2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Combining inertial sensors and optical flow to assess finger movements: Pilot study for telehealth applications

Katherin Zumaeta[1,2], Stefano E. Romero[1], Estiven Torres[1,2], Leslie Urdiales[1,2], Andrea Ramirez[1,2], Isabel Camargo[3], Karlo J. Lizarraga[3,4,*] and Benjamin Castaneda[1,*]

***Abstract*— Parkinson's disease is the fastest growing neurological disorder worldwide. Traditionally, diagnosis and monitoring of its motor manifestations depend on examination of the speed, amplitude, and frequency of movement by trained providers. Despite the use of validated scales, clinical examination of movement is semi-quantitative, relatively subjective and it has become a major challenge during the ongoing pandemic. Using digital and technology-based tools during *synchronous* telehealth can overcome these barriers but it requires access to powerful computers and high-speed internet. In resource-limited settings without consistent access to trained providers, computers and internet, there is a need to develop accessible tools for telehealth application. We simulated a controlled *asynchronous* telehealth environment to develop and pre-test optical flow and inertial sensors (accelerometer and gyroscope) to assess sequences of 10 repetitive finger-tapping movements performed at a cued frequency of 1 Hz. In 42 sequences obtained from 7 healthy volunteers, we found positive correlations between the frequencies estimated by all modalities (ρ=0.63-0.93, P$<$0.01). Test-retest experiments showed median coefficients of variation of 7.04% for optical flow, 7.78% for accelerometer and 11.79% for gyroscope measures. This pilot study shows that combining optical flow and inertial sensors is a potential telehealth approach to accurately measure the frequency of repetitive finger movements.**

***Clinical relevance*— This pilot study presents a comparative analysis between inertial sensors and optical flow to characterize repetitive finger-tapping movements in healthy volunteers. These methods are feasible for the objective evaluation of bradykinesia as part of telehealth applications.**

I. INTRODUCTION

Bradykinesia is required for the diagnosis of Parkinson's disease (PD) and it refers to the slowness of movement with a progressive reduction of either the frequency or the amplitude of repetitive movements. The Movement Disorders Society sponsored Unified PD Rating Scale (MDS-UPDRS) is a validated rating scale that includes several items for the examination of bradykinesia [1]. In the MDS-UPDRS, item 3.4 evaluates repetitive finger-tapping (FT) by instructing the subject to "tap the index finger on the thumb 10 times as quickly and as big as possible". As such, this assessment provides semi-quantitative and relatively subjective data that is dependent on direct visual inspection of the speed and amplitude of the movements by trained providers [2]. Quantitative characterization of repetitive FT could provide more accurate and sensitive assessments of bradykinesia. Previous studies using counters or keyboards to record the number of taps have reported unpredictable results with low temporal resolution [3]. Tri-axial accelerometers have been used to analyze FT and showed significant differences between people with PD and healthy controls [2]. Gyroscopes have the advantage that they are free from gravitational artifact. They have been used for assessment of bradykinesia but larger studies are needed to confirm their potential [4]. Computer vision techniques have been used successfully to identify the presence of hand tremor and to discriminate individuals with PD from healthy controls. For instance, in the framework of *Langevin et al.* [5], videos recorded by webcams were analyzed by the Farnebäck algorithm for optical flow (OF) estimation, which considers the distance from the camera and the number of FT movements. *Williams et al.* [6] used another OF method based on the Horn–Schunck algorithm and Support Vector Machine (SVM) to predict bradykinesia using smartphone videos. Similarly, the frequency of hand tremor has been quantified with the Lukas Kanade OF algorithm and SVM to distinguish tremor from non-tremor periods [7]. In a comparative analysis, *Nemade et al.* [8] showed that the Farnebäck algorithm presents better results in terms of execution time. *Husseini* [9] noted that the Farnebäck algorithm is more accurate than the Lukas Kanade algorithm, except for outdoor scenes. During the ongoing pandemic, synchronous telehealth applications are able to generate valid and reliable data for the diagnosis and monitoring of the motor manifestations of PD. Synchronous telehealth requires access to powerful computers and high-speed internet. In resource-limited settings, the diagnosis and monitoring of the motor manifestations of PD is a major challenge due to the lack of consistent access to trained providers, computers and internet. Thus, it is still necessary to develop accessible tools for implementation as part of

*These authors contributed equally to this work as senior authors.

