The development of a biomechanical leg system and its neural control

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***Abstract*— The function of the locomotor system in human gait is still an open question. Today robot bipeds are not able to reproduce the versatility of human locomotion. In this article a robotic knee joint and an experimental setup are proposed. The leg function is tested and the acquired data is compared to human leg behaviour in running observed in experiments.**

***Index Terms*— Biomimetics, Central pattern generators, Biologically-inspired robots, Bipeds, Passive joints.**

I. Introduction

The purpose of this article is 1) to prove biomechanical concepts of human running in a robotic testbed, 2) to show how such a biomimetic leg design can be controlled based on a central pattern generator and reflexes. To achive these goals, we implemented a two-segmented leg capable of reproducing the experimentally observed knee joint function with switchable elastic behaviour. The function of the neuro-mechanical system is analysed by simulating running with the robotic testbed on an instrumented treadmill.

The paper is organised as follows: in section II the design of a biologically inspired robot leg and the testbed are described. Section III explains the neural control of the leg. The experiments and results are discussed in section IV. Conclusions and an outlook on future research are given in the last section.

II. The biomechanically inspired robot leg

The conceptual understanding of locomotion in animals and humans keeps motion scientists and engineers busy since decades. Stability, robustness and versatility of motion in nature still outperforms the abilities of technical sytems. State of the art motion analysis has given insights into kinematics, kinetics and internal muscle properties (e.g. activation) of bipedal locomotion [1].

Biped locomotion is an alternating sequence of energy exchange. In human running kinetic and potential energy in flight phase is partially converted into elastic energy stored in muscles and tendons during stance phase. The use of intrinsic elastic properties is of vital importance to protect the mechanical system from damages by impacts [2], to regain energy [3] and to improve gait stability [4].

A. Biomechanical background

The knee joint in human running is integrating two mechanical functions: being resistive (like a spring) in stance and flexible in swing to provide sufficient ground clearance [5]. The experimentally identified knee elasticity in fast human running exceeds $15 Nm/^o$ [6] and a high, internally generated torque would be required to bend the knee in swing against this stiffness. With disengaged knee stiffness during swing phase the knee joint is flexing passively due to the inertia of the shank and the active propulsion of the thigh. The folded leg facilitates high protraction speed by reducing the leg's moment of inertia. As a result, the risk of stumbling is avoided.

B. Biomimetic approach

To overcome the limited locomotor dynamics of todays antropomorphic biped robots and gain robustness and efficiency a deeper understanding of biomechanical leg functions is indispensible [7].

In computer models the effect of compliant leg behaviour was examined [8], [9]. Thus the control of robot biped running is challenged by two general issues: protract and retract the leg alternatively and compensate unwanted energy conversion through a single hip actuator.

A series of knee joint designs has been proposed, which implement a switchable knee joint compliance. In contrast to computer models the complete gait cycle including swing must be implemented. This requires a testbed, able to simulate different loading conditions during gait cycle. The mechanical design is shown in Fig.1. A DC-motor drives the thigh back and forth. The knee joint is equipped with a switchable compliant mechanism consisting of a leaf spring that can be engaged and disengaged by a pull-type solenoid. The solenoid operates in parallel to the joint axis. It locks the leaf spring to engage during stance phase. The foot is made of foam and fixed to the shank. During swing phase the vertical movement of the hip is inhibited by the activation of the electro-magnet mounted on top of the hip. This mimics the action of the opposite leg not represented in the current setup. During stance phase, in contrast, the magnet is turned off and

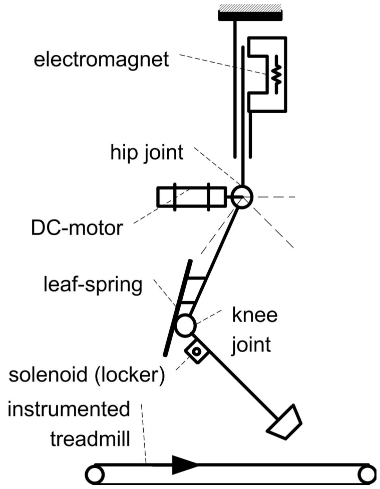

Fig. 1. Scheme of robotic leg and testbed.

the hip can move vertically (Fig.1). An elastic strap spans the hip joint connecting frame and shank. This causes a deceleration of the shank in the final phase of hip joint flexion. (see http://www.nld.ds.mpg.de/ poramate/ROBIO09/Bioleg.mpg).

