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FUZZY AND LEARNING CONTROL OF FES INDUCED GAIT

T.J.A. de Vries, W.J.R. Velthuis, J. van Amerongen and P.H. Veltink

EL–BSC–RT, University of Twente, P.O.Box 217, 7500 AE Enschede, Netherlands
phone: +31–53 489 28 17, fax: +31–53 489 22 23, e–mail: T.J.A.deVries@el.utwente.nl

Abstract: Research is done to restore gait by means of functional electrical stimulation for people suffering from paraplegia. Difficulties are that muscle fatigue and heavily changing patient conditions deteriorate the performance of such systems. The design of feedback controllers is considered that adapt stimulation parameters to compensate for this deterioration. Conventional control (PID) gives good performance when muscle and leg dynamics are known, but requires recurring identification. By using fuzzy controllers based on general, qualitative knowledge, and by providing self–tuning capabilities through learning, identification might be avoided. Simulation studies confirm this.

Keywords: fuzzy control, learning control, adaptation, neural networks, splines, biomedical systems

1. INTRODUCTION

An injury of the nervous system in the spinal cord of a human being may result in paralysis of the muscles in the legs. The muscles are still able to function, but do not receive any electrical stimulation signals. They can be activated by artificially generating and delivering an electrical stimulation signal; this is referred to as *functional electrical stimulation* (FES; Veltink, 1993). Research is done to restore human gait using FES (Petrofsky, 1986). FES induced gait has to satisfy 3 *swing phase objectives* (Franken et al., 1995):

- The range of the angle of the hip joint, the *hip range*, has to be sufficient to obtain a desired step length.
- The *knee extension* has to be such that upper and lower leg are in line with each other at the moment the foot touches the ground.
- In the forward swing, the minimum distance between heel and ground, the *foot clearance*, has to be sufficient.

The relation between the electrical stimulation signals and the resulting leg movement depends on the leg and muscle dynamics. To obtain a satisfactory movement, a feedback controller is used to determine the stimulation parameters (figure 1). After each step taken, the controller may adapt parameters of the stimulator on basis of measurements of the movements of the leg.

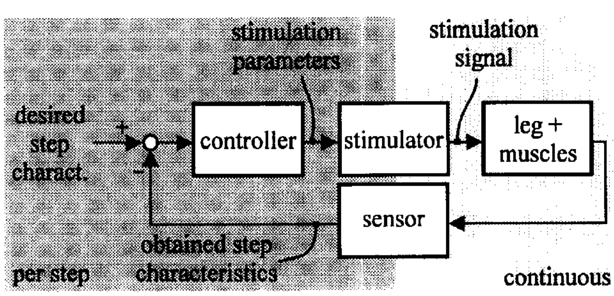

Fig. 1 Feedback control of FES induced gait

In control of FES induced gait the following two difficulties arise:

- Due to muscle fatigue, the muscle dynamics change during gait. Conventional control (PID) is able to give good performance when the muscle and leg dynamics are known (Franken et al., 1995). Hence, time–consuming identification is required before such controllers can be applied.
- The leg and muscle dynamics differ from patient to patient, and even from day to day for one patient. This implies that the above mentioned identification procedure needs to be done often.

General (qualitative) knowledge about which control action to take for particular situations is available beforehand. Such knowledge can easily be incorporated in a fuzzy controller (Lee, 1990). Therefore, use of a fuzzy controller might make identification superfluous. This is the first idea pursued in this paper.

It is well known that fuzzy controllers often require considerable tuning activities before a satisfactory performance is obtained. This can be avoided by making the controller self–tuning. One approach to obtain this, in line with the above, is to make use of a spline network (Brown and Harris, 1994) which has learning capabilities. This is the second idea that is discussed in this paper.

In section 2, the process is described shortly, i.e. the FES unit and leg and muscle dynamics. The design of the fuzzy controller and the learning controller are discussed in sections 3 and 4, respectively. Section 5 deals with simulation results obtained with both controllers. Conclusions are listed in section 6, finally.

