RGB-D Human Pose Estimation to Assess Instability in Parkinson's Disease: a Multi-center Evaluation.

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***Abstract*—Postural instability is a major source of disability in Parkinson's disease, as impaired balance increases fall risk and accelerates loss of independence in daily life. In clinical practice, instability is commonly assessed through the pull test during outpatient visits. However, this task is difficult to replicate in telemedicine settings, where patients must perform evaluations at home, often without direct clinical supervision. Therefore, extracting quantitative markers of instability from simple standing tasks may provide a practical proxy for conventional assessment. This approach requires technologies capable of detecting subtle center-of-mass oscillations through non-invasive, easy-to-use systems. In this study, we evaluate a deep learning–based human pose estimation framework using an RGB-D camera to monitor patients during two 60-seconds standing tasks (eyes open and eyes closed). Kinematic features related to postural sway are estimated from body pose and correlated with reference clinical scales. Data from 40 patients recruited across two clinical centres show moderate agreement with clinical scores (Spearman $\rho = 0.49$), confirming the efficacy of the acquisition technology. Moreover, results suggest that 20 s recording with eye closed may be sufficient to capture clinically-relevant stability parameters.**

***Index Terms*—Human Pose Estimation, Parkinson's Disease, RGB-Depth camera, Postural Instability**

I. Introduction

Postural instability is one of the most disabling symptoms of Parkinson's disease (PD), often emerging in the mid to advanced stages of the disease and strongly associated with falls, reduced mobility, and loss of independence in daily activities [1]. Quantitative assessment of balance impairment is therefore essential both for monitoring disease progression and guiding therapeutic strategies. Clinically, postural stability is commonly evaluated through the pull test, incorporated in item 3.12 of the Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [2]. During this test, the examiner applies a sudden backward pull to the patient's shoulders and evaluates the corrective stepping response on an ordinal scale from 0 to 4. Despite its widespread clinical adoption, the pull test presents several limitations, including variability in the perturbation delivered by clinicians and limited reproducibility across examiners [3]. Moreover, the test is difficult to reproduce in telemedicine settings, where remote assessments are increasingly required for continuous patient monitoring.

Recent advances in markerless motion capture and computer vision have opened new possibilities for objective and scalable motor assessment in neurological disorders [4]. RGB-D cameras, such as Microsoft Azure Kinect, combined with deep learning models for Human Pose Estimation (HPE), enable three-dimensional tracking of body joints without the need for wearable markers or complex laboratory setups, providing a low-cost and non-invasive monitoring tool [5]. Previous studies have shown that these technologies can provide sufficiently accurate joint tracking to estimate postural control parameters and approximate center-of-mass motion during balance and gait tasks [6]–[8]. Such technologies are particularly promising for telemedicine and home-monitoring applications, where simple sensing systems may enable repeated and standardized evaluation of motor symptoms.

In PD, quantitative measures of postural sway have been proposed as objective indicators of balance control and fall risk [9]. Vision-based systems using RGB-D cameras have also been explored for remote motor assessment, showing encouraging results in extracting kinematic features related to posture and movement [7], [8]. However, it remains unclear whether

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quantitative sway measures derived from simple standing tasks can provide clinically meaningful information comparable to established assessments of postural instability such as the pull test.

The present work addresses this question by investigating whether postural sway parameters extracted from RGB-D pose estimation during static standing tasks correlate with the clinical instability classification derived from MDS-UPDRS item 3.12. Using a multi-center dataset of PD patients performing 60-seconds standing tasks with eyes open and eyes closed, we analyze body oscillations and related kinematic features derived from skeletal tracking.

The study is guided by the following research questions:

- **RQ1**: Can quantitative postural sway features extracted from RGB-D pose estimation provide information consistent with the clinical assessment of postural instability (pull test) and distinguish between clinically stable and unstable Parkinson's disease patients?
- **RQ2**: Are specific experimental conditions or temporal segments of the task (e.g., eyes open vs closed condition or early vs. late phases of the test) more informative for capturing instability-related behaviour?

