Fall Risk Assessment Using Wearable-Based Turn Detection: Comparison of Different Algorithms During Real-World Monitoring

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Abstract: Turning deficits have been linked to aging and movement disorders and are a common cause of falls and fractures. Despite previous works on the automatic identification of turns and on its relation to fall risk, different algorithms for turn identification have been used, but their agreement and differences have not been investigated. In this study, we compared the two most-used turn-validated algorithms (El-Gohary and Pham) using a dataset comprising real-world data from 171 community-dwelling older adults monitored for one week with a single wearable sensor. The quantity and quality of turn parameters were calculated and used as predictors of future falls. After the analysis, the El-Gohary and Pham algorithms identified 1,063,810 and 942,845 turns, respectively. The agreement of the algorithms showed a very high to moderate correlation for all turn parameters. We found that prospective fallers take longer to perform a turn, and their movements are less smooth when compared to non-fallers. A fall risk assessment model built only on turn parameters showed reasonable performance for both algorithms (AUC = 0.6). Our results show that differences between turn parameters in the algorithms, when averaged at the single-subject level, are less of a concern when looking for associations with prospective falls.

1 INTRODUCTION

Turning represents a major component of everyday walking behavior, as between 35 and 45% of steps occur within turns (Glaister et al., 2007). However, up until recent years, studies only focused primarily on straight-ahead walking. Turning requires a continuous change of the center of mass and multi-limb coordination, so it is not surprising that its deficits are associated with movement disorders and the risk of falling.

Several studies have noted that turns can challenge stability maintenance and increase energy expenditure, and that turning time, steps per turn, and variability in the number of steps across different turns are valuable features for distinguishing fallers from non-fallers (Mancini et al., 2016). Subtle fall-risk-related gait-based measures may become highly effective fall-risk indicators when applied to turns due to the increased challenge to stability compared to straight walking. Individuals at high risk of falling employ different turning methods than healthy individuals.

Assessment of turning is not trivial. Optical systems have been widely used in previous studies but are cumbersome, expensive, and can only be used in controlled environments (Marín et al., 2020; Thigpen et al., 2000). Wearable sensors, which can measure for days or even weeks, are a promising

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alternative. Hence, they are ideal in unconstrained environments over long periods of time.

Algorithms for analyzing the turning movements of older adults and Parkinson' disease patients have already been published. To the best of our knowledge, only two algorithms based on one inertial sensor (accelerometer and gyroscope) worn on the lower back have been validated against video observation (gold standard) with reasonable agreement. These algorithms have been and are currently used by other studies to extract relevant turning parameters associated with movement disorders and the risk of falling (Haertner et al., 2018; Leach et al., 2018; Roussos et al., 2022; Thierfelder et al., 2022). However, using different algorithms increases heterogeneity in remote monitoring studies; validation and adoption of standardized digital mobility biomarkers is an ongoing task being addressed by different initiatives.

In this study, we tested two algorithms to identify turns and extract turning characteristics in real-world conditions. We aim to compare here the performance of the two algorithms and their impact on assessed turn quantity and quality during a week of monitoring relative to prospective falls. To the best of our knowledge, this is the first study characterizing different turning biomarkers worn on the lower back for fall risk assessment in real-world conditions.

2 METHODS

Study Participants and Settings

The present study is based on data from the 4th wave of the "Invecchiare in Chianti" (InCHIANTI) study. One hundred and seventy-one community-dwelling older adults over 65 (79·7±6·6) years, 50·9% female, were monitored for 5–9 days using a smartphone (Samsung Galaxy SII), embedded with a tri-axial accelerometer and gyroscope with a 100 Hz sampling rate, worn on the midsagittal plane of the lower back during all waking hours.

Participants brought the device home, used it for one week, and then returned it to the clinical staff at the end of the monitoring period. Telephone interviews were used to collect prospective fall incidence data between 6 and 12 months after the start of continuous monitoring. Participants who did not fall were defined as non-fallers [NFs] and participants who fell one or more times were defined as fallers [Fs].

The study protocol was approved by the ethical committee of the Italian National Institute of Research and Care of Aging and complies with the Declaration of Helsinki. All participants received a detailed description of the study purpose and procedures and gave their written informed consent.

Turns

Two validated algorithms for turning detection were implemented in Python 3.8

(El-Gohary et al., 2013) algorithm measures the angular rotational rate of the pelvis about the vertical axis (w_z). Candidate turns are detected in segments where the maxima of the low-pass filtered ($f_c = 1.5\ Hz$) w_z exceed a threshold of 15°/s. The start and end of turns are found when the filtered signal drops below 5°/s. The direction of the turn (right or left) was defined by the sign of w_z.

