U-Turn Detection during Walking

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***Abstract*— Instrumented gait analysis is usually focused on the analysis of human locomotion along rectilinear trajectories. However, in the last years, quantitative analysis of curvilinear walking has found a great interest in different research areas, such as gait analysis, motor rehabilitation monitoring, and pedestrian mobility. Expert operators often manually perform the identification of turning/pivoting walking by looking at the video recording of walking tasks. However, this procedure is time-consuming and highly affected by intra- and inter-operator variability. This contribution aims at introducing and validating a *k*-means clustering approach for the automatic detection of the curvilinear trajectories based on gait features extracted from knee-joint kinematics and foot-floor contact signals. More specifically, two different *k*-means clustering approaches have been tested and compared against a common ground truth obtained by means of manual segmentations: (*a*) a single *k*-means classifier applied to gait features extracted from both left and right lower leg, and (*b*) two k-means classifiers applied to gait features extracted from left and right lower leg separately. Results revealed excellent performances of the tested approaches (Accuracy > 97.0%, Precision > 95.2%, Recall > 99.6%, and F1-score > 97.3%), suggesting that the *k*-means clustering approach can be successfully applied to all those applications requiring accurate and precise identification of U-turns.**

Keywords—Gait analysis; pedestrian mobility; curved-path walking; clustering; k-means.

I. Introduction

Gait analysis often focuses on the study of human locomotion along rectilinear tracks. However, in the last decade, literature raised attention on the analysis of curvilinear walking, with applications in both rehabilitation engineering and pedestrian mobility [1], [2]. Indeed, in many cases subjects navigate following curvilinear trajectories, rather than rectilinear ones, both in outdoor and indoor spaces.

Recent works highlighted the importance of analyzing U-turns (sharp 180° direction changes) to investigate turning impairments in Parkinson's Disease (PD) patients [3], [4]. In particular, when performing instrumented gait analysis along a hallway, it may be important to automatically segment the epochs of rectilinear trajectory from turning/pivoting walking [5], [6].

Expert operators often manually perform the selection of the rectilinear and curvilinear trajectories by synchronously looking at gait signals and video recordings [7]. However, this procedure is time-consuming and highly affected by intra- and inter-operator variability. Thus, Inertial Measurements Units (IMUs) has been recently used to identify curvilinear path [7], [8], [9], [10], [11] by either evaluating step-by-step angle or using characteristics extracted from IMU signals, such as angular velocity [12], [13], [14], movement of the center of mass [9], [10], [11].

Alternative approaches, such as machine learning-based approaches, are being explored to perform signal classification and pattern recognition. Among the different possible approaches, we choose *k*-means clustering [15] to detect U-turns, since it is one of the most widely used unsupervised machine learning algorithms. The objective of the *k*-means clustering is to group similar observations together into *k* clusters for discovering underlying patterns.

The aim of this contribution is to develop and assess the applicability of an algorithm, based on *k*-means clustering, for separating straight-path from U-turn walking cycles. The performance of two different *k*-means approaches is evaluated and compared in terms of accuracy, precision, recall, and F1-score.

II. Materials and Methods

A. Subjects

Gait data from a group of 20 healthy subjects were retrospectively analyzed (age: 55.2 ± 9.6 years; gender: 7 males and 13 females; height: 1.7 ± 0.1 m; mass: 70.9 ± 15.7 kg) [4]. None of them presented musculoskeletal, neurological, or other diseases altering gait at the time of the experimental sessions.

B. Experimental Setup

A wearable electrogoniometer (accuracy: 0.5°) is fixed at the lateral side of each lower limb, and three foot-switches (size: 10 mm × 10 mm × 0.5 mm; activation force: 3 N) are mounted under each barefoot sole in correspondence of the heel, the first, and the fifth metatarsal head (STEP32 system, Medical Technology, Italy). Through these sensors, knee-joint kinematics in the sagittal plane and gait events are recorded, continuously and simultaneously, both along straight- and curved-path (U-turns) walking at a sampling frequency of 2 kHz. The signals were then offline-processed through custom routines developed in MATLAB® release R2021b (The MathWorks Inc., Natick, MA, USA).

All the enrolled volunteers underwent the same experimental protocol consisting of an overground walking. More specifically, each subject walks barefoot for approximately 5 minutes, at self-selected speed, back and forth along a straight path of 9 meters, U-turning at the end of the path (clockwise or counter-clockwise). Fig. 1 shows the experimental setup. Fig. 1A shows the acquisition system mounted on a representative subject of the sample population, while Fig. 1B schematically represents the walking path.

C. Features Extraction

From gait data, four features were extracted, for both the left and the right lower limbs of each subject, as detailed in the following.

