Wearable assistant for load monitoring: recognition of on–body load placement from gait alterations

Marco Benocci[†]*, Marc Bächlin[‡], Elisabetta Farella[†], Daniel Roggen[‡], Luca Benini[†], Gerhard Tröster[‡]
[†]Electronics, Computer Sciences and Systems - DEIS, University of Bologna, Italy,
[‡]Wearable Computing Lab, Swiss Federal Institute of Technology Zürich, Switzerland
*Corresponding author: marco.benocci@unibo.it

***Abstract*—Daily life activities such as working and shopping may cause people to carry overloaded bags, frequently borne in an incorrect way (e.g. only on one shoulder, asymmetrically worn). When these activities alter the gait, back pain incidents can occur. Critical conditions can be monitored taking advantage from a wearable assistant, extracting contextual information by on-body acceleration signals. By acquiring data on trunk, limb and foot during gait, we are able to detect five walking tasks on loaded conditions: two–straps backpack carried on shoulders, backpack carried with a single strap on right and left shoulder, bag carried with the right and left hand. Seven subjects participated walking at self-selected speed on a treadmill carrying a load between 10-12% of their body weight. Subjects repeated each task for five times over three weeks. We classified the activities for a single user by use of KNN, naïve Bayes and SVM classifiers. KNN achieved the best recognition accuracy of 96.7% for day dependent classifier training. The sensors placement, which resulted to be different along consecutive days, affects performance evaluation: a $+3^\circ$ rotation on the coronal plane decreases the accuracy to 76.0%.**

Keywords: ***gait, back pain, load carriage, wearable assistant, accelerometer.***

I. Introduction

Carrying loads is a typical task for all of us. Children and students wear daily their schoolbag with their books and stationeries; businessmen bring planners, laptop and documents; hikers and soldiers carry their supplies and personal equipment for long distance; even daily shopping involves carrying groceries home. Bobet et al. [4] reports that carrying heavy load leads to stress and asymmetry on the muskoskeletal system and is the cause of back and shoulder pain, muscles soreness and numbness. Furthermore, additional weight can alter the posture control system [5] and increase the risk of falls and injury [6]. Problems such as plexus and peripheral nerve injury, metatarsalgia, functional scoliosis and thrombosis are the most common problems resulting from inappropriate loads [51], [52]. Surprisingly, even low load conditions may be related to orthopedic, musculoskeletal, or soft tissue injuries [7].

Back pain in the lower trunk affects up to 90% of Americans at some point in their lifetime [1]. After headache, back pain is the second most common neurological upset in the United States where it affects the American Health Care Expenditures at least $50 billion each year [2]. Losses can be quantified also in terms of business costs: UK spends £5 billion a year on missing working days [3].

The negative consequence of temporary carried loads are well studied [8]. In most case, the related symptoms vanish after a few days but low back pain starts to become a serious problem when it shifts from the acute to the chronic forms. Long-term effects of carrying a load are yet not fully understood. However, orthopedists warn about the impact of these repeated activities [8]. One long-term effect may be the permanent postural changes causing compressive forces upon the spine and related pathological back problems such as degenerative disk disease or disk herniation [9]. Since loads as low as the 10% of body weight starts to be critical, in particular when repeated over the time, common activities that seem innocuous can become problematic. A wearable assistant able to detect and warn about potentially harmful walking activities can play an important role on the diagnosis and prevention of neurodegenerative or chronic diseases.

In this work we aim at automatic recognition of on-body load distribution from wearable sensors, during a common activity such as walking(i.e. we aim at the recognition of load distribution during locomotion). We have two complementary motivations – corresponding to different user groups – for this work:

- Since even subjectively small loads can have harmful effects in the long term, automatically recognizing load during walking may enable users and allows them to become conscious of their load-carrying habits and make necessary adjustments.
- Since long-term effects of load-carrying are still debated, a wearable load-monitoring system can provide relevant data for medical doctors, by collecting load-carrying patterns in daily life situations, over extended periods of time.

We focus on the following on-body load placements: two-straps backpack carried on both the shoulders (i.e. rucksack carried while hiking), backpack carried using a single strap on the right or left shoulder (i.e. a laptop bag) and backpack carried on the right or left hand using the top strap (i.e. groceries).

We introduce a wearable system implementing context-recognition algorithms for detecting weight placement (> 10% of body weight) among these locations. Our key principle is to measure and classify gait alterations between walking without load and walking with a load. In order to measure

PERVASIVEHEALTH 2010, March 22-25, Munchen, Germany

DOI 10.4108/ICST.PERVASIVEHEALTH2010.8894

gait alterations we use accelerometers placed on-body. Accelerometers offer unobtrusive integration in our outfit, and the rich information present in the acceleration signal during walking may be later on exploited to combine load detection with other contextual aspects, such as modes of locomotion, estimation of terrain profile, or gait trend analysis as well as more complex recognition of patterns of daily activities from gait.

The key contribution of this paper are the following:

- Selection of the relevant features characterizing gait alterations due to load.
- Classification of different altered gait conditions.
- Identification of the simpler real-life setup to guarantee high classification accuracy.

The reminder of this paper is organized as follows: a literature review about the normal gait behaviors can be found in Section II. The description of the experiments setup and the walking protocol is in Section III. Section IV describes the results in terms of features selection and correct classification while Section V concludes the paper.

II. Load-related illnesses, postural and gait alterations

On-body load affects gait and posture, and has been identified as risk factor for ulterior back pain and disability. Spinal pain was shown related to load weight in young people [13] as well as in adults [14], and correlations between backpack weight and occurrence of back pain were identified [16].

