A HYBRID METHOD BASED ON FUZZY INFERENCE AND NON-LINEAR OSCILLATORS FOR REAL-TIME CONTROL OF GAIT

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Abstract: Robust generation of motor commands for real-time control of locomotion with artificial means is crucial for human safety. This paper addresses the combination of fuzzy inference for determination of rules with a non linear oscillator system, as generators of motor commands for the control of human leg joints during walking, by means of external gait compensators, e.g. exoskeletons, functional electrical stimulation or hybrid systems. The response of the proposed method is evaluated for variations in stride frequency and step length. The testing during gait conditions is performed considering inertial sensing as feedback in a simulation study. The reference data considered is obtained in multiple experiments with healthy subjects walking with a controllable exoskeleton designed to compensate quadriceps weakness. A model of the operation of the knee joint compensation provided by the exoskeleton is obtained as reference to evaluate the method based on real data. The results demonstrate the benefits of both incorporating a) the fuzzy inference system in cyclical decision making for generation of motor commands and b) the dynamic adaptation of the timing parameters of the external compensator provided by the van der Pol oscillator.

1 INTRODUCTION

Robust generation of motor commands for real-time control of locomotion with artificial means is crucial for human safety. Broadly, current active external compensators of pathological gait under research can be configured as functional electrical stimulators (FES), (Popovic et al., 1999), (Skelly and Chizeck, 2001) controllable leg exoskeletons or orthoses, (Blaya and Herr, 2004), (Irby et al., 1999), (Moreno et al., 2005) or as a combination of both, known as hybrid systems, (Gharooni et al., 2000), (Goldfarb and Durfee, 1996). From the control point of view, the design of robust controller of locomotion with such devices, towards real life application, must be easy to customise, adapt dynamically to typical variations in gait pase and preferably should incorporate a coordinated development with the user.

1.1 Gait Compensation

A wide range of external gait compensators, e.g. exoskeletons, functional electrical stimulation or hybrid systems, have been considered to restore human gait. In particular leg exoskeletons or orthoses, can be prescribed for cerebrovascular accident, polyo myelitis or cerebral palsy patients with leg muscle weakness, in order to provide knee stability, reducing falling risk and enabling a certain degree of mobility.

In order to control an exoskeleton, it is not clear the hypothesis that instantaneous control of trajectory of the joint angle is essential for the lower limb system, since the reduced mechanical output —joint torque— limits its transitory response, in relation with the inertial properties of the musculoskeletal system (Franken, 1995). Velocity or position control loops are more appropriate and safe in training and rehabilitation applications where controlled generation of joint trajectories is required, with application of oscillatory signals and modulation techniques during gait

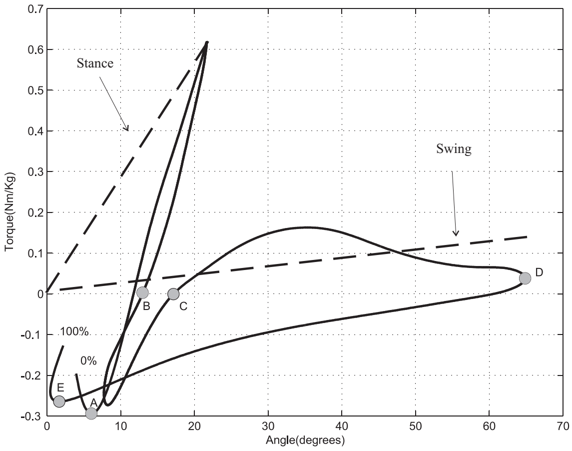

Figure 1: Mechanical adaptation for gait compensation during one gait cycle at the knee joint.

cycles for training subjects following neural/motor injuries.

Our previous work has consisted in the implementation of intermittent control of resistance of the knee joint with an unilateral exoskeleton applying selectively different constant stiffnesses depending on gait phase, to approach more natural profiles and avoid collapsing of the knee and risk of falling, see fig. 2.

