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An Expert System for Supporting the Conceptual Design of Controllers for Lower Limbs Rehabilitation Systems

V.C. Moulianitis, V.N. Syrimpeis, N.A. Aspragathos
Mechanical Engineering and Aeronautics Dept.
University of Patras
Patras, 26500, Greece.

E.C. Panagiotopoulos
Department of Orthopedic Surgery
General University Hospital of Patras
Patras, 26504, Greece.

***Abstract*—In this paper, an Expert System (ES) for supporting the conceptual design of a closed loop control scheme for the rehabilitation of lower limb disabilities is presented. The design of the controllers is based on the exploitation of experts knowledge concerning the gait cycle and uses pathological muscles electromyographical (EMG) data for feedback signals. EMGs from normal muscles are also used to detect the gait phases and an expert system for supporting the selection of the suitable set of muscles is developed. The acquired knowledge concerning the gait phases and the muscles EMGs is presented. Finally, a case study of designing a controller for the correction of the drop foot syndrome is presented.**

Keywords-expert system, control system, EMG, gait phases

I. Introduction

The neuromuscular system of lower limbs is a very complex control system. Many rehabilitation techniques such as Orthotics, Prosthetics and Functional Electrical Stimulation (FES) were proposed for the rehabilitation of the lower limbs pathologies. Orthotics, Prosthetics and FES present different advantages and disadvantages and the choice among them as the rehabilitation technique is based on the pathology aspects. Whenever FES can be applied, it helps towards preventing muscle disuse atrophy, improving skin blood flow and preventing pressure sores, improving spasticity and preventing contractures.

One of the first applications of FES to the lower limbs is the correction of the Drop-Foot Syndrome through the stimulation of the common peroneal nerve [1]. FES based Drop-Foot rehabilitation systems are better than other orthosis systems, since the active contraction of the muscles stimulates the blood circulation, there is better afferent feedback, walking distance is increased, the system is not custom made, the movement is energy efficient, and finally, the correction system is cosmetically better accepted [2].

The development of Drop-Foot correction systems based on Functional Electrical Stimulation (FES) has gone through the following stages [3]: Hard-wired single-channel surface Drop-Foot stimulators (DFS); Hard-wired multichannel surface DFS; Hard-wired single channel implanted DFS; Micro-processor based surface and implanted DFS; Artificial and "natural" sensors as replacement for the foot-switch; DFS systems incorporating real-time control of FES and completely implanted DFS systems. In addition, EMGs from lower limb's muscles that can be used as input to the FES rehabilitation control system are proposed in [4]-[7].

The use of "natural" sensors is a great contribution to the development of completely implanted DFS systems. The implanted systems eliminate part of the problems appeared in surface DFS. Control systems approaches based on Artificial Intelligence for the rehabilitation of the lower limbs pathologies are very promising, since it is very difficult to obtain an exact model of the neuromusculoskeletal system. In addition, even the approximate models are so complex, that cannot be used in conventional controllers due to high computational time requirements. Reference [8] combined machine-learning techniques, mostly an Adaptive Logic Network, for control of FES using natural sensors. In [7] a fuzzy logic control scheme is presented that uses electromyographic data from muscles to identify the gait phases and to correct the drop foot syndrome by stimulating specific muscles or nerves.

In order to design control systems for the rehabilitation of lower limbs disabilities, it is necessary to have full knowledge considering the gait phases and gait events of the gait cycle. The detection of the gait phases and events of a gait cycle is necessary for the determination of the correct timing of the pathological, muscles or nerves, stimulation.

Gait event detection has received considerable attention using various signal sources including the use of foot switches, tilt sensors, accelerometers and sensory nerve activity [9].

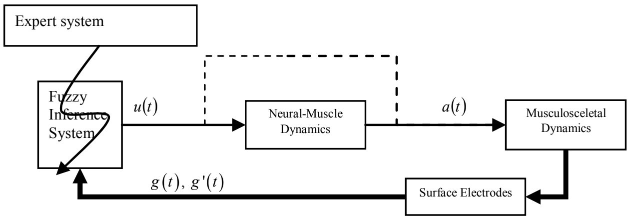

Figure 1: The considered control scheme

Surface EMG signals from upper trunk muscles were used to predict intended lower extremity movements for reciprocal walking or postural correction for static standing [10]. In [9], implanted electrodes were used in subjects with spastic diplegia as a result of cerebral palsy (CP) in order to detect the gait events. In 80% of the event detection, the prediction error was less than 0.3%. The results of these works are encouraging towards using only EMG measurements for gait event detection for the design of FES control systems.

