Assessment of Walker-assisted Human Interaction from LRF and Wearable Wireless Inertial Sensors

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Abstract: This paper describes the assessment of basic walker-assisted human interaction based on a laser range finder (LRF) sensor and two inertial wearable sensors. Thirteen osteoarthritis patients and thirteen healthy subjects were selected to be part of this pilot experiment, which intends to acquire and calculate spatiotemporal and human-interaction parameters from walker-assisted ambulation. A comparison is made between the spatiotemporal parameters of healthy subjects and the ones of patients with osteoarthritis. Moreover, it is made an analysis of the effect that change of direction in walker-assisted ambulation can have on spatiotemporal parameters. Results have shown that 1) velocity, step length and distance to the walker are significantly affected by the change of direction, and 2) distance to the walker and step length can distinguish between healthy subjects and patients with osteoarthritis. In terms of human-interaction parameters, results show that a LRF sensor can correctly describe the trajectory and velocity of the user in relation to the walker. However, just the wearable sensors can characterize changes in direction. These results will be further used in the development of a robotic control that intends to detect the user's intention through LRF and inertial sensors, and respond accordingly.

1 INTRODUCTION

The increase of human average lifespan demands the need for patient-care technologies. Patient-care facilities and nursing homes provide a supporting environment for those elderly and other patients with motor disability but are labour intensive and hence expensive and limited.

Currently, canes and wheelchairs are the most used assistive devices. However, canes do not provide enough support for the muscles and the use of the wheelchairs may lead to lower limb muscle atrophy (Martins et al., 2011). Therefore, research started to focus on walkers, which are devices that improve mobility and independent performance of mobility-related tasks.

Individuals requiring walkers have a reduced ability to provide the supporting, stabilizing, propulsion or restraining forces necessary for forward progression. By decreasing the weight bearing on one or both lower limbs, walkers may help these individuals, alleviating pain from injury or clinical pathology such as osteoarthritis (Martins et al., 2011).

However, some problems have been reported in the literature (Bateni and Maki, 2005) regarding such devices, related to the lack of security and the cognitive demands. Users must take overly cautious steps not to push it out too far forward and they are unsafe to use on uneven/slope terrain.

Thus, researchers on the robotics field started to investigate how to promote safe mobility, and tried to standardize and create an effective way to assess and evaluate human-robot interaction in assisted-walker gait. In this context, the Smart walkers emerged (Martins et al., 2011), conventional walkers adequately instrumented for control purposes, such as the inference of the walker's user intent in order to control its speed, direction and distance accordingly.

Research often addresses the study of interfaces that try to recognize the user's movement and/or intent without requiring exhaustive manual operations. Examples include recognition using cameras (Martins et al., 2011), detection of human gait using force sensors (Frizera et al., 2010) and

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ultrasonic sensors (Kuan et al., 2010).

JaRoW (Lee et al., 2011) was developed to provide potential users with sufficient ambulatory capability in all directions and easy-to-use features. This walker was integrated with laser range finder (LRF) sensors to detect the location of user's lower limbs in real time (Lee et al., 2011). A Kalman and particle filters were applied to estimate and predict the locations of the user's lower limbs and body, in real time. A PID controller was used that, despite the good results, it is not certain to be effective when tested with elderly people, whose behavior has unpredictable changes, affecting the Jarow dynamics. In addition, the rotation detection algorithm, that detects when the user wants to curve, is based on pre-defined limits that could not be respected when dealing with elder people, thus generating false decisions.

In (Ochi et al., 2011), it is proposed a walking assist system for a body weight support walker NILTWAMOR to track the walking trajectory of the user. By using the LRF range sensor, the body center point (BCP) of the user is estimated and used to control both the gait velocity and the direction of the user. The relationships between the facing direction of the body and the inclination angles of both legs are taken into account to control the walker's direction. However, the manuscript does not discuss in detail the obtained results. Besides that, tests were performed with normal healthy subjects.