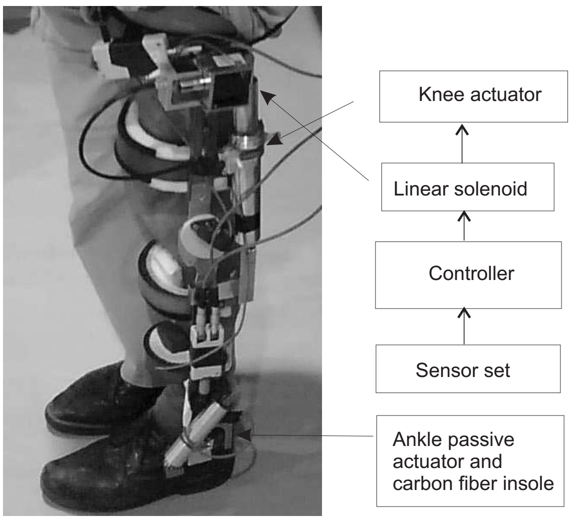

Figure 2: Controllable ambulatory exoskeleton.

Under this approach, a knee actuator is controlled to apply a given impedance K_1 in the stance phase, during a period of time ensuring the joint stability and shift during swing phase releasing the joint for a free swing while applying K_2 ($K_1 >> K_2$), for smooth transition and storage/recover of energy to assist the leg extension, see figure 1.

1.2 Rule based Control

Reliability of control in such a wearable solution for pathological cases is a critical issue that has an impact in human safety.

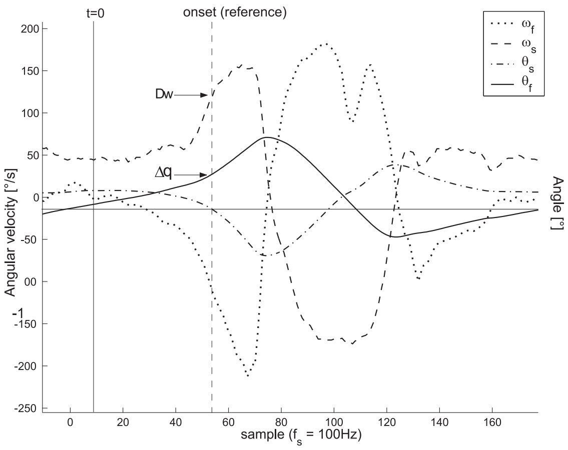

Figure 3: Typical normal gait pattern of foot and shank segments rotations and rotational velocities (sagittal plane) during a walking task at 34 m/min speed, with the cable-driven exoskeleton, after training of the subject. A system with a cable triggers the knee mechanism (onset) depending on a fixed degree of dorsiflexion.

The output of the controller is the motor command for the actuator, characterized by two parameters: activation *onset* and *period*. The activation onsets during each stride are calculated by rule-based conditions, evaluated according to segments orientation or rate velocity (See pattern during stance phase, figure 3). The system is a reactive controller performing according to the motion of the leg. The criteria to cyclically adapt the activation period (pulse width) of the actuator is defined considering temporal parameters relative to stance phase of current S(k) and past S(k-1) strides, and initial conditions S(0), given by average expected values.

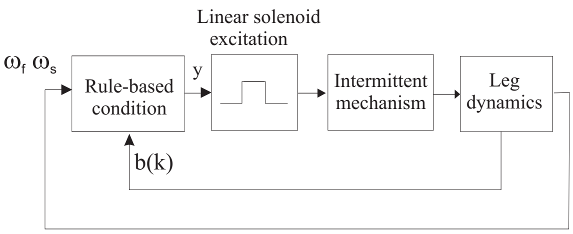

Figure 4: Control scheme for walking.

Experimental trials have demonstrated short-term adaptation of human motor system when applying functional compensations with customized tunning of the discrete rule-based controllers ,(Moreno, 2006). The adaptation of cyclical activation, has demonstrated proper results at self-preferred constant speeds. The next proposed method is an improvement intended to provide the required dynamical adaptation to changes of step frequency/length by the user.

