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Posture and movement estimation based on reduced information. Application to the context of FES-based control of lower-limbs

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1. Introduction

Complete paraplegia is a condition where both legs are paralyzed and usually results from a spinal cord injury which causes the interruption of motor and sensorial pathways from the higher levels of central nervous system to the peripheral system. One consequence of such a lesion is the inability for the patient to voluntary contract his/her lower limb muscles whereas upper extremities (trunk and arms) remain functional. In this context, movement restoration is possible by stimulating the contraction of muscles in an artificial way by using electrical impulses, a procedure which is known as Functional Electrical Stimulation (FES) (Guiraud, et al., 2006a; 2006b).

When attempting to control posture and locomotion through FES, an important issue is the enhancement of the interaction between the artificial FES system controlling the deficient body segments and the natural system represented by the patient voluntary actions through his valid limbs motion. In most FES-systems, voluntary movements of valid limbs are considered as perturbations. In the case of valid persons, the trunk movements strongly influence the postural equilibrium control whereas legs have an adaptive role to ensure an adequate support base for the centre of mass projection. Collaboration between trunk and legs sounds therefore necessary to ensure postural balance, and should be taken in account in a FES-based control system. Indeed, generated artificial lower body movements should act in a coordinated way with upper voluntary actions. The so-obtained synergy between voluntary and controlled movements will result in a more robust postural equilibrium, a both reduced patient's fatigue and electro-stimulation energy cost.

At the moment, in most FES systems, controls of valid and deficient limbs are independent. There is no global supervision of the whole body orientation and stabilization. Instead, it would be suitable to: 1) inform the FES controller about valid segments state in order for it to perform the necessary adaptations to create an optimal and safe configuration for the deficient segments and 2) give to the patient information about the lower or impaired body orientation and dynamics in order for him to behave adequately. The patient could therefore use his valid body limbs to somehow "*teleoperate*" the rest of his body (see Fig.1.). Involving valid segment movements in the control of the artificial system, and therefore voluntary action of the person is also a way to give the patient an active role in the control

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of his/her movements which would have positive psychological effect. The FES-assistance system should adapt to patient behaviour and intentions expressed through his valid limbs motions, instead of imposing an arbitrary motion on the deficient limbs (Heliot et al., 2007).
The need for cooperation between healthy and deficient limbs led us to the idea that valid limbs should be observed in order to improve the artificial control as well as deficient limb states should be somehow fed back to the patient in order for him to be able to behave efficiently.

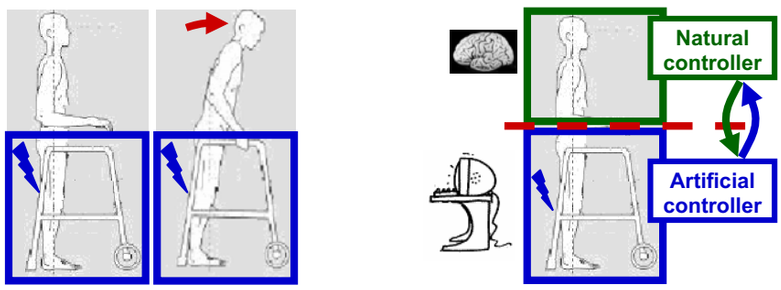


Figure 1. From no interaction to an efficient collaboration between artificial and natural controllers of patient deficient and valid limbs

These considerations led us to investigate the feasibility of characterizing and estimating patient posture and movement by observing the valid limbs by means of a reduced amount of information. Indeed, to be viable in everyday life context, the sensors involved have to be non obtrusive, easy and fast to position by the patient. On the contrary, laboratory-scale classical systems such as optoelectronic devices or force plates restrict the user to a constrained working volume and thus are not suitable.
In this chapter, we will develop two approaches for non-obtrusive observation:

1. The first one takes advantage of the available walker which is today still necessarily used by the patient. Hence, two six-degrees-of-freedom force sensors can be mounted onto the walker's handles in order to record upper limbs efforts. However, for safety reasons, the walker will be replaced in the sequel by parallel bars.
2. The second one disposes on patient's body, miniature sensors such as accelerometers. These sensors will be wireless and maybe implantable in the future.

We will illustrate the possible applications of these approaches for the estimation of posture while standing, for the detection of postural task transition intention and for the monitoring of movement's phases.
All the patients and subjects gave their informed consent prior to the experiments presented in this chapter.

2. Estimating posture during patient standing

In this section, we will show how one can reconstruct the posture of a patient, while standing, by using the measurement of the only forces exerted on the handles of parallel bars (Ramdani, et al., 2006 ; Pagès, et al., 2007).

2.1. The experimental procedure

2.1.1. Participants

Four spinal cord injured male subjects, with complete spinal lesions between T6 and T12, participated in the standing study program. The main selection criteria were the following: (1) participants show high motivation to the study, (2) post-injury standing experience, (3) appropriate contractions of the leg muscles in response to electrical stimulation, (4) sufficient upper body arm support strength to lift oneself up and maintain standing, (5) no cardiac or respiratory illness, (6) no previous stress fractures of upper and lower extremities, (7) no excessive body weight, (8) acceptable amount of spasticity and contracture in legs, (9) no psychological pathology.

2.1.2. Materials and Instrumentation:

For leg muscle stimulation during standing, an eight channel stimulator was used (see Fig.2). The self-adhesive surface electrodes were placed over the motor point areas of the quadriceps, the gluteus maximus, the tibialis anterior and the biceps femoris muscles of each leg. The stimulation device was driven directly in real time through a serial link by a PC. During active standing, patients were stimulated to predetermined FES constant currents, set up for each channel, in order to ensure safe standing. A video motion analysis system which included four infrared cameras was used to acquire kinematics data. The reaction forces measuring system, comprising two six-axis transducers, was attached to handles on adjustable supporting parallel bars. The six components of the handle reactions were measured and displayed throughout a real time implemented force sensor interface software. The handles height and separation were set to comfort for each patient.

2.1.3. Description of the protocol

In a first session, the subjects have been exposed to daily FES exercises, for up to 1 hour per day during 5 days, in order to strengthen their quadriceps, gluteal maximus/medius, biceps femoris and tibialis anterior muscles. In a second session, following a thorough explanation of the study procedure, the patients, under FES, were instructed to stand up from a chair, assisted by parallel bars, and stay in standing position and sit back down. The standing phase was as long as one minute. This training phase has been repeated several times in order for the participants to become familiar with the testing equipment. At session three, measurements were performed.

