Automatic Detector of Gait Alterations using RGB-D sensor and supervised classifiers: a preliminary study

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***Abstract*—Alterations in walking patterns are widespread in the elderly population due to the motor decline typical of aging and other comorbidities related to movement disorders, such as Parkinson's disease, or the consequences of acute events such as stroke. Early detection allows promptly activating specific rehabilitation treatments to reduce the risk of falls, injuries, and hospitalizations. This paper presents a non-invasive solution based on Azure Kinect and machine learning to detect gait alterations (i.e., slow-speed gait, short-step gait, and dangling gait). The body tracking algorithm captures the 3D skeletal model during gait on a straight walking path compatible with domestic environments. Some parameters are estimated from the virtual skeleton to characterize gait objectively. These parameters are then fed to supervised classifiers to distinguish between normal and altered gait (binary classification) and between types of alterations (multi-classes classification). Preliminary results obtained on healthy volunteers simulating alterations are presented and discussed.**

***Index Terms*—Azure Kinect, gait analysis, remote monitoring, fall risk, machine learning**

I. Introduction

The increase in the elderly population of developed countries creates new and complex challenges related to their health management: specific needs, both physiologically associated to aging and to other comorbidities, arise in these subjects. National healthcare systems are economically burdened and often unable to satisfy these needs only through outpatient visits: clinical evaluations are seldom, especially when access to hospital facilities is difficult, as demonstrated by the Covid pandemic. For these reasons, economical and easy-to-use telemedicine solutions that could support a large number of patients in the prevention and daily management of diseases are being sought. From this perspective, motor decline correlated with aging or with other comorbidities has great relevance in the elderly care. The change in physical abilities, balance and stability is relevant both in the diagnostic phase and in the monitoring of pathologies like Parkinson's Disease (PD) [1] [2] [3], arthritis [4] or consequences of acute events such as stroke [5] [6] [7]. It also plays a key role in fall prevention [8] [9]. Falls are now recognized as a major issue for subjects over 65 years and their health management, as well as their quality and length of life [10]. New preventive approaches are proving their usefulness [11] [12] [13]. In this framework, gait assessment plays a central role, with demonstrated discriminatory features in assessing fall risks for elderly [14]. In particular, the focus has moved from traditional in-hospital gait analysis toward assessment methodologies that could be applied also in unsupervised settings (home, patients' associations) [15] through low-cost instrumentation such as wearable sensors [16] [17] [18], smartphones [19] [20] optical sensors [21] [22] [23] [24]. In particular, Kinect-based optical techniques are widely investigated [25], with promising results with respect to the gold standard of motion capture (MOCAP) systems [26]. For rehabilitation or prevention purposes, Kinect is used to capture movement through a markerless 3D tracking of human body joints which makes it a suitable tool for the characterisation of human gait and in the evaluation of performances during dynamic motor tasks. Examples of this use are found in physiotherapy [21] [27], post-stroke rehabilitation at home [28] [29], neurorehabilitation [30], multiple sclerosis [31], risk of fall assessment and prevention [8] [32]. Furthermore, this technology has often been applied in the evaluation/diagnosis of PD, allowing also the study of tremor intensity and postural dysfunctions [21] [17] [33].

Gait analysis using Kinect is generally performed through the estimation of spatiotemporal parameters and kinematic measures [34] [35] [36] such as the angles formed by leg swing, speed, and distance of each gait step, with significant results even in patients with neurological diseases [37] [38]. The last generation device, Azure Kinect, has recently started to be investigated for such applications. Preliminary results seem to confirm that this new sensor outperforms previous models (Kinect v1, v2) in real-time body tracking accuracy in general [39] and in gait analysis [40] for different viewing angles [41].

This study proposes an automatic detector of gait alterations based on Azure Kinect: the camera captures the subject while performing a 5-m-long straight walk and extracts, through native body tracking algorithm, a 32-joints 3D skeleton. From this virtual reconstruction, a set of relevant spatiotemporal parameters is estimated. Afterwards, multiple supervised classification methods are used to automatically identify abnormalities in walking patterns. The performances of the detector are tested simulating altered walking patterns typical of elderly and pathological subjects with gait disorders.

II. Material and Methods

The automatic detector pipeline is organised in two macro-sections: the first component (hardware and software) is the data acquisition system, which captures the walking task performed by the user in front of the camera. The second component (only software) is responsible for data processing, i.e., automatic features extraction from collected tracking data, and classification of gait. Fig. 1 summarises the complete system.

