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Implementation of an iPod wireless accelerometer application using machine learning to classify disparity of hemiplegic and healthy patellar tendon reflex pair

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Abstract

The characteristics of the patellar tendon reflex provide fundamental insight regarding the diagnosis of neurological status. Based on the features of the tendon reflex response, a clinician may establish preliminary perspective regarding the global condition of the nervous system. Current techniques for quantifying the observations of the reflex response involve the application of ordinal scales, requiring the expertise of a highly skilled clinician. However, the reliability of the ordinal scale approach is debatable. Highly skilled clinicians have even disputed the presence of asymmetric reflex pairs. An alternative strategy was the implementation of an iPod wireless accelerometer application to quantify the reflex response acceleration waveform. An application enabled the recording of the acceleration waveform and later wireless transmission as an email attachment by connectivity to the Internet. A potential energy impact pendulum enabled the patellar tendon reflex to be evoked in a predetermined and targeted manner. Three feature categories of the reflex response acceleration waveform (global parameters, temporal organization, and spectral features) were incorporated into machine learning to distinguish a subject's hemiplegic and healthy reflex pair. Machine learning attained perfect classification of the hemiplegic and healthy reflex pair. The research findings implicate the promise of machine learning for providing increased diagnostic acuity regarding the acceleration waveform of the tendon reflex response.

1. Introduction

The tendon reflex is a standard component of the neurological evaluation. Integral aspects of the central and peripheral nervous system derive the features of the tendon reflex response.

The central nervous system provides supraspinal influence and integration at the spinal cord,

which significantly impacts the quality of the tendon reflex response. Afferent and efferent neurons of the peripheral nervous system affect the attributes of the reflex loop. The tendon reflex may be evoked by briskly tapping the Achilles tendon or the patellar tendon. Dysfunction to the tendon reflex response may imply trauma to either the central or peripheral nervous system. The observation of an irregular tendon reflex response may support the diagnostic decision process and consequentially treatment and action plan [1,2,3,4].

The current clinical strategy quantifies the tendon reflex response using an ordinal scale. Two predominant ordinal scales for reflex quantification are the NINDS Myotatic Reflex Scale and Mayo Clinic scale. The NINDS Myotatic Reflex Scale entails five ordinal components. The Mayo Clinic scale encompasses nine ordinal components [2,3,4,5,6]. The reliability of the ordinal scale approach for quantitatively classifying reflex response is debatable [3,4,5,6]. Through applying the ordinal scale method, even highly skilled neurologists have disputed the presence of reflex pair asymmetry to a considerable extent [7].

The wireless quantified reflex system has enabled an accurate, reliable, and reproducible alternative for measuring tendon reflex response relative to the conventional ordinal scale strategy. The inherent components were a potential energy impact pendulum attached to a reflex hammer, capable of precise energy settings and targeting of the patellar tendon. The reflex response was objectively quantified through a wireless accelerometer mounted in proximity to the lateral malleolus. With a synchronized wireless accelerometer mounted to the potential energy impact pendulum, the latency of the patellar tendon reflex was acquired [3,4,8,9,10,11]. The continuous improvement of the wireless quantified reflex system led to the exploration of more ubiquitous devices that were functionally capable of wirelessly conveying an acceleration waveform, such as the response of the patellar tendon reflex.

The iPod and iPhone both consist of software applications that enable their accelerometer subsystems to function as wireless accelerometer platforms for transmitting the reflex response acceleration waveform wirelessly as email through the Internet. Both applications are uniquely suited for disparate settings. The iPhone wireless quantified reflex system is appropriate for rural settings without local wireless Internet connectivity. The iPod wireless quantified reflex system is more lightweight than the iPhone wireless quantified reflex system and does not require the cost of supporting cell phone coverage [12,13].

Previous research has advocated the implementation of machine learning to classify neurological status [3,4,10]. The current research synthesizes machine learning with the iPod wireless quantified reflex system to detect hemiplegia from individual trials. The objective of the iPod wireless quantified reflex system was to definitively classify the disparity of hemiplegic affected and unaffected patellar tendon reflex response using machine learning operating on data from an engineering proof of concept perspective.

2. Background

2.1 Neurological organization of the tendon reflex

Since the tendon reflex neurological organization consists of the central nervous system and peripheral nervous system, the quality of the tendon reflex response provides an initial perception for nervous system health and preliminary diagnostic information [1,2,14]. Striking the patellar tendon with a reflex hammer can elicit the patellar tendon reflex [2]. The strike of the reflex hammer excites the local muscle spindles that convey a neural signal through the peripheral nervous system 1a afferent neurons to the spinal cord. The central nervous system contributes supraspinal modulation and integration at the spinal cord interneuron. The 1a afferent neurons synapse with the associated alpha motor neurons. The efferent signal of the peripheral nervous system induces the relevant muscle to contract [1,14].

