# Accuracy of smartphone video for contactless measurement of hand tremor frequency

Authors:

Stefan Williams MBBS, BSc (1)

Hui Fang PhD (2)

Samuel D Relton PhD (1)

David C Wong PhD (3)

Taimour Alam MBChB (4)

Jane E Alty MD, MA, MBBChir (4, 5)

Affiliations

1. University of Leeds, Leeds Institute of Health Science, Leeds, UK

2. Loughborough University, Department of Computer Science, Loughborough, UK

3. University of Manchester, Division of Informatics, Imaging and Data Science, Manchester, UK

4. Leeds Teaching Hospitals NHS Trust, Leeds UK

5. University of Tasmania, Hobart, Australia

Corresponding Author:

Stefan Williams

Leeds Institute of Health Science, Worsley Building, University of Leeds, Clarendon Way, Leeds, UK LS2 9LU

Phone: 0113 343 0839

umswi@leeds.ac.uk

ORCID: 0000-0002-4786-1356

Word count: 2506

Tables: 1

Figures: 5

Video Figure: 1

Running Title: Contactless Video To Measure Tremor Frequency

Key words: Parkinson’s , Essential Tremor, Functional, Computer Vision, Artificial Intelligence, optical flow

## Abstract

### Background

Computer vision can measure movement from video without the time and access limitations of hospital accelerometry / electromyography, or the requirement to hold or strap a smartphone accelerometer.

### Objective

To compare computer vision measurement of hand tremor frequency from smartphone video with a gold standard measure, accelerometer.

### Methods

37 smartphone videos of hands at rest and in posture, were recorded from 15 participants with tremor diagnoses (9 Parkinson's, 5 Essential Tremor, 1 Functional Tremor). Video pixel movement was measured using the computing technique of optical flow, with contemporaneous accelerometer recording. Fast Fourier Transform and Bland-Altman analysis were applied. Tremor amplitude was scored by two clinicians.

Results

Bland-Altman analysis of dominant tremor frequency from smartphone video compared with accelerometer showed excellent agreement: 95% limits of agreement -0.38 Hz to +0.35Hz. In 36 out of 37 videos (97%) there was <0.5 Hz difference between computer vision and accelerometer measurement. There was no significant correlation between the level of agreement and tremor amplitude.

Conclusion

The study suggests a potential new, contactless 'point and press' measure of tremor frequency within standard clinical settings or telemedicine.

Tremor disorders are common [1], but frequently misdiagnosed. In one report, 37% of essential tremor diagnoses were found to be incorrect [2], and another study showed up to 20% inaccuracy in specialist clinician diagnosis of Parkinson's from standardised videos of tremor patients [3]. The Movement Disorders Society consensus statement on the classification of tremors defines the clinical features on three axes: body distribution, activation condition, and tremor frequency [4]. Of these, tremor frequency is probably the most challenging for clinicians to determine accurately at the bedside. Gold standard neurophysiology with accelerometer and/or electromyography is a limited and time-consuming resource, usually reserved for a subset of patients in specialist hospital settings [5]. Whilst smartphone accelerometers can measure the dominant frequency of hand tremors, the patient must hold the phone or have it strapped in place [6]; and this will potentially alter tremor characteristics.

There remains a need for a clinical tool that provides clinicians with quick objective measurements of tremor frequency, analogous to other bedside measurements in medicine. Computer analysis of video can measure other neurological signs such as finger tapping bradykinesia [7]. In this article we propose a new approach using computer vision tremor analysis [8-11] of smartphone video. One advantage of this is that standard clinical examinations may be recorded without any equipment physically touching the patient, so that they are unaltered by the weight or physical restriction of a measurement tool. In addition to observing more 'natural' tremor from the patient without physical measuring equipment, we anticipate an increase in contactless tools in the coming years due to social changes related to the COVID-19 pandemic and improved infrastructure enabling telemedicine and home-monitoring of disease progression [12]. In this study, we evaluate computer vision applied to smartphone video of hands in tremor disorders and hypothesise that it can quantify dominant tremor frequency in good agreement with accelerometer results.

