2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

Legs Tracking for Walker-Rehabilitation Purposes

M. Martins, A. Frizera, *Member, IEEE*, R. Ceres, C. Santos, *Member, IEEE*

Abstract— **Clinical evaluation during walker-assisted gait is the first step to assess the evolution of a patient during rehabilitation and to identify his needs and difficulties. Advances in robotics made it possible to integrate a gait analysis tool on a walker to enrich the existing rehabilitation tests with new sets of objective gait parameters. This paper focuses on the legs detection method to estimate legs position during an assisted walk and the detection of gait events. In this paper, a walker is equipped with a laser range sensor (LRF) and encoders to analyze the spatiotemporal parameters of the walker users. Preliminary results obtained on ten subjects show that relevant data using a LRF can be extracted for gait analysis with a small error.**

I. Introduction

Gait analysis has been an important research field for rehabilitation purposes. Although cameras made it possible to acquire gait information, processing the data can be time-consuming and inefficient. As technology developed and computers enabled faster computation, gait analysis became more efficient. A common method in gait analysis is tracking and there are many precise methods to do this. The problem with such methods is that they are usually too expensive and need special laboratories for analysis, which results in both economical and practical disadvantages.

Nowadays, many studies focus on the research of gait tracking with portable sensors placed on the subject. Inertial [1] and pressure/force sensors [2, 3] are very well known examples to measure joint rotations, dynamics and spatiotemporal parameters.

Regarding gait analysis systems integrated on external devices like walkers, there are a large variety of examples [4]. This research is very important since clinical evaluation of walker users is the first step to decide the degree of assistance they require. This evaluation is only performed once and by observation, using standard scales and questionnaires. Advances in robotics made it possible to integrate sensors on conventional walkers to act as portable gait analysis systems. This advance allows evaluating the evolution of some disorders and enhances diagnostics in ambulatory conditions.

However the majority walker studies focuses on developing systems based on force sensors located in the handles [5], or in the frame of the device to detect the bending force that is applied on the walker [6] to identify the body weight load of the user on the walker.

M. Martins and C. Santos are with the Industrial Electronics Department of Minho University, Guimarães, Portugal (corresponding author to provide phone: +351 253 510190/604705; e-mail: mariam(cristina) @dei.uminho.pt).

A. Frizera is with Electrical Department of Federal University of Espirito Santo, Vitória-ES, Brazil (e-mail: anselmo@ele.ufes.br).

R. Ceres is Bioengineering Group of CSIC, Madrid, Spain (e-mail: ceres@iai.csic.es).

Other potential of integrating sensors on the walker is to infer the trajectory that the user wants to follow and help him doing it. JaRoW [7] integrated with a laser range finder (LRF) sensor to detect the location of user's lower limbs in real time [7]. A Kalman filter was applied to estimate and predict the locations of the user's lower limbs, in real time. Despite the good results, it is not certain to be effective when tested with elderly people, since their legs are usually closely spaced, and their algorithm does not consider this hypothesis. This can lead to false detections, making the algorithm to only detect one leg. In addition, it was only tested with one subject, which does not prove that the algorithm is efficient for different subjects and it does not make a gait analysis study.

So, it remains the challenge to find a more reliable algorithm system that can deal with different legs postures and subjects to allow the correct calculation of gait parameters and trajectory of the user.

Thus, this paper intends to present the design and development of a LRF system integrated on a smart walker that continuously determines, in real time, the relative position of the subject's legs relative to the walker during its use; deals with different legs postures and it is calibrated for each different subject. In addition it is developed a system that detects gait events and measures spatiotemporal parameters associated with the walker's use. This system will provide clinical insight to clinicians, while maintaining an objective and low cost system without the need of equipping the patient with sensors.

Section II gives an overview of the ASBGo walker. Section III presents a brief state of the art in leg detection algorithms based on laser tracking. Section IV presents the purposed legs' tracking algorithm. The detection of gait events and the calculation of spatiotemporal parameters are presented in Section V. Section VI shows experimental results and discussion. Finally, in Section VII it is presented some conclusions and future work guidelines.

II. ASBGo Walker

The ASBGo (Assistance and monitoring System Aid) walker has a mechanical structure that allows the installation of motors, sensors and other electronic components. It has four wheels and a supporting structure that holds the user. Its front casters can freely rotate and turn. Two motors drive its right and left rear wheels independently.