On-body load exert forces impacts on the posture strategies by acting on calf, limb, trunk and head - eventually affecting the user's gait. Body load was identified as potential cause for changes of the spinal posture in adults and young people [15], [17], as well as more specific user groups such as soldiers [18], backpackers [19], and in some of the working population such as postmen [20].

A weight on the back increases forward trunk lean, rounds the shoulders and causes an alteration on the spine from its neutral position [21]. Compensatory pelvic motions increased torque and linear forces on bodily structures [22]. Using video-based analysis, Pascoe et al. [8], described how the different modality to carry a load can influence the posture. A bag carried on both the shoulder significantly decreases stride length, increases stride frequency, reduces the support phases. A bag carried on a single shoulder leads to accentuated angular movements of the trunk and the head. Under load, forward leaning increases (up to 6 °) as well as lateral bending of the spine (up to 12 °) [20].

Based on epidemiological, physiological and biomechanical approaches, Brackley et. al defined a load weight limit of 10–15 % of the body weight to still perform a safe walk in children [25]. Hardin et al. [23] suggested a maximum backpack weight of 30% of the body weight for physically fit adults.

Although automatic, walking is a activity involving complex coordination of movements; multiple body segments have to move in sync to maintain balance. Besides, feet, hips, spine, arms, shoulders and head are also involved. Through this causal chain, postural alteration due to load result in modified gait profiles. [1].

A. Gait analysis techniques

Gait analysis is used to assess the way we walk and highlight biomechanical abnormalities. Three distinct subsets of physical variables are included when measuring locomotion data: (1) kinematic, (2) kinetic and (3) myoelectric.

Kinematic data includes position, velocities and accelerations of body segments, as well as angles, angular velocities and angular accelerations between segments. Kinematic measurement methods include [26]: (a) exoskeleton systems where an electrogoniometer records changes in angles of hip, knee and ankle joints; (b) inertial sensors such as accelerometers that measure linear acceleration of the body segments; (c) stereo metric methods that reconstruct in 3D instantaneous positions of a moving point in a global coordinate system.

Kinetic data relate to the forces and the moments exerted when the body interacts with its surroundings. A typical kinetics measurement method is ground reaction force (GRF) measurement, for which platforms such as Pedobarographs and pressure insole systems with discrete or matrix sensors can be used. Other examples are the gait mats, consisting of a long walking strip integrating embedded pressure sensors.

Myoelectric sensors measure physiological variables originating in the human body and describe changes associated with skeletal muscle activity.

The traditional measurement systems are mostly opto-electronic camera-based motion tracking systems for stereo-photogrammetric [8] or dynamometric platforms. These systems often require large spaces and are generally expensive [31] and they are adequate only for hospital or laboratory stationary settings. Furthermore these systems need a complex setup and a calibration managed by a specialized technician. Markers placement has to obtain maximum visibility from multiple cameras to avoid occlusions while minimizing the "blind zone".

Nowadays, a number of wearable systems are developed to achieve less invasive measurements, typically for gait monitoring in daily life situations. These systems usually rely on wearable inertial platforms that can substitute stationary systems for several applications ([27],[28]). Some systems also provide wireless communications ([29],[30],[32]). Wearable systems have been proposed to estimate stride length, walking speed, and foot inclination in the sagittal plane during walking by means of a biaxial accelerometer and a rate gyroscope embedded in a unit on the shoe [33]. Other studies presented system able to detect gait phases with application in motor rehabilitation and evaluation, based on inertial [34],[35] and magnetic sensors [36].

B. Context and load placement recognition from gait

In literature most of the works on gait recognition involve machine vision techniques. Video analysis, based on specific

[1]The gait profile is the movement pattern of body parts during walking

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

markers placement, defined load alteration on static posture [54], dynamic condition [53], [10] or both [8], [20]. Several load carriage methods were investigated: Pascoe et al. [8] examined one-strap backpack, two-strap backpack, one-strap athletic bag; Smith et al. [53] used a bag carried unilaterally and on both the shoulders; Fowler et al. [20] investigated about the influence of one strap bag on walk.

Critical bag weight was also examined. Yusuf et al. [54], and Xian Li et al. made a comparison on the spine misalignment by a backpack on the shoulders with a weight 10%, 15%, 20% of the subject weight.

Studies with focus on dynamic condition introduced templates related to characterize the body segment movement during gait. These templates can be used to extract information such as mean, variance, maximum and minimum value or to make a comparison between different body segments behaviors. Whittley [38] gave a description about the knee rotation template during gait while Osaku et al. [39] described a comparison on the compensatory arms-foot movement. Leteneur et al. [40] extracted a template useful to evaluate trunk and lower trunk inclination during the stance phase of gait. Hirasaki [41] analyzed the effect of different walking speed on the trunk translation and head pitch/translation. Relevant gait information can be extracted by the sensors placement on the lower trunk, identified as the body's center of gravity where the balance starts. During a walk the hip motion appears as two separate, overlapped rotations: firstly, the hip rotate along the axis of the spine, forward and back with the legs. Orendurff et al. [42] shown the Center of Mass (CoM) trajectory on a health subject during walking. They reported a relationship between the vertical and mediolateral CoM excursions and the walking speed.

A large use of accelerometers was made to detect the human body orientation where the subject posture was estimated by attaching sensors on two or more body's segments (i.e., trunk, thigh, shank). Aminian [44] and Veltkin [45] recognized posture at rest such as standing, sitting and lying. Jonghun et al. [46] extended the static recognition detecting activities such as walking, running, upstairs and downstairs climbing with a single accelerometer on the waist and a neural network classifier. Bächlin et al. [12] showed that on-body loads can be detected from gait alterations, as well as different shoes worn, and walking surfaces can be identified. They also showed that gait is specific to each individual, to the extent that it may be used for gait-based authentication. However, they identified natural day-to-day variations in the gait profile that makes gait-based context-recognition approaches challenging for long-term use.