A. Data Acquisition System

To collect walking data, an acquisition system was developed that includes three elements: an RGB-Depth sensor (i.e., Microsoft Azure Kinect DK [42]), an elaboration unit (mini-pc or laptop), and a monitor to display the graphical user interface (GUI). The system acquisition software running on the elaboration unit is primarily based on the Software Development Kits (SDKs) of Azure Kinect: these allow accessing the color and depth streams of camera at approximately 30 frames per second and estimating from them 3D human movements, using Azure Body Tracking algorithm. The ouput is a time-based evolution of a skeletal model composed of 32 virtual joints.

Moreover, the system is also equipped with custom-written software, implemented in Unity, to manage the acquisition procedure, collect data and save the skeletal model evolution over time at the end of the acquisition. Data are saved in JSON files, containing the position, rotation, and confidence of each 3D body joint, for the subsequent gait analysis and characterization. The GUI is thought for a supervised scenario where the data acquisition is managed by a caregiver, therapist/clinician, or technician. Nevertheless, it consists of a few interactive buttons, audio and textual messages to be as easy to use as possible.

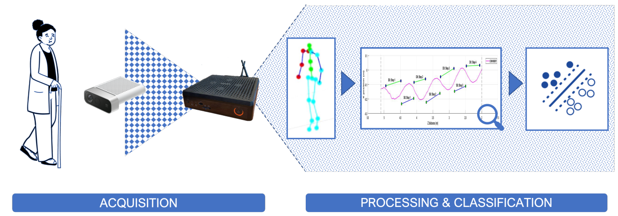

Fig. 1. Pipeline of the proposed automatic detector

B. Participants and acquisition protocol

To evaluate the ability of the system to detect alterations in walking patterns, we enrolled ten healthy volunteers (average age: 50.2 ± 15.8; age range: 45-66; five males and five females). Each subject was preliminarily instructed on the system and the experimental procedure. Then, each subject performed the required trials under the supervision of technical staff. All the subjects performed the trials under the same system setup [43]: since the system is thought for home monitoring of gait alterations, we considered a domestic scenario.

The acquisition protocol included three sessions for each subject separated by a 5-minutes pause: normal pace walking session (NPS), low-speed and short-step walking session (RPS), dandling walking session (DPS). The last two sessions (RPS and DPS) were included in the acquisition protocol to simulate altered walking patterns typical in elderly and pathological subjects with gait disorders, such as parkinsonian and post-stroke individuals with hemiplegia. For each session, three walking trials were performed. According to the acquisition protocol, each subject started 5-meters-away and walked toward the RGB-Depth sensor along a straight path (Fig. 2). In this way, the subject entered the virtual gait analysis path (VGAP, approximately from 4.5m to 2m from the RGB-Depth sensor) fully operational, allowing the correct detection of each step and estimation of gait parameters.

C. Gait parameters

The gait analysis procedure relies on the 3D trajectories of the skeletal model collected during walking sessions. In particular, joints related to ankles, which are more stable than foot joints [44], are used to estimate some spatiotemporal parameters, as in [43]. In addition, since lateral and forward sways during walking could indicate a potential risk of fall in dynamic conditions, some parameters related to the 3D trunk center of mass (COM_T) are also estimated. COM_T is computed from the skeletal model as the average of two body segments: neck-to-chest (i.e., NECK and SPINE-CHEST joints) and chest-to-pelvis (i.e., SPINE-CHEST and PELVIS joints). Table I shows the list of the estimated gait parameters.

Before estimating gait parameters, the 3D trajectories of joints are pre-processed using resampling (50 Hz) and filtering (low-pass Butterworth filter, third order) methods to remove jittering and high noise frequencies. The COM_T is used to automatically detect when the subject enters and leaves the VGAP. Inside the VGAP, left and right steps are segmented

Fig. 2. Scheme of the acquisition protocol

from ankles 3D trajectories [43] to estimate spatiotemporal parameters. The COM_T trajectory is also used to evaluate lateral and vertical sways inside the same area. While gait parameters estimated for the left and right sides are maintained separated for statistical analysis, they are averaged to obtain a single value for gait classification purposes to reduce the number of features to consider for each trial.