For this work, the device is also equipped with one laser range sensor (LRF). This sensor is used to track both legs, to then estimate the trajectory and gait parameters.

These parameters are important to evaluate the state of the user and to infer his evolution in the rehabilitation program. Many disorders are characterized by spatial temporal parameters, and their modification can bring insight into the

978-1-4799-3127-9/6/14/$31.00 ©2014 IEEE

diagnostic of the user. Many examples can be presented: after a fall, people tend to enlarge their support base and present higher stance duration; Parkinsonian festination corresponds to an inconstant speed and short steps; multiple infarcts syndromes are related to small steps; Ataxic patients increase their support base, small steps, low velocity and very insecure gait [7].

Figure 1. ASBGo walker.

A. LRF system

The LRF (URG-04LX URG01) performs a scan of 240° with an angular resolution of 0.36 °. The time spent in each scan is 100ms, time that meets the requirements for the measurement of parameters associated with human gait. In a full scan, the sensor acquires 682 points (approximately one point per 0.36 °) from left to right.

This system aims to acquire the distance between the legs and the walker. It can be deduced, mistakenly, that the most appropriate position for fixing the sensor would be a few centimeters from the ground so that the feet of the user can be intercepted by the scanning plane of the laser. However, during the gait process, the user's feet rise above this plane, so that, in these moments, no information regarding the lifted foot is detected.

To prevent undesired detection of the shoe or knee, the sensor is positioned to scan a plane, which is distant 30 cm from the ground and parallel to it. This plan was chosen according to [8].

III. Overall Legs' Tracking Methods

For the development of an algorithm to track the legs, a state-of-art research was made. Many studies already present methods of legs tracking with a LRF.

In [9] it was used the geometric approach with the Bounding box method. This is a method for checking geometric features of a set of candidate data that is to be classified as "human legs". The classification is based on the length of the diagonal of an imaginary rectangle, among other features, which has two opposite vertices that correspond to legs points. However, according to [10], is not able to capture critical information for efficient detection of legs.

Another method is known in the literature as Circle fitting [11]. This method assumes that the data from laser scanning concerning to human legs appears with a curved shape. Although other objects during scanning may also have curved forms, it is considered that the radius of curvature of human legs is normally between two specified limits. This builds up the classification method for verifying the radius of curvature of the detected shape. The disadvantage of this approach lies in the fact that the type of clothing can change the geometry.

In [13] it is used a LRF to identify patterns of legs which can be separated legs, legs together or not parallel legs, in order to allow interaction between a person and a mobile robot. Despite dealing with different legs postures, these patterns are pre-defined with the help of features whose values are found off-line. The approach presented in [12] does not classify the legs posture into pre-defined patterns. They divide the space into two sub-regions (right and left) and classify the legs as right or left by observing the sub-region in which they operate. This division of regions is made by an imaginary line passing through the centre of the LRF scanning. This approach could work well if implemented on a walker, however just in straight-line paths, since in a curve one leg could invade the sub-region of the other.

In this work, it was developed a technique for detection of legs similarly to [13] since it deals with the problem of different legs postures. The difference relies on the online calibration of features that characterize the legs of different subjects to detect their legs, and the fact that it deals with noise and situations of non-pattern.

IV. Algorithm for Legs' Tracking

The legs' detection method presented in this paper is based on [12] and develops improvements since the previous work does not deal with noise, non-patterns and different user's legs dimensions and clothes. The detection algorithm developed is divided into four parts: (1) Pre-processing of data; (2) Detection of Transitions; (3) Calibration Mode; (4) Pattern analysis and estimation of the coordinates of the legs.

A. Pre-processing of data

Each point distance is represented by m_i, where i is the index of the point of acquisition. Thus, i vary from 1 to the maximum number of points of the scanning (682 points for a full scan). Each measurement point i, in each scan, is represented as follows:

$$m_i = (\alpha_i, r_i) \quad (1)$$

where a_i is the angle calculated from the i index and r_i corresponds to the measured distance (mm). Thus, the point set that is acquired in a full scan can be represented by:

$$U = \{m_1, m_2, ... m_{682}\} \quad (2)$$

In order to limit the background, a boundary of the region of interest is performed. This region of interest seeks to address the whole area where the legs will be positioned during walking. All measurements that are outside the limits of the definition will not be considered ($256 < i < 426$ ($-30° < \alpha_i < 30°$), r_{max}=1000 mm). This procedure aims to make the LRF to only identify the person who is using the walker, thus preventing people and objects that are near the walker to interfere with the detection of the user's legs. Figure 2a) shows the top view of the walker in a situation where a person P1 is with the legs inside the defined region and a person P2 is outside that region.

