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Real-time visual verification of leap motion controller measurements for reliable finger tapping test in Parkinson's disease

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In today's world, there is a high pressure to change lifestyle, which is increasing the incidence of neurological diseases, such as Parkinson's disease. To assess motor dysfunction in these patients, approaches based on markerless motion capture (MMC) technology have been tested in recent years. Despite the high sampling rate and accuracy of commercial depth sensors such as the Leap Motion Controller (LMC), their versatile use is limited due to irregular sensing or processing errors. These affect their reliability and question clinically meaningful data. To mitigate the impact of errors during measurements, we introduce visual feedback for the specialist physician in the form of a real-time display of the measurement data recorded by the LMC. In this proof-of-concept study, we evaluate data from 10 patients with Parkinson's disease and 12 healthy subjects during the finger tapping test (FTT). To verify the suitability of using the LMC sensor for this purpose, we validate the results by simultaneous measurement with digital camera and two contact sensors: an accelerometer and two three-axis gyroscopes placed on the fingertips. The preliminary results confirmed the effectiveness of introducing visual feedback when performing FTT by reducing the impact of LMC sensor failure by 4.3%. Additionally, we used machine learning techniques to determine the clinical relevance of the measured and extracted features, achieving an average classification accuracy of 90.41%.

Keywords: Parkinson`s disease, leap motion controller, finger tapping, visual feedback, bradykinesia

1 Introduction

Currently there is a trend in the objective technology-based assessment of neurological diseases, potentially improving the diagnostic process and therapy outcomes. Parkinson`s disease (PD), a chronic degenerative movement disorder with an increasing incidence due to the aging population, is clinically most often characterised by a motor syndrome that manifests itself as tremor, rigidity, postural instability, and bradykinesia [1]. According to the diagnostic criteria of the Queen Square Brain Bank, bradykinesia is defined as the slow onset of voluntary movement with a progressive reduction in the speed and amplitude of repetitive actions [2]. The latest diagnostic criteria also include the incidence of hesitations or halts in repetitive movement as the defining features of bradykinesia [3]. Being an essential motor symptom, bradykinesia can be used as the main criterion for the diagnosis of Parkinson`s disease and other parkinsonisms. Even with significant progress in neuroimaging, Parkinson's diagnosis is based primarily on neurological examination, most often in the form of neuropsychological tests to examine motor functioning [4]. These are dynamic tests such as keystroke analysis, gait analysis, finger tapping, and others that assess the patient's cognitive and motor skills. In daily clinical practice, the finger-tapping test (FTT) is commonly used to evaluate bradykinesia of the upper extremities as part of clinical assessment scales. In its most common form, FTT consists of tapping the index finger on the thumb using both the dominant and non-dominant hand as quickly and as widely as possible for each side separately. The test is performed over several seconds with pauses between repetitions. The most common classification is based on the Movement Disorder Society-sponsored revision of the Unified Parkinson`s Disease Rating Scale (MDS-UPDRS) [5], where finger tapping is rated on a 5-point Likert-type scale (ranging from 0 to 4), with higher scores indicating more severe pathology. As an examiner, a specialist physician visually assesses PD symptoms such as finger tapping speed, hesitations, number of halts, decrease in amplitude, and others while the patient performs the FTT. Due to the subjectivity of the evaluation, the observed symptoms are subject to intrarater and interrater variability [6], which has led to the need for an objective technology-based assessment. Movement can be quantified by specific optical systems, inertial sensors (accelerometers, gyroscopes, magnetometers) or by customized analytic programs from videotapes (for a review, see [7]). An affordable example of an optic system is an off-the-shelf commercially available sensor Leap Motion Controller (LMC) originally developed by Ultraleap™ for hand tracking in virtual reality video games. The LMC was shown to be sufficient, reliable and relatively accurate in the motor performance of the