TABLE I
LIST OF GAIT PARAMETERS

Spatiotemporal and COM_T Parameters		
Parameter	***Unit***	***Meaning***
$STEP_L$	[m]	Length of step[a]
$STEP_T$	[s]	Duration of step[a]
$STANCE_D$	[%]	Stance phase duration (% of Gait Cycle)[a]
$SWING_D$	[%]	Swing phase duration (% of Gait Cycle)[a]
GC_L	[m]	Length of Gait Cycle[a]
GC_T	[s]	Duration of Gait Cycle[a]
$GAIT_{SP}$	[m/s]	Gait Speed
$CADENCE$	[step/min]	Number of steps/minute
ML_{RANGE}	[m]	Range of COM_T mediolateral sway
V_{RANGE}	[m]	Range of COM_T vertical sway

[a]Parameters that are estimated for left and right side

D. Statistical Analysis

For statistical analysis, we have considered parameters related to the left and right sides separately; the other spatiotemporal features and COM_T parameters have been treated as a single value for each trial. Due to the reduced dataset size, the Shapiro-Wilcoxon test has been considered to check the normality of each parameter: since parameters showed a non-normal distribution, a non-parametric analysis has been considered. The Mann-Whitney U test (significance level 95%) has been used to determine the significance of parameters in discriminating between groups of trials (i.e., NPS vs. RPS; NPS vs. DPS; RPS vs. DPS).

In addition, to support the analysis with a correlation metric, Spearman's rank-order correlation coefficient has been used to verify the correlation between parameters and type of sessions ("normal" vs "altered" walking patterns, thus considering RPS and DPS as unique category), to select the most significant parameters for gait alterations assessment. The statistical analysis has been performed using Jamovi, an open-source statistical spreadsheet built on R statistical language.

E. Automatic Gait Alterations assessment

For the automatic assessment of gait alterations, we have considered three supervised classifiers that are available in MATLAB 2019b toolbox: k-Nearest Neighbours (kNN), Discriminant Analysis (DA), and Support Vector Machine (SVM). For each classifier, several configurations have been considered: SVM with a linear kernel (LSVM), SVM with a quadratic kernel (QSVM), SVM with a cubic kernel (CSVM), kNN with k=1 (1NN), kNN with k=3 (3NN), kNN with k=5 (5NN), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA). The first test concerned a binary classification problem (two classes), where the gait trials were classified into "normal" or "altered" walking patterns; the second test concerned a multiple classification problem (three classes), where the gait trials were classified according to a more precise type of alteration (i.e., NPS, RPS, DPS). Initially, classifiers were trained using all the estimated gait parameters (10 features). Then, the training procedure was repeated selecting only the parameters with $|\rho| > 0.6$ (8 features) and finally only the most relevant parameters with $|\rho| > 0.8$ (5 features) resulting from the statistical analysis to remove potentially confounding and irrelevant gait parameters. The k-fold (k=5) cross-validation procedure was applied to test the classifier's performance on the available dataset.

III. RESULTS

A. Data Collection

All the subjects were able to perform the sessions as required. Nevertheless, some trials for RPS and DPS have been discarded during the processing of the 3D trajectories due to external factors that interfered with body tracking. Table II resumes the number of sessions and valid trials that make up the dataset used for statistical analysis.

TABLE II
COLLECTED SESSIONS AND TRIALS

Number of sessions and trials		
Session Type	***Session Number***	***Valid Trials***
NPS	10	30
RPS	10	26
DPS	10	28

B. Gait Parameters and Statistical Analysis

In this subsection, the statistical analysis results on spatiotemporal and COM_T parameters are presented. As previously mentioned, non-parametric statistics have been considered due to the non-normal distribution of parameters: so median (with first and third quartiles) and Spearman's coefficient (ρ) are shown in Table III. Parameter values are grouped according to the session type. The results in Table III concerning correlation indicate a significant statistical difference between parameters, which are so able to discriminate "normal" and "altered" walking patterns. The only exceptions are related to cadence and vertical sway of COM_T. The sign of Spearman's coefficient (ρ) denotes the parameter's trend according to the type of session. In particular, a negative sign indicates an inverse relationship, so a parameter that reduces its value with an increasing level of alteration (e.g., $STEP_L$).

On the contrary, a positive sign denotes a direct relationship, so a parameter that increases its value with an increasing level of alteration (e.g., $STANCE_D$). The Mann-Whitney U test was used to deepen and complete the previous results by identifying the most significant parameters in discriminating between the types of sessions. The sessions were considered in pairs for this analysis, as shown in Table IV. Table IV confirms the significant statistical difference in comparing NPS vs. RPS and NPS vs. DPS for all parameters, except $CADENCE$ and V_{RANGE}. However, only M_{RANGE} is able to discriminate between RPS and DPS: this could indicate that dandling walking patterns impact other gait features, thus resulting in similar spatiotemporal parameters.