**The authors acknowledge the support of CONCYTEC (Peru). In particular, Stefano Romero was under the doctoral scholarship program in Computer Science (174-2020- FONDECYT- PUCP). In addition, Benjamin Castaneda was supported by the PUCP Research Period Award.

[1]K. Zumaeta, S. Romero, E. Torres, L. Urdiales, A. Ramirez and B. Castaneda are with Laboratorio de Imagenes Medicas, Departamento de Ingenieria, Pontificia Universidad Catolica del Peru (PUCP), (emails: kzumaeta@pucp.edu.pe, sromerog@pucp.pe, estiven.torres@pucp.edu.pe, lurdialesb@pucp.edu.pe, andrea.ramirezc@pucp.edu.pe, castaneda.b@pucp.edu.pe).

[2]K. Zumaeta, E. Torres, L. Urdiales, A. Ramirez are with the Biomedical Engineering Program Pontificia Universidad Catolica del Peru - Universidad Peruana Cayetano Heredia, Lima, Peru.

[3]I. Camargo and K. J. Lizarraga are with Facultad de Medicina, Universidad Nacional de San Agustin de Arequipa, Peru and with the Neurology Peru-Rochester exchange program (NeuroPRO) (emails: icamargo@unsa.edu.pe, karlo.lizarraga@gmail.com).

[4]K. J. Lizarraga is with the Department of Neurology and the Center for Health and Technology, University of Rochester, Rochester, NY, USA.

telehealth applications to remotely diagnose and monitor the motor manifestations of PD [10] [11]. In this pilot study, we simulated asynchronous assessments to develop and pre-test a comparative analysis between OF (based on the Farneback algorithm) and inertial sensors (accelerometer and gyroscope) to assess repetitive FT movements performed at a cued frequency of 1 Hz by seven healthy volunteers. We evaluated and compared the characterization of the frequency of repetitive FT movements by the three modalities using frequency peak analyses, Spearman-rank test and coefficient of variation (CV).

II. Optical flow estimation

Optical flow estimates the change in the brightness of each pixel in the (x,y) coordinates of an image I. This algorithm is based on 2 assumptions: spatial smoothness and constant brightness intensity [8]. An OF equation can be expressed by (1):

$$I_x V_x + I_y V_y + I_t = 0 \tag{1}$$

Where $\mathbf{I}_x$, $\mathbf{I}_y$, $\mathbf{I}_t$ are the image gradients from horizontal, vertical and time domain, respectively. Additionally, $\mathbf{V}_x$ and $\mathbf{V}_y$ are the temporal vectors, whose components represent horizontal and vertical velocities, respectively. These vectors were estimated using the Farnebäck algorithm as previously reported [12]. This algorithm uses a polynomial expansion transformation to approximate the motion between the current and previous frames as obtained by equation (2):

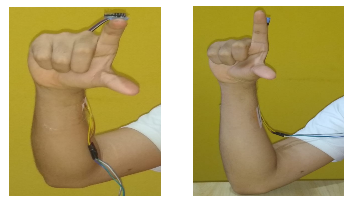
$$f(x) \sim x^T A x + b^T x + c_1 \tag{2}$$

Where $\mathbf{x}$ is a vector that includes the running variables x and y, $\mathbf{A}$ is a symmetric matrix, $\mathbf{b}$ is a vector and $\mathbf{c}_1$ is a scalar.