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upper limb of healthy adults [8] and the groups of patients [9], including the assessment of bradykinesia [10]. However, measurements on patients are notoriously difficult due to variations in movement and disease symptoms. This problem is even more pronounced if we take into account the difficulty of patient coordination when performing a neuropsychological test that examines motor functioning. The purpose of our study is to introduce visual feedback to the specialist physician during FTT evaluations in real-time to develop a valid, quick and contactless objective method to measure features for the diagnosis of PD and mitigate LMC sensor failure. The real-time visual verification process is illustrated in Fig. 1. The patient (left) performs the finger-tapping test according to the instructions and a specialised physician (right) monitors the measurements, video feed and a 3D model of the hand in real-time. Based on the observed events (model failure, measurement or human errors), he provides verbal feedback to the patient, correcting and guiding him, thereby minimizing errors and verifying data correctness.

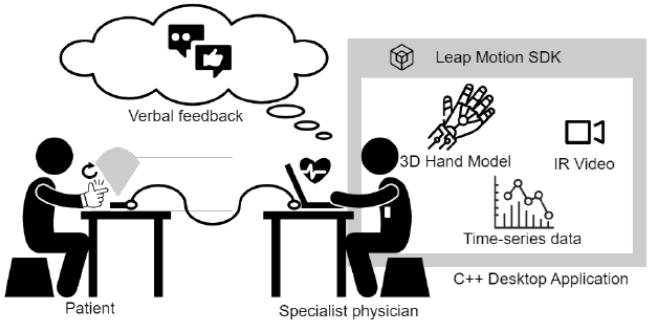

Fig. 1. Schematic illustration of the real-time visual verification process

2 Methods

2.1 Validation of the LMC sensor measurements

Verification of measurements was carried out on a healthy control group, consisting of staff from the Center for Movement Disorders at the 2nd Department of Neurology of the University Hospital Bratislava, and students and staff of the Institute of Robotics and Cybernetics, Faculty of Electrical Engineering and Information Technology (FEI STU) of the Slovak University of Technology. In all experiments, volunteers were asked to place the hand approximately 30 cm above the sensor and perform the FTT consisting of tapping the index finger on the thumb as quickly and as widely as possible for a minimum of 10 seconds as part of the standard protocol.

2.1.1 Validation with an accelerometer

During the validation, a single axis acceleration transducer was placed and fixed on the distal phalanx of the index finger while the signal was detected and recorded on a Neurosoft® Neuro-MEP-8 EMG machine. The measurement was performed 10 times simultaneously using both sensors, while the data were aligned and the frequencies of the measured signals were compared (Fig. 2).

Fig. 2. Simultaneous measurement with Leap Motion Controller and an accelerometer

2.1.2 Validation with two three-axis gyroscopes

The validation is based on the method proposed by Djuric-Jovicic et al. [11]. Two STMicroelectronics® L3G4200D 3-axial digital gyroscope breakout boards (model GY-50) were placed and fixed on the fingertips of the index finger and the thumb positioned so that the x-axes of both inertial sensors were directed outward from the fingers. Both breakout boards were interconnected with the Arduino® UNO microcontroller board via the I2C communication interface. Two gyro sensors attached to the fingers track the angular rotation rate of the thumb and index finger with respect to the fixed inertial frame (testing room). However, their readings are in their own local coordinate systems, because of the relative movement of fingers during the FTT. To understand how the fingers move relative to each other, we need to know how the local coordinate systems are oriented. This is done during a 5-second calibration phase, performed at the beginning of each measurement. The fingers are joined and the whole hand subsequently performs a circular or other drawing movement in the air so that the sensors record the relative rotation rate of both coordinate systems. Since the relative position of these sensors is fixed during the execution of the movement, both sensors should measure identical angular velocity vectors. Since their

local coordinate systems are not parallel, the measured angular velocities are different. In order for these values to be the same, in the calibration process we map the coordinate system of the thumb to the coordinate system of the index finger through a transformation (rotation) matrix, the values of which are optimized by the non-linear simplex method (Nelder and Mead method [12]) to obtain the initial relative orientation of the two coordinate systems. As tapping occurs, the two coordinate systems rotate relative to one another. Therefore, the transformation matrix needs to be updated through a time-stepping process from which the tapping angle α describing rotation around a primary axis can be estimated [11]. During validation, measurement was performed 10 times simultaneously using the LMC and three-axis gyroscopes, while the data were aligned with the baseline removed, and the signals were visually compared.

