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Identifying balance impairments in people with Parkinson's disease using video and wearable sensors

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ABSTRACT

Background: Falls and near falls are common among people with Parkinson's (PwP). To date, most wearable sensor research focussed on fall detection, few studies explored if wearable sensors can detect instability.

Research question: Can instability (caution or near-falls) be detected using wearable sensors in comparison to video analysis?

Methods: Twenty-four people (aged 60–86) with and without Parkinson's were recruited from community groups. Movements (e.g. walking, turning, transfers and reaching) were observed in the gait laboratory and/or at home; recorded using clinical measures, video and five wearable sensors (attached on the waist, ankles and wrists). After defining 'caution' and 'instability', two researchers evaluated video data and a third the raw wearable sensor data; blinded to each other's evaluations. Agreement between video and sensor data was calculated on stability, timing, step count and strategy.

Results: Data was available for 117 performances: 82 (70%) appeared stable on video. Ratings agreed in 86/117 cases (74%). Highest agreement was noted for chair transfer, timed up and go test and 3 m walks. Video analysts noted caution (slow, contained movements, safety-enhancing postures and concentration) and/or instability (saving reactions, stopping after stumbling or veering) in 40/134 performances (30%): raw wearable sensor data identified 16/35 performances rated cautious or unstable (sensitivity 46%) and 70/82 rated stable (specificity 85%). There was a 54% chance that a performance identified from wearable sensors as cautious/unstable was so; rising to 80% for stable movements.

Significance: Agreement between wearable sensor and video data suggested that wearable sensors can detect subtle instability and near-falls. Caution and instability were observed in nearly a third of performances, suggesting that simple, mildly challenging actions, with clearly defined start- and end-points, may be most amenable to monitoring during free-living at home. Using the genuine near-falls recorded, work continues to automatically detect subtle instability using algorithms.

1. Introduction

People with Parkinson's (PwP) fall twice as often as healthy older people [1–3]; 75% PwP reported near-falls in one year [4]. Fall prevention is a healthcare priority; programmes in PwP improve balance, although few demonstrated a reduction in fall rates [3,5–8]. Monitoring falls and instability could be beneficial for inactive people in poor health who fall frequently and sustain more injuries than healthy active adults [9,10].

Interest in automated fall detection is growing [11]. Although falls are unintentional, to date wearable sensor fall detection studies often focussed on simulated falls [12]. Only 7% of wearable sensor reports included monitoring in 'a real-world setting' [13]; few researchers recorded natural falls [14,15]. Wearable sensors revealed differences between fallers and non-fallers with Parkinson's and correlations with other measures of fall risk, such as the Timed Up and Go Test (TUG), [16]. They have predicted time to first fall (from gait variability) better than traditional measures [17] and the response to a change in medication [18]. In one study, researchers provoked PwP into taking missteps by asking them to perform a protocol of increasingly challenging balance tasks in a laboratory [19]. Misstep detection was calculated by dividing the number of sensor detected missteps by the number of

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missteps identified by clinicians. The algorithm achieved a ‘Hit ratio’ of 93% and was used to detect ‘suspected missteps' in the home environment. Missteps were reported among a higher proportion of fallers than non-fallers but there was no way of establishing sensitivity or specificity [19].

Interest in ‘cautious gait’ [20–24] is growing. Observational gait analysis suggests elderly people with ‘cautious gait’ walk slowly, taking short strides [13,14], appear unsteady [20] and reduce the velocity of their centre of mass [21]. Yet despite recognising ‘traditional tools’ in evaluating fall risk could be augmented [19], few researchers have attempted to detect caution or near-falls automatically [19,25,26].

Automatic detection of subtle instability could provide an opportunity to intervene at the near-falls [4] stage. Therefore the aim of this study was to explore the use of wearable sensors, in comparison to expert clinician video analysis, to detect subtle instability (caution or near-falls). For this study, the clinically based ground truth was the identification of ‘subtle instability’ made by the movement analysts (interpreting movement, facial expressions and comments) from video, cross checked with the raw data from wearable sensors (accelerometer and gyroscope).

2. Methods

Ethical approval was obtained by the University of Southampton, Faculty of Health Sciences. The researcher contacted Parkinson’s UK (a UK charity) in Southampton, Reading and Newbury as well as the University of the Third Age (a UK organisation providing educational and leisure activities to retired and semi-retired individuals). With branch chair approval, the study was publicised in newsletters and branch meetings. We invited participation by leaving information packs with freepost envelopes with group chairs. Those who were able to provide consent, walk unaided indoors, follow simple instructions and perform mobility tests for one hour were eligible to take part. Twenty-four people, 10 PwP (mean age 74 (SD 7), Hoehn and Yahr 1–5, 6 female) and 14 healthy adults (mean age 74, 13 female) returned the completed reply slip indicating their interest to take part and were subsequently recruited to the study.