The central and peripheral nervous system both have crucial roles for the organization of the tendon reflex. Dysfunction of the tendon reflex response can imply trauma to the nervous system [1,2,14]. For example, trauma to the central nervous system can lead to impairment of supraspinal modulation. Decremental supraspinal modulation can manifest hyperexcitable aspects of the tendon reflex [3,4,15,16]. Methodologies have been incorporated to attempt to quantify the features of the tendon reflex response [3,4,8].

2.2 Ordinal scale scheme for quantifying tendon reflex response

The conventional scheme for quantifying reflex responses uses ordinal scales. The clinician evokes the tendon reflex by tendon strike, and then applying expert, although subjective, interpretation regarding the nature of the reflex response. Based on the observation of the response and the guidelines for the ordinal scale, the clinician best selects an appropriate ordinal scale value. The ordinal scale provides a means of translating subjective observation to a quantified value. Two predominant ordinal scales for the reflex response are the NINDS Myotatic Reflex Scale and Mayo Clinic scale [2,5,6].

Litvan *et al.* conducted a study to evaluate the NINDS Myotatic Reflex Scale reliability. The study involved concerned both an interobserver and intraobserver perspective. The interobserver perspective established moderate to substantial reliability classification. The intraobserver viewpoint determined substantial to near perfect categorization. Based on these findings, Litvan *et al.* advocates the NINDS Myotatic Reflex Scale as a universal reflex scale [5].

A later study by Manschot *et al.* disputes the reliability claims of the ordinal reflex scale strategy. Manschot *et al.* evaluated the reliability of both the NINDS ordinal scale and the Mayo Clinic ordinal scale. The interobserver agreement did not transcend the reliability classification of fair, in consideration of both ordinal scales. A notable issue with the NINDS Myotatic Reflex Scale was there are only five ordinal categories [6].

Further concern for the ordinal scale strategy was demonstrated by the research of Stam and van Crevel, which assessed the nine-point Mayo Clinic scale. A considerable level of disagreement among the neurologists was ascertained. Neurologists disagreed by a minimal

two ordinal scale units regarding 28% of the examinations. Notably, neurologists disagreed with respect to the presence of asymmetry regarding 45% of the reflex pairs [7].

2.3 Mechanized systems for quantifying tendon reflex response

Mechanized sensor architectures have been promoted as an alternative to the subjective interpretation inherent for the ordinal scale strategy. Attempts have been made to quantify reflex response and reflex initiation [3]. For quantified elicitation of the tendon reflex, Van de Crommert *et al.* and Faist *et al.* incorporated a one kilogram motorized system, and the response was measured by EMG (Electromyogram) [17,18]. Similar reflex quantification system was demonstrated by Cozens *et al.* with a servo-position device for evoking the tendon reflex with response quantified by EMG [19].

As an alternative to EMG measurement of reflex response sensor systems have been evaluated [3]. Pagliaro and Zamparo used a load cell attached to the ankle by a cable to quantify reflex response [20]. Kocaja and Kamen synchronized an electromagnetic solenoid for quantified input and measured reflex response by a strain gauge device, while deriving a functional latency [21,22]. Along a similar perspective, Liebdowska and Fisk acquired response through a strain gauge apparatus using a sweep-triggering hammer to evoke the reflex [23]. Zhang *et al.* synchronized an instrumented reflex hammer with torque sensor to quantify the reflex response and functional latency under isometric conditions with the knee positioned at a specified knee flexion angle [24]. Mamizuka *et al.* synchronized an instrumented reflex hammer with a triaxial accelerometer for obtaining the reflex response and functional latency [25].

Tham *et al.* incorporated an optical motion analysis system for quantifying the patellar tendon reflex response. Multiple forces settings for quantified reflex input were derived from a reflex hammer attached to a protractor [26,27]. During 2006, LeMoyne *et al.* conducted a similar themed reflex modulation study. An impact pendulum mounted to a reflex hammer evoked the patellar tendon reflex. Three potential energy settings enabled a reflex response modulation study. The response of the tendon reflex was quantified by a wireless accelerometer [28,29]. Wireless accelerometer systems have been advocated as superior for quantifying human motion, such as the patellar tendon reflex response, in contrast to optical motion analysis systems, which are relatively expensive and have issues regarding line of sight requirements [3,4,8].