2.1.3 Validation with digital camera

During validation, a Sony™ A6500 digital camera mounted on a DJI Ronin RSC2 compact stabilizer was placed in front of the Leap Motion Controller at a distance of about 70 cm for easier handling and control. The camera resolution was set to full HD (1920 × 1080p, 16:9) shooting at 100 fps and the testing room was illuminated with natural light. The video recorded from the camera was later processed by a desktop application created using OpenCV (version 4.5.5.64) and MediaPipe Hands (version 0.8.9.1) libraries in the Python programming language. The goal of the application was to create a hand landmark model for each frame. From the detected keypoints of the tips of the thumb and index finger, the Euclidean distance in pixels representing the distance between the fingers during the measurement was subsequently calculated and plotted as a time series. During validation, the FTT was repeated 70 times simultaneously using the LMC and the digital camera, while the data were aligned with the baseline removed, and the signals were visually compared [13].

2.2 Measurement with leap motion sensor

All experiments were carried out in patients with PD (5 women and 5 men, with average age 56.7 ± 5.95 years) and a healthy control group (7 women and 5 men, with average age 60 ± 7.37 years), consisting of patients and staff from the Center for Movement Disorders at the 2nd Department of Neurology of the University Hospital Bratislava. All patients with PD were in the initial phase of the disease (Hoehn and Yahr stage 1–2), had bradykinesia with tremor in at least one hand, and were evaluated according to MDS-UPDRS, part III motor examination protocol [14]. The patient was seated at the table with the LMC positioned flat on the table in front of them. The computer screen showing the real-time measurements was concealed from the patient's sight during experiments, which were conducted identically to the validation part with one difference. All measurements were alternately repeated for the right and left hand 4 times with breaks between experiments. The distance between the thumb and index finger was obtained as the *PinchDistance* (mm) parameter from the 3D hand model provided by the software development kit (SDK). The measured data were resampled with a 5 ms period using linear interpolation. Along with amplitude, additional features such as speed and acceleration of finger movements were also computed. The speed of finger movements is derived from the amplitude, computed as the change in amplitude divided by the sampling interval. The derivative of the amplitude signal was further filtered using a Savitzky-Golay filter [15] with a 4-order polynomial and a 15-sample window. The tapping amplitude A_t and period of tapping T_t are calculated at the maximum values of measured amplitude as shown in Fig. 3.

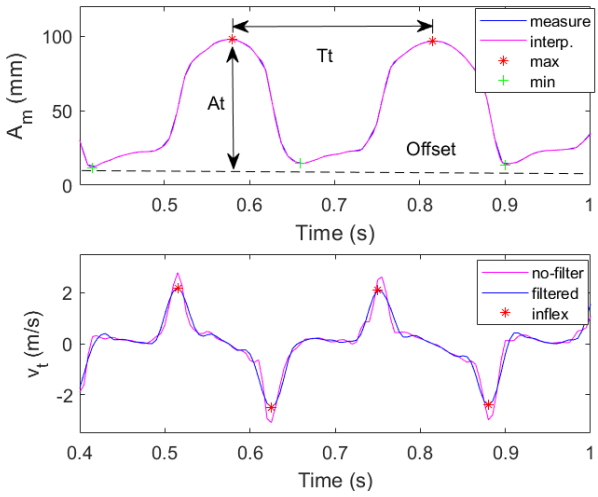

Fig. 3. Amplitude measured signal A_m and computed speed of tapping fingers v_t

3 Instruments

The Leap Motion Controller is a commercially available device that allows users to control digital content with their hands and gestures (non-contact measurement), with potential applications across various industries. It has a high spatial accuracy that ranges from 0.01 mm to 0.4 mm according to the manufacturer's specifications and previous studies [16]. The sensor captures the image of the hands with two infrared cameras in the near-infrared light spectrum (850 nm) and uses this stereoscopic image information to create a 3D model of the skeleton and joints of the hand in real-time from the calculated depth video frames. The stereo-