2. FES UNIT AND LEG AND MUSCLE DYNAMICS

The FES unit and the muscles that are stimulated during gait are presented in figure 2. The FES unit consists of:

- *Sensors*, measuring the angles of the knee and hip joint.
- A *controller* determining stimulation parameters
- A *stimulator* that generates stimulation signals
- *Electrodes*, delivering the stimulation signals to the muscles.

To enable gait the following muscles have to be stimulated (figure 2):

1. *Hip flexors*. By stimulating these muscles, the hip range can be influenced
2. *Hamstrings*. Contraction of the hamstrings causes hip extension and knee flexion. Stimulation of these muscles gives control over the foot clearance in the forward swing

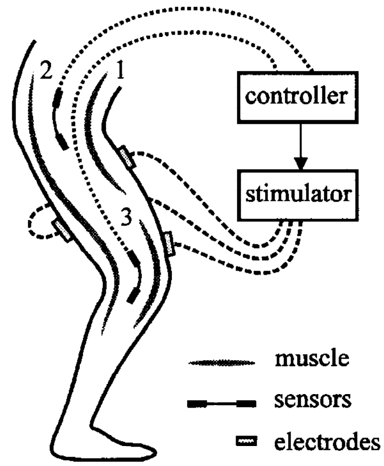

Fig. 2 FES unit and stimulated muscles

3. *Quadriceps*. The quadriceps mainly provide knee extension.

For each swing phase objective a particular muscle group needs to be stimulated. Therefore, 3 decoupled controllers are used, each determining the stimulation of one muscle group. The stimulation consists of a series of electrical pulses (figure 3). In this research, the controller can adapt the wait time (*WT*) and/or the burst time (*BT*). The stimulation signal is generated when the angle of the hip joint reaches a reference angle.

3. DESIGN OF THE FUZZY CONTROLLERS

The task of the *fuzzy hip range controller* is to obtain a desired hip range (*hr*). Initially the patient stands still, i.e. *hr*=0. The patient now has to accelerate until the desired step length is reached. This is done by increasing the desired hip range according to a trajectory such that the ultimately desired hip range (0.8 rad) is reached after the patient has taken a number of steps. So when starting to walk, the step lengt of the patient will increase smoothly.

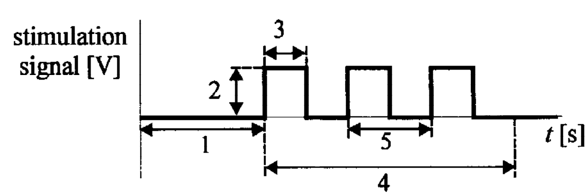

Fig. 3 Stimulation pattern.
1 = wait time (WT) 4 = burst time (BT)
2 = pulse amplitude 5 = interpulse interval (IPI)
3 = pulse width

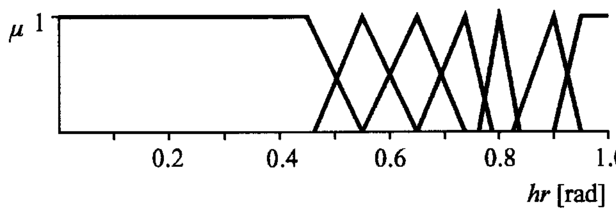

Fig. 4 Premise sets for the hip range controller

At the end of a step k the burst time BT of the hip flexors stimulation is adapted in order to let hr follow the desired trajectory. The response of hr to adaptations of BT is slow. Therefore, $hr(k+1)$ will not only be affected by the adaptation of BT at the end of step k, $\Delta BT(k)$, but also by $\Delta BT(k\text{-}1)$, $\Delta BT(k\text{-}2)$ ... The effect of previous adaptations of BT on $hr(k+1)$ can be accounted for properly by taking $hr(k)$, $hr(k\text{-}1)$ and $hr(k\text{-}2)$ as input variables for the hip range controller. Each of these 3 input variables is covered by 7 fuzzy premise sets, as shown in figure 4. The large number of fuzzy premise sets and the specific placement is chosen to enable sensitive control. The output of the fuzzy logic controller is $\Delta BT(k)$. The output variable is covered by 5 fuzzy consequence sets (figure 5).