## Methods

The study was approved by the London-Fulham Research Ethics Committee of the United Kingdom Health Research Authority, IRAS no. 224848.

A convenience sample of 16 patients from Leeds Teaching Hospitals NHS Trust (United Kingdom) participated in the study, with the following established diagnoses: 5 essential tremor, 2 functional tremor, 9 Parkinson's disease. The diagnoses had previously been made in routine clinical practice by movement disorder specialist neurologists, according to Movement Disorder Society guidelines [4,13]. Participants were recruited in order of recent clinic attendance (i.e. there were no special selection criteria). All patients gave written, informed consent for participation.

The participants were seated, and each hand was individually filmed. A resting tremor recording was made with the forearm on the chair arm and the hand suspended over the end, camera facing the dorsum of the hand. A postural tremor recording was made with hand and arm extended horizontally forwards from the shoulder, with the camera in a lateral position. Only those videos with visible tremor were used, making a total of 40 videos.

A smartphone, placed on a tripod, recorded an approximately 60 second video, at 60 frames per second, 1920 x 1080 pixel resolution (standard 'full high definition' smartphone video). Distance from camera to hand was not tightly controlled, but in practice was around 1m, with only the hand and forearm visible within the video frame. An example video frame is shown in **Figure 1**.

Figure 1.

In accordance with standard methods of tremor accelerometry [5], a single axis accelerometer (‘Natus neurology tremor sensor’) was attached to the dorsum of each participant’s hand, aligned with the long axis of the hand. Acceleration was recorded contemporaneously with the video (without an exact time-lock mechanism), at a sample rate of 3.84 kHz.

The first 2 seconds of the video and accelerometer recordings were removed to reduce any voluntary movement artefacts as the patient settled into position. The endings of both recordings were cropped at 60 seconds.

The videos were processed with custom-written MATLAB code [14] that we have made freely available for download at this link: [https://github.com/DrStefanWilliams/tremor-optical-flow]. It allows a bounding box to be manually drawn around the hand region for one frame of each video, together with a line to mark the long axis of the hand, a process that takes approximately 15 seconds for the user to complete. A Histograms of Optical Flow method [15,16] was used to measure the direction and amplitude of pixel movement within the box between pairs of video frames. This converts the region within the bounding box into an optical flow field. Each position within the field corresponds to the vector pixel movement of a point object between two sequential frames. We calculated a time series of the magnitude of pixel movement for two directions perpendicular to the line marking the long axis of the hand, and converted this to a one dimensional time series by subtracting the movement in one direction from that in the opposite direction (for each pair of video frames).

We converted the resultant accelerometer and video time series into the frequency domain using Fast Fourier Transform (FFT) ('scipy.fftpack') within Python [17], and then removed frequencies below 2 Hz (low-frequency drifting movements) and above 14 Hz (higher than hand tremor) from the analysis. Examples of accelerometer and video signal time series and their FFT are shown in **Figure 2**.