Therefore, we can state that an extensive collection of results from real-life on load carriage is still missing. In fact, existing dataset refers to ambulatory acquisition and selected population; acquisition is often performed in limited areas due to the use of camera-based techniques to capture the walking behaviours. The aim of the present work is to put the premises to implement a wearable device, enabling long-term capture of walking behaviours on broader subjects populations in real-life conditions. Enabling long term monitoring is crucial to gain a complete understanding of the impact of daily physical activities on user health. Such information can be provided to clinicians in case of injuries or contractures to perform more accurate diagnosis and prescribe ad hoc treatments.

Finally, a wearable device working on the detection of critical walking conditions can be used also to advise the user; for example providing precautionary feedback if he is incurring in critical tasks or using statistics to advise the user of incorrect behaviours repeated over time.

III. Wearable Assistant for Load Monitoring: Methodology and Experimental Setup

A. Experimental protocol

We defined six walking conditions, commonly involved in daily activities, defining different ways of carrying a load. Tasks are defined as follow: normal gait – without weight– (N); two-straps backpack carried on the shoulders (SB); backpack carried using a single strap on the right shoulder (SR) and on the left shoulder (SL); backpack carried on the right hand (HR) and on the left hand (HL). The backpack weight was chosen between 10-12% of the subject weight.

Experiments start with a reference task (R) to align sensors orientation to the external reference system defined by the gravity vector and the floor plane. The duration of each task is 2 minutes. It is not mandatory for the subjects to stare a visual target during the walk.

In order to have a controlled setup, trials are performed on a treadmill. Murray et al. [47] have shown that walking on a treadmill is similar to normal gait. Subjects walked on a treadmill at self-selected speed. Before data collection, each subject walked for 2 minutes on the treadmill to select a comfortable speed which was later used for the recordings on all the others days. Walking speeds vary between 3 and 3.5 Km/h (average speed was 3.25($\pm$0.25) Km/h). Subjects were asked to wear always the same shoes for all the recordings; most of them chose their running shoes.

The seven tasks were repeated five times on three weeks, two times per week: 700 minutes of data. The task execution sequence was randomized to prevent the measuring of possible fatigue effects from the users.

Seven subjects participated in this study (4 males, 3 females). Their average age, height and weight are 35.5 ($\pm$11.6) years, 174 ($\pm$10.0) cm and 65.9 ($\pm$6.8) Kg, respectively. Details are given in Table I. None of the subjects presented history of neuroskeletal disorder.

B. System setup

The proposed system is based on four tri-axial sensors. Wireless accelerometer nodes [48] have a range of $\pm$ 6g and a resolution of 1mg. The sampling rate is set out 32Hz to guarantee an adequate signal quality and the maximum lifetime of the battery supply: 20h. The sampling rate value was chosen in agreement with [49] that identifies, using video analysis on several walking speed, the typical bandwidth of normal subjects gait between 4 and 6 Hz.

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

Sub	Age [y]	Gender	Height [cm]	Weight [Kg]	Load [Kg]	Speed [km/h]
1	30	M	176	71	8.4	3.5
2	28	F	165	56	5.6	3
3	28	M	190	83	8.4	3.5
4	30	F	166	55	5.6	3
5	59	F	162	52	5.6	3
6	47	M	175	75	8.4	3.5
7	26	M	186	74	8.4	3.5
Tot	**35.50** ± 11.60		**174** ± 10.00	**65.90** ± 6.80	**7.20** ± 1.50	**3.5** ± 0.25

Table I
SUBJECTS SUMMARY CHARACTERISTICS

In Figure 1 the red circles mark the sensors placement and the axis orientation. Sensors were attached to the body locations using Velcro belts: two of them are placed on each heel, to detect opposite foot gait phases, one on the lower trunk (fifth lumbar) and one on the chest, both to capture body tilt-related parameters. In a preliminary setup sensors were placed also on the knees, wrists and head. However knees-related information was considered redundant with respect to the features extracted from heels. Sensors placed on head and wrists capture gestures involved in many different activities not only related to the specific problem observed (carriage of a load), thus confusing the results. The data is sent via Bluetooth to a PC which synchronizes the recordings of all four sensors.

Figure 1. Accelerometer sensors placement and axis orientation

IV. DATA PROCESSING

Monitoring the user in quiet stance, the sensors position is aligned by the introduction of an adequate rotation matrix. Experiments start with a reference task to align sensors orientation to the external reference system defined by the gravity vector and the floor plane.

Features on time-series data are extracted on repeatable events taking as reference the model reported in Chambers [37] (2). The model identify the gait cycle on a single foot tagged by the heel strike event. Stance (S) and swing phases (s) are related to the events: hell strike (HS) and toe off (TO). Features are extracted on a sliding temporal window, identified by two consecutive right heel strikes ($t = T$): $[f_1(T), f_2(T), ..., f_n(T)]$.

