Unobtrusive Assessment of Bipedal Balance Performance

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ABSTRACT

Reduced postural stability are symptoms of many medical conditions. Depending on the conditions, there are training or medication strategies to ameliorate the balance of a subject. After medical treatment (surgery etc.) or in the context of an intervention/recovery strategy, these patients are often assessed in functional gait assessments (FGA). An expert, e.g. a Physio Therapist, can decide based on the outcome of such an assessment on future treatment plans. FGAs are often performed with no technological assistance: a subject performs pre-defined tasks and the performance is evaluated visually by an expert. Existing technological assessment tools are scarcely used due to time and monetary restrictions. In this paper, we present a wearable sensor system that can be used for FGAs. Our system comprises a pressure-sensing component and inertial sensors to assess features known to correlate with balance. We validated our system against technological state of the art. We used the system on 6 patients and 5 healthy subjects. The system can distinguish between normal stance and stance with reduced postural control with an accuracy of more than 93%. Walking episodes were classified into two categories with 91%. Based on features of stance and features of gait, our system can discriminate between healthy subjects and subjects with reduced postural stability with an accuracy of 94%

1. INTRODUCTION

There is a large number of possible illnesses and conditions that have an impact on features of gait and on the balance performance of a subject. Everyday causes like sleep deprivation might be sufficient to affect the balance of a person [16]. However, conditions like damages to the vestibular system (located in the inner ear), strength deficits in limb or core muscles, visual impairment etc. can manifest in difficulties maintaining a balanced posture. Even though some patients show improved stability in a dynamic situation, i.e. walking, they would move even more stable without any balance impairments. It is save to state that balance difficulties are reflected in static and dynamic situations. Hence, if one could assess features of balance in a static state and features of gait in a dynamic case one would be equipped with measures to get a notion on the overall balance performance of a subject. We call this *bipedal performance* and it comprises stance stability and gait stability.

The stability of a person walking can be estimated by measuring the variance of step frequency [1]. Measuring directly a subject's balance is more involving as it translates into the task of continuously estimating a subject's center of mass, COM. As long as the projection of the COM onto the ground plane falls into the convex polygon spanned by a subject's feet, a *balanced posture* is assumed [14]. Continuously estimating the COM would require accurate measurements of a subject's physical properties and a way of tracking her body-dynamics. Previous work achieves this by using optical motion capture or a multitude of inertial measurement units, IMU, attached to various parts of the body. Related work has shown, though, that there exists a correlation between the dynamics of the center of pressure, COP, beneath a subjects feet and the quality of her balance [18].

In clinical settings, e.g. for functional gait analyses (FGA) most of the assessments are performed *manually*, by the interpretation of a well-trained expert. This expert could be a physio therapist, PT, or a medial doctor. FGAs are usually multi-item physical tasks that need to be performed by a patient. The PT would then characterize or rate a patient's performance for each item. However, this rating is difficult and not always unambiguous. Other assessments also include feedback from the patients. Due to limited resources both in time and space, technological support is only sought rarely. Systems like GAITRite [20] or Zebris [9] require to be pre-installed in a room and require multiple experts to be operated.

Common practices to assess bipedal performance can be clustered into three classes: *immobile systems* installed in a dedicated facility, *mobile* or *wearable systems* that require a multitude of sensors on a subject and *technology rare* approaches relying on expert knowledge and possibly on subject feedback. For clinical assessments, a combination of all three classes is desired: the *ease of use* of an pen-and-paper assessment combined with the *comprehensive assessment* of a wearable system topped by the *robustness* of a pre-installed system.

We are not going to present the silver bullet, but we think that our solution facilitates objective assessments of bipedal performance. We built a high-resolution pressure sensor system combined with an inertial measurement unit (IMU). We

BODYNETS 2013, September 30-October 02, Boston, United States

DOI 10.4108/icst.bodynets.2013.253532

presented the technical features of our system earlier in [2]. We will show in this paper that the combination of a pressure insole with an IMU enables us to assess bipedal performance in dynamic and static situations. Our system is unobtrusive and allows for continuous assessment of static balance and dynamic gait stability. Additionally, it comprises a display device, e.g. a smart phone, that not only acts as a controlling device, but also gathers data from a subject's shoe sensors and calculates balance features. Each foot sensor tracks the center-of-pressure and sends the coordinates to a smart phone. On a mobile device, an algorithm calculates a surrogate for bio-mechanical stability estimation: a Stabilogram Diffusion Analysis, SDA, is calculated in real-time. As will be motivated later, this calculation provides reliable estimates on a subjects balance. Raw sensor data and features can be stored on the sensor devices for later analysis. On the smart phone, real-time information can be presented to a user (PT, medical doctor).
We evaluate the performance of our system and show that it matches the requirements on an assessment tool that might support PTs or medial doctors for evaluations of bipedal performances. We compared our system to state-of-the-art (SotA), the ZEBRIS system [9], to validate the sensory and algorithmic system performance. To show applicability and classification performance of our system, we tested 5 healthy subjects and 6 patients. We attended various FGAs and asked the patients if they would wear our system during the tests. A selected set of these test items were then performed by the group of healthy subjects. We show that our system is capable of detecting episodes of reduced bipedal performance with an accuracy of above 91%. Our system continuously calculates features known to correlate with balance performance [5, 18] by utilizing the dynamics of the center of pressure, COP. During standing, episodes of limited balance are detected more than 93% correctly. Our system can further distinguish between healthy subjects and patients with an accuracy above 94%.

