Quantification of the Finger Tapping Test Based on the Flex Sensor – A Single Case Study

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Abstract. Bradykinesia is one of the main motor symptom caused by Parkinson's disease (PD). Together with other impairments, PD can severely impact activities of daily living. A proper diagnosis and continuous monitoring of PD can lead to motor rehabilitation and the use of medication that can severely ease the burden of the symptoms. One of the tests used to assess the severity of the PD is the Finger Tapping Test (FTT), which is already extensively used along with several methods to quantify hand movements and verify the presence of slowness of movement and/or its increase over time, however these methods can be rather expensive and hard to implement in a clinical scenario. In this research, we present a relatively cheap and easy-to-use device, capable of measuring certain hand movements made during the FTT, namely pinch movements, using an ink-based flexion sensor (Flex Sensor). Comparing readings made with this sensor with data acquired through inertial sensors, it was possible to confirm the reliability of this alternative method for quantifying the FTT.

Keywords: Parkinson's Disease, Bradykinesia, Finger Tapping Test.

1 Introduction

Parkinson's Disease (PD) is a neurodegenerative disorder which causes significant motor disabilities. One of its main signs of incapacitation is bradykinesia, defined as the progressive reduction of the velocity and amplitude of motion associated with general motor actions. The slowness of movements causes difficulties in carrying out activities of daily living [1].

The Movement Disorder Society – Unified Parkinson's Disease Rating Scale (MDS-UPDRS) is considered the gold standard for the clinical evaluation of PD [2, 3]. In the Part III of the scale, which is related to motor examination, the item 3.4 proposes the Finger Tapping Test (FTT). It has been widely applied for the evaluation of the severity of PD. An inadequate performance on the FTT can be associated with the loss of neurons in the substantia nigra [4, 5]. However, the subjectivity of the MDS-UPDRS can lead to results that are hard to reproduce, causing difficulty in the interpretation of results [6], hence the need for quantitative methods which are simple and easy to apply.

Some studies present the possibility of measuring the finger tap movements using inertial sensors [6], special cameras [7], and other types of sensors [8]. In clinical practice, it is desirable to use devices that are inexpensive and simple to operate, characteristics generally not associated with the instruments aforementioned, as high-quality cameras can cost thousands of US dollars (e.g. OptiTrack, USA), and inertial sensors have complex features [9] that can be unnecessary for this type of analysis.

Considering the need of an easy-to-operate device dedicated to the evaluation of bradykinesia in the clinical practice this study presents a solution capable of acquiring and analyzing parameters involved in the application of the FTT. The system employs an ink-based flexion sensor, called Flex Sensor. Preliminary description and results of the system were reported in [10].

In the present work, the main features of the developed hardware and software are presented. Ergonomic advancements of the system are discussed, although the focus is the validation of the Flex Sensor for the measurement of the speed of pinch. The results, which are based on a single case study, are compared with those obtained from inertial sensors available in the well-established TREMSEN (Precise Tremor Sensing Technology, the National Institute of Industrial Property, Patent number BR 102014023282-6 A2), which was developed by our research group and has been applied in several studies [11–13].

2 General Description of the Device

2.1 Sensor and Hardware

Fig. 1 shows the main sensor of the device, which is a resistive ink-based flexion sensor, the Flex Sensor, produced by Spectra Symbol (USA). Its relevant characteristics are high durability (it can withstand over 1 million flexions), compact size, and versatility, as it is extremely straightforward to use, functioning as if it were a simple resistor with a variable resistance.

Fig. 1. The Flex Sensor.

The sensor has a flat resistance value, which increases depending on how much it is being bent, up to at least two times the flat resistance at an angle of 180º. With the intention of capturing this change in resistance, the sensor was connected to a voltage divider, alongside a resistor, properly dimensioned as to provide a significant range in the output voltage, taking into consideration the minimum and maximum values of resistance of the sensor and the expected input and output of the voltage divider. As suggested by the manufacturer, an operational amplifier (namely the LM324) was employed between the voltage divider and the final output, to reduce possible unwanted fluctuations in the readings due to the source impedance of the Flex Sensor when used with a voltage divider.

