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# Whole-body isometric force/torque measurements for functional assessment in neuro-rehabilitation: User interface and data pre-processing techniques

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ABSTRACT

A diagnostic platform for the early functional assessment of post-stroke patients was designed in order to perform isometric measurements during activities of daily living (ADL) tasks. The outcome of these measurements can contribute to verify the integrity of a post-stroke existing or altered "internal model" for a particular functional task. A complete and reliable software application for the diagnostic platform was designed, developed and tested in three European hospitals.

The software application was divided into two main modules: a graphical user interface (GUI) and the data pre-processing techniques for the interpretation of recorded biomedical and clinical data.

This paper presents the software application associated to the platform, aimed at analysing and interpreting the huge amount of data recorded and collected during the experimental trials. Its main objective is related to validating the onset detection and data reduction.

The software application presented in this paper has been working and validated with success in three different clinical centres in Europe and it can be effectively used both as assessment tool in rehabilitation and as research tool in neuroscience.


## 1. Introduction

The approach for assessing the recovery state of stroke patients presented in this paper relies on repeated measurements of motor efforts during movement initiations for specific tasks. As the emphasis in stroke rehabilitation is on the improvement of functional performance, an ideal measuring tool must use activities of daily living (ADL) tasks [1–4] as a principle for its quantitative measurements. This

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**Fig. 1 – The Alladin Diagnostic Device.**

work is inspired by the assumption that the initiation and the execution of a task have the same functional properties as performing the task [5–8].

An innovative diagnostic platform for the functional assessment (ADD, Alladin Diagnostic Device) (Fig. 1) was designed and developed by a team of European researchers. It can record time trajectories of forces and torques in isometric conditions from eight force–torque sensors, placed on the whole-body. Each sensor has six degrees of freedom (DOF): the simultaneous recording of data from 48 channels represents a novelty in the rehabilitation domain.

The ADD is capable of measuring isometric force/torque (*F*/*T*) trajectories during the initiation of six different ADL tasks ('drinking a glass of water', 'turning a key', 'picking up a spoon', 'lifting a bag', 'reaching for a bottle' and 'lifting and carrying a bottle') from the trunk (at the patient's back), the lower trunk (below the patient's posterior), the impaired lower arm, the impaired foot and toe, the impaired middle finger, index finger and thumb. Every subject executed each task 3 times.

*F*/*T* measurements recorded at the initiation of a voluntary movement are associated to the trajectories planning [9].

The main objective of the isometric *F*/*T* measurements is to obtain quantitative evidence for recovery from stroke during rehabilitation: every isometric measurement can be used to determine the actual status of the patient and support the clinical staff to early planning of individually tailored rehabilitation therapies.

The mechatronic platform was designed to guarantee a same anatomical start position for all subjects and, consequently, the intra and inter-reliability of the measurements. The force measurement resolution was 0.1 N and signals were sampled at 100 Hz.

The measurement protocol started with showing to the subjects a video of a particular task performed by a healthy subject. Immediately after and in response to both visual (green light on a traffic light) and sound cue, the subjects attempted to perform the task. During the attempts, force and torque signals were recorded from the sensors both in *X*, *Y* and *Z* direction [10–12].

As it is very important that the position of the subject is fixed in an exactly duplicable way over different trials, an isometric setting was selected: in fact, it allows to measure the movement initiation in a standardized way, during the first stages of motor recovery, when the patient's active range of motion may be very limited.

It has been shown that the isometric force and torque patterns of patients with hemiparesis are different from healthy subjects [13,14]. Previous research concentrated on features such as maximum force and/or torque values or on movement smoothness. The following research uses traditional features and constructs new features as well with the aim to better quantify and predict functional recovery.

It has to be noticed that the recordings lead to a large amount of data per experiment: (6 ADL tasks per experiment) × (3 repetitions per ADL task) × (8 sensors) × (3 spatial directions per sensor) × (2 types of measurements: force and torque) = 864 measurements in total.

This paper describes the solutions adopted for recording, storing, sharing and interpreting the multi-dimensional clinical data collected during the clinical trials. The following issues have been faced in close collaboration with the clinical experts, namely: (i) recording *F*/*T* measurements in isometric conditions and visualizing the related signals for clinical interpretation, (ii) detecting the onset movement time and identifying the corresponding time window, since it has a particular interest to understand the recovery mechanisms after a neurological damage, (iii) data pre-processing, which aims at extracting useful information from the recorded force–torque signals, (iv) data mining algorithms that, on the basis of parameters obtained from the data pre-processing, extract patterns containing information on the recovery process of neurologically impaired patients.

In detail, the paper addresses the validation of the first three issues presented above, whereas a paper focused on the fourth aspect was already presented [15].

## 2. Methods

### 2.1. *GUI functional and technical specifications*

A top-down approach was used during the design of the GUI (Fig. 2): through a collaboration with seven medical experts, the following software specifications were identified: (1) performing force/torque measurements, (2) storing data, (3) managing patient profiles and different users profiles, (4) synchronizing the local and global database (DB), (5) interfacing to a PDA using an automatic speech recognition module.

To fulfil these specifications, the software was composed by different modules, namely data acquisition (DAQ), data visualization, database and automatic speech recognition module. Moreover, a cover application that incorporates the above mentioned modules and presents a unified application from the perspective of the end user was developed.

