Real-time gait assessment with an Active Depth sensor placed in a walker

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Abstract— **Assisted gait monitoring can benefit from the measurement of feet positions and orientations. Thus, in this paper, rollator type walkers are equipped with one active depth sensor for gait assessment. Also, a real-time feet positions and orientations algorithm is proposed and a gait assessment method is provided for clinical evaluation purposes. Results using the proposed algorithm are compared with motion capture system, as reference data (ground truth) and tested with hospitalized elderly. The proposed gait assessment was able to extract important frail elderly gait characteristics.**

Keywords—Elderly gait assessment; walker; feet tracking; active depth sensor; rehabilitation.

I. INTRODUCTION

Aging of population of developed countries for the coming decades are now well known: by 2060 the number of people aged 70 and over will double and the number of people aged 90 and over will quintuple. If we can see the increase in the quality of life of older people, many remain frail and therefore at high risk of loss of autonomy. The aging of the population is accompanied by an increase in the number of dependent elderly. The loss of autonomy in the elderly may be physical and/or cognitive or both. Physical dependence is strongly related to the quality of walking, which turns impaired in over two-thirds of the elderly more than 85 years old [1]. Gait disorders are frequent for about a third of elderly and often lead to the use of technical aids [2]. Similarly, about 20% of seniors exhibit balance disorders and have a disabling postural instability [3], [4]. For the clinicians the need for technical assistance is a frailty index, used to predict a patient's risk of functional decline. Moreover, clinical gait analysis evaluates the evolution of pathology or rehabilitation results for diagnosis purposes. Gait analysis is often divided in (1) patient qualitative observation, (2) a description phase and (3) a biomechanical analysis. Description phase and biomechanical analysis vary according to the availability of the equipment in the hospital or clinics [5]. Since most clinics and hospitals do not have proper equipment, simple gait analysis systems should be available [3], [6]. Performance of gait analysis should thus be based on objective assessments of a person's functional physical state [3]. Research has been focused on this problem by addressing the characterization of human gait parameters and other aspects with the use of walkers [7]. Moreover, some studies started to relate clinical and functional features of disorders to the specificities of the type of walker [8]-[9].

In order to well diagnose and follow rehabilitation with the use of a walker, a gait assessment measurement system has to be accurate but also affordable to reduce unequal access to health care and to improve medical follow-up (i.e. to allow to be used in physiotherapists' office and even at home). Similarly, the gait analysis system should be portable and adaptive to the majority of walkers. The method should be contactless to be used in daily routine, improve comfort and decrease the time of analysis. If the system enable real-time analysis, data could be used directly during the consultation by the physician and eventually at home for motivational purposes or monitoring the quality of walk (to predict any forthcoming deterioration of a user's gait).

Classical motion capture systems, even if they are the most accurate systems for gait analysis do not fit with the previous requirements. They are really expensive, not portable and use markers [10]. In addition, with assisted gait walks, occlusions often occur.

The inclusion of embedded systems on the walker seems more appropriate to our application. Indeed, the inclusion of embedded systems on the subject such as accelerometers [11] or force sensitive insoles [11] are affordable but the first one is not contactless and the second one lacks of portability as special shoes are needed.

Approaches with walkers used ultrasound sensors (US) [12], Infra-red (IR) [13], Laser Range Finder (LRF) [14] and active depth sensor (ADS) [15-16]. Since US require markers, they were not considered. IR and LRF showed sensitivity to different clothes as large pants, and thus camera depth sensor was chosen for this study.

Hu et al. [15] and Joly et al. [16] proposed methods based on camera depth sensor but precision seemed not sufficient and their systems were not tested with elderlies. Moreover, processing time was important for enabling immediate use.

In this paper, a gait assessment system based on an embedded ADS is used. It was first developed with healthy subjects [17] and satisfied the required qualities to fit the goal (affordable, portable, markerless and real-time processing). The aim of this paper is to present needed adaptations to fit specific elderlies' behavior issues as well as the elderly gait characteristics extraction.

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The paper is organized as follow. Section II describes the group of patients selected for this study, the protocol, and presents the proposed method for feet tracking using an ADS. In Section III the gait assessment tool is shown. Finally, Section IV presents the results and validation and Section V the discussion. Finally, in section VI conclusions are presented.

