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Monitoring Activities with Lower-Limb Exoskeletons

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1. Introduction

Advances in sensor technologies and data storage have led to the development of portable systems that can measure aspects of human behaviour in everyday life. Measuring the progressive change in physical activity in people with different types of diseases in real conditions means that rehabilitation, training and physical education programmes can accordingly adapt. Monitoring activities has been acknowledged as an integral part of optimum healthcare. [2]. There are multiple disciplines in which activity is monitored, such as medicine, physiotherapy, behavioural sciences, psychophysiology and ergonomics.

Parallel development in techniques for measuring movement and mass storage means that it is possible to measure physical activity in real conditions. Daily physical activity is defined as the total voluntary movement produced by the musculoskeletal system during daily functioning, [3]: measuring movement with sensors is related to measuring body movement or specific parts of the body depending on the location of the sensor.

Different configurations of monitors of physical activity have been primarily applied on rehabilitation programmes of different types of pathologies. To configure pulmonary rehabilitation in people with chronic pulmonary diseases the application of activity monitors that help with daily activity and physical activity have been researched. The development and application of such systems involves measuring movement, and methodological, practical and analytical aspects. A review presented by Steele, [91], describes different monitoring systems of daily activity and exercise with movement sensors in people with pulmonary diseases, by analysing the different sensor technologies used in commercial devices. Among the clinical uses, observation processes are included which are of interest to obtain variables like improved exercise and increased daily activity. Functional capacity, self-sufficiency for movement, quantification of gait and measuring physical capacity by calculating energy consumption over time are the principal variables of interest that have been calculated with systems that use movement sensors, [8], located on the waist, ankle and wrist of subjects.

As well as the energy consumption associated with any type of physical activity (both static and dynamic), the estimate of variables related to gait and lower-limb movements, such as the number of steps or distance covered, are measurements that have also been shown to be valid and have been obtained with high reliability in versions of pedometers available

commercially, like the Digiwalker pedometer, which measures wrist vertical accelerations, or the Caltrac system, [3], which uses uniaxial accelerometers located on the hip and estimates energy consumption depending on the age, height and gender of the user. It has been observed that estimates with these devices may vary according to:

- the velocity and frequency of the movement or activity;
- the location and degree of freedom of the sensors;
- the calibration equations applied.

The quantification of activity is a method to measure physical activity that may help as a motivation tool. Advanced monitors of physical activity aim to establish the type of activity according to the data captured using portable systems to measure movement. In the literature we find portable systems that classify movement into different applications. It is important to mention the recent exploration of applying accelerometers on body segments to study activities. The concept of an activity monitor based on ambulatory measurement of posture and movement, albeit not new, is mentioned in relatively few cases in the literature.

Recognising activities from signals of accelerometers mounted on the torso has been researched in, [7], whereby a model of multiple classes was proposed by combining Markov chains and Gaussian models from characteristics extracted from the analysis with the fast Fourier transform (FFT). In a study analysing different accelerometer orientations on the sternum, to recognise activities and postures, [7], the viability of discriminating dynamic and static activities with methods for processing signals to extract characteristics was confirmed.

In the literature we found, [49], the combination of accelerometers with gyroscopes integrated into a portable device on the waist of subjects and a proposal to analyse the morphology of the signals from/ of the two types of transducers and the application of thresholds to discriminate specific activities. The classification method proposed identifies the level of velocity of movements in categories according to fuzzy rules. Another system for monitoring activities, presented by Groeneveld, [9], proposes training a neuronal network to classify movement data.

Among the classification methods applied to identify activities we find Bayes classifiers, hidden Markov chains, decision trees, Gaussian models and frequency component analysis. Generally, a problem found in obtaining a model to classify multiple activities (classes) is the high probability of overadjusting the data to the group of training data with the resulting loss of expected generality. It is important to note that the quantitative comparison of the validity of systems for monitoring activities is a complex task and not always attainable given the differences between the classification, adjustment and application criteria of the different methods proposed. However, it is possible to do qualitative comparisons, knowing the methodology applied to obtain the results of a system and the behaviour of different methods to discriminate specific activities.

The most relevant studies found to date in the literature pose discriminating activities with portable sensors of movement mounted directly on the torso or waist. Only pedometers, as monitoring methods offering specific information, have been applied to the lower limb and configured as commercial systems to count steps or estimate energy output. Instruments available in the market to monitor activities from wrist motion (Motionlogger, Ambulatory Monitoring, Inc.) enable long-term data logging and objective detection of sleep,

hyperactivity or daytime activity levels. Other devices attached to the lower limb are capable of measuring important motion variables and foot pressures for analysis of walking features, e.g. WalkinSense, Tomorrow Options. To date, we have not found any study on monitoring physical activities in users with ambulatory gait aids in the literature. We present the concept and experimental study of monitoring activities with lower-limb exoskeletons below.

2. Exoskeleton activity monitor (EAM)

Traditional techniques to analyse gait (video- and force-platform-based systems) restrict mobility and do not represent very natural conditions due to spatial limitations. In a preliminary study, [1], where a multidisciplinary group of experts involved in the manufacture, prescription and evaluation of lower-limb orthoses was considered, the necessary guidelines were defined to include devices to monitor users with lower-limb functional compensation systems both in the laboratory and in real-world conditions, so that new objective information might be obtained that could be used by physiotherapists, orthopaedic specialists and physiologists.

The exoskeleton activity monitor (EAM) approach presented is based on these requirements and fits into a context of clinical application as a tool to analyse the daily activity of subjects in a clinic or rehabilitation centre and the functioning of the gait aid system in an orthopaedic workshop. The portable gait compensation system is equipped with the activity monitor that captures lower-limb movement. In the application scenario, the subject develops one or several activities freely with the system that captures biomechanical data. Later in the clinic or rehabilitation centre the session data related to the subject information (data bases with anthropometrical, historical, statistical data, etc), are downloaded into a base platform where they are processed and presented to assess the daily activity and keep a track record of system use. Figure 4.1 shows a diagram of this concept of monitoring subjects with lower-limb exoskeletons or orthoses.

