The Pursuit of Modeling Biped Agents

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Abstract

This paper describes an analysis of the biped robot domain. Papers in the robotics literature focus on bipeds that walk and run. Typically biped research is centered on the use of one or more models of the motion dynamics. This paper presents three categories of these models: 1) Joint level models 2) leg level models, and 3) body level models. A contribution of this paper is to expose the way these models are used and to show the simplifying assumptions that are used to employ them to control a biped. The second contribution is to cast the simplifications into a qualitative framework and open the field to the idea of using qualitative reasoning for dynamic robot control.

Background and Philosophy

Sensory-motor control, with emphasis on controlling dynamically changing systems, unifies most avenues of exploration in physical agents or robots.

Navigation cannot be completely decoupled from the dynamic motion of the agent. In fact it is advantageous to use dynamic features of the agent and its environment in order to manipulate and navigate throughout it. It is important for a car-driving agent to recognize and react to the feel of slippery pavement under spinning tires. Navigation can involve an analysis of the dynamic flow of traffic. Obstacle avoidance is of course necessary for driving under any real situation. Even the vibarations of the steering wheel and the brake and accelerator pedals provide important feedback.

Vacuuming floors in an ordinary house is more than finding the best floor covering method. There may be moving obstacles. The vacuumer may cause an object to move and may have to deal with the consequences (oops, catch that lamp before it crashes to the floor!). Dealing with pets requires alot of knowledge about how to deal with dynamic situations.

Any AI system that interacts with the physical world must be able to deal with dynamic situations and employ perception-action behaviors. Furthermore the agent should be able to learn from its experiences. I have explored these areas in the past by using engineering control methods to control robots (Djaferis-87 & Franklin-88). I have also combined these methods with reinforcement learning via artificial neural networks (ANNs) to improve control (Franklin-89) and used ANN methods alone to control dynamic systems (Benbrahim-92,Gullapalli-94). I have also used ANNs in manufacturing process monitoring (Franklin-92). This experience has led me to the following conclusions.

Seldom are conventional engineerings methods used alone to control research robots anymore without some form of adaptation or learning. Conversely, ANN methods alone are not sufficient for controlling a real robot without augmenting them with some form of rudimentary control at least; for either the robot will be dangerous to itself and others or it will not be able to learn.

At some point both conventional control and ANNs fall short in providing an agent with the ability to reason about a dynamic situation and to plan ahead. It is at this level that qualitative reasoning about physical systems (QR) will be useful. I have examined QR and its potential for control (Franklin-90) and used an envisionment of a simple dynamic system (deKleer-77) to provide goals and an input representation for an ANN learning controller (Franklin-92a).

The next step is to use a qualitative reasoning ability to make high level control decisions on-line. I am in pursuit of that step. In addition my mission in any research is to use real systems rather than simulation. Most of my past work has used hardware robotic systems. Any agent developed to interact with the physical world must in fact do that, else why bother?

The Biped Agent

I am in the preliminary stages of using a biped robot to study the hybrid use of control, connectionist learning, and QR. Besides standard sensory-motor control, two legs offer imaginative high-level uses for a robotic agent such as kicking the refrigerator door shut or blocking the exit of a pet through a door with one leg.

To understand the problem of using a biped I have

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studied various dynamic biped models and have categorized them in three levels, according to their use in control: joint control, leg control, and body control. The description of these models is the main content of this paper.

Joint Level

In joint level control, given the desired body and leg trajectories, the controller must control the position and/or torques at the joints of the biped in order to produce desired trajectories. At the joint level, the Lagrangian dynamic model is generally used.

The Lagrangian dynamic model is based on the use of the Lagrangian, the difference between the kinetic and potential energy of a system: $L = K - P$ (see Paul-81). Given that q_i are the coordinates in which the energies are expressed, (generally the joint angles) then the forces (or torques) F_i in those coordinates are given by:

$$F_i = \frac{d}{dt}\frac{\partial L}{\partial \dot{q}_i} - \frac{\partial L}{\partial q_i} \qquad (1)$$

where the $\dot{q}_i$ are the corresponding velocities. This formulation is directly applicable to finding the dynamic relationship between the positions and velocities of the joints of a biped and the corresponding forces or torques.