By addressing these questions, the study aims to evaluate whether low-cost RGB-D vision-based sensing can provide a practical proxy for traditional clinical stability assessments.

II. Materials & Methods

A. Recruited subjects

A total of 40 patients (12 females, 28 males) with PD, diagnosed according to the Movement Disorder Society clinical criteria [10], were recruited during routine outpatient visits at the Department of Neuroscience "Rita Levi Montalcini" (University of Turin) and at the Movement Disorders clinic of "Sapienza" University of Rome. Both centres adopted the same recruitment protocol and standardized inclusion/exclusion criteria. Inclusion was limited to patients with moderate-to-advanced PD (Hoehn & Yahr stage 2.5–4) [11]. Exclusion criteria were: signs of atypical or secondary parkinsonism; cognitive impairment (MoCA $\leq$ 21) [12]; inability to provide informed consent; and orthopedic, rheumatologic, neurological conditions or previous surgeries significantly affecting gait or balance. The study complied with the Declaration of Helsinki and was approved by the local ethics committee (Comitato Etico Territoriale interaziendale AOU Città della Salute e della Scienza di Torino; Protocol 0080563 No. 512/2023, June 17, 2024). All participants provided written informed consent. Approximately one week before instrumental testing, participants underwent a comprehensive clinical assessment of motor, cognitive, and quality-of-life domains, including a postural stability evaluation through the standard pull test (MDS-UPDRS, item 3.12). Subsequently, participants completed an instrumental acquisition session including motor and non-motor tasks. The present analysis focuses only on tasks related to static postural control. All evaluations were conducted in the ON pharmacological state, under usual dopaminergic therapy, to reflect real-life clinical conditions and ensure safety and compliance.

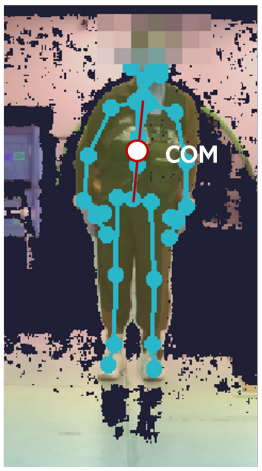

Fig. 1. Example of body tracking data produced by the Azure Kinect Body Tracking algorithm, with highlighted the center of mass (COM) used for calculation of postural stability parameters.

B. Acquisition setup and protocol

The complete experimental setup of the instrumental acquisition session included two Microsoft Azure Kinect cameras recording synchronized RGB-D data at 30 frame per seconds (fps). The cameras were not stereoscopically calibrated, to reduce acquisition burden and to make the setup easier to be reproduced between centres. The dual-camera setup was mainly studied to enlarge acquisition volume for complex dynamic tasks such as gait and in place turning, which were part of the complete study protocol. For the standing tasks, only the frontal recording camera was considered, as the one providing the complete observation of the body without self-occlusions. Additional devices, such as inertial measurements units and surface electromyography sensors were included in the study protocol, but their analysis not in the scope of the current work.

The protocol for the postural instability assessment followed the Romberg test [13] procedure: the patient was instructed to stand still for 60 seconds, first with Eyes Open (EO); then rest; finally, stand still with Eyes Closed (EC), again for 60 seconds. Each subject was positioned facing the frontal camera, at approximately 2-2.5 m from its centre, where tracking confidence was found to be maximal [14]. The two tasks were individually recorded and processed to extrapolate the stability parameters described in the next section. During the first seconds of each recording, the patients were asked to raise their left arm to allow synchronization across all the devices involved in the experimental protocol.

C. Postural instability parameters

Videos were processed offline to extrapolate 3D skeletal reconstructions using the Microsoft Azure Kinect Body Tracking SDK (v1.1.0). Its HPE algorithm is based on a deep learning models that estimates, for each video frame, 33 points

TABLE I
POSTURAL STABILITY PARAMETERS DERIVED FROM COM MOTION IN AP, UD AND ML DIRECTIONS.

