Adaptive Character Motion Synthesis By Qualitative Approach

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Abstract

Adaptive motion synthesis normally involves complicate computation from physical simulation. However some biological researchers believe that the neural system takes little effort in motor control. Instead of planning motion from ground up, living creatures may only maintain or tweak some basic motion pattern for qualitative properties of complicate interaction between body and environment. Inspired by this idea, in this paper, we proposed a new method for adaptive motion synthesis based on the qualitative control theory. Adaptive motion control is achieved through enhancing the structural stability, rather than counteracting perturbations. Compared with current simulation method, our algorithm is more computational efficient and has the potential to be accelerated by GPU.

KEYWORDS

Character Motion Synthesis, Qualitative Dynamic, Physics Based Animation

1 INTRODUCTION

Human beings are very sensitive to motions. From the variety in motion details, humans can infer the changes in mental states, health conditions or even the surrounding environment. This makes Character Motion Synthesis (CMS) a difficult task. In industry, high quality motions are still majorly generated manually, animators need to tweak and set key frames for a large number of joints. To make things worse, it is very difficult to reuse these motion data. When the environment or the character changed, new motions have to be redesigned manually. To save animator from these tedious manual works, many researchers are trying to generate lifelike motions by simulating the dynamic effects between body, environment and the neural control system.

In Biology, lots of researchers have been working on the secret of motions for centuries and discovered some important motion features of live creatures:

**Adaptive** Natural motions are adaptive to the changes in the environment or body. For example, a human being can easily adjust its gait according to different terrains.

**Agile** The reaction of human and most animals is very fast. Even in a complicated changing environment, human can adapt their motions in real time.

**Energy Efficient** According to Darwin’s Theory of Evolution, a natural motion should be energy efficient. Live creatures spent far less energy than we expected. An example is that the energy consumed by human walking is only 10% of that for a robot of the same scale.

Features above are very difficult to achieve by current CMS methods. In this paper, we will bring in the Qualitative Control Theory (QCT). From the viewpoint of QCT, a natural motion is in nature a **structural stable autonomous** system. Adaptation to different environment or characters will be produced automatically with very little control effort. All the above three natural motion features can be achieved from our system. It especially suits repetitive and low energy motion tasks which are most challenging for current researches. Besides, our approach is computational efficient and has the potential to be accelerated by GPU.

2 RELATED WORKS

2.1 Dynamic Motion Synthesis and Control

Dynamic Motion Synthesis synthesizes character motion through simulating the mechanics of the body. The most difficult task is to design system with functionality of biological neural systems. Early research applied classical PD controllers; first for locomotion (Raibert and Hodgins, 1991), later for different tasks like running, bicycling, vaulting and balancing (Hodgins et al., 1995). Limit Circle Control (LCC) (Laszlo et al., 1996) provided an alternative method for lower energy locomotion. However both methods need predefined motion trajectories and are not good at generating adaptive motions.

Because of large number of redundant DOFs, in most cases, motion solutions are not unique. Many optimization methods have been applied to choose the “best” motion. A popular idea is to minimize the energy cost $V$, such that

\[
V=\int_{t0}^{t1}F_{a}(x)^2dt
\]

where  is the active force generated by actuators like motors or muscles. This is introduced to CMS research as the **Spacetime Constraints** (Witkin and Kass, 1988), and serves as the foundation for many modern CMS researches. Jain et al. (2009) provided an example for locomotion; Macchietto et al. (2009) found a method for balance maintaining movement. Liu (2009) proposed a method for object manipulating animation.

The Spacetime method may adapt the motion. However it is in nature a variational optimization method and faces several problems.

**Efficiency** In many cases, it will take long time to find the "best" solution and there is no guarantee the optimal solution can be achieved. For complex body structures the computation will takes prohibitive long time (Anderson and Pandy, 2001). Optimization techniques like time window and multi-grid techniques were proposed by Cohen (1992) and Liu et al. (1994). Still only a few researches (Popović and Witkin, 1999) proposed Spacetime Constraint for full body dynamic animation.

**Sensitive and Over Specific** Current numeric methods are very sensitive to model accuracy and initial conditions. Precise model for both the environment and body have to be prebuilt. Liu (2005) points out that spacetime constraint methods only suit high energy motions like jumping and running; for low energy motion tasks like walking the results don’t look natural. This is mainly because the muscle effects are neglected. Motions like heart beating, breathing, or motions of other animals such as the swimming of fish and jellyfish, flying of birds have not been synthesized with dynamic methods, mainly for the lack of a feasible dynamic model.