From knee joint kinematic in the sagittal plane we estimated:

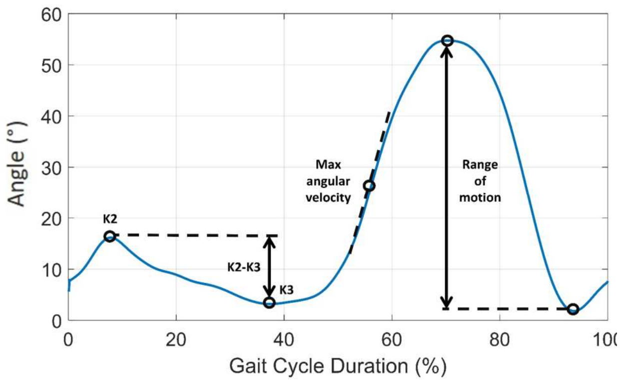

Fig. 2. Features extracted from the knee joint kinematic signals to be used as inputs of the two tested classifiers.

- Range of motion (expressed in °);
- Range of motion in early stance phase: K_2-K_3 (expressed in °), where K_2 is the maximum flexion at loading response, and K_3 is the maximum extension in stance;
- Maximum angular velocity (expressed in °/s).

From foot-switch signal (or "basography"):

- Gait cycle duration (expressed in s).

Fig. 2 provides an example of the three features extracted from the knee joint kinematics for a representative gait cycle of a healthy subject.

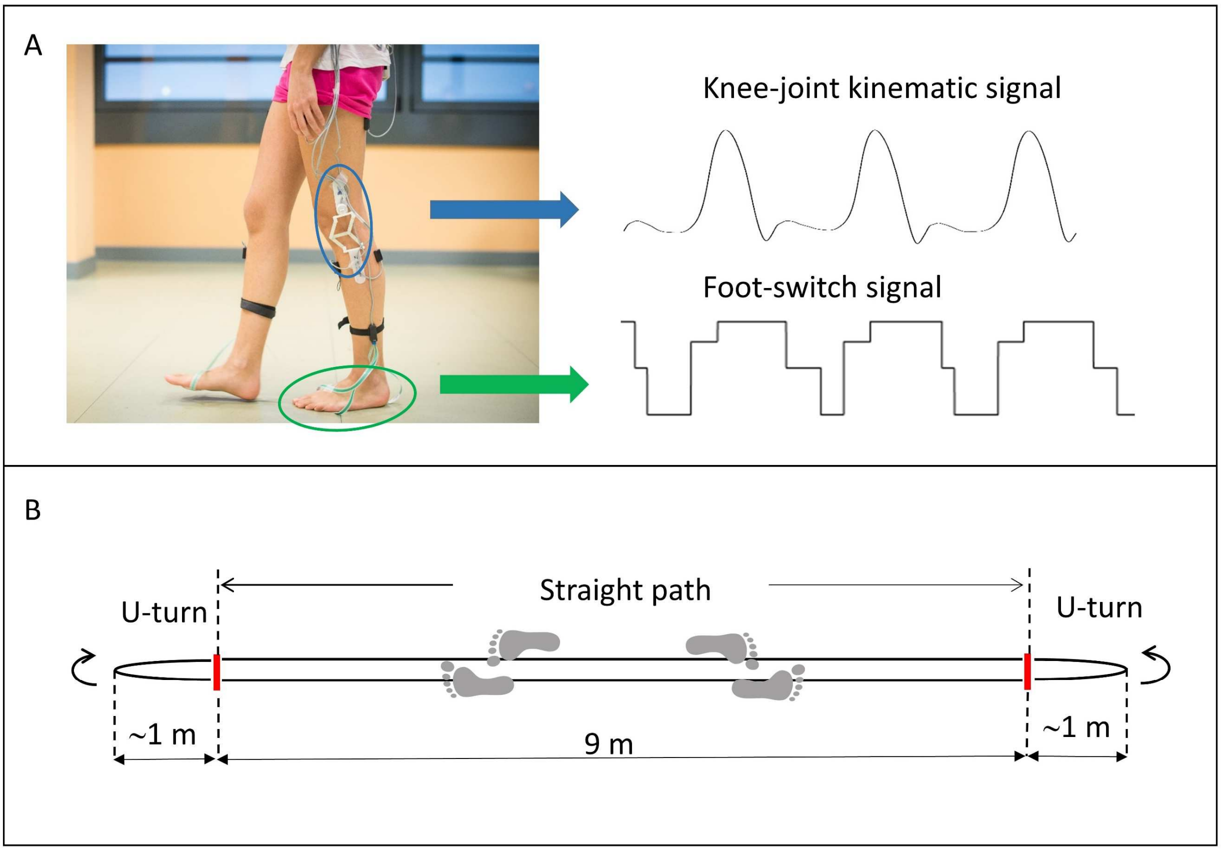

Fig. 1. Experimental set-up. Panel A: Subject with electrogoniometer and foot-switches. Panel B: walking path (Straight Path and U-turns).

