Assessing motor skills in Parkinson's Disease using smartphone-based video analysis and machine learning

Andreas Stergioulas
andrster@iti.gr
Information Technologies Institute, Centre for Research and Technology Hellas
Thessaloniki, Greece

Sofia Balula Dias
CIPER, Faculdade de Motricidade Humana/Universidade de Lisboa
Lisbon, Portugal
sbalula@fmh.ulisboa.pt

Beatriz Alves
Faculdade de Motricidade Humana/Universidade de Lisboa
Lisbon, Portugal
ft.beatriz.alves@gmail.com

Ghada al Hussein
Faculdade de Motricidade Humana/Universidade de Lisboa
Lisbon, Portugal
Khalifa University of Science and Technology
Abu Dhabi, UAE
Ghada.alhussein@ku.ac.ae

Sevasti Bostantjopoulou
Third Neurological Clinic, Papanikolaou Hospital
Thessaloniki, Greece
bostkamb@otenet.gr

Zoi Katsarou
Third Neurological Clinic, Papanikolaou Hospital
Thessaloniki, Greece
katsarouzoe@gmail.com

Ioannis Dagklis
Third Neurological Clinic, Papanikolaou Hospital
Thessaloniki, Greece
gdag2005@yahoo.gr

Nikos Grammalidis
Information Technologies Institute, Centre for Research and Technology Hellas
Thessaloniki, Greece
ngramm@iti.gr

Kosmas Dimitropoulos
Information Technologies Institute, Centre for Research and Technology Hellas
Thessaloniki, Greece
dimitrop@iti.gr

ABSTRACT

Parkinson's disease (PD), the second most prevalent neurodegenerative condition, lacks a cure, but its symptoms can be managed. Its complex diagnosis and assessment need ongoing monitoring, highlighting the potential use of digital assessment tools for enhancing patient management, even outside the clinical settings. In this vein, this paper proposes a smartphone-based video analysis approach for assessing motor skills, particularly balance and posture, in individuals diagnosed with PD. In particular, the Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) ratings for items "3.8" (leg agility), "3.9" (arising from chair),"3.13" (posture) and "3.10" (gait) are estimated by capturing and analysing video from PD patients, while performing a Comprehensive Motor Function Test. Specifically, a 3D pose landmark detection (skeleton extraction) model based on the the MediaPipe Machine Learning Platform is used and different motion features are estimated from the captured videos that may correlate with the MDS-UPDRS assessments provided by clinicians. A machine learning pipeline (evaluating five different ML classifiers) is then proposed to examine the feasibility of using these features for monitoring the balance and posture of PD patients. Experimental results, obtained using a cohort of 17 Greek PD patients, voluntarily participating in this study, demonstrate that certain features have significant correlation with the clinical MDS-UPDRS ratings. These promising results showcase the potentiality of digital assessment to provide objective representation of the PD patient's motor skills, supporting both PD clinical assessment and self-management. Ongoing work within the AI-PROGNOSIS project will further validate these findings within a larger cohort and from additional countries.

CCS CONCEPTS

• **Applied computing** → **Consumer health**; **Health informatics**.

KEYWORDS

Parkinson's disease, Motor skills assessment, Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS), AI-PROGNOSIS, MediaPipe, Machine learning