This results in a general model for a robot with n generalized coordinates that is a set of second order differential equations given below (Vukobratovic-83).

$$P = H(q)\ddot{q} + h(q,\dot{q}) + \Sigma_{l=1}^{L}\delta_l g_l(q) F_l \qquad (2)$$

for

P - nx1 vector of generalized forces in the joints
q - nx1 vector of generalized coordinates
$H(q)$ - nxn inertial matrix
$h(q,\dot{q})$ - nx1 vector of Coriolis, centrifugal and gravitational moments
$\delta_l = \{$ 1 if contact exists in the l^{th} point, 0 otherwise$\}$
$g(q)$ - nx3 vector of positions of l^{th} contact point wrt the centers of joints
F_l - vector of force acting on the l^{th} contact point

This model of robot dynamics is highly nonlinear and coupled. To gain an understanding of the complexity of these equations, consider the simple planar biped of Figure 1. Golliday and Hemami (Golliday-77) give the free-fall dynamics of this simple kneeless planar robot, for α, β, γ coefficients of mass, inertia, and leg parameters, as

$$\begin{aligned}
&\ddot{\theta}_1 - \alpha_a(\ddot{x}_h cos\theta_1 - \ddot{y}_h sin\theta_1) + \beta_a sin\theta_1 = -\gamma_a M_2 \\
&\ddot{\theta}_2 + \alpha_b(\ddot{x}_h cos\theta_2 - \ddot{y}_h sin\theta_2) - \beta_b sin\theta_2 = \gamma_b(M_2 + M_4) \\
&\ddot{\theta}_3 - \alpha_c(\ddot{x}_h cos\theta_3 - \ddot{y}_h sin\theta_3) + \beta_c sin\theta_3 = \gamma_c M_4 \\
&\ddot{x}_h - \alpha_{d1}(\ddot{\theta}_1 cos\theta_1 - \dot{\theta}_1^2 sin\theta_1) + \alpha_{d2}(\ddot{\theta}_2 cos\theta_2 - \dot{\theta}_2^2 sin\theta_2) \\
&\quad -\alpha_{d3}(\ddot{\theta}_3 cos\theta_3 - \dot{\theta}_3^2 sin\theta_3) = 0 \\
&\ddot{y}_h + \alpha_{d1}(\ddot{\theta}_1 sin\theta_1 + \dot{\theta}_1^2 cos\theta_1) - \alpha_{d2}(\ddot{\theta}_2 sin\theta_2 + \dot{\theta}_2^2 cos\theta_2) \\
&\quad +\alpha_{d3}(\ddot{\theta}_3 sin\theta_3 + \dot{\theta}_3^2 cos\theta_3) + g = 0
\end{aligned} \qquad (3)$$

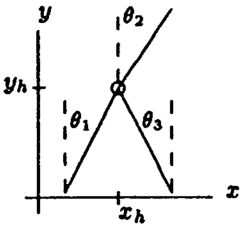

Figure 1: Simple 3 joint, kneeless planar biped

Simplified Models at the Joint Level

In control, generally the goal is to find the forces and torques that will produce desired position and velocity trajectories. However, controllers do not exist that can directly use the Lagrangian model above. If we just insert the desired positions and velocities and compute the torques, errors in the model will produce errors in the robot. This is why we use feedback in control. Errors in desired vs. actual trajectories are used to adjust the torques applied to the joints. The way in which the adjustments are computed, based on stability criteria, largely, is the basis for much of control theory.

Most control methods require a certain form of model. The most prevalent is a linear model. One way to address this requirement is to linearize the model. There are several methods. One method is to linearize the system by subtracting the nonlinear terms. This is accomplished by directly using them as part of the control signal. A feedback controller is then designed for the remaining linear part of the system (Hemami-83,Freund-82).