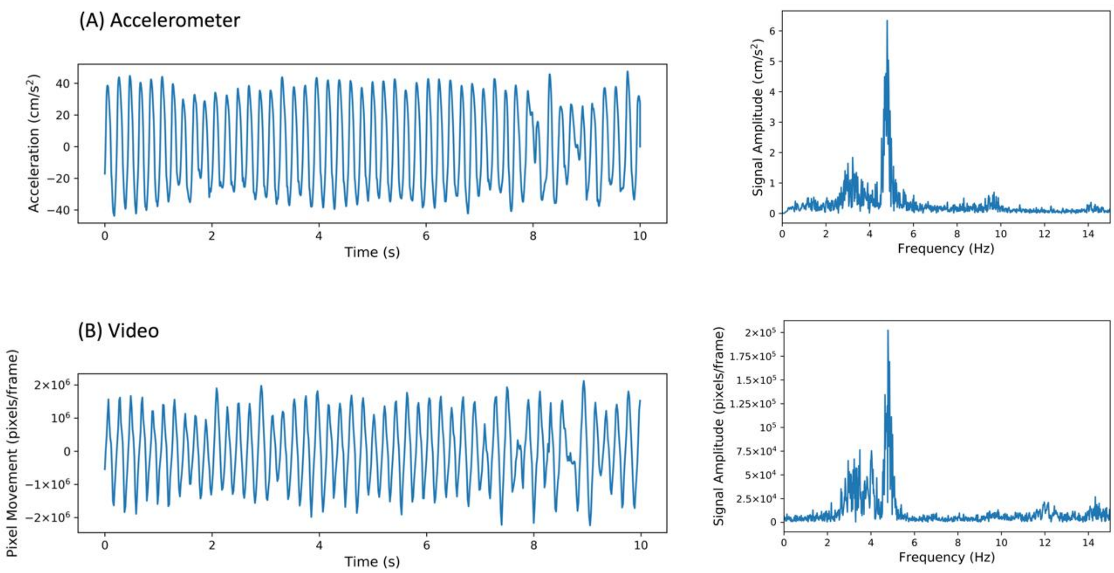


Figure 2

The recordings from one patient with functional tremor showed widely dispersed frequency distributions (on both accelerometer and video derived FFT) for the 60 second recording, without any obvious dominant peaks. This is consistent with the known clinical variability of functional tremor over time (i.e. the frequency can vary greatly over 60 seconds, so that there is no single, consistent, dominant frequency). These 3 recordings were removed from the final analysis.

For the remaining 37 videos, the dominant frequency derived from video was compared with the dominant frequency derived from the accelerometer. We calculated the mean absolute error and undertook a Bland-Altman analysis [18] to provide the bias (mean difference), 95% limits of agreement, and associated confidence intervals. We considered ±0.5 Hz to represent *a priori* clinically acceptable 95% limits of agreement.

A minority of recordings showed two distinct and prominent frequency peaks. We considered a frequency spectrum to have two peaks if a secondary peak was at least 70% of the dominant peak amplitude, and if the frequency of the secondary peak was at least 0.5 Hz from the primary peak, see example in **Figure 3**. Given that clinical assessment of tremor assumes only one dominant frequency, we selected the peak with highest frequency in these scenarios.

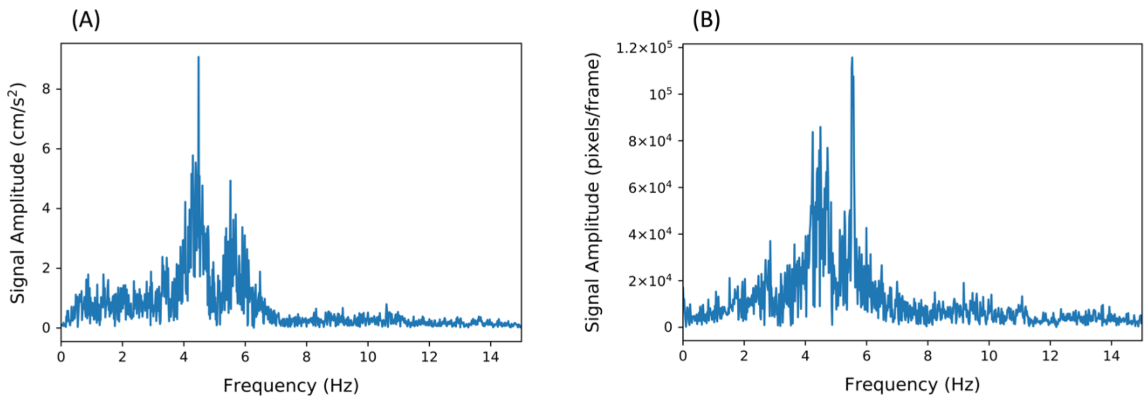


Figure 3.

