2015 IEEE International Conference on Robotics and Automation (ICRA)
Washington State Convention Center
Seattle, Washington, May 26-30, 2015

Fast embedded feet pose estimation based on a depth camera for smart walker

Solenne Page[1,2,3], Maria M. Martins[4], Ludovic Saint-Bauzel[1,2,3], Cristina P. Santos[4],Viviane Pasqui[1,2,3]

***Abstract*— Assisted gait monitoring could benefit from the measurement of feet position and orientation. These measurements could also be used to implement intention-based control laws for smart walkers. Several works have been dedicated to the detection of lower limbs. The proposed methods are usually fast, but only detect the position of the legs. Others may even be more complete, but are not adapted to reactive applications. Also, they often use markers attached on the feet, which is unsuitable in daily routine.**

In this paper, a fast feet position and orientation detection algorithm is proposed. It is based on a camera depth sensor and does not require the use of any marker. The obtained results are compared with a ground truth provided by a motion traking system to experimentally assess the performances of the proposed algorithm.

I. Introduction

A. Context

Conventional walkers are widely prescribed since they provide the users with a wider support base, thus increasing stability and safety [1]. Their use has however been reported as leading to security issues and increasing the cognitive load [2], especially in the elderly. The conventional walkers could be replaced by smart walkers to cope with these issues.

For control purposes, some smart walkers exhibit an interface (like button control) that requires some cognitive efforts from the user to guide the walker and consequently a discouraging learning phase. Most of the devices propose a theoretically intuitive command based on force sensors, for example [3], [4]. However, these sensors have some limitations in terms of obtaining a stable signal for providing a comfortable drive of the walker to the user. Since one needs to tune the virtual inertia of the sensor to increase stability and sensitivity to the driving, elders usually feel tired since they need to push the walker. To get around this difficulty, this article proposes to use non physical interaction to obtain data that are needed to control the device. This solution should also be fast to comply with the time specifications of control applications.

Gait monitoring could also be achieved based on the same method. This monitoring could be used for safety purposes. Nejatbakhsh et al. [5] use velocity data to constrain walker's movements in case of excessive amount of velocity. More precise data on gait could also help for following rehabilitation and for diagnosis purposes. Haussdorff et al. in [6] showed that stride-to-stride variability is a good parameter to predict the tendency of the subjects to fall. The majority of the embedded gait analysis studies were performed with accelerometers or force sensitive insoles [6]. This kind of sensors cannot in general be installed by patients themselves and thus require an assistive person to install and uninstall them. Moreover, they are unconfortable for users and increase the global cost of the device. That is why, despite a possible large number of applications of gait monitoring data, they are never meant to be used in daily routine. To solve this problem new sensors have to adapt to changing environmental conditions as clothes and to be contactless. Some contactless sensors have been tried [7]–[14].

B. Related work on contactless sensors for lower limbs detection

In the literature, four different sensors have been used to measure lower limbs' position and orientation : Ultrasonic Sensors (US), Laser Range Finder sensors (LRF), Infra-Red sensors (IR) or camera depth sensors.

Even if they can achieve good performances [7], US sensors only are not a viable solution to detect lower limbs in smart walkers. Indeed, their experimental setup relies on markers attached on the feet. Markers could be unconfortable to the user and cannot be used in a daily routine. For instance, in case the control is based on feet detection, if one marker falls, the user risks to be isolated with an assistive device in failure, it becomes a risk of falling situation.

IR [8] and LRF [9], [10], [11] have been proposed to achieve markerless estimation of lower limbs' position. These markerless solutions are quite simple and fast. JaRoW [10] was integrated with LRF sensor to detect the location of users lower limbs in real time. A Kalman filter was applied to estimate and predict the locations of the user's lower limbs. However, false detections occur when feet are detected instead of legs during walking [11] or with large clothes [10]. False detection is not the only problem of the methods associated with theses sensors. For example, RT-Walker [9] uses LRF sensor to estimate the center of gravity of the user for fall prevention purposes. However, they only detect legs position, which is not sufficient to infer the user's intentions in terms of turning, neither to follow the orientation changes during walking.