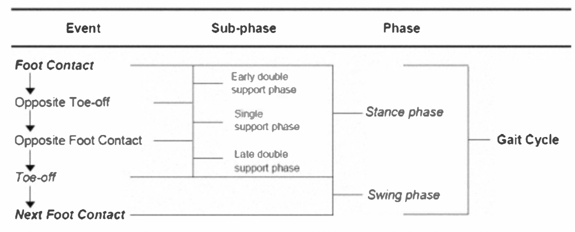


Figure 2. Double Support Gait Model from [37]

The average value of the features is computed on the overlapped window of the previous N samples to reduce the data variability ($N = 5$).

$$\begin{cases} \overline{f_1}(T) = mean(f_1(T), f_1(T-1), ..., f_1(T-N)), \\ \overline{f_2}(T) = mean(f_2(T), f_2(T-1), ..., f_2(T-N)), \\ .... = ... \\ \overline{f_n}(T) = mean(f_n(T), f_n(T-1), ..., f_n(T-N)). \end{cases}$$

To guarantee independence between the features and improve classification performance, a feature selection, evaluating the entropy of each feature entropy in the classification process, was performed.

Classification is based on the KNN classifier ($K = 3$). The task is estimated each $t = T$: $C_{temp}(T) = f(\overline{f_1}(T), \overline{f_2}(T), ..., \overline{f_n}(T))$. Class assessment is improved by the Majority Voting algorithm: the class with the maximum number of instances on the previous K estimates ($K = 5$) is taken as the most probable: $C(T) = [C_{temp}(T), C(T-1), ..., C(T-1-K)]$. In this specific case, transitory activities, such as switches from different carriage load methods, are not detected.

A. Signal analysis

Willemsen et al. [50] present an accelerometer-based template to detect automatically stance, push-off, swing down, swing up and heel strike on the ankle joint, shown in Figure 3, where HS and TO events are related to the maximum signal peaks on the accelerometer vertical axis. With the purpose to detect only these two main events, we developed a simpler algorithm to detect the maximum values in the signal of the heel sensors. The maximum peak, in the vertical y-axis, closest to the minimum peak in the z axis (gait direction) identifies HS events (see Figure 4).

Since sensors are fixed with Velcro stripes, artifacts affect the signal (Figure 5, blue curve). To improve maximum peaks detection, we apply a low pass filter to the signal (3dB point at 10Hz) and evaluate peaks on the norma of the signal (Figure 5 - red curve).

In Figure 6 the temporal features extracted are represented:

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

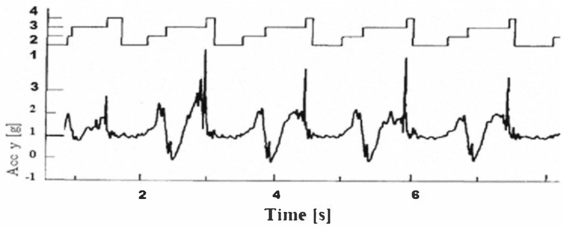
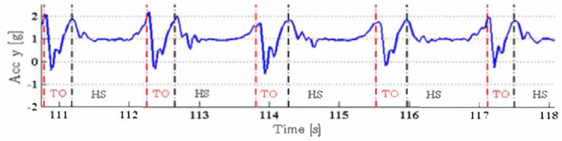
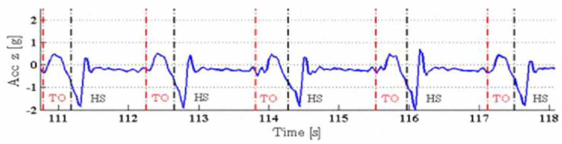


Figure 3. Equivalent acceleration at the ankle joint [50]



(a) Vertical direction



(b) Forward direction

Figure 4. Right heel acceleration sensor

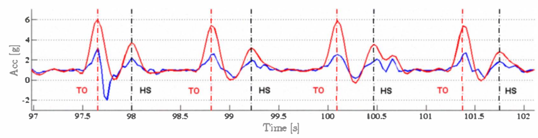


Figure 5. Signal processing on the right heel acceleration signal on vertical axis to enhance gait phases detection

- single foot gait duration ($G_x, where : x \in right, left$): time interval defined between two consecutive heel strikes on a single foot;
- single foot stance duration ($S_x, where : x \in right, left$): time interval defined between heel strike and the consecutive toe off a single foot;
- single foot swing duration ($s_x, where : x \in right, left$): time interval defined between toe off and the consecutive heel strike on the single foot;
- overlapped phase duration between two feet ($O_y, where : y \in right/left, left/rightrl$);

For example, starting with the HS of the right foot, HS_{right}, and defining: TO of the right foot, TO_{right}, HS of the left foot, HS_{left}, TO of the left foot, TO_{left}, the events sequence involved in a gait cycle is: $HS_{right}, TO_{left}, HS_{left}, TO_{right}$, overlapped phases can be described as follow:

- $O_{rl}(T) = TO_{left}(T-1) - HS_{right}(T)$

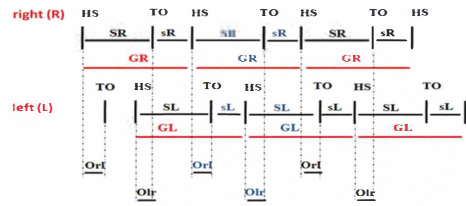


Figure 6. Double support temporal relations

- $O_{lr}(T) = TO_{right}(T) - HS_{left}(T)$
- $G_{right}(T) = HS_{right}(T+1) - HS_{right}(T)$
- $S_{right}(T) = TO_{right}(T) - HS_{right}(T)$
- $s_{right}(T) = HS_{right}(T-1) - TO_{right}(T)$

When a load is carried on a body side, the walking behaviour presents temporal asymmetry. One way to evaluate this asymmetry is to make a comparison between the duration of the stance and swing duration. This parameters is calculated:

- $SsRatio_{right}(T) = S_{right}(T)/s_{right}(T)$
- $SsRatio_{left}(T) = S_{left}(T)/s_{left}(T)$

Sensors placed on the hip and upper trunk allow to monitor body oscillations in the sagittal and the coronal plane. As reported in literature – see Section II-B –, we assume that carrying a load can be identified on the thank to the extraction of the rotation features: $Rot(j, k, m) where$: sensors position, $j, \in Trunk, Limb$, rotation plane, $k, \in Sag, Cor$). We measured the values: $m \in Mean, Std, Max, Min$.