TABLE III
MEDIAN, QUARTILES, SPEARMAN'S CORRELATION

Parameter	**Median (1° quartile, 3° quartile)**			ρ^a
	NPS	***RPS***	***DPS***	***"normal" vs "altered"***
$STEP_L$	0.55 (0.52, 0.60)	0.39 (0.30, 0.41)	0.32 (0.28, 0.35)	-0.81 ***
$STEP_T$	0.68 (0.63, 0.73)	0.92 (0.81, 0.96)	0.87 (0.78, 1.08)	0.66 ***
$STANCE_D$	57.1 (53.2, 59.4)	70.5 (66.8, 74.2)	70.5 (65.7, 74.0)	0.81 ***
$SWING_D$	41.4 (39.6, 44.5)	27.0 (23.5, 29.2)	26.5 (24.0, 31.0)	-0.81 ***
GC_L	1.13 (1.05, 1.22)	0.80 (0.61, 0.84)	0.67 (0.61, 0.74)	0.81 ***
CG_T	1.37 (1.27, 1.55)	1.79 (1.63, 1.98)	1.82 (1.62, 2.15)	0.63 ***
$GAIT_{SP}$	0.80 (0.68, 0.89)	0.36 (0.33, 0.45)	0.34 (0.30, 0.44)	-0.81 ***
$CADENCE$	66.0 (64.0, 69.1)	66.1 (56.3, 74.0)	65.6 (53.3, 76.2)	-0.06
ML_{RANGE}	0.07 (0.05, 0.09)	0.10 (0.09, 0.11)	0.15 (0.12, 0.18)	0.64 ***
V_{RANGE}	0.04 (0.04, 0.05)	0.04 (0.03, 0.04)	0.04 (0.04, 0.05)	-0.19

[a] *** ($\rho < 0.001$), ** ($\rho < 0.01$), * ($\rho < 0.05$)

TABLE IV
MANN-WHITNEY U TEST FOR PAIRED SESSIONS

Parameter	**U test results and significance**^{a}		
	NPS vs RPS	***NPS vs DPS***	***RPS vs DPS***
$STEP_L$	0.00 ***	4.50 ***	215.00
$STEP_T$	58.50 ***	51.50 ***	261.00
$STANCE_D$	1.50 ***	1.50 ***	286.00
$SWING_D$	1.50 ***	6.00 ***	274.00
GC_L	0.00 ***	3.00 ***	214.00
CG_T	70.00 ***	59.00 ***	265.00
$GAIT_{SP}$	6.50 ***	1.00 ***	233.00
$CADENCE$	283.00	254.00	274.00
ML_{RANGE}	101.00 ***	26.00 ***	107.00 ***
V_{RANGE}	186.00 *	258.00	206.00

[a] *** ($\rho < 0.001$), ** ($\rho < 0.01$), * ($\rho < 0.05$)

C. Automatic Gait Alterations Assessment

Table V and Table VI report the accuracies of selected supervised classifiers for binary and multi-classes classification problems, respectively. For each classifier, the accuracies are reported for the three investigated methods: training using all the estimated features (10 features); training using features with $|\rho| > 0.6$ (8 features); training using the most significant features with $|\rho| > 0.8$ (6 features). The three subsets were considered in order to reduce the number of features necessary to discriminate between gait patterns. Another relevant metric for the analysis of classification performance is the number of classification errors, thus it was included in the tables.

Regarding binary classification (Table V), the highest accuracies are related to all SVMs and 1NN using all the features: all the trials were correctly classified as "normal" or "altered" walking patterns. The other classifiers show reduced performance, due to some misclassifications. When classifiers were trained with only eight features ($|\rho| > 0.6$), accuracies slightly worsen due to the misclassification of one "normal" gait trial: discard of the V_{RANGE} parameter affected the classification of this normal trial. Further reduction of the number of features seems not to affect the classifiers' performance under a binary condition. The only performance improvement is related to linear discriminating classifiers, even though they show, in general, the worst accuracies.

More interesting are the results related to multi-classes classification. In this case, overall performance is worse than binary classification, an expected behavior when the number of classes increases. The best classification performance is related to the 1NN classifier with all parameters. Reducing the features during the training phase degrades the overall classification performance for all classifiers. The number of misclassifications increases. However, the analysis of the confusion matrices reveals that the classification errors are associated only with RPS and DPS trials, denoting the difficulties of classifiers in fine discriminating the two classes. Nevertheless, this is consistent with the statistical analysis results where no relevant statistical difference between the parameters of the two classes was identified.