The input and output voltage of the voltage divider, as well as the control of all other features in the hardware, are handled by the microcontroller board Arduino Uno, an entry level board from the prototyping platform Arduino, widely used by both novices and professionals for projects in the field of electronics. Some of the output ports of the board (5V) were used to supply the voltage divider, two LEDs, and other secondary features, which will be mentioned ahead. The output of the voltage divider is read by an analog port and then converted by the board's 10-bit resolution analog-to-digital converter, that produces 1024 discrete values, or levels, available from the conversion. The pins have an operating voltage of 5V, meaning the resolution of the converter is of approximately 4.88 mV.

Following the results from the initial assessment of the device reported [10], some aspects were changed, accompanying some new features, shown in Fig. 2 and described below.

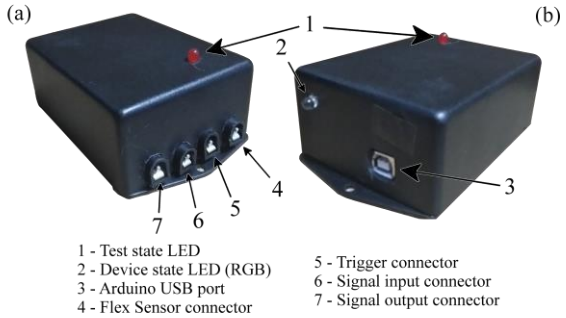

Fig. 2. Identification of the main features of the device. (a) Front view. (b) Rear view.

Two LEDs are available, one indicating that the device is operating (feature 2), and the other one that a test protocol is running (feature 1). The last one can be used to provide visual feedback for a subject while performing a task.

The system has 5 inputs, which are indicated in Fig. 2. The trigger is used for data annotation purposes. A pushbutton is connected to the trigger input (feature 5) so that the user can generate annotations whenever necessary. An auxiliary signal can be connected to one of the inputs (feature 6) and it will be reproduced in the output (feature 7).

2.2 Software

The source code for the Arduino board, written in the Arduino Language, based on the well-known and widely used C++, is responsible for controlling the LEDs and the other features, as well as for setting the sample rate for the sensor data acquisition, which is 200 Hz. The signal is sent to the serial port of the PC via an USB cable.

The online plotting and general handling of the signal is made with the high-level, general-purpose programming language Python, where ready-to-use code is available in countless libraries, or modules, mostly made by the community, covering a broad range of areas. The main modules utilized in this project are: PyQt5, dedicated to building complete, fully-operational graphical user interfaces (GUIs); Matplotlib [14], also dedicated to GUIs, focusing on publication-quality image generation; and the scientific computing tools package SciPy [15], used to efficiently deal with constant flow of data, and for statistical analysis.

2.3 Sensor Positioning and Ergonomics

Another point to be taken into consideration is the positioning of the sensor on a subject's hand. Originally, the Flex Sensor was positioned directly between the thumb and index finger [10], but it turned out to be not ideal.

Currently, the positioning that seems to work best is in the region that comprehends the metacarpus and the proximal phalanx of the index finger. In this way, the hand movement is unobstructed, and the impact of the fingers does not interfere on the detected signal. To avoid the need for tape or any other kind of tool for fixating the sensor to the hand, a fingerless glove was employed. Velcro strips were added to the points in the glove correspondent to the areas described above. Fig. 3 depicts the glove, the position chosen for the sensor and the finger positioning in beginning and end of the FTT.

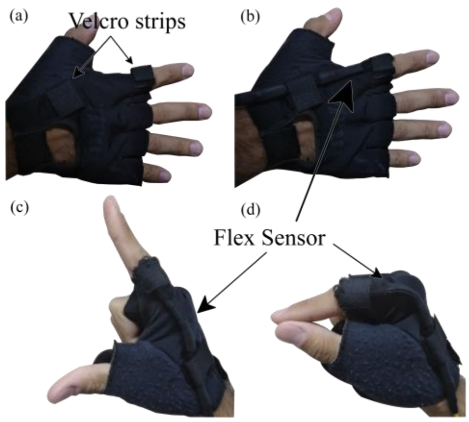

Fig. 3. (a) The glove with the added Velcro strips. (b) The sensor positioning. (c) The beginning of the pinch movement. (d) The end of the pinch movement.