Despite these studies, no attention has been given to a quantitative evaluation of human-robot interaction, *i.e.* to infer which signals related with posture orientation and gait pattern can detect user's intentions while guiding the walker. Moreover, this evaluation should be made with target users, like the elder and other patients with motor disabilities.

So, the challenge to find a more reliable manner to control the walker remains. As a first step, it is necessary to access and analyse in detail the signals of user-walker interaction to infer which ones are better suited to indicate velocity and orientation intentions of the user. Afterwards, it is possible to develop a natural user interface between the walker and patients and to employ a simple closed-loop control without requiring any demanding cognitive-effort from the patient.

In this context, this paper intends to access, study and analyse basic walker-assisted human interaction parameters of a walker model with forearm support with knee osteoarthritis (OA) patients. For this, it was used a LRF sensor placed on the walker-lower base and two wearable inertial sensors: one mounted on the walker and the other placed on the patient's body. Specifically, this paper aims to specify and justify which interaction parameters are better to interpret user's velocity and orientation intention, to then advance, in the next studies, for the development of a robotic control. The human-walker interaction measurements consist on the acquisition of the: Distance between the user body center point (BCP) and the walker; Angle of BCP orientation relatively to the walker; Angle between linear velocity vector and human-walker interaction line; Angular velocity of the user and Linear velocity of the user.

It will also be presented a gait evaluation based on spatiotemporal parameters extracted from the built-in LRF sensor. This evaluation intends to detect the effect that a change in direction (making a curve) has on spatiotemporal parameters. The calculated spatiotemporal parameters were the gait cycle, identification of stance and swing phases, cadence and step length. These parameters were chosen with base on previous studies (Debi et al., 2009; Debi et al., 2011; Elbaz et al., 2011) that compared knee OA subjects with healthy ones walking without assistance. In those studies it was suggested that an objective measurement tool such as spatiotemporal parameters can help in evaluating knee OA severity, effectiveness of treatment and might help in disease management. Thus, the calculation of these parameters with LRF sensor can be a useful tool in the future to diagnose this type of patients in assistance gait.

Results were derived from thirteen knee OA subjects and thirteen normal subjects (control samples). It is noteworthy that this study was done with the motors shut down, to enable the evaluation of the real interaction between the user and the walker without the interference of any control strategy.

This paper is organized as follows. Section 2 describes the methodology of this work, where it is presented the walker and sensors system, the experimental procedure and the human-walker interaction parameters. Section 3 presents the acquired results patients and normal subjects, and provides for a discussion. Finally, conclusions are presented in Section 4.

2 METHODS

2.1 Participants

For this study, 40 patients were chosen for inclusion of individuals of both sexes over 55 years of age, able to walk unaided for at least 25 meters, not having done any rehabilitation treatment for at least 2 months and not be making use of painkillers in the last 7 days. Diagnosis of Osteoarthritis (OA) was based on clinical and radiographic criteria of the American College of Rheumatology, which confer 91% sensitivity and 86% specificity for the diagnosis (Altman et al., 1986)performed by an orthopedic surgeon with over 30 years' of experience in evaluating patients with osteoarthritis and surgery Total Knee Arthroplasty (TKA), aided by a physical therapist with 10 years of experience in manual therapy and functional assessment.

Exclusion criteria of subjects during the selection process were: recent traumas; history of previous surgery of the lower limbs, pelvis or lumbar spine; neuromuscular diseases, other pathological forms of arthritis, presence of neurologic sequel; and cardiovascular diseases that contraindicate the performance of experiments.

At the end of recruitment, 13 participants met all inclusion criteria (Figure 1).

The control group consisted on 13 healthy volunteers without any dysfunction on the lower limbs.

Subjects read and signed an information and consent form, which was approved by the Federal University of Espirito Santo's Health Science Center Ethics Board.