2.2. Modelling the human body and arm support

According to observations from human gait, most of joint movements during locomotion appear to take place in the sagittal plane. In our study, motion in the frontal plane during standing occurs at very low velocities. Moreover, stimulation on the different muscle groups of the lower limbs predominantly generates movement in the sagittal plane. For these reasons, the design of a two-dimensional model of the human body in the sagittal plane is sufficient for this study. During FES-standing, stimulation of the quadriceps and the hamstring locks the knee in extension, and therefore prevents knee movement. During stance, we consider that the distance between the thigh and the handle is constant, which allows us to assume that the ankle is immobilized. Hence, the lower limbs are here treated

as a single rigid link. The human body is thus regarded as a four bar linkage with a three degrees of freedom dynamic structure defined in the sagittal plane, as shown in Fig. 3.

Figure 2. The experimental arrangement and placement of electrodes

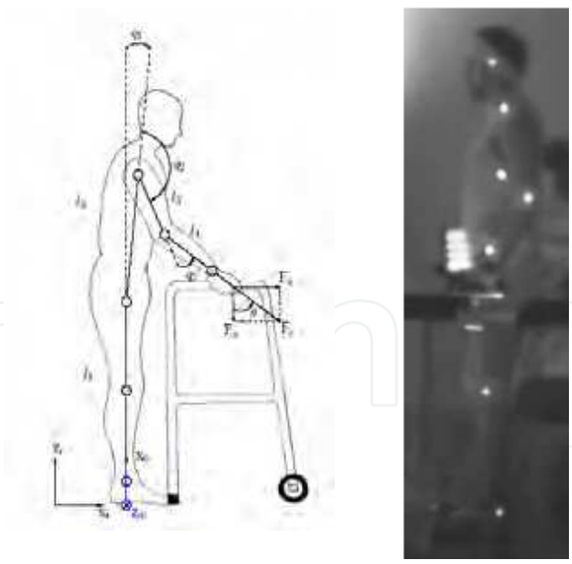


Figure 3. The four bar linkage human model (left). Actual captured image (right)

All links are assumed to be rigid bodies. We define $q = [q_1\ q_2\ q_3]^T$ as the joint angle vector, which is a function of time. It is expressed as a column vector with indices 1, 2 and 3 referring to the hip, the shoulder and the elbow joints respectively. The segments lengths are denoted by l_j. In Fig. 3, the variables q_1 and q_2 indicate positive angle directions while q_3 indicates a negative one, with respect to the zero position. Denote P_x and P_z the coordinates of the handle in the sagittal plane. The segmental model is given by (Khalil & Dombre, 2002)

$$P_x = l_2\sin(q_1) + l_3\sin(q_1+q_2) + l_4\sin(q_1+q_2+q_3) \quad (1)$$

and

$$P_z = l_1 + l_2\cos(q_1) + l_3\cos(q_1+q_2) + l_4\cos(q_1+q_2+q_3) \quad (2)$$

During FES-supported movements, paraplegic patients need their arms to maintain balance and sustain desired movement. Support is taken in charge by two handles, each equipped with the six axis force/torque sensor, mounted on the supporting frame.
Contact between the human hand and the handle creates a closed chain kinematics linkage. This interaction is described by the components of the resultant force vector F_c measured in the x and z directions. Under the assumption of working in the sagittal plane and considering that the orientation of the forearm is colinear to the resultant force F_c, which is true when the x-axis component of the resultant force satisfies $F_x \geq 0$ and the z-axis component satisfies $F_z < 0$ (see Fig.3), it is reasonable to write the following hypothesis :

$$q_1 + q_2 + q_3 - \pi \approx \arctan(F_x/F_z) \quad (3)$$

2.3. A Set membership identification of posture

Equations (1)-(3) can be re-written as

$$g(\mathbf{q}) = \mathbf{y} \quad (4)$$

where $\mathbf{y} = [P_x, P_z, \arctan(F_x/F_z)]^T$.
The patient's posture is given by the $\mathbf{q}$ vector, which can be obtained by solving (4). If the measured quantities $\mathbf{y}$ and anthropometric parameters l_j were known with no uncertainty, then the problem could be solved analytically through state-of-the-art tools by using inverse kinematics. Solving (4) when y is subject to uncertainty with classical techniques based on possibly weighted least squares optimisation for instance, derives reliable results only if the errors are stochastic and with known probability laws. In fact the measured data are subject to either stochastic or deterministic uncertainties and it is not easy to derive a reliable characterization of the probability distribution for these errors. Moreover, the model used may be based on some simplifying hypotheses for which a full probabilistic description might not be reliable. Consequently, it is more natural to assume all the uncertain quantities as unknown but bounded with known bounds and no further hypotheses about probability distributions. In such a bounded error context, the solution is no longer a point but is the set of all acceptable values of the q vector, which makes the model output $g(\mathbf{q})$ consistent with actual data $\mathbf{y}$ and prior error bounds.
Denote $\mathbf{E}$ a feasible domain for output error and $\mathbf{Y} = y + \mathbf{E}$ the feasible domain for model output. The set $\mathbf{S}$ to be estimated is the set of all feasible postures:

$$\mathbf{S} = \{\mathbf{q} \in \mathbf{Q} \mid g(\mathbf{q}) \in \mathbf{Y}\} \quad (5)$$

where the set $\mathbf{Q}$ is an initial search space for the q vector. Characterizing the set $\mathbf{S}$ is a set inversion problem which can be solved in a guaranteed way using a set inversion algorithm

based on space partitioning, interval analysis and constraint propagation techniques (see (Jaulin, et al., 2001) and the references therein). This algorithm explores all the search space without losing any solution. It makes it possible to derive a guaranteed enclosure of the solution set **S** as follows:

$$\mathbf{S}_{inner} \subseteq \mathbf{S} \subseteq \mathbf{S}_{outer} \tag{6}$$

The solution set **S** is enclosed between two approximation sets. The inner enclosure $\mathbf{S}_{inner}$ consists of the boxes that have been proved feasible. To prove that a box [**q**] is *feasible* it is sufficient to prove that g([**q**]) ⊆ **Y**. If, on the other hand, it can be proved that g([**q**])∩**Y**=∅, then the box [**q**] is *unfeasible*. Otherwise, no conclusion can be reached and the box [**q**] is said *undetermined*. It is then bisected and tested again until its size reaches a threshold to be tuned by the user. The outer enclosure $\mathbf{S}_{outer}$ is defined by $\mathbf{S}_{outer} = \mathbf{S}_{inner} \cup \Delta\mathbf{S}$ where Δ**S** is given by the union of all the *undetermined* boxes. The outer enclosure $\mathbf{S}_{outer}$ contains all the solutions, if they exist, without losing any of them. It contains also some elements that are not solution.