1.3 Bipedal walking with Central Pattern Generators (CPGs): Simulation

It has been demonstrated previously how the use of the dynamical systems paradigm can realize a walking behavior in robotic walking platforms (Veskos and Demiris, 2006). The neural architecture has demonstrated successful operation in swinging and planar walking in a bipedal platform, incorporating van der Pol oscillators as generators of motor commands.

Medium and short term application of a walking real-time controller for the mentioned application scenarios, ought include mechanisms that provide adaptability and stable response to variations of frequency in the feedback signals, can led to an approach of cooperative development with the user/environment. In the following, the analysis of the response of the proposed hybrid controller to variations in gait frequency is evaluated with real data measured with the orthotic walking platform.

2 METHODS

2.1 Gait Patterns with Knee Joint Compensator

Subjects wearing an exoskeleton, need to adapt their walking strategy to drive the system to successfully switch between two knee spring damper configurations. During the entrainment of the subject with the controllable exoskeleton it is necessary to reach a certain ankle dorsiflexion angle which is variable during normal gait. Although this angle is adjustable, subjects change their gait pattern until they learn to use the exoskeleton. The learning process (which can be seen as an adaptation) in the use of the controllable exoskeleton has been previously studied in (Forner-Cordero et al., 2006). In order to obtain sampled data of different gait speeds, experimental trials with a healthy subject have been conducted after the adaptation process, consisting in walking back and forth along a 10 meter path, with definition of the step length with marks on the floor and the gait speed by means of a metronome, and systematic adjustments of the cable mechanism to provide a comfortable gait pattern (see table 1). The gait velocity and step length variations were defined according to average values taken from Perry, (Perry, 1999), consisting in feasible combinations of 100%, 70%, 60% and 50%. Rate gyroscopes fixed at the shank and leg segments of the external device were used to measure rotational velocities along the sagittal plane. Motions of interest occur at normal (2.6 km/h) and low (2 km/h) gait speeds, and therefore, signals outside the band frequency related to gait kinematics (0.3–20 Hz), are rejected from the sensor outputs with -3 dB low pass filters, refer (Moreno et al., 2006) to for details. A precision angular position sensor was fixed at the knee joint to track the knee joint angle in the sagittal plane. A resistive pressure sensor (5 mm in diameter active area, 0.30 mm thickness) is used to monitor the activation status of the knee actuator.

Collection of input/ouput data is utilized to generate training and checking data sets, of both multiple speed trials, and constant speed separated trials.

2.2 Validation Model

A robust Model describing the dynamics of the knee-orthotic hinge system during cyclic walking conditions can be used as a reference to analyze the performance of the advanced control system. We propose the identification of the model the activation patterns provided by the cable driven exoskeleton, with time-series of kinematic data. A broadly used signal processing paradigm is the state-space model. Defined by two equations, the state-space model has been broadly applied in signal processing (Smith and Brown, 2003). A first equation describes how the hidden state or latent process is observed and a second (state) equation that defines the evolution of the process through time. Based on the formulation given by (Haverkamp et al., 1996), we propose identification of a multiple-input single-output continuous-time model from the experimentally collected input and output data.

Considering the state-space model in the innovations form

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) \quad (1)$$

$$y(t) = Cx(t) + Du(t) \quad (2)$$

where $u(t)$ denotes the sampled inputs, being the foot and shank rotations in the sagittal plane during walking, for continuous measurements at 100 Hz sampling frequency, with transitions from low to high speed, and progressive variations in step length and given the measured output reference; $y(t)$, as the entrained knee joint status (actuator activation period)

Table 1: Systematic variations of healthy subject walking with the cable driven prototype (* Not feasible combinations).

Percentage	Step length[m]	Stride length[m]	Speed[m/s]			
100	0.73	1.46	1.35	0.94	0.81	0.67*
70	0.51	1.02	0.94*	0.66	0.56	0.47
60	0.44	0.88	0.81*	0.56	0.48	0.40
50	0.37	0.73	0.67*	0.47	0.40	0.33
		Cadence (step/min)	111	78	67	56
		Metronome (bpm)	1.85	1.30	1.11	0.93

for normal walking, $x(t)$ is the internal state of the system and $[A,B,C,D]$ are the deterministic system matrices.