This paper introduces an expert system that will support the conceptual design scheme for the design of rehabilitation control systems in cases of lower limb's disabilities. The concept of the closed loop control scheme and its requirements are presented. The knowledge acquired by experts and the bibliography concerning the gait cycle, its refinement, organization and finally the integration in a single system that proposes the suitable selection of muscles for the detection of the gait cycles is presented. Finally, the results are analyzed and discussed.

II. THE CONCEPTUAL DESIGN OF THE CONTROL SCHEME

The muscles are excitated by the nerves, so the main functional requirement of the considered control scheme is to rehabilitate the function of an intact set of muscles that are not correctly excitated due to nerve malfunction.

The main requirement of the control system is to excitate the set of muscles that are not excitated due to nerve malfunction, with the correct electrical signal at the correct timing. In order to satisfy this specification two sets of muscles are needed:

The 1st set includes muscles that are not excitated from the nerves and have to be excitated by electrical pulses.

The 2nd one is the set of muscles that is normally excitated by the nerves and can be used to tune the excitation electrical signal at the correct timing.

Since the lower limb is a very complex system and it is very difficult and practically impossible to be modelled and particularly to identify an accurate model for a specific subject, a fuzzy logic based control scheme that exploits the expert knowledge concerning the gait cycle is leading to a promising solution without dealing with high complexity models. The expert knowledge is acquired by extensive bibliographical review as well as by interviewing experts in this field.

Both sets of muscles as well as the integrated knowledge are used in the rule base of the Fuzzy Inference System (FIS) as it is shown in Fig.1. The output of the FIS is the stimulation signal $u(t)$ to the pathological nerve or the stimulation signal $a(t)$ straight to the muscles, by passing the neural-muscle dynamics, as it is shown in Fig.1. The feedback $g(t), \dot{g}(t)$ is used as input to the FIS.

The knowledge extracted from normal lower limbs muscle EMGs concerning the detection of gait phases is integrated in an ES in order to derive automatically the most suitable muscles for phase detection.

In the following, the knowledge used to derive the Fuzzy Inference System Rule Base is presented.

III. KNOWLEDGE CONCERNING THE GAIT CYCLE

In this section the domain knowledge is presented in terms of the gait phases that should be detected and of the muscles that are used to detect the required gait phases.

According to [11], the gait cycle (fig. 2) is divided in one event and seven phases namely:

- **Heel Strike** (HS) or **Initial Contact** (IC).
- **Loading Response** (LR).
- **Mid Stance** (MSt).
- **Terminal Stance** (TSt).
- **Pre Swing** (PSw).
- **Initial Swing** (ISw).
- **Mid Swing** (MSw).
- **Terminal Swing** (TSw).

Every muscle in a normal gait cycle presents a pattern EMG. Fig.3 shows the EMG patterns for Adductor Magnus muscle and Soleus muscle in a normal gait cycle. The knowledge derived from these EMGs is the level of excitation that the muscle should have during the gait phases. For example, Soleus should have an excitation of 0.2 approximately during LR phase, 0.35 during MSt, 0.8 during TSt and 0 during the other phases. This is the reference stimulation signal that the control system should maintain during the gait cycle. Taking into account the feedback signal $g(t), \dot{g}(t)$ measured by surface electrodes, the error is formed and is expressed by three (3) rules, for each of the eight (8) gait phases:

If error is positive then the excitation should be higher.

If error is negative then the excitation should be lower.

If error is zero then the excitation should not change.

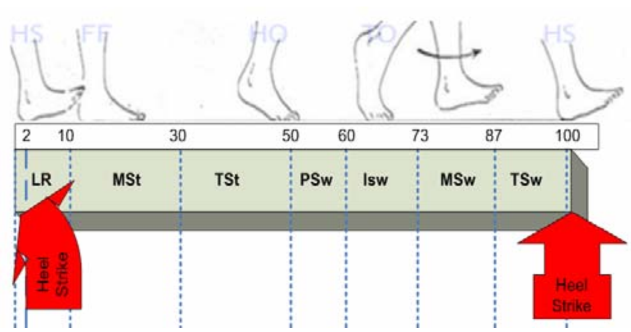

Figure 2: The gait cycle

This method produces twenty four (24) rules but the information for stimulation timing, that is when the excitation should start and stop is missing. The prototype signal cannot be used since people walk with a range of velocities.