2.4. The estimated posture

Posture estimation was done during the standing phase. The subject's actual posture during that time interval were measured as :

$$q_1 \approx 0°,\ q_2 \approx 192°,\ q_3 \approx -36° \tag{7}$$

representing respectively the hip, shoulder and elbow joint angles. The body segment lengths were directly measured on the patient and are given by :

$$l_1 \approx 0.954 \text{ m},\ l_2 \approx 0.518 \text{ m},\ l_3 \approx 0.334 \text{ m},\ l_4 \approx 0.262 \text{ m} \tag{8}$$

The feasible domain for model output are taken as:

$$\begin{aligned} P_x &\in [-0.02, 0.02] \text{ m} \\ P_z &\in [0.895, 0.995] \text{ m} \\ \arctan(F_x/F_z) &\in [-18.63, -15.63]° \end{aligned} \tag{9}$$

The prior search space **Q**, corresponding to the joints articular motion limit, is taken as:

$$[-11, 90]° \times [90, 210]° \times [-103, 0]°.$$

The projections of the computed inner and outer solution sets, $\mathbf{S}_{inner}$ and $\mathbf{S}_{outer}$ onto the $q_i \times q_j$ planes are given in Fig.4. Contrary to any optimization based techniques, there are no optimal solution, therefore any posture taken within the solution set is an acceptable one. Extreme postures taken from solution set are also plotted in Fig.5. These figures clearly show that the solution sets contain the actual posture (see also Table 1).

Joints	Projection of inner enclosure	Projection of outer enclosure
q_1	[-1.35 , 25.52]	[-4.14 , 28.79]
q_2	[192.5 , 213.66]	[190.34 , 215.32]
q_3	[-74.10 , -31.05]	[-77.81 , -28.28]

Table 1. Projection of solution posture

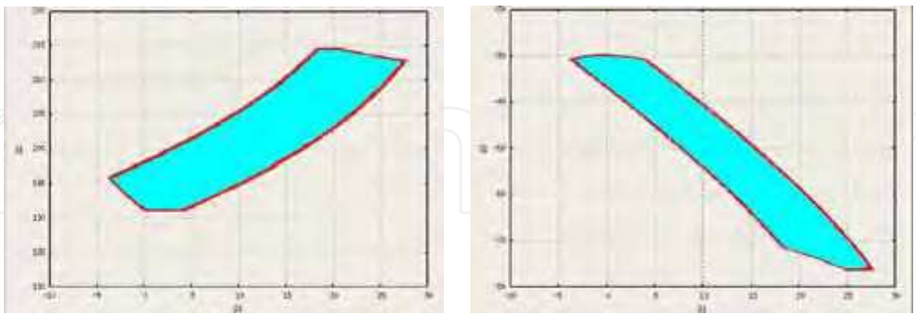


Figure 4. Projection of solution set onto $q_1 \times q_2$ (left) and $q_1 \times q_3$ (right)

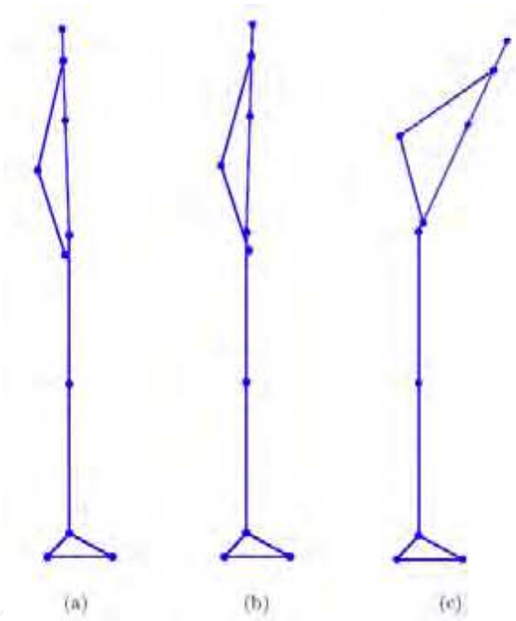


Figure 5. Postures taken from the solution sets:
(a) Patient leaning back, (b) Actual patient posture, (c) Patient leaning forward

Indeed, the experimental method introduced in this section is capabale of reconstructing the posture of a patient but with fairly large uncertainties. This reflects the fact that for a fixed position of the forearm taken within the feasible domain calculated by force measurements in the sagittal plane only, the hip, the shoulder and the elbow joints still have the possibility to reach other positions, while being consistent with the defined geometrical constraints. In order to further reduce the solution set, and hence have a more precise estimation of patient's posture, new constraints has to be introduced by using dynamic modelling and ground reaction forces measurements, for instance.

3. Observing valid limbs to detect patient intention

In this section, we propose an approach for the recognition of the "signature" of the postural task the subject intends to realize (sit-to-stand, object grasping, walking, stair climbing, gait initiation/termination...) through voluntary movement observation. This detection should occur as soon as possible after the subject has decided to initiate the task. It is particularly important to detect the transitions between activity modes as soon as possible after the patient has taken the decision to modify his functioning mode, in order to allow for optimal posture preparation and execution.
A good illustration for this is the transfer from sit to stand. In our FES context it is essential to optimize this task, muscle fatigue being a major issue. Minimizing efforts of rising up could improve the following activities of the patient. For this reason, classical techniques consisting of maximum stimulation of knee extensors throughout the rising process are not suitable and involve an over-use of arm support.
Two approaches are considered in the following to estimate patient attitude: the instrumentation of the walker and body-mounted micro-sensors.