The DB is divided into local and global application. The former consists of relational database and a set of consistently organized data files, the latter being based on a MySQL DB

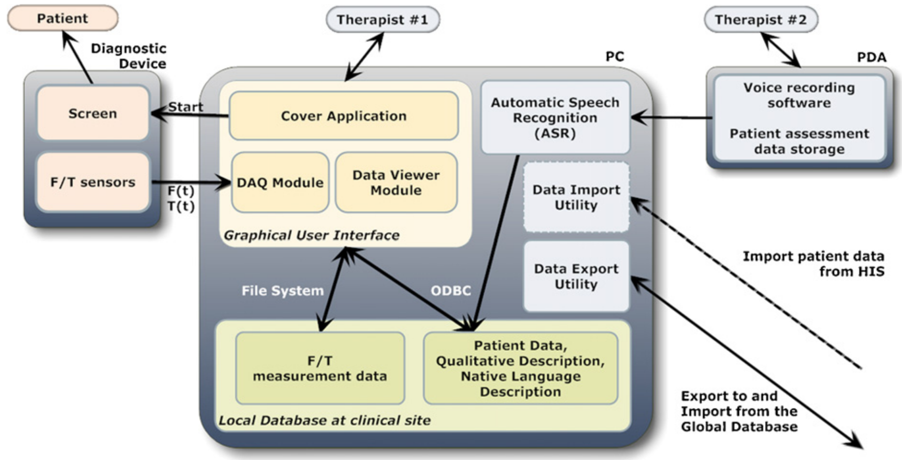


Fig. 2 – The software functional architecture.

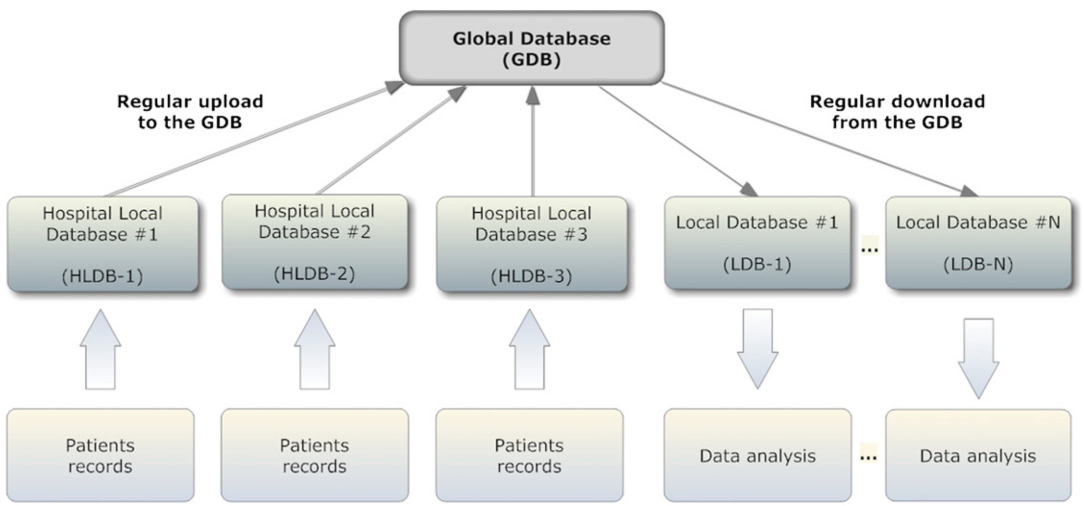


Fig. 3 – Connections with databases.

[16]. The local DB was implemented using Microsoft ACCESS 2000 and it is accessed using the Open Database Connectivity (ODBC) interface [17]. Data files are physically located on the same workstation where the measurements are acquired. This guarantees that the local DB is accessible at any time and its access time is short. Communication to/from the global DB is encrypted through a secure shell (SSH) protocol [18].

The medical staff may upload data files from the local DB to the global DB on a periodical basis. The data files can thus be downloaded from the global DB for an appropriate data analysis. Data type and interfaces specifications of both the cover application and the DB were given using the Unified Modeling Language (UML) notation [19].

The GUI was implemented using Visual Basic (VB) release 6.0 (Fig. 4). The VB environment provides a safe and robust way to connect the GUI with the DB and other software modules, such as the libraries (DLLs) implementing the functionalities offered both by DAQ and data visualization modules.

The GUI offers the following functionalities: (1) open a patient record, (2) start a new session of measurements, (3) create a new patient's record, (4) edit a patient's profile, (5)

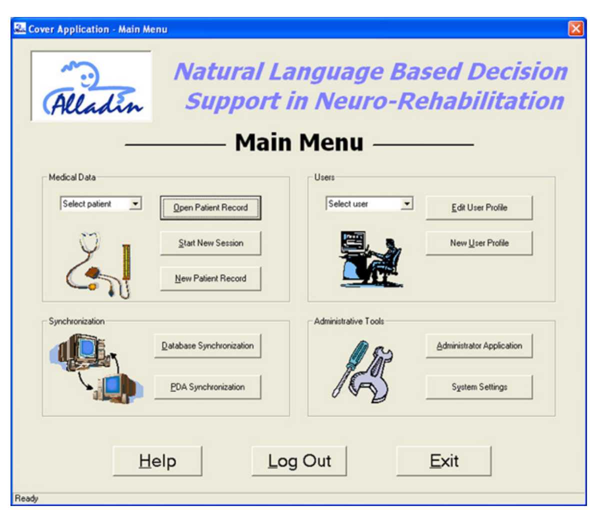


Fig. 4 – The graphical user interface main window.

