# The identification of multiple U-turns in gait: comparison of four trunk IMU-based methods

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## ABSTRACT
The identification of turns during walking allows for the segmentation into straight and turn walking bouts. Several IMU-based methods were developed to this purpose, however many of them were tested on specific subject population. In this study, we tested four methods for the identification of turns in walking tasks with multiple U-turns that did not exploit any *a-priori* knowledge of the turn occurrences. We evaluated their robustness by recording IMU data on healthy and pathological subjects (healthy elderly, stroke survivors, patients with Parkinson disease and choreic patients) walking at two different speeds along a closed loop formed by straight bouts and U-turns. Overall, all methods identified correctly the totality of the U-turns when elderly and Parkinsonian patients were analyzed. When stroke survivors and choreic patients were analyzed, U-turns were either missed or erroneously detected in a limited number of cases. The only method using the magnetometer signals was the best performing, highlighting the usefulness of the magnetometer when turns are being investigated.

## CCS Concepts
**•General and reference~Measurement**
**•General and reference~Validation**
**•Hardware~Microelectromechanical systems**

## Keywords
Walking; Gait analysis; U-Turn; Inertial sensors; Gyroscopes; Accelerometers; Monitoring.

## 1. INTRODUCTION
Gait analysis is used in clinical contexts to quantitatively assess individuals with conditions affecting their ability to walk, with the goal of limiting motor impairments or rehabilitating from traumatic events [4]. Measurements are usually carried out using either stereo-photogrammetric systems or inertial measurement units (IMUs). As opposed to vision-based systems, wearable IMUs allow for the low-cost analysis of gait in both ambulatory and unsupervised settings.



Traditionally, gait analysis focuses on the study of straight walking. As a result, protocols and definitions for the estimate of spatio-temporal parameters (step and stride duration and length, etc.) are clearly defined and widely accepted when the analysis is carried out on bouts of straight walking [20]. However, the mentioned parameters lack of a standardized definition in some variants of gait such as those including stairs and/or turns [10].

Numerous clinical motor tests may include one or more turns between straight gait segments, either due to space constraints or to analyze the subject’s motor ability under more challenging tasks. In fact, it has been observed that in pathologic subjects turning can pose more difficulties in goal-directed locomotion. For instance, functional turning is a common problem in people with Parkinson’s disease (PD), who take more steps to turn than those without PD [12]. Similarly, hemiparetic post-stroke subjects tend to struggle with sensory and neuromotor organization and so with controlling movement: it has been demonstrated a relationships between physical impairments, locomotor capacities and frontal plane gait parameters [3].

Such difficulties can be revealed by a widely used clinical test: the Time-Up-and-Go (TUG), where a 180 degrees turn (U-turn) is expected approximately in the middle of the trial followed by a second one toward the end. U-turns were therefore chosen to be studied in this work, since they are commonly employed in such clinical examinations [5, 9, 16, 18, 22].

The correct U-turn identification is the primary step to segment a walking trial. The gait bout can thus be segmented into straight walks and turns, so that the standard gait parameters can be computed from the isolated portions of straight walk, and peculiar traits of the U-turns can be described.

Identifying turns during walking is of great interest also in remote monitoring applications aiming at describing activities during daily life, including straight walking and turns.

In the literature, two main approaches have been employed to identify and analyze turns in gait. One consists in segmenting the gait into steps, defining a direction of progression (DoP) for each step, and identifying as turns those steps whose DoP shows an angle with the previous one [11]. This methodology is mostly used in pedestrian navigation applications [1, 2]. The second approach identifies a turn from the analysis of the IMU signals

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characteristics, and works independently from step detection [6, 8, 13, 14].

The objective of the present study is to perform a comparative evaluation of four automated methods to be used in a clinical context during a walking trial to identify U-turns. The algorithms were designed to segment a gait bout into straights and turns without the preliminary determination of the gait cycles. Furthermore, the selected methods distinguish multiple U-turns without the a-priori knowledge of their number and timing in the walking bout, contrary to others [7, 17, 22].

The selected methods have shown satisfactory performance when applied to the specific pathological populations, however their applicability over a variety of different pathological gait conditions or different gait speeds has not been systematically explored.