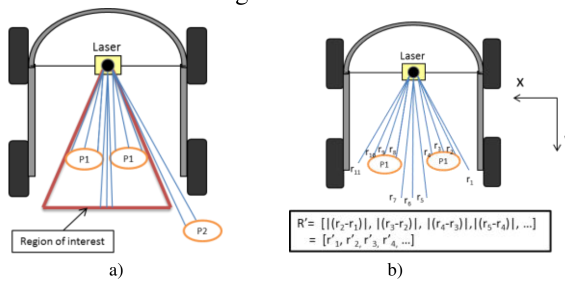


Figure 2. a) Top view of the walker and delimitation of the region of interest; b) Representation of the transitions' detection procedure.

B. Detection of transitions

This section is intended to calculate transitions in each scan of the LRF signal. These transitions are defined as the difference between two consecutive *i* points of scan *j*.

After the delimitation of the region of interest, vector R_j = [r_{256j}, r_{257j}, ... , r_{426j}] is created and contains the distances measured in scan *j*. For the transitions' detection it is created vector R'_j= [r'_{256j} , r'_{257j} , ... , r'_{425j}], which contains the transitions. Each element is calculated as follows:

$$r'_{ij} = \left| r_{(i+1)j} - r_{ij} \right| \text{ , } 256 < i < 425 \qquad (3)$$

Vector R'_j is then used to infer which transitions correspond to the bounds of a leg. For this, each value of the vector R'_j is compared to a threshold l (this constant is calculated online as it will be explained in the next section). If a transition value r'_{ij} is higher than l, it corresponds to a bound of a leg. Figure 2b) shows an example of this detection, where r'_1 and r'_4 of vector R' correspond to leg bounds.

C. Calibration Mode

For the correct detection of the legs some features must be assessed to determine if there is one leg, two legs or something else in the region of interest. This evaluation aims to distinguish legs from other objects that could be in the region of interest between the user and the walker. In order to do this the follow features are addressed: opening angle of the leg (lp) to check if it is one or two legs; and space between the legs in the sagittal plane (l) to detect transitions and thus legs' boundaries. These features are illustrated in Figure 3.

This paper proposes an online calibration (OC), during which the individual only needs to take two steps, at his own pace, with the walker to estimate *lp* and l and there is no time limit. l is the difference between *r* of each *i* point of a scan. l*p* is calculated as the difference between α_i of two consecutive transitions that correspond to a leg.

Please note that OC should be performed with clothing that allows distinguishing the two legs and both legs must be spaced from one another during OC. It is also noteworthy that as more acquisitions are obtained during OC the better the results, since the values of the features that will be evaluated are based on average values of all scans. These values are used for the same person, in the same conditions. If the person and/or conditions change, a new OC has to be done.

Figure 3. Features for calibration.

D. Patterns Detection

During assisted gait, the user can present different legs' patterns. This makes the laser to capture different data patterns, and thus the calculated center of each leg will be different.

The detection of patterns is based on the classification of the position of the legs according to the number of detected transitions. Three different patterns can be identified: separated legs (SL), legs together (LT) and overlapping legs (OL). Figure 4 illustrates the three presented patterns and the acquired raw LRF data on these situations.

To classify the patterns, first the number of transitions is calculated through the l value (calculated on OC). Then, if the number of transitions corresponds to one of the values of Table 1, the pattern is classified and the center of each leg is transformed onto polar coordinates (r, α). Later, for spatiotemporal parameters calculation these coordinates are converted to Cartesian.