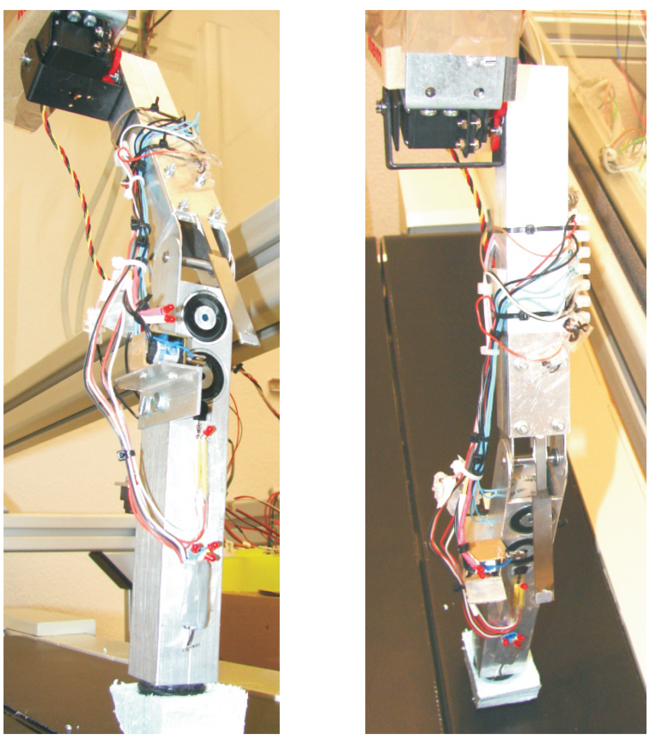

Fig. 2. Leg mounted on instrumented treadmill including DC-motor for hip motion, knee joint with leaf spring (disengaged) and locking mechanism.

III. Neural control of the biomechanical leg system

To control the biomechnical leg system described above, we employ modular neural control [10] with a reflex mechanism [11]. However, different methods can be applied but this modular neural control is selected in order to provide the basic control structure to the system where a neural learning mechanism for synaptic plasticity could be simply integrated for adaptive walking (not shown but see [12]). Furthermore, this controller has been successfully applied to control different kinds of walking machines [10]. Here it is used to activate hip movement while the reflex mechanism serves to control a pull-type solenoid at a knee joint as well as a loading/unloading device. The complete neural control network linking to the biomechanical leg system is shown in Fig. 3.

The modular controller consists of three subordinate modules: a neural oscillator network module serving as a central pattern generator (CPG) [13] (Fig. 3A), a neural CPG postprocessing module (Fig. 3B), and a velocity regulating network module (VRN, Fig. 3C). The neural oscillator network produces two periodic output signals. Here only one signal is used to control an active hip joint indirectly passing through the neural CPG postprocessing module and the VRN module. Thus, the basic rhythmic leg movement is generated by the neural oscillator network while the neural CPG postprocessing unit and the VRN are for shaping the CPG signal. Additionally, the VRN can also regulate an amplitude of the signal [10]. The reflex mechanism, on the other hand, uses a hip angle sensor signal filtered through a neural preprocessing network to control the activations of a solenoid and an electromagnet actuator. Submodules of the modular controller and the reflex mechanism are described in detail in the following subsections.

All neurons of the control network are modelled as standard additive non-spiking neurons with their time-discrete dynamics are given by:

$$a_i(t+1) = \sum_{j=1}^{n} W_{ij}\sigma(a_j(t)) + \Theta_i \quad i = 1, \ldots, n \qquad (1)$$

where n denotes the number of units, a_i their activities, Θ_i represents a fixed internal bias term together with a stationary input to neuron i, and W_{ij} the synaptic strength of the connection from neuron j to neuron i. The output of the neurons in the neural oscillator and VRN modules is given by $\sigma(a_i) = \tanh(a_i)$ while in the CPG postprocessing and sensory preprocessing modules is governed by threshold and linear functions, respectively.

