CLOUD ARCHITECTURE AND THE INTERNET OF THINGS

Sensor devices for biomedical application have evolved considerably from the era of concept to application. These devices, such as portable accelerometers, originally applied data logger and tethering configurations, which have become progressively outmoded with the transition to wearable and wireless sensor applications [1,2,27]. The advent of the Internet of Things promotes considerable opportunity for wearable and wireless biomedical sensors, as the telecommunication capability involves access to the Internet [35].

In order to enable cloud-computing architecture that synergizes with the Internet of Things a local wireless capability would be instrumental. Bluetooth wireless technology enables a low power alternative for communicating with larger scale devices, such as a tablet [48,49]. This configuration enables the possibility for low-power and wearable sensor technologies to synchronize their data with cloud computing resources through accessing the Internet.

Recently, the capability to apply wearable and wireless inertial sensors with machine learning to classify gait patterns for people with Friedreich's ataxia has been demonstrated [47]. An inherent feature of the application is the incorporation of the Texas Instruments Sensor Tag, which has been envisioned for usage with the Internet of Things [47,50]. The architecture records a trial sample of a subject's gait, such as the timed 25-foot walk test, which was recorded by the sensor devices that were connected by Bluetooth Low Energy wireless to a local tablet. Upon completion of trial sample the data package was conveyed to a secure cloud computing system. Post-processing the data can be performed remotely, such as for the consolidation of the data into a feature set for machine learning. Considerable machine learning classification was attained through the implementation of a multilayer perceptron neural network [47].

CONCLUSION

A quantum leap regarding biomedical engineering and patient specific healthcare has been enabled through the progressive evolution of wireless and wearable systems for telemedical applications. These wireless and wearable systems have emphasized the utility of accelerometer and/or gyroscope sensors with transitional evolution to localized nodes to wireless platforms through smartphones and portable media devices. An advantage of the wireless accelerometer and wireless gyroscope platform for smartphones and portable media devices is the capacity to apply the experimental and post-processing resources remotely, even on other ends of the world. Given the ergonomic and robust nature of these wearable and wireless sensor systems a subject can be monitored in a relatively autonomous environment for protracted durations as opposed to traditional techniques, such as a brief clinical observation. The quality and acuity of neurorehabilitation can be greatly advanced to a patient specific level. Machine learning of the quantified data can be distilled in to a feature set for objective differentiation of progressive treatment and recovery. Gait and the associated tendon reflexes, such as for people with hemiplegia from traumatic brain injury, and also movement disorders, such as Parkinson's disease and essential tremor, have been objectively quantified through the use of wireless and wearable systems. Recently a new wireless and wearable architecture has been developed that applies a localized sensor node, which connects by Bluetooth wireless to a tablet. The tablet enables connectivity to the Internet and cloud computing resources. This configuration has been successfully applied to distinguishing with machine learning between a subject with and without a progressive neurodegenerative disease that affects gait. In the future the role of wireless and wearable systems in the context of telemedicine is anticipated to considerably evolve into a ubiquitous presence for biomedical engineering and personalized healthcare, while radically advancing the ability to provide efficacious rehabilitation and treatment for neurodegenerative diseases.

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