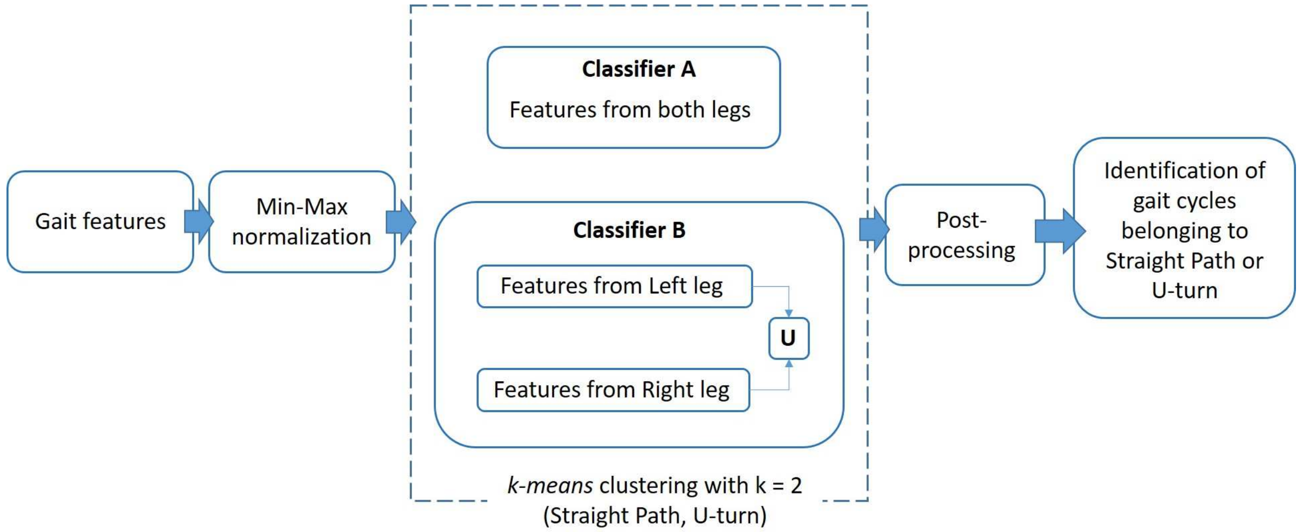

Fig. 3. Schematic representation of the steps followed to compare the two classifiers (Classifier A and Classifier B).

Since the range of values of the extracted gait features were different, each gait feature was normalized in amplitude in the range [-1; 1] ("*rescale*" MATLAB® function) so that each feature may equally contribute to the classification process without biasing the results.

D. K-means Clustering

The principal computation steps of *k*-means clustering [15] are the following:

i. *k* initial cluster centers (centroids) are chosen through the *k*-means++ algorithm;

ii. Point-to-cluster-centroid distances of all observations to each centroid are computed;

iii. Observations are assigned to the clusters with the closest centroid;

iv. The average of the observations in each cluster is computed to obtain *k* new centroids;

v. Steps from *ii.* to *iv.* are repeated until cluster assignments do not change or the maximum number of iterations is reached.

In this study, *k*-means clustering was applied to gait features extracted from joint kinematic and foot-switch signals for distinguishing between gait cycles belonging to straight path walking and those belonging to U-turns.

Fig. 3 schematically represents the procedure steps followed in the present contribution. Details on the implementation of each block are provided in the following paragraphs.

More specifically, *k*-means clustering was performed through the MATLAB® function "*kmeans*" setting the following input parameters: 2 as number of clusters in the data (i.e., straight path and U-turns), 1000 as maximum number of iterations, 15 as number of replicates, and squared Euclidean as distance metric. *K*-means++ algorithm [16] was implemented to choose the *k* initial cluster centers, obtaining faster convergence to a lower sum-of-squares point-to-cluster-centroid distance than the original *k*-means formulation by Lloyd [15]. The Statistical and Machine Learning Toolbox of MATLAB® release R2021b was used to perform the clustering.

In this study, two different *k*-means clustering approaches were tested for identifying U-turns during gait: Classifier A and Classifier B, defined as follows:

- Classifier A: gait features extracted from both left and right leg are used to identify U-turns;
- Classifier B: gait features extracted from the left leg and right leg are separately used to identify U-turns. The final classification is then obtained by performing the logical union of the output of the two classifiers (i.e., the one for the left side and the one for the right side).