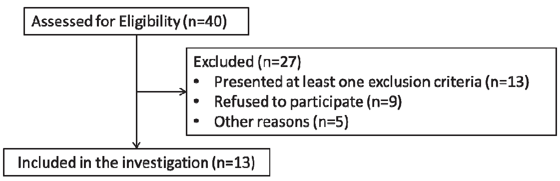

Figure 1: Diagram of selection and exclusion of study knee OA patients.

2.2 Protocol

2.2.1 Walker and Data Acquisition Systems

The Smart Walker is presented in Figure 2. This new robotic walker consists basically of a mechanical structure with an adaptable height to support the user in the forearms.

The developed acquisition system consists of a ZigBee Health Care (ZHC) network that has two types of devices: three ZigBee End Devices (ZED) and one ZigBee Coordinator, which is connected to the PC and receives patient´s signal data from ZEDs (Cifuentes,2010). The sensors are shown in Figure 2.

One ZED (C) is used to acquire and transmit signals from the LRF sensor (scanning sensor Hokuyo URG-04lx) (A) that is connected to a system microcontroller (B) that performs legs' path detection (position and orientation). Specification of LRF performance and the leg's path detection algorithm can be found in (Lee et al., 2011).

The other two ZEDs are integrated with IMU sensors (ZIMUED) developed in previous research (Cifuentes et al., 2010). One ZIMUED is located in the trunk of the patient (D) and the other one is over the walker (E). These sensors record orientation and angular velocity of the user and walker.

The IMU signals are obtained every 50 Hz and the LRF signals every 10 Hz.

Figure 2: Smart Walker hardware architecture.

2.2.2 Experimental Procedure

First, it was established that the walker should have the motors shut down and the user should walk with a self-selected speed, during assisted-ambulation. This was important to obtain the preferred gait speed of the subject while using the walker without inducing any artificial motion patterns that could bias the final results.

Height of the forearm-support is the other parameter that has been established. It should be equal to height measured between the elbow of the user and the ground, trying to force an upright posture.

All subjects (thirteen osteoarthritis patients and thirteen normal subjects) were barefoot and asked to walk three times along a pre-defined 8.9 meters path (see Figure 3).

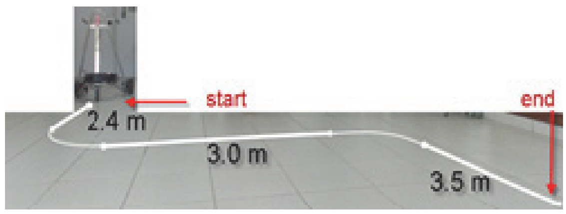

Figure 3: Trajectory that user's performed with the walker.

2.2.3 Human-Walker Interaction and Temporal Distance Parameters Calculation

The parameters described in this section are presented in Figure 4 and surveyed in Table 1.

The human-walker interaction parameters consist on: Distance between the user body center point (BCP) and the walker (*d*), Angle of BCP orientation relatively to the walker (θ), Angle between linear velocity vector and human-walker interaction line (ϕ), Angular velocity of the user (*wh*), Linear velocity of the user (*vh*) (Table 1).

Spatiotemporal parameters of gait were also determined, which reflect the dynamic activity during human walking: gait cycle (*G*), identification of stance (*ST*) and swing phases (*SW*), steps length (*SL*) and cadence (*CAD*). The selection of these parameters was based on previous studies (Debi, 2009;Debi,2011;Elbaz,2011)that compared knee OA subjects with healthy ones walking without assistance. In those studies it was suggested that spatiotemporal parameters are sufficient to evaluate and manage the knee OA disease. Results of these studies state that patients with knee OA walk slower; have a shorter step length; shorter swing phase and consequent longer stance phase.

Table 1: Human-walker interaction and spatiotemporal parameters.