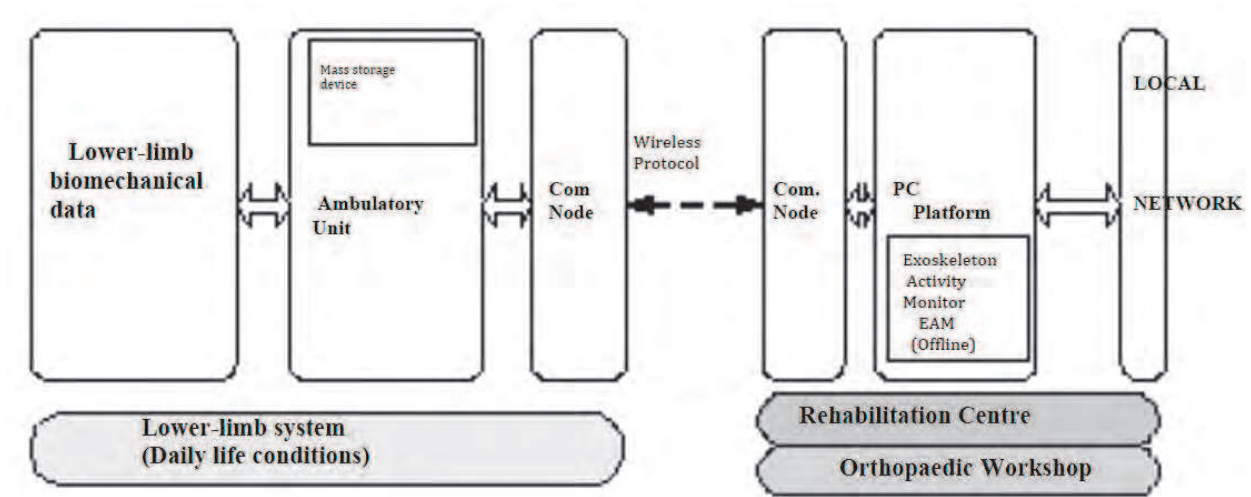


Fig. 4.1. Diagram of the context of monitoring physical activities with a lower-limb exoskeleton activity monitor (EAM).

2.1 Objectives

The monitor aims to offer information on the exoskeleton by monitoring a set of activities or categories. Accordingly, we also consider the following subset of activities:

- Sitting
- Standing
- Walking on level ground
- Walking (going up/down) ramps of approximately 5 degrees
- Going up or down stairs
- Other or not known

2.2 Ambulatory platform

The entire system includes hardware, methods for recognising activities and the positioning of sensors on the lower limb. The ambulatory unit that controls the exoskeleton contains two 8-bit AVR microcontrollers, which manage acquisition (up to 16 analogue channels), wireless communication and data storage on SD (Secure Digital) card removable flash memory. The autonomy of the activity monitor must be such that measurements can be taken for one whole day. The prototype that we have developed is fed by a 900-mAh lithium-ion battery that offers 4 hours of autonomy in continuous use. The storage capacity of this prototype is conditioned by the storage capacity of the SD flash card and the capacity of the battery used. The Atmega32L microcontroller manages the data writing and reading, updates an initialisation file containing the session record, the times (given by a real-time clock) and the sensor gains according to prior calibration. The sensors used in the monitor are a uniaxial accelerometer on the foot, gyroscopes on the foot and leg (to measure rotations on the sagittal plane) and an angular position sensor on the knee.

The monitoring system in offline mode continually measures and stores the sensor configuration signals at a frequency of 33 Hz, with an 8-bit resolution. The attachment of the inertial sensor boxes to the exoskeleton structure reduces to a great extent the appearance of artefacts because of relative vibrations or movements between the sensor and the segment in question. The ambulatory measurement unit is attached to the subject's waist. The vector of input variables of/from the activity monitor describes movement in relation to the state of the lower limb is defined in accordance with the following expression:

$$u(t) = \{a_y \text{ foot } (t), \omega \text{ foot } (t), \omega \text{ leg } (t), \theta \text{ knee } (t)\} \quad (4.1)$$

From the conclusions of the analysis of movement in 3D, we assume that in the subset of activities of interest, the components resulting from movements outside the sagittal plane and changes in direction of movement are low and their effect is negligible on the results of the identification methods that we propose below

3. Methodology

The processing method concept is based on processing a posteriori the lower-limb movement signals to extract the discriminating characteristics that make it possible to group

them into a number of known categories, where univocal transitions between the different activities are not assumed. The data processing consists of several stages: (1) filtering; (2) extracting characteristics to detect static activities, cyclical activities and to analyse the energy of the time series for which two methods are proposed; and (3) discriminating a subset of categories.

- Signals
- Standardisation
- Filtering

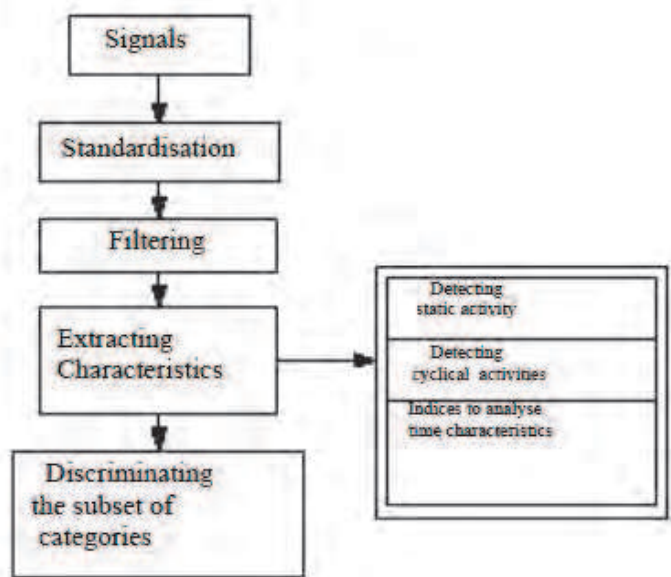


Fig. 4.2. Activity monitor schema.