The output of both classifiers (Classifier A and B) was finally binarized into a segmentation mask (y), defined as follows:

- $y = 1$ when gait cycles belong to U-turn walking;
- $y = 0$ when gait cycles belong to straight-path walking.

E. Post-processing

The output of both classifiers was then processed through the same post-processing step to detect unclassified U-turns within straight-path walking. First, the median of all the straight-path walking time durations (i.e., the time between two consecutive U-turns) was computed. Second, *k*-means clustering (Classifier A or Classifier B) was repeated considering only those straight-path walking epochs that lasted more than a temporal threshold (Th) empirically defined as it follows:

$$Th = median(T_{Straight}) + 3 \times std(T_{Straight}) \quad (1)$$

where $T_{Straight}$ represent the time durations of the straight-path walking epochs.

Finally, U-turns detected through the second application of *k*-means clustering were merged with the original

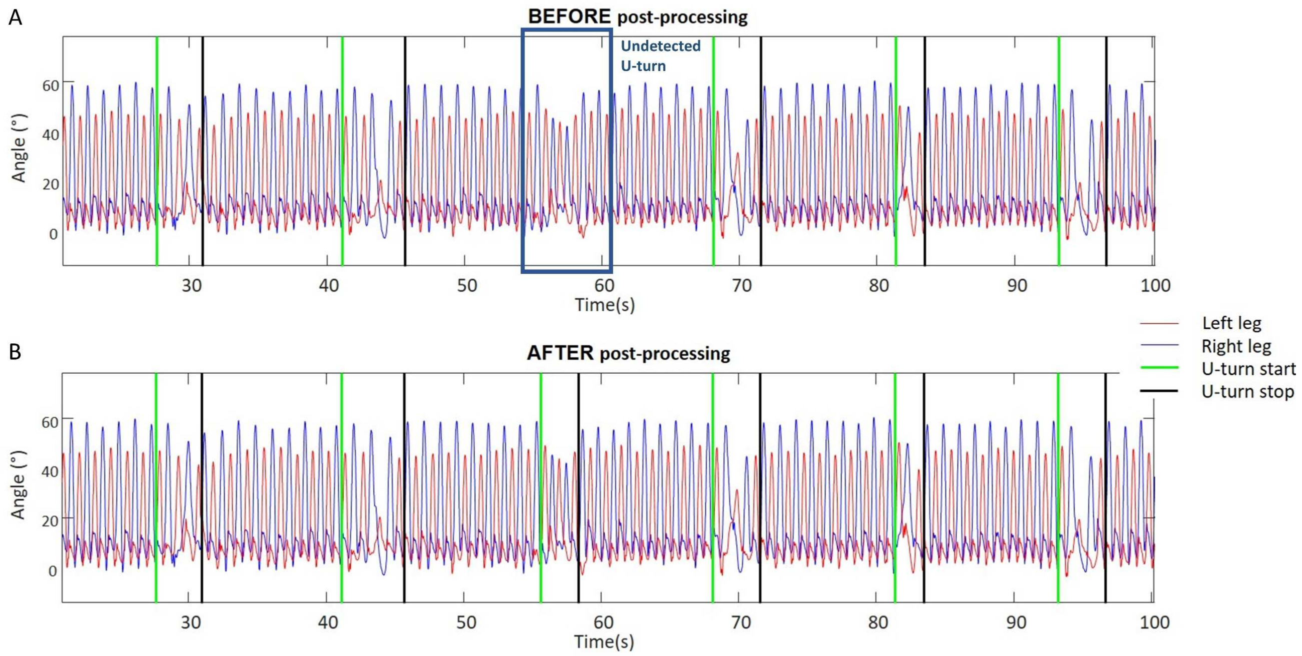

Fig. 4. Output of Classifier B for a representative subject of the sample population before and after the application of the post-processing step. (A) Without any post-possessing step a U-turn is missing (the algorithm does not recognize it, as highlighted by the blue-colored rectangle). (B) After post-processing all the U-turns are correctly detected.

estimations (i.e., those obtained before post-processing) to obtain the final classification.

Fig. 4 illustrates this concept by providing an example of post-processing results on the knee joint kinematic signals of a representative healthy subject. Fig. 4A represents the output of Classifier B before the post-processing step, while Fig. 4B shows the output of Classifier B after the application of the post-processing step.