A. Neural oscillator network

The neural oscillator network (Fig. 3A) consists of two neurons $O_{1,2}$ with full connectivity. Its synaptic weights

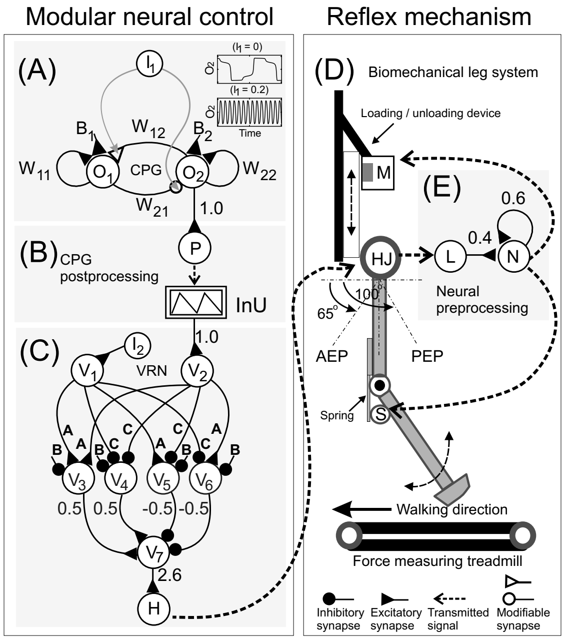

Fig. 3. Neural control of the biomechanical leg system consisting of the reflex mechanism and the modular neural control formed by three submodules. (A) The neural oscillator network functioning as a central pattern generator (CPG). It generates various shapes and frequencies of the periodic output signals with respect the control parameter I_1. Upper right diagrams present low and high frequency periodic output signals at the control parameter value of 0 and 0.2, respectively. (B) The neural CPG postprocessing module transforming the CPG signal into a sawtooth signal through the threshold neuron P and the integrator unit InU. (C) The velocity regulating network (VRN) shaping the sawtooth signal and also regulating its amplitude via the amplitude control parameter I_2. The output of this VRN is finally transmitted to the hip actuator HA of the leg through the motor neuron H. (D) The biomechanical leg system consisting of the leg and a loading/unloading device. The leg walks on a force measuring treadmill for monitoring a ground reaction force during experiments. (E) The neural preprocessing network of a hip angle sensor. It filters the sensory noise. Its neuron L works as a linear buffer which maps the raw sensor data onto the interval $[-1, 1]$. The mapped signal is filtered through the low-pass filter neuron N. Eventually the preprocessed sensory signal is used to define the anterior extreme position (AEP) and posterior extreme position (PEP) in the reflex mechanism. The AEP and PEP are for controlling the activations of the solenoid S at a knee joint and the electromagnet actuator M of the loading/unloading device. All connection strengths together with bias terms are indicated by the small numbers except some parameters of the VRN given by A = 1.7246, B = -2.48285, C = -1.7246. W_{12}, and W_{21} are modifiable synapses governed by Eqs. 2, 3 while $W_{11,22}$ and $B_{1,2}$ are set to 1.4 and 0.01, respectively.

($W_{11,22,12,21}$) and bias terms ($B_{1,2}$) are selected in accordance with the dynamics of the 2-neuron system [14] staying near the Neimark-Sacker bifurcation where the quasi-periodic attractors occur. Such that the network has the capability to generate various sinusoidal outputs having different frequencies and asymmetric shapes [10], [14]. This kind of asymmetrical periodic signals is appropriate for walking found in humans where swing and stance phases differ in duration, being intrinsically asymmetry [15]. For example, choosing $W_{11,22}$ = 1.4, W_{12} = 0.18, W_{21} = -0.18, and $B_{1,2}$ = 0.01, the network produces very low-frequency sinusoidal outputs with asymmetrical shapes of descending and ascending. This low frequency is then used for slow stepping behaviour (not shown). To increase the frequency, it could be simply achieved by modifying only $W_{12,21}$ determined by Eqs. 2, 3 while other parameters are still fixed.

$$w_{12} = -I_1 - 0.18, \qquad (2)$$

$$w_{21} = I_1 + 0.18, \qquad (3)$$

I_1 is a control parameter which is here varied between 0.0 and 0.5[1]. Note that positive and negative values in Eqs. 2, 3 are given in order to obtain default periodic signals. In stepping experiments of this study here we set I_1 = 0.2 yielding the optimal stepping speed of the leg. Setting I_1 = 0 it drives slow stepping behaviour, while increasing to 0.5 it generates fast motion. Nevertheless, we will later apply additional sensor signals, e.g., accelerometer sensor signal, to this control parameter to modulate different stepping frequencies of the leg with respect to terrains.