scopic near-infrared frames are captured in the hardware part of the sensor and sent via USB port to a PC, where segmentation, hand tracking, and creation of the 3D hand model itself are performed using the SDK tracking library software. Fig. 2 shows the position of the hand when measuring the movement of the finger above the sensor. The most suitable position for the hand when measuring is approximately in the middle of the sensor and at a height of 30 cm. The Leap Motion sensor measures physical quantities in the following units: time (μs), distance (mm), speed (mm.s^{-1}), angle (rad). Using the SDK, we created a standalone C++ application with a simple user interface to capture and display measured data in real-time. The Bradykinesia application displays a 3D model of the hand, time series data of the measured and computed features, and an image from the sensor's IR camera, based on which the specialised physician can correct the patient during the measurement (Fig. 1). In this way, the application allows the neurologist to introduce visual feedback to correct the position of the patient's hand during the measurement and offers opportunities to improve the reliability of the LMC sensor.

4 Results

4.1 Validation of the LMC sensor measurements

4.1.1 Validation with an accelerometer

Figure 4 shows the measured amplitude signal A_m as the distance between the thumb and index finger of the LMC sensor and the acceleration a_m measured from accelerometer. After detection of maxima of these signals, we evaluated the period and frequency of finger tapping, which are found in Tab. 1.

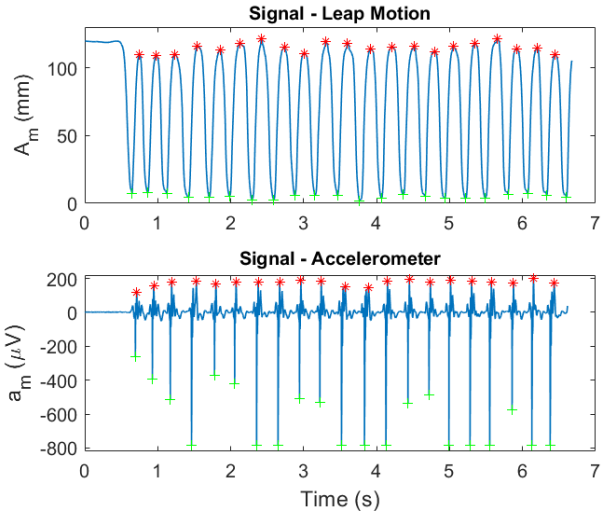

Fig. 4. Comparison of measured signals from LMC and accelerometer sensors

Table 1. Computed values of periods and frequency from LMC and accelerometer sensor signals

Measured	Min. period (s)	Max. period (s)	Mean period (s)	Mean frequency (s^{-1})
LMC	0.2350	0.3200	0.2850	3.51
Acceler.	0.2330	0.3150	0.2845	3.52

We achieved more precise frequency measurements using the LMC sensor by analyzing the peak values of the amplitude signal and found that in all 10 repeated measurements, the frequency deviation between the LMC and the accelerometer was within the ±0.5% range.

4.1.2 Validation with two three-axis gyroscopes

Figure 5 shows the tapping amplitude of the LMC sensor and the tapping angle computed from the measured signals of the inertial sensors attached to the ends of the thumb and index finger. Ten measurements were carried out, where only a characteristic example of the comparison is shown. The tapping angle obtained is time-aligned with the baseline removed for comparison in one graph with the LMC sensor. From the time series shown, you can see a very good shape match of the measured signals. However, deviations can be seen at the minimum and maximum amplitude values as a result of the gyroscope drift.