		Variable	Sensor
Human-Walker Interaction Parameters	*Distance between the BCP and the walker*	d	LRF
	Angle of BCP orientation in relation to the walker	θ	LRF
	Angle between linear velocity vector and human-walker interaction line	Φ	LRF + IMU
	Angular velocity of the user	wh	IMU
	*Linear velocity of the user**	Vh	LRF
Spatiotemporal Parameter	*Gait cycle*	G	LRF
	Stance Phase	ST	LRF
	Swing Phase	SW	LRF
	Step Length	SL	LRF
	Cadence	CAD	LRF

* *Linear velocity of the user* will be also considered as Spatiotemporal parameter.

The detection and calculation methods of these parameters are described in the next subsections.

i. Distance between the user's BCP and the walker (d) and Angle of BCP orientation in relation to the walker (θ): The applied detection method of the legs to calculate the position of the BCP, is based on the work developed in (Lee et al., 2011). The detection algorithm is divided into four basic tasks: pre-processing of data, detection of transitions, pattern's extraction and estimation of the coordinates of the legs. In the pre-processing phase it is performed the delimitation of the region of interaction. Then, in the detection of transitions phase it is analyzed the performed laser scanning and seeks to identify transitions that exceed a certain threshold. In Figure 5a it is presented a situation where four transitions are found (indicated by arrows). These transitions are then stored. Finally, the coordinates of each leg are estimated and the algorithm starts to estimate the BCP. This, in turn, is accomplished by taking the midpoint of the segment that joins the coordinates of the legs, as illustrated in In Figure 5b by the cross.

Thus, this algorithm detects the two legs, and the midpoint of the segment that joins the coordinates of

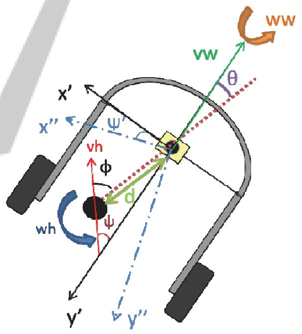

Figure 4: Scheme of the interaction parameters. Variables are defined in Table I. Black circle represents user's BCP and the yellow box represents the LRF sensor.

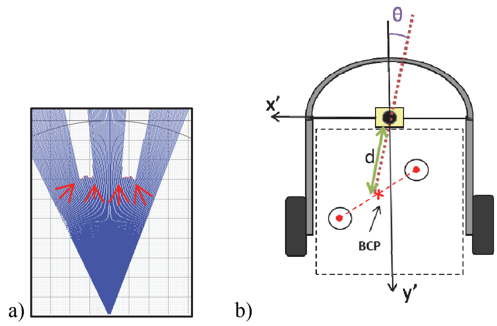

Figure 5: a) Detection of transitions: 4 transitions; b) Illustration of the CoM estimation (its location (x,y), distance between user-walker (d) and orientation (θ)).

the legs is calculated as the BCP position. With this information, one can know the coordinates (x,y) of the BCP, and consequently the distance (d) orientation (θ) that the user is from the walker.

ii. Angle between linear velocity vector and human-walker interaction line (ϕ), Angular velocity of the user (wh): The IMU placed on the user's CoM provides for the user's orientation (ψ). The IMU placed on the walker provides for the walker's orientation (ψ'). From these two angles and θ one determines (ϕ). Finally, the angular velocity (*wh*) is obtained from the gyroscope located in the user's IMU.

iii. Linear velocity of the user (vh): This parameter is the rate of change of the position of a leg detected by the LRF and is given by:

$$vh = (ds1+ds2)/dt, \quad (1)$$

where *ds1* and *ds2* are the peak-to-peak amplitudes between two legs of the acquired LRF sensor signal and *dt* is gait cycle time. Figure 6 illustrates these variables.

iv. Spatiotemporal parameters: Stance phase (ST) (swing phase (*SW*)) begins (ends) when the foot contacts with the ground and ends (begins) when the same foot leaves the ground. Gait cycle consists on the sum of stance and swing phases time.