2.4 The evolution of the wireless quantified reflex system

Over the course of half a decade from 2005 to 2010, LeMoyne *et al.* progressively evolved the wireless quantified reflex system [3,4,8,9,10,11,28,29,30]. The design approach of the wireless quantified reflex system incorporated a wireless accelerometer for measuring reflex response and an impact pendulum attached to a reflex hammer for delivering discrete potential energy levels to evoke the patellar tendon reflex. The wireless accelerometer was mounted to the lateral malleolus of the ankle. Mounting another synchronized wireless accelerometer to the impact pendulum could derive reflex latency. LeMoyne *et al.* successfully demonstrated that the wireless quantified reflex system could accurately, reliably, and reproducibly quantify patellar tendon reflex response and latency [3,4,10].

2.5 iPod/iPhone wireless quantified reflex system

The next evolutionary step for the wireless quantified reflex system is the incorporation of the iPod or iPhone for measuring reflex response. The reflex response acceleration waveform was recorded by an iPod/iPhone application that would subsequently convey the recording wireless through email as a Microsoft Comma-Separated-Value file for subsequent post-processing. Preliminary demonstrations of the iPod and iPhone for quantifying reflex response were conducted by supra-maximal stimulation of the patellar tendon reflex [31,32]. The wireless quantified reflex system incorporating either an iPod or iPhone are applicable to disparate settings. For instance the iPod wireless quantified reflex application is most appropriate for areas with wireless Internet coverage; however the iPhone wireless quantified reflex application is also capable of functioning in rural settings with only cellular phone coverage [12,13]. The iPod wireless quantified reflex application provided accurate and reliable quantification of the patellar tendon reflex response [12].

2.6 Machine learning diagnostics synthesized with the iPod wireless quantified reflex system

The current ordinal scale approach to quantifying patellar tendon reflex response has been established as a topic of controversy [3,4]. Stam and van Crevel demonstrated that skilled neurologists, with their expert yet subjective interpretation, disputed the presence of asymmetry regarding reflex pairs [7]. The use of wireless accelerometers for quantifying the patellar tendon reflex response has been demonstrated as accurate, reliable, and reproducible [3,4,10]. A further extrapolation of the wireless quantified reflex system involved the implementation of a robust and automated decision process through machine learning for contrasting disparate classifications of reflex response.

The objective of this research was to acquire the reflex response of a hemiplegic affected and unaffected leg through the iPod wireless quantified reflex system. Machine learning was subsequently applied to objectively classify between the patellar tendon reflex response affected hemiplegic and unaffected healthy leg. The iPod wireless quantified reflex system incorporates an iPod application capable of recording the reflex response acceleration waveform and transmitting the acquired data by email through wireless connectivity to the Internet. The iPod was mounted to the lateral malleolus through an elastic band. The patellar tendon reflex was evoked through a precisely targeted reflex hammer attached to impact pendulum using a discrete potential energy setting. For engineering proof of concept a chronic hemiplegic subject was evaluated using the iPod wireless quantified reflex system synthesized with machine learning diagnostics to classify the patellar tendon reflex response of the affected hemiplegic and healthy unaffected leg.

3. Methods and Materials

3.1 iPod wireless quantified reflex system

The iPod wireless quantified reflex system consists of two essential subsystems: the iPod and potential energy impact hammer. The iPod is equipped with an application that obtains an approximately 10 second recording of the patellar tendon reflex response acceleration waveform, sampled at a rate of 100Hz. The application conveys an email of the acceleration

waveform through email by wireless Internet connectivity. The iPod 5 Touch has a mass of 88 grams [33]. A reflex hammer attached to a potential energy impact pendulum evoked the patellar tendon reflex response. The potential energy impact pendulum was capable of specified targeting of the patellar tendon and precise potential energy settings. Figure 1a demonstrates the functional simplicity of the impact pendulum mounted to a reflex hammer. Figure 1b exhibits the precise targeting of the reflex hammer and lateral malleolus mounting position of the iPod device for recording the acceleration waveform of the reflex response.

3.2 Weka machine learning software

Weka was an open source software package that trains and implements many state-of-the-art machine learning algorithms in a common framework [34]. As a Java applet, it was capable of efficiently applying machine learning on a wide variety of platforms and could be learned relatively quickly.

3.3 Data Acquisition

Engineering proof of concept was demonstrated by obtaining the reflex response of a chronic hemiplegic subject, regarding both the affected and unaffected leg. The iPod wireless quantified reflex system acquired the acceleration waveform of the hemiplegic affected leg and unaffected leg reflex response. The acceleration waveform was recorded for a span of approximately 10 seconds and sampled at 100Hz. The following experimental protocol was implemented to obtain 40 trials respective of both the hemiplegic affected and unaffected leg:

1. Orient the subject to sit in a comfortable position, such that the foot and ankle of the leg to be evaluated are free of contact with any objects that could alter the natural movement of the patellar tendon reflex loop.
2. Mount the iPod to the above and adjacent to the lateral malleolus by an elastic band, such as a sock. Align the iPod parallel to the tibia, such that the top of the iPod was oriented superior.
3. Aim the reflex hammer attached to the potential energy impact pendulum level to the tibial tubercle.
4. Activate the iPod wireless accelerometer application for acquiring the patellar tendon reflex response acceleration waveform.
5. Retract the potential energy impact pendulum 30 degrees relative to gravity vector.
6. Release the potential energy impact pendulum.
7. Transmit the reflex response acceleration waveform through email by wireless connectivity to the Internet.
8. Wait a minimum of 15 seconds before commencing the next trial.