3.1 Signal acquisition and filtering

The inertial sensors are located on the foot and leg. The accelerometer gives an output equal to zero when its measurement axis is perpendicular to the gravity acceleration axis. The gyroscopes give a signal equal to zero in static conditions and a voltage proportional to their rate velocity. The angle of the knee estimated from the position sensor measurement on the exoskeleton joint may vary between approximately 0 to 100 degrees during the set of activities. Signal acquisition is done with an 8-bit resolution AD converter, at a sampling frequency of 33Hz, values that were established by a compromise between resolution, autonomy and computation time (a sampling frequency sufficient for gait at natural velocity and corresponding to the maximum rate of writing in SD format for our data package structure). The signals are filtered initially using a first-order, low-pass filter with a cutoff frequency of 30 Hz.

3.2 Detecting static activity

In static conditions, constant acceleration on the sensor depending on the inclination φ_{foot} of the segment, in relation to the axis of the force of gravity g , can be calculated via the cosine, according to the expression

$$A_i = -g \cos(\phi_{\text{foot}}) + n \quad (4.2)$$

where n is white noise.

On the other hand, during static activities the gyroscope signals will be equal to zero. These conditions can be used to determine whether the activity is dynamic or static. In the literature we find the application of this principle proposed by Veltink, [97], establishing the attachment of accelerometers on the trunk (middle sternum) as the methodology for discrimination. The method that we propose for the EAM to detect the nature of the activity from measuring lower-limb segment movement consists of: i) low-pass filtering of the accelerometer signal on the foot segment with a cutoff frequency of 0.2 Hz, ii) demodulation of the signal (absolute value) and application of a second-order, low-pass, Butterworth filter with a cutoff frequency of 0.1 Hz to obtain the signal envelope and weight it (by multiplication) with the velocity magnitude (filtered with a low-pass filter of 0.2 Hz) of the foot rotation, iii) application of a threshold to the resulting signal. Once the detection of the static activity has been generated it is possible to discriminate directly between the sitting and standing categories, by applying a threshold to the knee flexion angle.

3.3 Detecting periods of cyclical activity

Earlier studies have indicated the viability of separating the activities of body segments into cycles using accelerometers mounted on the human torso [5]. We propose a method using accelerometers and gyroscopes on the lower limb. By estimating the intervals corresponding to dynamic activities (gait on level ground, going up and down ramps, going up and down stairs) we pose the possibility of detecting cyclical activities with a combined technique of: a) identifying high-sensitivity heel or foot contact, considering different support types (such as flat support on stairs, initial support after point drag, etc.) and detecting minimums of the time series of foot angular velocity and b) signal oversampling in fixed width time windows, between periods of dynamic activity greater or equal to a window width that defines the detector time resolution. Below this threshold the dynamic activities will be considered in the indeterminate category and could correspond to activities not considered in the subset of categories or to transitions between these activities.

3.4 Extracting characteristics

From the input signals at each instant of time measured, methods are applied to discriminate rotation intervals (RIs) from the segments and intervals of cyclical dynamic activity. Likewise, methods are proposed to extract signals representing dynamic movement characteristics, for which two discriminating indices (EAF and PFT) and the frequency contents (FC signal) are proposed. We describe the procedures to obtain each of the characterisation signals used in the activity monitor below.

3.4.1 Frequency response

The inertial sensor signals are passed through a finite impulse response (FIR) digital filter designed to pass frequencies in the 0.3-2 Hz band, (limits in the 0.1-3 Hz band) generating FC signals, with the frequency content in the oscillatory bandwidth of interest, whose

instantaneous amplitude is related to the signal frequency content of linear acceleration and rotation velocities.

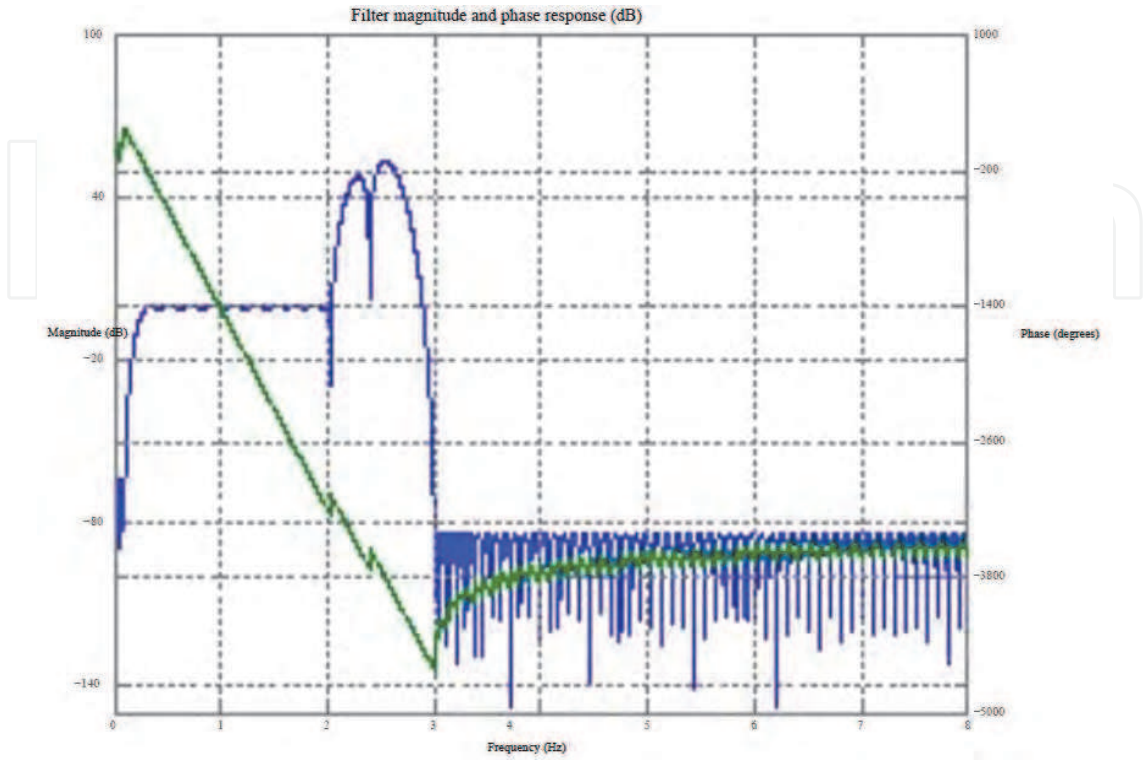


Fig. 4.3. Band pass filter magnitude and phase response to extract signal frequency characteristic from segment movement.