To test for an inverse correlation between tremor amplitude and the accuracy of tremor frequency derived from video, we undertook two approximate measures of tremor amplitude. The first calculated an approximate measure of movement amplitude from the accelerometer signal. After converting the units from microvolt to cm/s$^2$, we used Python [17] to scale the accelerometer data to have a mean of 0, and then used the midpoint rule to estimate the first integral (velocity), followed by eliminating drift by subtracting the line of best fit (using the ordinary least squares method). We then used the midpoint rule again to estimate the second integral, followed by calculating the standard deviation of mean displacement from the baseline. As a second measure of tremor amplitude, two neurologists (SW, JA) clinically rated postural and rest tremor amplitude from the videos, according to MDS-UPDRS items 3.15 and 3.17 respectively (grade 0 = no tremor, grade 1 = <1cm amplitude, grade 2 = 1-3cm amplitude, grade 3 = 3-10cm amplitude, grade 4 = >10cm amplitude). The median amplitude rating was MDS-UPDRS grade 2 (interquartile range 1-3). Spearman's correlation coefficient was calculated to test for relationships between these amplitude measures and video accuracy (absolute error, Hz).

Results

Participant and video details are given in **Table 1**.

| | Essential tremor | Parkinson's disease | Functional tremor |
|---|---|---|---|
| **Number of participants** | 5 | 9 | 1 |
| **Age (Std. Dev.) years** | 63 (10) | 66 (12) | 41 |
| **M:F** | 1:4 | 7:2 | 0:1 |
| **Resting tremor hand recordings** | 9 | 14 | 2 |
| **Postural tremor hand recordings** | 7 | 5 | 0 |
| **Median dominant accelerometer frequency (IQR), Hz** | 5.5 (5.1-5.9) | 5.4 (4.1-5.9) | 8.0 |

Table 1

The dominant tremor frequencies from video (pixel optical flow) showed a mean absolute error of 0.10 Hz (standard deviation ±0.16 Hz) compared with the accelerometer frequencies. In 36 out of 37 videos (97%) there was less than 0.5 Hz difference between the computer vision and accelerometer frequency measurements. Bland-Altman analysis of the dominant frequencies from video vs accelerometer showed a mean difference (bias) of -0.01 Hz, **Figure 4**. with 95% limits of agreement -0.38 Hz to 0.35 Hz. The 95% confidence intervals for the limits of agreement were -0.48 Hz to -0.31 Hz for the lower limit and 0.28 Hz to 0.46 Hz for the upper limit.

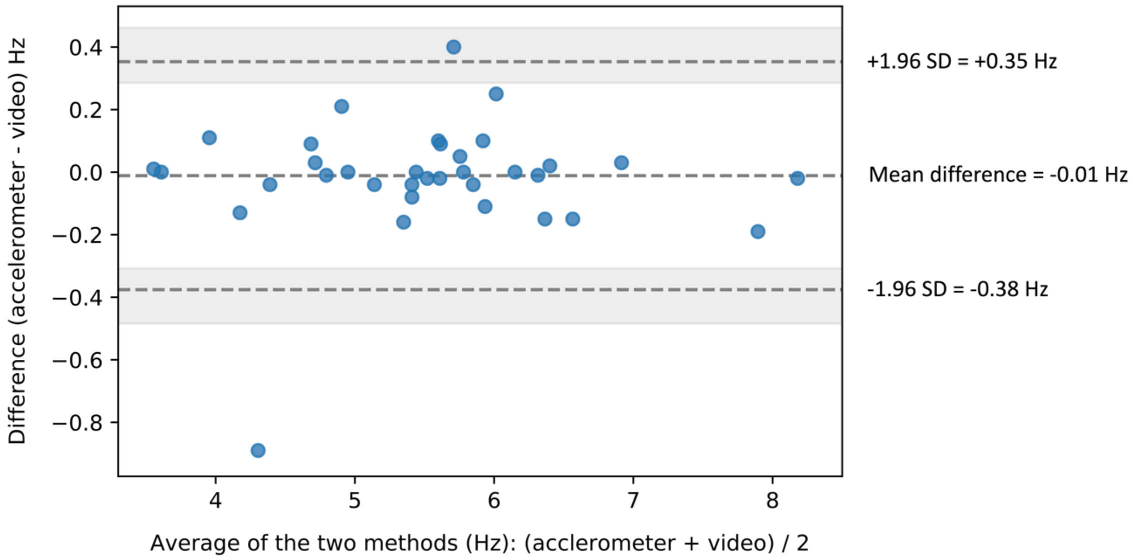


Figure 4.