2.2 Biological Research

In biological research, motor control is an age old problem full of paradoxes. Motor control in nature is a complex process involving many chemical, electrical and mechanical effects. An immediate idea is Motor Control will involve complicated computation. However, the characteristics of biological neural systems are on the opposite (Glynn, 2003). Neural signal transmitting speed is very slow; and there is a long delay between neural signal firing and force generation in muscles. Besides, the neural signals are also noisy. The body structure and environment are nonlinear, noisy and time varying.

Current research evidences and common life experience show that motor control involves little control effort. Many experiments show motion can happen even without brain input. Despite the complexity of body structures and environment, the natural motor control strategy seems simple and involves very little computational work. For many animals, the neural structure active in motor control is the **Central Pattern Generator (CPG)** which generates rhythmic signals.

Many biological ideas provide space for an efficient motion adaptation. **Uncontrolled Manifold Hypothesis** proposed that some DOFs are not controlled and freely influenced by the environment (Latash, 2008). **The Equilibrium Point Hypothesis** (EPH) suggested that what the neural systems controls is not trajectory, but the final position. **The Impedance Control Hypothesis** (Hogan, 1985) refined the idea of EPH by providing an explanation of the functionality of the extra DOFs. Extra DOFs provide a way to control the stability and admittance of final position according to the motion purpose. **Morphological Computation Theory** (Nishikawa et al., 2007; Pfeifer and Iida, 2005) believed that both the body structure and the environment play a crucial role. Basic motion patterns are generated by body and environment; the neural systems only maintain or tweak basic motion patterns.

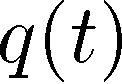
3 QUALITATIVE Control Theoy For CMS

Inspired by the biological research, in this paper we adopt a different strategy for motion adaptation. Perturbations are allowed to freely affect the motion, and motion control is applied to maintain the qualitative properties.

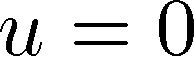
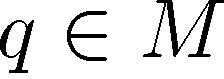
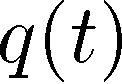
3.1 The Qualitative Control Theory

The Qualitative Control Theory is a mathematical description of the Morphological Computation Theory. In qualitative control theory the basic patterns of motion are called **motion primitive**. We propose that in mathematic viewport, motion primitives are **structural stable autonomous systems**.

3.1.1 Basic Concepts of Qualitative Dynamics

The configuration of system is described by state vector $q$,  is the state space which is a manifold, motion is a trajectory, which is usually represented by ordinary differential equation in the form (1).

\begin{equation}
\dot{q}=F_{u}(q)=F(q,u),q\in M
\label{eq:ode}
\end{equation}

where $u$ is the control effort. $F$ is determined by the system’s natural property. If , systems of no control input are **autonomous systems**. For every point , $F$ and $u$ determines a derivative vector $\dot{q}$. All the vectors over the full space of  form the **vector field** $V$.  is the integral curve of $\dot{q}$, which is defined as flow$\Phi$, all the flows form the **phase portrait**, which illustrates all the possible motions of the dynamic system.

On the phase plane, flows only intersect at some special position, **Fix Point**
$\{ q_{e} \mid H(q_{e})=0 \}$
 and **Limit Circle**$\{ q \mid H(q(0))=H(q(T)) \}$
**,** both of whichare also called **equlibria**.

At each **equilbria**, the local space can be divided into three subspaces: **centre manifold**, **stable manifold**, and **unstable manifold**. They divide the state space into different regions, result in a cellular topological structure. In each region, all the flows converges to one **attractor**, the corresponding region is called **basin of attraction**.

3.1.2 Motion Adaptation and Structural Stability

A mechanical system can be stable without any control effort. This kind of stability is rough stability or structure stability (Andronov and Pontryagin, 1937) which is determined by the topology structure of the system (Jonckheere, 1997). Motion adaptation can be modeled as homeomorphism. Homeomorphic flows share the same topological structure, but with different shapes, which means motions are of different trajectories but qualitatively the same. Structure stable autonomous systems maintain its topology structure under perturbations, thus automatically generate adaptive motions that are qualitatively invariant. Qualitative control will preserve the three natural motion features for the following reasons.

**Adaptive** Different perturbations will generate different motions.

**Efficient** Motion will be generated passively and follow the least energy path.

**Agile** Topological structure can be manipulated and maintained with very little computation.

In our research, only the final motion is concerned. In mathematical viewport, only the attractors of flows are controlled, while the flow shape is not considered in motion control. According to the types of attractors, motion can be categorized into two groups.

**Discrete Motion** Such motions have fix point attractors. Typical motions include posture control and picking up motion of the arm.