Recent studies take advantage of camera depth sensors which are now available at reasonable costs [12], [13], [14]. Paolini et al. [12] proposed real time feet position

[1] Sorbonne Universités, UPMC Univ Paris 06, UMR 7222, ISIR, F-75005, Paris, France page@isir.upmc.fr
[2] CNRS, UMR 7222, ISIR, F-75005, Paris, France
[3] INSERM, U1150, Agathe-ISIR, F-75005, Paris France
[4] ALGORITMI CENTER, University of Minho, Portugal mariam@dei.uminho.pt

and orientation traking for treadmill use. Their position errors are lower than $27mm$ (RMSD). Their orientation error (bearing angle) are below 10%RMSD. They obtained 3D orientations of the feet, but angles around vertical axis should be sufficient for gait analysis and control purposes. Although these results are really good, the proposed method is not suitable for our application since it is based on the use of markers attached to the feet.

Two teams proposed the use of a camera depth sensor without markers. In [13], 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) and are considerably bigger than the ones obtained with markers (27mm) [12]. In [14], another parametrized model is matched on the camera data. If the principle is the same as in [13], in [14], 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 $15\,°$), and due to occlusion problems, data are not available in all the gait cycle phases. 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, especially in [12], and cannot currently be implemented in real-time, making it unsuitable for control applications.

C. Proposal

The Institute for Intelligent Systems and Robotics (ISIR, Paris, France) have conducted a project on the development of a smart walker for many years. Facing limits of force sensor based control on the current prototype presented in [15] (figure 1), we decided to implement depth camera based control. The ALGORITMI research center (Guimarães, Portugal) decided at the same time to use this sensor for gait monitoring purposes. To achieve these two goals, one first needs to evaluate the efficiency of the feet pose estimation with a camera depth sensor placed on the smart walker. Thus, the required evaluation is presented in this paper. First, related work to lower limbs' pose estimation is examined. Then, the proposed algorithm for feet pose estimation is explained and results are compared against a ground truth.

II. Feet position and orientation detection

The proposed algorithm is implemented with an Active Depth Sensor (Asus Xtion Pro - ADS) placed on the walker device. The main used library is OpenCV [16].

A. Calibration

The calibration aims at converting (u,v,depth) coordinates on the Walker frame into (X_w, Y_w, Z_w) coordinates of points in meters in the walker frame (see figure 2). The calibration of ADS for feet tracking is done in 2 steps. The calibration process uses the ADS frame (X, Y, Z) as an intermediate frame.

Fig. 1: The ISIR's smart walker prototype with the ADS

1) Camera Intrinsic parameters: To express the point coordinates in meters in the ADS frame, one have to know the intrinsic parameters of the ADS, gathered in the following matrix:

$$F = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

where fx and fy are the focal lengths and cx, cy the coordinates of the center of the image. To get this matrix, the OpenCV method of calibration was used with the RGB image associated to the ADS. One assumes that the intrinsic parameters of the RGB camera are close enough to those of the camera depth sensor. With the intrinsic parameters matrix, points in the ADS frame (X, Y, Z) are obtained by multiplying the vector $[u, v, 1]$ by inverted F and by the depth (s) in the (u, v) coordinates:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = F^{-1}. \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} .s(u, v)$$

2) ADS frame to walker frame: The geometric relation between the ADS frame and the walker frame is assumed to be a simple rotation along X. To find the angle of this rotation two methods can be used: measure the angle

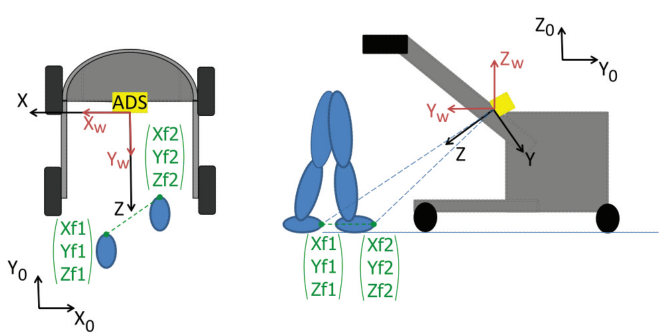


Fig. 2: ADS and walker frames

manually (poor precision) or use the Point Cloud Library (PCL) to segment the ground plane. With this, a rotation matrix R is obtained to calculate the ADS coordinate points in meters in the walker frame.

$$\begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} = R^{-1}. \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

B. Feet segmentation

The image issued from the ADS contains feet but also legs (with perturbation of the clothes) of the user, background, floor and wheels of the walker. The aim is to extract the feet so the process is applied to the image.