3 Methods for Data Analysis

To ensure the data acquired with the Flex Sensor is consistent with the hand movements, at least to the point where it can be used to determine the period between pinches, the TREMSEN system was used simultaneously during data acquisition. It is safe to assume that the inertial sensors available with the TREMSEN, each one equipped with an accelerometer, a gyroscope, and a magnetometer, if properly utilized, can precisely describe the type of movement being analyzed.

3.1 Data Acquisition

This study was approved by the Ethics Committee on Human Research (CAAE: 65165416.4 0000.5152) of the Federal University of Uberlândia. Prior to participation in the study, the participant received a detailed explanation, who then voluntarily signed a consent form.

A single healthy subject, aged 20 years old, was instructed to perform the fine pinch movement repeatedly, in four different test blocks. In the first three, the subject was prompted to try and follow the rhythm provided by a digital metronome, set to different frequencies (3.33 Hz, 1 Hz and 2 Hz, respectively). In the last task, the movement was performed without the audio stimulus, but with the instruction to try and keep a uniform rhythm. In each block, the subject executed at least 40 pinches.

Fig. 4 shows the placement of the inertial sensors, with their respective axis orientations, as well as for the glove with the Flex Sensor.

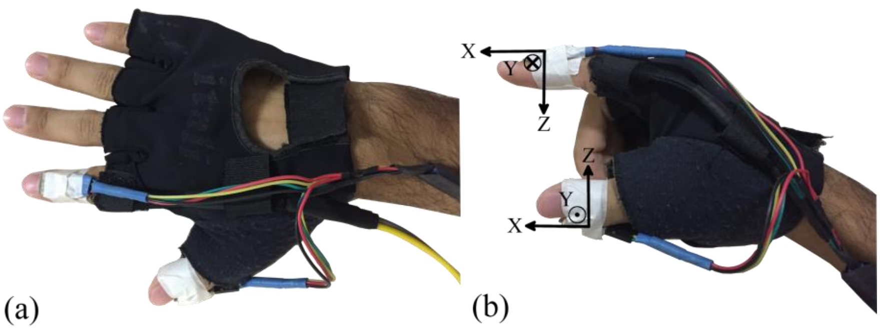

Fig. 4. (a) Top view of the hand with all sensors positioned. (b) Orientation of the axes for the inertial sensors during the pinch movement.

3.2 Signal Pre-processing

As the validation is based on the detection of central points in the signals, and they generally present a substantial amount of noise, applying a filter is essential to improve the performance of the algorithm responsible for detecting these points. A second order low-pass digital Butterworth filter, with a 15 Hz cutoff frequency, was applied to the signal from both sensors. Although the amplitude may be attenuated by the filter, the signal does not get displaced in time, guaranteeing that this analysis will still generate consistent results.

Since each sensor has its own unique measurement unit (volts for the Flex Sensor, Gauss for the magnetometer, degrees per second for the gyroscope, and g-units for the accelerometer), to facilitate operating with data from different sensors simultaneously, all signals were normalized between 0 and 1, using Equation 1,

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where x is the input signal, x_i is the sample to be normalized, $\min(x)$ and $\max(x)$ are the minimum and maximum values of x, and x_i' is i-*th* normalized sample.

The z axis of the accelerometer placed on the index finger (A_z) was chosen as the reference for comparison with the data acquired with the Flex Sensor.