B. Neural CPG postprocessing

The neural CPG postprocessing module (Fig. 3B) consists of two hierarchical subunits: 1) the threshold neuron P and 2) the signal integrator unit InU. First P transforms the CPG signal into a pulse signal after that it passes through InU in order to obtain continuous ascending (swing phase) and descending (stance phase) signals by using linear interpolation. Note that a threshold value of P is empirically tuned, as a result it is set to, e.g., 0.85. Figure 4 shows the CPG signal after postprocessing by each unit.

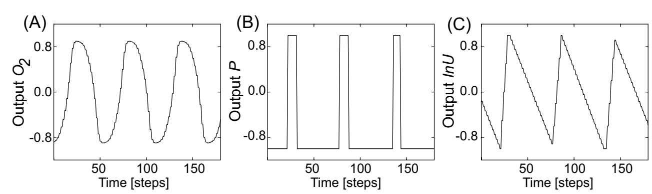

Fig. 4. (A) Output signal of the neural oscillator network O_2. (B) Output signal of the threshold neuron P. (C) Output signal of the signal integrator unit InU.

C. Velocity regrating network

The VRN (Fig. 3C) is a simple feed-forward network which was partly constructed and partly trained by using the backpropagation rule (see [10], [16] for details). The network output controls the hip joint HA through its motor neuron H. Because the VRN behaves qualitatively like a multiplication function [10], it therefore has capability to increase or decrease the amplitude of the periodic signal by the magnitude

[1]Note that increasing I_1 beyond 0.5 the oscillator provides too fast oscillating signals for the leg system.

of the input I_2. Consequently, the stepping speed of the leg will be regulated, i.e., the higher the amplitude of the signal the larger the step length leading to faster motions (not shown in the current set of experiments but see [10]). Furthermore, due to the nonlinear characteristics of the network, it also shapes the postprocessed CPG signal resulting to smooth motion (Fig. 5B). For stepping experiments here, we set I_2 to 1.0. However, we will later apply additional exteroceptive or proprioceptive signals to modulate stepping speed and even to stop the motion through I_2 (Fig. 5C).

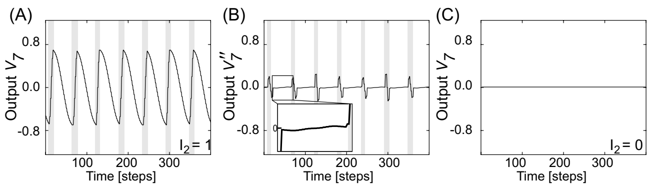

Fig. 5. (A) Output signal of the neuron V_7 at I_2 = 1. (B) Second derivative of the output signal of the neuron V_7 defining acceleration of motion. The zoom window shows that the leg decelerates at the beginning of a stance phase and afterwards it slightly accelerate to appropriately push forwards resulting in smooth motion. (C) Output signal of the neuron V_7 at I_2 = 0. Gray areas define a swing phase while white areas mean a stance phase.

D. Reflex mechanism

The reflex mechanism (Figs. 3D and E) is controlled by an afferent signal, which is elicited by the angle sensor of the hip joint HA. The raw sensory signal (Fig. 6A) is linearly mapped onto the interval $[-1, 1]$ at the neuron L and then filtered through the linear recurrent neuron N performing as a low-pass filter. Afterwards the preprocessed sensory signal (Fig. 6B) directly controls the activation of the solenoid S and the electromagnet actuator M (Fig. 6C) of the loading/unloading device with respect to the AEP (Anterior Extreme Position, see Fig. 3D) and the PEP (Posterior Extreme Position, see Fig. 3D). That is the solenoid and the electromagnet actuator are deactivated as soon as the hip movement attains the AEP. As a result, the solenoid locks a knee spring while the electromagnet releases the leg to touch a ground and a stance phase begins. On the other hand, if the leg retracts until it reaches the PEP, the solenoid and the electromagnet are activated such that the knee spring is free and the leg is held in order to start a swing phase. The AEP and PEP are set to 65 and 100 degrees. These parameters are obtain from the study of human walking [17].