4.1.3 Validation with digital camera

During validation, we compared the LMC measured signal with a visual measurement made by an external digital camera, which we considered as a reference signal. We manually watched and checked each measured signal with the reference video captured by the camera. The experiments were carried out under unconstrained conditions (different position of the hand above the sensor, movement of the hand during measurement, and simulated situations of changes in the amplitude and speed of finger tapping occurring simulating a real patient measurement). Of the 70 validation measurements (3 participants), the 65.27% (46 cases) of all measurements showed good shape agreement with the reference signals captured by the camera from which the 40% (28 cases) of all measurements showed very high agreement. The following deficiencies were represented in the measurements: failure of the hand model 4.3% of the cases, medium inaccuracies in amplitude 32.8% of the cases, small inaccuracies in amplitude 80% of the cases, inaccuracies in joining fingers 42% and large inaccuracies in joining fingers 15% of the cases.

Imprecise measurements resulted from the malfunctioning of the 3D hand model and significant amplitude errors during the opening and joining of the fingers. These problems mainly occurred if the hand was not in the correct position, which can be influenced by the neurologist who can correct the patient. The remaining minor inaccuracies in the amplitude can be suppressed by averaging or filtering.

4.2 Measurement with leap motion sensor in patients

All measurements in this section were performed using the LMC sensor together with the Bradykinesia application. An example of measuring the amplitude A_m and the calculated speed of finger tapping v_t in a patient with PD is shown in Fig. 6. The tapping amplitude A_t and frequency F_t signals from the FTTs were calculated from the maximum peaks of the measured amplitude signal. Since the amplitude and frequency waveforms are not continuous over time, we applied a Gaussian filter to smooth them (Fig. 7). Subsequently, we calculated the minimum, maximum, and mean value of amplitude A_t, frequency F_t, speed v_t, and acceleration a_t of finger tapping (Fig. 8 and Fig. 9), which represent motor symptoms for specialised physicians. Figures 8 and 9 demonstrate good consistency of symptoms observed at the mean values of the measurements. Differences in mean values of amplitude, speed, and acceleration on the left and right hands were also observed. An example of the measured data in a patient with PD is shown in Fig. 10. A decrease in finger tapping amplitude A_t or frequency F_t was observed in most measurements in patients with PD (Fig. 11). The chosen features (symptoms) served as input parameters for categorizing into two groups using a multilayer perceptron neural network (MLP) [17]. A total of 32 input features were used as input parameters, with 16 features allocated to each hand. We used the minimum, maximum and mean values from the filtered amplitude, filtered frequency, speed and acceleration of finger tapping. From the amplitude, frequency, speed of opening and closing of the fingers, we used only the mean value. The MLP network consisted of a single hidden layer containing 45 neurons, each utilizing hyperbolic tangent activation functions. In the output layer, there were two neurons employing the softmax activation function to classify into two categories (healthy, Parkinson's). Binary cross-entropy was used as the loss function and the scaled conjugate gradient backpropagation method was used to train the MLP network. The training process was stopped early if the loss function reached 0.002, and the number of epochs was limited to 30. To augment the training dataset, parameter combinations from both the left and right hands were utilized. This yielded 140 samples for individuals without Parkinson's and 111 samples for those with the disease. The entire dataset was randomly split, with 20% allocated for training and 80% for testing. By assigning a small number of training samples, we compensated for the use of several measured samples from one patient during training, as a countermeasure against overtraining, which we also supplemented with augmentation. We repeated the neural network training 50 times with random resampling in each experiment. The average accuracy of 50 attempts on the test data reached 90.41% on the total data 92.32%. The precision for classifying healthy controls (specificity) averaged 93.6%, while the precision for identifying Parkinson's disease (sensitivity) averaged 89.0%.