II. Methods

A. Participants

A group (N=11) of elder subjects with various diagnoses leading to gait dysfunction were tested (Table I). The study was conducted at Charles Foix Hospital in Paris, approved by the Ethical Committee, and all the patients signed the informed consent.

TABLE I. Characteristics of the 11 patients.

	Age	Weight (Kg)	Diagnosis
1	86	69	Recurrent falls and compression of vertebrae T12.
2	86	62	Recurrent falls and oedema.
3	88	65	Fall with head trauma.
4	79	93	Pulmonary abscess.
5	90	75.3	Confounding syndrome that led to a loss of autonomy.
6	84	75	No autonomy and has cognitive limitations
7	71	82	Post-surgical Knee Osteoarthritis
8*	89	39	Psychomotor agitation
9*	91	51.5	Brain breed
10*	91	68	Lower limbs ulcer and acute decompensated heart failure
11*	85	40	Heart failure and femoral head fracture.

*These patients used walker on the left of fig.1. The others used walker on the right.

B. Protocol

One trajectory consisting in a U-turn was performed by the subjects. Each subject performed the trajectory two times. For validation of the obtained data with the proposed ADS system, ground truth trajectories are provided by the motion capture system Codamotion System [18]. The technology uses miniature infra-red active markers. The sampling period was set to 100Hz and data processing was made on MATLAB (version 2012b). Positions and orientations of the feet are then compared between data obtained from ADS and from a ground truth (Codamotion).

C. Experimental setup

An Active Depth Sensor (Asus Xtion Pro - ADS) was placed on two different four-wheeled walkers, as shown in fig. 1. ADS position is identified by a red square. Such position was chosen to have a good visualization of both feet over all gait cycle.

D. Feet tracking

1) Related Work

Recently, new studies appeared suggesting an active depth sensor approach for feet detection [15], [16]. In [15], a parametric model of legs and feet is adapted to the camera images using point clouds. Only position errors are reported by the authors (less than 60mm). In [16], another parameterized model is matched on the camera data. The principle is the same as in [15], however in [16] the model is simpler and the correspondence with the model is made with the depth map. Only orientation error is reported by the authors (less than 15º). Despite being a good approach, the actual set up presented some occlusions in data. As these two methods use legs, they require two separated sets of points for legs, thus large clothes and skirts will lead to false detection. Moreover, because of complex segmentation, the image processing is long, not allowing a real time processing of data. In addition, no tests were performed with actual walker users as elderlies.

Fig. 1 Two patient using two different four-wheeled walkers with ADS system.

The proposed system described in this paper was presented in [17]. It presents a better visualization of both feet in all phases of gait cycles and presents a much more simple and effective approach for feet tracking. To improve the reliability against environmental conditions (especially clothes), we propose to extract main data about the walk (feet position and bearing angle) only by segmenting feet. By this way, the processing time is reduced and the algorithm can be used in real time application. When [15] has a processing time around 15s, the proposed algorithm [17] takes around 0.1s to process with similar computers.

In this paper, the algorithm proposed in [17] will be validated with a walker like rollator and hospitalized elderly (Table I) in order to evaluate efficiency and precision.

2) Feet tracking algorithm

In order to detect and track the feet with the active depth sensor (ADS), three main steps have been implemented: (1) Calibration, (2) Feet segmentation and (3) Computation of feet distances and orientations. The workflow is presented on fig. 2. This algorithm has been developed and tested with healthy subjects in [17].

In (1) Calibration, two matrix should be determined. The first one corresponds to the intrinsic parameters of the camera and is determined once through camera. The second corresponds to the relative position between the camera and the ground and should be evaluated each time the camera is installed on a walker [19]. As the experiments with elderly were made with different walkers, static parts of the walker could appear in the feet region (like wheels) and their positions are recorded and stored at this step.