It is important to note that the neural controller could be extended for controlling two legs [10] where the other leg will receive a signal either from the output neuron O_1 of the oscillator or using a delay unit determining a phase shift between legs.

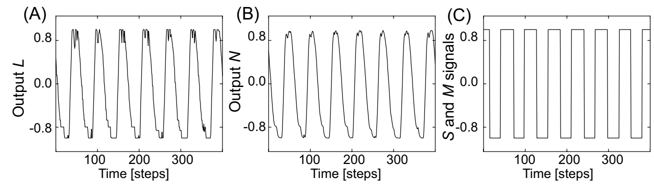

Fig. 6. (A) Output signal of the neuron L. (B) Output signal of the low-pass filter neuron N. (C) Signal controlling the solenoid S and electromagnet actuator M.

IV. Experiments and Results

A. Methods

To validate the concept the implemented network has to maintain two mechanical functions:

1) **stance:** engage knee spring, apply load on the leg and retract thigh
2) **swing:** disengage knee spring, unload the leg and protract thigh.

The leg operates on an instrumented treadmill (TAR.EI, HEF Tecmachine, Andrezieux Boutheon, France) with force sensors. The speed of the treadmill is adjusted manually to $0.6 m/s$, thus a smooth touch-down can be observed [18]. For demonstration four subsequent complete gait cycles are choosen for this preliminary study that was conducted to proof not only the mechanism but also the experimental setup (Fig.7).

The measured vertical ground-reaction-force (GRF) data

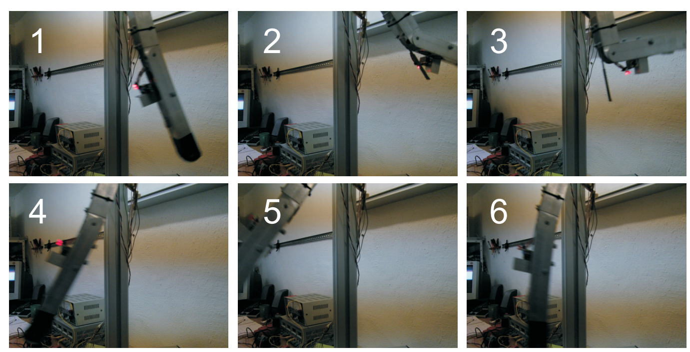

Fig. 7. Gait cycle shown in six frames captured with high-speed imaging: (1) late stance, spring engaged (2) early swing, knee bend passively (3) mid-swing, accelerated shank (4) late stance, knee extending (5) anterior extreme angle, knee extended (6) retraction before touch-down. See also video at http://www.nld.ds.mpg.de/∼poramate/ROBIO09/BioLeg.mpg

contains noise caused by the eigenfrequency and its harmonics of the treadmill. The data is processed to eliminate linear drift by approximating and substracting a linear drift function. Noise is reduced applying a low pass filter. The normalised, vertical center-of-mass (CoM) excursion is calculated by integrating the processed force data twice. The touch-down is defined as the time, when the force starts to rise. The

CoM-position at touch-down is considered to be the rest-length of the spring. Position and force are normalised to rest length. The spring-like behaviour in stance is characterised by a vertical leg stiffness determined through linear fitting. The spring constant is calculated as follows

$$c = \frac{F}{CoM_{rl} \cdot CoM_n}[N/m] \tag{4}$$

where CoM_{rl} is the spring rest length and CoM_n is the normalised change in length of an equivalent linear spring.