The acceleration waveforms for the affected and unaffected reflex response were acquired. Significant features of the acceleration waveforms were identified in order to enable robust machine learning classification. Three types features were quantified from the reflex response acceleration waveform: global parameters based on the maximum acceleration of

the reflex response, temporal organization of the maxima and minima of the acceleration waveform, and spectral features based on the reflex response frequency domain.

Global parameters are derived from the maximum acceleration of the reflex response: maximum acceleration, maximum derivative of acceleration, auto-correlation of maximum acceleration, and auto-correlation of derivative of acceleration. The global parameters were considered significant parameters for quantifying the features of the reflex response acceleration waveform based on the extensive research of LeMoyne *et al.* [3,4,8,9,10,11,12,13]. During the post-processing of the longitudinal patellar tendon reflex response data, patterns were observed regarding the temporal organization of the maxima and minima [3,4,10]. The temporal organization of the initial maxima, minima, and subsequent maxima of the patellar tendon reflex acceleration waveform were identified as significant features. The temporal disparities between the initial maxima to minima and minima to subsequent maxima were also included as important features. The frequency domain of the reflex response was elucidated through a wireless accelerometer reflex quantification system [3,4,11]. Preliminary inspection of the frequency domain hemiplegic affected and unaffected leg patellar tendon reflex response implicated the potential to identify quantifiable disparity of reflex asymmetry [35,36]. Intuitively, the magnitude of the spectral peaks constitutes essential features of the tendon reflex response acceleration waveform.

3.4 Feature Extraction

We measured features of the reflex waveform from three different perspectives: (1) global properties, (2) the relationship between local peaks and (3) the magnitude of spectral peaks. These perspectives represent equally valid ways of analyzing a time-series signal. We assess if mean of each feature was different in the hemiplegic leg compared to the unaffected leg using two sample Student's t-tests with unequal variances.

The global properties included the maximum acceleration achieved, the maximum discrete derivative of acceleration achieved, the autocorrelation of acceleration with respect to a shift of one data sample and the autocorrelation of the discrete derivative of acceleration with respect to the same shift. The maxima can be interpreted as the maximum force generated and also the consistency with which force was generated. The auto-correlations measure the smoothness of the reflex waveform over time.

To get a more focused and biologically interpretation of the waveform, we inspected the height and separation between the first three local peaks in the reflex waveform. We included the absolute magnitude of these local peaks and also the time between each peak as potentially meaningful features. To improve the reliability of finding these peaks, we used the Otsu threshold that adapts to the properties of the individual trial [37]. We implemented this by considering the distribution of measured accelerations. We then applied the Otsu threshold on the absolute magnitude of acceleration to find candidate peak points. Starting with the first candidate peak in time, we considered the next data sample was larger in magnitude than the first candidate peak. If it was, we iteratively continue the same process, taking the larger magnitude peak as the first candidate peak. This process ends when we have found the first local maximum of acceleration. To find the next local peak, we re-

calculated the Otsu threshold using the remainder of the reflex waveform and found the next local maximum that was of opposite sign to the first local peak. Note that this method assumes that the recording of acceleration continued for at least a small period of time after the leg came to rest.

Lastly, we inspected the spectral power of the waveform at different frequencies. After mean centering the signal, the spectral power can be used to measure how much signals at particular frequencies contribute to the overall signal. Using the training examples from the hemiplegic leg, we identified local peaks in the power-frequency plot at 0.2, 2.3, 4.8, 7.7, 10 and 12 Hz. In comparison, the unaffected leg had local peaks at 0.2, 2.3, 4.8 and 7.0 Hz. These peaks were consistent across all training sets. To simplify our feature space, we only considered the value of log spectral power at the local peaks identified in the hemiplegic examples. In addition, we recognized that the magnitude of the oscillations in the hemiplegic leg were larger therefore we also considered the sum of spectral power across all frequencies.

3.5 Model Learning and Cross-Validation

Using these features, we trained a least squares Support Vector Machine (SVM) on each subset of features and also on all potential features using Weka [34]. The details of the soft margin ($C=1$) least squares SVM algorithm are described elsewhere [38]. We expect each of the features measure different aspects of the same underlying pathology, therefore there may have been a complex dependency structure. We chose an SVM because it efficiently understands this dependency structure, is resistant to outliers and focuses on the hard to classify cases.