Figure 7 illustrates the impact on the upper trunk posture due to carrying: a) symmetrically a rucksack; b) asymmetrically a hand bag.

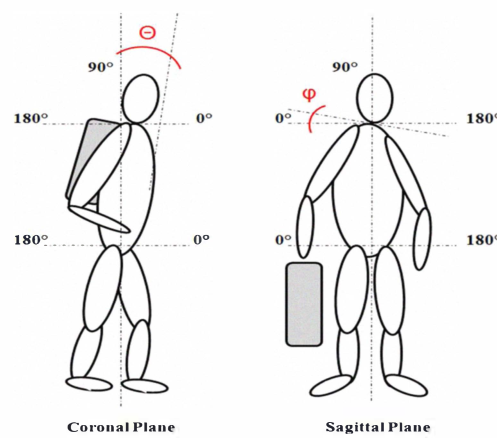


Figure 7. Posture alteration due to load carriage

Not only kinematic but also energy information can be extracted from the sensor placed on the lower trunk. Energy expenditure (EE) provides the quantitative measure of the metabolic energy expanded in physical activity. Mathie et al. [43] compute EE on the dynamic accelerometer components of a sensor placed on the lower trunk.

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

Body inclination and energy expenditure features are normalization to the gait interval duration.

B. Features selection

Haal et al. proposed the filter [57] to select the most relevant features by ranking entropy of each feature in the classification process. The score is a value in the range [0–F], where F is the number of folds that build the validation set from the whole dataset. The score with F value means the highest feature relevance in the classification process.

User–specific and time–independent features are selected by running the described process on D days for each subject. Subject specific features scores $(S_1, S_2, ..., S_7)$, in the range of $[0 - F * D]$, are visible on columns in Table II.

To select user–unspecific and time–independent features, scores from each subjects were added; the final score is shown in the "FS" column.

Features	S_1	S_2	S_3	S_4	S_5	S_6	S_7	FS
$Gait_{right}$	1	0	0	0	0	0	0	1
$Gait_{left}$	1	1	0	0	1	0	0	3
$Stance_{right}$	1	0	0	1	1	0	0	3
$Stance_{left}$	0	1	0	1	0	1	0	3
$Swing_{right}$	0	0	0	0	0	0	0	0
$Swing_{left}$	0	0	0	0	0	0	0	0
$SsRatio_{right}$	0	0	1	1	0	0	1	3
$SsRatio_{left}$	0	0	1	0	0	0	3	4
$Overlap_{rl}$	0	0	2	0	0	0	0	2
$Overlap_{lr}$	0	0	4	1	0	0	0	5
$RotTrunk_{SagMean}$	18	18	16	17	15	15	14	113
$RotTrunk_{SagStd}$	6	2	0	3	0	6	2	19
$RotTrunk_{SagMax}$	18	11	9	16	16	16	14	100
$RotTrunk_{SagMin}$	10	8	4	12	12	8	7	61
$RotTrunk_{CorMean}$	20	20	20	17	20	20	20	137
$RotTrunk_{CorStd}$	5	0	0	6	5	5	3	24
$RotTrunk_{CorMax}$	16	17	18	15	20	19	18	123
$RotTrunk_{CorMin}$	20	19	19	14	19	16	15	122
$RotLimb_{SagMean}$	12	8	20	18	20	17	15	110
$RotLimb_{SagStd}$	3	3	2	6	2	4	1	21
$RotLimb_{SagMax}$	5	6	5	13	10	9	7	55
$RotLimb_{SagMin}$	7	6	16	10	20	12	10	81
$RotLimb_{CorMean}$	15	17	16	20	17	20	20	125
$RotLimb_{CorStd}$	10	6	5	13	3	8	7	52
$RotLimb_{CorMax}$	4	9	2	17	12	10	4	58
$RotLimb_{CorMin}$	9	9	2	14	9	10	6	59
$EE_{rightMean}$	4	4	0	0	0	3	3	14

Table II

FEATURES RELEVANCE IN THE FILTER SELECTION PROCESS BY RANKING ENTROPY OF EACH FEATURE IN THE CLASSIFICATION PROCESS. NUMBER OF FOLDS, $F = 4$; NUMBER OF DAYS, $D = 5$

Features selected by thresholding ($threashold = 100$) are: $RotTrunk_{SagMean}$, $RotTrunk_{SagMax}$, $RotTrunk_{CorMean}$, $RotTrunk_{CorMax}$, $RotTrunk_{CorMin}$, $RotLimb_{SagMean}$, $RotLimb_{CorMean}$. Both temporal features and the feature to highlight a possible walking asymmetry (swing-stance duration ratio) are not selected because there is not relevant variability over different tasks. This can be due to a bag weight too light or to the use of the treadmill instead of acquiring data in free walking conditions. Therefore, tests with heavier loads can reveal if these features,defined in [20] as the most relevant to detect altered walking, can be re-considered.

C. Walking alteration recognitions results

Three different data analysis methodologies can be applied: (a) user specific and time dependent: a single subject monitored on a single day; (b) user specific and time independent: a single subject monitored on several days; (c) user non-specific and time independent: more subjects monitored on several days. In this paper, we analyze the case (a) evaluating classification performance in terms of Correct Classification Rate (CCR).