In (2) Feet segmentation, a binary image is computed to select points in the feet region according to the distance of the measured points from the ground. The binary "blob" technique (based on the identification of different regions [20]) labels the different objects in this region. Wheels and artifacts are isolated to keep only feet candidates. During experiments with elderlies, sometimes feet came into contact of wheels. These events are detected by area information and solved by image subtraction. The next phase is to find feet among the remaining candidates according to the position of their centroids.

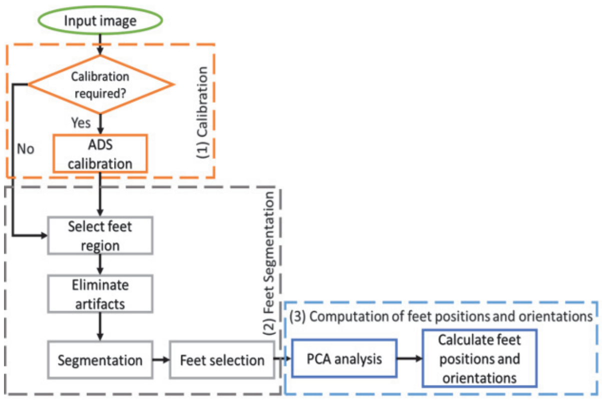

Fig. 2 Schematic of the proposed feet detection algorithm.

Elderly's gait usually presents decreased stride and step length and an increase in the walking base [21]. However, walking base is reduced when ambulating with the walker [22]. This pattern causes the feet to touch during the walk and so to appear together on the images captured by ADS. When such situation is detected through area information, the "blob" is eroded until two "blobs" appear. If this method does not allow to identify the two feet, the image is skipped.

Finally in (3) Computation of feet distances and orientations, the centroid of each foot is extracted. In order to calculate the orientation of each foot, Principal Component Analysis (PCA) is used to find the highest variance of the points that correspond to each foot.

The algorithm and image processing was done using OpenCv library.

III. Gait Parameters Assessment

A. Spatiotemporal Parameters Calculation

In this article, it is proposed to calculate some specific spatiotemporal parameters. These parameters are important to evaluate the state of the user, for example to infer his evolution during the rehabilitation program. In order to calculate these parameters it is needed to identify some gait events in the feet signals in forward direction: heel strike and toe off.

The gait cycle (Fig. 3) has its beginning and ending in successive events of the same foot, thus identifying repetitive events that can be characterized by one cycle time. During the gait cycle, the relative distance between the foot and walker varies as follows: increases when the foot moves more slowly than the walker or when it is stopped (stance phase); decreases when the foot moves forward with a faster speed than the walker (swing phase). These variations are illustrated in fig. 3 for one foot. We can also observe that the distance between the foot and the walker is maximum at the end of the stance phase and before the beginning of the swing phase (time when the foot goes from the state of being stopped to the state of approaching the walker). Thus, the maximum values of the signal correspond to toe-off (TO) events and the minimum values correspond to heel-strike (HS) events [23].

After identifying the latter events, the following parameters can be calculated (Fig. 3):

1) *Stride Length (StL) and Gait Cycle (GC):* are the distance and time, respectively, between TO and HS from the same foot. It is calculated through the difference between the maximum distance and consecutive minimum of the same foot. Gait cycle is calculated through the correspondent time of such points.

2) *Step Length (SpL) and Step Time (SpT):* is the distance and time, respectively, between HS of one foot and consecutive HS of the other foot.

3) *Cadence:* number of steps per minute.

4) *Velocity:* distance walked in each gait cycle.

5) *Stride width (W):* is the distance between both legs in X_w direction.

6) *Swing duration (SWD):* is the time corresponding with the oscillation phase, when the foot are not on the ground. It is calculated as the time between TO and HS of each foot.

7) *Stance duration (SD):* is the time corresponding with the support phase, when the foot is on the ground. It is calculated by the time between heel strike and toe off of each foot.

8) *Double support time (DST):* is the time when both feet are on the ground. It is calculated when both signals present a positive derivate. This happens between the HS of one foot and the TO of the other foot.

However, if we calculate the distance-based parameters directly from the forward direction signal, their values will correspond to the distance between the user and the walker. To obtain the spatiotemporal parameters relative to the world it is necessary to estimate the displacement of the subject in the world reference. Thus, the displacement of the subject's foot is needed regarding the displacement of the walker in the world. Such displacement of the walker can be calculated through two approaches: encoders' information (odometry) [24] or stance foot distance [23]. Since we are not working with a robot walker, in this paper the stance foot distance will be applied.