To assess the generalizability of our model, we utilized cyclical leave-one-out cross validation (CLOOCV). In this procedure, we removed one trial from the dataset then find the spectral peaks in the hemiplegic trials (see above) and learn the SVM using just the remaining trials. We tested the predictive performance of this SVM on the removed validation trial. Lastly, we permuted the identity of the validation trial so that each trial was the validation case once and only once. We pooled the results across validation trials. We then compared this pooled CLOOCV accuracy to the accuracy of a chance classifier, 50%, using the z-test of proportions.

4. Results & Discussion

Figure 2 presents considerable disparity between the average acceleration waveform of the affected hemiplegic leg and unaffected healthy leg. The hemiplegic patellar tendon reflex illustrates hyperexcitable patellar tendon reflex response representative of impaired supraspinal regulation of tendon reflex [3,4,15,16]. Notable feature disparities representative of hyperactive hemiplegic reflex response in contrast to healthy reflex response were evident in consideration of the global properties initial maxima, temporal relationship between maxima and minima, and the spectral peaks of the frequency domain. This was especially notable from the uniform increase in spectral power across all frequency bands (Figure 3).

In the time domain, this hyperexcitability was evident in larger and faster deflections in the measured acceleration (Figure 4 & 5). The only feature not consistent with this explanation was the increase in time between the lowest acceleration valley and the next subsequent acceleration peak (Figure 5B). There was no clear biological explanation for this latter empirical finding. By incorporating the feature disparities into a machine learning algorithm, the patellar tendon reflex response of the hemiplegic affected leg and healthy unaffected leg were definitively classified.

An advantage of the iPod wireless accelerometer reflex quantification system augmented with a machine learning algorithm was the demonstrated capability to achieve perfect classification for distinguishing between a hemiplegic affected and healthy unaffected patellar tendon reflex pair. Previous research demonstrated that even highly skilled and trained neurologists disputed the presence of reflex pair asymmetry to a considerable degree [7]. The three primary components of the machine learning augmented wireless reflex device were:

- the ubiquitous iPod including an application for recording the acceleration waveform wireless by email through Internet connectivity
- a simple impact pendulum device attached to a reflex hammer for evoking the patellar tendon reflex by discrete levels of potential energy with precise targeting of the patellar tendon
- a machine learning algorithm achieving perfect classification regarding a hemiplegic affected and healthy unaffected patellar tendon reflex pair based on feature extraction of the reflex response acceleration waveform

The iPod wireless reflex quantification system emphasizes simplicity and minimizes need for scarce medical resources. The acquired acceleration waveform can be stored, providing information over the course of a subject's rehabilitation program. Based on the research findings, broader clinical trials are warranted.

4.1 Classification of individual waveforms

These large average differences between the waveforms also resulted in exceptional single-trial performance. This suggests that our methods may be directly applicable to clinical medicine. All intervals quoted below indicate 95% confidence intervals. All p-values indicate two tailed tests. When harnessing all quantitative descriptors of the waveform, we achieve perfect discrimination between the hemiplegic and unaffected reflex waveform (93-100%, $p < 10^{-100}$). When only utilizing descriptors from one of the three perspectives, our accuracy was extremely high, but not perfect (Figure 6).

We hypothesize that the structure of the support vector machine (SVM) algorithm facilitated its impressive performance. Other algorithms were able to discriminate a majority these waveforms but their error rate was higher than the SVM (data not shown). During training, the SVM focused on the examples that were hardest to discriminate (support vectors) and ignored easy to classify examples. This focus likely allowed the SVM to increase performance from 95% to 100%.

These results reveal that the average reflex waveform of hemiplegic and unaffected legs were exceptionally discriminable. The individual waveforms, however, were more difficult to discriminate. This suggests that even though there are many visual differences between the waveforms, there was no simple feature that could perfectly detect hemiplegia. This suggests that visual inspection may accurately detect a majority of hemiplegic waveforms, but there will be a non-zero error rate. By understanding the multivariate relationship between each of the waveform characteristics, our automated algorithm was able to perfectly diagnose hemiplegic reflex asymmetry. This illustrates how automated analysis could be applied to help characterize hemiplegic reflex asymmetry.

In order to achieve perfect separation, however, the waveforms needed to be described using three different perspectives. The global, local, and spectral features described only subtly different characteristics of similar phenomena. As expected, this subtle difference resulted in only slightly modified performance when using each type of feature alone. The finding that combining all perspectives resulted in perfect performance suggests that this subtle difference could be meaningfully harnessed to further improve the description of the waveform. This demonstrates that, just as clinicians must attempt to describe each facet of a patient's injury to fully treat the patient, automated algorithms can and should combine subtly different features to maximize performance.