3.4.2 Segment rotation interval

Signal frequency characterisation corresponding to leg rotation velocity, ω_{leg} , is rectified. Two consecutive zero-pass instants, which correspond to the changes in gyration direction of the segment, define the intervals. Throughout these intervals a numerical integration is applied obtaining,

$$IR(n) = \sum_i^{i+1} \theta_k,$$

(4.3)

which are defined as the rotation intervals of the dataset. Two methods (indices) to characterise the signals for clustering into activities are proposed below.

3.4.3 RLM index

We define the rotational and longitudinal movement (RLM) index as the characteristic for classifying the cyclical activity between the subset of categories. The RLM index is calculated from the signal resulting from the composition of acceleration filtered signals at Y on the foot, a_y foot , and angular velocities of the foot, ω_{foot} , and leg, ω_{leg} . For each sample k of the period n of cyclical activity of duration s, the RLM index is calculated using the signal composition integral.

$$RLM(k, n) = \{a_y \text{ foot}[k] * \omega_{\text{foot}}[k] * \omega_{\text{leg}}[k]\} \quad k=s \quad k=0 \quad (4.4)$$

Accordingly, an RLM value is defined for each dynamic activity interval. This index is directly related to the mean amplitude of the acceleration and angular velocity signals and is an indication of the quantity of combined movement (rotational and longitudinal) of the two segments, required for the activity. We propose calculating the integral over the composed signal because rotational and longitudinal movements are thereby considered at each instant of time. The possibility of grouping data from the RLM mean value calculated at each period of cyclical activity is considered by obtaining specific thresholds for separating categories.

$$PFT(n) = \int_{k=0}^{k=s} \log(\sigma_M)$$

3.4.4 Frequency vs. time: PFT index

Analysis of the signal power spectrum over time is a characteristic which, similarly to the RLM index, can be used to define a metric for classifying activities. The calculation on the pre-defined signal composition is done with the FFT of a specific number of samples, with an H-size Hamming window and number of overlapping samples n_s . As a criterion for analyser design, we select the n_s value from which we calculate the size of the window using the expression

$$H = ((n_s * (K - 1)) / K) + 1 \quad (4.5)$$

where K is the total number of samples of the composed signal. We thus obtain the frequency component matrix in M frequency $[f, t]$ of $1024 \times (K - n_s)$ elements. The mean and standard deviation of the frequency components obtained at each instant are measured from the total signal power for each sample. An abrupt change in the content of $M[f]$ between consecutive samples, can be detected by tracking the deviation from a reference value at each instant. We define the PFT index as the area under the curve from the result the standard deviation σ_M , for each period n of cyclical activity. The logarithmic function was used to change the base to adapt the range of the output of the matrix M elements and define thresholds.

4. Experimental methods

4.1 Subjects

A group of experiments were conducted with 3 subjects with no mobility problems (numbered 1, 2 and 3), with ages ranging between 25 and 35 years, stature between 1.70 and 1.88 m and weighing between 60 and 70 kg. The passive version of the exoskeleton was attached to the subjects. The exoskeleton was equipped with the monitoring system to evaluate the activity monitor: detecting static periods, cyclical activities and discriminating the total set of activities.

4.2 Protocol

The group of experiments were developed following a specific protocol that determined a sequence of activities that included repetitions of the categories selected in a circuit: cyclical and non-cyclical dynamic activity (ramps, stairs, gait on level ground), and static activity

(standing, sitting). The circuit defined the trajectory of the subject, adopting his preferred velocity of movement and for the static activities fixed intervals of time were defined. In order to divide the movements into activities a posteriori, either assisted direct observation with a chronometer or observation of a video afterwards was used. The sensors were calibrated statically prior to each trial and signal unbalances were corrected to guarantee that the measurement conditions were identical. All the signals corresponding to each trial were stored in files in the mass storage device of the exoskeleton ambulatory measuring system. The data processing methods that the activity monitor applied were programmed in the base platform of the system.

4.3 Detecting static activity

To detect static activities, a threshold equal to 0.05 was applied to the filtered and rectified signal. The threshold applied to the knee angle to detect sitting activity was 30 degrees.

4.4 Detecting periods of cyclical activity

Signal frequency oversampling was 100 Hz. The detector time resolution was defined by applying a window width to discriminate cyclical activities equal to 1.5 seconds. The sensitivity of the method for detecting minimums (section 5.3.1.3) was adjusted to obtain errors less or equal to 1%.

4.5 Discriminating dynamic and static activities

From the inertial sensor signals with the impulse response filter (IRF) (with limits in the 0.1-3 Hz band) the FC signals were generated for each subject assay. From the leg angular velocity rectified signal the RIs were found in the datasets.

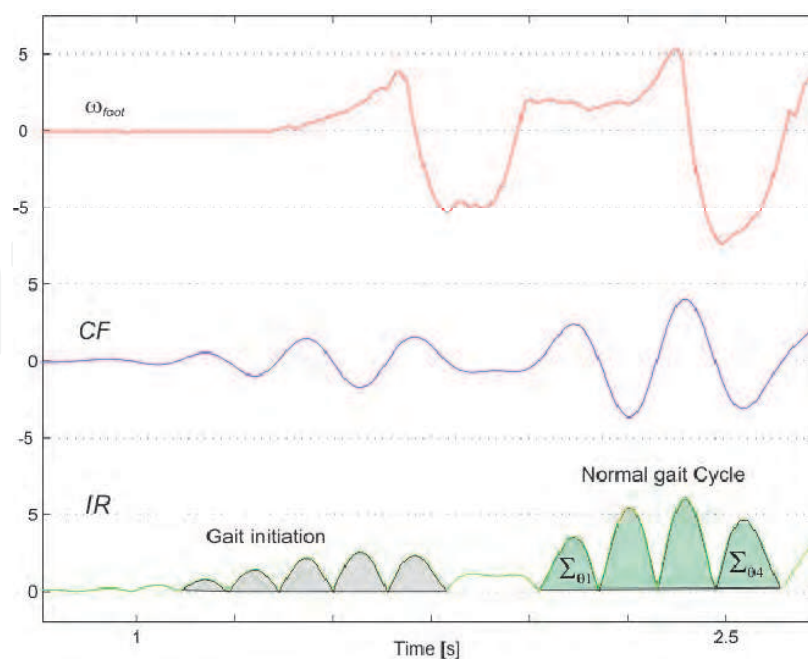


Fig. 4.4. Example of extracting dynamic characteristic signals during foot transitions (static condition) to gait on level ground. The signal measured ω_{leg} is used to calculate FC and RI.