By measuring the relative distance between the walker and the foot, which is on the stance phase (Fig. 3), it is possible to infer how much the walker displaced. The foot that is in the stance phase is fixed on the floor, thus the variation in distance measured by ADS (black side of the graph in fig. 3) is due only to the displacement performed by the walker. Since there is always a foot on the ground during gait, it is possible to measure such displacement.

Having both the distance walked by the subject relative to the walker and the distance performed by the walker, the difference between them will give the actual walked distance by the user on the environment.

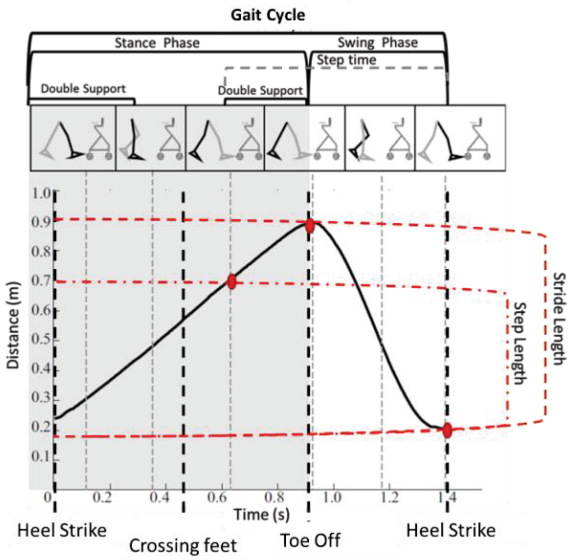

Fig. 3 Relative distance between one foot and the walker, during one gait cycle.

B. *Statistical Analysis*

Gait parameters derived from ADS system were compared on a step-by-step basis against the data derived from the Codamotion as a reference, using Intraclass Correlation Coefficient (ICC(2, k) as reported previously [24]. The mean true error between these two systems was also examined on a step-by-step basis. Such error was calculated for all spatiotemporal gait parameters as the difference between the ADS and Codamotion values. Then, ANOVA (analysis of variance) will be performed for each parameter error to verify if there are differences among patients in terms of errors and parameters. The result of this analysis will inform if the errors can be considered systematic. The level of significance was set to $p<0.05$.

IV. RESULTS

A. *Feet detection and segmentation results*

Fig.4 shows two frames of different phases of the performed trajectories. The first frame shows the moment that the right foot is beginning to cross with the left foot in a straight line. The second frame shows the feet performing a curve for the right. The first image of each frame corresponds to the original input image captured by the ADS. After applying the feet tracking algorithm, the second image of each frame is obtained. Some unknown objects can appear in the image, while the subject is walking, leading to a feet false detection. However, the algorithm was capable of discarding such objects.

Each foot is labeled as right foot (green) or left foot (blue). With the detection of the feet, the point of interest of each foot can be calculated. Then, PCA is applied to calculate the orientation of each foot. The image shows a representation of the axis of inertia (line of each foot) that allows the calculation of the angle of orientation of the feet. It can be seen that different foot orientations are well identified by the PCA algorithm.

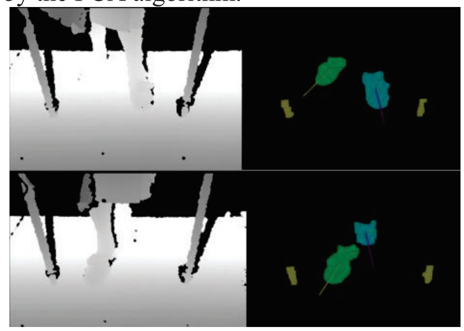

Fig. 4 Two Frames representing the feet tracking algorithm result. First frame represents the patient #5 walking forward. Then, second frame represents the same patients turning right. Right foot is green and left foot is blue. The line represents the result of PCA,, giving the orientation of each foot.