4.2 Average differences in each quantitative descriptor

To understand more about the differences harnessed by the SVM, we inspected the mean difference of each feature between trials from the hemiplegic leg and the unaffected leg. The global features indicated that the hemiplegic leg produced a more forceful reflex that changed substantially more over the course of the reflex (Figure 4). The mean of the maximum acceleration was 2.11 g (2.03-2.19 g) for the hemiplegic leg compared to 1.50 g (1.44-1.56 g) for the unaffected leg ($p < 10^{-17}$). There was no significant difference in the autocorrelation of the acceleration ($p > 0.20$). The maximum change in acceleration over 0.01 s was also significantly higher in the hemiplegic leg ($p < 10^{-9}$): 95.7 g/s (95.4-96.0 g/s) compared to 91.8 g/s (90.8-92.7 g/s) for the hemiplegic and unaffected leg, respectively. Despite this large maximum change, the autocorrelation of change was 54% (50-57%) in the hemiplegic leg compared to 17% (12-22%) in the unaffected leg.

The local features parallel these changes by reaching larger acceleration peaks in a compressed amount of time (Figure 5). The first peak positive deflection was 1.83 g (1.71-1.94 g) for the hemiplegic leg compared to 1.42 g (1.38-1.45 g) for the unaffected leg. Similarly the second peak acceleration was 0.75 g (0.72 – 0.78 g) in the hemiplegic leg compared to 0.81 g (0.78- 0.82 g, $p < 0.003$). Lastly the third peak was 1.92 g (1.86-1.98 g) for the hemiplegic leg and 1.33 g (1.30-1.35 g) for the unaffected leg ($p < 10^{-23}$). The average time between the first and second peak was 0.231s (0.223-0.238s) in the hemiplegic leg and 0.308s (0.301-0.314s, $p < 10^{-26}$) in the unaffected leg. The average time between the second and third peak was similarly smaller at 0.183s (0.173-0.192s) and 0.164s (0.157-0.171s) for the hemiplegic and unaffected legs, respectively ($p < 0.003$).

The spectral features further confirm that the amplitude of the reflex waveform is larger for the hemiplegic leg in all cases. The average sum of spectral energy from 0 to 50 Hz was 938

g^2 (889-987 g^2) for the hemiplegic leg compared to 509 g^2 (469-550 g^2) for the unaffected leg ($p < 10^{-20}$). At the specific frequencies studied, the spectral energy was consistently higher ($p < 10^{-9}$ Figure 3).

4.3 Future directions

The iPod wireless accelerometer reflex quantification system augmented by machine learning has potential implications for expanded medical diagnostic applications. Future extrapolations of the technology could involve far more diverse and reliable medical diagnostics, in contrast to current ordinal scale strategies. The iPod device can be applied to the titration of medication for rehabilitation, using the reflex response classification as a feedback modality. The machine learning classification technique may be further refined to discretize progressive convergence of long-term rehabilitation, such as the optimization of therapy strategy.

The current research application achieved perfect classification for patellar tendon reflex, regarding an asymmetric hemiplegic affected leg and healthy leg reflex pair. The patellar tendon reflex features also represent the health status of the peripheral nervous system [1,2,14]. Previous designs of the wireless reflex quantification device have successfully acquired the reflex loop latency through synchronized wireless accelerometers [3,4,9,10,11]. Future applications of the iPod wireless accelerometer reflex quantification system augmented by machine learning, could provide diagnostic insight regarding the integrity of the peripheral nervous system. For instance, a machine learning algorithm could eventually be applied to diagnose the status of diabetic peripheral neuropathy.

5. Conclusions

We have demonstrated here that automated, quantitative methods could provide a clinically meaningful description of a patient's neurological status, such as the identification of an asymmetric hemiplegic and healthy patellar tendon reflex pair. The technique incorporates the synthesis of an iPod wireless accelerometer reflex system and machine learning. The acceleration waveform of the patellar tendon reflex response was acquired through an iPod application, which was conveyed wireless through the Internet as an email attachment. The iPod was mounted to the lateral malleolus by an elastic band. An impact pendulum attached to a reflex hammer evokes the tendon reflex, using a specific amount of potential energy and precise targeting of the patellar tendon. Three types of features were identified from the reflex response acceleration waveform: global parameters, temporal organization, and spectral features. The three feature types were incorporated into machine learning. Machine learning achieved perfect classification for distinguishing a subject's hemiplegic and healthy patellar tendon reflex pair.

Based on the research findings, machine learning is anticipated as an objective and quantified diagnostic of the reflex response acceleration waveform. Medication may be titrated as a function of machine learning derived diagnostics. Therapy strategy and dosage may be optimized using machine learning diagnostics. A logical future goal is to identify features associated with the reflex response for peripheral neuropathies and develop a machine learning platform for medical diagnostics.