Parameter	Description
RMS	Mean sway amplitude
$AREA_{95}$[a]	95% confidence ellipse area of the sway points
$CONVEX_{HULL}$[a]	Convex hull area of all sway points
$SWAY_{TOT}$	Total sway displacement (sum of successive differences)
$SWAY_{RANGE}$	Maximum sway range, as difference between max and minimum position reached on that axis
VEL_{MEAN}	Mean absolute sway velocity
VEL_{STD}	Standard deviation of sway velocity
VEL_{PEAK}	Peak velocity along the axis

[a] computed on the ML-AP plane.

TABLE II
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS

Variable	All ($N = 40$)	Rome ($n = 13$)	Turin ($n = 27$)	p
Age, yr	70.0 (65.0–73.0)	71.0 (70.0–74.0)	67.0 (64.0–71.0)	**0.041**
Sex, M/F	28/12	10/3	18/9	0.716
LEDD Tot	933.8 (615.9–1118.0)	832.0 (655.0–1000.0)	950.0 (575.0–1144.1)	0.623
H&Y	3.0 (3.0–3.0)	2.5 (2.5–3.0)	3.0 (3.0–3.0)	**0.004**
UPDRS III Totale	29.0 (24.8–41.0)	33.0 (26.0–44.0)	28.0 (23.5–38.5)	0.340
Instability Class (Stable/Unstable)	28/12	11/2	17/10	0.271

Med (IQR); p: Mann–Whitney U or Fisher exact test.

referring to the main body joints of the recorded individual. The trajectories of such joints over time were analysed in a window of 40 s, starting 3 s from the synchronization gesture at the beginning of the postural task. The terminal part of the task (around 10 s) was excluded to avoid potential artifacts due to the patient moving or receiving assistance by the experimenter at the end of the trial.

Pre-processing of the joint trajectories included upsampling at 50Hz to remove timestamp jitters and ensure a uniform temporal baseline. Then a 10-sample median filter was applied to each trajectory component (X, Y, and Z) to remove sporadic spikes or outliers, followed by a low-pass Butterworth filter (4th-order, 5 Hz cut-off frequency) to retain only frequency components relevant to postural instability. For the computation of postural instability parameters, a proxy of the body centre of mass (COM) was computed by considering the mid point between the segment joining the mean point of hip joints and the mean point of the shoulder joints (Fig. 1). Stability parameters were then computed separately for the three main axes of movement: antero-posterior (AP) considering the Z axis, up-down (UD) considering the Y axis, and medio-lateral (ML) considering the X axis. Measures refer to total quantity of motion performed by COM and its velocity, in term of mean value, maximum and standard deviation over time. A summary of the estimated features is reported in Table I. Parameters were computed considering: the full 40 s window (TOT), the first 20 s (P1) and the last 20 s (P2), to account for changes between the first and the last part of the two standing tasks, due to fatigue or adaptation effects.

D. Statistical analysis

The distribution of postural stability parameters was studied considering recruited patients divided in two classes: the *Stable* one corresponds to subject which had MDS-UPDRS item 3.12 (i.e. *Postural Stability*) equal to 0 or 1 (i.e., no or slight impairment); the *Unstable* class refers instead to subjects with score $>= 2$ (i.e., mild to severe instability). The grouping of higher severity cases was necessary to make statistical analysis robust. Indeed, only few patients among those recruited received a score $>= 2$ for this item.

Statistical analysis was performed using non-parametric methods due to the non-normal distribution of the data, tested through the Shapiro-Wilk test. Spearman's rank correlation (ρ) was used to assess associations between HPE-derived postural features and the stability class. Group differences between clinically-defined *Stable* and *Unstable* patients were evaluated using the Mann-Whitney U test. Paired Wilcoxon signed-rank tests were employed, instead, to compare variation in stability, within the same patient, between the EO and EC tasks (i.e., Romberg effect). Additionally, the ratio between the first and the last intervals (P1/P2) of each task was analyzed to investigate whether temporal variations in sway have a direct relationship with the stability class defined. All tests were two-tailed with significance set at $\alpha < 0.05$.