1) Extract the "feet zone": The ADS image is filtered to display only the "feet zone". The "feet zone" is defined in Z (height) direction. It is the set of data that are between few millimeters above the ground to a threshold height that is obtained experimentally.

2) Feet segmentation: The "feet zone" image is converted to a binary image and filtered with a closing/opening filter to eliminate artifacts as can be seen on figure 4. Then, the binary blob technique (based on [17]) is used to segment feet candidates.

3) Selection of the feet: The centroid of each foot candidate is processed and the two closest centroids from the center of the image are labeled as right and left foot. This selection methods eliminates candidates close to the walker wheels and other objects in the background (due mainly to the imperfect estimation of the ground plane).

C. Computation of feet distances and orientations from the walker

The feet data will be used for gait analysis and for the control of a Smart Walker.

Clinical gait analysis is currently only performed with positions of the feet in Y_w direction. Width between feet (difference in positions in X_w) could be used, to know if users have a tendency to increase their support polygon and thus give clues to predict falls [18].

[19] demonstrated that the toe orientation have some consequences on the knee osteoarthristis. Having this information monitored during daily life walk while using smart-walker can provide an asset to rehabilitation process.

The existing way to control a smart walker thanks to the feet position is presented in [10]. They have a discrete approach that obtains the rotation of the robot from the position of the foot. The limitation of their approach is that the position of the foot must be strictly different from a straight motion or a sliding motion. However, with some elderly the gait evolves the stride size is decreasing and the strategy of turning could be affected as presented in [20]. A measure of orientation can provide complimentary set of information to robustify such a controller.

1) Monitoring the feet positions: Two points are candidates to monitor the positions of the feet: the centroids of the feet and the toe tips. However, none of these two solutions are perfect since the centroid does not correspond to a fixed point of the foot as well as the toe tip point estimation due to changes (noise) on the blobs limits. Thus, we chose to select (X_f,Y_f) as coordinates in the walker frame (see figure 2) as the mean of the abscissa of the foot and the ordinate of the closest point of the foot to the ADS. Despite the presented disadvantages, it also takes the centroid of each foot into account for further purposes.

2) Calculate the feet orientations: As was explained before, the detection of fixed points of the feet is not accurate and the foot orientation calculation thereby cannot be based on the line between centroid and toe tip. To solve this problem, Principal Component Analysis (PCA) is used to find the highest variance of the points that correspond to each foot, thus obtaining the information on the orientation of each foot. PCA is used for many different applications where correlation between variables is required and creates a new space where this correlation is defined. Consider p variables and n samples, the first step of this method is to calculate the covariance matrix (size pxp) that takes the n samples into account. Then, the eigenvectors of this matrix are calculated and give the principal directions of the correlation (p is the maximal number of directions that can be found) and the eigenvalues will give the importance of the resulting correlations. In this specific application, PCA will be used to find the axis of inertia of each foot. It is applied with two parameters ($p = 2$) that correspond to the feet coordinates (x and y), the n samples correspond to the number of detected points of each foot and $\bar{x}$ and $\bar{y}$ correspond to their means. The covariance matrix for each foot is defined as the following:

$$\begin{bmatrix} \frac{1}{N}\sum_{i=1}^{n}(x_i-\bar{x})^2 & \frac{1}{N}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y}) \\ \frac{1}{N}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y}) & \frac{1}{N}\sum_{i=1}^{n}(y_i-\bar{y})^2 \end{bmatrix}$$

Then, the eigenvectors are calculated to find the axis of inertia that will give the orientation of each foot.

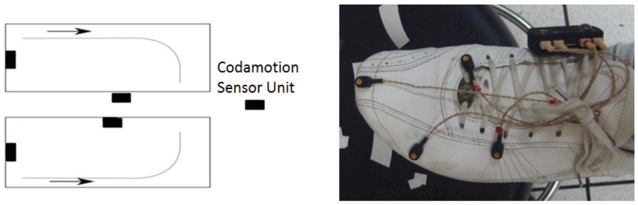
3) Double support instants detection: To detect the double support instants (DSI), the distance between the feet is calculated. The modulus of the distance is maximum when the derivate of the depth signal (Yw direction) turned negative or positive. If this condition is verified, a double support instant is detected. The altitude signal was not used for double support instant detection since even if altitude is well estimated, the DSI are not as clear on the z signal as on the y signal.