**Table 1 – Access rights policy for the different users.**

| | GPI | Diagnosis | ICD | ICF | F/T | NLD | FM | MAS | Adverse event | System settings |
|---|---|---|---|---|---|---|---|---|---|---|
| ADD-PT | C/M | R | R | – | C | – | – | – | C/M | R |
| NL-PT | C/M | R | R | C/M | – | C/M | C/M | C/M | C/M | R |
| PI | C/M | C/M | C/M | R | R | R | R | R | C/M | R |
| ADM | C/M | C/M | C/M | C/M | C/M | C/M | C/M | C/M | C/M | M |

GPI, general patient information; ICD, International Classifications of Diseases codes; ICF, International Classification of Functioning, Disability and Health codes; F/T, force/torque measurements; NLD, natural language descriptions, FM, Fugl–Meyer scores; MAS, Motor Assessment Score; C, create an entry (no modification), M, modify an entry (no creation), R, read an entry (no modification). Shaded fields indicate a restricted area, where the ADD-PT and NL-PT have access only to those patient records they compiled.

create a new user's profile, (6) edit a user's profile, (7) synchronize with the global database, (8) synchronize with the PDA, (9) manage the application as administrator, (10) edit system settings and (11) manage a remote assistance.

The synchronization with the PDA allows to automatically import the natural language audio recordings, perform speech recognition analysis and translate speech into text, let user manually validate the results and store the verified results into the local DB.

The main types of data collected, uploaded to a local DB (Fig. 3) and managed by the GUI are (i) patient data and related metadata, (ii) standard outcome measures (SOM) scores, (iii) natural language descriptions of the patient's status, (iv) voice records of the descriptions and (v) *F/T* measurements recorded during ADL exercises.

The GUI allows to define four different user account types: Administrator (ADM), Alladin Diagnostic Device Physiotherapist (ADD-PT), Natural Language Physiotherapist (NL-PT), Principal Investigator (PI) and uses an access right policy in order to assure data safety and to respect data privacy (Table 1).

### 2.2. Data pre-processing

Stroke patients demonstrate an abnormal time activation of muscular patterns due to limitations in forward model generation, motion planning, supervision and sensory-motor control [20,21]. Therefore, the sequence of activation of the different sensors (i.e. movement onset timing) and the relative time delays during the execution of the same task represent an estimate of the patients' distance to normality. On this basis, the main assumptions underlying data pre-processing are:

1. stroke patients typically demonstrate reduced ability in controlling generated forces and torques, both in intensity and in spatial direction; therefore vector direction and amplitude of such variables reflects the presence of impairments which can be assessed by comparing deviations between current mean vector and previous signals;
2. parameters characterizing the *F/T* signals are calculated for both force and torque measurements on the three repetitions of the specific task, for all the sensors and all the tasks in each session;
3. amount of recorded multidimensional data is huge, which means that it should be processed by data mining algorithms.

Firstly, our interest was focused on the identification of parameters conveying an estimation of patients' distance to normality. Moreover, as the measurements are recorded during the movement initiation task, different strategies for the automatic movement onset detection were analysed and tested.

### 2.3. Time window of interest

The basic hypothesis underlying the development of the ADD is that features extracted from the movement preparation and initiation in isometric conditions are determinants for the functional assessment of the recovery after stroke.

The human ability to interpret the large amount of raw data recorded through the ADD platform is limited by non-systematic search patterns and by the presence of noise in the signals. Moreover, the visual inspection is a burdensome task which may also cause oversight errors or loss of useful information. To overcome these limitations, dedicated software tools were developed. However, as the length of the recorded *F/T* signals increases, also the computational burden increases. In order to keep it as low as possible, a novel approach for the development of pre-processing techniques was proposed: the basic idea is that only the portion of signal containing a significant content, in terms of relevant information on the subject's motor behaviour, can be used for further processing, rather than using the whole raw signal. Indeed, the choice of an appropriate time window may have a key role for the understanding of recovery mechanisms after a neurological damage.

The selection of a suitable time window must handle the trade-off between keeping any useful information and reducing the computational burden. The measurement recording time during different ADL tasks ranges from a minimum of 2.4 s to a maximum of 6.0 s, depending on the specific ADL task (Table 2). From a clinical point of view, the data of interest to be extracted from the ADD measurements are conveyed by the very initial part of each recording. Therefore, in order to extract meaningful parameters, the complete *F/T* signals at a given sensor were considered only within a finite-length analysis frame. Time window starts from the estimate of the onset time and lasts a few hundreds of milliseconds, corresponding to a finite number $N$ of samples.

