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An artificial neural network that utilizes hip joint actuations to control bifurcations and chaos in a passive dynamic bipedal walking model

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Abstract Chaos is a central feature of human locomotion and has been suggested to be a window to the control mechanisms of locomotion. In this investigation, we explored how the principles of chaos can be used to control locomotion with a passive dynamic bipedal walking model that has a chaotic gait pattern. Our control scheme was based on the scientific evidence that slight perturbations to the unstable manifolds of points in a chaotic system will promote the transition to new stable behaviors embedded in the rich chaotic attractor. Here we demonstrate that hip joint actuations during the swing phase can provide such perturbations for the control of bifurcations and chaos in a locomotive pattern. Our simulations indicated that systematic alterations of the hip joint actuations resulted in rapid transitions to any stable locomotive pattern available in the chaotic locomotive attractor. Based on these insights, we further explored the benefits of having a chaotic gait with a biologically inspired artificial neural network (ANN) that employed this chaotic control scheme. Remarkably, the ANN was quite robust and capable of selecting a hip joint actuation that rapidly transitioned the passive dynamic bipedal model to a stable gait embedded in the chaotic attractor. Additionally, the ANN was capable of using hip joint actuations to accommodate unstable environments and to overcome unforeseen perturbations. Our simulations provide insight on the advantage of having a chaotic locomotive system and provide evidence as to how chaos can be used as an advantageous control scheme for the nervous system.

Keywords Locomotion · Gait · Walking · Chaos · Variability · Artificial neural network · Connectionism

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1 Introduction

Human locomotion is typically described as having a periodic movement pattern. For example, it can be readily observed that the legs oscillate to-and-fro with a limit cycle behavior that is similar to the pendulum motions of a clock (Clark and Phillips 1993). Any variations from this periodic pattern have traditionally been considered as "noise" within the neuromuscular system (Hausdorff et al. 1995). However, recent investigations of human locomotion have confirmed that variations from one step to the next are not noise. Rather these variations have a chaotic structure (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1997, 1998, 1999, 2000; West and Griffin 1998, 1999; Stergiou et al. 2004a,b). Several authors have noted that the chaotic structure present in human locomotion is influenced by the health of the neuromuscular system and have speculated that chaos is related to the neuromuscular control of locomotion (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1998, 2000; Stergiou et al. 2004a,b). However, no efforts has been made to explain how chaos can provide control of the locomotive pattern or why a chaotic gait pattern is necessary.

A chaotic system is typically described as being both stable and flexible (Li and Yorke 1975; Allgood et al. 1997; Baker and Gollub 1996). Chaotic systems have an ergodotic property where their trajectories come close to a fixed point's neighborhood but never converge to the specific point (Allgood et al. 1997; Baker and Gollub 1996). This ergodotic property has been used to describe a chaotic system as being flexible since they are capable of maintaining a stable and variable pattern. The degree of these variations in the state space have been linked to the health of a biological system (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1998, 1999, 2000; Goldberger et al. 2002; Stergiou et al. 2004b). For example, several investigations have determined that a heart rhythm that has chaotic pattern is healthy, while heart rhythms that have a more periodic pattern are more susceptible to heart disease (see Goldberger et al. 2002 for review). Although chaotic flexibility appears to be quite an advantage from a clinical standpoint, an additional benefit of having a chaotic system is that small perturbations can be used to drive the system to stable trajectories that are embedded in the chaotic attractor (Starrett and Tagg 1995; Ott et al. 1990; Shinbrot et al. 1993). For example, a small perturbation along the unstable manifold of a point in the attractor can promote the system to transition from a chaotic pattern to a periodic pattern (Starrett and Tagg 1995; Ott et al. 1990; Shinbrot et al. 1993). This property comes from the fact that multiple points found in a chaotic attractor have both unstable and stable manifolds (Starrett and Tagg 1995; Ott et al. 1990; Baker and Gollub 1996; Allgood et al. 1997). Periodic systems cannot demonstrate such transition flexibility because no points in the attractor have unstable manifolds (Starrett and Tagg 1995; Ott et al. 1990; Allgood et al. 1997; Baker and Gollub 1996; Abarbanel 1996). The ability to transition to various stable patterns embedded in the chaotic system truly demonstrates ultimate flexibility. It is possible that the nervous system may use the principles of the chaotic attractor to control gait patterns and ensure stability in uncertain environments. Hence, chaos may be necessary to allow the nervous system to accommodate a variety of locomotive strategies by using well-timed perturbations that promote the central pattern generator to switch to stable locomotive patterns available in the rich chaotic attractor. No effort has been made to explore if such a perturbation scheme could be used to control locomotion.