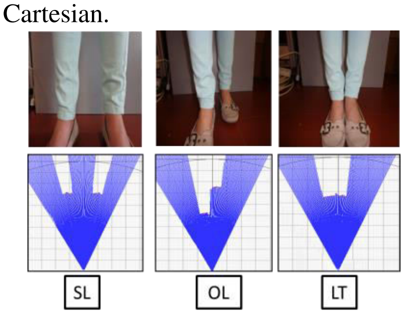


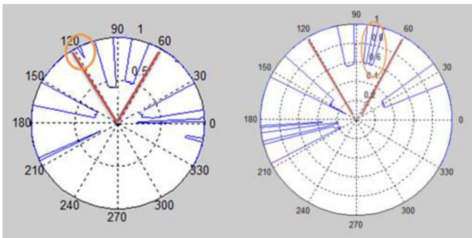
Figure 4. Legs' Patterns.

TABLE I. NUMBER OF TRANSITIONS FOR EACH LEG PATTERN

	Pattern		
	SL	***OL***	***LT***
Number of transitions	4	3	2

E. Non-Patterns Detection

More than 4 transitions can be acquired and a non-pattern is detected. The occurrence of this situation appears when the laser detects an object or noise in the region of interest. In the case of detecting 5 transitions, it means that the laser detected noise or OC was not properly carried out. In the case of 6 or more transitions, it means that an unknown object was detected on the region of interest (Figure 5a) or a noise occurrence divided one leg in two parts (Figure 5b). If these situations are detected the following procedures are executed:



a) b)

Figure 5. Situations where the algorithm detects 6 transitions.

(i) Transition pairs verification

First, the pairs of transitions are verified to check which pairs correspond to a leg. Two conditions are verified and both have to be valid: (1) Is the difference between α of two consecutive transitions higher then *lp*? If yes, it means that probably a leg was found and if not it is not a leg, like the situation illustrated on Figure 5a; then (2) Is r_{i+1} (*i* corresponds to the position of a transition) lower than 1000mm (r_{max})? This condition eliminates false legs, since the space between the legs can present a distance greater than *lp*. If both conditions are verified, only the pairs of transitions that correspond to legs are saved.

(ii) State sequence verification

After the first verification, the number of detected transitions is compared with the number of transitions of the previous scan. This comparison is based on state sequence verification. A state is characterized by a number of transitions.

This state sequence is composed by four states (based on the number of transitions): 4T (4 transitions), 3T (3 transitions), 2T (two transitions) and 0T (no transitions detected, which means no legs). All states are bidirectional and from scan to scan the same state can be verified. Observing Figure 6, possible transitions between states are identified by arrows.

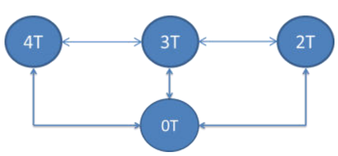


Figure 6. The correct state sequence.

In case incorrect state sequences are detected, a flag is set with value 1 and the current legs' coordinates acquire the value of the coordinates of the past state. An example of this latter situation is illustrated on Figure 5b. In this case, the verification (i) will eliminate one leg (the right one) since it will consider that this acquisition only has the presence of one leg. Thus, 4T will pass to 2T, which is an incorrect state sequence.

(iii) *System error*

To verify if the latter two verifications worked, the algorithm verifies if the distance between two samples is greater than 200mm (the distance walked between two samples is never greater than this value). If that happens, the distance of scan *j* is equal to scan *j-1* and a flag is set equal to zero (the flag is only recorded to count how many times the system had a verification error, for analysis purpose).

V. Spatiotemporal Parameters

This paper aims to calculate some specific spatiotemporal parameters while the user is walking with the walker. These parameters are important to evaluate the state of the user and infer his evolution in the rehabilitation program.

The following spatiotemporal parameters are calculated: step and stride length, stride width, stride time, cadence, velocity, stance and swing and double support duration [14]. In order to calculate these parameters it is needed to calculate some gait events in the LRF signal in y direction for both legs (axis directions are depicted in Figure 2b).

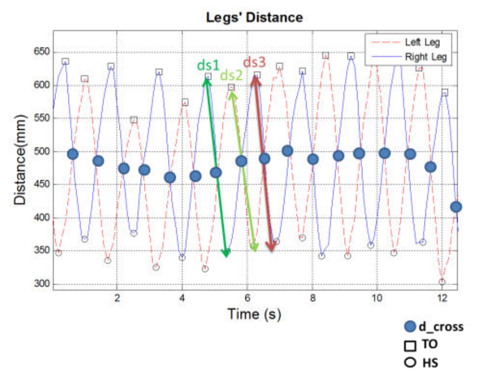


Figure 7. Distance LRF signal of both legs in y-direction. The squares correspond to toe-off events (TO), the white circles to heel-strike events (HS) and the blue circles to legs crossing events (d_cross).