The second set of working muscles is used to solve this problem. Using EMGs from normal muscles the gait phases can be detected. For example, Adductor Magnus is the only lower limb muscle that during a gait cycle presents its maximum excitation in the HS event. Therefore Adductor Magnus EMG can be used to detect the HS event as it is shown in Fig.3. Therefore, in the rules presented above, the detection part of the gait phases must be included.

The knowledge concerning the detection of the gait phases is organised and an ES is developed that produces the set of muscles that are needed in order to detect one or more gait phases.

IV. The Expert system for Phase detection

The development of the ES is based on the knowledge concerning the human locomotion acquired from literature and by interviewing experts.

The inputs of the ES are the gait phases and the HS event that should be detected, as well as constraints posed by the muscle's functionality. An experienced user may use the constraints for decreasing the searching time while an inexperienced user may not use any constraints.

The output of the system is the suitable set of muscles that can be used in order to detect the desired gait phases and HS event. A scheme of the expert system is shown in fig. 4.

A screenshot of the ES interface is shown in Fig. 5.

The ES includes knowledge concerning the gait phases, presented in the previous section, and electromyographic data provided by normal muscles. As it is shown in [11], every muscle presents a certain prototype EMG during a normal gait cycle. Studying these prototype EMGs, results are extracted concerning the phases that can be detected easier.

The characteristics, namely *width* and *activation percentage*, of the muscles EMGs of the lower limb are presented in Table 1.

W*idth* is the number of the phases that a muscle is activated during the gait cycle. The fewer phases a muscle remains activated, the better for the detection of the gait phases, since the muscle presents a characteristic behavior. For example, as Fig. 3 shows, Soleus is activated in three gait phases (LR, MSt and TSt) and Adductor Magnus is activated also in three gait phases (HS, LR and TSw).

The *activation percentage* is the maximum normalized activation of a muscle in a gait cycle. The normalization is achieved by measuring the activation each muscle can perform during the Maximum Manual Muscle Test [11] which is usually higher than the activation that is presented during a gait cycle. The higher activation a muscle presents in a gait phase, the better for the detection of the gait phase. For example, as Fig. 3 shows, Adductor Magnus has an *activation percentage* of 0.4 approximately during the HS event.