For each task, after a time window was identified and applied to the original signals, a set of candidate

**Table 2 – Measurement recording time during different ADL tasks.**

| ADL task | Recording #1 (baseline) (s) | Recording #2 (video) (s) | Recording #3 (1st attempt) (s) | Recording #4 (2nd attempt) (s) | Recording #5 (3rd attempt) (s) |
|---|---|---|---|---|---|
| Glass | 3.0 | 5.4 | 5.4 | 5.4 | 5.4 |
| Key | 3.0 | 3.7 | 3.7 | 3.7 | 3.7 |
| Spoon | 3.0 | 3.4 | 3.4 | 3.4 | 3.4 |
| Bag | 3.0 | 2.4 | 2.4 | 2.4 | 2.4 |
| Reaching | 3.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Moving | 3.0 | 6.0 | 6.0 | 6.0 | 6.0 |

parameters was identified, extracted and then refined in order to identify those that allow estimating the "distance from normality" of patients during the rehabilitation process.

### 2.4. Parameters definitions

A recording is here defined as the set of force and torque measurements at a given measurement site, for a given patient, during a given session and for a given task. The recordings for all these combinations represent a large amount of raw data to be processed in order to capture relevant features characterizing the motor recovery of post-stroke patients. The iterative identification process of suitable parameters was done in collaboration with the seven clinical experts participating in the experimental trials.

It is assumed that effort direction is a relevant feature of the volitional movement [22]: based on this assumption, patients were not asked to actually perform the movements but only initiate them, according to the protocol design. Given a recording, for the sth sensor, we compute the mean force direction features as the colatitude and azimuth angles of the mean force vector with respect to its referential. The colatitude $\phi_{F,s}$ is defined as the angle between the z-axis of the mean force vector and the azimuth $\theta_{F,s}$ as the angle between the positive x-axis and the line from the origin to the end of the mean force vector projected onto the xy-plane. These angles are obtained by converting the cartesian coordinates of the mean force to spherical coordinates (Eqs. (1)–(3)):

$$\rho = \sqrt{F_{s,x}^2 + F_{s,z}^2 + F_{s,z}^2} \tag{1}$$

$$\phi_{F,s} = \arccos\left(\frac{F_{s,z}}{\rho}\right) \tag{2}$$

$$\theta_{F,s} = \arctan\left(\frac{F_{s,y}}{F_{s,x}}\right) + \pi\, u_0(F_{s,x})\, sgn(F_{s,y}) \tag{3}$$

where $u_0$ stands for the Heavyside unit step function (Eq. (4))

$$u_0(x) = \begin{cases} 0 & \text{if} \quad x \le 0 \\ 1 & \text{if} \quad x > 0 \end{cases} \tag{4}$$

and sgn(·) function denotes the signum function (Eq. (5)):

$$sgn(x) = \begin{cases} -1 & \text{if} \quad x < 0 \\ 0 & \text{if} \quad x = 0 \\ 1 & \text{if} \quad x > 0 \end{cases} \tag{5}$$

Such angles can be computed similarly from the mean torque vector to characterize the mean torque "direction".

Finally, the following four main categories were identified:

- *Angular deviations from the mean direction*. The underlying hypothesis relies on the consideration that trajectories in pathological subjects could show larger deviations from the mean direction than in normal controls.
  Given a recording, for the sth sensor, the angular deviation $\delta_{F,s}[k]$ between the kth force sample $(F_{s,x}[k], F_{s,y}[k], F_{s,z}[k])$ and the mean force $(\bar{F}_{s,x}, \bar{F}_{s,y}, \bar{F}_{s,z})$ is computed as the inverse cosine of the normalized scalar product, i.e. the dot product of the corresponding unit-norm vectors (Eqs. (6)–(8)):

$$\vec{a} = (\bar{F}_{s,x}, \bar{F}_{s,y}, \bar{F}_{s,z}) \tag{6}$$

$$\vec{b} = (F_{s,x}[k], F_{s,y}[k], F_{s,z}[k]) \tag{7}$$

$$\delta_{F,s}[k] = \arccos\left(\frac{\vec{a}}{\|\vec{a}\|} \cdot \frac{\vec{b}}{\|\vec{b}\|}\right) = \arccos\left(\frac{(\bar{F}_{s,x}F_{s,x}[k] + \bar{F}_{s,y}F_{s,y}[k] + \bar{F}_{s,z}F_{s,z}[k])}{\sqrt{\bar{F}_{s,x}^2 + \bar{F}_{s,y}^2 + \bar{F}_{s,z}^2}\sqrt{F_{s,x}[k]^2 + F_{s,y}[k]^2 + F_{s,z}[k]^2}}\right) \tag{8}$$

- *Angular deviations between successive effort samples*. The smoothness of the effort can be evaluated by computing the angle between successive force and torque samples.
  Following the same conventions adopted above, the angular deviation $\varphi_{F,s}[k]$ can be computed as the inverse cosine of the normalized scalar product, i.e. the dot product of the corresponding unit-norm vectors (Eqs. (9)–(11)):