The reference sampled input and output data $u(t)$ and $y(t)$ is obtained from experiments with healthy subjects wearing a orthotic walking platform, manually adjusted at each velocity to trigger the knee actuator based on the ankle dorsiflexion.

The goal of the state-space model identification process implemented in MATLAB is to find the system matrices $[A,B,C,D]$ according to the model structure. This resulted in a second order model as the best to the input-output behavior of the system, selected upon the analysis of the singular values (1st order, 53.23; 2nd order, 3.77; 3rd order, 0.34; 4th, 0.30).

The continuous-time model describes the relation between the foot and shank segments angular velocities and the output activation at the knee joint actuator for the range of tested speeds, by the state differential equation 1 and the output equation 2, where

$$A = \begin{bmatrix} 0.994 & -0.063 \\ -0.003 & 0.933 \end{bmatrix}; \quad (3)$$

$$B = \begin{bmatrix} -3.05e^{-6} & -8.28e^{-6} \\ -2e^{-5} & -3.39e^{-5} \end{bmatrix}; \quad (4)$$

$$C = \begin{bmatrix} 14.55 & -0.009 \end{bmatrix}; \quad (5)$$

Assuming the initial state as zero, from the evaluation of the transient (impulse) response of the second order system, it can be concluded a stable system with t_p = 0.5 s, as the time to reach the peak value, and a settling time t_d of approximately 10 s, after persistent excitation.

Evaluation of the response of the model compared against the external compensator operation is then performed, with the checking data set corresponding to multiple speeds. The crossing zeros (time interpolation) of the oscillatory output signal during the steady state are detected as equivalent onset and offset timings of the measured events. The correlation coefficient r^2, calculated for the modeled and measured outputs is 0.999.

2.3 Architecture

The control scheme consists of different modules (see figure 6). A fuzzy inference system with two inputs and a single output node is identified and trained to map the inputs and trigger the actuator. The crisp output of the fuzzy inference system during each cycle is critical in providing transition between restrained knee flexion in stance to a free swinging leg. The activation period of the knee actuator (pulse width) during the swing phase is cyclically adapted by a second module composed by an nonlinear oscillator. This nonlinear system incorporates real-time estimated gait temporal parameters as feedback in the generation of an oscillatory signal which adapts the duty cycle of an external compensator.

2.3.1 Fuzzy Inference System

Conventional PID controllers have been applied in the control of cyclical movements in legs of paraplegic subjects (Franken, 1995). Introduction of dynamical adaptation of the rules commanding FES systems has been investigated, in order to cover a wider range of unsafe and uncertain situations in application of stimulation . A Sugeno system is suited for modeling nonlinear systems. A training scheme with a fuzzy modeling network structure has been combined to develop a gait synthesis learning scheme, (Horikawa et al., 1990).

Obtaining a fuzzy system corresponds with approximated reasoning, which refers to methodologies to describe physical systems which include complexity due to nonlinearities and uncertainties. Let us suppose that our unknown system is a black box only capable of measuring a set of inputs x_1,...,x_n and outputs y_1,... ,y_m. A fuzzy system with a crisp output and the following type of rules is to be obtained

$$R_i : \text{IF } x_1 \text{ es } S_{i1} \text{ and…and } x_m \text{ es } S_{im}, \text{ THEN } \mathit{and} \text{ es } c_i \quad (6)$$

The fuzzy inference system is generated by means of the grid partition method. For the identification a