III. Material and Methods

A. Data acquisition

Seven right-handed healthy adults from Lima, Peru, volunteered to participate in this study (4 male, mean age ± SD = 33.9 ± 26.9 years-old, range = 20–79 years-old). According to the the principles outlined in the Helsinki Declaration of 1975, which were revised in 2000, these volunteers gave their informed consent to participate in the following experiments. Under guidance of 2 technical assistants (ET , LU), each of the 7 volunteers performed 6 sequences of repetitive FT movements by tapping the index finger on the thumb of their right hand for 10 times at a cued frequency of one tap per second (i.e. 1 Hz). During the movements, the assistants counted seconds out loud while volunteers performed taping movements. Three of the 6 sequences were performed while keeping the right elbow resting on a desk and the other 3 sequences were performed while lifting the right elbow off the desk (Fig. 1). Before movement initiation, the technical assistants placed a calibrated MPU-6050 sensor, which includes a tri-axial accelerometer and a tri-axial gyroscope, on the middle phalanx of the right index finger with its Z axis aligned vertically and perpendicularly to the finger (Fig. 2). During FT movements, an Arduino UNO was employed to acquire the acceleration and the angular velocity values from accelerometer and gyroscope, respectively. This data was acquired at the sampling frequency of 28 Hz, which allows to compute 230 samples from each recording. The same FT movements were also video recorded by the technical assistants using a Motorola G7 power smartphone camera with a resolution of 12 megapixels. The assistants adjusted the smartphone until a proper camera focus was achieved, making sure to include the fingers in the video at all times. During the recordings, no moving objects were present as part of the background. The video recording frequency was 25 frames per second and the videos were resized to a resolution of 320x240 pixels and stored in MP4 format without the audio track to reduce storage requirements and processing time.



(a) (b)

Fig. 1: (a) Raised elbow and (b) resting elbow conditions.

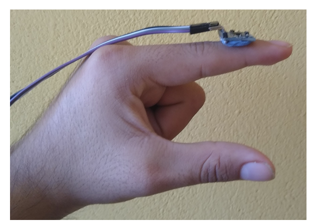


Fig. 2: Position of the MPU-6050 sensor in the index finger prior to finger-tapping movements.

B. Data processing

1) Optical flow: The axial components of the vectors between two consecutive frames of a video were calculated by the Farnebäck algorithm, which generates a matrix of values for each of those consecutive frames. We obtained the average of those values to calculate a new array for each video. From these arrays, the Fast Fourier Transformation algorithm was performed to obtain the frequency peaks of axial movement in each video. All the offline processing was performed using MATLAB R2019b.

2) Inertial sensors: The values for acceleration and angular velocities were stored as arrays and computed using the Fast Fourier Transformation algorithm to obtain the corresponding frequency peaks. All the offline processing was also performed using MATLAB R2019b.

C. Statistical Analysis

Spearman-rank tests assessed correlations between the frequency measurements obtained by the three modalities. Test-retest experiments were conducted to obtain the CV of each modality for each individual. Statistical significance was predefined at the P<0.01.

IV. Results

Fig. 3 (a) shows the vectors in the axial direction calculated by the OF algorithm applied to a representative video. Fig. 3 (b-d) shows the comparison of the frequency peaks of axial movement obtained by each modality during three FT sequences performed by one volunteer with raised elbow. Fig. 4 and Fig. 5 show the computed frequency values for the three sequences of FT movements performed by each volunteer with raised elbow and resting elbow, respectively; and analyzed by the accelerometer (a), gyroscope (b) and OF (c). In both figures, (d) shows the values of the CV for the three sequences of FT measured by each modality. Fig. 6 shows the CV of the computed frequency values obtained by the three modalities during each sequence of FT movements. Table I shows the results of the Spearman-rank test analysis.