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1 INTRODUCTION

The incidence of Parkinson's disease (PD), a progressive neurodegenerative disorder, is rapidly increasing, making it the fastest-growing neurological condition. PD manifests with a variety of motor symptoms, such as bradykinesia, dyskinesia, tremors, and gait abnormalities [1]. The World Health Organization (WHO) estimates that just in 2019, PD caused more than 300,000 deaths and around 6 million disability-adjusted life years (DALYs) [2]. Unfortunately, there is currently no cure for PD; however, with effective symptom management, individuals with the condition can greatly enhance their quality of life (QoL) [3]. Accurately identifying the motor symptoms of PD has been considered crucial for optimizing treatment choices and guiding clinical judgment [4]. The two primary clinical assessment tools currently utilized are the Unified Parkinson's Disease Rating Scale [5] and its modified version, the MDS-UPDRS [6, 7], developed by the Movement Disorder Society (MDS). These tests have been used to evaluate both motor and non-motor symptoms in PD. Other scales used by clinicians include the modified Bradykinesia rating scale (MRBS) [8], and the WHIGET Tremor Rating Scale [9]. Nevertheless, these tests tend to be subjective and lack granularity which can cause ratings to vary [10–12]. In addition to that, they rely on observations made within clinical settings, which may cause them to miss symptom variations and introduce errors when measuring symptoms outside of these settings [13, 14]. Considerable efforts have been made to address the shortcomings of conventional assessment methods and enhance the monitoring and evaluation of motor symptoms related to PD using digital technologies [13]. Digital assessment techniques, such as wearables, motion sensors, and smartphone apps, offer the possibility of objective, continuous motor function monitoring in both clinical and daily situations [15]. These tools have the potential to fundamentally change the management of PD by offering real-time data on symptom severity and progression. This enables tailored therapy, assessment, and early intervention strategies. The current study is part of the AI-PROGNOSIS Horizon Europe research initiative (https://www.ai-prognosis.eu/), which aims to advance digital tools using artificial intelligence for PD risk assessment and prognosis. Specifically, our approach involves utilizing smartphone-based video analysis to assess motor skills, focusing on aspects, such as balance and posture, in individuals with PD. By evaluating video data captured during a Comprehensive Motor Function Test, we aim to provide clinicians with objective assessments of motor function that correlate with traditional clinical evaluations. The rest of this paper is structured as follows: Section 2 presents the related work, outlining existing literature on the topic. Section 3 describes the methodologies employed and provides information about the study participants and experimental setup. Section 4 presents the results and the discussion, while Section 5 concludes the article.

2 RELATED WORK

The advent of digital tools for PD assessment contributes to the growing body of research that looks at how technology might improve the management of the condition. Previous studies indicate that tracking PD patients' motor symptoms, medication compliance, and disease progression can be accomplished effectively and practically using a variety of digital approaches, including wearable sensors, smartphone apps, and telemedicine platforms [16]. Research has demonstrated, for instance, that wearable sensors are capable of precisely measuring gait characteristics and identifying alterations in motor function linked to PD [17, 18]. Smartphone applications that assess tremor severity and medication response in real time have integrated motion analysis algorithms, providing useful information to clinicians and patients alike [16]. On the other hand, telemedicine systems allow for remote consultations and monitoring, which makes it easier for people living in remote or underserved locations to get specialized treatment [19]. Using digital technologies into PD assessment is one way to improve patient outcomes and clinical practice. Through the use of data analytics, machine learning, and remote monitoring, researchers and doctors can obtain a more profound understanding of how PD develops and customizes treatment plans to each patient's specific requirements. Inexpensive sensors, such as cameras and smartphones hold promise for home-based monitoring, as highlighted by [20, 23]. Recent advancements include the development of intelligent motor assessment tools and depth camera-based systems (e.g., Microsoft Kinect) for differentiating PD stages and to capture body motion [20–22, 24]. Additionally, smartphone-based depth sensors and skeleton tracking in three-dimensional space, have shown promise, offering enhanced precision and accuracy in motion analysis [25]. Video recording, coupled with pose estimation tools, such as AlphaPose, has also been utilized to extract human joint coordinates [25, 26]. However, to fully realize the potential of digital health solutions for PD management, continued research and collaboration in this sector are needed. Building upon these technical developments, the present study aims to investigate balance and posture assessment in individuals with PD. We focus on important MDS-UPDRS items that are essential for assessing motor symptoms, such as leg agility, rising from a chair, walking, and posture, by using smartphone-based video analysis. These particular motor items are important markers of posture and balance that are closely related to the key motor aspects of PD. These selected items focus on balance and posture, which are fundamental motor features affected by PD [27]. Through the use of modified MDS-UPDRS-related motor tests and the examination of patient videos taken during a Comprehensive Motor Function Test, we aim to obtain a more sophisticated knowledge and precise approximation of corresponding scores for these motor assessment items. The proposed approach represents a significant advancement in the assessment of this complex movement disorder beyond the limitations of traditional clinical settings. It also holds promise for enhancing the accuracy of PD assessment while simultaneously increasing accessibility for patients.