Perform a user specific and time dependent analysis means to distinguish each defined walking alteration on a fixed day by training the classifier on day X_a and testing on day X_b, where: $X \in day_{1,...,5}$; a represents the first 30 seconds of a single task in the dataset while b are the last 90 seconds.

In Table III performance about the tested classifiers is shown. KNN classifier provides the highest accuracy (96.7%), when compared to naïve Bayes (96.5%) and SVM (85.2%) classifiers.

In Figure 8 the True Positive Rate matrix (TPR) values averaged on all the subjects is shown. KNN ($K = 3$) is the classifier used. Real task are reported on each row, while estimated tasks are in the columns of the table.

Classifier	S_1	S_2	S_3	S_4	S_5	S_6	S_7	CCR
KNN	98.8%	95.1%	94.5%	99.5%	92.8%	98.0%	97.3%	**96.7%**
NB	99.5%	96.1%	95.8%	99.7%	91.1%	97.7%	97.1%	**96.5%**
SVM	88.9%	86.6%	85.0%	83.7%	79.0%	86.3%	87.2%	**85.2%**

Table III

USER–SPECIFIC, TIME–DEPENDENT CLASSIFICATION RESULTS COMPARISON FOR DIFFERENT CLASSIFIERS. CROSS–VALIDATION, 4 FOLDS, ON A SINGLE–USER IN A SINGLE–DAY

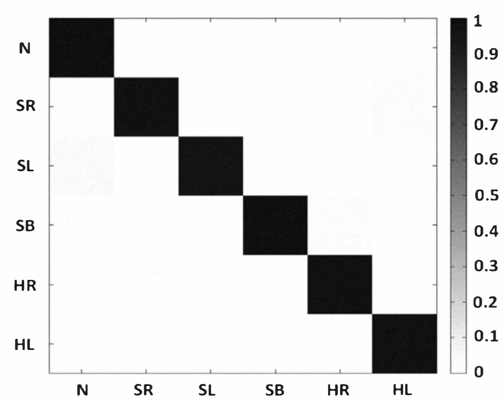


Figure 8. 96.7% of accuracy for user–specific and time–dependent case.

Another approach can be used to train the classifier to limit day-by-day training activity. The classifier can be trained with a sufficient amount of data on the day d_1 and update the classifier only on the day in which is used.

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

We trained the classifier on the first 20 seconds of day d_1 and the first 5 seconds of the day d_j. Testing dataset is represented by the last 115 seconds of d_j.

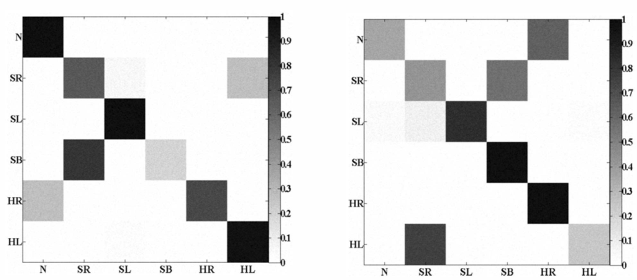
Classifier accuracy has the average value of 92.1%. The classifier stores only the training set of the first day d_1 while in the following days few steps are sufficient to update the classifier.

Assessment across multiple days, ensures robustness against natural daily fluctuations in gait, taking advantage from the classifier update on the day of use. In Table IV single user classification results on five different days are visible.

CCR	Single Trunk Sensor	All Sensors
TrainD1-TestD1	95.1%	92.8%
TrainD12-TestD2	89.4%	94.0%
TrainD13-TestD3	90.1%	91.1%
TrainD14-TestD4	83.9%	89.7%
TrainD15-TestD5	92.3%	93.1%
Mean	**90.2%**	**92.1%**

Table IV
ONLINE CALIBRATION – CLASSIFIER TRAINED ON 20 SECONDS OF THE DAY d_1 AND THE FIRST 5 SECONDS OF THE DAY d_j AND TESTED ON THE REMAINING SECONDS OF THE DAY j

The relevance of the calibration done to cope with errors on the sensor placement is verified by training classifier on day 1_a and testing on day 1_b; a is the dataset with calibrated sensors placement; b is the dataset where the sensor on the trunk is artificially rotated.



(a) TPR on day d_1, $+3\,°$ artificial rotation on Z axes

(b) TPR on day d_1, $-3\,°$ artificially rotation on Z axes

Figure 9. TPR matrix on artificially rotation for sensor on trunk

In Figure 9, the TPR matrix for two artificial trunk sensor rotations over the Z axes is shown. A rotation of $+3\,°$ decreases accuracy down to 76%. SB and SL tasks are incorrectly detected as SR task while the bag carriage on the right hand is estimated as N. Viceversa, on a rotation of $-3\,°$, opposite considerations can be done. Table V presents results in terms of accuracy obtained from simulations in which the position of sensors has been rotated. The rotation of $+5\,°$ on Z axis produced very inaccurate results.

D. *Minimal sensors setup*

A sensors setup for a real-life scenario requires a simple design that involves the minimum number of sensors, to

	$0\,°$	$+1\,°$	$+2\,°$	$+3\,°$	$+5\,°$
CCR	100%	100%	94.4%	76.0%	42.1%

Table V
ACCURACY ON ARTIFICCIALY TRUNK SENSOR DISALIGNEMENT OVER THE Z AXES

be integrated in garments. This vision can be explored by performance evaluation for a single sensor. We assume that a user wears a shirt integrating a sewed accelerometer on the chest. A performance comparison between the setup based on the single chest sensor and the four sensors setup is reported in Table IV. The average accuracy of 90.2% can be reached taking advantage from the online calibration on the day of use. A single sensor on the chest can be used to detect each defined task for a single user over time.