TABLE V
CLASSIFICATION RESULTS (2-CLASSES)

Classifiers	**Accuracies (misclassifications)**		
	All parameters	$|\rho| > 0.6$	$|\rho| > 0.8$
LSVM	100.0 % (0)	98.6 % (1)	98.6 % (1)
QSVM	100.0 % (0)	98.6 % (1)	98.6 % (1)
CSVM	100.0 % (0)	98.6 % (1)	97.2 % (2)
1NN	100.0 % (0)	98.6 % (1)	98.6 % (1)
3NN	95.8 % (3)	98.6 % (1)	98.6 % (1)
5NN	98.6 % (1)	98.6 % (1)	98.6 % (1)
LDA	97.2 % (2)	97.2 % (2)	100.0 % (0)
QDA	95.8 % (3)	88.9 % (8)	94.4 % (4)

IV. CONCLUSION

The paper presents a non-invasive and easy-to-use solution for detecting and characterizing gait alterations in clinical and home environments, which could be used as a tool for preventing the risk of falls in elderly subjects or subjects with movement disorders caused by neurological pathologies or acute events. The system is implemented by combining an RGB-Depth optical sensor (in particular, Microsoft Azure Kinect DK) and its body-tracking algorithm with machine

TABLE VI
CLASSIFICATION RESULTS (3-CLASSES)

Classifiers	Accuracies (misclassifications)		
	All parameters	$\|\rho\| > 0.6$	$\|\rho\| > 0.8$
LSVM	79.2 % (15)	77.8 % (16)	68.1 % (23)
QSVM	77.8 % (16)	77.8 % (16)	66.7 % (24)
CSVM	75.0 % (18)	77.8 % (16)	70.8 % (21)
1NN	86.1 % (10)	81.9 % (13)	69.4 % (22)
3NN	69.4 % (22)	75.0 % (18)	66.7 % (24)
5NN	70.8 % (21)	72.2 % (20)	66.7 % (24)
LDA	77.8 % (16)	83.3 % (12)	66.7 % (24)
QDA	65.3 % (25)	62.5 % (27)	68.1 % (23)

learning methods and supervised classifiers to detect normal or altered walking patterns along a straight walking path suitable for domestic settings. To this end, some volunteers were recruited for preliminary experimental tests involving only healthy subjects. However, they were asked to simulate slow and dangling gaits, typical patterns in walking disorders that healthy individuals can easily mimic. Each participant performed several walking trials grouped into three sessions, as established by the experimental protocol: normal, slow, and dangling. Each trial was analyzed to extract space-time and center-of-mass parameters of the trunk starting from the 3D trajectories of the joints of the skeletal model collected during walking. Statistical analysis was applied to identify the most relevant parameters to distinguish between normal and altered gait patterns and, in addition, to discriminate the type of alteration. This information was subsequently used to train some supervised classifiers and identify the best-performing ones in binary and multiclass classifications.

Preliminary results show that the system is able to capture differences between the types of gait patterns, as demonstrated indicatively by the average values of the estimated parameters. Moreover, this trend is confirmed by the statistical analysis results, from which it emerges that most of the estimated parameters (8 out of 10) are able to discriminate between normal and altered patterns (Spearman's correlation coefficient $|\rho| > 0.6$). A more in-depth analysis, considering pairs of categories, has shown that the same parameters allow discrimination of "NPS vs. RPS" and "NPS vs. DPS" gait patterns. On the contrary, there is no statistically significant difference in the "RPS vs. DPS" comparison, except for lateral trunk sway as expected. This result could indicate that the dangling gait impacted the overall kinematic walking profile, resulting in very similar parameters. The classification results reflect this trend, where the accuracies in the multiclass case are lower due to a more relevant number of misclassifications belonging to the RPS and DPS categories: none of the classifiers examined is able to perfectly discriminate the two types of alterations due to an overlap between categories. Conversely, very high accuracies are obtained for the binary case, confirming the statistically significant differences between normal and altered gait. The results on binary classification are in line with other studies investigating various methodological approaches to detect differences in gait patterns for healthy controls and pathological subjects, generally achieving high classification accuracy [45] [46] [47] [48] [49]. However, only a few studies report results on in-depth analysis [50] [51] to detect a more refined classification of the type of alterations, which could be relevant, for example, to activate more specialized rehabilitation treatments. The study has been conducted only on a few healthy subjects and simulations of impaired gaits. Nevertheless, we are planning a further acquisition and analysis campaign on subjects with "real" walking disorders: the preliminary results obtained make us confident of being able to reproduce and improve these findings on a broader spectrum of gait profiles.

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