The biomechanical requisites and engergetics of human locomotion have been successfully explored with a class of passive dynamic bipedal robots that walk down a slightly sloped surface (Kuo 2001, 2002; Kurz et al. 2005; Garcia et al. 1998; McGeer 1990; Collins et al. 2005; Groswami et al. 1996; Howell and Baillieul 1998). These bipedal models are composed of an inverted double pendulum system where one leg is in contact with the ground and the other leg swings freely with the trajectory of the system's center of mass (Fig. 1). Recently, Groswami et al. (1996) and Garcia et al. (1998) have demonstrated that a simple passive dynamic walking model can exhibit a cascade of bifurcations (i.e. period 1, period 2, period 4...) that converges to a chaotic locomotive pattern. Numerical experiments by Garcia et al. (1998) suggested that the basin of attraction for a stable chaotic gait is bigger than the basin for a periodic fixed point gait. This suggests that a chaotic gait may be more robust because it has a greater basin of stability. Additionally, Garcia et al. (1998) suggested that since the basin of stability is larger for chaotic systems it may be useful to add control to the passive dynamic walking system to maintain locomotive pattern within the chaotic region. However, no further investigations have been conducted to extend Garcia et al.'s (1998) concepts. It is possible that slight joint actuations may perturb the locomotive system to stay within the chaotic basin of attraction. Further investigation of these concepts may prove to be fruitful in further understanding why a chaos is present in human locomotion.

In this investigation, we have extended Garcia et al. (1998) passive dynamic walking model by incorporating a hip joint actuator for the swing leg (Fig. 1). We hypothesized that the central nervous system may use such hip joint actuations to provide a perturbation to the chaotic locomotive system. Potentially, joint actuations will cause the passive dynamic bipedal model to transition to new stable locomotive patterns embedded in the chaotic attractor and help to maintain the gait within the basin of the chaotic attractor. Additionally, we further explored how chaos can be used as a control scheme by developing a biologically inspired artificial neural network (ANN) that selects hip joint actuations for the model's gait. We hypothesized that the simulated nervous system would be able to utilize hip joint actuations to transition to a stable locomotive pattern embedded in the chaotic attractor during unpredictable environments and when unforeseen external perturbations are encountered.

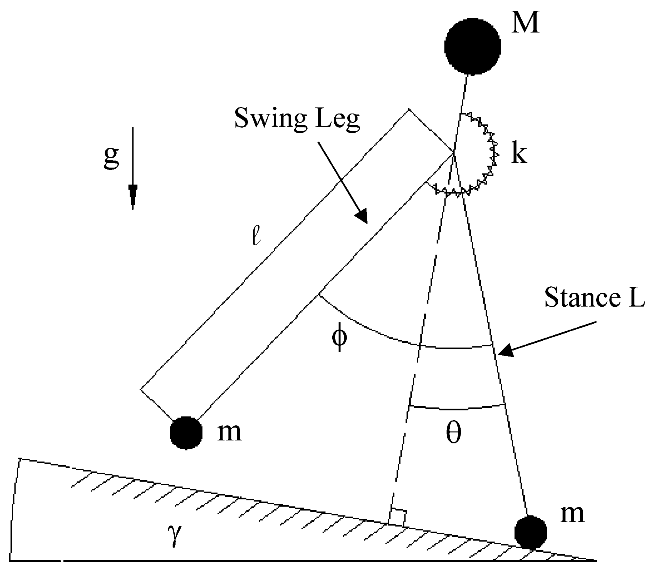

Fig. 1 The passive dynamic walking model where ϕ is the angle of the swing leg, θ is the angle of the stance leg, γ is the angle of inclination of the supporting surface, and g is gravity. Both legs are of length l