5 Discussion

For the evaluation of the neurological finger tapping test, we created the Bradykinesia application, which enabled non-contact measurement and real-time visualization of finger movement using the LMC sensor. The previously reported LMC error rate was approximately 1.9% [18] caused mainly by the failure to map the measured data to the 3D model. However, developers reported a much higher error rate at around 20% [19], raising questions about the reliability of the LMC sensor measurements for diagnostic purposes. Despite the sensor error rate and various limitations (such as limited bandwidth), Kincaid et al. [20] showed that it is still possible to reduce these effects with appropriate signal processing methods to obtain an estimate of the measured signals. In this work, we directly compared the measurements made by the LMC sensor and verified the accuracy of the measured frequency during FTT using an accelerometer. By simultaneous measurement with the Leap Motion sensor and at the same time with the accelerometer, we recorded approximately the same values of the measured frequency, which differed within ±0.5\%. Subsequently, we verified the shape of the signals using a system of two 3-axis gyroscopes placed on the fingertips and also using a digital camera. In both validation cases, we verified that the LMC captures the finger movement correctly with reasonable accuracy. From the camera measurements, we found that the most common problem with sensor measurements during the FTT was correctly capturing edge movement positions, for example, when the fingers were joined together or the furthest from each other. We noticed a problem with incorrect measurements and 3D model mapping when the fingers were joined in 42% of the cases, while 15% of them were

significantly inaccurate. This was also observed and pointed out by Butt et al. in their study [9]. In the assessments conducted on both patients and healthy individuals, we showed that the average values of amplitude, frequency, speed, and acceleration of finger taps exhibit high repeatability in the computed symptoms. Thus, it is essential to utilize the average values of the measured quantities in diagnostics or implement methods to compensate for wrong finger detection by the LMC sensor, such as applying Gaussian filtering to the computed amplitude and frequency of finger tapping. We then used the obtained features through the MLP network for binary classification for the diagnosis of PD, where we managed to achieve the 90.42% accuracy on the test set. The results achieved are comparable to those of other authors who also used machine learning methods [21].