3.1. Sit to stand dynamics analysis

Assuming that the body structure is rigid, continuous dynamics can be expressed under the Lagrangian form:

$$\mathbf{M}(\mathbf{q})\mathbf{q}''+\mathbf{N}(\mathbf{q},\mathbf{q}')\mathbf{q}'+\mathbf{G}(\mathbf{q})=\mathbf{\Gamma}+\mathbf{\Gamma}_{ext} \quad (10)$$

where: $\mathbf{q}$ stands for the parametrization vector of the whole configuration space of the biped considered as free in 3D, $\mathbf{\Gamma}$ is the joint actuation torque, $\mathbf{M}$ is the inertia matrix, $\mathbf{N}$ is the matrix of centrifugal, gyroscopic and Coriolis effects, $\mathbf{G}$ is the generalized gravity force vector. $\mathbf{\Gamma}_{ext}$ are torques generated by external forces such as ground contacts, interaction with a chair, a thrust, etc. They can be expressed as:

$$\mathbf{\Gamma}_{ext}=\mathbf{C}(\mathbf{q})^T\boldsymbol{\lambda}(\mathbf{q},\mathbf{q}') \quad (11)$$

$\mathbf{C}(\mathbf{q})$ is the Jacobian matrix of the points of the biped to which the external forces are applied and $\boldsymbol{\lambda}$ corresponds to the amplitudes of these forces. Biped dynamics are characterized by the existence of variable constraints resulting from interaction with the ground. Ground efforts correspond to a set of forces applied to the points of the biped in contact with the ground (Azevedo et al., 2007a).
Using this framework, we propose to express the sit-to-stand transfer as an optimization problem, where the posture configuration q minimizes a cost function over a time horizon h:

$$J=(H_{com}-H_{comd})^T(H_{com}-H_{comd}) \quad (12)$$

where $H_{com}(t)=[X_{com}(t); Y_{com}(t); X_{com}(t+1); Y_{com}(t+1);\ldots; X_{com}(t+h); Y_{com}(t+h)]^T$ is the sequence of centre of mass positions over the time horizon h, $H_{comd}=[X_{comd}; Y_{comd};\ldots; X_{comd}; Y_{comd}]^T$ is a vector made of the repetition of the *desired* position of the centre of mass (standing posture) over the time horizon h. The solution to this problem is illustrated in Figs.6 & Fig.7-a. The biped goes directly from seated posture to standing.

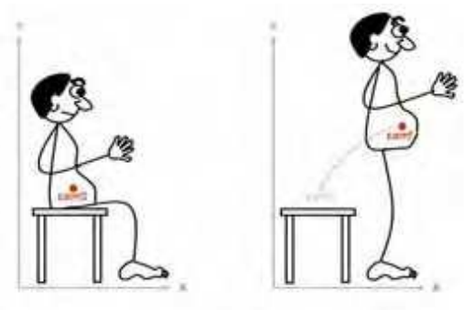
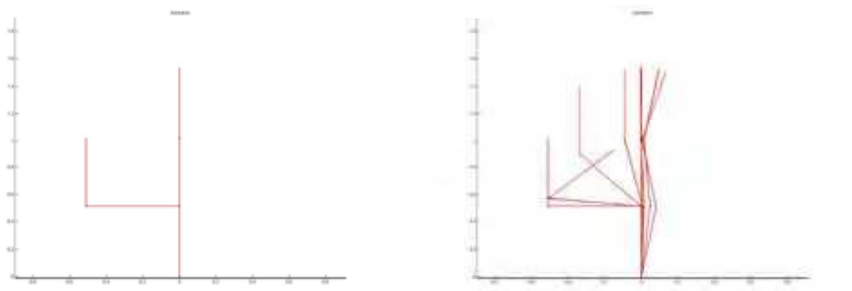


Figure 6. Illustration of the problem of sit to stand consisting in transferring the centre of mass projection from seat to feet



a- no constraint b- constrains on torques

Figure 7. Simulation of sit to stand transfer by solving an optimization problem minimizing distance between actual and desired center of mass position over a sliding time horizon

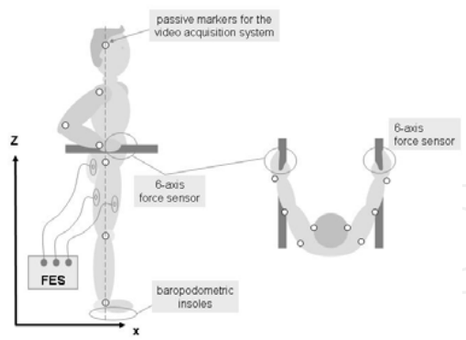


Figure 8. Description of the experimental protocol

If now some constraints are added to the problem in terms of limitation of joint torques, i.e.

$$\boldsymbol{\Gamma}_{min} \leq \boldsymbol{\Gamma} \leq \boldsymbol{\Gamma}_{max} \tag{13}$$

the result is that the system has to use its trunk inertia to achieve the movement (fig.7-b), upper body bends forward before legs initiate movement. This simulation results explain clearly the important need of coordination between upper and lower limbs to execute a transfer from seat to stand when available torques are limited, which is obviously the case for muscles. Without this coordination additional external efforts are needed, such as arm support.
Based on these preliminary considerations, we propose two approaches for the detection of sit-to-stand movement.

3.2. Walker instrumentation

We first investigate the possibility of considering body supportive forces as a potential feedback source for FES-assisted standing-up control (Azevedo et al., 2007b). The six-degrees of freedom force sensors were mounted onto handles fixed on parallel bars in order to record upper limbs efforts and insoles were fitted in the patient's shoes to record plantar pressure distribution (Fig.8). Eight volunteer complete paraplegic patients (T5-T12) were verticalized by means of adapted FES. The same training protocol as presented in the previous section was used. A video motion analysis system recorded the positions of passive markers placed on the body allowing us to measure kinematics. The results show that the transfer (phase 1) is mainly ensured by arm support in all our patients (Fig.9). We gave instruction to the patients to bend their trunk in preparation to the chair rising. An important observation when looking at trunk, knee and ankle angles is the low intra-variability between trials of one given patient (Fig.10). A main difference between valid subjects and patients is the onset of leg movement in regards to trunk bending (Fig.10). To be efficient, trunk bending forward should start before and last during knee and ankle movement. This was never the case in our trials on FES-assisted standing.
Minimizing arm support contribution is possible only if trunk inertia is used. This implies a good triggering of muscle contraction regarding limb movements. Trunk behaviour could be indirectly observed by analyzing efforts applied by arm support (Fig.11). Indeed, normal force decreases (pulling) while momentum around transversal axis increases. From these results we can say that proper threshold detection based on these signals could be used to initiate the leg stimulation and improve greatly the sit to stand. The same may be used for stand to sit as shown in Fig.11.

3.3.1. Body-mounted instrumentation

In parallel to the approach presented in the previous section, we have also worked on demonstrating the pertinence of observing the trunk using a movement sensor placed on the back of valid subjects (Azevedo & Héliot, 2005). Indeed, as seen before, the trunk normally initiates the sit-to-stand transfer. We have placed on the back of 10 valid subjects, at anatomical C7 level, an accelerometer. Trunk acceleration patterns present low intra and inter-variability as well as a high temporal reproducibility and are therefore a nice characteristic "signature" of the sit-to-stand transfer (see Fig.12).
It is possible to apply techniques such as abrupt changes theory (Basseville & Nikiforov, 1993) to detect the pattern of sit to stand "intention". This technique allows detecting robustly the transfer initiation with a good sensitivity. The algorithm is able to reject a "false" sit-to-stand movement involving trunk movements such as grasping an object placed in front of the person. Indeed, the acceleration pattern signs selectively the motion.