Now that the fuzzy premise and consequence sets are given, the rules that define the relation between them can be discussed. A fuzzy consequence set has to be assigned to each combination of fuzzy premise sets. Therefore, the total number of rules will be $7{\cdot}7{\cdot}7=343$. For each rule the following procedure was followed:

1. Take a combination of 3 fuzzy premise sets (one for each input variable). Consider $hr(k-2)$, $hr(k-1)$ and $hr(k)$ to be equal to the input value where the grade of membership μ of the respective fuzzy sets equal 1
2. Predict $hr(k+1)$ in case the burst time BT is not adapted. This is done by considering a slow response of the hip range and damping in the hip joint
3. Determine the fuzzy consequence set on the basis of the difference between the desired and the predicted value of $hr(k+1)$. In case the desired value is larger/smaller than the predicted value, BT needs to be increased/decreased.

In figure 6 an example of the determination of the fuzzy

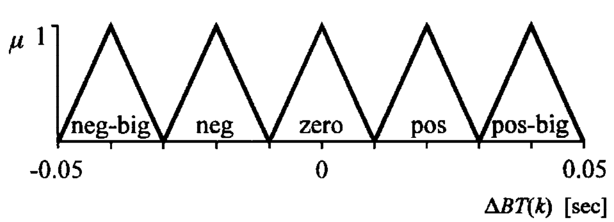

Fig. 5 Consequence sets, hip range controller

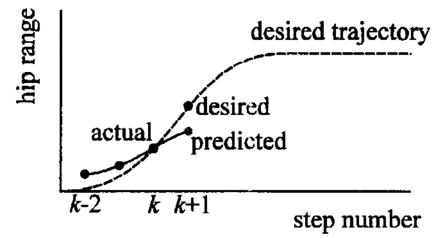

Fig. 6 Prediction of next hip range hr(k+1)

consequence set is given. In this example the predicted value of $hr(k+1)$ is somewhat smaller than the desired value. Therefore, the fuzzy consequence set 'pos' will be assigned to the combination of fuzzy premise sets.

Due to the large number of rules, tuning of the fuzzy hip range controller becomes time–consuming and complex.

The *fuzzy knee extension controller* has to guarantee that the upper and lower leg are in line with each other at the moment the foot touches the ground. Therefore, two conditions have to be fulfilled:

– The *rate of extension re*, $\varphi_{\text{upper leg, max}} - \varphi_{\text{lower leg, max}}$, has to be 0.
– $\varphi_{\text{upper leg, max}} - \varphi_{\text{upper leg, } \varphi\text{lower leg = max}}$, a measure for the *timing of extension te*, has to be 0.

These conditions can be fulfilled by adapting both the burst time BT and the wait time WT of the stimulation of the quadriceps. The qualitative knowledge about knee extension needed to control the stimulation of the quadriceps, is summarised in table 1. This knowledge can be incorporated in two fuzzy logic controllers:

– One for controlling the rate of extension by adapting BT. The input variable is the rate of extension, covered by 3 fuzzy premise sets {too small, ok, too large}. The output variable, $\Delta BT(k)$, is covered by 3 fuzzy consequence sets {neg, zero, pos}
– One that controls the timing of extension by adapting WT. The input variable is the timing error of extension and is covered by 3 fuzzy premise sets {too early, ok too late}. The output variable, $\Delta WT(k)$, is covered by 3 fuzzy consequence sets {neg, zero, pos}.

The *fuzzy foot clearance controller* has to provide for a minimum foot clearance in the forward swing. The

Table 1: Qualitative knowledge about the knee extension

too small	ok	too large	too early	ok	too late
increase *BT*	-	decrease *BT*	increase *WT*	-	decrease *WT*

Table 2: Qualitative knowledge about the foot clearance

too small	ok	too large
increase BT	-	decrease BT

qualitative knowledge needed to control the foot clearance is shown in table 2. The input of the controller is the foot clearance; the output is the adaptation of the burst time BT of the hamstrings.