In order to estimate these two parameters, it is necessary to detect the foot strike moments during each cycle. For the LRF signals, these correspond to the minimum values (dots in Figure 6). In a step cycle, the stance phase corresponds to the signal going from the minima to the maxima. The swing phase is the rest of the cycle.

The step length is the distance (in meters) between a specific point of one foot and the same point of the other foot. For the LRF signal, this is calculated as the difference between the maximum of one leg and the minimum of the other leg in the same instant of time, *i.e*, it corresponds to 'ds1', for example, in Figure 6.

The cadence is defined as the rhythm of a person's walk and is expressed in steps per minute (step/min).

2.2.4 Statistical Methods

The spatiotemporal parameters were considered for repeated measures ANOVA to test for significance. A mixed design was used, with within-subjects of direction (Forward/Curve) and a between-subjects factor of type of subject (Healthy/Patient). The level of significance was set at 5%.

3 RESULTS AND DISCUSSION

The values summarized in Table 2 represent the average value of the calculated Spatiotemporal parameters of each individual, as well as the distance (d) human-walker interaction parameter. For the patients (*PTs*), the values were calculated based on the signal of the leg that suffers the most with osteoarthritis. In the case of healthy individuals (*HIs*), the right leg was the one analyzed (no criteria of choice was used, since they are considered symmetrical).

In both groups (PTs and HIs) the parameters were separated by direction. This separation gives the information of how they can be affected when the user is changing his direction, by performing a curve after going forward.

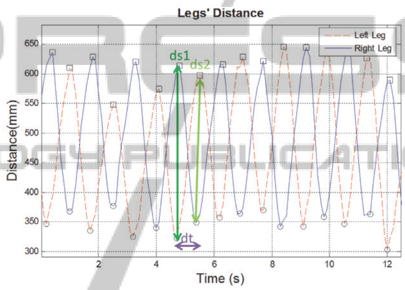

Figure 6: LRF sensor signal of the user's distance to the walker. The dots indicate the minimum points that correspond to foot strike events.

Figure 7 shows the acquired LRF and IMU signals, while one of the PTs (PT #3) walks with the walker following the pre-defined path. 'ψ Angle' and 'Angular Velocity' represent the signals read by IMUs placed both on the walker and PT. 'Legs Distance' graph illustrates the distance of both PT legs from the walker and 'Legs Orientation' shows the orientation of each leg relatively to the walker.

'Human linear velocity (*vh*)', 'Human and Walker Orientation' and 'θ and ϕ' graphs depict data calculated from the previous graphs only when the legs of the PT crossed (this event is represented by circles in the previous graphs) and they are represented in strides and steps to better analyze them. It is noteworthy that these graphs present discontinuities since they are calculated in the specific event of crossing legs.

In the following subsections it will be presented and discussed these results in detail.

3.1 Spatiotemporal Parameters

In the 'Legs Distance' graph in Figure 7, the diamonds and crosses identify the beginning and end of stance, respectively. These instants allowed calculating spatiotemporal parameters, as shown in Figure 6 and explained in section 2.2.3.

By analysing Table 2, it is possible to verify that PTs present longer duration of stance, slower velocity and shorter step length than HIs. This is in accordance with the results presented in (Debi et al., 2009; Debi et al., 2011; Elbaz et al., 2011), where a complete evaluation and comparison of spatiotemporal parameters was made between knee OA patients and healthy subjects without assistance.

In addition, PTs tend to be closer to the walker than HIs. This happens since PTs tend to be more supported on the walker, in order to feel more comfortable, safe and to alleviate knee pain. HIs tend to be more deviated from the walker since they do not need an extra support to walk.

Since this study intends to compare the spatiotemporal parameters between the two types of subjects, PTs and HIs, and between two types of direction, forward and curve, it was made a repeated measures ANOVA to test for significance.

Gait cycle (G) does not present main changes due to direction (p=0.252) and type of subject (p=0.655) and no significant interactions between direction and type of subject (p=0.222). However, it tends to increase in HIs and decrease in PTs. This happens because, when HIs perform a curve they prolong their step; and PTs tend to reduce their time with the feet on the ground, increasing the number of steps.