15 of the 37 videos were rated as <1cm amplitude by both clinician raters (i.e. MDS-UPDRS grade 1 or 0). No significant inverse correlation was found between the absolute error of video tremor frequency (Hz) and tremor amplitude, either measured by clinician amplitude rating (Rater 1: Spearman's rho -0.07, p=0.70; Rater 2: Spearman's rho -0.15, p=0.37) or accelerometer displacement (Spearman's rho 0.25, p=0.14), **Figure 5**. **Video 1** shows an example of two tremors with low amplitude (UPDRS grade 1) in which there was excellent agreement between the video and accelerometer frequencies (6.41 vs 6.39 Hz for the first hand shown in the video, and 5.60 vs 5.62 for the second hand shown in the video).

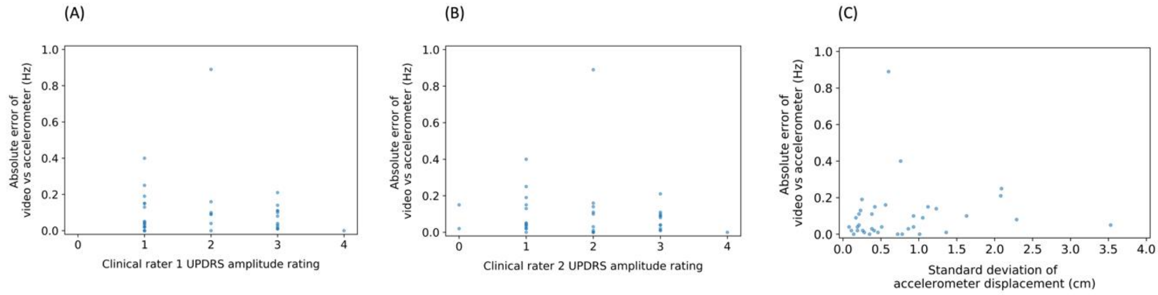


Figure 5.

Discussion

We found that computer vision could measure the dominant frequency of hand tremor from smartphone video, and this showed excellent agreement with a gold standard measure of tremor frequency, accelerometery (95% limits of agreement -0.38 Hz to +0.35 Hz). The method appears to remain accurate across a range of amplitudes with no significant inverse correlation detected between absolute error and tremor amplitude.

Frequency is an important characteristic of tremor, especially to aid diagnostic classification [4,5], but can be challenging to determine accurately. Unlike accelerometers (clinical or within smartphones), our video method is contactless, does not involve specialist equipment or patient interaction with an app, and simply visually records what the clinician sees during a standard neurological examination. The hardware required already exists in the pocket of most clinicians, so that our approach is an equitable one, that bypasses many of the usual cost and geographical barriers. In essence, our method is largely automated, without a need to tightly control camera distance, lighting or background. There are only three manual procedures that are currently inherent to our method: (1) setting the smartphone camera to record video, (2) drawing one bounding box around the hand, and (3) drawing one line for the long axis of the hand. Steps (2) and (3) involve drawing just two items (one box and one line) for a single frame of the video, and even this process could be automated in future work. We would expect our method to detect any oscillatory movement that is visible in the video, regardless of distance of the camera from the body part, because the technique is a measure of pixel movement. Purposefully, we did not tightly constrain the distance between the hand and camera as we recognised that flexibility in this parameter would be important in a clinical setting. If hand pixels are moving in an oscillatory manner, the pixel movement will be detected and the frequency of that oscillation measured.

Contactless tremor measurement using optical flow has recently been described using the (markerless) Microsoft Kinect 3D camera system [19]. However, this method is limited by the need for specialist costly hardware, and inaccuracy in tracking smaller movements, such that tremor smaller than 2cm cannot be reliably detected [19].