Note: this setup does not involve sensors on heels, used to detect gait phases for signal segmentation. A different approach to extract gait phases from the sensor placed on the trunk can be used (Figure 10 – red curve). Trunk acceleration on forward direction defines toe off instances for each foot as well as the signal on the vertical direction from the sensors on the feet.

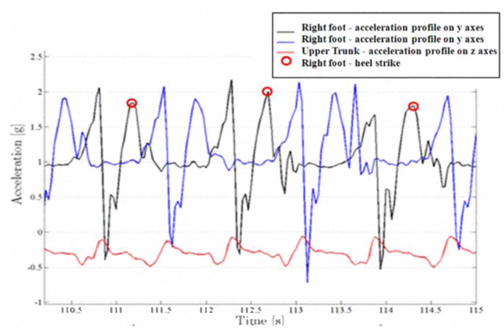


Figure 10. Swing and stance phases identification by the trunk sensors

V. CONCLUSION

We presented a study to identify relevant features characterizing gait alteration due to load. We applied a user specific and time dependent analysis, demonstrating that the most relevant features are those related to upper trunk rotation both on the coronal and the sagittal plane. Each task can be identified for a single user with high accuracy when sensors placement calibration is introduced. In fact, the study demonstrates that the sensors placement affects performance evaluation.

A minimal sensors setup was identified to guarantee classification accuracy. It is based on a single sensor placed on the upper trunk.

In a future work, we will address time independent analysis methodologies to ensures robustness against natural daily fluctuations in gait. Assessment on multiple users is the final challange to obtain a user independent system. Among the approaches that may be used to improve the detection,

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894

segmenting the population (e.g. in terms of weight and sizes) could be further explored.

REFERENCES

[1] http://www.emedicinehealth.com, Sept. 2009

[2] http://www.ninds.nih.gov/disorders/backpain, Sept. 2009

[3] http://www.personneltoday.com/articles/2005/06/03/30163/, Sept. 2009

[4] J. Bobet, R.W. Norman, "Effects of load placement on back muscle activity in load carriage", 1984, European Journal of Applied Physiology, Vol. 53, Page(s): 71-75

[5] T. Ledin et al. , "Effects of postural disturbances with fatigued triceps surae muscles or with 20 % additional body weight", 2004, J. Gait & Posture, Vol. 19, Page(s): 184-193

[6] B.E. Maki, P.J. Holliday, A.K. Topper, "A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population", J. Gerontology, 1994, Vol. 49(2), Page(s): 72-84

[7] S. Negrini et al. ,"Backpacks on Scoolchildrends perceptions if load, associations with back pain and factors determining the load", Spine 2002, Vol. 27, Page(s): 187-95

[8] D. Pascoe et al. , "Influence of carrying book bags on gait cycle and posture of youths", 1997, Journal of Ergonomics, Vol. 40(6), Page(s): 631-641

[9] C.C. Norkin, P.K. Levangie, "Joint Structure and Function: A Comprehensive Analysis", 2nd ed. , Philadelphia, PA: FA Davis Company, 1992

[10] J. Xian Li et al. , "Age difference in trunk kinematics during walking with different backpack weights in 6 to 12 years old children", 2004, In–Proceedings of the XXII ISBS

[11] http://www.nlm.nih.gov/medlineplus/ency/article/003199.htm, Sept. 2009

[12] M. Bächlin et al. , "Quantifying gait similarity: user suthentication and real-word challenge", 2009, Advances in Biometrics, Page(s): 1040-1049

[13] K. Grimmer et al. , "Gender-age environmental associates of adolescent low back pain", 2000, Applied Ergonomics, Vol. 31, Page(s): 343-360

[14] R.F. Johnson et al. , "Symptoms during load carrying: effects of mass and load distributions during 20 Km road march", 1995, Perceptual and Motor Skills, Vol. 81, Page(s): 331-338

[15] Y. Hong et al. , "Gait and posture responses to backpack load during level walking in children", 2003, Gait & Posture, Page(s): 28-33

[16] D.L. Skaggs et al. , "Back pain and backpack in school children", 2006, J. Pediatr. Orthop. , Vol. 26, Page(s): 358-63

[17] A. Steele et al. ,"The postural effects of load carriage on young people: a systematic review", 2003, BMC Muck. Dis. , Page(s): 4-12

[18] M.F. Heller, "Changes in postural sway as a consequence of wearing a military backpack", Gait & Posture 30 (2009), Page(s): 115-117

[19] J.J. Vacheron , "Changes of contour of the spine caused by load carrying", 1999, Surg. Radiol. Anat. , Vol. 21(2), Page(s): 109-113

[20] N.E. Fowler, "Changes in stature and spine kinematics during a loaded walking task", Gait & Posture, 2006, Page(s): 133-141

[21] P.E. Martin et al. "The effect of carried loads on the walking pattern of men and women", 1986, Ergonomics, Vol. 29, Page(s): 1191-1202

[22] T.C. Cook, "The effects of load placement on the EMG activity of the lower back muscles during load carryin by men and women", 1987, Vol. 30, Page(s): 1413-1423

[23] D. Hardin, B. Kelly, "You and your gear: physical fitness", 1975, Backpacker, Vol. 3, Page(s): 3-31

[24] H.J. Voll, "Strain in children caused by schoolbags", O.G. , Vol. 39, Page(s): 369-378

[25] H.M. Brackley, J.M. Stevenson, "Are children's backpack weight limits enough? A critical review of the relevant literature", 2004, SPINE, Vol. 29, Page(s): 2184-2190

[26] V. Medved, "Measurement of human locomotion", 2001, Journal of Biomechanics, Vol. 36(1), Page(s): 147-148

