TRANSLATING MOVEMENT DATA IN PERFORMANCE OR DISABILITY METRICS USING BARCODE AND SIGNATURE

Mathieu Falbriard[1], Rebekka Anker[1], and Benoit Mariani[2]

Laboratory of Movement Analysis and Measurement, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland[1]
Gait Up SA, Lausanne, Switzerland[2]

This paper present two recent collaborative developments for translating movement data into relevant information measuring objectively performance or disability. Using the signals from body-worn inertial units (Physilog®) combined with advanced data fusion algorithm, daily-life motor performance on one side and running performance on the other side were measured and analysed using new descriptive metrics referred as “Barcode” and “Signature”. The development and validation of those two applications in the case of Stroke patients and Amateur athletes are described, and their potential use in clinical and sports routine will be discussed.

KEY WORDS: inertial sensors, activity barcode, running performance, movement signature.

PHYSICAL ACTIVITY BARCODE AND UPPER-LIMB SIGNATURE: Worldwide around 5 million people are left permanently disabled after stroke each year (www.world-heart-federation.org/cardiovascular-health/stroke/). Objective assessment of everyday motor performance and physical activity can provide valuable feedback to therapists for optimization of rehabilitation. However, previous methods measuring performance of the upper limbs in stroke patients mostly provided quantitative information about arm usage only (Noorkõiv, Rodgers, & Price, 2014). Algorithms treating data of wearable inertial sensors attached to the upper arm and the trunk have previously been developed for first quantifying physical activity barcode, and second evaluating the arm movement signature in orthopaedic patients (Coley, Jolles, Farron, & Aminian, 2008; Coley, Jolles, Farron, & Aminian, 2009).

Table 1
Confusion matrices for the classification of the activities with corresponding evaluation metrics. The confusion matrices are expressed in number of posture apparitions. Abbreviations: SEN = Sensitivity, SPE = Specificity, CCR = Correct Classification Rate.

		Classification					
		Lie	Sit	Stand/Move	SEN	SPE	CCR
		Stroke participants					
Reference	Lie	53	1	0	98.15%	100%	90.27%
	Sit	0	104	22	82.54%	87.16%	
	Stand/Move	0	27	135	83.33%	87.78%	
		Healthy participants					
Reference	Lie	60	0	0	100%	100%	92.80%
	Sit	0	100	40	71.43%	89.18%	
	Stand/Move	0	1	179	99.44%	89.21%	

The goal of this project was to combine these two algorithms for use in chronic stroke patients. Physilog® wearable sensor data was collected from 10 healthy and 10 stroke participants during a laboratory setting. The sensor configuration included 5 wearable sensors, one attached to the trunk and one on each upper arm and wrist. The ten chronic stroke patients were in addition monitored in their home environment for two hours wearing the wearable sensors to identify clinical relevance of Barcode and Signature metrics. The posture recognition algorithm had a correct classification rate of over 90% in the laboratory for both participant groups (Table 1).

The Gini index (G) was used as a measure of the distribution of the length of the sedentary periods (Chastin & Granat, 2010). G ranges from 0 to 1 where G=1 means that there are only a few but long bouts and G=0 indicates that all lengths of bouts contributed equally to total time which means that the pattern is more fragmented. In the example in Figure1 the Barcodes of two chronic stroke patients are shown and the corresponding G were calculated.

