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A computational framework for the standardization of motion analysis exploiting wearable inertial sensors

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Abstract — **Movement analysis is a powerful tool for the diagnosis of neurological conditions, as well as patient assessment and follow-up during rehabilitation programs. In spite of the available systems allowing a quantitative analysis of a subject's movement control performances, the clinical assessment and diagnostic approach still relies mostly on non-quantitative exams, such as clinical scales. Further, studying balance control, gait and activities of daily living poses relevant technical challenges, which greatly limit the availability of testing facilities. The goal of our project was therefore to develop a new system based on wearable sensors for movement analysis and scoring of performances. A prototype 3-sensors system was tested on a group of 4 normal subjects while carrying out a set of full body movement exercises drawn by clinical scales for the assessment of movement and balance control.**

I. Introduction

The assessment of motor and balance control is key to the diagnosis of cerebellar pathologies such as ataxias, the evaluation of the recovery of post-stroke patients and of patients affected by peripheral and central vestibular pathologies. While there are many approaches to quantitative movement analysis, ranging from simple force platforms providing center of pressure (COP) data, to motion capture systems providing detailed limb movement information, clinical assessment is most often based on clinical scales that do not involve quantitative measurements. These have the advantage of challenging the patient in performing daily living activities, while laboratory testing approaches often ask for unnatural exercises which end up assessing indirectly the patient abilities to carry out the tasks that are commonly faced in everyday life. On the other hand, though, the scoring is a somewhat subjective procedure in which the expert eye of the clinician evaluates the performance of the patient. Motion capturing tools could also be used to quantitatively analyze patients' performance in carrying out the exercises foreseen in clinical scales, yet they are generally too expensive to be deployed systematically in clinical or rehabilitation centers. When a rehabilitation expert examines a patient carrying out exercises involving different motor tasks, the therapist is asked to assign a score to every task, choosing among a limited number of values (e.g., 0-3). Medicine tolerates this approximation, while engineers prefer answering the following question: *what does a physical therapist focus on, while looking at a patient during balance assessment?* Some of the most commonly used evaluation tests require to notice peculiarities such as completeness of the action, number of incomplete tries before success, duration of a task, presence of perturbations or reactive events.

Hence, we set out to design a simple and low-cost system for recording, identifying and measuring the most relevant features that an expert eye gathers in scoring the performance of patients. Experts don't actually have a formal standardized method to quantify when exactly a perceived motor perturbation occurs and what is its magnitude. Therefore, our study was developed in order to automatically recognize movement tasks and quantify a significant part of the features that an expert eye could pay attention for while examining the performance of a patient in carrying out such exercises.

II. Materials and Methods

A. Experimental Setup

With these objectives in mind we chose to record the performance of a group of four normal subjects (3 male, 1 female, 25-40 y.o.) while carrying out an exercise that was built by piecing together movement tasks selected among those included in the most common balance assessment tests (e.g. Tinetti test [1], Berg Balance Scale [2], BESTest [3]). This approach led us to exercises that considered the following seven steady postural states: *standing, sitting, placing the right foot on a stool, bending forward, bending backward, lifting the right arm, picking up a pen from ground*. In the following, such postures will be called *states*. Each exercise was made of three repetitions of every item movement, arranged in a predefined random order, for a total of 18 items per trial. The whole set of items was interleaved by 19 transitions through the upright stance state (i.e. a standing subject asked to sit and step on a stool implies *stand-to-sit*, *pause in sitting state*, *sit-to-stand, pause in upright stance, step on a stool*). Every subject was asked to perform the whole exercise 8 times: twice at a normal pace, twice *faster*, twice on foam, twice faster on foam. In the "faster" condition the subject was asked to change posture faster and thus remain in the desired state for a shorter time. All the trials were repeated while standing on a foam support surface in order to create more challenging balance tasks. The resulting overall database of actions available for analysis would have comprised therefore comprises at least (4 subjects, 8 trials, 36 transitions) 1152 *events*.

During the recordings subjects stood on a force platform (Balance Board BB, Nintendo) while wearing a set of three

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tri-axial accelerometers (ADXL330) placed on the right thigh, chest and right forearm. Accelerometers were connected to a data acquisition card with wires (length: 2 m) and the data stream from the BB was ensured by a Bluetooth connection to the same PC. Limb accelerations and feet ground pressure signals were sampled at 120 and 60 Hz, respectively. A custom-software was designed for simultaneous acquisition and synchronization of the acquired data, which were then saved in text files. Additionally, every experiment was video-recorded using a commercial webcam, thus providing a reference to determine the type of activity being carried out at all times.