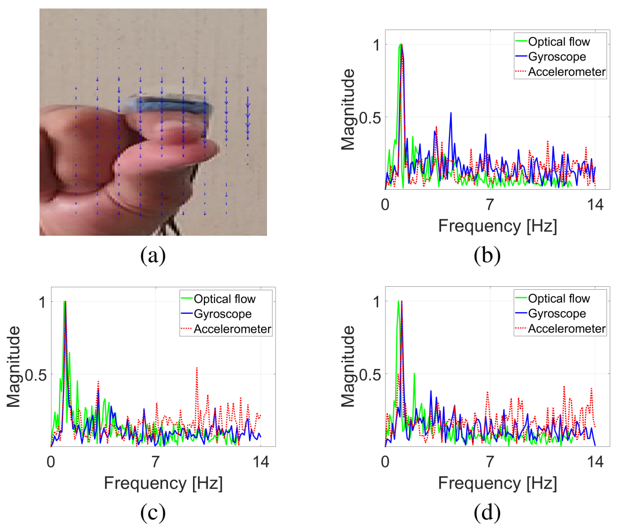


Fig. 3: (a) Representative frame showing the axial vectors produced by the optical flow algorithm. Representative normalized frequency peaks from the (b) first, (c) second and (d) third sequence of finger-tapping movements performed by one of the healthy volunteers with raised elbow.

		Accelerometer	OF
Raising elbow	Accelerometer	-	ρ: 0.81 P: 7.97e(-6)
	Gyroscope	ρ: 0.74 P: 1.12e(-4)	ρ: 0.80 P: 1.56e(-5)
Resting elbow	Accelerometer	-	ρ: 0.70 P: 4.79e(-4)
	Gyroscope	ρ: 0.93 P: 1.32e(-9)	ρ: 0.63 P: 0.0023

TABLE I: Correlations between the frequency estimations obtained by the three modalities during the raising elbow and resting elbow conditions (coefficient ρ) and P-value (P) obtained by the Spearman-rank test.

V. Discussion

In this study, we aimed to 1) develop and pre-test accessible tools and 2) refine protocols for future data acquisition to

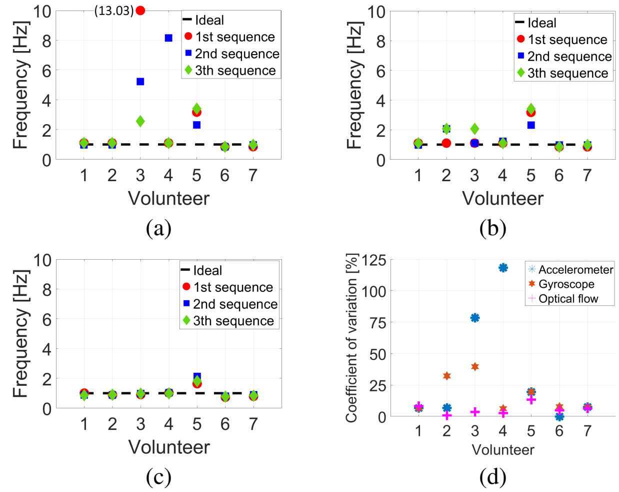


Fig. 4: Maximum frequency values from the three sequences analyzed by (a) accelerometer, (b) gyroscope and (c) optical flow method from each volunteer while raising elbow. (d) Coefficient of variation of the frequency values obtained for each volunteer by the three modalities.