4. DESIGN OF THE LEARNING CONTROLLER

Above, it was shown that the design of the fuzzy knee extension and the fuzzy foot clearance controller is relatively simple. Therefore, these controllers do not need to be self tuning. The design of the fuzzy hip range controller is time consuming and complicated though, due to the required tuning. This is why a learning controller is considered for control of the hip range. The learning controller has the same input and output variables as the fuzzy controller. However, each input variable is covered by a larger number of fuzzy premise sets (i.e. second order splines) as shown in figure 7. The output is obtained as a weighted summation of the grades of membership of the inputs. This structure resembles that of a neural network, and hence is referred to as a *spline network*.

Before operation, the weights of the network have to be initialised. This is done by learning the input–output relation of fuzzy controller discussed in the previous section. In this way, a-priori knowledge of process control is incorporated in the spline network.

The real time control and learning proceeds as follows:
1. Determine the adaptation of the burst time, $\Delta BT(k)$.
2. Stimulate with the adapted BT and evaluate the effect on the hip range at the end of the step by comparing the actual and the desired value of $hr(k+1)$. If actual value << desired value (actual value >> desired value), the error in the applied output of the network, $\Delta BT(k)$, is considered to be + (–) one interpulse interval .
3. Adapt the weights of the network on basis of the error in the output (Brown and Harris, 1994; Van Luenen, 1993).

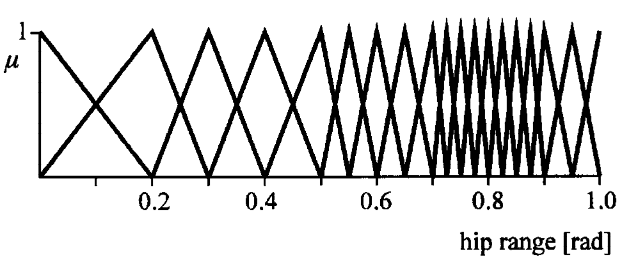

Fig. 7 Premise sets, learning hip range controller

5. SIMULATION RESULTS

In the simulations discussed here a setup is considered that will be used in future for real world experiments as well. The setup guarantees safety for the patient, yet resembles the pose during normal gait. The patient sits on a saddle, with one of his legs supported by a block. The other leg cannot touch the ground and is able to swing freely. The muscles of this leg are stimulated by electrodes. The FES system is started by softly pushing the free leg.

All results presented here are obtained through simulation of a model of this setup of mediate complexity (Velthuis, 1995). Included are time variations (muscle fatigue) and non-linearities (muscle dynamics, activation limits). A 4th order Runge–Kutta integration method was used.

5.1 Fuzzy controllers

First the fuzzy controllers are applied to the nominal process (for which the hip range controller has been tuned). Figure 8 shows the obtained step characteristics for subsequent steps of the patient. This clarifies that in simulation, the fuzzy controllers are able to control the stimulation process, such that the swing phase objectives are satisfied. Compared with PID control (Franken et al., 1995), the fuzzy controllers perform better; they cause less

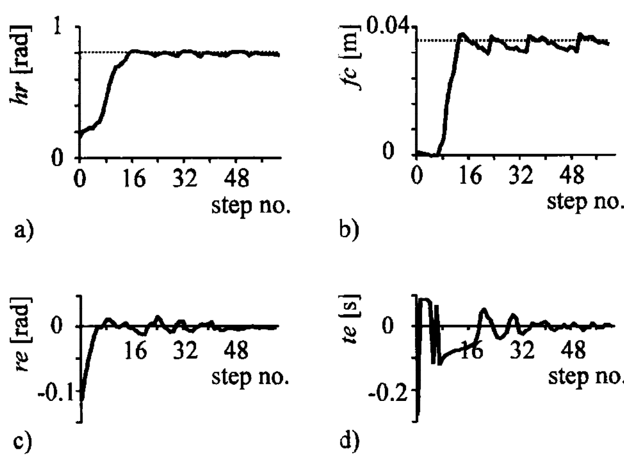

Fig. 8 Performance when fuzzy controllers are applied to the nominal process
a) hip range (hr) b) foot clearance (fc)
c) rate of extension (re) d) timing of extension (te)