(Pham et al., 2017) algorithm estimates the angular displacement around the vertical axis through attitude estimation. The start of a right turn is defined by a change from an increase to a decrease of the angular displacement, and the end by a change from a decrease to an increase of the angular displacement. The opposite operation is applied to the definition of a left turn.

Both methods rely on a single inertial sensor worn on the lower back to detect turns. Still, different post-processing cutoffs are suggested to improve the performance of the algorithm based on heuristics. The thresholds were optimized and validated using video observations according to the information reported by the authors of the algorithms. Table 1 presents a description of both algorithms.

Table 1: Characteristics of turn algorithms.

	El-Gohary	Pham
Sensor	accelerometer + gyroscope	accelerometer + gyroscope
Location	Low back	Low back
Identification method	Maxima from filtered vertical angular velocity	Changes in vertical angular displacement
Turn duration threshold*	0.5 – 5 s	0.1 – 10 s
Turn angle threshold*	45°	90°

* Thresholds Suggested by Authors

To standardize the comparison of both algorithms, turns with angles between 50–200° and durations between 0.5–5 seconds were applied in the implementation of the algorithms and were analyzed.

Turns were divided into three subsets based on turn angle (small (50–100°], medium (100–150°], and large (150–200°]) to account for different motor planning strategies within our analysis.

Following what was defined in previous studies, we calculated different quantity and quality turn parameters. Turn quantity was characterized by the number of turns per hour (TPH). Turn quality was characterized by the turn duration (DUR), turn angle (ANG), mean velocity (MV), and peak turn velocity (PV)(Caby et al., 2011; Leach et al., 2018), and the spectral arc length (SPARC)(Figueiredo et al., 2020; Gulde & Hermsdörfer, 2018).

Statistical Analyses

The degree of agreement for turn detection between the two algorithms was calculated using a correlation matrix of quantity and quality parameters of turns.

Univariate and k-fold cross validation logistic regression analysis was used to evaluate the association of turn parameters with prospective falls for both algorithms. The quantity and quality turn parameters were included as independent variables in the univariate model. The correlation between quantity and quality parameters was used to select a set of possible explanatory variables in the multivariate model. All analyses were performed using Python 3.8. All p values were two-tailed, and $p < 0.05$ was considered significant.

3 RESULTS

Cohort and Fall Status

Table 2 presents demographic and clinical data about participants included in the study, labeled as fallers and non-fallers.

Table 2: Cohort characteristics for 12-month prospective falls.

	Non-Fallers [NFs] (N=142)	Fallers [Fs] (N=29)	Combined (N=171)
Gender (M/F)	73/69	11/18	84/87
Age (years)	79.4 ± 6.7	81.1 ± 5.5	79.7 ± 6.5
Height (cm)	159.8 ± 9.1	159 ± 9.5	159.6 ± 9.1
Weight (kg)	70.7 ± 13.1	70.2 ± 14.4	70.6 ± 13.3
MMSE	27.3 ± 1.9	27.1 ± 1.8	27.3 ± 1.8

Turns Characterization

A total number of 1,063,810 and 942,845 turns were detected from the dataset with El-Gohary and Pham algorithms, respectively (Figure 1).

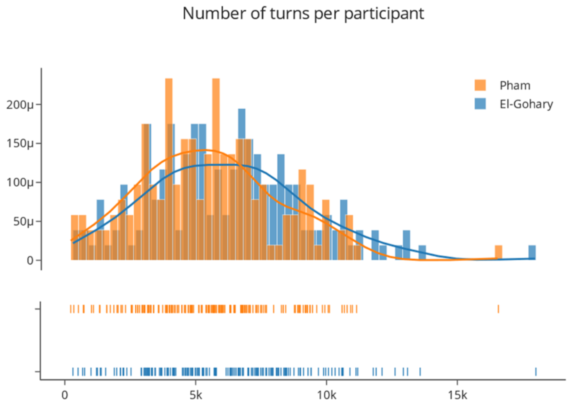

Figure 1: Turns identified during real-world monitoring.

The average across days was computed for each participant. "El-Gohary and Pham algorithms showed very high agreement on TPH ($R^2 = 0.97$), high agreement on DUR, ANG, and SPARC (R^2 between 0.74 and 0.82) and moderate agreement on PV and MV (R^2 0.51-0.61) (Figures 2-3, Table 3).