III. RESULTS

Table II reports a summary of the characteristics of the patients recruited across the two study centres. Statistical differences in the two groups were assessed using the Mann-Whitney U test or the Fisher exact test for categorical data. The Turin cohort was on average younger but slightly more severe according to Hoehn & Yahr scale, whereas no notable differences was found for the total UPDRS III score. Most of the subjects in the *Unstable* class, however, were recruited in the Turin centre (10/12). No differences were detected instead for Levodopa Equivalent Daily Dose (LEDD) and Sex.

A. Clinical relevance of stability parameters

Figure 2 visualizes the Spearman correlation ρ of the HPE-derived stability parameters with the stability class of the subject, considering separately the two standing tasks (i.e., EC, EO) and the different time windows in which the parameter was computed (i.e., TOT, P1, P2). Only parameters with at least one statistically significant correlation are reported for clarity. As it can be appreciated, the strongest correlations are observed in the EC condition, where the visual input for postural control is removed. In particular, the first phase of the task appears as the most relevant to appreciate parameter values connected to the clinical classification, whereas the same parameters, when computed only in phase P2 of the same task, appear less relevant. A similar trend verifies also in the EO task, but with a more moderate drop in correlation between P1 and P2. The strongest correlations are observed for parameters describing the motion of COM in the AP direction, in particular the $SWAY_{TOT}$ ($\rho = 0.46$, $p = 0.002$), quantifying total quantity of motion and the velocity parameters VEL_{MEAN} and VEL_{STD} (all $\rho = 0.46$ in TOT, $p \approx 0.002$).

For these relevant parameters, box plots are reported in Figure 3, visualizing, only for the TOT window, the distri-

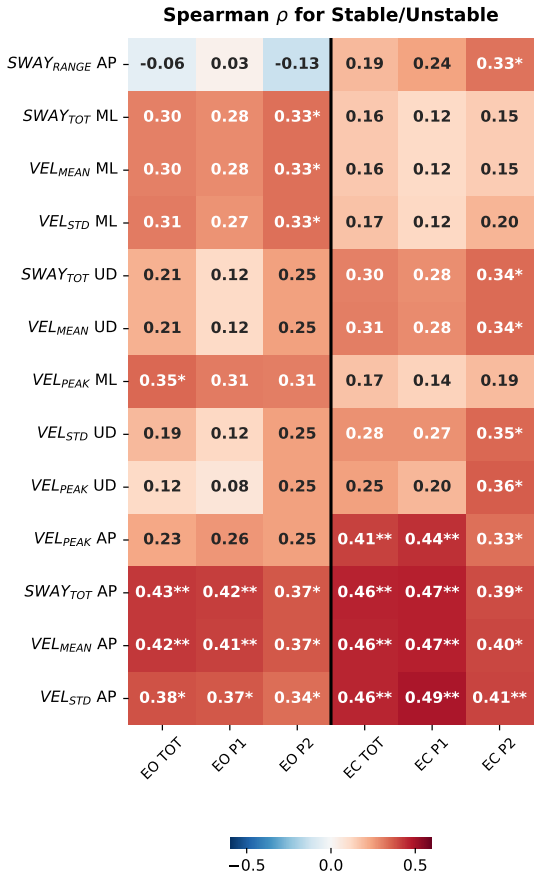

Fig. 2. Spearman correlation of stability parameters, computed in EO, EC and in the three considered time windows (TOT, P1, P2), with the clinical instability class of patients.

bution in the two tasks, for each stability class. An outlier in the EC condition is clipped and visualized with a triangular marker, to ensure a better visualization: this point was not removed as it corresponds to one of the subjects with the most severe impairment (MDS-UPDRS 3.12 with value 3), rather than a technical malfunctioning. As it can be appreciated, the *Unstable* group exhibits higher median $SWAY_{TOT}$ denoting larger oscillations, both in the EO and in the EC tasks. In both conditions, the parameter reaches statistical significance with a large effect size (rank-biserial correlation r): in EO, $p = 0.0086$, $r = 0.53$; in EC, $p = 0.0036$ and $r = 0.59$. The same verifies for the two velocities parameters: VEL_{MEAN} in EO $p = 0.0107$ and $r = 0.52$, in EC $p = 0.0036$ and $r = 0.59$; VEL_{STD} in EO $p = 0.0083$ and $r = 0.54$, in EC $p = 0.0023$ and $r = 0.62$.