B. Data Analysis

Sensors' data were processed offline as synchronized time series and the overall processing consisted in two complementary stages. The first was a preliminary sensor calibration and filtering, which was followed by parallel incremental algorithms for the extraction of complex information on body motion. The second phase incrementally processed the data stream in an attempt to simulate real time conditions. Accelerometers were calibrated, prior to being worn, by aligning them with and against gravity, so that their signals could be further normalized with respect to 1 g (9.81 ms^{-2}). Raw data were low-pass filtered at 8 Hz in order to eliminate accelerations not related to human motion. Gravitational components on sensors axes were then extracted through 0.4 Hz zero-phase low-pass filtering (4^{th} order Butterworth [6]) and used to reconstruct the instantaneous 3D orientation of each sensorized limb, with respect to verticality. Lower frequency content was used to compute rotation matrices, which were specific to the limb where each sensor was placed.

Any kind of signal integration was unreliable due to the resulting drift, so that the orientation with respect to verticality (e.g. *pitch* θ and *roll* φ angles) were obtained based on individual data samples. The elements of the rotation matrix for each limb depended exclusively on the instantaneous projection of gravity on the axes of each accelerometer. Given that sensor position on the specific body part was fixed and known, the overall limb inclination could be computed as mediolateral (ML, roll) and antero-posterior (AP, pitch). Pitch and roll angular displacements of limbs with respect to a reference body configuration (upright stance, arms down along sides) were the *arccosine* of gravity as projected on sensor axes. It is well known that this processing leaves the rotations in the horizontal plane (e.g. yaw) undetermined unless recurring to different technological and computational tools, such as magnetometers or gyroscopes. Initial reference values were taken into account and saved as offsets and every subject was asked to start the trial from the reference position, so that the offset calibration routine could record the initial inclinations of accelerometers as placed on the clothing. Though this was a procedure worth being repeated every time the accidental displacement of a sensor was suspected (detachment, elastic bands slip), we never replied it during the recordings. It is important to note that the reference positioning of the sensors needs to be approximately known for the system to be independent from inter-trial and inter-subject variation of sensor placement. Finally, full-band [0-8 Hz] content of signals was used to compute the signal magnitude vector (SVM) [6] while the lower frequency [0-0.4 Hz] content was processed to get the Euclidean norm Γ of time derivatives of both angular displacements (angular velocities, $\| d\theta/dt \;\; d\varphi/dt \|$) as candidate measures of the subject's activity. These figures were considered as approximate measures of the power associated to any limb-specific motion.

C. Events detection

In order to design a system able to discriminate subject's rest and non-rest periods, SVM and Γ were run in combination of a heuristic threshold (set to 0.03 g) and a mode filter (running on a 50 samples-wide window). These two were then compared as candidate indicators of subject's activity and Γ was adopted as the flag variable. This choice was motivated both by the lower noise level and the more intuitive biomechanical meaning of such measure. Thus, the onset (or *trigger*) of limb movements corresponded to the time when Γ exceeded the heuristic threshold of 0.03 g. The rubustness of the approach was further increased by automatically discarding consecutive triggers if occurring at times closer than 150 ms that is the resulting resolution of the system. A "movement" was thus identified as non-rest time interval, that is included between two consecutive over- and under-threshold triggers.

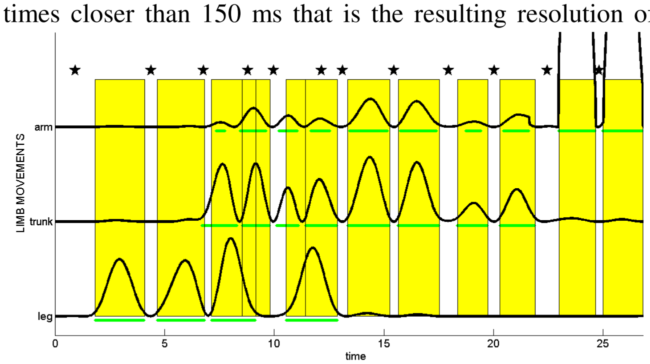

Fig. 1. Graphical representation of automatic identification of motion events, interleaved by states of rest (stars). Γ quantifies limb activity. Reference onset time corresponds to that of the most intense limb-specific movement trigger.