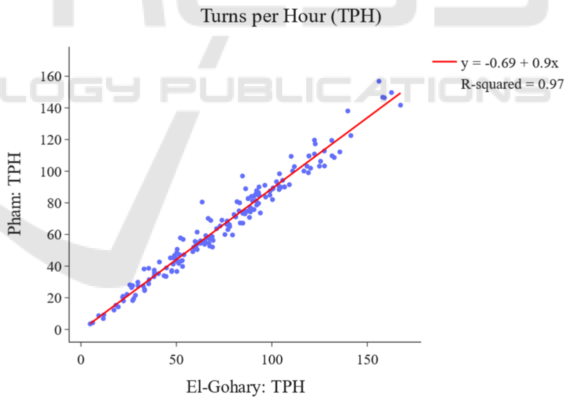

Figure 2: Turn quantity correlation identified by turn algorithms.

Table 3 summarizes descriptive characteristics for turn quantity and quality parameters. Computed DUR, ANG, and SPARC revealed high agreement between quality turn characteristics identified by both algorithms. MV and PV showed moderate correlation among the computed parameters.

While not reported in the present manuscript, outliers were identified in MV and PV, which may be responsible for the lower agreement.

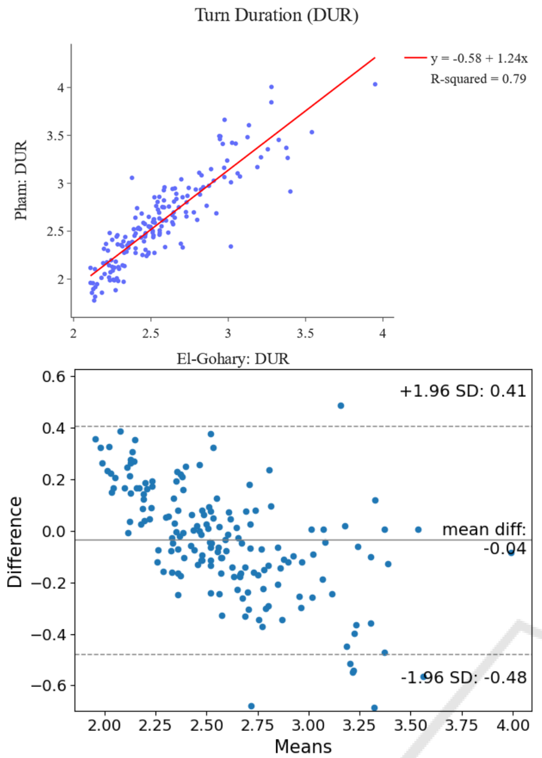

Figure 3: Correlation (upper) and Bland-Altman plot (bottom) for turn duration (s).

Table 3: El-Gohary and Pham correlation and mean difference.

	Overall means ± SD		R^2	Mean diff
	El-Gohary	Pham		
TPH (/h)	74.87±34.8	66.44±31.71	0.97	8.43
DUR (s)	2.57±0.33	2.61±0.46	0.79	0.04
ANG (°)	86.77±3.88	99.08±4.47	0.74	12.31
MV (°/s)	43.76±7.02	44.8±4.9	0.61	1.04
PV (°/s)	96.04±16.16	92.07±8.4	0.51	3.97
SPARC	-2.14±0.09	-2.04±0.07	0.82	0.1

Taking physical properties of body movement into account, it is expected that some of the quality parameters extracted from turns will be correlated (angle, velocity, duration). Therefore, to avoid collinearity problems in the following multivariate analysis, we analyzed potential correlations between parameters. Figure 4 shows the correlation matrix for all parameters (turn quantity and quality).

To account for different motor planning strategies individuals take when performing a turn, three subsets based on turn angle (small (50–100°], medium (100–150°], and large (150–200°]) were analyzed. As shown in figure 5, despite a high agreement in angle estimation of both algorithms, the subtle differences in the estimation techniques lead to considerable differences when differentiating turns based on their angle ranges.