Another method is to take only the first order terms of a Taylor series expansion about an operating point. For example, Golliday and Hemami (Golliday-77) linearize about the 0 point: the upright stand-still position of the biped.

A third method of linearization is simply to neglect terms. Miura and Shimoyama (Miura-84) obtain a model in which the accelerations and velocities of the joints are linear in the joint positions and torques, by neglecting centrifugal, coriolis, and gravity terms:

$$\dot{x}_r = Ax_r + Bu_r + E, \; \dot{x}_p = Cx_p + Du_3 \qquad (4)$$

for x_r a vector of joint positions and velocities in the frontal plane and x_p a vector of joint positions and velocities in the saggital plane (see Figures 2 and 3). They also assume a stilt type, kneeless robot and this eases model manipulation. It is more accurate to neglect terms in this simple biped than in one that is highly articulated.

Another method of simplification is decoupling. Golliday and Hemami find a nonlinear equation for each of 4 walking phases (based on equations 3):

right leg support phase
right leg to left leg support exchange phase
left leg support phase
left leg to right leg support exchange

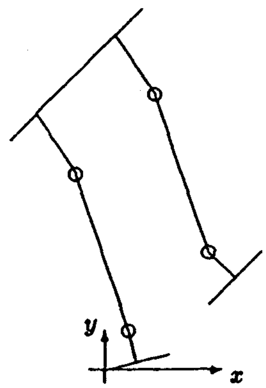

Figure 2: Frontal Plane of Biped Robot

and then linearize, using the Taylor Series expansion about the 0 point. They then decouple, ignoring terms that couple the joints together. They are also using a kneeless biped. It is also possible to derive a decoupled model that is still nonlinear, if desired.

Another issue in model simplification is simplifying because of the goals or purposes. A goal may be to apply a well-known control method. We may also constrain the robot's activities (e.g. not allow the velocity to reach a large enough magnitude to produce inter-joint coupling effects). A goal may also be able to conceptualize the system in order to reason about its behavior. If we can neglect some terms and recast the model in certain ways, we may be able to determine its behavior. This is more relevant at the leg and body levels of control.

Dynamic models expressed in generalized coordinates or joint level coordinates are appropriate when examining the dynamics at the joint level, and manipulating torques at the joints. However, at the leg and body levels, the models are usually expressed in Cartesian Coordinates, with respect to some reference point on the ground.

Leg Level

In leg level control, the controller is given the desired trajectories of the legs and must determine foot placement and step length. One way to model the legs is to focus on the Cartesian position of each foot as a function of time. These positions can be determined from the kinematic equations of motion. The model may be simplified by considering only the effects of a single leg's joint positions and velocities on the placement of its foot.

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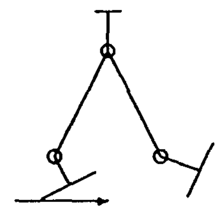

Figure 3: Saggital Plane of Biped Robot

Figures 2 and 3 show views of the frontal and saggital planes of a biped robot with 7 joints, 4 in the frontal plane and 3 in the saggital plane. These views are modelled after Zheng's SD-2 biped (Zheng-89) which in part provided a basis for the construction of the hardware biped described in last section.

Leg models are often derived in terms of desired foot placement. For example, Zheng and Shen (Zheng-90) develop a transitional gait for a biped walking from level ground to a sloping surface. The position and orientation of the foot is generated by using force information from sensors at the bottom of the feet. Then the transitional phases are first derived in terms of foot placements and these are changed into joint trajectories.

Another idea is to use the stilt model and then get each leg to emulate stilt model motion. In this way each leg functions on its own with trajectories given by the stilt model. These trajectories in turn provide trajectories for the biped joints.

Miller (Miller-94) decouples the legs kinematically to generate approximations of hip and knee joint angles for gait control. He uses a simple planar model of leg kinematics and ignores coupling between leg segment orientations in the frontal and saggital planes, and coupling between legs.