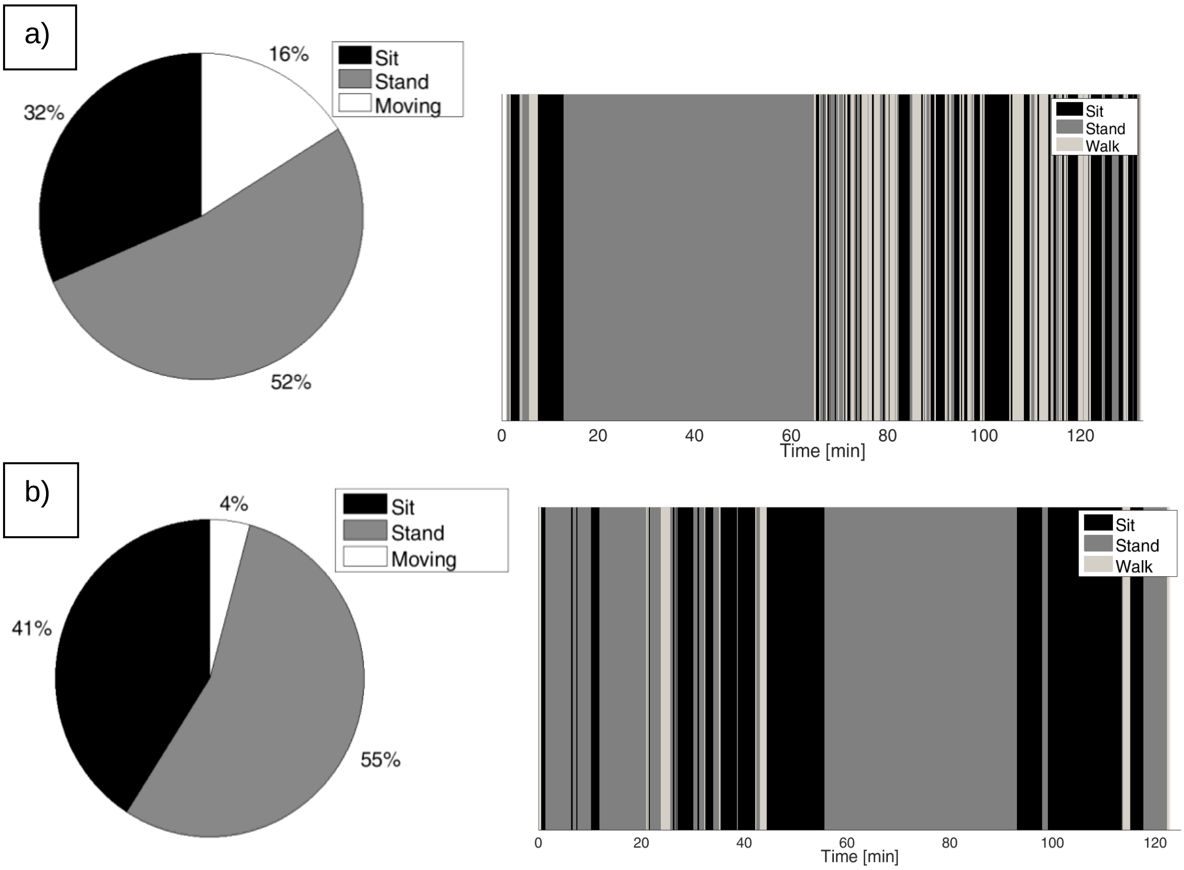

Figure 1: Sample activity ratios and Barcodes of a) active (G=0.58) versus b) sedentary (G=0.63) Stroke patients during home measurement

The symmetry index of arm usage in sitting and standing during the long-term measurement presented excellent correlation with the upper limb Fugl-Mayer Assessment scores of the subjects. From the measurement of movement speed it was concluded that medium and fast speeds were only rarely achieved with the affected upper limb. The symmetry index of the weighting score (as defined in Coley et al., 2008) of arm elevation showed a good correlation with the FMA scores. The system and methods used in this work have produced promising results for the evaluation of upper limb function in everyday life in the stroke population.

RUNNING FOOT SIGNATURE: Walking activity has been widely analysed with inertial sensors and the analysis of foot signature has shown to be particularly relevant to assess gait performance in a variety of patient populations (Mariani & Aminian, 2012). However, there is a lack in running analysis even though this activity represents the main sport practice in active population. A recent systematic review on inertial sensors concluded on the reliability of these sensors for running analysis and pointed out the critical weight of post data analysis for generating valid results (Norris, Anderson, & Kenny, 2013). In this respect, several challenges can be noted. First recorded signals should be calibrated (e.g. aligned with foot anatomical frame) in order to avoid the influence of sensor location. Then, the temporal signal events (e.g. foot strike) should be detected in the presence of high impact noise due to shocks at each foot strike. Moreover, motion data recorded through wearable inertial sensors provide derivatives of kinematics (e.g. acceleration and angular velocity), while signal integration to estimate displacement and orientation generates important drift and noise, which need to be removed for accurate estimation of kinematics. This paper and demonstration show the first preliminary results of a new method to adapt gait signature measurement and analysis to the case of running.