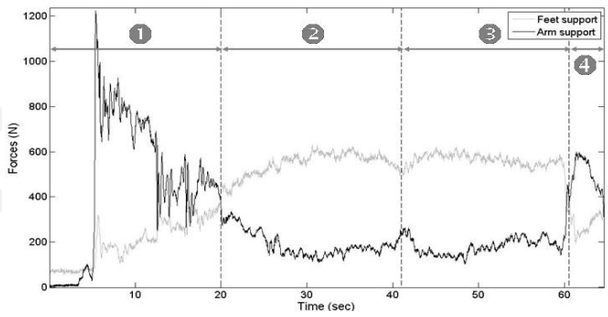


Figure 9. Patient #3, trial 6. Total feet and arm support. Phase labelled 1 corresponds to sit to stand phase, 2+3 corresponds to standing, and 4 to knee flexion

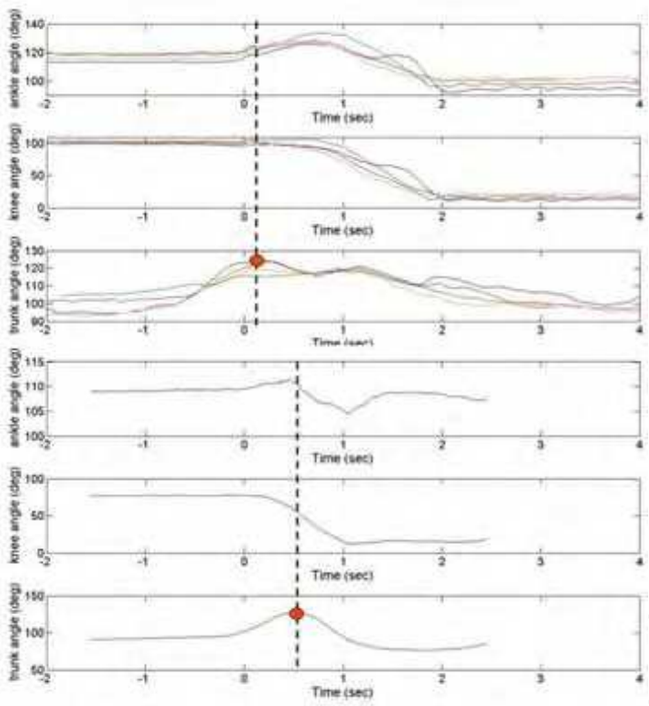


Figure 10. Posture coordination during sit to stand. Top**:** Patient #1, over 4 trials, Bottom**:** valid subject. The red dot indicates the maximum trunk bending

It is important to notice here that the detection of transfer has to occur as soon as possible before the legs should start moving to displace the body centre of mass from the seat to the feet (Fig.12). Around 600ms separate the instant when the trunk starts bending forward and the instant when the legs enter in extension movement. It is also necessary to recall here, that lower limb muscles start to contract before the legs move in order to prepare the

motion. These so-called anticipative postural adjustments should take place ideally together with trunk movement.

In order to apply these results on patient FES-assisted sit to stand it is necessary to train paraplegic patients in executing an optimal trunk movement in order to benefit from its inertia in the standing transfer. The detection algorithm should then be able to recognize patient intention to stand and trigger the proper stimulation sequences.

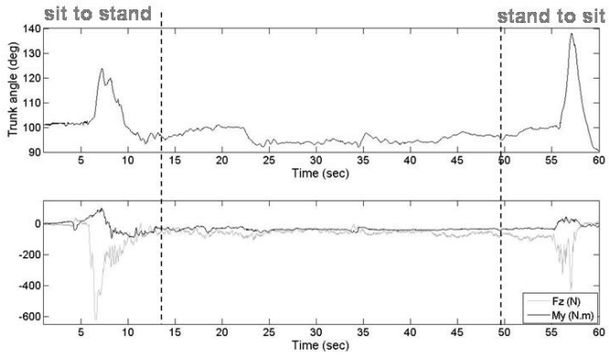


Figure 11. Correspondence between trunk angle and handle information. Patient #1, Trial 1. Top: angle, Bottom: right side vertical force and momentum around hip axis

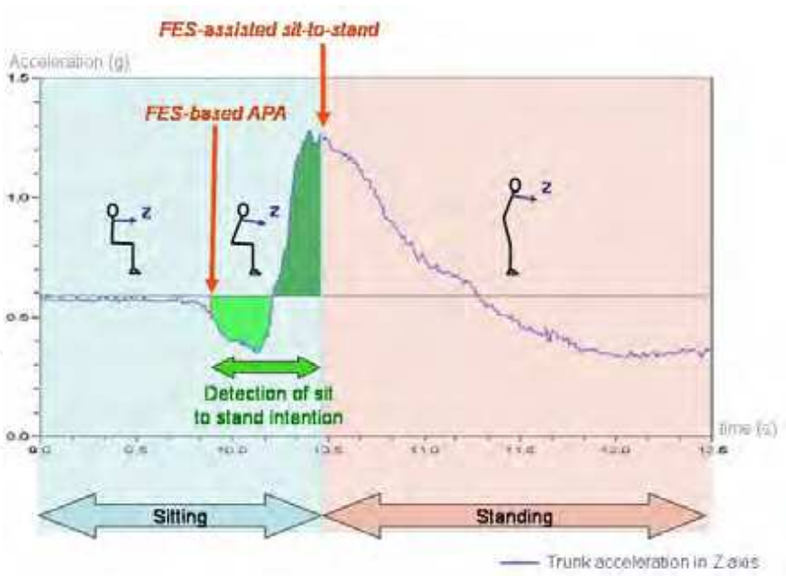


Figure 12. Principle of the detection of sit-to-stand based on the observation of trunk acceleration

The results presented in this section of the article clearly demonstrate the need for collaboration between lower and upper limbs in FES-assisted sit to stand. Triggering FES on arm support observation appears to be possible. A more anticipated timing of FES would be possible by detecting sit to stand trough trunk accelerations.

4. Classifying patient motor activities

In this section, we will address the issue of online classification of patient postures and motor activities, such as standing, sitting or walking for instance. Such a technique could be used to design a discrete-event based controller whereas the state estimation of the different joint angles could be used for a continuous controlling system. Both may be used in a hybrid controller where the best control strategy could be selected depending on the movement to be achieved.