III. Results

This section aims to present the results with healthy young individuals by tracking their feet with the proposed system using an ADS. It has a resolution of (640x480) pixels and 16 bits depth precision.

A. Experimental setup

Two trajectories were tested with 3 healthy subjects: walk along a straight line and then turn right (resp. left, see figure 3(a)). For validation of the obtained data with the



(a) Trajectories performed by the subjects

(b) Codamotion markers on the left foot

Fig. 3: Codamotion setup

proposed ADS system, reference trajectories are provided by the Codamotion capture system [21]. The technology uses miniature infra-red active markers, positionned on each foot, see figure 3(b), to track the key positions on any subject. Signals from the markers are beamed to Codamotion sensor units (black rectangles on figure 3(a)). The spatial error of this sensor is less than $0.33mm$. The sampling period was set to 100Hz and data processing was done in MATLAB©(version 2011b). Positions and orientations of the feet are compared between data obtained from ADS and from a ground truth (Codamotion).

B. Feet detection and segmentation results

1) Visual validation: After the experiments, the sequence is processed offline by the proposed algorithm for feet tracking. In figure 4, three frames are presented showing different phases of the performed trajectory. The first frame shows the moment where the right foot is starting to cross the left foot. The second frame shows the feet following a straight trajectory in a double support instant. The third frame shows a double support instant on a turning moment. In figure 4, the left image of each frame corresponds to the original input depth image captured by the ADS. The second image shows the result of the "feet zone" selection. On the third image, unknown objects are rejected and feet are labelled. Moreover, the axis of each foot (green line) can be seen, representing the different foot orientations identified by the PCA algorithm.

2) Position errors: In figure 5, the signals obtained with the position coordinates in the (X_w,Y_w,Z_w) frame are represented when the subject is walking forward. Coordinates of the feet from the Codamotion system in the world frame (X_0,Y_0,Z_0) are transformed into coordinates in the walker frame (X_w,Y_w,Z_w). Thus, in figure 5, each position from ADS is compared with positions obtained with the Codamotion system. As in [12], Root Mean Square Deviation (RMSD) is used to quantitatively compare the Codamotion and ADS position data. The results are shown in table I. On position precision, the z signal is the more precise and precision on x and y are about the same. On figure 5(c), main differences between ADS data and ground truth occur when the feet are far away from the ground. Indeed in this case, a smaller part of the foot is in the feet zone leading to less precise measurement. On figure 5(b), the pattern is detected with ADS data as well as with the Codamotion data. On figure 5(a), even if the difference seems bigger due to the scale, position error is about the same as for Y_w. The precision of the proposed method is compared to [12] (method with markers) in the table I. It can be seen that a long way remains if one wants to obtain the same precision of markers based method. However, when we compare these results to [13], a markerless solution, (see table II) using step length and width error as in [13], we can see that the proposed method is more precise (about 25%). This method is also faster because we do not use 3D model. When [13] has a processing time around 15 seconds, the proposed algorithm takes around 30 ms to process with similar computers. In addition, our method is more complete, as orientation was not evaluated in their paper. Even if the precision of the proposed method is not as good as in [12], it seems acceptable for gait analysis and for control purposes. Tests must still be performed to assess whether it is sufficient for these applications.

In figure 6, it can be seen that double support instants are difficult to extract from z-signal as no threshold in altitude between "on the ground" and "out of the ground" can be easily defined. Double support instants are well detected by the proposed method (green picks on figure 6) with a precision around $0.1s$. This signal will be used for controlling a smart walker in future work.