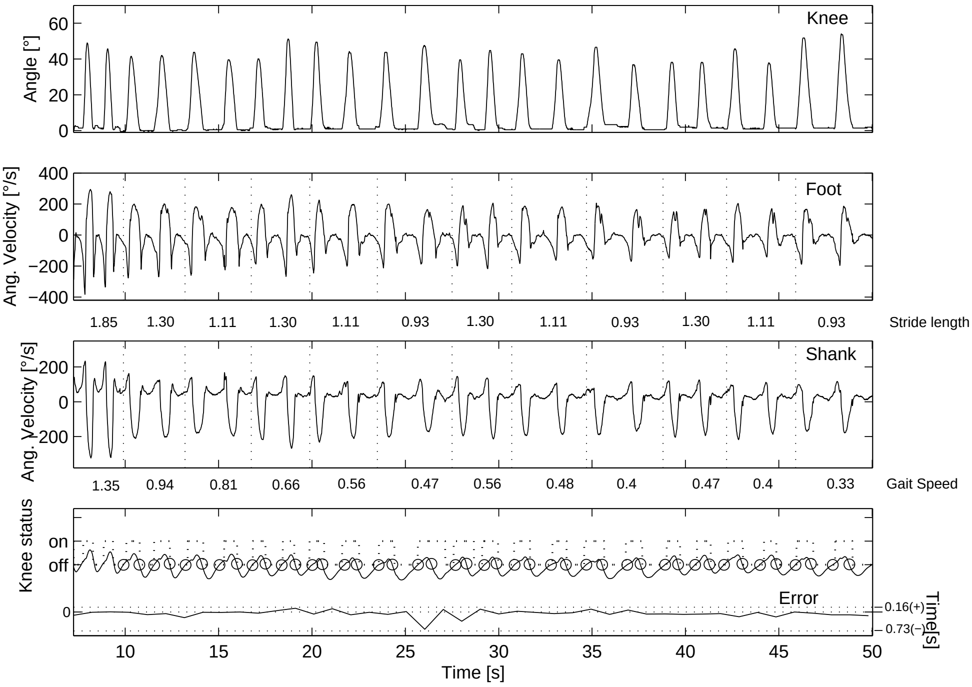

Figure 5: Data of measured input/ouputs of healthy subject with the compensator, after adaptation, at multiple gait speeds and space-state model performance. (a) Knee joint measured angle with external compensation, checking data set of (b) Foot angular velocity and (c) Shank angular velocity; (d) the measured activation status of the actuator (dotted line), model ouput (dashed line) onset and offset timings given by the model (circles), and time difference per cycle.

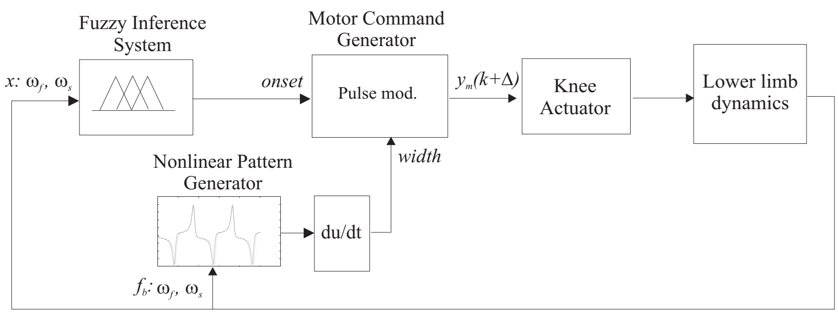

Figure 6: Hybrid architecture for control of gait external compensation at knee level, based on inertial sensing data. First module contains the fuzzy inference system with a crisp output The second module contains a nonlinear system predicting the activation period of the knee actuator as function of gait frequency (forced oscillator), with proprioceptive feedback.

training data set is generated from the experimentation. The identification method consists in the application of the adaptive network fuzzy inference system (ANFIS) proposed by Jang, (Jang, 1993), in order to build the fuzzy rules with membership functions to generate input/output data pairs. Iteratively, input parameters of the membership functions are learnt by means of back-propagation in an adaptive network and while the parameters of output functions are optimized by the least squares fitting method. The *adaptive network* is a feedforward multilayered network, with a supervised learning scheme. The functions of given nodes in a layer are similar. For means of simplicity, we consider a first order Sugeno type model, as the inference system. Having the kinematic inputs, the output $E(t)$ and n fuzzy rules:

$$\begin{aligned} R_n \quad : \quad & \text{IF } \dot{\theta}_s \text{ is } A_n, \text{ AND } \dot{\theta}_f \text{ is } B_n \\ & \text{THEN } E = p_1\dot{\theta}_s + \dot{\theta}_f + t \end{aligned} \tag{7}$$