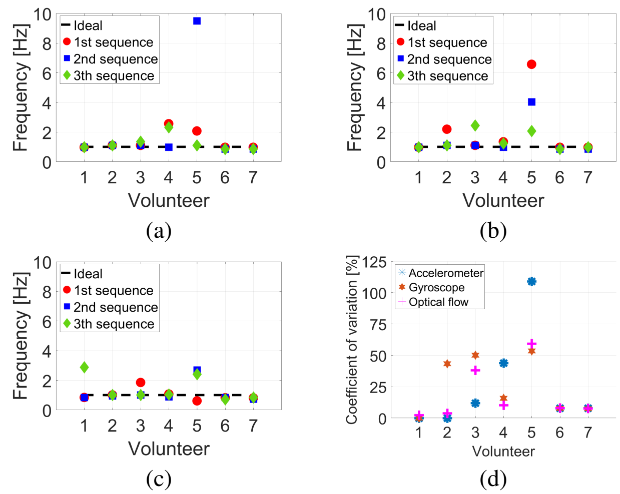


Fig. 5: Maximum frequency values from the three sequences analyzed by (a) accelerometer, (b) gyroscope and (c) optical flow method from each volunteer while resting elbow. (d) Coefficient of variation of the frequency values obtained for each volunteer by the three modalities.

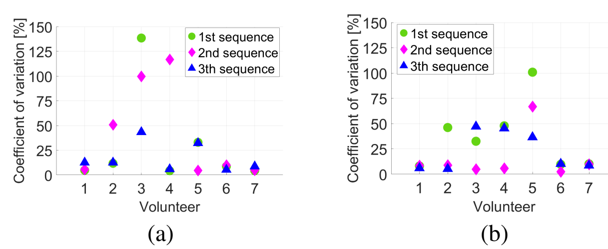


Fig. 6: Coefficient of variation of the frequency values from the three sequences analyzed by each modality while (a) raising elbow and (b) resting elbow.

characterize repetitive FT movements by combining inertial sensors and OF in a controlled environment. Our study was performed in healthy volunteers repeating FT movements at a cued frequency of 1 Hz, however it cannot be guaranteed that this frequency was maintained in all volunteers. The FT experiments were repeated by the same healthy volunteers to compare results in two clinically relevant conditions (raising elbow and resting elbow) while simultaneously using three modalities to estimate the frequency of repetitive FT movements: accelerometer, gyroscope and OF. We found a strong positive (ρ= 0.74-0.81) and significant ($P<0.01$) correlation between the frequency estimations obtained by the three modalities when repetitive FT movements were performed while raising elbow. The OF approach generated precise values in the test-retest experiment. For instance, the maximum CV was 13.32% for volunteer 5. In contrast, both inertial sensors generated high variation in the frequency estimation (maximum CV was 118.19% for volunteer 4 and 39.59% for volunteer 3). This difference could be attributed to the abrupt movement of the fingers during the test, which generates noise peaks in the signals, especially in those obtained by the accelerometer. Future studies could include signal filtering in order to obtain more accurate results for the inertial sensors. When FT movements were performed while resting the elbow, the correlation between the accelerometer and gyroscope modalities was positive and stronger (ρ= 0.93) than that obtained when raising the elbow (ρ=0.74). In comparison, the correlations between inertial sensors and OF, obtained in the resting elbow condition (ρ=0.63-0.70) are not as strong as those found for the raising elbow condition (ρ=0.80-0.81). Regardless of the raising or resting elbow condition, the OF modality generated low CV (Fig. 4 (c), Fig. 5 (c)) in the test-retest experiments when compared to both inertial sensing modalities. We also found that the maximum CV was 108.87% for accelerometer measures and 53.53% for gyroscopic measures (both for volunteer 5). Notably, volunteer 4 had the highest CV result for OF (59.35%). The fact that the variation during each sequence was lower in the resting elbow condition (Fig. 6) could be beneficial when testing patients with PD, who may have difficulties raising their elbow to perform FT movements. In general, our results show that OF, accelerometer and gyroscope measures provide appropriate estimations of the frequency of repetitive FT movements in several sequences. This is in line with previous work that suggests that more than two FT test sequences are necessary to accurately evaluate movement characteristics [13]. These preliminary observations need to be confirmed in larger studies but differences in video acquisition and muscle contraction during each condition could be contributing to the differences we have observed.