B. *Position and orientation errors results*

Since the goal is to extract gait parameters from the collected images, the signals obtained with the position coordinates in walker's frame are represented when the subject is walking forward. To validate these positions, coordinates of the feet from Codamotion system in the world frame were transformed into coordinates in walker's frame to be compared with the ADS signals. As it can be seen in fig. 5 the positions estimated with the sensor are very similar with the ones captured by Codamotion system. As it was previously said the walker may bring motion occultation, which means the Codamotion system will miss data that will increase the difficulty to study the gait. Such situation is observed in fig. 5 where Codamotion system signals present missing data and errors due to occlusions. Another situation where occlusion of data appears is during U-turning. The Codamotion system loses the markers, and it is not possible to acquire data in such event. However, our proposed system it is capable of tracking the feet even in such situation. In fig. 6 it is presented a full trajectory of U-turn with 2D-positions and feet orientation (begin and end of turning are identified by a rectangle). One can verify that the ADS system detects both feet through the all trajectory. Since Codamotion system data presented many occlusions, one can verify in [25] the algorithm is stable enough to acquire the necessary data.

These results enable to conclude that this system is better suited for gait motion analysis in assisted gait with a walker device than Codamotion system.

Root Mean Square Deviation (RMSD) is used to compare quantitatively Codamotion system and ADS position data. The results can be seen in Table II and are compared to [17] (same method but used with healthy subjects). It can be seen that the error increases with elders. Despite this fact, with these results, it is possible to conclude that the proposed algorithm is suitable to be used for feet tracking, acquiring the necessary data to be used in a gait assessment tool.

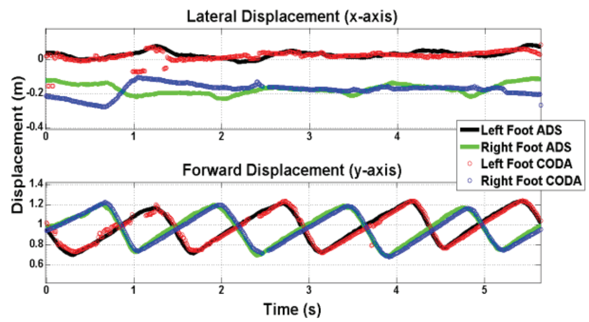

Fig. 5 2D feet positions acquired by Codamotion capture system and ADS sensor on the different axis with patient #1.

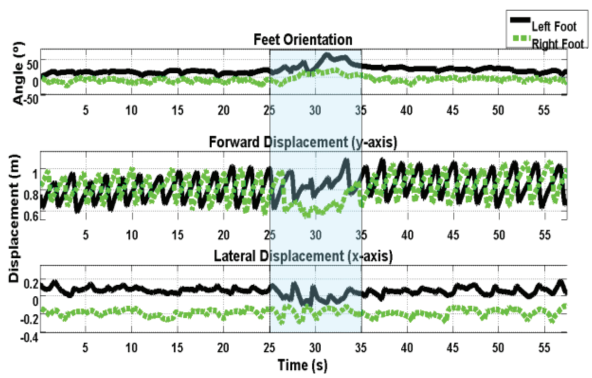

Fig. 6 2D Feet position and orientation acquired by ADS sensor of patient #5 describing a U-turn. The rectangle represents the interval between the beginning and ending of turn.

TABLE II. COMPARISON OF RESULTS BETWEEN THE ALGORITHM USED WITH HEALTHY SUBJECTS [17] AND WITH ELDERS REGARDING POSITIONS ERRORS. MEAN±STANDARD DEVIATION IS PRESENTED.

	RMSD (mm)	
	X (lateral direction)	Y (forward direction)
Healthy approach [17]	28.9±2.03	30.8±2.82
Elders approach	35.2±2.87	40.1±7.03

C. *Gait assessement results*

Fig. 7 illustrates the gait events detection (HS and TO) that enable to calculate the spatiotemporal parameters (section II.E). Consecutive strides are represented for two subjects in % of gait from HS event of the left foot to the next HS event on the same foot. On this figure, intra-individual variability can be observed in space and time but also inter-individual variability. One can see that the patient #7 has an asymmetrical gait with step length smaller on the right side than on the left side. The patient #8 presents an even more asymmetrical gait as his/her feet do not cross each other. Despite these variabilities, the feet tracking algorithm has still the capacity to track both feet and the developed gait assessment tool detects all gait events.