Gaussian membership functions have been selected for smooth transition. A total of 4 Sugeno type fuzzy rules were defined, with a network with 21 nodes. These rules were of AND (minimum) type antecedent. The defuzzification method, calculating the output, is performed by the centroid method. The clustering radius r = 0.2 was adjusted for tunning. The optimization process spanned 13 epochs, with the training data set. The figure depicts the output surface of the final identified system given the two inputs.

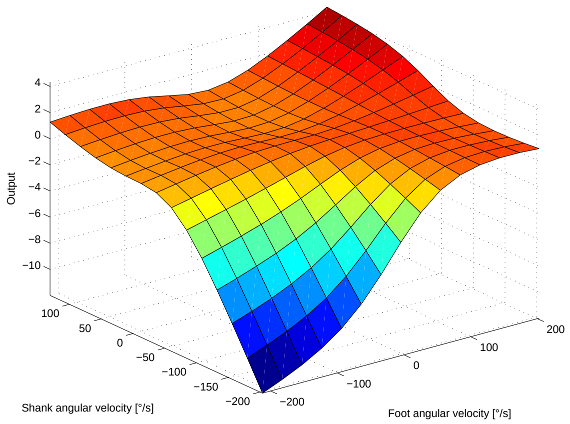

Figure 7: Inputs (foot and shank angular velocities) output (knee actuator activation) surface of the fuzzy system.

2.3.2 Forced Nonlinear Oscillator

The dynamic robustness of a pattern generator to noise and other external disturbances can be improved by incorporating nonlinearities to the system. A van der Pol oscillator, requires a reduced number of parameters, and has the advantages of robustness and ease of computational implementation. Such nonlinear system can be applied as an adaptive oscillator during the swing phase to determine the time of activation of the external compensator. To unlock the frequency of the oscillator and provide it with adaptability to the leg motion, the nonlinear system is forced to oscillate at a frequency, which depends on the spatio-temporal behavior of gait. Let us consider the forced nonlinear oscillator

$$[!top]\dot{x} = y \tag{8}$$
$$\dot{y} = -\mu(x^2-1)y - \omega x + A\cos\theta t \tag{9}$$

with ω as the natural frequency μ as the damping parameter, θ as the forcing frequency and A as the amplitude of the forcing function. An approximate solution of the non-linear system, satisfying the initial conditions x = 0, y = 0 is calculated during each cycle i with

$$\theta_i = \frac{T_{ST}}{R} \tag{10}$$

where T_{ST} is the stance phase period in cycle i, and R, a frequency scaling factor. T_{ST} is estimated from consecutive local minima (peak) values from the foot rotational velocity, as described in (Moreno et al., 2006).

2.4 Hybrid Controller

Local minima values are detected from the output of the fuzzy system, upon numerically integration. The sensitivity of the local minima detector is given by δ, which corresponds to the minimum difference in amplitude with the neighbor samples. With the calibrated gyroscopes raw data, a δ = 40 was satisfactory for all conditions. Thus, cyclically the fuzzy system provides the activation *onset*, the controller incorporates the output of the nonlinear oscillator to predict the *width* τ or duration period for the knee external compensator, with

$$\tau = \frac{D}{2\omega} \tag{11}$$

where D determines the duty cycle percentage. Incorporating the prediction given by the forced oscillator, D = 0.8 was defined and remained constant in all further experiments.

