Motor Learning and Optimisation in Gait Control

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Abstract
Gait control is a complex process which has an intrinsic focus on planning, execution and adaptation of the whole-body movement by the CNS. An underlying assumption in our work is that the motion of healthy people is optimal with respect to speed, positioning accuracy, and energy expenditure. Motor control may become much more complicated for people having stroke, traumas or neurological diseases. Patients need to restore their motor control functions and motion performance to the best possible level. Various assistive devices may be used for restoration of human movement abilities: crutches, prostheses, passive and active orthoses, robotic exoskeletons, etc. To meet the above challenges, it is very important how to properly decompose complex modelling, identification and optimisation tasks into sets of much easier-to-find satisfactory solutions. It is of primary importance to properly identify the structure of the walking dynamics for every locomotion phase and the corresponding control functions. At first, a set of variables (controlled outputs) that best characterize human dynamic performance in the locomotion task has to be defined. Second, we have to find those driving forces/torques that mostly contribute to the dynamic performance in this task. The proposed concepts and algorithms could be very useful in designing an adequate control strategy for efficient gait analysis and performance optimization.

1 Introduction

The usual performance requirements in walking are for movement accuracy, speed, and energy expenditure [1,2]. The human musculo-skeletal system is an extremely complex dynamic system and the challenging question is how it is controlled by the central nervous system (CNS) and the human performance - optimized with respect to these complicated requirements.
Besides to able-bodied individuals, we have to pay special attention to disabled people for their efficient and effective motor rehabilitation, [3,4]. A great number of people with movement disorders due to stroke, trauma, or neurological diseases need to recover their motor control performance in some optimal way. Depending on the disability, we may have to solve various optimisation problems for the skeletal, muscular and neural subsystems.
To meet the above challenges, it is very important how to properly decompose complex modelling, identification and optimisation tasks into sets of much easier-to-find satisfactory solutions. For the purposes of efficient rehabilitation and sport performance optimization, we need advanced concepts for sensorimotor learning and appropriate system identification of the controlled human motion, [5,6,7,8]. It is of primary importance to properly identify the structure of the dynamic models and the corresponding control functions.
At first, a set of variables (controlled outputs) that best characterize human dynamic performance in the required motion task has to be defined. Second, we have to find those driving forces/torques that mostly contribute to the dynamic performance in this task. The relationship between the control inputs and the controlled outputs can be represented by a properly specified control transfer function (matrix). The main elements of that function can be determined applying the so-called multibody system (lumped parameter) approach [9,10,11] and the Newton-Lagrange formalism.
We have found [12], both theoretically and in numerous computer simulations, that efficient optimization of the dynamic performance can be achieved by test control functions with triphasic, bang-pause-bang, shape. The positioning accuracy, movement execution time and the energy expenditure are mostly sensitive to the parameters describing such control functions: control magnitudes, switch times and pause lengths.

2 Methods

2.1 General Control System Modelling

The usual performance criteria for goal-directed movements are: the positioning accuracy, the movement execution time and the energy consumption. Such movements can be generated by the corresponding muscles or by robotic orthoses (exoskeletons). The excitation signals naturally come from the brain and they may be processed via brain-computer interface (BCI) and/or EMG/FES devices.
With a given motion task, it is indispensable to know the structure of the controlled human motion:
- number and location of control forces (inputs)
- number and location of controlled outputs
- which are the main terms to be used in nominal dynamics models

- what is the type/shape/structure of the control functions;

In general terms, the structure of the controlled body dynamics can be described by the following system of differential equations

(1) $$\ddot{q} = M(q)^{-1}(Bu - C(q,\dot{q}) + g(q))$$

where, q is the vector of the performance variables/controlled outputs, M is the inertia matrix, C is the vector of velocity forces, g stands for friction and gravitation forces, matrix B represents the actuator location, and u is the vector of control inputs (forces, torques).

The control magnitudes $\bar{u}_i$ are supposed to satisfy the following natural condition for controllability:

(2) $$\operatorname{sign} \ddot{q}_i = \operatorname{sign} u_i, \quad \text{if} \quad |u_i| = \bar{u}_i \;,\; i = 1,...,n$$

Mathematically speaking, such a condition is satisfied when the control transfer matrix (TM) $A = M^{-1}(q)B$ is generalized diagonal dominant (GDD), [13, 14]:

(3) $$c_i A_{ii} > \sum_{j \neq i} c_j \mid A_{ij} \mid, \text{ for some } c_i > 0 \;,\; i = 1,...,n$$

2.2 Optimal Motor Learning Procedure

The main steps in our procedure for iterative motor control learning and optimization are as follows:

1. Choose a set of appropriate test control functions: The term "appropriate" concerns the structure, shape, and bounds of the test control functions. Simple linear-spline control functions of "bang-pause-bang" (Fig. 1) or "bang-slope-bang" shape can be used for a first-order optimization. Parameters, describing the test control functions, like switch times, slopes, or pause lengths, mostly influence the reached position and the performance criteria. Their consistency with advanced neuro-physiological studies is described in [12].
2. Define the most relevant pairs of control parameters and control outputs: It means that for each controlled output we have to assign a control input, which mostly influences it. Regarding the controllability in multijoint tasks, the input-output pairs will be most relevant if couplings between these single-input single-output subsystems are to be as small as possible.
3. Solve shooting equations and perform control parameter optimization: With the above input-output pairing, the given goal-directed motion task is transformed into systems of learning parameter equations with respect to the switch times. They are solved applying natural bisection algorithms and this is the first level of our control synthesis procedure. At the next level, the rest of the control parameters are varied to optimize the movement execution time and the energy consumption.

A block diagram for learning control synthesis is given in Fig. 2.

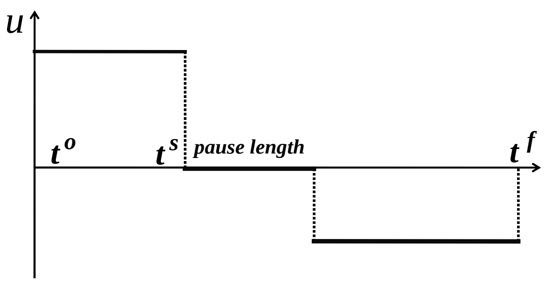

Fig. 1: Test control functions

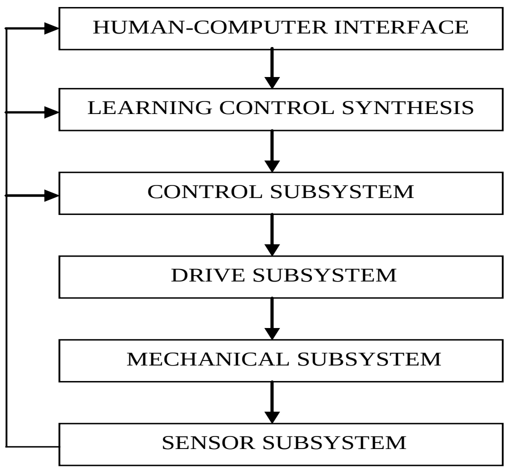

Fig. 2: Block diagram for learning control synthesis

Following the above approach, we can find satisfactory suboptimal solutions with minimum number of control parameters to be learnt. Existence of feasible solutions and convergence of the bisection algorithms are guaranteed, which ensures feasibility and efficiency of our control learning procedure.

2.3 Main Phases in Human Locomotion

In the process of performing a step, we distinguish four phases: double-support (DS), taking-off (TO), single-support (SS) and landing (L):

- DS-phase: Both legs are on the ground and the state reached at end of the previous phase (the landing phase) is adjusted to the state needed as the initial condition for the next phase (the taking-off phase).
- TO-phase: During this phase the leg to be transferred is only pushing-off the ground and hence takes a relatively short time. The biped dynamics for this action can be characterized by the dynamics of the "trunk-supporting leg" system which has two degrees of freedom: one at the ankle of the supporting leg and one at the hip. Two actuators are used to control this double-inverted pendulum system - one at the hip of the supporting leg and the other is the transferring leg itself which exerts a torque on the supporting leg due to the interaction between the actuator at the ankle of the transferred leg and the ground. The TO-phase ends at the moment when the new transferring leg leaves the ground surface.
- SS-phase: This phase is when the biped is pivoting around the ankle joint of the supporting leg. The other leg is rotated with respect to the supporting one until it reaches the configuration required before landing at the specified foothold. At this stage, the robot motion is controlled via three torques - two in the trailing leg (hip and knee), and one at the hip of the supporting leg.
- L-phase: Here the leg, which has been swinging, touches the ground and produces a force (by the same actuators as in TO-phase) thus opposing the biped's motion to reduce its velocity to an appropriate value.

The most complicated control problem is posed during the SS-phase when almost all the joints are to be actuated and the joint motions are in general strongly interacting. We decompose SS-motion into two unconstrained, goal-directed movements as shown in Fig. 3.