Body Level

At the body level, the height of the biped may be controlled, a desired gait may be implemented, or a certain behavior (or sequence of behaviors) may be required. The robot may walk, run, climb stairs, hop, kick, shuffle sideways, or even dance. How are these behaviors modelled?

The joint and leg levels are somewhat "introspective" in that the robot controller is more concerned with the robot itself. At the body level, interaction with the outside world is the purpose. The use of a particular model will depend on environmental circumstances as well as the goals of the robot's interaction. Besides understanding how to model these behaviors, understanding how to choose and use the models is essential.

The models used at the body level of control represent desired qualitative behaviors of the whole biped, generally irrespective of the number of joints or the exact configuration of the biped. There are two simple

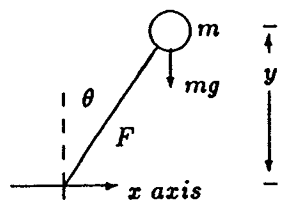

Figure 4: Extended Pole Model, 2D Case

models of body level dynamics that are widely used for walking bipeds. They are the inverted pendulum model and the center of gravity model. Both can be represented visually by Figure 4.

As Latham (Latham-92) shows in the pendulum model the height of the biped (in 2D, the y component of the cartesian position) is fixed at a constant value h. This produces the desired behavior of maintaining a stable platform for carrying and balancing objects for instance. The length of the supporting link changes to accomodate the fixed height, as the biped walks. This is accomplished by bending each leg in turn as required.

Unlike a constant length pendulum, the dynamic equations for a constant height pendulum are linear (Kajita-92,Latham-92):

$$\ddot{x} - \frac{g}{h}x = 0 \tag{5}$$

where x is the horizontal position of the 2D biped. This means there is a closed form solution (Latham-92) and therefore there is a clearcut way to provide trajectories to the leg controllers.

Zheng (Zheng-89) uses the 2D center of gravity model. The height y of the mass of the pendulum can change, as well as the horizontal component x. The notion of decoupling the body center of mass from the dynamics of the legs was first developed by Miyazaki and Arimoto (Miyazaki-80). The center of gravity body model is

$$I\ddot{p} + M[-yx][\ddot{x}\ddot{y}]^T = -Mgx \tag{6}$$

where I is the inertia of the body, M is its mass, and g is gravitational acceleration. Zheng relates the desired center of gravity trajectory to joint motions. His goal is to supply the biped with the ability to recover from perturbations (i.e. catch its balance). The controller that is derived is based on a simplified joint level model that ignores coriolis, centrifugal, and gravity terms.

Another interesting model that is receiving alot of current attention is that of the central pattern generator (CPG). Bay and Hemami (Bay-87) study the use of coupled van der Pol oscillators to generate body behaviors for biped robots (and also to model biological systems). They use n oscillators, one for each joint, given by

$$\ddot{x}_i - \mu_i({p_i}^2 - {\bar{x}_i}^2)\dot{x}_i + {g_i}^2\bar{x}_i = q_i \tag{7}$$

$i = 1, \cdots, n$, where p_i is an amplitude parameter, g_i is a frequency parameter and q_i is an offset parameter. $\bar{x}_i$ is the result of a coupling equation with the states of the other oscillators. For example, $\bar{x}_1 = x_1 - \lambda_{21}x_2 - \lambda_{31}x_3$ in the four-link biped scenario where each of the four oscillators is coupled with 2 others, forming a ring configuration. The oscillator parameters, μ_i, p_i, g_i, q_i, and coupling parameters, λ_{ij} are tuned (in magnitude and sign) to produce various body behaviors such as

Phase Shift Transition - trotting to galloping transitions
Amplitude Modification - changes muscle extension
Frequency Modification - faster or slower motions
Exclusions (decoupling of oscillators) -
to allow a joint to remain stationary
despite motions of neighboring joints;
e.g. swinging one leg freely while
the other remains stationary, in order to kick

The CPG model can be manipulated to generate control signals for various walking and jumping maneuvers. The model is used by Bay and Hemami to directly generate joint or leg trajectories, depending on the configuration of the oscillators. It is also used by Miller (Miller-94) to generate joint trajectories, given desired step length, step interval, and actual foot forces.