Based on such processing, a wider scope algorithm was devoted to identify *events* from a whole-body point of view by grouping quasi-concomitant limb movements as those having onset times closer than 1.5 s (Fig.1). As a consequence the expected number of detected events was supposed to be always lower than those of individual limb movements .

Resting postures were then characterized based on θ and φ, whose representative values were obtained by averaging their values on a 50 ms-wide interval during rest states. This choice structured the system on sets of 6 values (2 values/sensor, 3 worn sensors), which provide a description of the body configuration during resting intervals. The resulting 6-dimensional space was then used for classifying posture states with a *template-based procedure*.

D. Events classification

The experimental session was followed by an automatic analysis of subjects' motion, aimed at simulating the online recognition of elementary actions and states. As previously detailed, every time series was automatically segmented into motor events and rest periods. Events were described by their onset time, the limbs involved, the duration of limb-specific movement and the mean angular velocity associated with every movement (TAB.1).

TABLE I
PROPOSED FORMALISM FOR THE DESCRIPTION OF MOTION EVENTS

Features	Values
Item Type	State-to-different-state transition or perturbation
Onset Time	Referred to the most intense movement trigger
Duration	Time interval btw 2 following triggers
Constitutive Movements	[Onset + Duration] Limb Involved: leg, trunk, arm. Mean Angular Velocity

Rest states were described by a 6-D vector of limb spatial inclinations: an intuitive format allowing to easily identify one of the *postures* that subjects were asked to reproduce experimentally. To verify whether the chosen representation of body configuration had logical correspondence with the predefined classes (the 7 posture items), the events dataset was first clustered in a subject-specific fashion using the *clusterdata* Matlab function bound to a maximum of 7 clusters with non-weighted euclidean distance function and centroid computed as the average of cluster elements. A set of template representative features for each of the predefined classes. A template, i.e. the centroid of each cluster, was then considered for every cluster and used to classify all of the

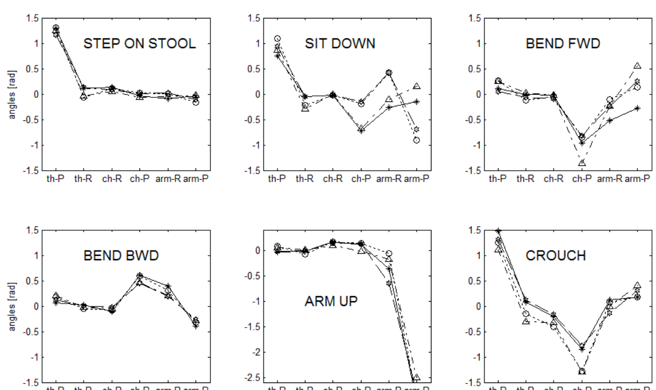

Fig. 2 Pitch and roll angular displacements referred to starting reference posture are used to describe limbs configurations. Six different patterns are connected to the posture items involved in the experiment.

resting states in the subjects' database. Every event between a pair of adjacent resting states was univocally labelled as "state (i-1) to state (i)" transition. State "*to-different-state"* events were considered *proper* transitions, while an event resulting in no state change was named *perturbation*: a spurious state transition.

III. RESULTS

A. Events detection

On average subjects changed their posture every 3.5s [3.38-3.78] during slow trials and every 2.5s [2.36-2.78] during faster ones. The average execution time of an 18-items exercise showed a reduction of 30% from normal to fast, as a proof of effective accelerated pace of subjects' movement.

Since each of the seven (6 + standing) posture items was repeated 3 times per complete recorded trial, the number of expected periods of rest was 18. All of the transitory stand-up states, corresponding to natural pauses between posture shifts, were thus expected to be 19. The average number of detected events was 20% higher than what expected (44±2 events, when 37 were expected), but every cluster always had at least 3 examples (i.e., the number of required repetitions). Thus the overall sensitivity was 100%.

B. Unsupervised clustering

The aim of unsupervised learning of executed trials was both to investigate the existence of natural clusters of resting states, and to further match those states with values that represented average configuration of limbs. The clustering test carried out on the normal pace time series – characterised by natural (slow) execution of actions – was successful: exactly 7 clusters were identified and all of the state transitions were detected. This preliminary unsupervised training allowed to build a set of representative values (e.g. *centroids*) for the predefined classes. One time series per subject was sufficient to discriminate the essential number of natural clusters, which were labelled progressively, in accord with the known fixed sequence of scheduled posture items. Before generalization was carried out, clusters were analyzed and internal coherence of clusters was computed as a relevant figure. On average, the distance among clustered elements was from 50 to 400 times smaller than the mean distance between two random elements of the dataset. The events dataset was then analysed and it was found that *surplus* detections were perturbations (e.g. *state-to-same-state* transitions), guilty of apparently breaking resting periods into two.