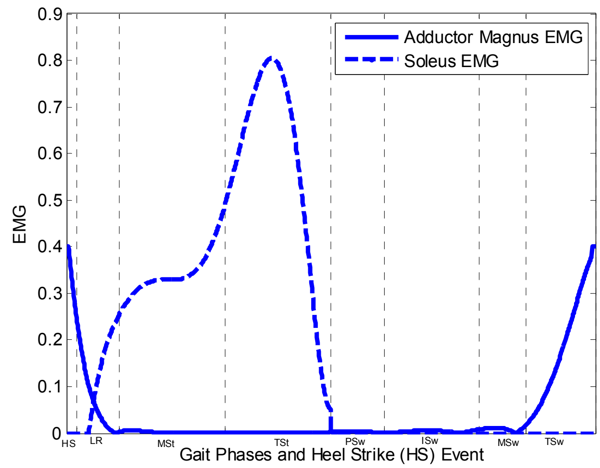

Figure 3: Soleus and Adductor Magnus EMGs in a gait cycle

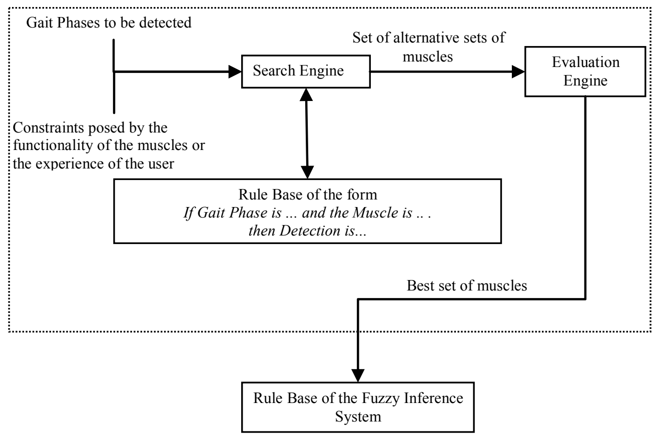

Figure 4: The expert system for phase detection

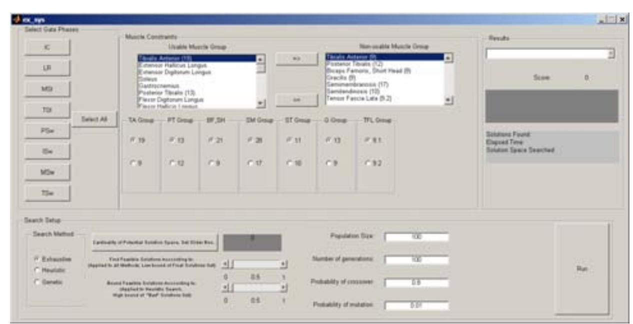
Figure 5: The Expert System

Table 1 EMG characteristics

Muscle	Width	Activation %
Tibialis Anterior (19)	6	42
Tibialis Anterior (9)	7	42
Extensor Hallicus Longus	6	40
Extensor Digitorum Longus	6	30
Soleus	3	87
Gastrocnemius	3	79
Posterior Tibialis (13)	3	40
Posterior Tibialis (12)	3	40
Flexor Digitorum Longus	2	41
Flexor Hallicis Longus	2	80
Peroneus Longus	3	42
Peroneus Brevis	2	29
Vastus Intermedius	4	21
Vastus Lateralis	4	29
Vastus Medialis Longus	4	20
Vastus Medialis Oblique	4	37
Rectus Femoris	2	20
Biceps Femoris, Short Head (21)	2	20
Biceps Femoris, Short Head (9)	3	20
Popliteus	7	20
Gastrocnemius	3	79

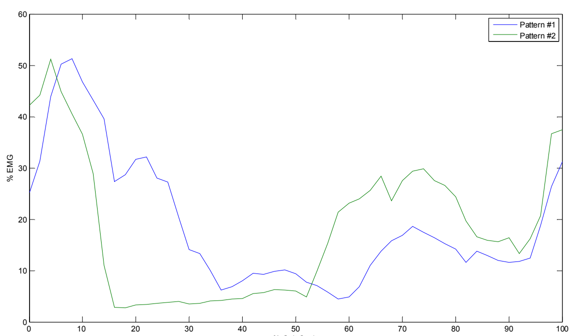

Figure 6: Tibialis Anterior prototype EMGs

In Table 1, three pairs of muscles present two prototypes EMGs for the normal gait cycle. This means that some people walk according to the one prototype, while the others walk according to the second prototype for the same muscle. In [6], both prototypes are analyzed and Fig. 6 presents the two prototypes for Tibialis Anterior muscle. In a sample of 28 normal walkers, 19 walk according to the green line prototype and 9 according to the blue line prototype, see Table 1 and Fig. 6. The constraints part of the ES offers to the user the capability of choosing the right prototype for a specific patient.

Table 2 Rules for the first four phases

Muscles \ Gait Phases	IC	LR	MSt	TSt
Tibialis Anterior (19)	nice	nice		
Tibialis Anterior (9)	nice	nice	mild	
Extensor Hallicus Longus	mild	mild		
Extensor Digitorum Longus	mild	mild		
Soleus		bad	mild	Nice
Gastrocnemius		Bad	mild	nice
Posterior Tibialis (13)		Mild	bad	nice
Posterior Tibialis (12)		Mild	mild	nice

Table 3 Rules for the last four phases

Muscles \ Gait Phases	PSw	Isw	MSw	TSw
Tibialis Anterior (19)	mild	Mild	mild	nice
Tibialis Anterior (9)	mild	Mild	mild	nice
Extensor Hallicus Longus	mild	Nice	mild	mild
Extensor Digitorum Longus	mild	Mild	mild	mild
Soleus				
Gastrocnemius				
Posterior Tibialis (13)				
Posterior Tibialis (12)				

The reliability of the phase detection depends on the activation percentage and the phases where the activation starts and finishes. The knowledge concerning the phase detection is formulated with 250 rules of the following type:

If Gait Phase is ... and the Muscle is .. .then Detection is... (3)

Table 2 and 3 show a part of the ES rule base where the columns indicate the Gait Phases, the rows the available muscles and the cells the detection quality of a gait phase using

the EMG of the corresponding muscle. Three qualitative values are used namely, Nice, Mild and Bad and are mapped to quantitative values [1, 0.6, 0.3].

The ES has three search strategies that use the quantitative values in order to find the acceptable muscle combinations that detect the gait phases:

- An exhaustive method that searches all the search space that has the following cardinality

$$n_c = \sum_{i=1}^{\min(n,m)} \binom{m}{i} \qquad (1)$$

Where, m is the available muscle number that can be used to detect the gait phases and n the number of the gait phases to be detected. Every alternative combination of muscles forms a vector with length equal to the number of gait faces that must be detected. For example in the case of three gait event detection and a set of two available muscles the search space contains three elements: $S_1 = (1,1,0.3)$, $S_2 = (0.6,1,1)$ and $S_3 = \max(S_1, S_2) = (1,1,1)$.