F. Performance Evaluation

Ground-truth is obtained by manual segmentation of epochs of straight-path and U-turn walking. While gait signals are sliding on the monitor (with adjustable speed), including a synchronized video of the scene, markers are positioned by the user to separate straight-path and U-turn epochs. For the epochs of straight-path, only the "steady-state" walking is considered (i.e. approximately constant velocity), while deceleration steps before the U-turn and acceleration steps after it are considered "transient" periods belonging to the U-turn.

The performance of the two classifiers (Classifier A and Classifier B) were quantitatively assessed against the manual ground-truth considering the following four parameters: (*i*) Accuracy, (*ii*) Precision, (*iii*) Recall, and (*iv*) F1-score of detecting U-turns. More specifically, performance parameters were computed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (2)$$

$$Precision = \frac{TP}{TP + FP} \qquad (3)$$

$$Recall = \frac{TP}{TP + FN} \qquad (4)$$

$$F1 - score = \frac{2 \times (Recall\ \times Precision)}{(Recall + Precision)} \qquad (5)$$

where TP describes the True Positive (i.e., number of gait cycles correctly classified as U-turn), FN the False Negative (i.e., number of gait cycles incorrectly classified as straight path), FP the False Positive (i.e., number of gait cycles incorrectly classified as U-turn), and TN the True Negative (i.e., number of gait cycles correctly classified as straight path).

G. Statistical Analysis

First, the Lilliefors test ("*lillietest*" MATLAB® function) was used to test the normality of the performance indexes' distributions. If the hypothesis of normality was rejected, a two-sided Wilcoxon rank-sum test was performed to test significant differences in the performance of the two classifiers, otherwise paired two-sided Student's *t*-test was performed. Statitical analysis was performed setting the significance level (α) equal to 0.05. The Statistical and Machine Learning Toolbox of MATLAB® release R2021b was used to perform the statistical analysis.

TABLE I. PERFORMANCE EVALUATION

	Performance indexes			
	Accuracy (%)	***Precision (%)***	***Recall (%)***	***F1-score (%)***
Classifier A	97.0±0.9 [a]*	95.2±1.5*	99.6±0.2	97.3±0.8*
Classifier B	99.3±0.3*	99.9±0.1*	98.8±0.5	99.3±0.3*
***p*-value**	**0.03** [b]	**0.01**	0.11	**0.03**

[a] For each performance parameter calculated for Classifier A and B, the average and SE of the population are reported.

[b] Statistically significant differences between Classifier A and B are marked by an asterisk ($p<0.05$) and the corresponding *p*-values are highlighted in bold.

III. Results

A. Performance Evaluation

The performance parameters, calculated for both classifiers, are reported in TABLE I with the indication of the statistically significant differences tested through the Wilcoxon rank-sum test ($\alpha = 0.05$). Results revealed statistically significant differences ($p < 0.03$) in the performance of two classifiers in terms of Accuracy, Precision, and F1-score. More specifically, Classifier B outperformed Classifier A, revealing the importance of considering gait features extracted from the left leg and right leg separately. No significant difference ($p = 0.11$), instead, was found in Recall between Classifier A and B.

IV. Discussion and Conclusions

In the last years, the identification and quantitative assessment of the curvilinear trajectories during walking has found a great interest in different research areas, including gait analysis, motor rehabilitation, and pedestrian mobility. Accordingly, several approaches, mainly based on features extracted from inertial or magneto-inertial measurement units, have been proposed in literature to distinguish between straight path and U-turns. However, to the best of the authors' knowledge, no works have been published focusing on U-turn detection based on knee-joint kinematic and foot-floor contact signals. Thus, this contribution aims at developing and validating a machine learning approach for the identification of U-turns based on gait features extracted from knee-joint kinematics and basography.

In this work, we developed and validated a methodology to segment gait epochs acquired during a continuous 5-minutes walk along a hallway, for separating the linear trajectory from U-turns. We compared two different *k*-means clustering approaches based on gait data features extracted from knee joint kinematics and foot basography.

The analysis performed demonstrated that the best approach (i.e., Classifier B) is to consider first gait features extracted from the left and right leg separately to identify U-turns, and, only as a second step, merge the output obtained from the two legs. The performance of this approach is very good, in terms of Accuracy (99.3%), Precision (99.9%), Recall (98.8%), and F1-score (99.3%).

A limitation of this study is that the proposed algorithm was validated only on a population of healthy individuals. Future studies can extend the validation to pathological populations affected by locomotion impairment, such as patients affected by Parkinson's disease.

The results of this contribution demonstrated that the *k*-means clustering approach and, more specifically, Classifier B can be successfully applied to all those applications requiring accurate, precise, and automatic identification of U-turns, such as gait analysis, pedestrian mobility, and motor rehabilitation monitoring.

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