[27] http://lmam.epfl.ch/page2856.html, Sept. 2009

[28] http://www.xsens.com/en/products/machine_ motion/mti.php, Sept. 2009

[29] V. Van Acht, E. Bongers, N. Lambert, R. Verberne, "Miniature Wireless Inertial Sensor for Measuring Human Motions", 2007, Engineering in Medicine and Biology Society, Page(s): 6278-6281

[30] http://www.mcroberts.nl/, Sept. 2009

[31] http://www.btsbioengineering.com/, Sept. 2009

[32] http://www.memsense.com, Sept. 2009

[33] S.J. Morris Bamberg, A.Y. Benbasat, D.M. Scarborough, D.E. Krebs, J.A. Paradis, "Gait Analysis Using a Shoe-Integrated Wireless Sensor System", 2008, Vol. 12(4), Page(s): 413-423

[34] A.M. Sabatini, C. Martelloni, S. Scapellato, F. Cavallo, "Assessment of Walking Features", Foot Inertial Sensing", 2005, Vol. 52(3), Page(s): 486-494

[35] I.P.I. Pappas, T. Keller, S. Mangold, M.R. Popovic, V. Dietz, M. Morari, "A Reliable Gyroscope-Based Gait-Phase Detection Sensor Embedded in a Shoe Insole", 2004, IEEE Sensors Journal, Vol. 4(2)

[36] E. Vildjiounaite, E-J Malm, J. Kaartinen, P. Alahuhta, "Location estimation indoors by means of small computing power devices, accelerometers, magnetic sensors, and map knowledge", Lecture Notes in Computer Science, 2002, Vol. 2414, Page(s): 211

[37] H. Chambers, M.D. and D.H. Sutherland, "A Practical Guide to Gait Analysis", 2002, J. Am Acad. Orthop. Surg. , Vol. 10(3), Page(s): 222-231

[38] M.W. Whittle, "Clinical Gate Analysis: A Review", 1996, Human Movement Science, Vol. 15, Page(s): 369-387

[39] K. Osaku, H. Minakata, S. Tadakuma, "A Study of CPG Based Walking Utilizing Swing of Arms", 2006, In Proceedings of the Conference AMC

[40] S. Leteneur et al. , "Effect of trunk inclination on lower limb join and lumbar moments in able men during the stance phase of gait", 2009, Journal of Clinical Biomechanics, Vol. 24, Page(s): 190-195

[41] E. Hirasaki, "Effects of walking velocity on vertical head and body movements during locomotion", 1999, Exp. Brain Res. , Vol. 127, Page(s): 117-130

[42] M. Orendurff et al. , "The effect of walking speed on center of mass displacement", 2004, Journal of Rehabilitation Research and Development, Vol. 41(6A), Page(s): 829-834

[43] M.J. Mathie et al. "A System for Monitoring Posture and Physical activity using Accelerometers", 2001, Proceedings of 23rd EMBS

[44] K. Aminian, "Temporal features estimation during walking using miniature accelerometers: an analysis of gait improvement after hip arthroplasty", 1999, Medical & Biological Engineering & Computing, Vol. 37, Page(s): 686-691

[45] P.H. Veltink et al. , "Detection of static and dynamic activities using uniaxial accelerometers", 1996, IEEE Transactions on Biomedical Engineering", Vol. 4(4), Page(s): 375-85

[46] B. Jonghun et al. , "Accelerometer Signal Processing for User Activity", 2004, Lecture Notes in Computer Science, Vol. 3215, Page(s): 610-617

[47] M.P. Murray et al. , "Treadmill vs. floor walking: kinematics, electromyogram, and heart rate", 1985, Journal of Applied Physiology, Vol. 59(1), Page: 87

[48] D. Roggen, M. Bchlin, J. Schumm, G. Trster, "A Bluetooth and wired sensor kit for wearable activity recognition", ETHZ Technical Report, 2010

[49] D.A. Winter, "The Biomechanics and Motor Control of Human Movement", 2nd ed. , 1991, Wiley

[50] A.Th.M. Willemsen et al. "Automatic Stance-Swing Phase Detection from Accelerometer Data for Peronal Nerve Stimulation", 1990, IEEE Transaction on Biomedical Engineering, Vol. 37(12)

[51] S.D. Kolodinsky et al. , "Axillary vein thrombosis in a female backpacker: Paget-Schrotter syndrome", Canadian Association of Radiologists Journal, 1989, Vol. 40, Page(s): 230-231

[52] E.L. Sutton, "Preparing for combat: athletic injuries occurred and performance limiting orthopedic and medical conditions", Medical Science in Sports and Exercise, 1976, Vol. 8, Page(s): 74

[53] B. Smith, "Influence of carrying a backpack on the pelvic tilt, rotation, and obliquity in female college students", 2006, Gait & Posture, Vol. 23, Page(s): 263-267

[54] S.S.M. Yusuf Al-Khabbaz et al. , "The effect of backpack heaviness on trunk-lower extremity muscle activities and trunk posture", 2008, Gait & Posture, Vol. 28, Page(s): 297-302

[55] L. Atallah, "Detecting Walking Gait Impairment with an Ear-worn Sensor", 2009, Page(s): 175-180

[56] H. George et al. , "Estimating Continuous Distributions in Bayesian Classifiers", Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence", Page(s): 338-345

[57] M.A. Hall et al. , "Correlation-based feature subset selection for machine learning", 1999, PhD Thesis, University of Waikato, Hamilton, New Zealand

Digital Object Identifier: 10.4108/ICST.PERVASIVEHEALTH2010.8894
http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8894