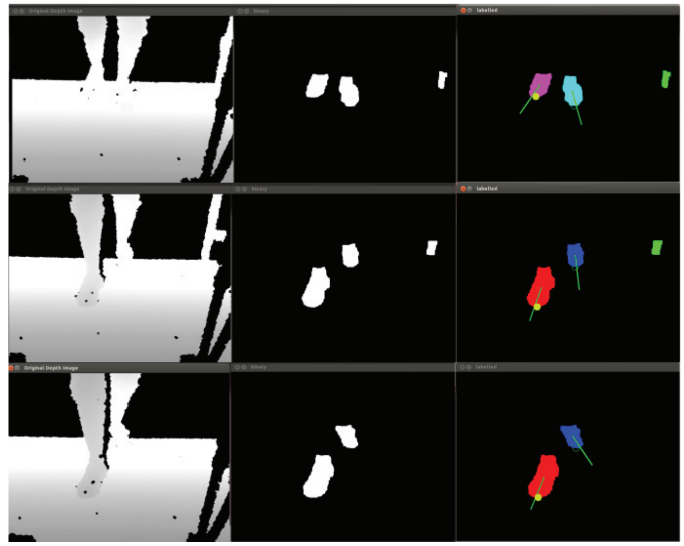
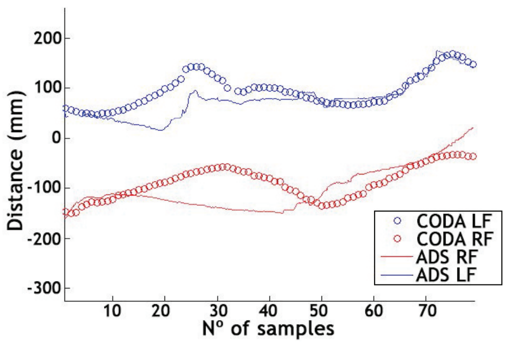


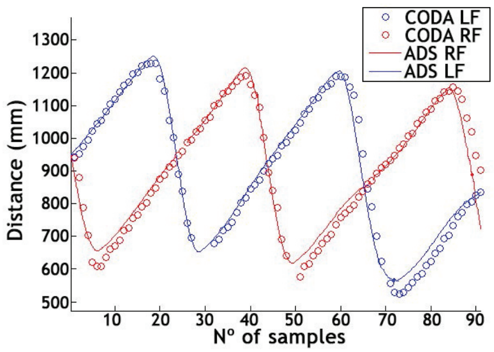
Fig. 4: Frames representing the image processing at different phases of the gait cycle

TABLE I: Comparison between [12] and the proposed method on positions and orientations errors

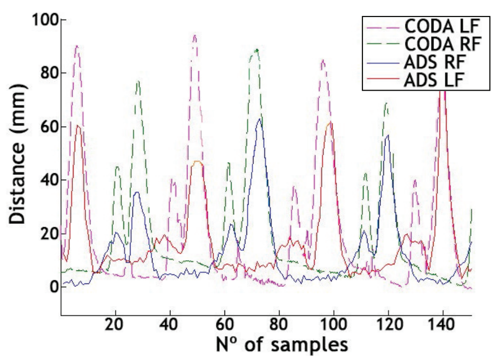
	RMSD (mm)			%RMSD (%)
	X_w	Y_w	Z_w	around Z_w
Proposed method	28.9 $\pm$2.03	30.8 $\pm$2.82	13.4 $\pm$3.37	21.1 $\pm$4.33
[12]	4.9 $\pm$1.4	19.4 $\pm$6.1	8.4 $\pm$1.7	7.9 $\pm$2.6



(a) X_w



(b) Y_w



(c) Z_w

Fig. 5: 3D feet positions acquired by CODA motion capture system and ADS sensor on the different axis.

TABLE II: Comparison between [13] and the proposed method on step length and width errors in mm

	Step length		Step width	
	mean error	std	mean error	std
Proposed method	28.5	16.7	17.6	8.25
[13]	33.6	22.0	25.5	20.6

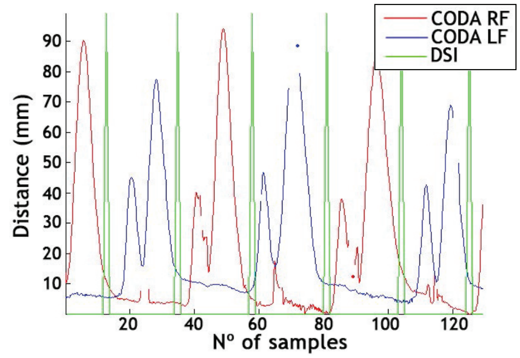


Fig. 6: Z_w position tracking with Codamotion system with double support instants detection by ADS sensor.