Online classification can be performed by using neural networks and sensors such as accelerometers, when the purpose is only to detect phases of movements. It has been successfully applied with ageing persons in order to detect falling and to perform global activity monitoring (Fourty, et al., 2006 ; 2007) and thus could be used with disabled patients employing FES systems.

The classification algorithms described in the literature (Rumelhart & Mac Clelland, 1986) are generally implemented on desk computers. In biomedical engineering, and more specifically in the domain of ambulatory monitoring (Iwata, et al., 1990), classification is performed "off-line" from data collected on wearable systems. Our approach to the ambulatory monitoring of human activities is based on the design of wearable devices for automatic labeling. The aim of the procedure is to save time, reduce memory size and obtain relevant data. This constitutes a pattern recognition problem under specific constraints. Before describing the classification implementation, we briefly present the portable acquisition system.

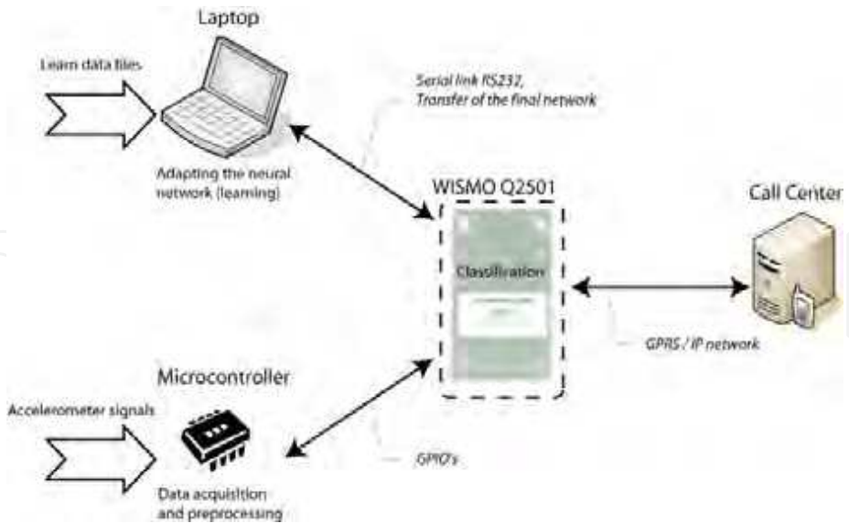


Figure 13. Hardware architecture

4.1. Materials

We use a microcontroller-based board with an ultra low power MSP430F169. One ADXL320 bi-axial accelerometer from Analog Device will sense activity. In order to quantify the patient's activity, some basic movements have to be recognised: steady-state movements (standing upright, sitting, walking, etc.) and transitional movements (sitting to standing, leaning to standing, etc.). This recognition in the system is done by the learning phase of an artificial neural network. Optimized learning can be done "off-line" on a classical computer, and only the pattern recognition algorithm and its associated memory have to be downloaded to the system. The Fig.13 describes the hardware system architecture.

4.2. A specific Artificial Neural Network (ANN)

To implement this classification we use hypersphere clustering with an incremental neural network. It is based on the evaluation of distances between the input vector and stored vectors in the memory. One n-dimension vector can be represented by a point in an n-dimensional space. Each component is a feature of the pattern to be recognized. Features can be raw data, or much more representative values given by feature-extraction procedures. A reference vector, the centroid, with its associated threshold, the radius, is labelled with a class. This defines a "prototype" which is represented by a hypersphere in an n-dimension space. A prototype is fired when an input point is situated within the hypersphere. Thus, fired prototypes participate in the final decision. This is the general functioning of hypersphere clustering-based methods.

4.2.1. Global structure and state dynamics

We are going to use some notations in this section:

- $I_0 = (I_{01},\ldots,I_{0n})$ and $I_1 = (I_{11},\ldots,I_{1n})$ are input vectors,
- I_{2j}, I_{3j} are output values of the second layer cell,
- R_j, $W_j = (W_{j1},\ldots,W_{jn})$ are radius (threshold) and coordinates of the centroid (reference vector) of the hypersphere (cell of the second layer)

Input layer (normalisation-saturation): The input layer performs a normalisation-saturation of the inputs in an eight bit resolution. An input value between Imin and Imax is transformed in the range of 0-255. Unexpected data below Imin or above Imax are set to 0 or 255, respectively. Each input comes from one real input datum, and each output is connected to all the cells in the hidden layer.

Hidden layer (prototypes): The hidden layer consists in prototype cells that compute distances between a normalised input vector and reference vectors (the centroids of the hyperspheres in the n-dimension space). Then, each cell makes a comparison between the computed distance and a threshold (the radius of the hypersphere) in order to obtain the following outputs: Output I2 is connected to a special cell that stores the minimum distance obtained, with the corresponding class. Output I3 is connected to only one output cell corresponding to the labelled class. The prototype is fired if the distance is less than the radius. The output also depends on the fact that the radius is set to the minimum, which means that during the learning phase it was reduced to the minimum value by examples from wrong classes. This situation occurs within an uncertain decision zone.

Norm: We will now consider the norm used to compute distances. In a continuous space the norms are strictly equivalent in a mathematical sense. But in a discrete space, things are different because parameters and data are integers. We can show that norm 1 is the best one

because it ensures the finest space clustering with the smallest step of number of points included in the hypersphere, with a unit increment or decrement of R. For a given radius the smallest number of points included within the hypersphere is also observed for norm 1. In terms of classification abilities, the radius can be tuned more precisely. Moreover, this norm requires only additions, subtractions, and comparisons. Norm 1 proves clearly to be the best, and was implemented on our algorithm.

Output layer (classes): Each cell of the output layer corresponds to one class and all the prototypes of the previous layer labelled with the same class are connected to it. Then, the operation carried out consists in a logical OR so that the output can be 0, 1, 2, or 3. Thus, the discriminent elements are only the types of prototype fired for each class :

0 : no prototype fired
1 : only reduced (R=Rmin) prototypes fired
2 : non-reduced prototypes fired
3 : both types of prototype fired

The most important characteristic of this algorithm is that it does not take into account statistical criteria (for instance the number of prototypes fired is not evaluated). This ensures the recognition of rare but well-defined events, a situation which frequently occurs in biomedical applications.

Fig.14 summarizes the global structure.