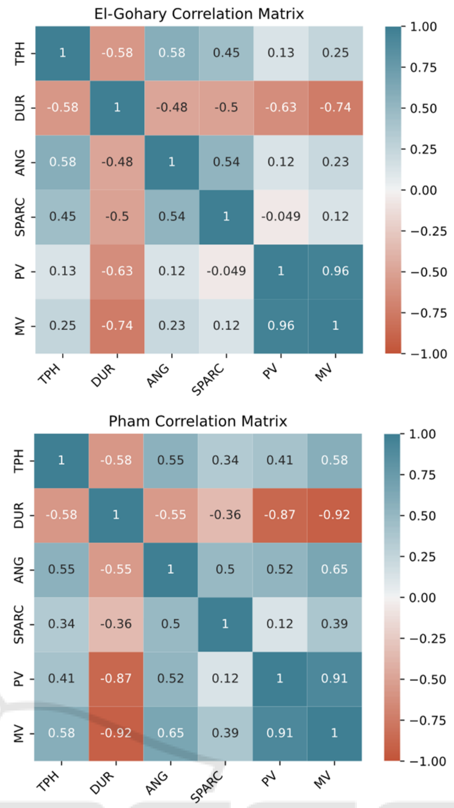

Figure 4: Correlation matrix for turn quantity and quality parameters.

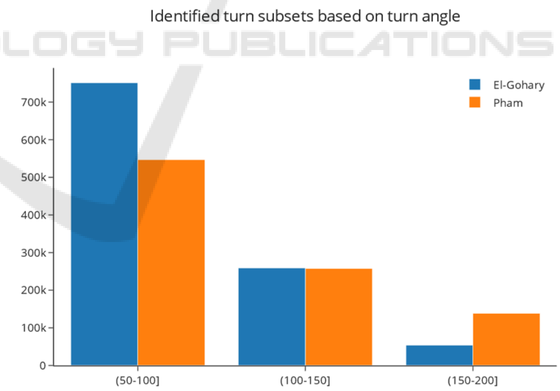

Figure 5: Turns' subsets division based on turn angle.

Turns and Prospective Falls

To identify associations between turn parameters and prospective falls, the fall incidence used in the analysis was calculated after a 6-month (NFs: 157, Fs: 14) and a 12-month period (NFs: 142, Fs: 29).

The odds ratios that quantify the univariate associations between turn quantity and quality parameters and fall status after 12 months are shown in Figure 6. Z-scored was applied for better visualization of the forest plot. The parameters were grouped by characteristics according to the algorithm used for turn detection and angle-range subsets (the prefix 50, 100, or 150 defines the type of subset analyzed).

Turn measures were associated with prospective fall status when analyzing all turns for both algorithms. Despite some differences, both algorithms identified the same parameters that were strongly associated with future falls. More TPH, longer DUR, and less smooth movements (SPARC) were associated with the risk of falling (Figure 6). PV and MV demonstrated similar trends to DUR, which is in agreement with findings in the turns characterization section (correlation matrix, figure 4). Finally, specific angle-range subsets (e.g., (150–200°] TPH) seemed to provide stronger evidence for turn associations with prospective falls.

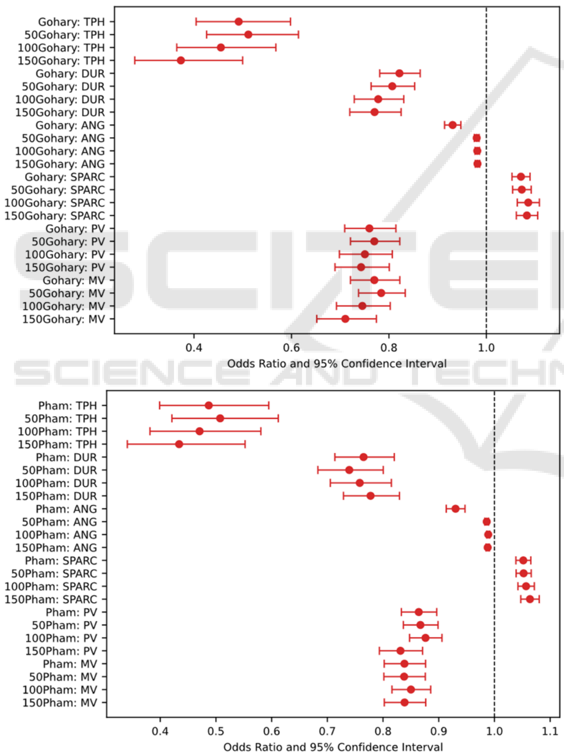

Figure 6: Forest plot of univariate analysis for turn parameters associated with 12-month prospective falls, El-Gohary (top), Pham (bottom).