2 Modeling bipedal locomotion

The passive dynamic walking model used in this investigation was a simplified mathematical model of the lower extremities based on the work of Garcia et al. (1998) and Kuo (2002) (Fig. 1). The model consisted of two rigid massless legs connected by a frictionless hinge at the hip. During locomotion, the stance leg swung like an inverted pendulum until the swing leg made contact with the supporting surface. At heel-contact, the swing leg became the stance leg and the stance leg became the swing leg for the next step. The swing leg was allowed to pass through the supporting surface during midstance and had a plastic collision with the surface at heel strike. Energy for the locomotive pattern was supplied to the model via a slightly sloped rigid walking surface ($\gamma < 0.0190$ rad). The simplified equations of motion for the passive dynamic bipedal walking model developed by Garcia et al. (1998) are presented in Eq. 1.

$$\begin{aligned} &\ddot{\theta}(t) - \sin(\theta(t) - \gamma) = 0, \\ &\ddot{\theta}(t) - \ddot{\phi}(t) + \dot{\theta}(t)^2 \sin\phi(t) \\ &\quad - \cos(\theta(t) - \gamma)\sin\phi(t) = k\phi(t), \end{aligned} \tag{1}$$

where γ is the slope of the walking surface, t is time, k is the stiffness of the hip torsional spring, θ is the angle of the stance leg, ϕ is the angle of the swing leg, and $\dot{\theta}, \ddot{\theta}, \dot{\phi}, \ddot{\phi}$ are the respective derivatives. Further detailed explanations regarding the derivation of the governing equations for the passive dynamic model used in this investigation can be found in Garcia et al. (1998) and Kuo (2002). Inspection of the governing equations indicates that hip joint actuation was applied to the swing leg via a torsional spring. The magnitude of the hip joint actuation was adjusted by increasing the value of k.

The governing equations were integrated using a modified version of *Matlab's* (MathWorks, Natick, MA) ODE45. The ODE45 was modified to integrate the equations of motion with a tolerance of 10^{-12} and to stop integrating when the angle of the swing leg angle was twice as large as the stance leg angle (Eq. 2).

$$\phi - 2\theta = 0. \tag{2}$$

The swing leg became the stance leg and the former stance leg became the swing leg when the conditions presented in Eq. 2 were satisfied. The switching of the roles of the legs was performed with a transition equation developed by Garcia et al. (1998) (Eq. 3).

$$\begin{pmatrix} \theta \\ \dot{\theta} \\ \phi \\ \dot{\phi} \end{pmatrix}^{+} = \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & \cos 2\theta & 0 & 0 \\ -2 & 0 & 0 & 0 \\ 0 & \cos 2\theta(1 - \cos 2\theta) & 0 & 0 \end{pmatrix} \begin{pmatrix} \theta \\ \dot{\theta} \\ \phi \\ \dot{\phi} \end{pmatrix}^{-} \tag{3}$$

where "+" indicated the behavior of the model just after the swing leg made contact with the ground and "−" indicated the behavior of the model just before the swing leg made contact with the ground. The transition equation assumes that angular momentum of the entire system was conserved about the swing foot point of contact and also for the former stance leg about the hip (Garcia et al. 1998). Therefore, the energy gained in the descent of the walking model was balanced by the energy lost at each heel-strike. Further information on the derivation of Eq. 3 can be found in Garcia et al. (1998).

Bifurcations and changes in the model's locomotive pattern were noted with Poincaré maps composed from initial stance leg angle of the model for a given step (Eq. 4).

$$\zeta_{n+1} = f(\zeta_n) \tag{4}$$

where ζ_n is the stance leg angle for the nth step and ζ_{n+1} is the stance leg angle for the proceeding step. The Poincaré maps provided a way to simplify the dynamics of the system by viewing the behavior of the system stroboscopically (Baker and Gollub 1996). This involves cutting or sectioning the attractor at regular intervals or events. An increase in the order of the gait pattern as a joint actuation was applied results in more points in the Poincaré map (i.e. Period 4–8). Alternatively, a decrease in the order as a joint actuation was applied results in fewer points in the Poincaré map (i.e. Period 8–4).