The grouping thresholds of the satisfactory RLMs in the classification in our studies are: i) gait on level ground: $RLM > 25$; ii) going up/down stairs: $RLM < 8$; iii) going up/down ramps: $10 < RLM < 20$. Calculation of the power spectrum was developed over time with an FFT of 2048 samples, on the composed signals, with an overlapping n_s equal to 81, applying the equation 4.5 for each assay with its specific number of samples K . For the grouping of the PTFs (equation 4.6) we define the following thresholds in our studies: i) gait on level ground: $PTF > 6$; ii) going up/down stairs: $PTF < 3.3$; iii) going up/down ramps: $3.5 < PTF < 5$.

5. Results

Figure 4.5 shows an example of the results of the activity monitor in the experiment with one of the subjects. These results show the discrimination of static and dynamic activity, the identification of Intervals of cyclical activity and the RLM and PFT indices. Based on video observation, situations were established where the monitor detected dynamic activities, either cyclical or indeterminate activities. This example represents the dynamic characteristic signals obtained and calculated from the methods proposed and the identification response of dynamic activities with the two grouping methods presented for a circuit with all the activities.

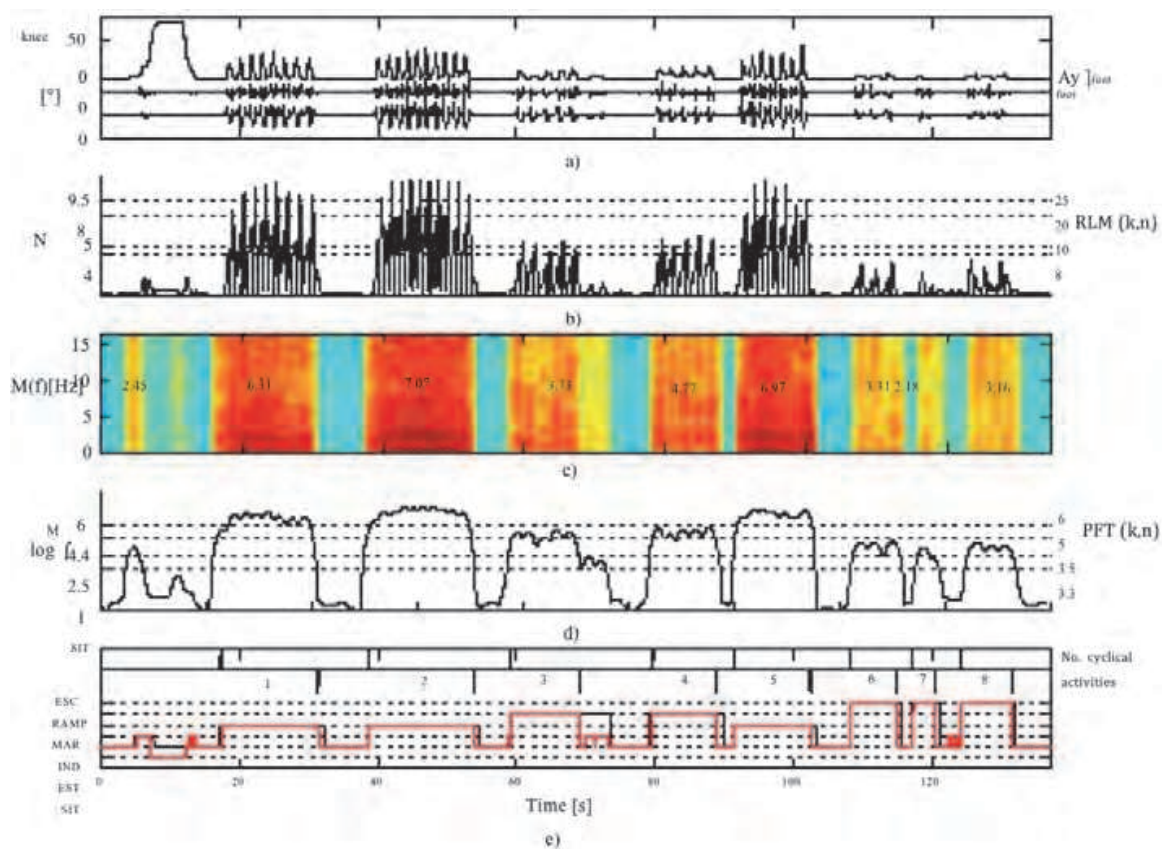


Fig. 4.5. Example of the EAM method results for subject 1 corresponding to a circuit of activities with the exoskeleton. Input signals to the monitor (a), signal N to extract the RLM index based on thresholding (b), instantaneous frequency components over time and average during periods of activity (c) to calculate the PFT index (d) and EAM outputs (e) calculated based on RLM (red) and PFT (black). The detector presents the classification in categories (ESC: stairs; RAMP: slopes; MAR: walking; IND: undetermined; EST: standing; SIT: sitting).

5.1 Detecting static activity

The results of detecting static activity based on the time invariant state of the foot accelerometer and gyroscope signals show the viability of detecting the static condition irrespective of type – sitting or standing– in the set of categories. Figure 4.6 shows an example of detecting static activity with the resulting filtered and rectified signal, obtained from the two sensor signals, in the transition between the two static activities. The configuration of the detector depends primarily on the threshold value applied to the resulting signal. The cutoff frequency value of the filter and its order are also configuration variables that define the attenuation level of the resulting signal. In our studies we conclude a second-order, Butterworth filter with a cutoff frequency of 0.1Hz and a resulting signal threshold equal to 0.2 as adequate values for the design of the static activity detector with the exoskeleton.