For multivariate analysis, we then performed a selection of parameters based on the univariate analysis and previous results from the correlation matrix analysis. Since PV and MV were moderately and highly correlated with DUR in the El-Gohary and Pham parameters, respectively, both parameters were removed from the following multivariate analysis.

The results of the ROC curve analysis using TPH, DUR, ANG, and SPARC to classify fallers vs. non-fallers over a 6-month and 12-month period are shown in Figure 7. A different set of parameters (e.g., based on specific angle ranges) was also analyzed and was found to only marginally improve the performance of the classifier.

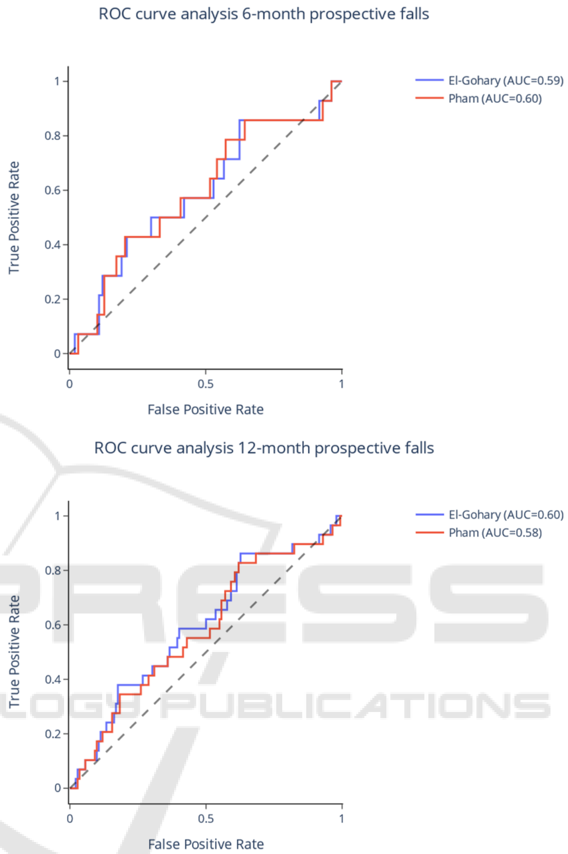

Figure 7: ROC curve for 6-month (top) and 12-month (bottom) prospective falls.

4 CONCLUSIONS

In this study, we compared two wearable-based turn detection algorithms and assessed their importance in real-world fall risk assessment.

Although both algorithms are based on the same "principle" (e.g., estimating turns based on the rotation of the pelvis around the vertical axis), different processing steps to identify turn events lead to significant differences in the number of detected turns and angles estimated by both algorithms. The readings from the gyroscope (i.e., the angular speed) are generally very accurate; however, drift might occur when integrating gyroscope readings over longer periods, such as in continuous monitoring experiments. Future studies could apply available techniques to avoid drifting, such as the integration of data coming from the orientation sensor (magnetic plus acceleration) and data coming from the gyroscope. The use of additional sensors combined with data fusion techniques could improve accuracy in the identification of turns while increasing computational and power costs.

Despite some differences and potential errors in estimating some quantity and quality parameters, both algorithms showed a moderately to very high correlation. We hypothesize that the differences among turn parameters at the single-subject level are less of a concern when looking for associations with prospective falls. In line with this discussion, we could summarize a pipeline-process: turn detection, calculation of turn parameters at the single-turn level, and calculation of the average over turns of each subject to extract turn parameters at the subject level. The last two steps downstream (probably, the average step in particular) attenuate the discrepancies, making the two algorithms exchangeable. Initial evidence for this statement is given by the similar performance of the logistic regression model built on the identified turning parameters with both algorithms.

All in all, the results and parameters presented here are in line with previous research studies and with current clinical standards tests. In fact, turning ability is a fundamental aspect of several walking tests, including the Timed Up and Go Test (TUG), which is used to discriminate fallers from non-fallers. Other cohorts could also be explored in prospective longitudinal studies, it should be noted that the percentage of fallers after 6 and 12 months in this cohort was significantly lower than the global statistics for falls in older adults.

Last but not least, a quick review of the literature shows an exponential increase in reports related to wearable-based monitoring for fall prevention. However, despite several efforts to use this technology for assessments of both healthy and pathological movement patterns, the high level of heterogeneity in the use of wearables (e.g., sensor location and extracted gait parameters) makes it hard to yield conclusive results. While some ongoing initiatives aim to establish the clinical validity of digital mobility biomarkers in different cohorts, some real-world characteristics, such as turning, deserve deeper analysis.

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