Stance (*ST*) and Swing (*SW*) also do not present main changes due to direction (p=0.644/p=0.640) and type of subject (p=0.935/p=0.931) and no significant interactions between direction and type of subject (p=0.316/p=0.317).

Despite the lack of statistical significance, one can observe that *PTs* present lower *ST* duration and higher *SW* duration when compared with *HIs*. This was expected since in (Debi et al., 2009; Debi et al., 2011; Elbaz et al., 2011)the *SW* was highlighted as an objective parameter in the comprehensive evaluation of a PT. They referred that *SW* may serve as a simple follow-up measurement in patients with OA. This importance is given because a knee OA patient attempts to avoid pain while walking by decreasing loads from the affected joint. However, *SW* parameter has no statistical significance in the current study with assisted gait. This means that as PT is better supported with the walker, he feels less pain when loading the affected joint, achieving to spend more time with the feet on the ground. This explains the little difference of *SW* that exists between *PTs* and *HIs.*

One can also observe that *PTs* tend to have lower *ST* and higher *SW* when performing a curve in comparison with the forward direction. These events are opposite to what happens with *HIs* and can be related to the confidence and sense of security HIs have when manoeuvring the walker. So, this decrease of *ST* (and consequent increase of *SW*) in *PTs* can be related to the difficulty that *PTs* have when performing a curve. Some of them complained to feel more pain on the knee and some confusion. Thus, they tend to support less time the foot on the ground, becoming more suspended on the walker (this was also observed in the gait cycle parameter).

Cadence (*CAD*) is a parameter that also presents no main changes due to direction (p=0.415) and type of subject (p=0.519) and no significant interactions between direction and type of subject (p=0.174). However, this parameter tends to decrease in HIs cases, and increase, in PTs cases, when performing a curve. As it was already discussed, when performing a curve, PTs tend to increase the number of steps and decrease their length.

The velocity parameter (*vh*) shows to be affected by direction (p=0.010), but not to type of subject (p=0.264). It also does not present significant interactions between direction and type of subject (p=0.140). So, this means that all subjects reduced their *vh* when performing a curve. Since it is a change in the path and more difficult to perform than to walk in straight line, it is understandable that subjects tend to reduce their velocity.

Step length (*SL*) is affected by within-subjects factor (p=0.014) and between-subjects factor (p=0.000), as well as their interaction (p=0.016). The distance to the walker (*d*) is affected by the type of subject (p=0.017) and by the interaction between direction and type of subject (p=0.036). However, it does not present main changes due to direction (p=0.477).

PTs tend to observe before walk when a curve appears, *i.e.* first they turn the walker and then they follow it. This causes an increased deviation from the walker (increases *d*) and a consequent increase of *SL*.

So, these spatiotemporal parameters, *vh, SL* and *d,* are important to be analyzed in these two situations. They can objectively inform about the level of difficulty and sense of security that *PTs* with osteoarthritis sense when maneuvering the walker, and this will depend on: comfort to guide the walker; pain on the knee, which influences the type of curve (close or open curve); and security and confidence on the device.

It can also be possible to differentiate between *PT*s and *HIs* by analyzing *d* and *SL*.

This is not in accordance with previous studies (Debi et al., 2009; Debi et al., 2011; Elbaz et al., 2011)where *SW* was recommended as an objective parameter to evaluate the degree of knee pain. Since the current study evaluated OA patients walking with assistance, the conditions changed as the patient has now an extra support that helps in alleviating pain. By this *SW* values do not differ significantly from the healthy subjects.

Table 2: Spatiotemporal parameters of walker-assisted gait. Average±Standard Deviation values.