3.3 Central Point Detection Algorithm

In the present work, the "central point" was defined as center point of a pinch movement. Fig. 5 depicts the main elements necessary for the definition of a central point. For its detection, firstly, the local maxima (peaks), and local minima (valleys), are detected. Based on each one of the peaks and their respective closest valley, a threshold value is set to 75% of the difference in amplitude between the two points. The first points to transpose the threshold are then marked, one to the left and one to the right. Based on these landmarks, the center point is determined as the half way point between them.

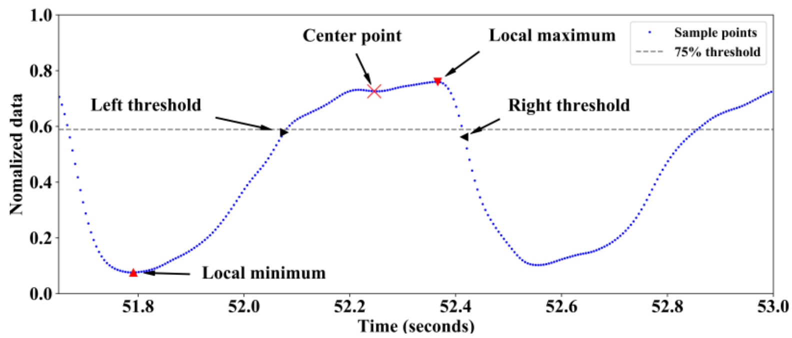

Fig. 5. Visual depiction of the center point detection algorithm.

Fig. 6 shows a sample from each one of the signals being analyzed, already filtered and normalized, along with the output from the center point detection algorithm.

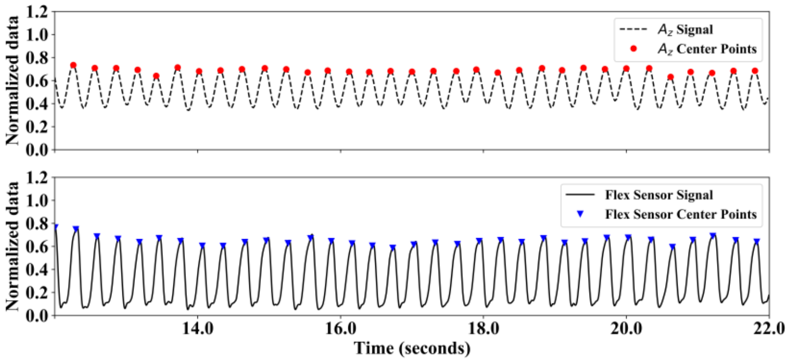

Fig. 6. Signals from the accelerometer's z axis and the Flex Sensor, filtered and normalized, with the center points marked.

3.4 Analysis of the Time Between Central Points

The final step in data processing was to estimate the period (Δt) for each pinch movement performed by the subject, to be used as the comparison parameter. This period is defined as the time elapsed between each central point and the following one. For each block, 31 points, or 30 periods, were considered.

Statistical Analysis. The Tukey Mean-Difference plot, a statistical method to assess agreement between two measurement techniques [16] was popularized in the field of medical statistics by Bland and Altman [17], thus being referred to as the Bland-Altman plot. This analysis became increasingly adopted over the last two decades [18], as it is extremely easy to apply and to interpret, and the results are highly reliable.

The analysis is based on what are called "limits of agreement", defined as the $\bar{x} \pm 1.96s$ interval, where $\bar{x}$ is the mean difference in measurements, and s is the standard deviation (SD) for the differences. If the differences are normally distributed, 95% of them will fall within these limits.

4 Results

Since there is no significant evidence in any of the 4 tasks that the differences between measurements made by the TREMSEN and the Flex Sensor are not normally distributed (Shapiro-Wilk test, p-value > 0.05), we can expect most of the differences to lie within the limits of agreement. Fig. 7 shows the Bland-Altman plot for each task.