$$\vec{a} = (F_{s,x}[k], F_{s,y}[k], F_{s,z}[k]) \tag{9}$$

$$\vec{b} = (F_{s,x}[k-1], F_{s,y}[k-1], F_{s,z}[k-1]) \tag{10}$$

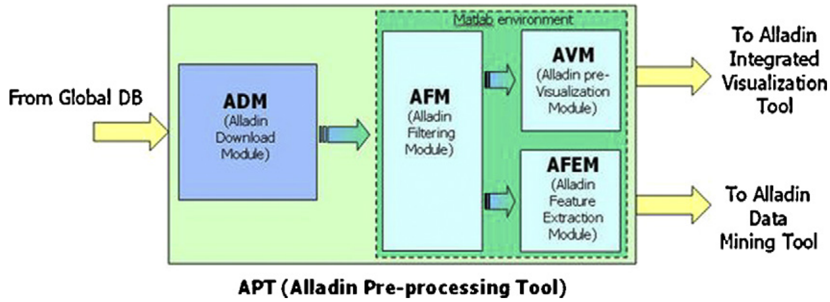


**Fig. 5 – The overall architecture of the Alladin pre-processing tool (APT).**

$$\varphi_{F,s}[k] = \arccos\left(\frac{\vec{a}}{\|\vec{a}\|}\cdot\frac{\vec{b}}{\|\vec{b}\|}\right) = \arccos\left(\frac{(F_{s,x}[k]F_{s,x}[k-1] + F_{s,y}[k]F_{s,y}[k-1] + F_{s,z}[k]F_{s,z}[k-1])}{\sqrt{F_{s,x}[k-1]^2 + F_{s,y}[k-1]^2 + F_{s,z}[k-1]^2}\sqrt{F_{s,x}[k]^2 + F_{s,y}[k]^2 + F_{s,z}[k]^2}}\right) \tag{11}$$

- *Cumulative sum of effort series*. The integrals of the effort signals are expected to convey some information on the velocity of the initiated movements. However, it needs to be emphasized that, strictly speaking, there is no real movement, while the objects were fixed in the isometric setting. Therefore, though these velocity features have no physical meaning, they could convey relevant information about the movement's execution.
  Given a recording, for the sth sensor, the norm $\|\vec{\gamma}_{F,s}[k]\|$ of the integral vector $\vec{\gamma}_{F,s}[k]$ of the force sample vector sequence at the $k$th time instant, within the analysis frame $k = k_0, \cdots, k_0 + N - 1$, is computed as the norm of the cumulative sum of the force sample vector from the $k_0$th time instant up to the $k$th time instant (Eqs. (12)–(14)):

$$\vec{\gamma}_{F,s,x}[k] = \sum_{l=k_0}^{k} F_{s,x}[l] \qquad \vec{\gamma}_{F,s,y}[k] = \sum_{l=k_0}^{k} F_{s,y}[l] \qquad \vec{\gamma}_{F,s,z}[k] = \sum_{l=k_0}^{k} F_{s,z}[l] \tag{12}$$

$$\vec{\gamma}_{F,s}[k] = (\gamma_{F,s,x}[k], \gamma_{F,s,y}[k], \gamma_{F,s,z}[k]) \tag{13}$$

$$\|\vec{\gamma}_{F,s}[k]\| = \sqrt{\gamma_{F,s,x}[k]^2 + \gamma_{F,s,y}[k]^2 + \gamma_{F,s,z}[k]^2}. \tag{14}$$

- *Cross-sensor time delay estimation*. For each of the proposed ADL task, a correct synchronization among the different parts of the body is needed for an optimal performance. The synchronization among the forces and torques during the recording of the isometric task can be computed by means the theoretical statistical dependency, known as mutual information [23]. It consists in calculating the delay between different sensors under which the mutual information between different sensors is maximized. Through the calculation of the mutual information the optimal delay can be found as (Eq. (15)):

$$a_{optimal} = \max_a I\left(\|\vec{F}_{s1}(k)\|, \|\vec{F}_{s2}(k-a)\|\right) \tag{15}$$

The mutual information under the above optimal delay $a_{optimal}$ could represent a useful feature (Eq. (16)):

$$I_{a_{optimal}} = I\left(\|\vec{F}_{s1}(k)\|, \|\vec{F}_{s2}(k-a_{optimal})\|\right) \tag{16}$$

The mutual information can be thus computed as according to Eq. (17):

$$I\left(\|\vec{F}_{s1}(k)\|, \|\vec{F}_{s2}(k-a_{optimal})\|\right) = \sum_{\|\vec{F}_{s1}\|}\sum_{\|\vec{F}_{s2}\|} p\left(\|\vec{F}_{s1}\|, \|\vec{F}_{s2}\|\right)\ln\left(\frac{p\left(\|\vec{F}_{s1}\|, \|\vec{F}_{s2}\|\right)}{p\left(\|\vec{F}_{s1}\|\right)p\left(\|\vec{F}_{s2}\|\right)}\right) = \sum_{k=k\min}^{k\max} p\left(\|\vec{F}_{s1}(k)\|, \|\vec{F}_{s2}(k-a)\|\right)\ln\left(\frac{p\left(\|\vec{F}_{s1}(k), \|\vec{F}_{s2}(k-a)\|\|\right)}{p\left(\|\vec{F}_{s1}(k)\|\right)p\left(\|\vec{F}_{s2}(k-a)\|\right)}\right) \tag{17}$$

The data pre-processing software is composed of different modules (Fig. 5), the functional description of which follows, and which have been implemented using the Matlab environment v6.5 (The Mathworks, Inc. Natick, USA).

### 2.5. *Onset time detection*

The latency between the start of the voluntary muscular contraction of different body segments and the start of *F/T* recording in hemiparetic subjects can be significantly prolonged [24]. Hence, the determination of the movement onset time in the recorded signals represents a fundamental issue of pre-processing analysis. It represents a challenging topic, whose reliability is crucial for analysing the neurophysiological recovery, as reported in the previous sections.