Figure 7 illustrates the relevant events detection. The maximum values (squares) correspond to toe-off (TO) events; the minimum values (white circles) correspond to heel-strike (HS) events; and when the signals are crossing (d_cross) it means that the legs are also crossing (blue circles) [15, 16]. These events enable to calculate:

- **Stride Length (StL)**: distance between toe-off and heel strike from the same feet. It is calculated by the difference between the maximum distance and consecutive minimum. This moment is indicated at different times by ds1, ds2 and ds3.

$$\begin{aligned} &Right\ StL = ds1_{max} - ds1_{min} \\ &Left\ StR = ds2_{max} - ds2_{min} \end{aligned} \tag{4}$$

- **Step Length (SpL):** is the distance between legs crossing and heel strike. It is calculated by the difference between the moments that two signals cross and the consecutive minimum.

$$\begin{aligned} &Right\ SpL = d_{cross}\text{-}ds1_{min} \\ &Left\ SpL = d_{cross}\text{-}ds2_{min} \end{aligned} \tag{5}$$

- **Stride time (Stt):** Time from initial contact of one foot ($tds1_{min}$) to initial contact of the same foot ($tds3_{min}$).

$$Stt = tds3_{min} - tds1_{min} \tag{6}$$

- **Cadence** (frequency of the signal) and **Velocity:**

$$V = ds1_{max} - ds2_{min} \ / dt \qquad (7)$$

- **Stride width:** is the distance between both legs in x-direction (Figure 2).
- **Swing duration (SWD):** is the time correspondent to the oscillation phase, when the feet are not on the ground. It is calculated as the time between the maximum ($tds1_{max}$) and minimum ($tds1_{min}$) values of ds1.

$$SWD = tds1_{max} - tds1_{min} \qquad (8)$$

- **Stance duration (SD):** is the time correspondent to the support phase, when the foot is on the ground. It is calculated by the time between the minimum and maximum values of ds1 and ds3, respectively.

$$SD = tds1_{min} - tds3_{max} \qquad (9)$$

- **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 instants related to $ds1_{min}$ ($tds1_{min}$) and $ds2_{max}$($t\ ds2_{max}$):

$$DST = tds2_{max} - tds1_{min} \qquad (10)$$

However, these values correspond to the distance between the user and the walker. Using odometry these values are converted to distances walked on the external environment (the explanation of this process is not on the scope of this article).

VI. Results and Discussion

A. Calibration Mode results

To acquire the *lp* and l values a set of tests for data collection involving 10 subjects with different body sizes and types of clothing are conducted. After conducting several experiments with data from LRF in order to detect what are the best values for *lp* and l that could detect legs for all subjects, it was concluded that these values are different from subject to subject. In Table 2 it can be seen that the standard deviation is slightly high.

TABLE II. Mean and Standard variation values for OC features.

Features	Dimensions	
	Mean	Standard Variation
lp	15º	9º
l	32 cm	18 cm

The possibility of setting the values for the use of several subjects is tested. A test with the LRF data of 10 subjects enables to calculate a rate of failure of 83%. Thus, OC is needed to decrease this rate.

After testing the same 10 subjects using the OC, it was concluded that: OC works great, presenting 2% to 0% rate of failure; if more steps are done by the subject during OC, more effective are both features to detect legs; it is necessary that during OC both legs are visible. In general it has been required an average of 1/2 steps, which corresponds to an average of 20 samples (*i.e.* 2s for OC since LRF has 100ms of acquisition period).

B. Transitions' and Patterns' detection results

To test the developed technique to detect legs, two types of experiences are performed: (i) Subjects stand in front of the walker; and (ii) Subjects push the walker while executing a straight forward trajectory. The achieved results are described next.

(i) Subjects stand in front of the walker

The real distance between LRF and the legs was measured through a metric tape and compared to the distance calculated by the LRF with 10 subjects. The error between these distances was lower than 2 cm for X coordinate and lower than 3 cm for Y coordinate (axis represented in Figure 2). This means that the algorithm is correctly detecting the center positions of the legs.