3 METHODOLOGY

A smartphone-based video analysis approach was designed for assessing motor skills, particularly focused on the assessment of balance and posture of individuals diagnosed with PD. More specifically, the approach focuses on the automated assessment of specific items (tests) from the MDS-UPDRS [6, 7], namely "item 3.8" (leg agility), "item 3.9" (arising from chair), "item 3.10" (gait), and "item 3.13" (posture), as shown in Figure 1. To facilitate the execution of the tests for PD patients, as well the motion capturing procedure, patients were instructed to perform four motor tests. The MDS-UPDRS guidelines were followed as closely as possible; however, some minor changes were inevitably required, as in a self-test case, the patient may have to capture the video alone, without support from a carer or physician. The following outlines the description of the four items encompassed within the proposed Comprehensive Motor Function Test (CMFT):

- Leg agility (item 3.8): Initially, the patient should sit in a straight-backed chair with arms and has both feet comfortably on the floor. The patient should then raise and stomp each foot (first the left foot and then the right) on the ground 10 times as high and as fast as possible.
- Arising from chair (item 3.9): Then the patient should cross his/her arms across the chest and try to stand up. If the patient is not successful, s/he should try to repeat this attempt up to a maximum of two more times, and if s/he is still unsuccessful, he/she can try to push off using her/his hands on the arms of the chair.
- Posture (item 3.13): After the patient stands up, s/he is asked to stand still for 5 seconds, so that her/his posture can be assessed.
- Gait (item 3.10): After completing the posture test, the patient should take 3 steps away from the chair, then turn around and return towards the chair, taking again 3 steps. Although the original MDS-UPDRS test requires the patient to walk for at least 10m, this test was adapted due to the limited field of view of the camera in the selected camera set-up, described below.

The video recording of the PD patient executing the CMFT described above can be conducted either by the PD patients themselves (self-capture) or with assistance from another individual, such as a family member or caregiver. An overview of the proposed approach is illustrated in Figure 2.

More specifically, the video recording of the patient performing an MDS-UPDRS item is first split into individual frames followed by a 3D Pose Landmark detection in each frame. Based on the detected landmark locations, a set of angles between specific body joints are computed for each frame, yielding a set of angle time-series. The next steps include a) preprocessing of these time-series, b) feature extraction, c) selection of features that exhibit high correlation with the provided medical assessment and, finally, d) a Machine Learning classifier that has been trained to yield an estimated assessment score. These steps are further elaborated in the following subsections.

3.1 Video analysis

The video of each PD patient is first automatically processed to extract relevant angle time series. More specifically, the video is first split into individual frames and then in each frame a set of body landmark locations (e.g. joints) are identified (Figure 1). Towards this goal, the MediaPipe Pose Landmarker task of the latest version of Google MediaPipe software was used to identify 33 key 3-D body locations ("pose landmarks"). According to the MediaPipe documentation [28], the software uses a variant of the BlazePose model based on GHUM, a 3D human shape modeling pipeline, to estimate the full 3D body pose of an individual in images or videos. The model employs a convolutional neural network similar to MobileNetV2 and is optimized for on-device, real-time fitness applications.

In this work, we opted for features based exclusively on angles formed between specific joints (skeleton bones), so as to decrease dependency on factors such as a) camera angle, b) distance of patient from the camera, and c) human body size/shape variations. Hence, for each assessment item, a set of relevant angles were identified, as shown in Table 1. These angles were computed in each frame from the detected 3-D coordinates of the indicated joints(bones).

Table 1: Angles used as features for each item included in the CMFT

Item	Angle(s) used
3.8L(left foot)	KNEE_L (HIP_L-KNEE_L and KNEE_L-ANKLE_L bones)
3.8R(right foot)	KNEE_R (HIP_R-KNEE_R and KNEE_R-ANKLE_R bones)
3.9	HIP_C (SHOULDER_C-HIP_C and HIP_C-KNEE_C bones)
3.13	HIP_C (SHOULDER_C-HIP_C and HIP_C-KNEE_C bones)
3.10F(forward), 3.10B(backwards)	BETWEEN_LEGS (HIP_C-KNEE_L and HIP_C-KNEE_R bones), SHOULDER_L(HIP_L-SHOULDER_L and SHOULDER_L-ELBOW_L bones), SHOULDER_R(HIP_R-SHOULDER_R and SHOULDER_R-ELBOW_R bones)

3.2 Preprocessing and feature extraction

As described in subsection 3.1, the video analysis pipeline yields a set of angle time series for each assessment item, which are then preprocessed and used to compute a set of features that may have correlations with the corresponding clinical scores. Regarding preprocessing, a low-pass filter was used to remove high frequencies, thus compensating both for a) MediaPipe pose detection errors, and b) any kinetic tremor effects that, according to the physicians, should not affect the UPDRS score. Since the video frame rate used is 30 fps, an optimal cutoff value of 8Hz was determined experimentally, as it was seen to provide improved estimation results. Also, for normalization purposes, the mean value (DC term) is subtracted from each time series.