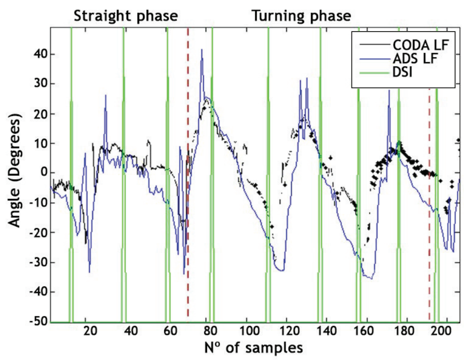
3) Orientation errors: Figure 7 and 8 represent angle measurements during a left and a right turn, respectively. Straight and turning phases are identified. [14] presented discontinuous angle measurements, as shown figure 7 and 8, the proposed method gives continuous measurements. ADS data and data from the Codamotion system display the same behavior. The error in orientation is about 20% (see table I) that should be sufficient to assess big changes. Indeed, it represents $\pm 7°$ and one can see that during straight phases angle could change of $\pm 10°$. During turning phases, angle variations increase. From the figure 7 and 8, one can observe than, in turning phase, the signals present opposite phases correlated to the turning direction. This is a feature that can be used to discriminate between a left turning motion and a right turning motion.

IV. Conclusion

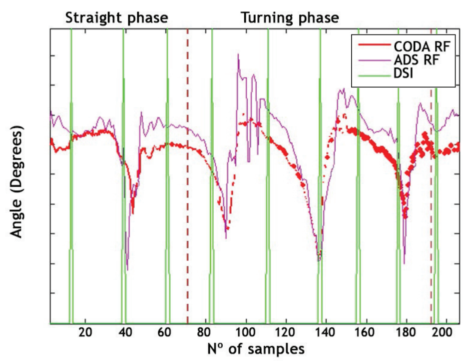
This paper proposed a new method to extract feet position and orientation data from a camera depth sensor. The main advantages of the presented method is that it is markerless, faster than using 3D models, robust against clothing variations and that continuously detect orientations of the feet. The precision of the presented method is better than the other markerless methods and seems sufficient for gait analysis. However, some improvements could be done, this algorithm works with a fixed "feet zone", an adaptative "feet zone" could improve the z measurement. The turning feature identified by the proposed method will be useful for the turning control of the smart walker. This whole system has to be implemented in a smart walker and tested with patients. This will be done in future work.

Acknowledgment

The authors wish to thank David Reversat for helping with programming the algorithm.

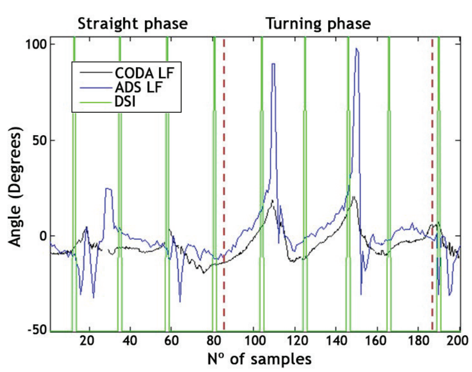


(a) left foot

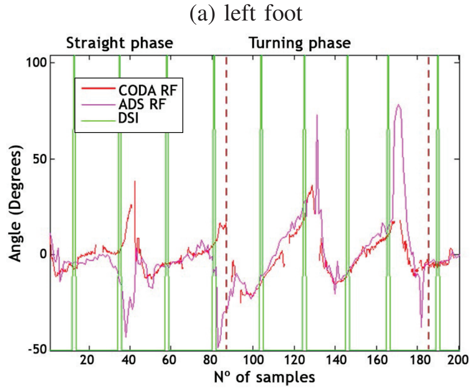


(b) right foot

Fig. 7: ADS and Codamotion signals for a left turn



(a) left foot



(b) right foot

Fig. 8: ADS and Codamotion signals for a right turn

REFERENCES

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

[2] H. Bateni and B. Maki, "Assistive devices for balance and mobility: benefits, demands and adverse consequences." Arch Phys Med Rehabil vol 86, jan 2005, pp 134-144.

[3] A. Tang and Q. Cao, "Motion control of walking assistant robot based on comfort." Industrial Robot: An International Journal, 2012, Vol. 39 Iss: 6, pp.564 - 579

[4] L. Saint-Bauzel, V. Pasqui and I. Monteil, "A Reactive Robotized Interface for Lower Limb Rehabilitation: Clinical Results," Robotics, IEEE Transactions on , vol.25, no.3, pp.583,592, June 2009

[5] N. Nejatbakhsh and K. Kosuge, User-environment based navigation algorithm for an omnidirectional passive walking aid system, in Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on, pp. 178181, 2005.