Subj.	PT		HI	
Direction	Forward	Curve	Forward	Curve
G (s)	1,52±0,160	1,51±0,256	1,51±0,028	1,63±0,057
ST (%)	58,06±6,535	56,72±7,395	55,33±2,350	58,89±1,922
SW (%)	41,92±6,531	43,24±7,388	44,67±2,354	41,11±1,922
SL (m)	0,22±0,046	0,21±0,032	0,37±0,062	0,31±0,0455
vh (m/s)	0,32±0,158	0,3±0,147	0,44±0,061	0,39±0,047
CAD (step/min)	79,54±7,895	81,01±13,146	79,13±0,01	73,15±2,547
d (m)	0,44±0,052	0,46±0,053	0,55±0,067	0,53±0,051

3.2 Human-walker Interaction Parameters

In the 'ψ Angle' graph of Figure 7, one can see that the IMU's signals provide information about the PT movement. He is going in straight line and then at t=1s, he begins to make a curve. Then, at t=3s, he goes again straight and makes a curve, at t=5s, for the other side until t=8s. From t=8s to t=10s, he continues to walk forward and straight.

The 'Angular Velocity' graph (Figure 7) indicates that he increases (in absolute) its angular velocity (w*h*) when he starts to curve, by analyzing the same instants of time as previously.

Therefore, these two parameters can be used to correctly detect the path that the user is following. In 'Legs Distance' graph (Figure 7), one can see that is hard to distinguish between going forward and making a curve. However, it can be noticed that maximum values of right leg are reduced when PT makes the first curve (t=1s to t=3s). However, this change is not perceptible or significant in the second curve.

After observing 'Legs Distance' signals from all the patients, it was concluded that there is a great variability on this signal. Which means that PTs can perform a curve in different manners: some hide one leg; others fend off the legs, or bring them together.

'Legs Orientation' (Figure 7) also presents small changes during the time PT is performing a curve (t=[3 4]s and t=[5 8] s). Once again, this signal presents a great variability through PTs.

A possible solution to increase the effects of making a curve on the LRF signal would be to put the LRF up to the foot's height, to detect their direction. However, this is not possible to detect with LRF sensor, because the signal becomes distorted and poor of information. So, the utilization of a camera, for example, could be a good solution to detect the feet's direction.

Thus, LRF sensor is good to detect spatiotemporal parameters, as it was analyzed before, but not too good to detect intention of changing direction.

Moreover, LRF sensor is essential to detect when legs are crossing with each other (identified by circles on the graphs). This is an important event to detect BCP position, since in these instants it is the midpoint between the legs.

So, Human-Walker Interaction parameters can be calculated every time the legs cross and are represented in Figure 7.*Distance between the user and the walker (d)* is acquired by the 'Legs Distance' signal and it is marked with circles. *Angle of BCP orientation in relation to the walker (θ)* is acquired by the 'Legs Orientation' signal, being the midpoint between each leg orientation, and is represented in 'θ and ϕ' graph. *Angle between linear velocity vector and human-walker interaction line (ϕ)* is calculated by the sum of ϕ angle of walker and ψ angle of human, both represented in 'ψ Angle' graph and *θ*. This angle is represented in 'θ and ϕ' graph by the designated signal 'ϕ'. *Angular velocity of the user (wh)* are the points marked with a circle in the 'Angular Velocity' graph . *Linear velocity of the user (vh)* depends on the time that the user takes to complete a stride (two steps) and is shown in 'Human Linear Velocity' graph.

Looking at 'Human Linear Velocity' graph (Figure 7), one can see that *vh* decreases when making a curve, which is in accordance with previous discussion.

Through 'Human and Walker Orientation (*ψ*)' (Figure 7), one can see that the walker turns first than the human. This could indicate that the intention of command is transmitted by the upper limbs. This needs to be further studied by placing a rotating handlebar with integrated IMU or force sensors.

In 'θ and ϕ' graph (Figure 7), one can see that *ϕ* is better to identify, with significant variability, the orientation of the subject when compared with *θ*.