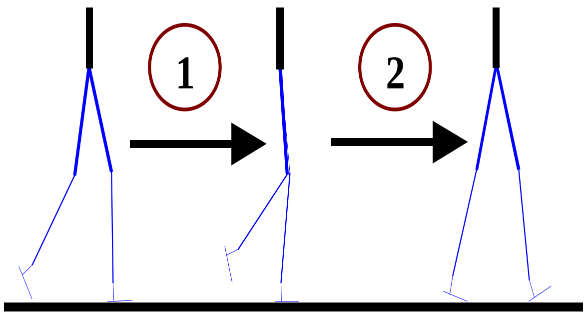

Fig. 3. Decomposition of SS-motion

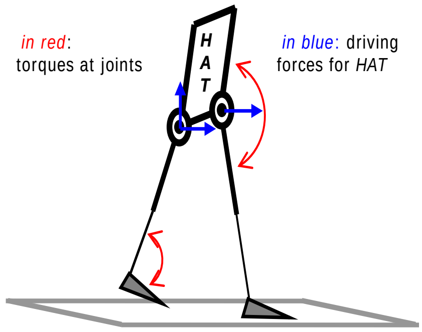

Fig. 4. On steps performing in 3D

For our study on 3D human locomotion, we consider the simplified human model in Fig. 4. There we can see the main driving forces for the HAT (head-arms-trunk) system during pushing-off the left leg. With this simple scheme it is not difficult to find answer to the challenging questions in 3D humanoid locomotion: What are the parameters that control the length and height of steps, the speed and direction of locomotion and how humanoids or disabled people to (re-)learn them?

Considering Figs. 3 and 4, we can see that human body motion at each phase can be simply represented as motion of a few coupled normal and inverted pendulums. These simple controllable mechanical systems are with one or two degrees of freedom and they are controlled either in open loop or closed-loop mode.

3 Results

Following the above proposed approach we can answer the challenging questions in 2D/3D humanoid locomotion: What are the parameters that control the length and height of steps, the speed and direction of locomotion and how humanoids or disabled people to (re-)learn them? Thus efficient structural identification of the controlled biomechanical system (whole human/humanoid body) can be performed.

Besides the mathematical proof and the neurophysiological consistancy, the concepts were also proved by computer simulation. Simplified dynamic models were used for all the locomotion phases. With the objective to optimize the locomotion speed, bang-bang test control functions were employed. Applying our control learning approach, the required goal-directed movements were synthesized with an acceptable accuracy after 10-20 test movements. A stick diagram is presented in Figure 5.

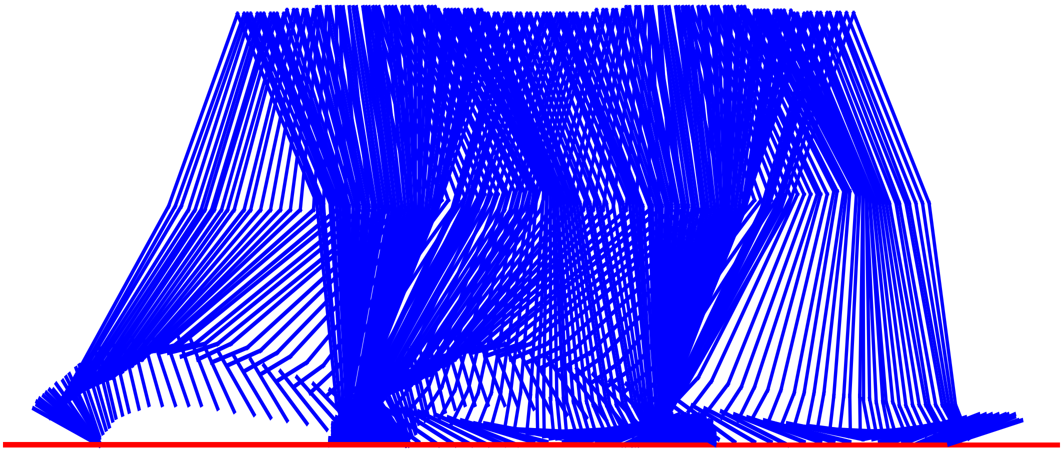

Fig. 5. Optimisation based synthesis of biped locomotion

4 Conclusion

We have proposed a generic conceptual framework for structure identification, analysis and design of control functions to achieve the best possible human motion. It is based on underlying principles and advanced concepts from optimal control theory, neurophysiology, and controlled multi-segmental dynamics. The proposed concepts and algorithms could be very useful in designing an adequate control strategy for efficient gait analysis and performance optimization.

Recent studies at leading R&D centers of neurological rehabilitation say that three important principles must be observed: assistance-as-needed, embodied motor control and learning, and motivate patients for self motor learning. Our control concepts and methodology for control design and optimal control learning are in accordance with these principles!

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