- A heuristic search method that combines only the best alternatives. The search method is presented thoroughly in [12].
- A genetic algorithm, where each gene represents a set of muscles and the length of the string depends on the number of events that the muscles must detect. In the worst case, the maximum length of the string is equal to the number of phases.

The first two methods produces a set of alternative solutions while the third one finds the best solution according to the evaluation score presented in the following. The metric function used to find the set of alternative solutions is the Euclidean space norm. If the norm of the vector is considered to be higher than a limit chosen by the designer then it is considered to be an alternative solution.

Because it is possible that a great number of muscles combinations could match to the functional requirements, constraints are applied to the available muscle set. An experienced user can exclude muscles that do not detect the desired gait phases. For example, Soleus is not activated during the swing phases, therefore it cannot be used for the detection of any swing phase.

The solutions are ranked according to three criteria using a compensatory technique:

$$Score = \frac{Cr_1 + Cr_2 + Cr_3}{3} \quad (2)$$

Where Cr_1 represents the detection quality of the muscle set according to the required gait phases, Cr_2 is the maximum of the activation percentages of the muscle set (Table 1) and Cr_3 is the maximum of the inverse of the width of muscles' set EMG (Table 1). For example assuming that the required phases to be detected are IC and MSt. According to Table 1, Tibialis Anterior (19) can detect nicely IC event, while it cannot detect the MSt. Soleus can detect mildely MSt phase while it cannot detect IC. The set of these two muscles present a [Nice Mild] or [1 0.6] detection quality for the required gait phases. The Cr_1 value is calculated using the Euclidean norm of the detection quality normalized by the Euclidean norm of the best detection quality

Table 4: Simulation results of the expert system

Solution #	Muscle Set
1	Soleus Adductor Magnus
2	Gastrocnemius Adductor Magnus
3	Posterior Tibialis Adductor Magnus
4	Peroneus Longus Adductor Magnus

[Nice Nice] or [1 1]. In this case $Cr_1 = \frac{\sqrt{1^2 + 0.6^2}}{\sqrt{1^2 + 1^2}} = 0.82$, $Cr_2 = \max(0.42, 0.87) = 0,87$ and $Cr_3 = \max(1/6, 1/3) = 0.33$.

V. Results

In [7] a control scheme for a drop foot correction system based in fuzzy logic has been presented. During the development of the system it was decided that the EMG taken from the Extensor Digitorum Longus, one of the main dorsiflexor of the foot, will be used as the feedback signal to correct the excitation signal of the peroneal nerve. For the detection of the gait event Initial Contact (IC) and the Terminal Stance (TSt) phase, the expert system, presented in this paper, was used and produced the results shown in Table 4. The set of the available muscles has 24 members forming a search space of 300 nodes according to (1).

For the FIS twenty four rules of the form were created:

$$\text{If } g_{AM}(t) \text{ is … and } \dot{g}_{AM}(t) \text{ is … and } g_S(t) \text{ is … and } g_{EDL}(t) \text{ is … Then } U(t) \text{ is …} \quad (5)$$

A 10 gait cycle simulation was executed and the errors produced did not cause serious trouble during the gait cycles [7].

Conclusions

In this paper, an ES for the conceptual design of the control scheme for the rehabilitation of lower limb disabilities has been presented.

The ES is used to find a suitable set of muscles that will be used to detect one or more gait phases. Feedback EMGs from these muscles and the pathological muscles are used to develop the rule base of a FIS that produces the required stimulation signal to correct the gait cycle.

The knowledge concerning the gait cycle, acquired by the bibliography and by interviewing experts is presented and organized in rules.

A prototype system developed in MATLAB was used to support the design of a controller for the correction of the drop foot syndrome.

The main contributions of this paper are the acquisition and organization of the knowledge concerning the gait cycle and EMG data, the application of previously developed search method s to produce the best set of muscles that will be used for the development of control systems for the rehabilitation of lower limb disabilities, as well as the development of a prototype system in MATLAB.

The results are promising towards the development of a system that will take into account EMGs from the opposite limb and will derive automatically the FIS for the closed loop control system. In association with a neural network the controller will be optimized and the restoration of the gait will be closer to the normal.

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