**Periodic Motion** Such motion have periodic attractors, typical motion include walking, running and heart beating.

3.2 The New Control Scheme from Qualitative Control Theory

An animal’s body and environment can be extremely complex. This usually leads to high dimensional manifolds with complicated topological structure. Many have asked the same question whether such complex system can be controlled with a simple method. Biology Research suggested that the motion is mainly controlled by the Central Pattern Generator (CPG). The existence of CPG is very common, from primitive animals like lamprey and fish, to high level animals like bird, mammal and human (Cohen, 1988). Motor control by CPG can be modeled as entrainment (González-Miranda, 2004). Entrainment is the phenomenon that two coupled oscillator systems synchronize. The phenomenon is universal, for some cases, stability can be enhanced and chaotic behavior can be suppressed.

In this section, we will discuss a new control scheme based on biological entrainment. The neural system forms one electrical oscillator; body and environment form the mechanical one. Mechanical oscillator can be controlled by the oscillation property of the neural system through entrainment.

3.2.1 The Structural Stability of Neural Oscillator

Equation (2) is the extensively studied neural oscillation model developed by Matsuoka (1985).

\begin{eqnarray}
\tau_{1} \dot{x_{1}}&=&c-x_{1}-\beta v_{1}-\gamma [x_{2}]^{+}-\sum_{j}h_{j}[g_{j}]^{+} \nonumber \\
\tau_{2} \dot{v_{1}}&=&[x_{1}]^{+}-v_{1} \nonumber \\
\tau_{1} \dot{x_{2}}&=&c-x_{2}-\beta v_{2}-\gamma [x_{1}]^{-}-\sum_{j}h_{j}[g_{j}]^{-} \nonumber \\
\tau_{2} \dot{v_{2}}&=&[x_{2}]^{+}-v_{2} \nonumber \\
y_{i}&=&\mbox{max}(x_{i},0) \nonumber \\
y_{out}&=&[x_{1}]^{+}-[x_{2}]^{+}=y_{1}-y{2} \nonumber
\label{eq:matsuta}
\end{eqnarray} (2)

where $x$ and $v$ are state variables, $\tau$,$c$,$\beta$,$\gamma$ are parameters of the oscillator.

Matsuoka oscillator is autonomous and adaptive; entrainments happen when it is coupled with different oscillators. But because of the nonlinear properties, its behavior has not been completely understood. Matsuota (Matsuoka, 1987) explained the adaptive properties by investigating location of the roots of characteristic equation. Wilimas (Williamson, 1998) explained the properties in frequency domain.



Figure 1: Matsuta Oscillator



Figure 2: Passive Walker

Here we provide an idea based on structural stability analysis. The topology structure of neural oscillator is simple; it includes one attractive limit circle and one repelling fix point. All the simulations we carried out converged to the same limited circle. In most of the case, the flow will converge to the limit circle within one period. Features above are shown in Figure 1.

These properties are very valuable in CMS research. An intuitive idea is that we can make the motion structural stable by coupling body with Matsuoka Oscillator.

4 APPLICATION and Results

The basic idea of qualitative control for motion synthesis is boosting structural stability by coupling the mechanical oscillator with neural oscillator. Our approach can be applied to many motion tasks. In this section, we will discuss just one example in details, the bipedal walking. This is mainly because bipedal walking is one of the most challenging and common locomotion styles. Bipedal walking is unstable which makes it very difficult for adaptive gaits. While for artificial system, robust bipedal walking is difficult to achieve. Many control method has been tried, but none of them shows comparable performance with human walking.

In dynamic research, natural looking gaits can be generated by passive method (McGeer, 1990a, 1990b), Passive walkers can walk down a slope without any effort, but the stabilities are very fragile.

From the Qualitative Control Theory, the reason behind passive walking is that there is a limit circle for the dynamic interaction between body and ground. The fragile stability means the basin of attraction is small. To generate adaptive walking gait, we plan to boost the stability of the passive walking machine by neural oscillation entrainment.

4.1 2D Passive Walking Model

The mechanical model we adopted is illustrated in Figure 2. Passive walking is a hybrid dynamic system. We separate the motion into two phases described by Equation (3, 4).