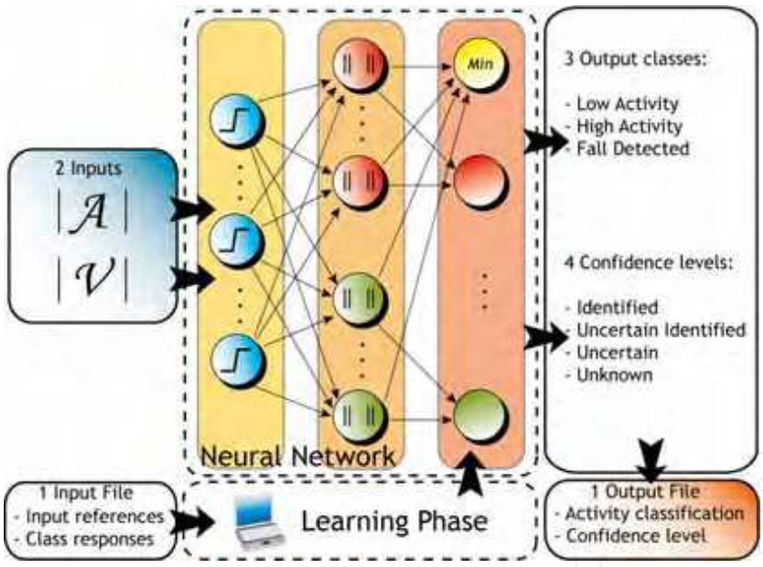


Figure 14. Overview of the ANN

4.2.2. Connection dynamics

Recognition process : The recognition phase is quite simple. The possible responses of the network are the following: unknown, uncertain, uncertain identified, and identified, depending on the criteria reported in Table 2. In all cases, a list of fired classes is given in decreasing order of confidence. We note that the nearest neighbour criterion is only used to

discriminate between uncertain classifications because this criterion is highly dependent on the way the network is learned (positions of the examples). Nonetheless, most of the time it becomes the best and simplest criterion when others have failed.

Learning rules : There are three main parameters in which a learning rule can be applied: creation/destruction of prototypes, displacement of the centroid, and adjustment of the radius. Papers on different algorithms using the creation/reducing radius (Nestor™ system), centroid position, and creation/position/radius have been published (Judge J., et al., 1996). Most of them do not affect more than one parameter at a time. Moreover, few algorithms can remove a prototype, and this could be useful when the set of examples includes errors. Some algorithms introduce an activation value for each prototype and use it in the recognition phase. We do not use this because of the statistical effect of this parameter. The learning phase becomes sensitive to the class representation in the learning set. Indeed, this explains why we developed our own algorithm, enabling creation and removal of prototypes, and simultaneous adjustment of the centroid position and the radius (increase or decrease) of the hypersphere (Table 3).

Four learning parameters appear: α and α′ set the amplitude of the correction (0 means no correction, 1 excludes the sample from the prototype); and β and β′ set the proportion between the centroid displacement (max when 1) and the radius adjustment (max when 0). Varying these parameters allows adjustment of the learning rule to the set of examples.

Identified	Only one class has obtained 2 or 3
Uncertain identified	Several classes have the same highest score but one class has the nearest neighbour (given by the "min " cell) Only one class has obtained 1 The nearest neighbour if no classes are fired (useful when a decision must always be taken)
Uncertain	Several classes have the same highest score but no nearest neighbour
Unidentified	No class fired and no nearest neighbour

Table 2. Recognition confidence level

Situation	Action
No prototype fired	Creation of a prototype where $W_i=I_{1i}$, R=Rmax or R=min distance of the centroid of prototypes of wrong classes Creation, if necessary, of a cell in the output layer, for the first occurrence of this class
At least one prototype fired	The nearest is approached and its radius is increased according to the formulae $R = R + \alpha(1-\beta)\left\|W - I_1\right\|_1 \quad \alpha,\beta \in [0,1]$ $W_i = W_i + \alpha\beta(I_{1i} - W_i)$ the increase of R is limited to Rmax.
R=Rmin	If this occurs subsequently n times, the prototype is removed
R>Rmin	Radius is reduced and the centroid is displaced according to the formula $\Delta = \alpha'\left(R - \left\|W - I_1\right\|_1 + 1\right)$ $R = R - (1-\beta')\Delta$ $W_i = W_i + \beta'\Delta\frac{(W_i - I_{1i})}{\left\|W - I_1\right\|_1} \quad \alpha',\beta' \in [0,1]$ R can be reduced up to Rmin.

Table 3. Summary of learning rules

The advantages of such a neural network are the following:

- It can be easily implemented on a microcontroller.
- It is an incremental neural network, so that a new configuration can be learned without the need for learning again with the whole set of examples.
- The neural network algorithm avoids the consideration of statistics, which provides a learning phase less sensitive to the learning set, and the rare events can be well identified
- Unexplored spaces provide unknown responses, thus avoiding misclassification. The unlabelled data are stored, analysed "off-line", and then learned.

4.3. Validation of the prototype

The measurement of acceleration along two axes (horizontal and vertical) enabling fall detection is used to monitor gait activity of the patient. The use of the neural network method presented previously needs relevant input vector in order to provide relevant classification. To find out the best input the Neural Network should be provided with, we have assessed many different cases such as acceleration along x and y axes, average and standard deviation of acceleration or magnitude of acceleration and velocity. The result of this evaluation is that the best inputs to analyse the gait activity of the patient are the magnitude of acceleration and velocity. We have chosen three different output classes representing low and high activity respectively for instance walking and running, and fall detection.

Computation of velocity: The main difficulty encountered with the computation of the velocity is the offset signal stemming from accelerometers that disturbs deeply the result of the velocity. We have observed this offset signal on experimental measurements. It is not a constant value. To overcome this problem, we propose to compute the velocity by using centred accelerations, where the average is computed over a sliding window, which can be adapted according to accelerometer types.

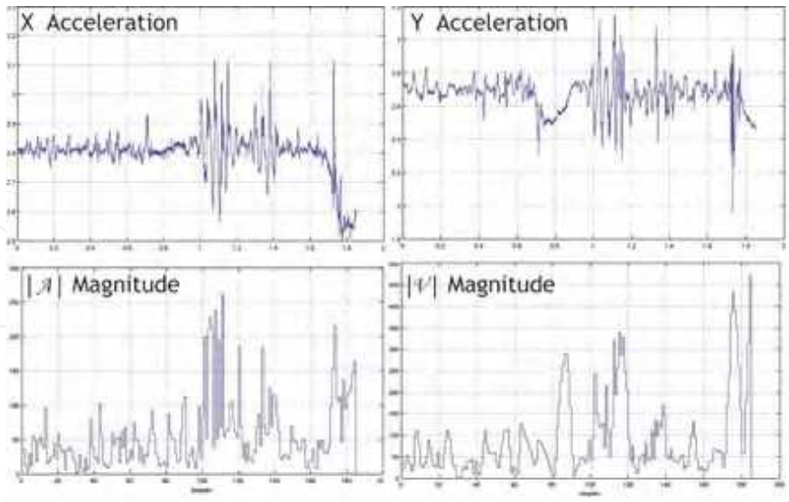


Figure 15. Sensor outputs and computed vectors

Learning Phase: We used some experimental data streams from elderly people simulating different activities such as walking, running and falling down. The reference file used is presented Fig.15. This file contains three different activities, which are:

- Low activity: t=0s, t=10s (walking, sitting)
- High activity: t>10s, t=16s (running)
- Fall detection: t>16s

Recognition phase: Fig.16 presents the recognition phase performing on the reference file by using the neural network. Each activity is well detected and recognised. The y axis of the Fig.16.b represents the classes such: 1→ low-activity, 2→ high-activity, 3→Fall.