(ii) Subjects walking with the walker

To test if the algorithm could detect all patterns and outline the non-patterns, 10 other subjects were asked to walk straight forward while being filmed. It was observed that all the patterns were detected and the non-patterns were outlined. Figure 8 illustrates a compilation of the three patterns and two situations of non-patterns that were detected throughout the experiments with the 10 subjects. As it can be seen in Figure 8, the detection of the legs was successful.

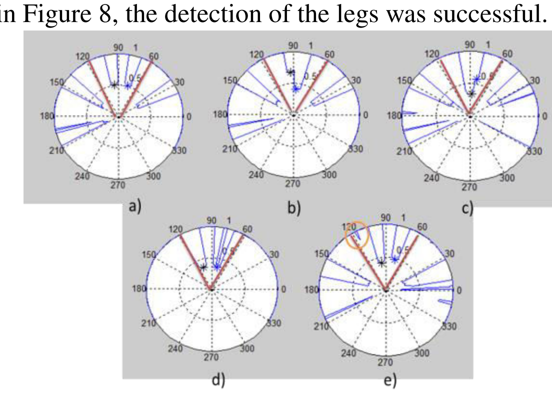


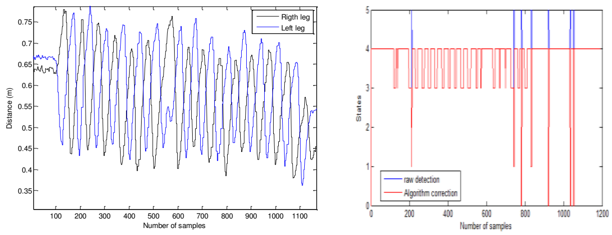
Figure 8. Patterns results: a) SL; b) LT; c) OL and Non patterns on d) and e).

In Figure 9a, it is shown an example of LRF distance signal in a straight-forward trajectory. In Figure 9b, in blue are represented the detected transitions and in red the algorithm correction. As it can be seen, when 5 transitions are detected, the algorithm sets a flag equal to 1 so that the right correction can be made. However, sometimes the algorithm cannot detect a solution for the problem and sets a flag equal to zero (Figure 9b). In this situation, the legs coordinates are set to the coordinated of the previous scan.

C. Spatiotemporal parameters results

Subjects were asked to walk straight-forward with a fixed step distance (marks on the floor). Figure 10a illustrates the gait events (heel strike, legs crossing and toe-off) that enable to calculate the spatiotemporal parameters and Figure 10b the results from the trajectory followed by the subject. This trajectory was calculated with the help of encoders' data (odometry model that is not on the scope of this article).

By detecting the samples where these events occur, one can then use the odometry model results and calculate the spatiotemporal parameters. Through the video records and by knowing the distance walked by the subjects an average error of 10% was obtained for the gait parameters.



a) b)

Figure 9. a) LFR distance signal and b) Number of detected transitions.

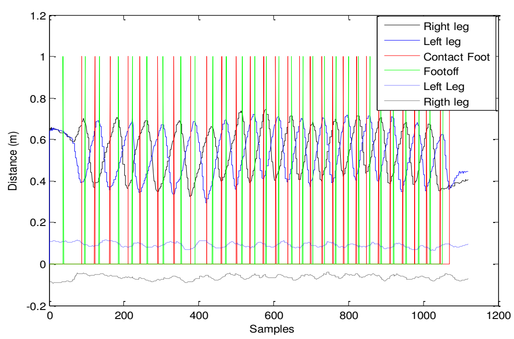
VII. CONCLUSION

This paper presents a system able to track the legs position during an assisted walk without equipping the user. A LRF sensor and encoders were used by a new detection algorithm that suits for all subjects through a calibration mode. Preliminary results show that this system has high potential to be used on clinical trials with patients on the hospital to give clinical insight to the clinicians.

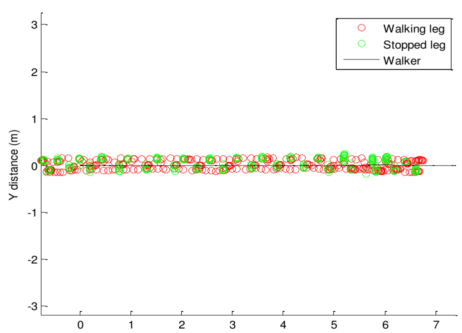
Further work is necessary to run more tests and reduce the errors associated with the calculation of spatiotemporal parameters. In addition, tests with patients will be done to infer if all patterns and situations were taken into account in this algorithm.