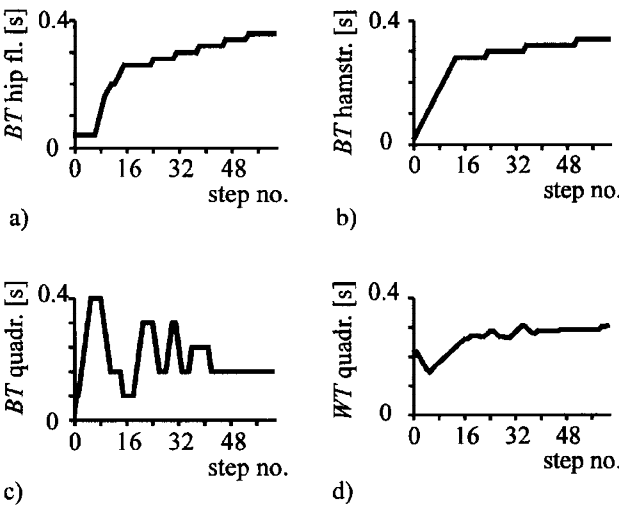

Fig. 9 Fuzzy controllers outputs
a) *BT* hip flexors b) *BT* hamstrings
c) *BT* quadriceps d) *WT* quadriceps

overshoot. However, results for PID control were obtained through actual experiments with patients, and hence are influenced by unmodelled disturbances like noise and muscle spasm. Therefore, a fair comparison between the PID controllers and the fuzzy controllers is not yet possible.

The stimulation parameters determined by the controllers are shown in figure 9. Parts a) and b) show that the controllers, after initialisation, indeed compensate for the effect of muscle fatigue.

In additional simulations, the robustness of the performance of the fuzzy controllers has been examined in the following situations:

1. Decreased maximum torque that the hip flexors can generate
2. Decreased mass and damping of upper and lower leg
3. Increased mass and damping of upper and lower leg.

It appeared that the performance was most sensitive for the 3rd test. Performance obtained then is shown in figure 10.

Due to the large damping and increased mass, the hip range no longer follows the desired path. Once the desired hip range is reached, it is maintained until about step 48. Foot clearance and knee extension do not change significantly. Altogether it seems that the performance obtained with the fuzzy controllers is reasonably robust; deterioration due to process variations is present but not significant.

The fuzzy controller outputs for the hip flexor and quadriceps in this case are shown in figure 11. It appears

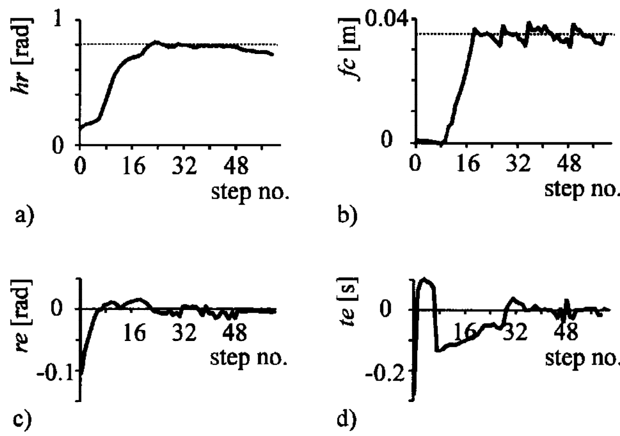

Fig. 10 Performance of fuzzy controllers when masses and dampings are larger
a) hip range (*hr*) b) foot clearance (*fc*)
c) rate of extension (*re*) d) timing of extension (*te*)

that the burst time of the hip flexor stimulator becomes equal to the maximum burst time in step 48; the effect of muscle fatigue can no longer be compensated, which explains why the desired hip range is not maintained from then on. A second interesting effect is that between steps 12 and 28, the burst time determined by the knee extension controller is 0; apparently, knee extension is obtained without using the quadriceps. This implies that the fuzzy controller has no control over knee extension in this period.