However, the isometric measurements typically involve the registration of *F/T* signals that are weak and often noisy, since they are collected from patients with physical impairments. Moreover, manual ticking of onset time cannot be a viable solution due to the vast amount of generated data.

To overcome these limitations, starting from the review of the state-of-the-art techniques and after an internal debate between engineers and clinical experts, candidate methodologies for automatic onset time estimation were identified by using:

1. the point where the force–torque signal reaches 2%, 4%, 6%, 8% and 10% of its peak value;
2. 2nd order derivative of the force–torque signal (with low-pass filtering at 3 Hz or at 5 Hz);
3. the spectral flatness measure (SFM) of the *F/T* signal, based on a maximal information redundancy criterion;
4. a probability density function (PDF) estimate of the force–torque signal through a kernel smoothing based method (ks-density).

- *The 2% rule*. Former neurorehabilitation research inspired the proposed technique [25]. The input to the threshold-based algorithm consists of the three components of the force $F_x$, $F_y$ and $F_z$ (or torque) signals. It computes the 2% 4%, 6%, 8% and 10% of the peak value on the signal and finds the minimum time corresponding to that value for each component. This value is taken as the onset time. These methods are referred to as Threshold 2, Threshold 4, Threshold 6, Threshold 8 and Threshold 10;
- *The second derivative method*. A previous study on the gait analysis inspired the present technique [26]. Three versions of the present algorithm (***a***, ***b***, ***c***) have been developed. The algorithm initially finds the threshold point on the 1st derivative of the input signal at the 15% of its maximum: ***a***. it searches the nearest maximum peak of the second derivative of the 3 Hz filtered signal (2nd derivative-filtered 3 Hz). ***b***. it searches the nearest maximum peak of the second derivative of the 5 Hz filtered signal (2nd derivative-filtered 5 Hz). ***c***. it searches backward the zero crossing in the first derivative line (2nd derivative-zero crossing). This is similar to the 2% rule, except that it scans backward from a higher speed, so initial small velocity peaks are neglected.
- *The SFM method*. The SFM method measures the amount of correlation structure existing in a signal [27].
- *The kernel smoothing based method (ks-density)*. The ks-density function computes a PDF estimate of the input vector. Typically stationary values (e.g. flat regions) of force–torque signal correspond to maxima of the PDF while values where the slope of the signal is high generally correspond to minima of the PDF. The algorithm locates the minimum of the local minima (minimum density point, MDP) in the ks-density function. A first version of the PDF estimation algorithm outputs the MDP as the onset time; it is referred to as *MDP* in the following. In a second version, labelled as MDP-1st, the intersection of the line passing through the MDP with a slope equal to the mean value of the first derivatives of an arbitrary interval around the MDP is computed.

**Table 3 – Probability of correctness (POC) of both the deterministic methods and the decision system (MDS).**

| Onset technique | POC force | POC torque |
|---|---|---|
| Threshold 2 | 0.76 | 0.72 |
| Threshold 4 | 0.79 | 0.76 |
| Threshold 6 | 0.76 | 0.75 |
| Threshold 8 | 0.78 | 0.77 |
| Threshold 10 | 0.78 | 0.76 |
| 2nd derivative (filtered 3 Hz) | 0.88 | 0.89 |
| 2nd derivative (filtered 5 Hz) | 0.88 | 0.89 |
| 2nd derivative (zero crossing) | 0.85 | 0.82 |
| MDP | 0.77 | 0.78 |
| MDP-1st | 0.74 | 0.78 |
| Specialist (mean value) | 0.90 | 0.90 |
| MDS kNN based | 0.90 | 0.92 |
| MDS MLP based | 0.92 | 0.93 |
| MDS SVM based | 0.91 | 0.85 |
| MDS BOO based | 0.93 | 0.86 |

Abbreviations: MDP, minimum density point; MDS, multi dichotomy system; kNN, k-nearest neighbour; MLP, multi-layer perceptron; SVM, support vector machine; BOO, AdaBoosting.

The outcome of such an analysis is the identification of the best method for automatic onset detection, which can be subsequently applied to determine the onset time for all the input samples. However, one of the major drawbacks of deterministic onset detection techniques is their dependency from the input signal structure, which can affect their efficiency. Therefore, the choice of a simple deterministic method cannot cope with the variability among different signals. Moreover, the results of each deterministic method, reported in Table 3 and discussed later, show that their performance, although promising, cannot be evaluated as satisfactory as less reliable than those manually ticked by clinical experts.

To tackle these issues, an approach that automatically identifies the most appropriate onset detection technique for each input signal has been proposed [28]. The proposed system, also referred to as multi dichotomy system (MDS) in the following, is composed of different binary classifiers, each one specialized in separating one class from the others. Different classifiers, such as k-nearest neighbour (kNN), multi-layer perceptron (MLP), support vector machine (SVM) and AdaBoosting (BOO) were tested as well.