In the within-subject paired analysis, performed separately for the two stability classes, no statistically significant differences were observed between the EO and EC conditions. This suggests that, within this cohort, the removal of visual input in the Romberg test did not systematically translate into measurable changes in the considered stability parameters, such as a clear worsening of balance in the *Unstable* group. However, when the same comparison was performed across the

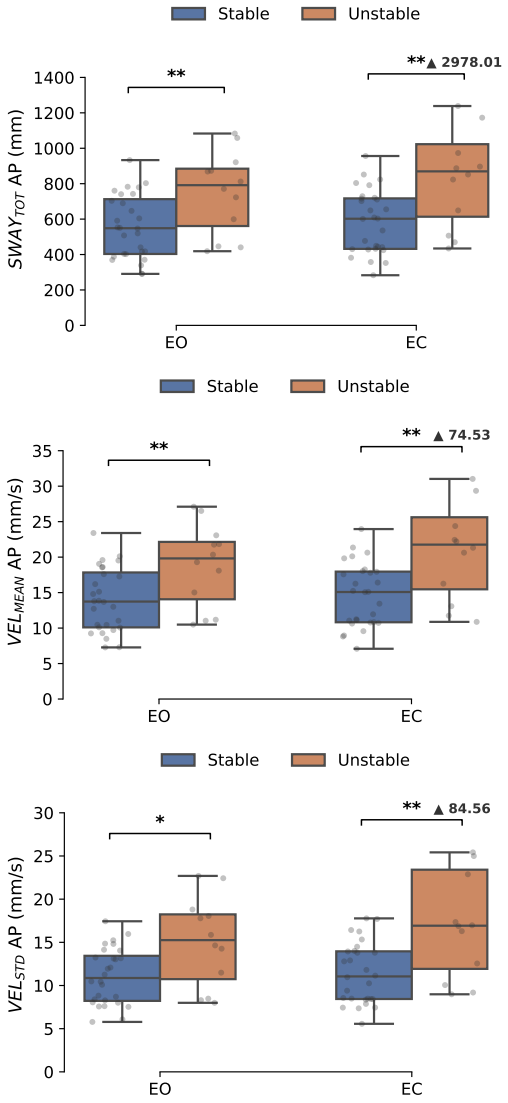

Fig. 3. Visualization of the distribution of relevant stability paramaters through box plots. On top, $SWAY_{TOT}$ in AP direction; in the middle, VEL_{MEAN} in the AP direction; at the bottom, VEL_{STD} in the AP direction. Statistical difference as probed by Mann-Whitney U Test is marked for: * $p < 0.05$ and ** $p < 0.001$. The triangle point represents an outlier clipped for visualisation purposes (actual value reported aside).

entire cohort, statistically significant differences with medium effect size emerged for $SWAY_{TOT}$ and VEL_{MEAN} in the AP direction, both over the full 40 s window and within the P1 phase. Considering the full 40 s interval, the median $SWAY_{TOT}$ increased from 595.13 mm in EO to 649.04 mm in EC ($p = 0.035$, $r = 0.38$), while the median VEL_{MEAN} increased from 14.91 mm/s in EO to 16.25 mm/s in EC ($p = 0.034$, $r = 0.38$). These results suggest that the effect induced by the Romberg test may not be fully captured by the binary stability classification adopted in this study. A more refined stratification of subjects may therefore be required to identify individuals for whom the absence of visual input leads to a relevant change in postural control.