# 2. MATERIALS AND METHODS

## 2.1 Experimental Setup

### *2.1.1 Instrumentation*

Data were recorded by an IMU (Opal$^{TM}$, APDM, Inc,) positioned on the low back between L4 and S2 [19]. The performance of the IMU was tested according to the guidelines proposed by [15]. The IMU recorded linear accelerations, angular velocities and local magnetic field with respect to the axes of a local frame (LF: xyz, z pointing upwards) aligned to the edges of the unit housing. The IMU was positioned so that its reference axes were oriented approximately along the three anatomical directions. An estimate of the LF orientation with respect to the global frame (GF: XYZ, Z coinciding with the gravity direction) was provided by an on-board Kalman filter. The signals from the IMU were recorded at 128 Hz, streamed wirelessly to a laptop and stored for offline analysis. A gait pressure mat (GAITRite Electronic Walkway, CIR System Inc) acquiring at 120 Hz was used for validation purposes. The instrumented mat returned the timing of all foot contacts, in particular initial and final ones for every passage on it. The IMU and the instrumented mat were synchronized (±1 sample).

### *2.1.2 Subjects*

Ten healthy elderly (ELD), ten PD subjects, ten stroke survivors (ST) and ten subjects with a choreic movement disorder (COR) were enrolled. Their sex and range age were 6F(4M), 61÷79 ELD; 5F(4M), 68÷79 PD; 2F(8M), 38÷76 ST; 5F(5M), 29÷79 COR. The ST group was equally divided into subjects with left or right most affected side. The Declaration of Helsinki was respected, all subjects provided informed written consent, and local ethic committee approval was obtained.

**Table 1. Total number of actual U-turns analyzed**

| | ELD | PD | ST | COR |
|---|---|---|---|---|
| NW | 48 | 41 | 30 | 47 |
| FW | 63 | 49 | 38 | 72 |

**Figure 1. Experimental setup**

### *2.1.3 Data acquisition Protocol*

Subjects were asked to walk along a pre-designed loop made of two U-turns, as depicted in Figure 1. At the beginning of each acquisition, subjects were asked to stand still for a few seconds. Subjects wore their own shoes, and walking aids such as canes or tripods were allowed if used routinely. Subjects could rest in between acquisitions if requested.

Two gait conditions were recorded for each subject: self-selected, comfortable velocity (Normal Walk, NW) and higher velocity (Fast Walk, FW). Each data acquisition lasted about one minute. The total number of U-turns performed for each group for both walking speeds is reported in Table 1.

## 2.2 Methods Description

### *2.2.1 Method A*

In the work of El-Gohary and colleagues, data were collected by an IMU positioned on the lumbar spine of 19 healthy subjects and 21 patients with PD [6]. As a first step, exploiting orientation estimates in the quaternion form, body frame sensor measurements were expressed in the GF. Angular velocity vertical component $\omega_Z$ was extracted and low pass filtered (Butterworth, 1.5 Hz cutoff frequency). Candidate turns were isolated for each $\omega_Z$ maximum higher than 15°/s, and their duration was set based on 5°/s threshold. Additional controls were performed to reduce false positives. First of all, candidate turns in the same direction separated by less than 50ms were merged. Then, turns lasting less than 0.5s or more than 10s were discarded. Finally, the relative turn angle was computed integrating $\omega_Z$ over the turn duration and, when resulting less than 45°, lead to the turn elimination. The remaining ones were detected as U-turns.

### *2.2.2 Method B*

In the work of Nguyen and colleagues, data were collected from 16 ELD by IMUs mounted on a motion capture suit [13]. Among other sensors locations, they determined that the IMU on the back was the best suited for identifying turns. A band pass filter was first applied to the raw z-component of the angular velocity (zero-phase, second-order Butterworth filter, low and high cut off frequencies set at 0.0025 Hz and 0.7 Hz, respectively). The filtered signal was then de-trended and normalized for uniformity across subjects. A U-turn was detected for each peak higher than 0.6 (absolute value), as shown in Figure 2. In addition, in our implementation when the time distance between two or more peaks was less than four seconds, they were associated to a single turn.