A set of 27 features are then computed, as summarized and categorised in Table 2, from each of these time series. More specifically, the first three categories include simple features computed directly from the time series, such as the minimum. maximum, mean, standard deviation, median, range (i.e., max-min) and interquartile range. In addition, similar features are extracted from the first and second derivatives of each time series, i.e., the angular speed and acceleration, respectively. Five additional features are obtained after transforming the time series in the frequency domain, namely i) the dominant frequency, ii) the corresponding dominant frequency magnitude, iii) the dominant frequency ratio (i.e., ratio of

Figure 1: The proposed CMFT including the MDS-UPDRS items for assessing motor skills: item 3.8 (Leg agility), item 3.9 (Arising from chair), item 3.10 (Gait), and item 3.13 (Posture).

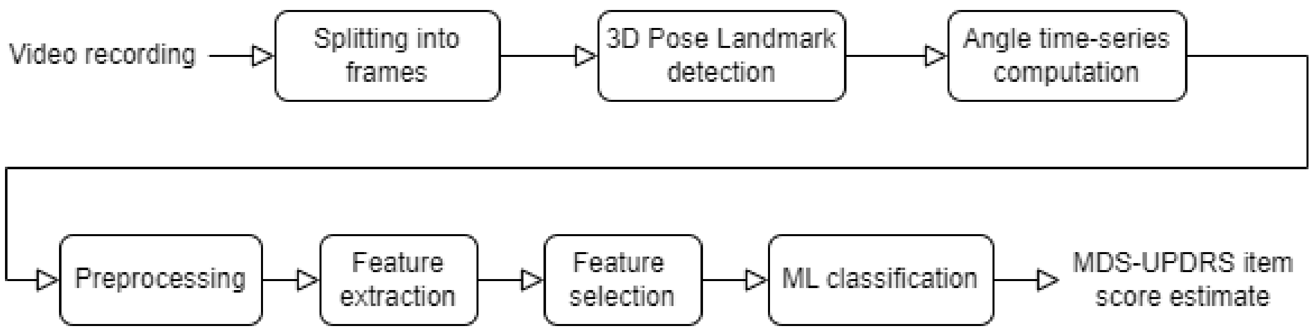


Figure 2: Overview of the proposed motor skill assessment approach

Table 2: Features (27 in total) that are computed from each angle time series

Category	Features
Angle features (5)	Min, max, mean, standard deviation (SD), range (i.e., max-min)
Speed features (6)	Min, max, mean, standard deviation (SD), median, interquartile range (iqr)
Acceleration features (6)	Min, max, mean, standard deviation (SD), median, interquartile range (iqr)
Frequency domain features (3)	Dominant frequency, dominant frequency magnitude, dominant frequency ratio
Spectral features (2)	Spectral entropy, spectral flatness
Additional angle features (5)	signal_rms (root mean square), signal_entropy, jerk_metric, iqr_of_autocovariance, mean_cross_rate

energy in the dominant frequency component to the total energy of the signal), iv) spectral entropy (obtained from the power spectrum using the standard formula for entropy calculation), and v) the spectral flatness (calculated by dividing the geometric mean of the power spectrum by the arithmetic mean of the power spectrum). Finally, five additional angle features that measure signal complexity are used, i.e., i) the rms (root mean square), ii) entropy (using the standard formula for entropy calculation), iii) a jerk metric, iv) the interquartile range of the angle autocovariance, and v) the mean (zero) cross rate. Note that for gait items, where features from three time series are extracted (see Table 2), the corresponding three feature vectors are concatenated together.