Lyapunov exponents were calculated to quantify the exponential separation of nearby trajectories in the reconstructed state space of the simulated locomotive pattern at the respective γ (Allgood et al. 1997; Baker and Gollub 1996; Abarbanel 1996; Stergiou et al. 2004a,b). This information was necessary to classify the locomotive pattern as periodic or chaotic. As nearby points of the state space separate, they diverge rapidly and can produce instability. Lyapunov exponents from a stable system with little to no divergence will be zero (e.g. sine wave). Alternatively, Lyapunov exponents for an unstable system that has a high amount of divergence will be positive (e.g. random data). A chaotic system will have both positive and negative Lyapunov exponents. Although a positive Lyapunov exponent indicates instability, the sum of the Lyapunov exponents for a chaotic system remains negative and allows the system to maintain stability (Allgood et al. 1997; Baker and Gollub 1996; Abarbanel 1996; Stergiou et al. 2004a,b). This notion can be seen by inspecting the largest Lyapunov exponent for a sine wave (0), a chaotic Lorenz attractor (0.100), and random data series (0.469). Hence a chaotic system lies somewhere between a completely periodic system and a completely random system. The *Chaos Data Analyzer* (American Institute of Physics) was used to numerically calculate the largest Lyapunov exponent for each γ. Previously, we had confirmed that an embedding dimension of three is necessary to calculate the largest Lyapunov exponent for Garcia et al.'s 1998 passive dynamic bipedal walking model (Kurz et al. 2005).

3 Analysis of locomotive patterns

We used systematic numerical simulations to confirm the influence of hip joint actuation on the locomotive patterns of our model. Analyses of the locomotive patterns of the model were performed from 5,000 footfalls with the first 500 footfalls removed to be certain that the model converged to the given attractor. Initial simulations were performed with no joint actuations (i.e. $k = 0\ \mathrm{s}^{-2}$). This was followed by a systematic exploration of the influence of hip joint actuations on the identified locomotive patterns at the respective γ.

4 Artificial neural network

Artificial neural networks are composed of biologically inspired neuron like elements operating in parallel (Russell and Norvig 2003; McClelland and Rumelhart 1981; Rumelhart and McClelland 1986; Morris 1989; Cohen et al. 1990; Thelen and Bates 2003). As in the human nervous system, the output of each neuron is determined by its interconnections with other neurons in the simulated nervous system. Each interconnection has a weight associated with the connected edge. It is the collective activity of multiple weighted edges that determines the behavior of the respective neuron (Russell and Norvig 2003; McClelland and Rumelhart 1981; Rumelhart and McClelland 1986; Morris 1989; Cohen et al. 1990; Thelen and Bates 2003). By adjusting the weighted connections between the respective neurons, the ANN learns to perform specific tasks for a given set of inputs. ANNs have been successfully used to model the neural activity associated with human cognitive behaviors (McClelland and Rumelhart 1981; Rumelhart and McClelland 1986; Morris 1989; Cohen et al. 1990; Thelen and Bates 2003). These models have advanced our understanding of the organization and performance of the central nervous system. We employed a similar methodology to explore how the nervous system can use the principles of chaos to control locomotion.

We developed a feed-forward ANN that had sixteen input neurons, four hidden neurons and one output neuron (Fig. 2). Neurons between each layer were connected via a series of weighted edges (w_{ij}). Each ith neuron had an input value x_i and an output value $y_i = g(x)$. A sigmoid function $g(x) = (1+e^x)^{-1}$ was used to determine the excitation of the neuron where the value of x was given by $x_i = \sum w_{ij} y_j$. The input to the ANN consisted of eight time delays of the model's initial right leg angle and angular velocity for a given step ($X_{n-1}, X_{n-2}, \ldots, X_{n-8}$). These time delays served as a cognitive memory for the past states of the locomotive system. Our decision to use time delays as input parameters was based on the current scientific literature that indicates human locomotion has a neural memory of past locomotive states (Hausdorff et al. 1995, 1997, 1998, 1999, 2000). These memories appear to serve as a basis for selecting the neuromuscular behavior of proceeding steps. Additionally, several investigations have determined that kinematic codes of past neuromuscular behaviors are stored in working memory (Shand 1982). The use of angular position and velocity as input parameters for the ANN was based on the prevalent literature that indicates the receptors in the muscle monitor the position and velocity of the limb trajectories (McCloskey 1978).