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References

1. Kandel, ER.; Schwartz, JH.; Jessell, TM. Principles of Neural Science. McGraw-Hill; New York: 2000.
2. Bickley, LS.; Szilagy, PG. Bates' Guide to Physical Examination and History Taking. Lippincott Williams and Wilkins; New York: 2003.
3. LeMoyné R, Mastroianni T, Coroian C, Grundfest W. Tendon reflex and strategies for quantification, with novel methods incorporating wireless accelerometer reflex quantification devices, a perspective review. *J Mech Med Biol*. 2011; 11:471–513.
4. LeMoyné, R. PhD dissertation. UCLA, Biomed. Eng. IDP; Los Angeles, CA: 2010. Wireless Quantified Reflex Device.
5. Litvan I, Mangone CA, Werden W, Bueri JA, Estol CJ, Garcea DO, Rey RC, Sica RE, Hallett M, Bartko JJ. Reliability of the NINDS Myotatic Reflex Scale. *Neurology*. 1996; 47:969–972. [PubMed: 8857728]
6. Manschot S, van Passel L, Buskens E, Algra A, van Gijn J. Mayo and NINDS scales for assessment of tendon reflexes: betweenobserver agreement and implications for communication. *J Neurol Neurosurg Psychiatry*. 1998; 64:253–255. [PubMed: 9489542]
7. Stam J, van Crevel H. Reliability of the clinical and electromyographic examination of tendon reflexes. *J Neurol*. 1990; 237:427–431. [PubMed: 2273412]
8. LeMoyné, R.; Coroian, C.; Mastroianni, T.; Opalinski, P.; Cozza, M.; Grundfest, W. The merits of artificial proprioception, with applications in biofeedback gait rehabilitation concepts and movement disorder characterization. In: Barros de Mello, CA., editor. *Biomedical Engineering*. Intech; Vienna, Austria: 2009. Ch 10
9. LeMoyné R, Coroian C, Mastroianni T, Grundfest W. Quantified deep tendon reflex device for response and latency, third generation. *J Mech Med Biol*. 2008; 8:491–506.
10. LeMoyné R, Mastroianni T, Kale H, Luna J, Stewart J, Elliot S, Bryan F, Coroian C, Grundfest W. Fourth generation wireless reflex quantification system for acquiring tendon reflex response and latency. *J Mech Med Biol*. 2011; 11:31–54.
11. LeMoyné, R.; Coroian, C.; Mastroianni, T. Wireless accelerometer reflex quantification system characterizing response and latency; Proceedings of 31st Int. Conf. IEEE EMBS; Minneapolis, Minnesota. Sep. 2009 p. 5283-5286.
12. LeMoyné, R.; Mastroianni, T.; Grundfest, W. Quantified reflex strategy using an iPod as a wireless accelerometer application; Proceedings of 34th Int. Conf. IEEE EMBS; San Diego, California. Aug. 2012 p. 2476-2479.
13. LeMoyné, R.; Mastroianni, T.; Grundfest, W.; Nishikawa, K. Implementation of an iPhone wireless accelerometer application for the quantification of reflex response; Proceedings of 35th Int. Conf. IEEE EMBS; Osaka, Japan. Jul. 2013 p. 4658-4661.
14. Seeley, RR.; Stephens, TD.; Tate, P. *Anatomy and Physiology*. McGraw-Hill; New York: 2003.
15. Dietz V. Proprioception and locomotor disorders. *Nat Rev Neurosci*. 2002; 3:781–790. [PubMed: 12360322]
16. Dietz V. Spinal cord lesion: effects and perspectives for treatment. *Neural Plast*. 2001; 8:83–90. [PubMed: 11530890]
17. Van de Crommert HW, Faist M, Berger W, Duysens J. Biceps femoris tendon jerk reflexes are enhanced at the end of the swing phase in humans. *Brain Res*. 1996; 734:341–344. [PubMed: 8896845]
18. Faist M, Ertel M, Berger W, Dietz V. Impaired modulation of quadriceps tendon jerk reflex during spastic gait: differences between spinal and cerebral lesions. *Brain*. 1999; 122:567–579. [PubMed: 10094263]