Their movements were observed at Southampton General Hospital gait laboratory and/or at home performing actions associated with falling [9], recording with a tripod-mounted HD video camera (at 25 frames/s) and five unobtrusive (wristwatch size) wearable sensors. The battery-powered, non-commercial, tri-axial wearable sensors containing accelerometers ($\pm$ 8 g range at 0.25 mg resolution) and gyroscopes (2000°/s at 0.06dps resolution) logged accelerations and angular velocities for subsequent downloading and analysis. The researchers recorded age, gender, height, weight, medical history and recent falls. They started the camera, activated and attached wearable sensors on Velcro straps round the waist, ankles and wrists, and measured limb-lengths and sensor positions and instructed participants to perform:

- **Chair Transfers** (**sit-to-stand** and **stand-to-sit**).
- **TUG** [16]: From a chair with arms, “Stand, walk 3 m, then return to sitting”
- **Standing-Start 180° Turn Test (SS-180)**, [27]: Facing away from the camera, turn freely left or right to walk toward it, then repeat but “turn in the opposite direction”
- **3 m Walk** [28]: “Walk 3 m toward the camera”
- **Tandem Walk** [29]: “Take 10 steps in-line toward the camera, so heel touches toe each time”
- **Rising-to-Walk** [30]: From sitting, “Rise to walk straight away (without pausing)”
- **Reaching High** and **Low** [31]: Touch a target above head height; pick a coin off the floor.

Participants attempted the SS-180 (consisting of two turns) once, and other tests three times. Before and after each trial, participants waved to generate a recognisable pattern in the wearable sensors data, facilitating synchronisation and processing. For the purpose of the study considered a near-fall (near-miss) as an occasion on which individuals would have had a fall if they did not manage to save themselves [4].

The following questions guided analysis:

1. How do video analysts identify caution and near-falls during mobility tests?
2. Can eyeballing raw wearable data detect the caution and near-falls?
3. On which tests (and parameters) do video and wearable ratings agree most closely?

Blind to each other’s evaluations, two researchers evaluated the videos and one the raw wearable sensor data using identical guidelines:

- Rate performance ‘cautious’ and/or ‘unstable’, respectively, if participants appeared concerned/alarmed about their balance (making sudden movements or saving reactions) in at least one trial.
- Time tasks onset of movement until participant is sitting still again (chair transfers and TUG), until onset of first walking step (Rise-to-Walk), from onset of first turning step until onset of first walking step (SS-180); onset of first step until a foot crossed the 3 m line (3 m Walk); and onset of first step until end of tenth step (Tandem Walk).
- Rate transfers (chair, TUG and Rise-to-Walk) using the **Parkinson Activity Scale (PAS)**, [32]: 4 = Normal, no apparent difficulty (2 if hands used); 3 = Mild Difficulty (toes dorsiflex, arms swing or ‘rocks’; uncontrolled landing); 2 = Difficult, many tries, slow; abrupt landing (1 if hands used).
- Count SS-180 turning and 3 m Walk steps
- Select **‘Turn Type’** [27].
- Score Tandem Walk **‘deviations from a straight line’** [29]: 0 = Normal for 10 steps; 1 = 1–3 deviations; 2 ≥ 3 deviations.
- Determine Rise-to-Walk **‘Fluidity’** (yes/no) from whether the participant moved smoothly from the transfer into walking without pausing [30].
- Rate the ‘Use of Support’ (yes/no) during high and low reaches, alongside high reach strategy (‘flat feet’ or ‘up on toes’), and low reach strategy (‘bend’ from the waist or ‘squat’ bending the knees) [31].

The video analysts rated cautious and/or unstable movements together; grouped their comments and generate descriptions of apparent caution and/or instability. The wearable sensor analyst reviewed the sensor data for each activity, and based on the sensor output and activity performed, rated the trials. This was achieved by visually inspecting the accelerometer and gyroscope output of the most appropriate sensors as follows:

1. Performances were rated ‘cautious’ based on the time taken to perform activities and ‘smoothness' in the accelerometer data, slower movements indicating caution, sudden or unexpected accelerations from the wrist, ankle and waist worn sensor data were rated ’unstable’.
2. Chair transfer, TUG and SS-180 were timed determining the beginning and end of movements from waist worn gyroscopes; timings for the 3 m and tandem walks were estimated from ankle worn sensors.
3. Chair transfers were assessed by exploring peaks in acceleration (and multiple attempts to stand) from the waist worn sensor. Symmetric and steady change in the accelerometer gravity vector from wrist sensors suggested use of hands (but could be confused with the hands resting on the knees or lap).
4. Turning step count was estimated from the ankle accelerometer and gyroscope data by examining the peaks in outputs.
5. Turn direction data was based on positive or negative rotation about