### 2.6. *The Alladin pre-processing tool (APT)*

The Alladin pre-processing tool (APT) is a software tool that automatically derives specific parameters from the ADD recordings and stores the output data into a structure using a format for subsequent data mining analysis that has to lead

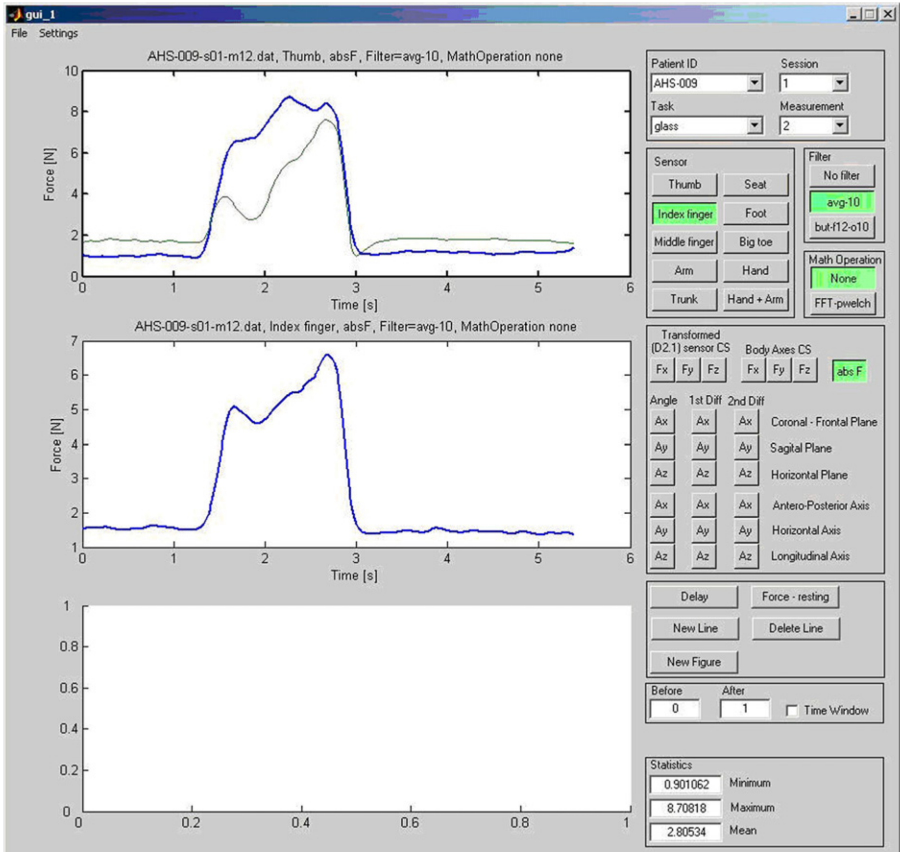


**Fig. 6 – The Alladin visualization module (AVM) main window.**

to the extraction of clinical markers and milestones, relevant for functional assessment of patients.

The functional description of the different modules which form the data pre-processing software tool, namely (a) filtering module, (b) visualization module and (c) feature extraction module, are now presented.

### 2.7. The Alladin filtering module (AFM)

A two-channel parallel low-pass filtering, one featuring a cut-off frequency at 40 Hz and another with a cut-off frequency at 2 Hz was proposed and implemented in order to provide two separate data sets for subsequent processing. The former frequency was selected considering that human muscles can generate mechanical signals up to a maximum frequency of 40 Hz (muscle sound) [29]. The latter frequency was chosen since human voluntary movement typically generates signals within the frequency range 0–2 Hz [30].

On this basis, the 40 Hz-channel is the main channel used for feature extraction, whereas the 2 Hz-channel is used for visualization and onset time estimation operations.

### 2.8. The Alladin visulization module (AVM)

The ALLADIN visualization module (AVM) allows visual inspection of data during the pre-processing operations (Fig. 6). Through the controls positioned on the main window, the patient ID, session, task and measurement number can be selected. Data filtering, computations and coordinate transformations can be applied to the measurements, and plotted for inspection.

A slightly different version of AVM was implemented with the aim of simplifying the clinical experts' task. The module allows manual selection of the onset time directly on the plot, by simply clicking on the window by using the PC mouse.

### 2.9. The Alladin feature extraction module (AFEM)

The Alladin feature extraction module (AFEM) extracts the statistical and temporal features presented in previous section on all the ADD measurements of the input data set filtered at 40 Hz by AFM.

The extracted parameters for every recording were stored in a hierarchical structure of strings, arrays and cell arrays containing the identification information as well. Every stored parameter presents a description and a value.

As mentioned in the previous paragraphs, a subset of six features has been extracted from the original set of proposed parameters as clinical markers for recovery assessment. The reduction of the initial number of features was solved by means of a hybrid filter-wrapper approach described in [15]: the implementation of a statistically optimal filter led to reduce the feature set from 59,472 features to 2637 features. The wrapper search on this smaller set reduced the feature set to a total of 6 features. A description of the 6 extracted features follows:

1. Standard deviation value of the integral of the sample vector within the time region of interest, in the middle finger sensor during the second attempt of the drinking task.
2. Maximum value of the angular deviation between the torque sample vector and the mean torque vector within the time region of interest, in the thumb finger sensor during the fourth attempt of the lifting bottle task.
3. Mean value of the angular deviation between the torque sample vector and the mean torque vector within the time region of interest, in the seat sensor during the third attempt of the drinking task.
4. Standard deviation value of the integral of the sample vector within the time region of interest, in the thumb finger sensor during the fourth attempt of the lifting bottle task.
5. Normalized sum of the residual, in the thumb finger sensor during the fourth attempt of the drinking task.
6. Mean value of the angular deviation between the force sample vector and the previous force vector within the time region of interest, in the index finger sensor during the fourth attempt of the lifting bag task.