No discussion of models of biped locomotors would be complete without including Raibert's models of hopping robots. Raibert (Raibert-84) describes hopping as a special case of running in which all legs give support to the body at the same time. Most models for walking assume rigid links. In Raibert's hopping model, there are two models used, one for flight and one for stance. During flight, when no legs give support, the motion of the center of gravity of the body is ballistic. During stance, when the legs provide support, the behavior is like the inverted pendulum, accompanied by spring-mass oscillation.

The frequency of oscillation is used to determine the stance time interval during repetitive hopping. In practice, Raibert has constructed actual spring-mass robot legs for his experiments. However, the same models can be applied as body behavior models to multilink robots whose legs can act as virtual spring-mass systems.

The spring-mass model is an oscillator with a natural frequency

$$\omega_n = \sqrt{\frac{K}{M}} \tag{8}$$

where K is the stiffness of the spring and M is the mass of the body plus the part of the leg that lies above the spring. This freqeuncy is used to determine the stance time interval during repetitive hopping:

$$T_{st} = \frac{\pi}{\omega_n} = \pi\sqrt{\frac{M}{K}}. \tag{9}$$

Finally, during flight the model is a gravity-mass oscillator. Thus the full hopping cycle has period

$$T = \pi\sqrt{\frac{M}{K}} + \sqrt{\frac{8H}{g}} \tag{10}$$

where H is the hopping height measured at the foot, and g is the acceleration of gravity.

The goals of most of the researchers developing these models have involved control of the biped with the purpose of walking, running, or hopping. It is beyond the scope of this paper to present the methods of control used. Methods are centered on linearization, computed torque, and neglection of nonlinear terms. ANNs have been used as well (Latham-92,Miller-94,Zheng-90). In general some type of hierarchical control is necessary to handle the matching of models at body and leg levels with the actual model or simplified model that drives the controllers at the joint level.

Qualitative Reasoning for Control

Qualitative reasoning (QR) about physical systems (Bobrow-84,deKleer-77,Forbus-84,Forbus-88,Hayes-85,Kokar-87,Kuipers-86,Weld-90a) is an area of AI that can aid robotic engineers in both modeling physical systems in more abstract ways and in manipulating these models. In some sense the goal of qualitative reasoning is to provide a language with which to manipulate descriptions of physical systems. In another sense, it is a way to both generalize and simplify the description of a system so that the analysis of its behavior is more tractable.

Most of the work of engineers in finding applications for qualitative reasoning has so far been in process monitoring, fault detection, and design (Arkin-90,Dvorak-89,Kokar-90,Machias-90,Mavrovouniotis-90). In order to use it for control, feedback must be employed.

Several researchers are using QR for control. Makarovic (Makarovic-91) has used a form of qualitative reasoning to control a 2 link inverted pendulum. He first derives the dynamic equations, based on the Lagrangian, and then simplifies them in a way that parallels conventional control methods. He determines which terms can be neglected and then finds the terms with the most influence. These are used in control rules that control the pendulum.

Lawton (Lawton-90) derives a spatial representation for purposes of navigation and control of a mobile robot. The representation has a qualitative level that is topological in nature, providing a global structure for navigation. The lower level is quantitative, based on cartesian coordinate systems, and is used for local computations in vision and low level control.

Forbus (Forbus-89) introduces the idea of integrating physics with actions taken by agents, resulting in "action-augmented envisionments." The actions are events that can occur in the qualitative world. In qualitative control, not only would actions be introduced, but the decision making step (the controller) would also become part of the qualitative reasoner. The use of on-line feedback needs to be included in this work, where feedback includes high-level information. A controller must not only be able to determine its options before choosing its control strategies, but must be able to gather information while carrying out its tasks in order to update its choice of strategies.