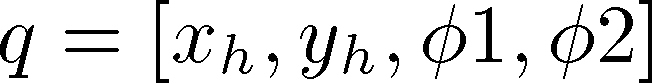
**Leg Swing Phase** During the swing phases, we suppose that one leg is fixed on the ground, the arc foot makes the passive dynamic walker rolling without sliding (Wisse and Schwab, 2005).

\[
\left[
\begin{array}{cc}
\bar{M} &D^{T}\\
D& 0 
\end{array}
\right]
\left[
\begin{array}{c}
\ddot{q} \\
F_{c}
\end{array}
\right]
=
\left[
\begin{array}{c}
\bar{F}\\
\ddot{D}\\
\end{array}
\right]
\] (3)

**Heel Strike Phase** We suppose the heel strike the ground in a short time, the angular momentum is preserved, as described by Equation(4) (Wisse and Schwab, 2005)

\[
\left[
\begin{array}{cc}
\bar {M}& D^{T}\\
D & 0
\end{array}
\right]
\left[
\begin{array}{c}
\dot{q}^{+}\\
f_{c} 
\end{array}
\right]
=
\left[
\begin{array}{c}
\bar{M}\dot{q}^{-}\\
0
\end{array}
\right]
\] (4)

where  is the state variable after the collision,  is the state variable before the collision.

In the Equations (3, 4),  is the inertia matrix,  ,$D$ is the constraint equation.  is the constrained force, and  is the constrained impulse.

4.2 Adaptive Walking Motion

The input of neural oscillator is defined by the difference angle between the two legs. Neural output will drive the biped walker; torque is applied at the hip joint. After adding the neural control, the equation of the dynamic system is as below.

\[
\left[
\begin{array}{cc}
\bar{M} &D^{T}\\
D& 0 
\end{array}
\right]
\left[
\begin{array}{c}
\ddot{q} \\
F_{c}
\end{array}
\right]
=
\left[
\begin{array}{c}
\bar{F}\\
\ddot{D}
\end{array}
\right]
+
\left[
\begin{array}{c}
\bar{U}\\
0 
\end{array}
\right]
\]

\[
U=[0,0,1,-1]*G_{out}
\]

**Passive Walking** When the passive walker walks down a slope, there is an equilibrium condition when the heel strike energy lost is equal to the potential energy input. Because there is no extra control energy input, such motion is the most energy efficient. Figure 3 shows the gait of the passive walker. After coupling the neural oscillator, the basic pattern is not changed as shown in Figure 4.



Figure 3: Stable Passive Walking Gait



Figure 4: Walk down Slope with Neural Control

**Walking On Plane** However, the passive walker can’t walk on plane. The step size will decrease after each step. Finally it will stop or fall over as illustrated in Figure 5.

After coupled with the neural oscillator, this walking machine can walk on plane, and exhibits gait similar to the passive walker.  Figure 6 shows the gait. From Figure 7(a) and Figure 7(b), we can see that the gait converged to a stable limit circle.



Figure 5: Passive Gait Can’t be Maintained on Plane



Figure 6: Gait on Plane with Neural Control



Figure 7: Gait on Plane with Neural Control

To verify the structural stability, we introduce a variety of perturbations to the passive walker.

**Different Initial Condition** The original passive walker is not very stable. A slight change in initial condition will result in walking failure. While after coupled with neural oscillator, a different initial condition can still lead to a stable gait, as show in Figure 8. This means the basin of attraction has been enlarged.

**Walking On Different Slopes** Even walking down a steeper slope, stable gaits can still be maintained, as shown in Figure 9. An important discovery is that although the walkers can walk down steeper slopes, it cannot walk up slope, no matter how control parameters are tweaked. We think that this is mainly because the proper limit circle does not exist anymore when walking up slope. Involving the upper body into this structure may help to solve this problem.

Figure 8: Gait of a Different Initial Condition



Figure 9: Gait on a Different Slop

**Leg Mass Variation** Mass of one leg is added up to 150% and the gait is still maintained. The step length and swing period of the two legs are different, this gait is similar to that with a crippled leg, see Figure 10.

**Leg Length Variation** Leg length is set to 1/8 shorter and the gait is maintained, see Figure  .



Figure 10. Gait of Different Leg Mass



Figure 11: Walking with shorter Legs

5 DISCUSSIONS and Future Work

Qualitative Control Theory can synthesize motion with adaptive behavior while keeping the qualitative properties. It provides a new method to synthesize adaptive motion efficiently. Since very little computation involved in each controller, compared with traditional optimization based method, this method can generate motions in real-time. And most importantly, our method is parallel in nature, in future; most of the computational burden of our method can be shifted to GPU. This will make our algorithm generating agile motions even with very complicated environment and involving whole body structures.

However since we bring in a new theory into the motion synthesis area, many works need to be done in the future. For example, our current model only involves the lower body structure, upper body and more joints will be considered in our future design. To proof the robustness, we will need experiment on more complicate terrain and perturbations.

More Central Pattern Generators are needed for different kinds of motions. And how to turn the CPG parameters for the animator purpose are still open. These topics will be covered in the future research.

Acknowledgment

We want to thank Richard Southern for the invaluable discussion and advice about organization of the paper. The knowledge of mechanics and questions of Jian Chang also help to make the paper more clear.

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