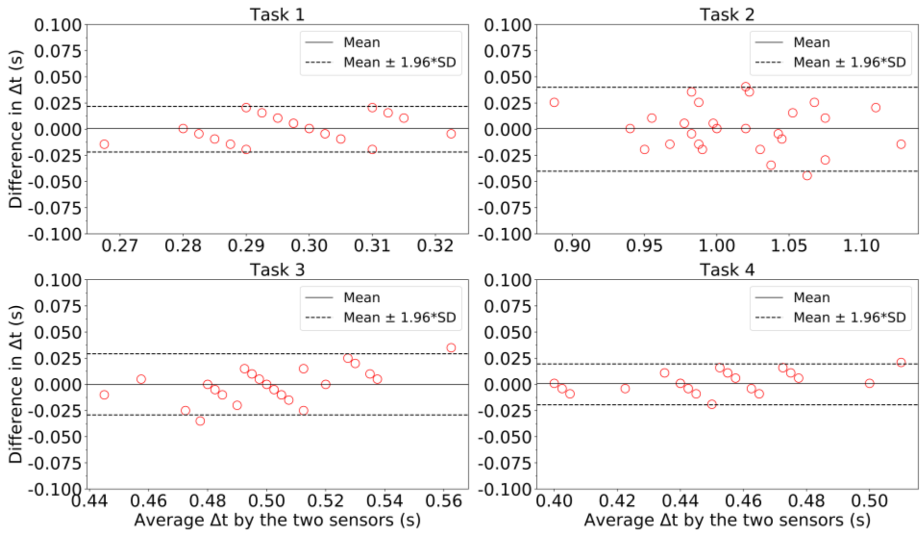

Fig. 7. Bland-Altman plot for each task performed by the subject. Task 1: 3.33 Hz audio stimulus. Task 2: 1 Hz audio stimulus. Task 3: 2 Hz audio stimulus. Task 4: no stimulus.

Table 1 presents relevant data from Fig. 7.

Table 1. Information from the data plotted in Fig.7.

Tasks	Mean ± 1.96 * SD (s)	Maximum Difference (s)
Task 1 (3.33 Hz)	0.0006 ± 0.0218	0.0200
Task 2 (1 Hz)	0.0006 ± 0.0401	0.0400
Task 3 (2 Hz)	0.0000 ± 0.0292	0.0350
Task 4 (No stimulus)	0.0010 ± 0.0195	0.0200

With these values, we can say with a high degree of certainty that, at least for pinch movements being executed at frequencies between 1 and 3.33 Hz, based on our worst case (task 2, pinches at a lower frequency), most of the measurements made with the Flex Sensor are expected to be up to 0.0395 seconds below or 0.0407 seconds above the same measurement made with the TREMSEN.

To determine whether these differences are clinically significant or not, we can evaluate how considerable they are in relation to our reference, in this case, the TREMSEN. Using the maximum differences (see Table 1), and each respective Δt measured with the TREMSEN, we observe the following disparities: 6.67% for Task 1, 3.85% for Task 2, 6.03% for Task 3, and 3.85% for Task 4.

5 Discussion and Conclusion

This research proposed a different approach for quantifying the Finger Tapping Test, an already stablished test for assessing severity of the Parkinson's Disease, using an ink-based resistive sensor, the Flex Sensor. The results display a satisfactory performance, showing that the Flex Sensor is reasonably adequate to acquire, at least, the speed of pinches (period of movement) from the FTT.

The worst difference (0.040 seconds, or 40 milliseconds, for Task 2) and the largest relative error in measurement (6.67% for Task 1), supported by the Bland-Altman analysis, suggest that the Flex Sensor will likely not deviate more than 40 milliseconds in a pinch period measurement, and that this deviation may not exceed 6.67% of the approximate actual period of the movement.

Given the disparity between the expected FTT response from a healthy subject, compared to one with PD, as well as the disparity between subjects with different degrees of severity of the PD, it can be said that this deviation of the Flex Sensor from the real measurement is negligible, and the possibility of a misclassification is quite remote, thus deeming the Flex Sensor fairly reliable for this application.

For the future of this project, a proper glove must be devised so that it cannot interfere on the hand movements. We then expect to be able to use this device on a longitudinal study with patients with PD.

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7 Conflicts of Interest

The authors declare no conflict of interest.

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