ACKNOWLEDGMENT

Work supported by Portuguese Science Foundation (grant SFRH/BD/76097/2011).



a)



b)

Figure 10. a) LFR distance signal in y and x with the detected gait events and b) Odometry results.

REFERENCES

[1] M. Henriksen, H. Lund, R. Moe-nilssen, H. Bliddal, and B. Danneskiod-samsøe, "Test – retest reliability of trunk accelerometric gait analysis," Gait Posture, vol. 19, pp. 288–297, 2004.

[2] R. Bachschimdt, G. Harris, G. Simoneau, "Walker-Assisted gait in rehabilitation: a study of biomechanics and instrumentation". In Proceedings of the 2001 IEEE Transactions on neural systems and rehabilitation engineering, vol. 9, nº 1, 2001 pp. 96-105.

[3] A.B. Deathe, R.D. Pardo, D.A. Winter, K.C. Hayes, J. Russell-Smyth, "Stability of walking frames" J Rehabil Res Dev 1996;33:30-5.

[4] M. Martins, A. Frizera, C. Santos, R. Ceres,"Assistive Mobility Devices focusing on Smart Walkers: Classification and Review". Robotics and Autonomous Systems, 2011. 10.1016/j.robot.2011.11.015

[5] F. Shi, Q. Cao, C. Leng and H. Tan. "Based On Force Sensing-Controlled Human-Machine Interaction System For Walking Assistant Robot". Proceedings of the 8th World Congress on Intelligent Control and Automation, Jinan, China, July 6-9, 2010.

[6] A. Fast, F. Wang, R. Adrezin, M. Cordaro, J. Ramis, J. Sosner, "The Instrumented Walker: Usage patterns and forces". Archives of Physical Medicine and Rehabilitation, vol.76, 1995, pp. 484-491.

[7] J. M. Hausdorff and N. B. Alexander Gait Disorders: Evaluation and Management, 2005 :Informa Healthcare.

[8] G. Lee, E. Jung, T. Ohnuma, N. Young Chong, B. Yi. "JAIST Robotic Walker Control Based on a Two-layered Kalman Filter". IEEE International Conference on Robotics and Automation, Shangai, China, 2011, pp. 3682–3687.

[9] P. Kmiotek, Y. Ruichek, Y. "Representing and Tracking of Dynamics Objects using Oriented Bounding Box and Extended Kalman Filter". Proc. Of the 11th International IEEE Conference on Intelligent Transportation Systems, China, 2008, pp. 322-328.

[10] H. Kheyruri, D. Frey, "Comparison of People Detection Techniques from 2D Laser Range Data" 2010. Accessed in http://ais.informatik.uni-freiburg.de/teaching/ws09/robotics2/projects/mr2-p1-paper.pdf

[11] J. Xavier, M. Pacheco, D. Castro," Fast line, arc/circle and leg detection from laser scan data in a player driver. Proc. of IEEE International Conference on Robotics and Automation, Barcelona, Spain, 2005, pp. 3930-3935.

[12] K.Yu, C. Lam, M. Chang, W. M Tseng, L. Fu, "An Interactive Robotic Walker for Assisting Elderly Mobility in Senior Care Unit" 2010 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO), 2010, pp. 24 – 29.

[13] N. Bellotto, H. Hu, "Multisensor-based human detection and tracking for mobile service robots", IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol 39, n 1, 2009, pp. 167-181.

[14] D. Winter, "The Biomechanics and Motor Control of Human Gait: Normal, Elderly and Pathological", in University of Waterloo Press, 2nd edition, (1987).

[15] M. Martins, C. Cifuentes, A. Elias, V. Schneider, A. Frizera, C. Santos. Assessment of walker-assisted human interaction from LRF and wearable wireless inertial sensors International Congress on Neurotechnology, Electronics and Informatics. Neurotechnix 2013. Portugal.

[16] C. Zong, M. Chetouani, A. Tapus, "Automatic Gait Characterization for a Mobility Assistance System" International Conference on Control, Automation, Robotics and Vision (ICARCV 2010), 2010, pp. 473-478.