3.3 Feature selection and ML classification

Given the feature vectors computed for each item, as described in the previous section, the objective is to train different ML classifiers to accurately predict the clinical assessment scores provided by the expert physicians. Five ML classifiers were trained for this Task, namely i) K-Nearest Neighbours (KNN), ii) Support Vector Machines (SVM), iii) Random Forest (RF), iv) PCA+KNN, and v) sPCA(Supervised PCA, [29])+KNN. The Leave-One-Out cross validation approach was used however, as initial results from all classifiers were not satisfactory, an additional feature selection step was employed to identify a subset of N features that have the largest correlation with the corresponding clinical scores. This additional step was seen to significantly improve performance for all ML classifiers. Furthermore, a grid search procedure was employed to optimise important hyper-parameters in each ML classifier, resulting to further performance gains.

4 EXPERIMENTAL RESULTS

4.1 Study participants

A cohort of 32 Greek PD patients from the "Thessaloniki Parkinson Patients and Friends Association" (Greece) voluntarily participated in this study. All participants signed a consent form in order to participate in the study. We have recorded these PD patients as they performed the Comprehensive Motor Function Test, however 15 of these recordings were discarded due to various reasons (e.g., camera setup different that the one described, patient moved outside the field of view, freezing of gait, etc.), yielding 17 valid videos for our experiments. Regarding the cohort demographics for the final cohort of patients used, there were 5 female participants (age: 71.4±5 years, mean disease duration 17.4 years) and 12 male (age: 72.1±8.9 years, , mean disease duration 9.2 years). Two independent, annotations for these videos (for each motor item) were provided by two expert physicians from the Thessaloniki Papanikolaou Hospital (Greece).

4.2 Experimental setup

Within AI-PROGNOSIS framework, a smartphone application (supporting Android and iOS devices) will be developed for monitoring different PD symptoms and/or tracking of key PD progression markers in daily living. This mobile app will include a module and Graphical User Interface (GUI) to assist the user in performing the capture of the video to assess progression of these motor tests. However, since this module is currently under development, all videos using the smartphone camera app were captured after placing the smartphone on a static location (e.g., tripod). In order to maximise the field of view, we used an angle of approximately 45^o between the camera axis and the movement of the patient, as shown in Figure 3. Although it is possible to record one video for each assessment item, in this work, we recorded instead a single video that includes the sequence of all items in the following order: 3.8L(left foot), 3.8R(right foot), 3.9, 3.13, 3.10F(forward), 3.10T(turn), 3.10B(backwards). This simplifies the recording procedure, also making it easier for the PD patients, but requires an additional segmentation step, where each recorded video is split into segments corresponding to each item by manually identifying the first and last frame of each segment.

4.3 Results

Figure 4(a-b) illustrates the computed knee angle time series for item 3.8L (left leg agility) for two PD patients with different assessment item scores (1 vs. 3). As seen, there is a significant difference in motion smoothness: slowing and interruptions of movement can be observed in Figure 4(b), which are also important cues used by physicians for clinical assessment.