VI. Conclusions and Future Work

This comparative analysis shows that combining inertial sensing and computer vision techniques is feasible to characterize the frequency of repetitive FT movements. Future studies will elucidate whether integrating sensor-based and computer vision techniques could refine acquisition protocols to achieve more accurate and quantitative characterization of the frequency and amplitude of FT as part of telehealth applications. These data could then be used to train an algorithm that 1) distinguishes patients with PD from healthy controls and 2) measures changes in the motor manifestations of PD over time.

Acknowledgments

The authors thank Dr. E. Ray Dorsey from the Center for Health and Technology at the University of Rochester, NY, USA, for his guidance. Isabel Camargo and Karlo J. Lizarraga thank the Faculty and trainees of the Neurology Peru-Rochester exchange program (NeuroPro).

References

[1] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel *et al.*, "Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (mds-updrs): scale presentation and clinimetric testing results," *Movement disorders: official journal of the Movement Disorder Society*, vol. 23, no. 15, pp. 2129–2170, 2008.

[2] J. Stamatakis, J. Ambroise, J. Crémers, H. Sharei, V. Delvaux, B. Macq, and G. Garraux, "Finger tapping clinimetric score prediction in parkinson's disease using low-cost accelerometers," *Computational intelligence and neuroscience*, vol. 2013, 2013.

[3] Ç. Barut, E. Kızıltan, E. Gelir, and F. Köktürk, "Advanced analysis of finger-tapping performance: a preliminary study," *Balkan medical journal*, vol. 30, no. 2, p. 167, 2013.

[4] J.-W. Kim, J.-H. Lee, Y. Kwon, C.-S. Kim, G.-M. Eom, S.-B. Koh, D.-Y. Kwon, and K.-W. Park, "Quantification of bradykinesia during clinical finger taps using a gyrosensor in patients with parkinson's disease," *Medical & biological engineering & computing*, vol. 49, no. 3, pp. 365–371, 2011.

[5] R. Langevin, M. R. Ali, T. Sen, C. Snyder, T. Myers, E. R. Dorsey, and M. E. Hoque, "The park framework for automated analysis of parkinson's disease characteristics," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 3, no. 2, pp. 1–22, 2019.

[6] S. Williams, S. D. Relton, H. Fang, J. Alty, R. Qahwaji, C. D. Graham, and D. C. Wong, "Supervised classification of bradykinesia in parkinson's disease from smartphone videos," *Artificial Intelligence in Medicine*, vol. 110, p. 101966, 2020.

[7] B. Soran, J.-N. Hwang, S.-I. Lee, and L. Shapiro, "Tremor detection using motion filtering and svm," in *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*. IEEE, 2012, pp. 178–181.

[8] N. Nemade and V. Gohokar, "Comparative performance analysis of optical flow algorithms for anomaly detection," in *Proceedings of International Conference on Communication and Information Processing (ICCIP)*, 2019.

[9] S. Husseini, "A survey of optical flow techniques for object tracking," B.S. thesis, 2017.

[10] J. L. Adams, K. J. Lizarraga, E. M. Waddell, T. L. Myers, S. Jensen-Roberts, J. S. Modica, and R. B. Schneider, "Digital technology in movement disorders: Updates, applications, and challenges," *Current Neurology and Neuroscience Reports*, vol. 21, no. 4, pp. 1–11, 2021.

[11] E. Dorsey, L. Omberg, E. Waddell, J. L. Adams, R. Adams, M. R. Ali, K. Amodeo, A. Arky, E. F. Augustine, K. Dinesh *et al.*, "Deep phenotyping of parkinson's disease," *Journal of Parkinson's Disease*, no. Preprint, pp. 1–19, 2020.

[12] G. Farnebäck, "Polynomial expansion for orientation and motion estimation," Ph.D. dissertation, Linköping University Electronic Press, 2002.

[13] Á. Jobbágy, P. Harcos, R. Karoly, and G. Fazekas, "Analysis of finger-tapping movement," *Journal of neuroscience methods*, vol. 141, no. 1, pp. 29–39, 2005.