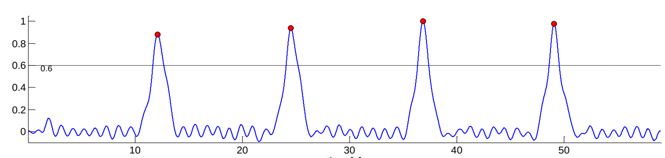


**Figure 2. Filtered, normalized angular velocity. Each red dot represents a detected U-turn**

### *2.2.3 Method C*

In the work of Novak and colleagues, data were collected by nine IMUs placed on the entire body of ten healthy subjects and one above-knee amputee [14]. Comparing different sensor locations, they found that using a sensor on the back yields the best results. Their work is based upon previous research by Mariani et al. and El-Gohary et al. ([6, 11]), and it combines the analysis of the orientation around the Z axis (Kalman filter output, angular displacement) and of the angular velocity (raw gyroscope output, $\omega_z$). The U-turn is detected by optimizing parameters of empirically-defined rules. Orientation angles were derived directly from the quaternions (estimated by the sensor through the Kalman filter). In our implementation, the Z-angular displacement was then filtered (zero-phase, second-order Butterworth filter with high cut-off frequency set at 1 Hz) and smoothed by means of mobile average windows two seconds long. The $\omega_z$ was also filtered (zero-phase, second-order Butterworth filter, 1.5 Hz high cut-off frequency). A U-turn is detected when a heuristically determined threshold is exceeded in the Z-angular displacement (90° in 3 s), or in the $\omega_z$ (45°/s).

### *2.2.4 Method D*

In the work of Fleury and colleagues, data were collected by a tri-axial magnetometer located on the upper trunk of eight healthy subjects [8]. They pre-processed the raw signal filtering in the bandwidth [0.5Hz; 2Hz] with a three order bandstop digital filter, and then low-pass filtering with a 4Hz cutoff frequency. "Activity windows" were then defined using the standard deviation computed on 2s windows. The turn was identified by measuring the change of the local magnetic field as measured in the magnetometer LF (plane xy). The Euclidean norm of the difference of the local magnetic field vector measured in two instants (2s apart) of the gait trial was computed over the entire signal. A U-turn is detected for each peak in the norm higher than empirically-fixed threshold.

## 2.3 Data Analysis

To facilitate the comparison between methods and avoid misinterpretation, those gait trials ending while the subject was performing a turn were truncated in order to eliminate the last turn.

### *2.3.1 Number of Missed and Extra U-turns*

The number of actual U-turns was provided by the mat. The number of U-turns detected was determined for each tested method. From actual and detected U-turns, missed U-turns and extra U-turns could be determined for each tested method, group and walking speed [21].

# 3. RESULTS

All four methods showed neither extra nor missed U-turns in the ELD and PD groups at both speeds.

Method A was the only method to detect two extra U-turns in the NW trials of the COR group, and one in the FW.

Method B showed no missed U-turns in the NW trials for all groups. For the FW trials, one and two missed U-turns were observed in the ST and COR groups, respectively.

Method C missed only a single U-turn in the NW trials of ST group.

Method D showed neither extra nor missed U-turns.

# 4. DISCUSSION

The aim of the present study was to test different methods for the identification of U-turns on various pathological groups walking at different speeds. In the original works, all the tested methods, except for method A, were applied and tested on the gait of healthy subjects.

When applied to the ELD group, none of the methods missed any U-turns or detected any extra ones, thus confirming their adequacy as long as physiological gait is analyzed. Interestingly, the same consideration applies to the PD group.

The results obtained indicate that the tested methods are more likely to fail when applied to the gait of stroke survivors and the choreic subjects, which is characterized by irregular walking patterns.

Method A only failed when applied to the gait of choreic subjects (three extra U-turns out of 109 total actual U-turns), probably due to the increased variability of the gyroscopic signals associated to the jerky nature of choreic motion.

Method B missed a few U-turns at fast walking speed, probably because the thresholds, defined on the normalized signal recorded at comfortable speed, resulted to be too high (scaled peaks below threshold were missed).

Methods C and D were the best performing on our dataset. Method C may take advantage of the combined analysis of the angular velocity and orientation angle, possibly reducing the probability of detecting extra U-turns.

Method D is the only one based on magnetometer signals, and it appeared to be extremely robust with respect to the location of the IMU. In fact, while its original version requires the IMU to be placed on the upper chest, we obtained excellent results from signals recorded by an IMU placed on the lower back. A limitation of this method though is the intrinsic low reliability of the magnetometer due to possible ferromagnetic disturbances.

Additional work will be necessary to test methods that identify and characterize turns other than 180 degrees. In fact, the use of the magnetometer might not be as successful as it was shown for U-turns identification.

In this study, we have shown that a single IMU located on the low back can better identify U-turns. However, as shown by [20], gait events and all the derived spatio-temporal parameters can be best detected with IMUs attached to the lower limbs. As a consequence, three IMU configuration (two IMUs on the lower limbs and one on the lower back) may effectively describe crucial features of both straights and turns in both healthy and pathological gait at different walking speeds.

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