5.2 Learning hip range controller

All simulations mentioned above were repeated with the fuzzy hip range controller replaced by the learning hip range controller. In figure 12, results that can be compared to those of figures 8 a) and 10 a) are shown.

Figure 12 a) clarifies that the learning controller is not able to improve upon the well-tuned fuzzy controller, but also does not deteriorate the performance. Figure 12 b) shows that the learning controller is able to optimise its

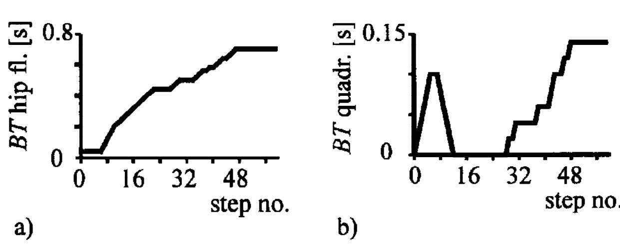

Fig. 11 Fuzzy controller outputs, off-nominal process
a) *BT* hip flexors b) *BT* quadriceps

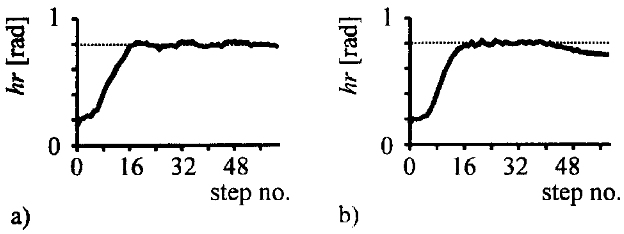

Fig. 12 Performance of the learning hip range controller
a) nominal process b) off–nominal process

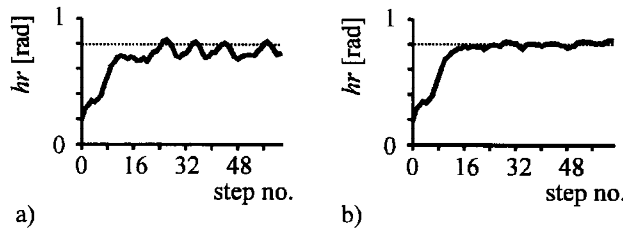

Fig. 13 Performance of the learning controller when initialised with sabotaged rules
a) no learning b) learning, 10th trial (of 60 steps)

performance; unlike the fuzzy controller, it allows the hip range to follow the desired trajectory (until the maximum *BT* is reached again, of course). Other simulations confirmed as well that the learning controller is able to outperform the fuzzy controller.

To research the learning abilities and the rate of learning under bad conditions, an additional experiment was done. The learning controller was initialised with a fuzzy controller in which several fuzzy implications were sabotaged: they were given fuzzy consequence sets that did not correspond with the guidelines given before. In figure 13, the performance of the hip range controller is shown both without and with learning.

This experiment indicates that the learning controller is able to restore a satisfactory performance for a badly tuned initialisation. During learning, only small adaptations of the input-output relation of the spline network were allowed (one interpulse interval per learning step). This has two effects:

1. Learning is robust; 'limit-cycle-like' effects are avoided. This is desirable.
2. Learning is slow; adaptation to patient specific characteristics takes time. This is less desirable.

6. CONCLUSIONS

The design of fuzzy controllers for knee extension control (both rate of extension and timing) and for foot clearance control is straightforward. Simulation experiments indicate that general, qualitative knowledge is sufficient to obtain well–performing controllers; muscle fatigue and changing leg and muscle dynamics are properly cancelled. Thus, identification is no longer needed here.

The design of a well–performing fuzzy controller for hip range control is more involved. The determination of fuzzy rules on basis of a–priori knowledge is simple, but tuning of these rules is quite complicated and time–consuming. This is caused by the fact that there are several input variables for this controller, each covered by a large number of fuzzy premise sets, leading to many rules.

If leg and muscle dynamics of a patient change, the fuzzy hip range controller no longer performs optimally. Simulation results indicate that a spline network is able to adapt to the patient, such that after learning it performs well again. Hence, by using a spline network that is initialised with a fuzzy controller that has been tuned in simulations, identification may be avoidable altogether.

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