## 3. Results

The software tool has been used in three European hospitals for clinical trials. The centres participating in the multi-centre clinical trials were:

- Algemeen Ziekenhuis Maria Middelares Sint-Jozef Hospital (AZMMSJ), Gent, Belgium;
- Adelaide & Meath Hospital (AMNCH), Tallaght, Dublin, Ireland;
- Szent János Hospital, Budapest, Hungary.

Altogether 270 subjects (120 healthy subjects, 150 hemiparetic subjects) were recruited during the clinical trials. The three clinical centres obtained the approval of the local ethics committees. Informed consent was obtained by each subject.

From the global patient database, a force and torque datasets consisting of 96 sample *F/T* measurements recorded using the ADD was selected and used for validation purposes.

As the automatic onset detection is concerned, Table 3 presents the results of the comparative analysis among the performance of the different techniques with respect to the reference performance of seven clinical experts working in the three centres participating in the trials.

Indeed, the mean onset reference values assessed by the experts, named as Mean Reference Vector (MRV) in the following, was computed taking into account the variability among the different onset times. To lower this variability, which can also affects the reliability of the ground truth used to train the decision system, the outliers were deleted.

The reference time is then computed as the mean onset time among the experts that fall between the 5th-percentile and the 95th-percentile of the mean value itself. Hence, for each iteration, the onsets that do not fall in this interval are disregarded, and the mean is again computed considering only the ticks that satisfy such a condition.

Then, the performance figure of the automatic onset detection method is expressed in term of probability of correctness (POC), which is calculated as the ratio $Nc/N$, where $N$ is the total number of samples and $Nc$ is the number of samples which fall between the 5th-percentile and the 95th-percentile of the MRV.

The comparison between manual and automatic methods was performed on a reference force and torque datasets composed by 96 ADD measurements, representative of the patients recruited in the three centres and homogeneous in terms of gender, age, initial severity of impairment and side of hemiparesis.

The patients performed the six different ADL tasks. As each measurement involves the eight sensors embedded into the ADD, the final force and torque datasets consists of 768 signals (96 measurements × 8 sensors), respectively [31].

Table 3 shows performance that is encouraging, but not satisfactory yet. Indeed the results achieved by clinical experts are better than those achieved by deterministic onset approaches.

The last four rows of Table 3 report the POC achieved by the pattern recognition system on both force and torque datasets using the different classifier architectures reported in the previous section.

As for force data, in three of four tests the pattern recognition system outperforms the specialists' performance, whereas in one case it achieves the same result of the human experts. Furthermore, in all cases the proposed decision approach performs better than each deterministic method. It was an expected result, since such a system dynamically chooses different deterministic methods on the basis of each signal structure.

As for torque data, when either kNN or MLP architecture are used as binary classifier, the recognition system outperforms the specialists' results. In the other two cases (SVM and BOO architecture), the recognition system does not exhibit a satisfactory performance. A possible reason is that the features set may not work well in conjunction with this classifier architecture, causing a performance drop of these classification algorithms. The presented results allow concluding that:

(i) the proposed techniques can be used to remove useless parts of the signal;
(ii) the first phase of the data mining stage should be dedicated to the identification and recognition of typical patterns, which then could lead to a narrower time windowing.

A second and larger reference dataset from 96 subjects recruited in the clinical trials was identified, prepared and delivered to the group of clinical experts in order to perform a second onset estimation. Such dataset was composed by 27,648 *F/T* measurements (i.e., 96 subjects × 8 sensors × 6 ADL tasks × 3 spatial directions per sensor × 2 types of measurements: force and torque). The additional comparative analysis between the automatic techniques and the extended set of manually detected onset times demonstrated that the results were not significantly different from those previously obtained.

## 4. Discussion and conclusions

This paper describes the design methodology, the development and application of both a GUI and a clinical data pre-processing software tool. An application to a mechatronic platform for whole-body isometric force–torque measurements for functional assessment in neuro-rehabilitation was presented.

Thanks to the close collaboration between rehabilitation medical staff and biomedical engineers, after several clinical tests, a multidisciplinary approach was proposed to simplify the problem of recording multidimensional data and handling the great amount of acquired raw data. In the proposed approach the relevant part of the raw signal (i.e., the part in which the *F/T* exerted by the patient is clearly visible) was selected through the use of a series of movement onset detection algorithms. Then a first set of parameters were extracted as possible feature candidates in a pre-processing stage.

These pre-elaborated data, if input to data mining, can be expected to strongly decrease the computational work load. The present paper presented a complete and reliable user interface and data pre-processing techniques to be used in conjunction with an innovative mechatronic platform which can be used both for functional assessment of post-stroke patients and for basic research in the neuroscience domain as well.

Future works will be aimed at including plans to clinically validate the automatically produced set of quantifiers in comparison with other ADL outcomes in healthy and neurologically impaired groups. Moreover, the ADD is being integrated with systems for surface EMG and brain imaging (e.g., PET, fMRI, MEG, NIRS, EEG) data recording to evaluate changes in motor performances induced by the rehabilitative treatments and reinforce the pattern recognition approach.

## Conflict of interest

None.


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