An example of the hybrid controller for cyclic gait at 0.94 m/s (stride length, 1.46 m) is depicted in fig. 8

3 RESULTS

The performance of the hybrid controller is compared with the validation model and the testing data set. The mean errors and standard deviations are calculated, considering 4 continuous gait cycles per each condition, for the output of the fuzzy inference system module and the nonlinear oscillator module (see Table 2). A negative error (in seconds) means anticipation with respect to the reference. For the tested conditions, the maximum average error for the fuzzy rule-based detection was 0.19 s demonstrating the robustness of a single fuzzy model to drastic variations in stride frequency. The discrete rule-based method, previous tests showed significantly better performance for the application of thresholds, during slow gait velocities in comparison with the results with higher velocities. The response with the fuzzy rule-based method can be regarded as uniform for the tested conditions. The maximum average error for the oscillator was 0.32 s and therefore, the robustness to the variations in the timing of the generated motor commands was observed. The evaluation with the continuous data set provide a good indication of the accuracy and robustness of the hybrid method.

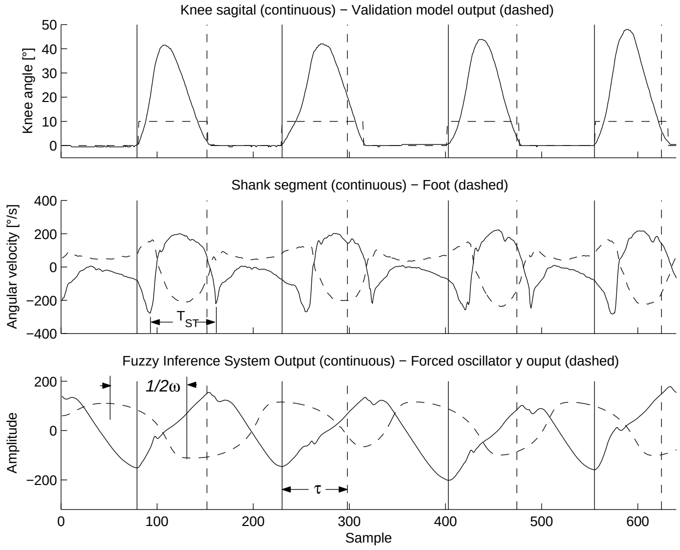

Figure 8: Example of the simulation results of the hybrid system at a relative fast speed. Measured knee angle and reference output given by validation model (top); Inputs (middle); Fuzzy inference system and forced linear oscillator outputs. The hybrid system generates the triggers (continuous vertical lines) and activation periods (dashed vertical lines).

Table 2: Results of the hybrid controller for the 12 testing conditions. Mean errors and standard deviations with respect to the evaluation model output are calculated taking 4 continuous gait cycles per each condition.

		Fuzzy System		**Forced oscillator**	
Step length[m]	Speed [m/s]	Mean error [s]	SD	Mean error [s]	SD
1.46	1.3505	0.0995	0.0123	0.005	0.0451
1.46	0.94535	0.041	0.0744	-0.025	0.0719
1.46	0.8103	0.154	0.1847	-0.245	0.0806
1.022	0.6617	0.0685	0.0296	-0.06	0.051
1.022	0.5672	-0.042	0.0238	-0.17	0.0497
1.022	0.4726	-0.13	0.1238	-0.1775	0.1072
0.876	0.56721	0.0335	0.023	-0.1275	0.0629
0.876	0.48618	-0.0125	0.0728	-0.1725	0.083
0.876	0.4051	-0.1075	0.12	-0.32	0.0668
0.73	0.47267	0.0025	0.031	-0.16	0.0462
0.73	0.4051	-0.1205	0.0689	-0.0625	0.0998
0.73	0.3376	-0.1915	0.1003	0.15	0.2149

4 CONCLUSIONS

The evaluation with the continuous data set provide a good indication of the accuracy and robustness of the hybrid method. For the tested conditions, the results demonstrate a proper means to combine a learning method which incorporates fuzziness with the adaptive nature of a non lineal oscillator, to generate motor commands to control gait. A validation model has been used in order to simulate the real mechanical system (human leg and exoskeleton) in this study. Further work includes a simulation study of the response of the methos to external perturbations (foot contact with the ground during the swing and obstacles) and testing with subjects of the embedded application.

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