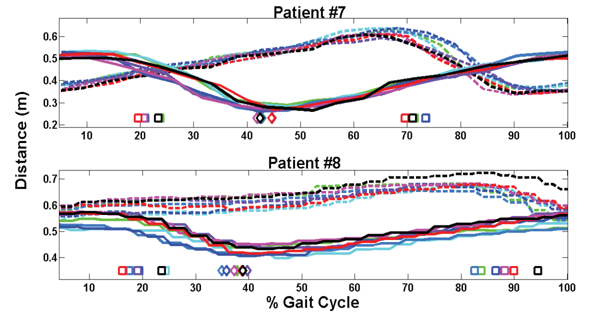

Fig. 7 Different strides from each foot are presented. Dashed line corresponds to left foot strides and continuous line corresponds to right foot strides. Squares are TO events and Diamonds are HS events.

It is noteworthy that, despite the experiments include a turn trajectory, gait parameters were only calculated in straight line trajectory.

With the correct detection of gait events, it is now possible to calculate the spatiotemporal parameters presented in section III.

D. *Spatiotemporal Gait parameters results*

For the measurement of spatiotemporal parameters, 15 steps were considered for each patient.

After calculating the errors between ADS and Codamotion for each gait parameter, one verified that the average errors of spatial parameters varied between 2 and 4 cm and the temporal parameters varied between 0.1 and 0.8 seconds. The greater errors correspond to patients with greater stride lengths. This happens because their feet in TO and HS are too far and too close from the camera, respectively. This will change feet's shape, which lead the centroid to change its position more often, increasing the error.

By performing ANOVA, all parameters presented significant differences between patients ($p<0.05$) showing that patients present significant different gait patterns between each other. Then, we verified that errors of most spatiotemporal parameters have no significant differences between patients ($p>0.05$). Only step width (W), stride length (StL) and step length (SpL) present significant differences ($p<0.05$), not being considered as systematic errors.

Despite this remark and the errors being significantly different among patients, they are small (less than 4cm and 0.8s) regarding the purpose of this study, which is the calculation of spatiotemporal parameters. In addition, the ICC for temporal parameters gait cycle, step, double support, swing and stance time was found to be greater than 0.86, indicating good agreement. Similarly, for spatial gait parameters—stride and step length, step width and velocity—the ICC was found to be greater than 0.90. These results show good to excellent concurrent validity in spatiotemporal gait parameters.

V. GENERAL DISCUSSION

This study brought a new gait analysis system that can be adapted for different walkers. Its low price, low weight and portability are the main advantages for this system. By this, physiotherapists can make routine analysis of their patients and infer the evolution and recovery of the patients. Thus, they can quantitatively assess their performance.

Nowadays, elderlies in their recovery process are sometimes evaluated with observational and timed scales like Time Up and Go (TUG) or 6-minute walk distance (6MWD) [6]-[11]. These scales are very poor in terms of evaluation parameters, since they provide only speed information. With ADS system it is possible to extend this evaluation for more parameters, since it is capable of acquiring feet position through any trajectory. The same did not happen with Codamotion analysis that was only capable of acquiring data when the patients were walking forward. Thus, occlusion problems are eliminated with ADS system.

Other advantage is to collect relevant data about the gait evolution and the adequacy of the device use. These data will be stored and processed to assess any misuse of the aid and to foretell any decline of walking capabilities.

VI. Conclusions

This paper presents a system able to track the feet position and orientation during an assisted walk without equipping the user. An active depth sensor was used with a new detection algorithm that suits for all subjects and walkers like rollator. The main advantages of our method compared to others realized with this kind of sensor is that it is markerless, faster than using 3D models, reliable against clothes conditions and detects continuously orientations of the feet. Preliminary results show that this system has high potential to be used on clinical trials with patients to give clinical insight to the clinicians.

In addition, this system can be used for smart-walker control, since the tracking of feet gives patients' orientation and positions intentions.

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