Three previous studies reported computer processing of standard video to measure tremor. In 2013, Hemm-Ode et al applied an optical flow algorithm to videos of two patients with hand tremor during Deep Brain Stimulation (DBS) and found “similar trends” in optical flow and accelerometer [20]. However the authors did not report any quantitative (Hz) measurement of tremor frequency and no summary statistics were provided. A second study measured change in one-dimension, by sampling pixel colour oscillation at static points to give tremor frequency, and showed results comparable with ours (<0.5 Hz difference in 94% of samples) [10]. The advantage of our technique that tracks pixel movement in two dimensions is that it allows potential future measurement of direction, magnitude change, and movement beyond simple tremor. The third previous publication in this area described measurement of tremor during superimposed large amplitude movement [11]. However, it used a more complex technique than ours that required human video labelling of multiple frames to train the computer to reliably detect hands, and agreement with accelerometer was considerably lower than our results (mean absolute error of 1.066 Hz for postural tremor and 1.253 Hz for rest tremor).

Our study has several limitations. Although 37 distinct videos were used (varying by participant, hand, rest/posture), the participant group was small, so we cannot yet be sure that the findings would generalise to a wider population. Although no significant inverse correlation was found between error and amplitude, we cannot rule out the possibility that a significant correlation might emerge in a larger or more diverse sample. Measurement of tremor frequency is most useful when paired with electromyography [21,22], and camera-based computer vision cannot yet measure muscle contraction. However, determining frequency alone can be useful, e.g. by demonstrating variation of tremor frequency over time in functional tremor [5], a potential future application of our technique (combined with Short-time Fourier Transform) [9]. A camera measurement is two dimensional and, similar to single axis (one dimensional) clinical accelerometer, movements exactly perpendicular to the camera angle potentially may not be recorded, but this could be rectified by moving the camera to a different angle [5]. Two dimensional video cannot measure absolute tremor amplitude but in principle the relative amplitude (e.g. in relation to finger width), or change in amplitude over time, could be derived from pixel movement in future work. We have not quantified the lower limits of amplitude for detection of tremor frequency using our method, but optical flow is known to be sensitive to small amplitude movement in standard video (provided there is not additional movement 'noise' in the background of the video frame), e.g. [23]. It is notable that 15 of 37 videos were rated as <1cm amplitude, and we did not find any significant relationship between tremor amplitude and video measure accuracy in our current sample. Finally, a tripod is not available in ordinary clinical settings, but smartphone cameras use image stabilisation software and in the future our method could include labelling of a static background reference point, or combination with hand tracking algorithms [24].

For several recordings, the frequency distribution showed two distinct peaks of similar height (power), with each being slightly higher than the other in video vs accelerometer measures. This is consistent with the recognition that tremor can have more than one contributing component with distinct frequencies [5]. However, to allow simple comparison of single number results, we selected the highest frequency peak in these situations. A future approach could perhaps provide a two frequency result to provide more detailed clinical information

In summary, we have described a simple method to measure hand tremor frequency from a 60 second smartphone video that shows good agreement with accelerometer measurements and has the potential to provide a 'point and press' contactless measure of tremor frequency within standard clinical settings.

Author Roles

1) Research Project: A. Conception, B. Organization, C. Execution
2) Statistical Analysis: A. Design, B. Execution, C. Review and Critique

3) Manuscript: A. Writing of the first draft, B. Review and Critique

Stefan Williams: 1A, 1B, 1C, 2B, 3A, 3B

Hui Fang: 1A, 1B, 1C, 2A, 2B, 2C, 3B

Samuel D Relton : 1A, 1B, 1C, 2A, 2B, 2C, 3A, 3B

David C Wong: 1A, 1B, 1C, 2A, 2B, 2C, 3B

Taimour Alam: 1A, 1B, 1C, 3B

Jane E Alty: 1A, 1B, 1C, 2C, 3A, 3B

Ethical Compliance Statement

- The study was approved by the London-Fulham Research Ethics Committee of the United Kingdom Health Research Authority, IRAS no. 224848.
- Informed consent was obtained from all participants.
- We confirm that we have read the Journal’s position on issues involved in ethical publication and affirm that this work is consistent with those guidelines.

Disclosures

Funding Sources and Conflicts of Interest:

No specific funding was received for this work. The authors declare that there are no conflicts of interest relevant to this work.