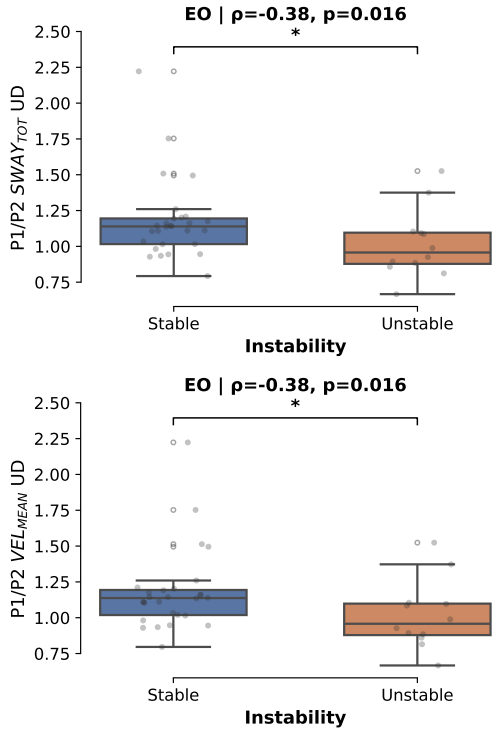

Fig. 4. Features showing statistically significant differences between the two stability classes (Mann–Whitney U test) for the P1/P2 ratio in the EO task. Top: P1/P2 ratio of $SWAY_{TOT}$ along the UD direction. Bottom: P1/P2 ratio of VEL_{MEAN} along the UD direction.

B. Phases comparison

As a final analysis, the ratio between the stability parameters computed in P1 and in P2 was evaluated and compared between the two stability classes. The Mann–Whitney U test revealed statistical significance only for $SWAY_{TOT}$ and VEL_{MEAN} in the UD direction, and only in the EO condition. Both parameters showed a Spearman correlation of $\rho = -0.38$ ($p = 0.016$) with the severity label. Figure 4 illustrates the distribution of the P1/P2 ratio for these two features. The *Stable* group generally maintained or improved stability in the second half of the task compared to the first. The *Unstable* group exhibited a similar trend, likely reflecting task adaptation, although with a weaker effect.

IV. Discussion

This study investigated whether postural stability parameters extracted from RGB-D human pose estimation can provide clinically meaningful information regarding balance impairment in Parkinson's disease. The results indicate that several sway-related features derived from the estimated center-of-mass motion show statistically significant associations with the clinical classification of instability. In particular, parameters describing the magnitude and velocity of motion in the antero-posterior direction (e.g., total sway displacement and velocity metrics) exhibited the strongest correlations with the stability class and significantly differentiated *Stable* and *Unstable* patients. These findings support the hypothesis that RGB-D human pose estimation models can quantify relevant aspects of postural control that are also reflected in clinical evaluations. Although the pull test remains the reference clinical examination for assessing postural instability [2], it relies on a manually delivered perturbation that may vary substantially between examiners. Recent work has highlighted considerable variability in pull test outcomes due to differences in perturbation delivery and patient responses [3]. In this context, objective measurements derived from body kinematics may provide complementary and potentially more reproducible indicators of balance impairment.

The results obtained in this study show moderate but consistent correlations between HPE-derived sway parameters and clinical instability classification, with the strongest values observed for parameters describing the displacement and velocity of the centre of mass along the antero-posterior axis. This observation is consistent with previous studies showing that postural sway characteristics are altered in Parkinson's disease and can be quantified using RGB-D cameras even in static tasks [7], [8].

Another relevant observation concerns the experimental conditions under which instability-related differences are most evident. The eyes-closed condition generally produced stronger correlations with the clinical instability classification. This is consistent with the principles of the Romberg test [13], where removal of visual feedback increases reliance on proprioceptive and vestibular inputs for balance control. In patients with impaired postural regulation, this condition can amplify instability and therefore reveal deficits that may be less evident when visual cues are available. However, when analysing the variation of stability parameters between the two tasks, according to the defined stability classes, the analysis did not highlight clear trends in within-subjects variation. Modest effects appeared instead when considering the overall cohort. This result suggests that a more refined stratification of subjects may be needed to systematically study Romberg effect within this cohort.