C. Generalization: classification of motion events

The subjective posture templates computed on slow trials were used to classify all of the detected states of rest. A newly detected state was associated to the closest identified template among those belonging to the database.

Decreasing classification accuracy was observed along with increasing speed of execution of motor tasks. A not significant accuracy decrease corresponded to increasing difficulty of the task, as in *balancing on foam*, even if the number of identified perturbations grew significantly. This fact agreed with the basilar expectations about the ability to highlight perturbed movements. As said before, *perturbations* were connected to movements not resulting in posture change. This characteristic was sufficient in order to isolate them from the global dataset and analyze them separately. What emerged was that a perturbation is

TABLE II
TYPICAL CHARACTERISTICS OF EVENTS AND PERTURBATIONS

Motor Item	ONSET TIME (S)	DURATION (S)	Limb-specific Movements
Right foot on stool	17.25	2.00	[0 - 2.00] leg 43.06°/s [0.21 - 0.74] trunk 9.88°/s
Stand→Sit	39.45	2.39	[-0.18 - 1.45] trunk 35.73°/s [0 - 2.21] leg 45.19°/s [0.02 - 1.28] arm 10.11°/s
Perturbation	61.33	0.49	[0 - 0.49] arm 30.14°/s

The example shows how a motor event leading to no state transition (perturbation) is connoted by shorter duration and lower number of limbs involved.

connoted by significantly shorter mean duration, lower number of limbs involved and lower energy expenditure (TAB.2). These observations are perfectly consistent with general common sense. With this approach the algorithm identifies no false positives.

IV. DISCUSSION

The preliminary unsupervised training gave robust results, meaning that the mathematical framework supports the aim of describing a motor task by means of simple functional features. The use of a euclidean metric then addressed the research of a classifier among the most intuitive ones. A template-base classification was selected because of its ease of use, the possibility of interpreting centroids in a biomechanical sense and visualizing the values they assume in a representative context without coordinates transformation (e.g. a 3-segments model of human body).

Leaving the classification results aside, the hard fact is that the heuristic formalization and the state-transition paradigm we have proposed here, represents a fundamental step towards the development of an automated system for fine analysis of human motor activities based on wearable inertial sensors. Table 1 presents a standardized format for an items library, made of states and transitions. These details relate to the recognized task, information on time (duration of the action and synchronization of limbs), amplitude and energy expenditure. The very restricted set of sensors is indeed essential and could be enlarged as desired. Here only a sample configuration was shown, but simple upgrades would consist in supplying the net with magnetometers, putting accelerometers on shins or gyroscopes on the top of the head. The latter would allow to describe actions involving rotations in the horizontal plane (e.g. trunk and arms, walking around a chair or rotating the head) as required for instance by the Cawthorne-Cooksey exercises for vestibular rehabilitation. What matters in the evaluation of gait tasks (DGI & TUG) are: detected asymmetry and time required to complete the task. We are dealing with those aspects and will write about them in our next paper.

V. CONCLUSIONS

By combining the most common approaches to problems like recognition and discrimination, we proposed a standardized approach to motion analysis based on wearable sensors signals. We made a fundamental step towards the creation of a well-characterized library of *motor events*, which will be useful for the automated study of movement in terms of performance assessment, adaptation and learning. The system is limb-oriented and its modular structure allows to implement automatic activity classification and enrich movement description with a plenty of functional details. As we have shown, the approach proposed in our work is particularly efficient in identifying the differences between an intentional movement and a perturbation. It also provides meaningful descriptive features of postural states and movement, which we foresee as being useful for the scoring of human performance, i.e. in evaluating clinical scales. The experimental session was not designed to be exhaustive of all possible cases or perturbations, but mainly focused on timing and detection, standardized feature extraction and labelling of elementary whole-body actions that our subjects were asked to perform. The methodology relies on a limited set of heuristics which are combined with common activity classifiers. It provides a reliable segmentation and identification of actions, automatic feature extraction and a fine description of limb movements. With a minimal setting and computation we reached a remarkable detail in movement description, based on representative variables, in a biomechanical sense. Further research will develop computational methods able to quantify what was treated with a qualitative approach and run standardized information through artificial intelligence tools.

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