Financial Disclosures (for the previous 12 months):

Hui Fang received grant funding from National Institute for Health Research (NIHR). Samuel D Relton received a Wellcome Trust fellowship and grant funding from NIHR. Jane E Alty received: honoraria from Allergan, Abbvie, and The Hunter Postgraduate Medical Institute; royalties from Taylor and Francis Group; grant funding from Fight MND and Sunovion; and stock ownership from ClearSky medical diagnostics Ltd. Stefan Williams and Taimour Alam have no disclosures to report.

## References


1. Louis ED, Ottman R. How many people in the USA have essential tremor? Deriving a population estimate based on epidemiological data. *Tremor Other Hyperkinet Mov (N Y)*. 2014;4:259. doi:10.7916/D8TT4P4B

2. Jain S, Lo SE, Louis ED. Common Misdiagnosis of a Common Neurological Disorder. *Arch Neurol*. 2006;63(8):1100. doi:10.1001/archneur.63.8.1100

3. Bajaj NP, Gontu V, Birchall J, Patterson J, Grosset DG, Lees AJ. Accuracy of clinical diagnosis in tremulous parkinsonian patients: a blinded video study. Journal of Neurology, Neurosurgery & Psychiatry. 2010 Nov 1;81(11):1223-8.

4. Bhatia KP, Bain P, Bajaj N, et al. Consensus Statement on the classification of tremors. from the task force on tremor of the International Parkinson and Movement Disorder Society. *Mov Disord*. 2018;33(1):75-87. doi:10.1002/mds.27121

5. Vial F, Kassavetis P, Merchant S, Haubenberger D, Hallett M. How to do an electrophysiological study of tremor. *Clin Neurophysiol Pract*. 2019;4:134-142. doi:10.1016/j.cnp.2019.06.002

6. Joundi RA, Brittain JS, Jenkinson N, Green AL, Aziz T. Rapid tremor frequency assessment with the iPhone accelerometer. *Park Relat Disord*. 2011;17(4):288-290. doi:10.1016/j.parkreldis.2011.01.001

7. Williams S, Zhao Z, Hafeez A, et al. The discerning eye of computer vision: Can it measure Parkinson's finger tap bradykinesia? J Neurol Sci 2020;416:117003. doi:10.1016/j.jns.2020.117003

8. Soran, B., Hwang, J., Lee, S., Shapiro, L.: Tremor detection using motion filtering and svm. In: ICPR. pp. 178–181 (2012)

9. Williams S, Shepherd S, Fang H, Alty J, O'Gorman P, Graham CD. Computer vision of smartphone video has potential to detect functional tremor. *J Neurol Sci*. 2019;401:27-28. doi:10.1016/j.jns.2019.04.016

10. Uhríková Z, Sprdlík O, Hoskovcová M, Ulmanová O, Hlavá V, Nugent CD. Validation of a new tool for automatic assessment of tremor frequency from video recordings. *J Neurosci Methods*. 2011;198:110-113. doi:10.1016/j.jneumeth.2011.02.033

11. Pintea SL, Zheng J, Li X, Bank PJ, van Hilten JJ, van Gemert JC. Hand-tremor frequency estimation in videos. In *Proceedings of the European Conference on Computer Vision (ECCV) 2018*

12. Papa SM, Brundin P, Fung VSC, Kang UJ, Burn DJ, Colosimo C, Chiang HL, Alcalay RN, Trenkwalder C. Impact of the COVID-19 Pandemic on Parkinson's Disease and Movement Disorders. *Mov. Disord.* 2020; 1–6. https://doi.org/10.1002/mds.28067.

13. Postuma RB, Berg D, Stern M, et al. MDS clinical diagnostic criteria for Parkinson's disease. *Mov Disord*. 2015;30(12):1591-1601. doi:10.1002/mds.26424

14. MATLAB Release 2017b. The MathWorks Inc. Massachusetts, USA.

15. Chaudhry R., Ravichandran A., Hager G., and Vidal R. Histograms of oriented optical flow and Binet–Cauchy kernels on nonlinear dynamical systems for the recognition of human actions. *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*. 2009; 1932–1939.