Temporal segmentation of the task also provided useful insights. The analysis comparing the first (P1) and second (P2) halves of the recordings suggests that the early phase of the task may already capture most of the relevant information related to instability. In particular, several parameters computed during the first 20 seconds exhibited stronger correlations with the clinical labels compared to those derived from the later portion of the recording. This observation may reflect adaptation or stabilization processes occurring during prolonged standing tasks, which could reduce the sensitivity of later measurements. In the open eye condition, the ratio between the two phases appeared to provide further information, by suggesting that patients with higher instability may require longer adaptation to reduce sway from P1 to P2, detectable through residual oscillation in the UD direction.

Overall, the results indicate that the proposed vision-based approach can extract quantitative stability indicators that align with clinical assessments, supporting the potential of RGB-D sensing as a practical tool for remote monitoring of postural

control in Parkinson's disease.

A. Limitations

Some limitations should be considered when interpreting the results of this study. First, the sample size of the *Unstable* group was relatively small, which however reflects the clinical distribution of the MDS-UPDRS item 3.12 scores in typical outpatient populations. This imbalance may reduce statistical power and limit the generalizability of the findings. Second, the study relied on a proxy estimation of the center of mass derived from skeletal joint positions rather than complex biomechanical measurements. Although such approximations are commonly used in vision-based motion analysis, they may introduce some inaccuracies compared to laboratory-graded instrumentation. Another limitation concerns the use of a single static task. While quiet standing tasks provide valuable information on postural control, postural instability in Parkinson's disease often becomes more evident during dynamic perturbations or gait-related tasks. Future studies could therefore combine static and dynamic motor tasks to provide a more comprehensive assessment. Finally, although the correlations with clinical instability classification were significant, they remain moderate. This is expected given that the pull test evaluates reactive balance responses to external perturbations, whereas the proposed approach measures spontaneous sway during quiet standing. Therefore, the two assessments may capture related but not identical aspects of postural control.

B. Protocol recommendations

The analysis of the experimental protocol provides several insights that may inform future implementations of vision-based stability assessments. First, the results suggest that the initial phase of the standing task already contains most of the informative signal. Features computed during the first 20 seconds (P1) often showed equal or stronger correlations with the clinical classification compared to those derived from the entire duration. This observation suggests that shorter recordings may be sufficient for stability assessment, potentially reducing the burden on patients and simplifying remote acquisition protocols. Second, the eyes-closed condition appears to enhance the detectability of instability-related features. Removing visual feedback likely increases reliance on other sensory modalities for balance control, which may amplify the differences between *Stable* and *Unstable* patients. However, performing this condition without supervision could increase the risk of falls, particularly in home settings. Therefore, while the eyes-closed task may provide stronger diagnostic signals, its implementation in unsupervised environments should be carefully considered, possibly requiring safety precautions or the presence of a caregiver. Finally, the results highlight the importance of standardized acquisition procedures. Compared to clinician-delivered perturbation tests, vision-based standing tasks offer the advantage of being easier to standardize and reproduce across sites and recording sessions, which is particularly valuable for longitudinal monitoring and telemedicine applications.

V. Conclusions

This study investigated the use of RGB-D human pose estimation to quantify postural instability in Parkinson's disease during simple standing tasks. Several kinematic parameters derived from center-of-mass motion were significantly associated with the clinical instability classification and differentiated between stable and unstable patients. Although the approach does not replicate the perturbation-based pull test, the observed correlations suggest that quantitative sway analysis provides complementary information on balance impairment. Thanks to its non-invasive and low-cost setup, RGB-D sensing combined with human pose estimation represents a promising solution for scalable and objective assessment of postural control. Future work will focus on larger and more stratified cohorts, additional motor tasks, and longitudinal studies to further validate this approach in telemedicine and home-based monitoring of Parkinson's disease.

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