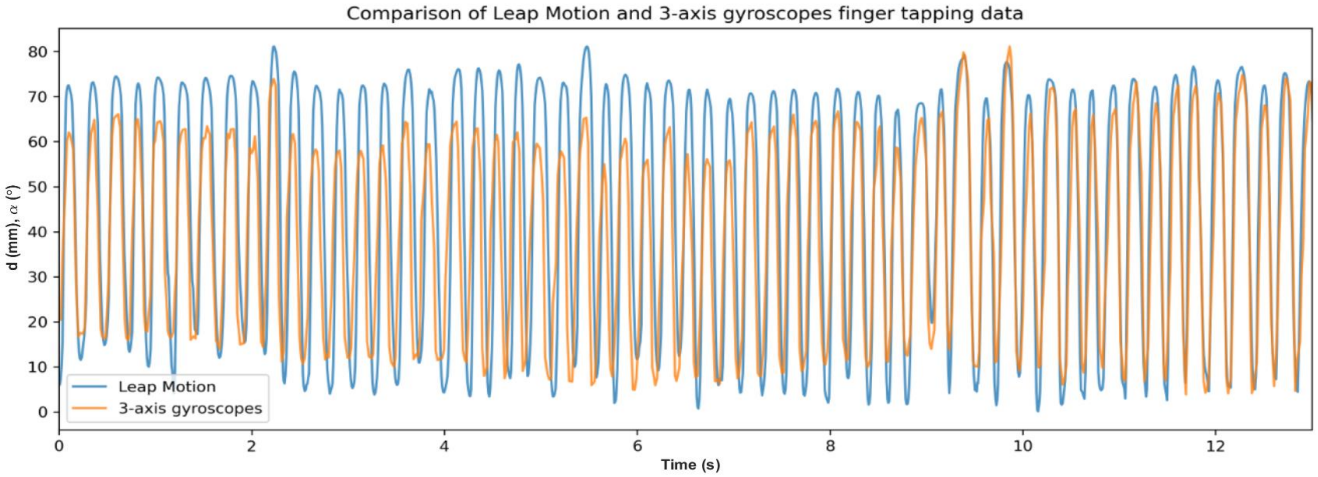

Fig. 5. Comparison of measured signals from LMC and gyroscope sensors

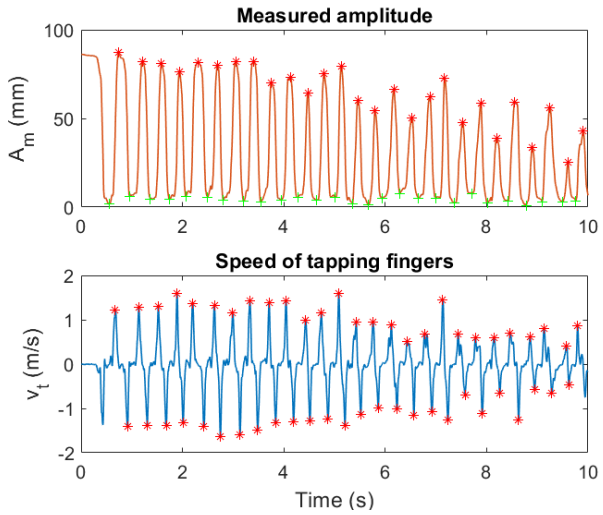

Fig. 6. Amplitude measured signal A_m and computed speed of tapping fingers v_t for PD patient

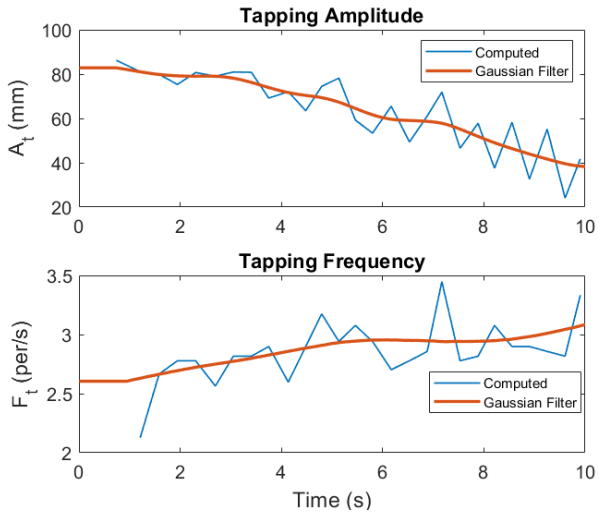

Fig. 7. Tapping amplitude A_t and tapping frequency F_t for PD patient

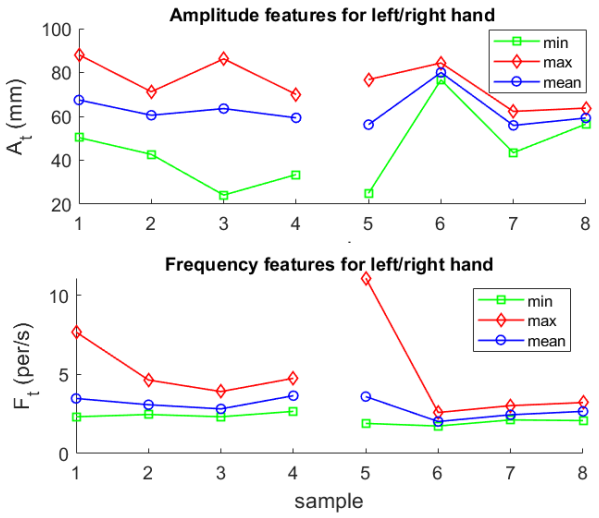

Fig. 8. Tapping amplitude and frequency features from eight measurements (four left and four right hand) for PD patient