2. RELATED WORK

Gait Analysis refers to research that focuses on features of gait. In [3] Bamberg et al. present a sensor system that provides three pressure measuring points as well as orientation data of the feet using inertial measurement units (IMU). All system components were integrated in a shoe. The authors use that system to analyze heel-strike and toe-off events during gait periods as well as the feet orientation. Kuys et al. [13] use the GAITRite® system[11] to evaluate spatio-temporal gait features of stroke patients. Adelsberger et al. [1] rely on IMUs attached to the subjects' legs to detect situations of higher cognitive load and a thereby induced reduction of gait stability.
Balance Assessment is a non-trivial task. Various authors (e.g. [10, 12]), tackle this problem by estimating a subject's center of mass (COM) which requires exact tracking of body posture and possibly calibration of physical properties of a subject (weight etc.). An optical or inertial motion capture (MoCap) system can then use this calibration to track the movement of the subject's limbs and trunk. However, setting up such an accurate COM-estimation system that meets these accuracy requirements can be time consuming since multiple markers are required per limb (see VICON® manual) or multiple sensor nodes need to be attached to the body.
Other work analyzes the relationship between COM and center of pressure (COP) beneath a subject's feet, cf. [5, 15, 4]. Tanaka et al. [18] decoupled the problem of balance estimation from COM estimation. In their work, look at statistics of COP motion. Inspired by Einstein's theory on Brownian Motion [8], they model the *motion* of COP similarly, by a *stabilogram diffusion analysis*, SDA, [5]. Their findings show that parameters of the Brownian motion model applied to COP position correlate well with postural stability/instability. Tanaka et al. [18] show that for an SDA, short term diffusion coefficients, D_S, are a good indicator of balance performance of a subject. Specifically, people with balance problems show significantly higher values for D_S than normal subjects. Also, mean square displacements are significantly larger in the group with balance issues than they are in the normal group.

3. SYSTEM DESCRIPTION

Our sensor system comprises for each foot a size adjustable pressure insole with about 1300 force sensing resistors (FSR), a sensor board that samples every FSR, and an inertial measurement unit (IMU) with a communication (ANT+) and a storage (MicroSD card) module. The insole is manufactured by TekScan and we modified it to be applicable in our system. The pressure-sensitive elements cover an area of $25mm^2$. The insole can be adapted and integrated into virtually any shoe of a large size range, e.g. from children size 13 up to male size 12.5. Since it is very thin ($< 0.5mm$) it is not noticed if installed below a regular shoe-insole. A remote device (e.g. Smart Phone) works as a controller to the shoe sensors. It also takes the role of a notification and display device. Figure 1 shows the shoe-integrated parts of the system. A more detailed description of the hardware and system capabilities can be read in [2]. For each foot, the system calculates in real-time the center of pressure (COP), i.e. the coordinates of the center of the ground-reacting forces.
For a well balanced, static posture weight would be evenly distributed onto both feet. For such (artificial) postures only the forward/backward movement of the COP needed to be estimated. However, in general, weight is not shared evenly between the feet due to different reasons. Thus, to calculate an estimate for a global COP of a human posture, COP_G, the estimates of both feet need to be combined:

$$COP_G = w_l \cdot COP_L + w_r \cdot COP_R.$$

Weights w_L and w_R reflect the lateral weight distribution, $w_{\{L,R\}} = W_{\{L,R\}}/(W_L + W_R)$, where $W_{\{R,L\}}$ represents the estimated weight on the right/left sole. See the right part in Figure 1 for a sample COP_R. At run-time, $COP_{\{R,L\}}$ are calculated and forwarded to the smart phone where COP_G is calculated. Our system is not able to track the distances between the feet due to lack of specific hardware (distance measurement). As a consequence, it cannot conclusively detect every state of the COP-coordinates that indicate an unstable posture. However, the combination of the pressures exerted on each foot as a weight factor for the calculation of COP_G resulted in an accurate classification.
At start-up, the smart-phone accumulates for 5 seconds the COP estimates before it starts estimating the parameters for the SDA. The initial idea behind SDA was motivated by analyzing Brownian Motion in liquids. From [8] it is known that the squared mean displacement, $\langle \Delta y_p^2 \rangle$, of a Brownian