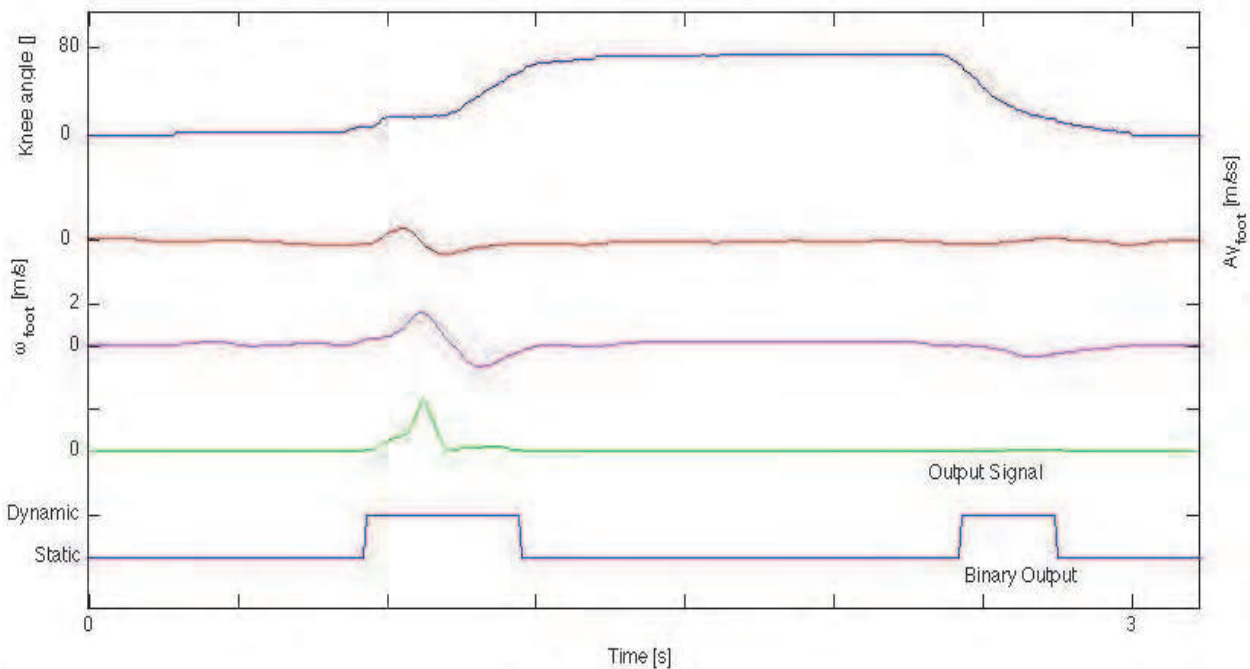


Fig. 4.6. Example of the static activity detector functioning when sitting down and standing up. The degree of knee flexion, foot gyration acceleration and velocity filtered signals a_{vfoot} and ω_{foot} , the signal from demodulation, calculation of envelope and weighting.

It is concluded that by combining the two inertial sensor signals, the static activities of the other activities can be clearly grouped. This fact is verified in the analysis on the plane of the mean values of the (FC) signals generated from the two sensor signals in the foot segment (see figure 4.10). The activity not identified as static in the dataset is labelled in this stage of the monitor as dynamic activity.

5.2 Detecting periods of cyclical activity

The method proposed and applied to the experimental dataset can identify the cyclical dynamic activities establishing the starting and finishing times of dynamic activity and determining roughly periodical contacts of the lower limb with the ground during this interval.

5.3 Discriminating dynamic activities

To detect minimums of the foot angular velocity signals, we consider a minimum point if it corresponds to the greatest value in a window with a width equal to a tenth of the sampling period and if this corresponds to an increase in velocity greater than 50 degrees/s, compared with the previous sample. The configuration of the width of the detector window must correspond to a criterion defined according to the application context. The instantaneous amplitude of the FC signals is used as a characteristic to apply the grouping indices of dynamic activity proposed.

Figure 4.7 shows the mean values and standard deviations of the FC signals calculated from the foot accelerometer and the leg and foot uniaxial gyroscope tangential signals in the entire periods of dynamic activity. A significant separation can be concluded between subjects for mean values of gait activity on level ground from the foot angular velocity sensor, as information for discrimination. For the FC of ω_{foot} with the Wilcoxon non-parametric signed rank test, [12], a mean probability of equality p in the data medians compared with the other activities equal to 0.1 was concluded. For FC of ω_{leg} , p was found equal to 0.2. The separation between the gait on sloping ground and stairs for the three subjects with foot gyration velocity showed a statistical distinction for the amplitude of the FC signals, with a p equal to 0.2 obtained using the Wilcoxon signed rank test.

No significant differences were found in the mean FCs of going up and down stairs and ramps, compared with gait on level ground. The activities labelled as indeterminate (transitions between cyclical static and dynamic activities) showed a significant statistical separation with the FCs of the three signals, greater for the FC calculated from the foot rotation velocity. The differences between subjects for cyclical gait signals, fundamentally due to the velocity assumed by each subject, make it possible to apply just one threshold to distinguish gait from the other activities. However, the standard deviations of the FC mean values of foot gyration velocity are statistically significant, so it is better to calculate the RLM discriminating index. Figure 4.8 shows the mean values and the standard deviations of the FC signals calculated from the foot accelerometer and the leg and foot uniaxial gyroscope tangential signals, averaged from individual periods (rotation intervals (RIs) in periods of cyclical activity. Using the mean value of the FCs of all the cycles of a cyclical activity, the distinction of gait activity on stairs with regard to gait on sloping ground using the gyroscope on the foot is significant, with p equal to 0.12, for all subjects. The mean standard deviation for each subject of the FCs of foot tangential acceleration in independent cycles of cyclical activity is greater for all subjects when the values for the entire periods of cyclical activity are considered, as can be observed in figure 4.10 with the grouping of activities. The conclusion is that it is best to use the mean values of the cyclical periods for calculating the RLM index.