The project involves the local university training centre, in order to collect feedbacks by professional coaches and athletes, and to grow easily the sample size of the database in the future. A running patterns database of Physilog® shoe-worn sensor data was already collected over 24 amateur athlete subjects, running at 5 different speeds on a treadmill. After 3D alignment of the sensor relative to foot axis thanks to previous method described in [6], algorithms for temporal events detection (e.g. midswings, terminal contact, initial contact) were then developed. The event detection was validated against force-instrumented treadmill (Figure 2), tested on the database, and implemented on the current beta version demonstrated in this workshop in the form of a mobile application with cloud-based processing.

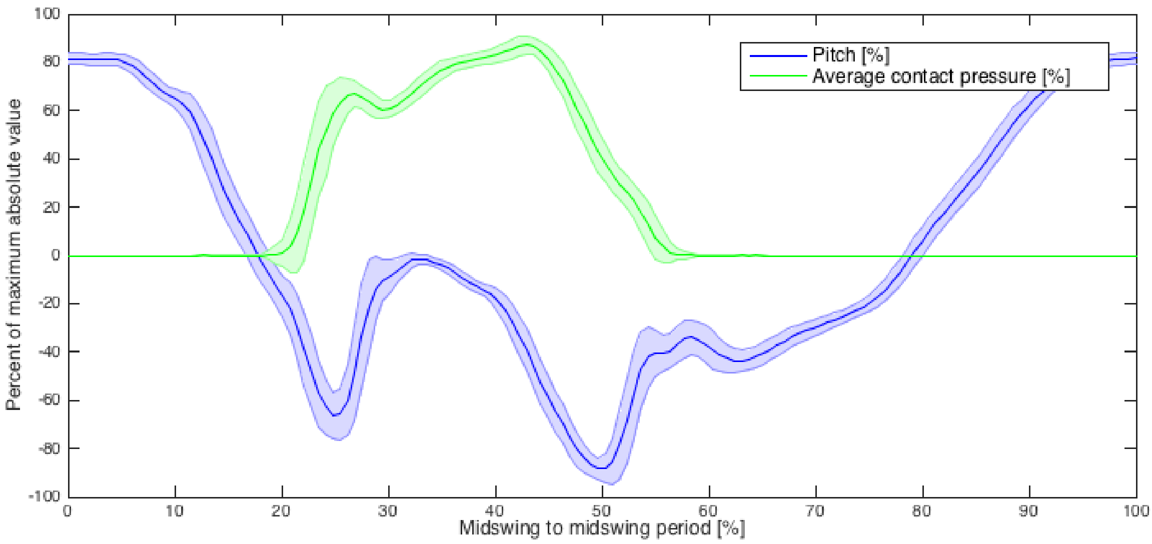

Figure 2: Average (Mean+/-standard deviation) signals of gyroscope around pitch axis of the foot (blue) and corresponding sum of pressure cells from the instrumented treadmill (green) over running cycle defined between two successive midswing events.

Defining the running stride (RS) between two successive midswing events of one foot, the preliminary results allow to identify the signature of initial contact (IC) around 25% of RS and terminal contact (TC) at 55% of RS on the gyroscope signals (Figure 2). Those events are characterized by a negative peak of pitch angular velocity for IC and a negative plateau for TC respectively.

Further research is ongoing to obtain the 3D kinematic signature of the foot during running strike, in order to obtain relevant information such as the amount of pronation/supination, and characterise the foot impact. The goal is then to provide a tool for coaches and sport clinician in order to improve running performance while keeping the runners safe. Comparing a runner's parameters with the reference database could give useful feedbacks about running techniques or avoid a possible injury due to a shoe misfit.

DISCUSSION: Two recent in-field applications of movement signature and barcode analysis obtained using inertial sensors has been presented in this paper and demonstrated during the workshop. They show that it is possible to process and interpret movement raw data in a way to provide easily accurate and meaningful information related to performance or disability during instrumented testing or long-term recordings. In the future, the use of such inertial sensors and algorithm by professionals in sports and clinics to collect in a practical and standardized way the barcode and signature of bigger pools of subjects could allow finding normative data for populations with various pathologies or performance levels, and ultimately increase the relevance of the system for injury prevention and patients follow-up.

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