B. Results

The filtered data shows two clearly distinguishable phases - a sinusoidal, single hump force peak in stance and no force in swing. Adequately the CoM descents towards its lowest position at about midstance and ascents beyond lift off until reaching the apex at about mid-flight as calculated by integrating (Fig.8). The force amplitude varies slightly as well as the touch down height. The CoM-motion is not calculated

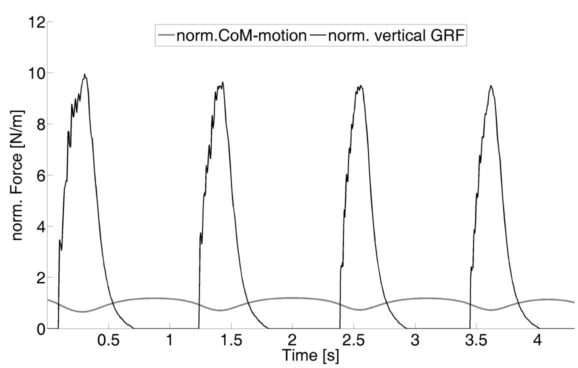

Fig. 8. Measured vertical ground-reaction-force (GRF) and calculated center-of-mass (COM) motion over time

correctly in flight-phase due to the use of the electro-magnet. In Fig.9 force in stance is plotted versus CoM-motion for serveral cycles. Except for the first step, the vertical force-displacement curves appear to be almost linear indicating a spring-like leg behaviour during stance. Therefore, the vertical leg stiffness can be approximated by linear regression ($k_{vertical} < -0.978, R^2 > 0.956$ for steps 1-4). Beside the envisioned spring-like leg function during stance phase, also the free flexion of the knee was steadily provided by the proposed mechanism. (Fig.9).

C. Discussion

This paper addresses a mechanism mimicking the leg function in human running characterised by elastic leg function in stance and leg flexion during swing phase. The results show, that the proposed compliant knee mechanism is able to mimick the knee function observed in human running. A compliant behaviour in stance is proven experimentally (Fig.9). Sufficient knee flexion for ground clearance was

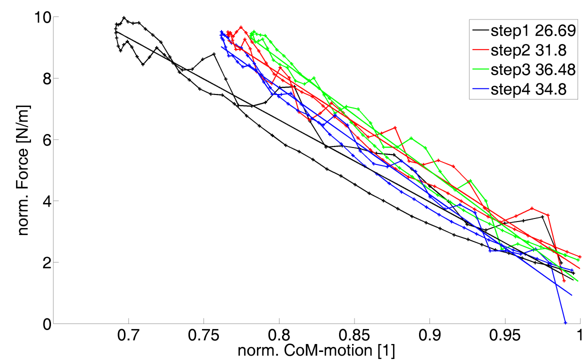

Fig. 9. Normalised force versus normalised CoM-motion and linear fit (fitted spring rate [N/m] in legend)

steadily observed using only passive dynamics of the segmented leg. Furthermore it could be shown, that mechanical devices inspired by biomechanical findings may be validated using gait analysis techniques. This analysis may include the measured ground reaction forces (in this study only vertical forces are used). In future kinematic data (e.g. joint positions and velocities) will allow a direct comparison to human gait data.

In the next steps the proposed mechanism will be improved to cope with disturbances and gait changes. This equally requires to develop control algorithms appropriate and sufficient to fully benefit from the underlying mechanical properties of the biologically inspired locomotor systems.

The proposed catch and hold mechanism is characterised by the small amount of energy needed for switching. The biological observed behaviour to engage or disengage only in unloaded state was intentionally implemented and differs from other switchable compliant mechanisms. The instantaneous excursive change in knee stiffness, well motivated by biomechanical findings, is essential to generate and reproduce the biologically observed behaviour.

V. Conclusions

The combination of passive compliant mechanisms with actuated joints improves the legged system. The described compliant system can absorb the impact at touch-down without affecting the mechanical integrety. Experimentally observed force patterns indicate that systems using switchable compliant knee mechanisms are able to better reproduce human running motion. The experimental setup is capable to generate data that can be compared with human data. This is a promising approach to evaluate biological inspired mechanisms. Both, the leg mechanism as well as the experimental setup are still not completely fulfilling the expectations. A further improvement of both is inevitable in terms of free timing for engaging the spring in case of disturbances for the mechanism and better three-dimensional force resolution

as well as optical motion capturing for the experiments.
The described work is a first step towards the translation of biomechanical concepts and models into technical mechanisms and systems. Aiming to build stable and robust legged systems capable of exploring their own mechanics using control algorithms, the proposed validation method will be of increasing importance to proof theoretical concepts of dynamic and kinematic behaviour in legged systems.

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