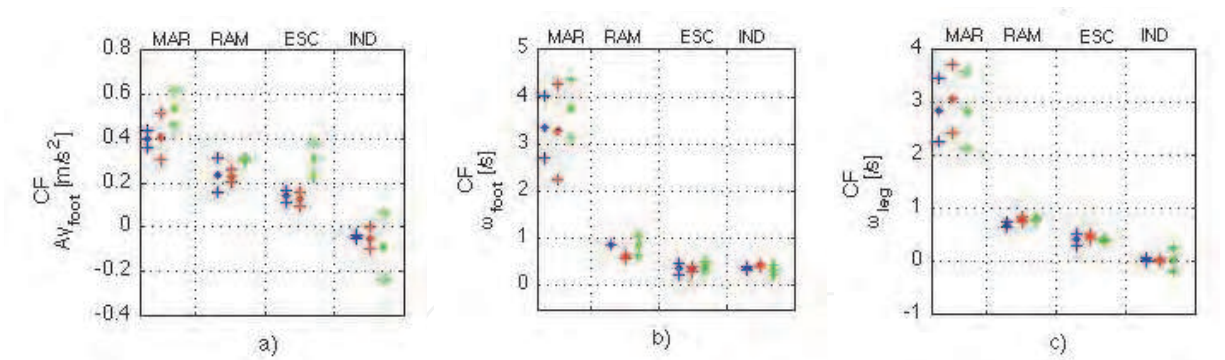


Fig. 4.7. Mean values (\pm standard deviation) of the FC signals calculated from the foot accelerometer and foot and leg uniaxial gyroscope tangential signals of the periods of indeterminate, cyclical activity /cyclical and indeterminate activity (MAR: gait, RAM: gait on sloping ground, ESC: stairs IND: indeterminate), for the three subjects (S1 blue, S2 red and S3 green).

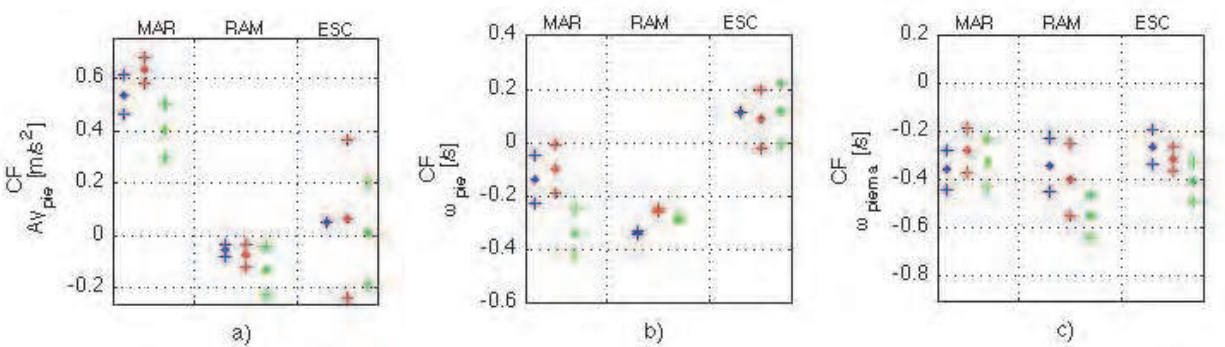


Fig. 4.8. Mean values (\pm standard deviation) of the FC signals calculated from the foot accelerometer and the foot and leg uniaxial gyroscope tangential signals of the total of individual cycles (rotation intervals, RIs) for each cyclical activity (MAR: gait, RAM: gait on sloping ground, ESC: stairs), for the three subjects (S1 blue, S2 red and S3 green).

5.4 RLM index vs. PFT index

The detection of dynamic activities was calculated with the RLM cyclical activity index (equation 4.4) and the PFT index based on the FFT with the thresholds found experimentally (shown in section 4.4.5). The dependency of the activity monitor response on the configuration of these thresholds must be researched according to the type of application and the subset of categories to be discriminated. Figure 4.9 compares the mean values of the RLM and PFT indices calculated for the three subjects. The detection errors were calculated by correlating the output signals using the two methods with the reference signal obtained from observation. The PFT indices vary to a greater extent than the RLMs for the standard deviations.

The variation in the RLM index for the subjects and repeated activities of going up/down stairs is significant and the detection mean error of this activity with this method is 8%. The detection mean error for the three subjects walking on sloping ground (RAM) with the RLM index was 10%, whereas for the detection with the PFT index the mean error was 18%. The detection of cyclical gait with the two methods did not reflect any significant differences statistically, with an overall mean error of 1.5%, a fact that was verified by separating the gait mean values from the other activities.

It is observed that the detections classified as indeterminate occur during the transitions between dynamic and static activity in 90% of the cases, as a result of overlapping between values of the indices discriminating activity on sloping ground and static activity. The overall viability for detecting activity in this study with the EAM is 4.2 %.

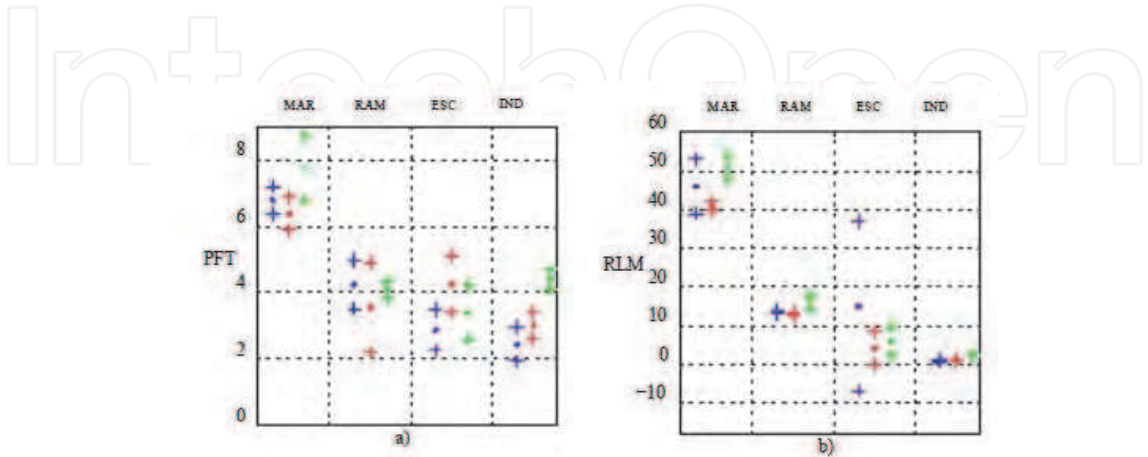


Fig. 4.9. Mean values (\pm Standard deviation) of the resulting PFT and RLM indices for discriminating dynamic activities (EST: static, MAR: gait, RAM: gait on sloping ground, ESC: stairs, IND: indeterminate), calculated for all the set of tests with the three subjects (S1 blue, S2 red and S3 green).