In order to introduce feedback control into qualitative reasoning, Gervasio and DeJong (Gervasio-89) have used explanation-based learning techniques. They develop "reactive operators" in a *reactive planning* system. Gervasio has further carried out this work (Gervasio-90) by integrating classical and reactive planning techniques that can be used for various classes of control problems.

DeJong (DeJong-90) also describes control from the perspective of an AI planning problem, and uses explanation-based learning techniques and qualitative reasoning to develop a learning controller that can monitor continuous quantities. This system is structured as a higher level system that reasons (and learns) about qualitative proportionalities between quantities, and is augmented by a low level, quantitative system that makes the continuous values accessible and usable as feedback. The low level system is based on linear interpolation. This is in effect a hierarchical control system.

What Now?

I am currently investigating the use of qualitative reasoning about physical systems at the body level of the hierarchy for biped robot control. The first investigation may be to use CPG models within the qualitative reasoning framework to make body level transitions. When the parameters reach certain critical points the biped will exhibit a transition to a different behavior. These transitions can either be observed or can be controlled. Using goals, such as kicking the refrigerator door shut on the way into the living room, a QR based planner will determine the appropriate transitions or the appropriate parameter changes that will enable the transitions.

QR may be used to switch between the body level models as well. An inverted pendulum model may be used for smooth walking. When a critical point in sensor readings is reached, a transition to a CPG or a hopping model may be made, say when a toy or a dog is suddenly in the path.

QR will also be useful in the interaction of 2 or more cooperating bipeds that are modelled by body level models. They might be carrying a heavy box together or even playing soccer.

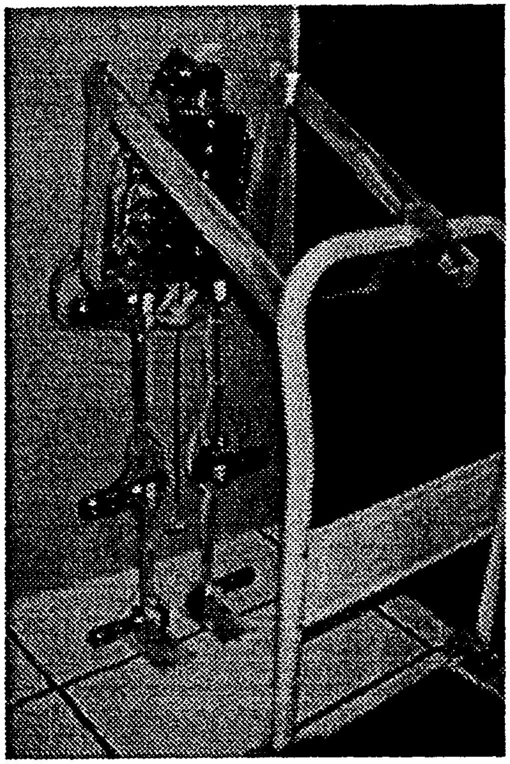

Figure 5: Biped Robot Hardware

My goal in this workshop is to interact with other researchers to determine how to use QR effectively at this level. I would like to match models and behaviors such as

- Don't stop now!
- Stop now!
- Kick that!
- Pry up that rock with a toe
- Rock back and forth
- Jump up
- Jump forward
- Jump back
- Jump to either side
- Crouch

and understand how to use QR to make transitions and use high level feedback to recover from reactive behaviors and resume the original biped goals.

A Hardware Biped Robot

Figure 5 is a picture of the biped robot that will be used in the quantitative and qualitative control experiments. While we have the motors and links constructed for a three dimensional biped, currently we have only assembled the hardware for two dimensional frontal plane movement. Also shown in the picture are the passive (non-motorized) arms that hold on to a hand cart. We are using this to provide some balance in the initial control and learning phases. It will also constrain movement to the frontal plane (i.e. keep the biped from tipping over sideways).

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