[6] J. Hausdorff, Gait variability: methods, modeling and meaning, Journal of NeuroEngineering and Rehabilitation, vol. 2, no. 1, pp. 19, 2005.

[7] A. Abellanas, A. Frizera Neto, R. Ceres, R. Raya and L. Calderón, "Ultrasonic Time Of Flight Estimation In Assistive Mobility: Improvement Of The Model-Echo Fitting." Em: 22nd international conference EUROSENSORS, 2008.

[8] Cong Zon, M. Chetouani and A. Tapus, "Automatic gait characterization for a mobility assistance system," Control Automation Robotics & Vision (ICARCV), 2010 11th International Conference on, pp.473,478, 7-10 Dec. 2010

[9] Y. Hirata, S. Komatsuda and K. Kosuge, "Fall Prevention Control of Passive Intelligent Walker Based on Human Model." In : Proceedings of the 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems Acropolis Convention Center, Nice, France, Sept, 22-26, 2008.

[10] G. Lee, T. Ohnuma, N. Chong and S.-G. Lee, "Walking Intent-Based Movement Control for JAIST" Active Robotic Walker Systems, Man, and Cybernetics: Systems, IEEE Transactions on, 2013, PP, 1-1

[11] T. Pallejà, M. Teixidó, M. Tresanchez and J. Palacn, "Measuring Gait Using a Ground Laser Range Sensor." Sensors. 2009; 9(11):9133-9146.

[12] G. Paolini, A. Peruzzi, A. Mirelman, A. Cereatti, S. Gaukrodger, J.M. Hausdorff and U. Della Croce, "Validation of a Method for Real Time Foot Position and Orientation Tracking With Microsoft Kinect Technology for Use in Virtual Reality and Treadmill Based Gait Training Programs," Neural Systems and Rehabilitation Engineering, IEEE Transactions on , vol.22, no.5, pp.997,1002, Sept. 2014

[13] R.Z.-L. Hu, A. Hartfiel, J. Tung, A. Fakih, J. Hoey and P. Poupart, "3D Pose tracking of walker users' lower limb with a structured-light camera on a moving platform," Computer Vision and Pattern Recognition Workshops (CVPRW), 2011 IEEE Computer Society Conference on, pp.29,36, 20-25 June 2011

[14] C. Joly, C. Dune, P. Gorce and P. Rives, "Feet and legs tracking using a smart rollator equipped with a Kinect." Workshop on "Assistance and Service Robotics in a Human Environment" in conjonction with IEEE/RSJ Int. Conf. on Int. Rob. and Sys. (IROS) (2013).

[15] V. Pasqui, L. Saint-Bauzel, C. Zong, X. Clady, P. Decq, F. Piette, V. Michel-Pellegrino, A. El Helou, M. Carré, A. Durand, Q.A.D. Hoang, J. Guiochet, P. Rumeau, V. Dupourque and J. Caquas, "Projet MIRAS : robot dassistance à la déambulation avec interaction multimodale", IRBM, Volume 33, Issue 2, April 2012, Pages 165-172, ISSN 1959-0318

[16] www.opencv.org

[17] A. Senior, A. Hampapur, Y.L. Tian, L. Brown, S. Pankanti and R. Bolle, "Appearance models for occlusion handling." Image and Vision Computing, 24(11), 1233-1243, 2006.

[18] V. Lugade, V. Lin and L.-S. Chou, "Center of mass and base of support interaction during gait", Gait & Posture, Volume 33, Issue 3, March 2011, Pages 406-411, ISSN 0966-6362

[19] A.J. Teichtahl, M.E. Morris, A.E. Wluka, R. Baker, R. Wolfe, S.R. Davis and F.M. Cicuttini, "Foot rotation – A potential target to modify the knee adduction moment", Journal of Science and Medicine in Sport, Volume 9, Issues 12, May 2006, Pages 67-71, ISSN 1440-2440.

[20] H. Bhatt, F. Pieruccini-Faria and Q.J. Almeida, "Dynamics of turning sharpness influences freezing of gait in Parkinson's disease", Parkinsonism & Related Disorders, Volume 19, Issue 2, February 2013, Pages 181-185, ISSN 1353-8020

[21] www.codamotion.com