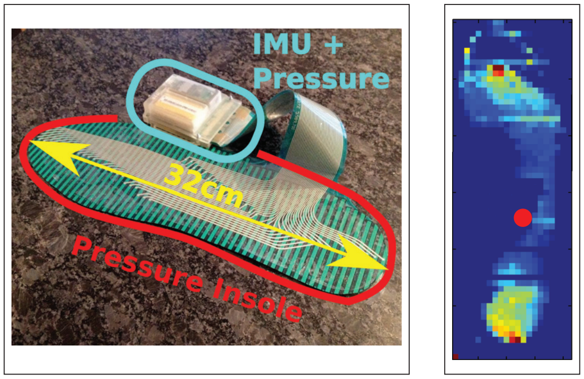

Figure 1: Left: Sensor System; **Right:** COP_R: red circle.

particle for a given time resolution, Δt, is proportional to Δt times a diffusion coefficient D, i.e. $\langle \Delta y_p^2 \rangle = 2D\Delta t$. The diffusion coefficient D is an average measure of the stochastic activity of a random walker and y_p is its displacement in space. In our work, y_p is the displacement of COP_G over time. Collins et. al [5] provide a probably more intuitive definition:

$$\langle \Delta y_p^2 \rangle_{\Delta t} = \frac{\sum_{i=1}^{N-m} (\Delta_i y_p)^2}{(N-m)} \quad (1)$$

with given Δt spanning m data points from a total of N data points. Δt ranged from $0.05s$ to $3.0s$ in our analysis since longer time intervals do not provide additional information ([15]) and also to promote a faster feature assessment due to shorter acquisition time. $\langle \Delta y_p^2 \rangle$ depends non-linearly on Δt, however it can be separated into two linear parts, one for small Δt ($I_s := [0s, 1.0s]$) and one for longer Δt ($I_L := (1.0s, 3.0s]$). Both parts can be approximated by a linear model ($\langle \Delta y_p^2 \rangle_{\{I_S, I_L\}} = \gamma_0 + \gamma_1 \Delta t$), however the model parameters differ significantly between the short-term interval and the longer-term interval. Consequently, the diffusion coefficients differ between the two time intervals. We define the diffusion coefficient for short-term intervals as D_S and the coefficient for longer-term intervals is dubbed D_L, resp. For each time interval, the diffusion coefficients D_S and D_L were found by fitting the data to a linear model with a least squares approach.
Concurrently to pressure data processing, the system acquires step timings. The variance of step frequency was calculated for the steps within a 5-seconds time window. Episodes of standing were detected using a combination of accelerometer data and pressure data.

4. SYSTEM VALIDATION

The ZEBRIS system comprises a treadmill with pressure sensitive points below the walking area of size ($150cm \times 50cm$). Every sensitive point covers an area of approximately $150mm^2$. The pressure data is sampled at 100Hz and forwarded to a PC where the analysis is performed. It is not published how the ZEBRIS system calculates COP coordinates. We assumed that it is similar to other related work [17]. We compared the COP coordinates of the ZEBRIS system with our results. Due to the fact that our sensor coordinate system is fixed to a subject, while with ZEBRIS a subject moves relatively to the coordinate system, a comparison of COP coordinates during gait would be error-prone. Hence, we recorded a subject standing on the treadmill wearing our system. Multiple features were compared: RMS-error of normalized COP coordinates and normalized coordinate variance. Coordinates were normalized to the bounding box of a foot. We also wanted to compare the sensor components of both systems, so we additionally used our own algorithms to calculate the COP and applied them to the raw data of the ZEBRIS system.

5. CLASSIFICATION

We attended FGAs of 6 patients. They were evaluated by a PT using a standardized 10-item test that contains items based on related work [6, 7]. For each item except number 10 the subjects needed to walk 20m. The table below lists the various items. Additionally, we asked the subjects to

#	Task	#	Task
1	Walk regularly (timed)	6	Step over an obstacle
2	Change speed on command	7	Walk straight, heel to toe
3	Walk; look left/right	8	Walk with closed eyes
4	Walk; look up/down	9	walk backwards
5	Walk; turn on command	10	Climb stairs