In conclusion, the Human-Walker Interaction parameters, in the overall are correctly detected and can describe the interaction between the PT and the walker.

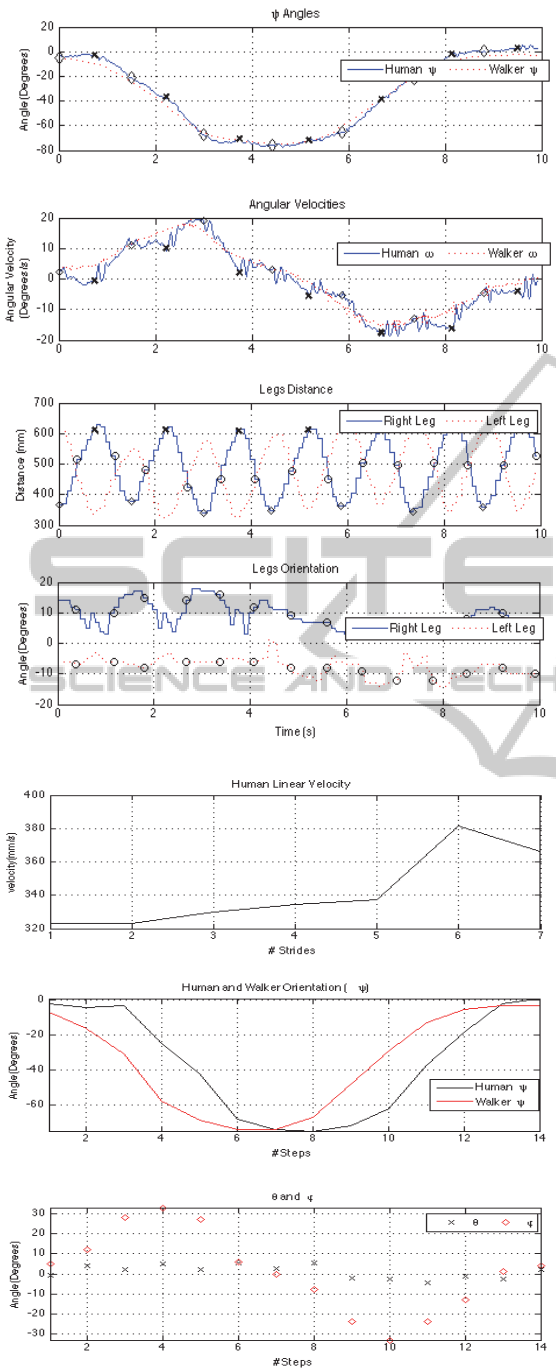

Figure 7: Human-Walker Interaction measurements with data acquisition systems.

4 CONCLUSIONS

In the literature there are few studies of walker-assisted biomechanics, especially regarding walkers with forearm supports, and there are none describing human-walker interaction nor gait evaluation regarding type of direction In relation to spatiotemporal parameters, the analysis has shown that 1) velocity, step length and distance to the walker are significantly affected by the change of direction, and 2) distance to the walker nd step length can distinguish between healthy subjects and patients with osteoarthritis. The Human-Walker Interaction parameters were correctly detected. LRF signals can detect the necessary event (when legs are crossing) to calculate them. However, is necessary, in further studies, to develop an algorithm, like the one in (Lee et al., 2011), to track the PT's legs. Afterwards, it is intended to advance for the development of a control strategy with these parameters and based on the cinematic of the walker illustrated in Figure 4.

The difficulty in human commands acquisition for the development of a control strategy is to find a parameter that can give the information of user's orientation, to then detect the orientation commands (go to the left/right).

Hence, this control should be based on the minimization of ϕ (should tend to zero), since it was concluded that this parameter can detect PT's orientation. However the authors are not sure if it is the correct parameter to estimate a change of direction, since PTs demonstrate to first use the upper limbs to transmit that command. This problem will be analysed in further studies.

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