16. Wong DC, Relton SD, Fang H, Qhawaji R, Graham CD, Alty J, Williams S. 2019. Supervised Classification of Bradykinesia for Parkinson's Disease Diagnosis from Smartphone Videos. *CBMS2019: IEEE 32nd International Symposium on Computer-Based Medical Systems* 2019, pp. 32-37

17. Python Software Foundation, https://www.python.org/

18. Altman DG and Bland JM. Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet* 1986; 1: 307–310.

19. Alper MA, Goudreau J, Daniel M. Pose and Optical Flow Fusion (POFF) for accurate tremor detection and quantification, *Biocybern. Biomed. Eng.* 2020; 40: 468–481.

20. Hemm-Ode S, Wettmann P, Kistler B, Behm P, Schkommodau E, Coste J, Lemaire J, Shah A, Intraoperative optical flow based tremor evaluation - a feasibility study, *Biomed. Tech.* 2013; 58: 1–2.

21. Elble RJ, McNames J. Using portable transducers to measure tremor severity. *Tremor and Other Hyperkinetic Movements*. 2016;2016:1-12. doi:10.7916/D8DR2VCC

22. Hess CW, Pullman SL. Tremor: clinical phenomenology and assessment techniques. *Tremor Other Hyperkinet Mov*. 2012;2:1-15. doi:10.7916/D8WM1C41

23. Y. Liu, J. Zhang, W. Yan, S. Wang, G. Zhao and X. Fu, "A Main Directional Mean Optical Flow Feature for Spontaneous Micro-Expression Recognition," in *IEEE Transactions on Affective Computing*, vol. 7, no. 4, pp. 299-310, 1 Oct.-Dec. 2016

24. Dibia V, Real-time Hand-Detection using Neural Networks (SSD) on Tensorflow. 2017. GitHub repository, https://github.com/victordibia/handtracking

Legends

**Figure 1**. Example frame from smartphone video of resting tremor.

**Figure 2**. Examples of time series and frequency domain after fast Fourier transform, for (A) accelerometer (dominant frequency 4.79 Hz) and (B) video (dominant frequency 4.80 Hz). (Video signal derived from pixel movement via Histograms of Optical Flow method.)

**Figure 3.** Example of frequency distributions (Fast Fourier Transform) with two peaks. The two peaks show the same frequencies in accelerometer and video, but each has a slightly higher power than the other in the alternative methods of measurement. (A) Accelerometer shows a first dominant peak of 4.47 Hz and a second dominant peak of 5.51 Hz; (B) video shows a first dominant peak of 5.53 Hz and a second dominant peak of 4.49 Hz. The

distributions and dominant frequencies are very similar. Where a second dominant peak was >70% the size of the first dominant peak (and separated by >0.5 Hz), we compared the highest frequency peak of the two in both methods of measurement (in this case 5.51 Hz and 5.53 Hz).

**Table 1.** Summary of Participant Characteristics (IQR = Interquartile Range)

**Figure 4.** Bland-Altman Plot showing the agreement between tremor measurements derived from video (pixel optical flow) and accelerometer. Dashed horizontal lines show mean difference (bias) and the 95% limits of agreement. Grey bands show the 95% confidence intervals for the limits of agreement. The relative outlier (0.89 Hz difference) was a Parkinson's hand at rest.

**Figure 5.** No significant inverse correlations were found between the absolute error of video tremor frequency and measures of tremor amplitude. Y axes show absolute error of video tremor frequency (the difference between video and accelerometer tremor frequency, Hz). X axes on graphs (A) and (B) show the grade of tremor amplitude rated by two neurologists ('rater 1' and 'rater 2'), using MDS-UPDRS items 3.15 for postural tremor and 3.17 for rest tremor (grade 0 = no tremor, grade 1 = <1cm amplitude, grade 2 = 1-3cm amplitude, grade 3 = 3-10cm amplitude, grade 4 = >10cm amplitude). The x axis on graph (C) shows the standard deviation of mean accelerometer displacement from baseline. Spearman's rho and p values for each graph: (A) rho -0.07, p=0.70; (B) rho -0.15, p=0.37; (C) rho 0.25, p=0.14.

**Video 1.** Two examples of smartphone video showing low amplitude tremor and excellent agreement between accelerometer and video (pixel optical flow) measures of tremor frequency