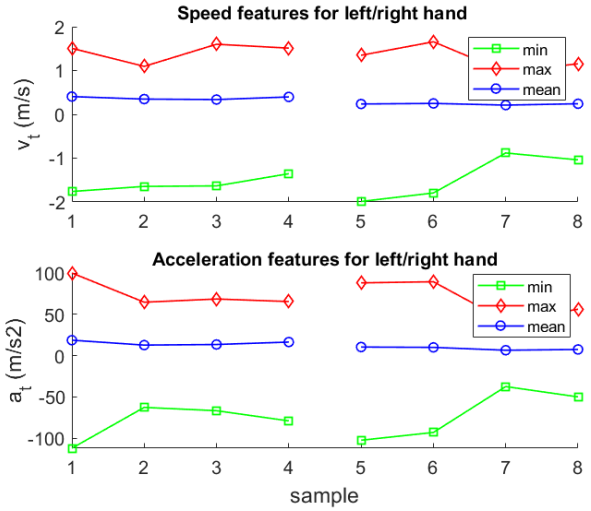

Fig. 9. Tapping speed and acceleration features from eight measurements (four left and four right hand) for PD patient

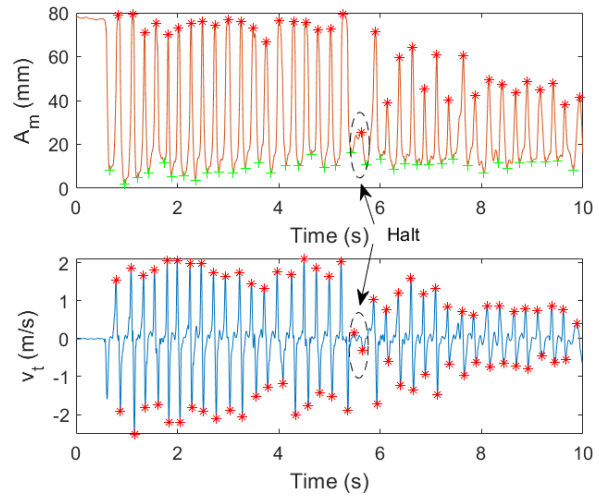

Fig. 10. Amplitude measured signal A_m and speed of tapping fingers v_t for PD patient

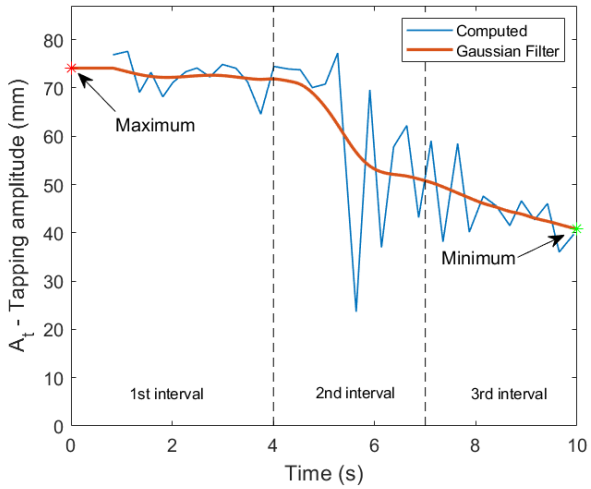

Fig. 11. Tapping amplitude A_t for PD patient

6 Conclusion

The introduction of visual feedback offers promising potential to mitigate the challenges associated with MMC technology, making it a valuable tool for assessing motor dysfunction in neurological diseases such as Parkinson's. The study demonstrates the potential of real-time visual feedback to improve the reliability of MMC technology for clinical applications in Parkinson's disease diagnosis and monitoring. In this work, we verified the accuracy of the LMC sensor measurement using three methods and described the problems associated with the use of the sensor for diagnostic purposes during FTT. We showed that these deficiencies can be identified and suppressed by visual inspection of the measured data during and immediately after measurement, which can be repeated if necessary under the guidance of an experienced physician. We anticipate that the second version of the LMC sensor will address and mitigate these shortcomings. Our findings suggest that the LMC sensor can be used as a simple and inexpensive tool for the initial diagnosis of Parkinson's disease. While the results are promising, it remains essential to explore new measurement techniques that guarantee the robustness and precision of the measurements without requiring repeated trials. This can be accomplished by enhancing the precision of measurements, tailoring the measurement process to the sensor, or employing alternative testing methods.

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