stand for 20 seconds with eyes open (item 11) and for 20 seconds with eyes closed (item 12). By closing the eyes any support from the visual system is removed and a subject is forced to rely on the vestibular system [19] and to some extend on the tactile feedback from the feet. We asked the healthy subjects to perform the items, 1,3,4,7,8,11,12. The other items did not challenge the balance of healthy subjects and all 6 patients but one did not show any special reactions. We video taped the sessions for labeling and verification.
We extracted for each of the test items features of COP_G, e.g. range, variance, standard deviation and for dynamic items also step-frequency variance. For the static items 11 and 12 we additionally calculated the SDA diffusion parameters D_S and D_L (using Equation 1) and mean displacements. D_S was calculated within $\Delta t \in [0s, 1.0s]$ and D_L was based on $\Delta t \in (1.0s, 3s]$ (cf. [6, 7]). Using the video footage, we labeled episodes of reduced bipedal performance and episodes of normal performance. We trained two-class SVMs to a) differentiate between episodes of normal and episodes of reduced bipedal performance, b) differentiate between healthy subjects and subjects with balance defects. The features presented to the SVM were the moving averages of the above features within a 0.5s window. The SVMs were trained on 80% of the samples from all subjects and their performances were evaluated on the remaining 20%. For a more accurate classifier performance assessment, we iterated this learning-testing procedure for 100 cycles, every time another random subset was assigned to the learning set.

6. RESULTS

For the evaluation we normalized the coordinates to make them comparable. This is necessary, because the sensitive area of our system comprises (21×60) points for each foot, while the ZEBRIS system works with one sensing area. We calculated a bounding box for each foot for every ZEBRIS data frame. Since the dimensions of the bounding box might change, we normalized the COP coordinates for our system and the ZEBRIS system, i.e. we mapped them to ($[0, 1] \times [0, 1]$). In a first step, we compared the COP coordinates reported by the ZEBRIS system (black box) to our coordinates. Table 1 (red) shows the results. Unfortunately,

	Dim	RMS-Error (mm)	var(Error) (mm)
■	x	5.33	2.82
■	y	5.28	3.13
■	x	1.34	1.21
■	y	1.88	1.73

Table 1: Validation.

the ZEBRIS system reports discrete values for the COP coordinates. This fact should be considered evaluating the results since one sensitive element is 6 times larger than one sensor point in our system. To compare the sensing hardware, we applied our own algorithms to calculate the COP for the ZEBRIS system. This way, we can remove the uncertainty due to the black-box nature of the ZEBRIS data. Table 1 (green) shows the results. We acquired data from 5 healthy subjects (m:4, f:1) and 6 patients (m:2, f:4). The healthy subjects' ages ranged from $21 - 34$, ($\mu = 28$ $\sigma = 4.74$). The patients' ages showed the following statistics: $19-65$, ($\mu = 45$, $\sigma = 15.7$). Healthy subjects followed a physically active lifestyle; the tests were performed in a gym. Their foot sizes ranged from 39 to 46 ($\mu = 42.6$ $\sigma = 2.60$). The patients were mentally healthy, but had balance defects due to several causes. Classification between healthy subjects and patients for the dynamic items (1,3,4,7,8) was based on statistical features calculated on COP_G (σ, range) and step frequency (μ, σ) within a 0.5 second window. On the items, 11, and 12 we performed an SDA to evaluate the subjects' balance stability and calculated D_S, D_L and $\mu(\langle \Delta y_p^2 \rangle)$. The SDA on COP_G-time series was performed for time slots ranging from $50ms$ to $3000ms$, see Table 2. On average, the range of COP coordinates was about 40%

	$\mu\,(D_S)$	$\sigma\,(D_S)$	$\mu\left(\left\langle \Delta y_p^2 \right\rangle\right)$ **(mm)**
H 11	8.17	3.12	20.18
P 11	15.83	7.44	31.92
H 12	16.39	8.01	30.24
P 12	20.18	9.87	49.11

Table 2: COP features for healthy subjects (H) and patients (P)

larger for patients than for healthy subjects, i.e. the instability was measurable. The SVM we trained for detecting unstable situations showed an accuracy of 93.32% on items 11 and 12. On items 1,3,4,7,8 the achieved classification accuracy was 91.28%. Bipedal performance of was assigned correctly to the specific subject group with an accuracy of 94%.

7. CONCLUSION AND OUTLOOK

We presented an unobtrusive system for automatic and continuous assessment of bipedal performance. A sensor insole connected to an acquisition system for pressure and inertial data calculates immediate features like center of pressure and step frequency. These features are submitted to a smart phone that aggregates the data, calculates higher-level features (SDA) and performs classification. We trained SVMs to classify between *episodes* of reduced bipedal performance (dynamic and static) and stable situations. Further, we trained SVMs to differentiate between healthy subjects and patients. The episode classification task could be performed with an accuracy higher than 91%, the subject classification worked correctly 94% of the times.

We showed successfully that we can estimate SDA features known to correlate with the bipedal performance of a subject. Further we showed that our system could provide valuable data to PT or medical doctors in their assessment tasks.

Our research focus lies on movement analysis, mainly targeted to the elderly population. We envision a system that unobtrusively and continuously tracks multiple features of gait and is able to detect trends of gait and stability performance. We believe that we added a major step into the direction of such a system.

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