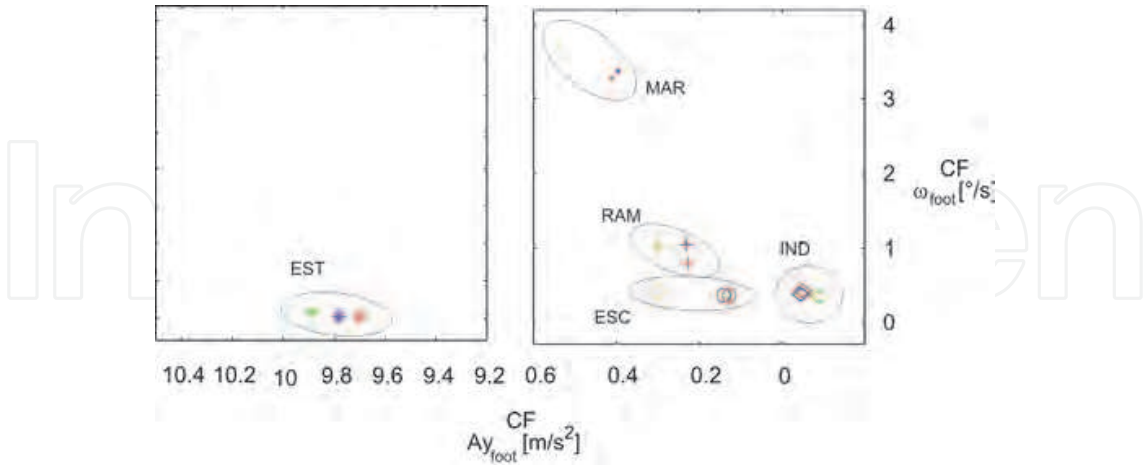


Fig. 4.10. Mean values on the plane of FC signals calculated from the foot accelerometer tangential signal vs. the foot gyroscope tangential signal, for periods of dynamic and static activity detected in the set of tests (EST : static, M AR : gait, RA M : gait on sloping ground, ESC: stairs, IND : indeterminate), for the three subjects (S1 blue, S2 red and S3 green).

Subject	Activity	PFT (log σ _M)	RLM
1	MAR	6.78 (± 0.41)	46 (± 7)
	RAM	4.25 (± 0.73)	13.59 (± 0.26)
	ESC	2.83 (± 0.63)	15.04 (± 21.84)
	IND	2.45 (± 0.51)	1.10 (± 0.32)
2	MAR	6.37 (± 0.49)	41 (± 4)
	RAM	3.55 (± 1.35)	12.87 (± 0.45)
	ESC	4.2 (± 0.85)	2.11 (± 4.19)
	IND	3.02 (± 0.4)	1.15 (± 0.23)
3	MAR	7.74 (± 0.94)	51 (± 3)
	RAM	4.1 (± 0.28)	16.25 (± 1.59)
	ESC	3.4 (± 0.81)	5.93 (± 3.96)
	IND	4.4 (± 0.27)	2.3 (± 0.3)

Table 4.1. Mean values and standard deviations of the RLM and PFT indices from all the set of repetitions, grouped into dynamic activities.

6. Discussion and conclusions

The discrimination of dynamic activities in the EAM groups characteristics with signal thresholds that describe morphological characteristics of the signals and the frequency content of lower-limb movements. It has been proven that sensitivity to differences between subjects is acceptable with this method, which does not require an initial reference measurement of each subject to configure the monitor. Nevertheless, a large scale study including a larger number of subjects will be required in order to test the robustness of the proposed method. In this study we have considered a set of five categories with a low classification mean error in a small group of healthy subjects. The capacity of the monitor to detect gait on sloping ground was lower, probably due to different strategies adopted by the subjects with the exoskeleton. The width of the detector window of the cyclical activity obtained in this study is satisfactory for the experimentation proposed to evaluate the activity monitor. Analysis of the standard deviation of the mean values of the two indices proposed showed a better functioning of the monitor with the proposed RLM discriminating index in the overall results, although it was more sensitive to subject differences. Moreover, the computational efficiency of applying this method, compared with the PFT, resulting from applying the FFT, is improved, with a ratio of 1 to 20, in processing time.

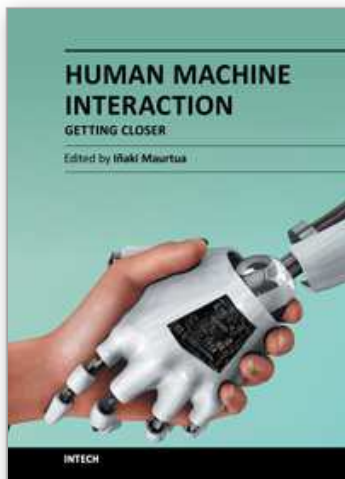
The capacity of the configuration of inertial measurement units in the exoskeleton segments and the knee angle precision sensor to distinguish movements and postures was confirmed. The transition between sitting down and standing up with the method proposed showed excellent functioning. The potential of this method in different applications for other types of portable technical aids (standing frames, walking frames, wheelchairs) is high.

It is important to highlight that the applicability of these methods to pathological cases considers that the gait compensation system approximates pathological patterns to normal patterns and, therefore, it is considered that the applicability is for general use. Adapting classification methods to particular cases, such as for patients who require a permanent joint block will necessitate adjusting the activity monitor subsystems. We take the study of pathological cases as a field of future work which will depend on the viability of the application during prolonged use of the compensation system (adaptations in the medium and long term).

With the system it is possible to quantify the number of knee flexions attained with the compensation system, depending on the time used and in relation to the dynamic activity. Thus, detector functioning and sensitivity to cyclical dynamic activities can be studied considering cyclical activities in different conditions where abrupt changes in trajectory or activity may occur. We highlight the need to analyse multiple aspects relative to the validity of the methods in different conditions and in the application of exoskeletons and orthoses in the daily life of subjects with muscular weakness.

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