19. Cozens JA, Miller S, Chambers IR, Mendelow AD. Monitoring of head injury by myotatic reflex evaluation. *J Neurol Neurosurg Psychiatry*. 2000; 68:581–588. [PubMed: 10766887]
20. Pagliaro P, Zamparo P. Quantitative evaluation of the stretch reflex before and after hydro kinesy therapy in patients affected by spastic paresis. *J Electromyogr Kinesiol*. 1999; 9:141–148. [PubMed: 10098714]
21. Kocaja DM, Kamen G. Conditioned patellar tendon reflexes in sprint- and endurance-trained athletes. *Med Sci Sports Exerc*. 1988; 20:172–177. [PubMed: 3367753]
22. Kamen G, Kocaja DM. Contralateral influences on patellar tendon reflexes in young and old adults. *Neurobiol Aging*. 1989; 10:311–315. [PubMed: 2682314]
23. Lebedowska MK, Fisk JR. Quantitative evaluation of reflex and voluntary activity in children with spasticity. *Arch Phys Med Rehabil*. 2003; 84:828–837. [PubMed: 12808534]
24. Zhang LQ, Wang G, Nishida T, Xu D, Sliwa JA, Rymer WZ. Hyperactive tendon reflexes in spastic multiple sclerosis: measures and mechanisms of action. *Arch Phys Med Rehabil*. 2000; 81:901–909. [PubMed: 10896002]
25. Mamizuka N, Sakane M, Kaneoka K, Hori N, Ochiai N. Kinematic quantitation of the patellar tendon reflex using a tri-axial accelerometer. *J Biomech*. 2007; 40:2107–2111. [PubMed: 17140585]
26. Tham LK, Abu Osman NA, Wan Abas WA, Lim KS. The validity and reliability of motion analysis in patellar tendon reflex assessment. *PLoS One*. 2013; 8:1–6.
27. Tham LK, Osman NA, Lim KS, Pingguan-Murphy B, Abas WA, Zain NM. Investigation to predict patellar tendon reflex using motion analysis technique. *Med Eng Phys*. 2011; 33:407–410. [PubMed: 21146440]
28. LeMoyne, R.; Jafari, R. Quantified deep tendon reflex device, second generation; Proceedings of 15th International Conference on Mechanics in Medicine and Biology; Singapore. December (2006);
29. LeMoyne R, Dabiri F, Jafari R. Quantified deep tendon reflex device, second generation. *J Mech Med Biol*. 2008; 8:75–85.
30. LeMoyne, R.; Jafari, R.; Jea, D. Fully quantified evaluation of myotatic stretch reflex; Proceedings of 35th Society for Neuroscience Annual Meeting; Washington D.C.. November (2005);
31. LeMoyne, R.; Coroian, C.; Mastroianni, T.; Cozza, M.; Grundfest, W. Quantification of reflex response through an iPhone wireless accelerometer application; Proceedings of 40th Society for Neuroscience Annual Meeting; San Diego, California. November (2010);
32. LeMoyne, R.; Mastroianni, T. Reflex response quantification using an iPod wireless accelerometer application; Proceedings of 41st Society for Neuroscience Annual Meeting; Washington D.C.. November (2011);
33. <http://www.apple.com/>
34. Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter*. 2009; 11:10–18.
35. LeMoyne, R.; Coroian, C.; Mastroianni, T. Wireless reflex quantification system classifying frequency domain analysis disparity of deep tendon reflex; Proceedings of 39th Society for Neuroscience Annual Meeting; Chicago, Illinois. October (2009);
36. LeMoyne, R.; Coroian, C.; Mastroianni, T. Consideration of the frequency domain as a strategy for classifying tendon reflex response; Proceedings of UCLA Brain Research Institute 2009 Neuroscience Poster Session; Los Angeles, California. November (2009);
37. Otsu N. A threshold selection method from gray-level histograms. *IEEE Trans Syst Man Cybern*. 1979; 9:62–66.
38. Cortes C, Vapnik V. Support-vector networks. *Machine Learning*. 1995; 20:272–297.

(A)

(B)

Figure 1.

iPod wireless quantified reflex system.

(A) Impact pendulum attached to a reflex hammer.

(B) Precise targeting of the reflex hammer and iPod mounted to the lateral malleolus.

Figure 2.

Average reflex waveform for the hemiplegic and unaffected leg. Waveforms were aligned so that the first local peak coincided in time. Line thickness reflects the standard error from the mean (SEM).

Figure 3. Univariate differences in spectral features between the hemiplegic and unaffected leg. (A) Sum of spectral energy across 0-50 Hz. (B) Difference in spectral energy at specified frequencies. Error bars reflect SEM.

Figure 4.

Univariate differences in global features between the hemiplegic and unaffected leg. The maximum acceleration (A) or change in acceleration (B) observed in the waveform. The average auto correlation of acceleration (C) or change in acceleration (D). Error bars reflect SEM.

Figure 5.

Univariate differences in local features between the hemiplegic and unaffected leg. (A) The magnitude of the local peaks in acceleration. (B) The temporal delay between the local peaks in acceleration. Error bars reflect SEM.

Figure 6. Cross-validation accuracy of the SVM when using global features, spectral features, local features or all available features to discriminate between the hemiplegic and unaffected leg. Error bars reflect SEM.