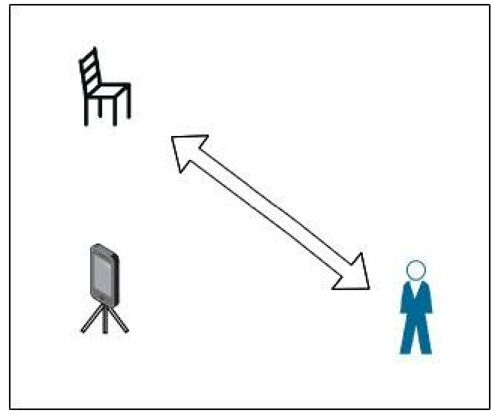


Figure 3: Video Capture setup

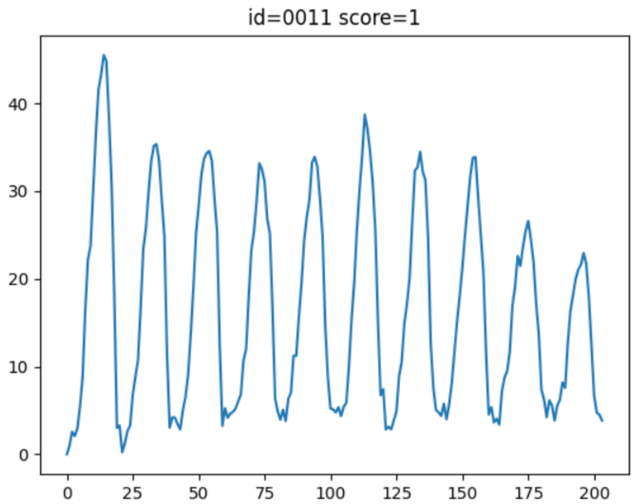
Table 3 presents the average weighted F1 scores for all assessment items and ML classifiers using Leave One Out cross validation. As explained in Subsection s:MLclassifier, a feature selection approach was used in all cases to select features with highest correlation with the clinical scores (an optimal number of three features ($N = 3$) was experimentally determined to maximise performance, except for gait assessment items 3.10F and 3.10B where we use $N = 9$). For instance, for item *3.8L*, the three features selected were *speed SD, speed iqr* and *speed min*, all having correlation factors higher than 0.75. This feature selection is in line with the corresponding clinical assessment criteria (evaluation of any speed variations, such as slowing or interruptions). As seen from Table 3, best results for most items are obtained using the KNN (Nearest Neighbor) approach (where optimal K values is usually 2 or 3). Results for gait assessment (items 3.10F and 3.10B), where the complex movement of both the legs and arms needs to be assessed, seem to have further room for improvement. Hence, calculation of additional gait features, such as step duration, swing phase duration [30], may be considered in the future.

	3.8L	3.8R	3.9	3.13	3.10F	3.10B
KNN	**0.755**	**0.676**	**0.748**	**0.812**	0.520	**0.677**
SVM	0.686	0.546	0.741	0.750	0.526	0.640
RF	0.698	0.496	0.677	0.750	**0.544**	0.542
PCA+KNN	**0.755**	0.588	0.678	**0.812**	0.541	0.629
sPCA+KNN	**0.755**	0.588	0.678	**0.812**	0.515	0.627

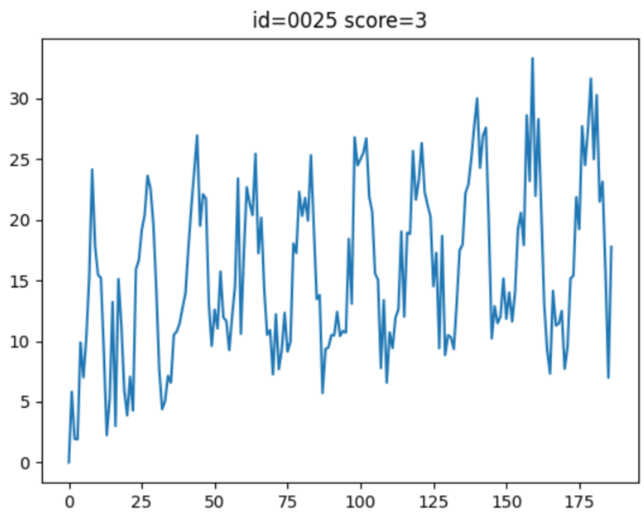
Table 3: Average weighted F1 scores for different assessment items and ML classifiers using Leave One Out cross validation. Best performing ML classifiers for each item are shown in bold.

5 CONCLUSIONS

Parkinson's disease (PD) is one of the most prevalent neurodegenerative diseases and the accurate identification of its motor symptoms is considered crucial for optimizing treatment and further clinical decisions. The proposed CMFT approach involves utilizing



(a)



(b)

Figure 4: Plots of KNEE_L angle time series for item 3.8L corresponding to two PD patients with different clinical assessment scores. Peaks correspond to the extreme leg positions during each of the 10 foot stomps.

smartphone-based video analysis to assess motor skills, focusing on aspects, such as balance and posture, in individuals with PD. The study used a cohort of 17 volunteer PD patients and captured videos of them performing a sequence of four items from the MDS-UPDRS motor tests. Based on video analysis using the MediaPipe software, we detect 3D pose landmarks in each frame and create time series of angles that are relevant to each item. We then compute a set of motion features based on these time series and identify those that have significant correlation with the corresponding clinical MDS-UPDRS ratings. Using these features, different ML classifiers are trained and evaluated for monitoring the balance and posture of PD patients based on standard smartphone video recordings.

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