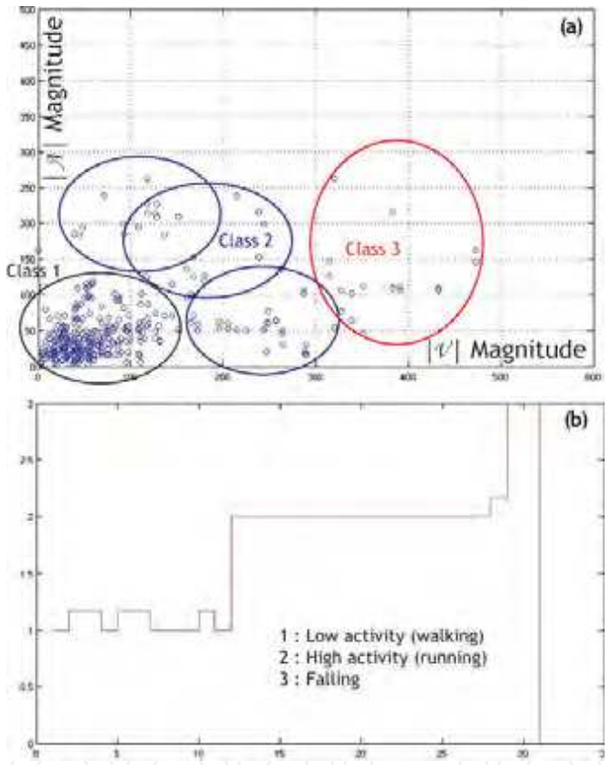


Figure 16. Recognition on learned file

Validation: To validate this development, we have performed the classification method on different patients keeping the previous learning phase as reference in order to estimate the robustness. Fig.17 shows the capacity to detect and discriminate the three phases even with a learning phase carried out on another patient. The results of the classification activities show the first period as an intermediate class between 1 and 2 (mean value is about 1,5). The second period is also higher than 2. These intermediate results (class 1,5 for instance) mean that there is an uncertainty between both of them (classes 1 and 2). Then, we compute an average value within this ambiguous period, which returns an intermediate class result. These results are

due to unknown activities detection which is obtained by using the nearest neighbour criterion. This criterion can propose alternatively class 1 or 2 as the nearest neighbour.

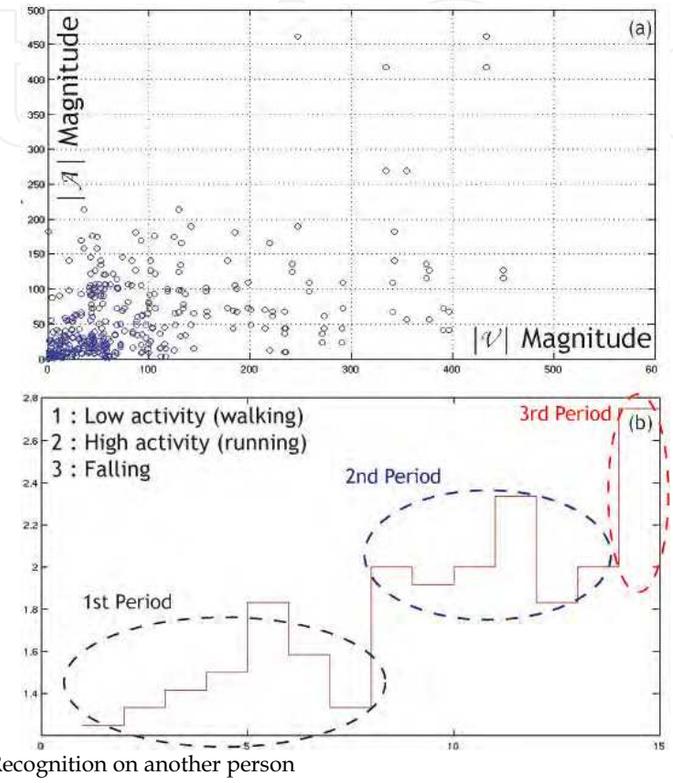


Figure 17. Recognition on another person

5. Conclusion

In this chapter we have introduced several approaches for the estimation, detection and classification of the posture or movement of disabled patients. They are founded on non-intrusive sensors and are meant for closed-loop control in the context of functional restoration via electrical stimulation.

While taking advantage of an available walker, we have investigated the potential of using only arm support measurements. Then, we found that we can reconstruct patients standing postures only with a fairly large uncertainty. However, we found that these measurements can be used for detecting patients trunk movement. When miniature sensors are attached onto the patient's body, then it is possible to efficiently detect transitions such as sit-to-stand or classify steady-state movements such as standing, sitting or walking. The two technologies could eventually be combined.

Finally, a synergy between artificial and voluntary movements can indeed be achieved by using these methods. For instance, in a FES-assisted sit-to-stand movement, the electrical stimulation should be triggered according to the patient's trunk movements.

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Human-robot interaction research is diverse and covers a wide range of topics. All aspects of human factors and robotics are within the purview of HRI research so far as they provide insight into how to improve our understanding in developing effective tools, protocols, and systems to enhance HRI. For example, a significant research effort is being devoted to designing human-robot interface that makes it easier for the people to interact with robots. HRI is an extremely active research field where new and important work is being published at a fast pace. It is neither possible nor is it our intention to cover every important work in this important research field in one volume. However, we believe that HRI as a research field has matured enough to merit a compilation of the outstanding work in the field in the form of a book. This book, which presents outstanding work from the leading HRI researchers covering a wide spectrum of topics, is an effort to capture and present some of the important contributions in HRI in one volume. We hope that this book will benefit both experts and novice and provide a thorough understanding of the exciting field of HRI.

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