We trained the ANN to select a hip stiffness (k in Eq. 1.) that would transition a period-n gait to a period-2 gait. Although it is unlikely that humans walk with a period-2 gait, we selected period-2 because it is feasible to visually inspect the performance of the model with Poincarè sections. Changes in the hip stiffness variable subsequently altered the hip joint actuation applied to the locomotive system. The training data utilized was from 0.0182 rad $> \gamma >$ 0.0183 rad. The assignment of edge weights in the final neural network was determined with a backpropogation algorithm where the output of the ANN was compared with the training data (Russell and Norvig 2003; Rumelhart and McClelland 1986). We tested the ANN performance at γ that it had not been trained (e.g. 0.0183 rad $> \gamma >$ 0.0191 rad). Additionally, the robustness of the ANN was tested by supplying an impulse directed toward the model's center of mass at the 150th step (Eq. 5 where $P > 0$). This impulse provided an unforeseen perturbation to the models gait at heel-contact. P was dimensionless and had a normalization factor $M(\mathrm{g\,l})^{1/2}$. When P was set to zero, the equation is the same as the transition equation presented in Eq. 3.

$$\begin{pmatrix}\theta\\ \dot\theta\\ \phi\\ \dot\phi\end{pmatrix}^{+} = \begin{pmatrix}-1 & 0 & 0 & 0\\ 0 & \cos 2\theta & 0 & 0\\ -2 & 0 & 0 & 0\\ 0 & \cos 2\theta(1-\cos 2\theta) & 0 & 0\end{pmatrix}\begin{pmatrix}\theta\\ \dot\theta\\ \phi\\ \dot\phi\end{pmatrix}^{-} + \begin{pmatrix}0\\ \sin 2\theta\\ 0\\ (1-\cos 2\theta)\sin 2\theta\end{pmatrix} P \tag{5}$$

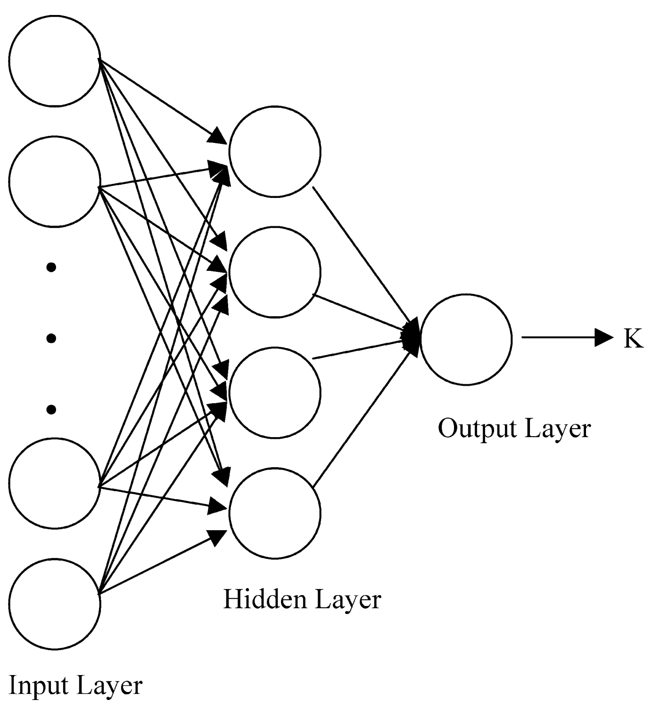

Fig. 2 Schematic for the artificial neural network that determines a stiffness value (k in Eq. 1) for modulating hip joint actuation

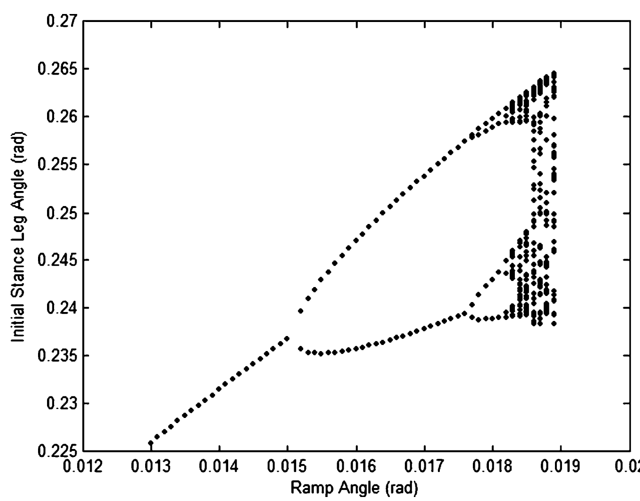

Fig. 3 Bifurcation map for the passive dynamic bipedal walking model with no hip joint actuations (e.g. $k = 0\,\mathrm{s}^{-2}$). Without hip joint actuation, no stable gait patterns are present beyond 0.0190 rad

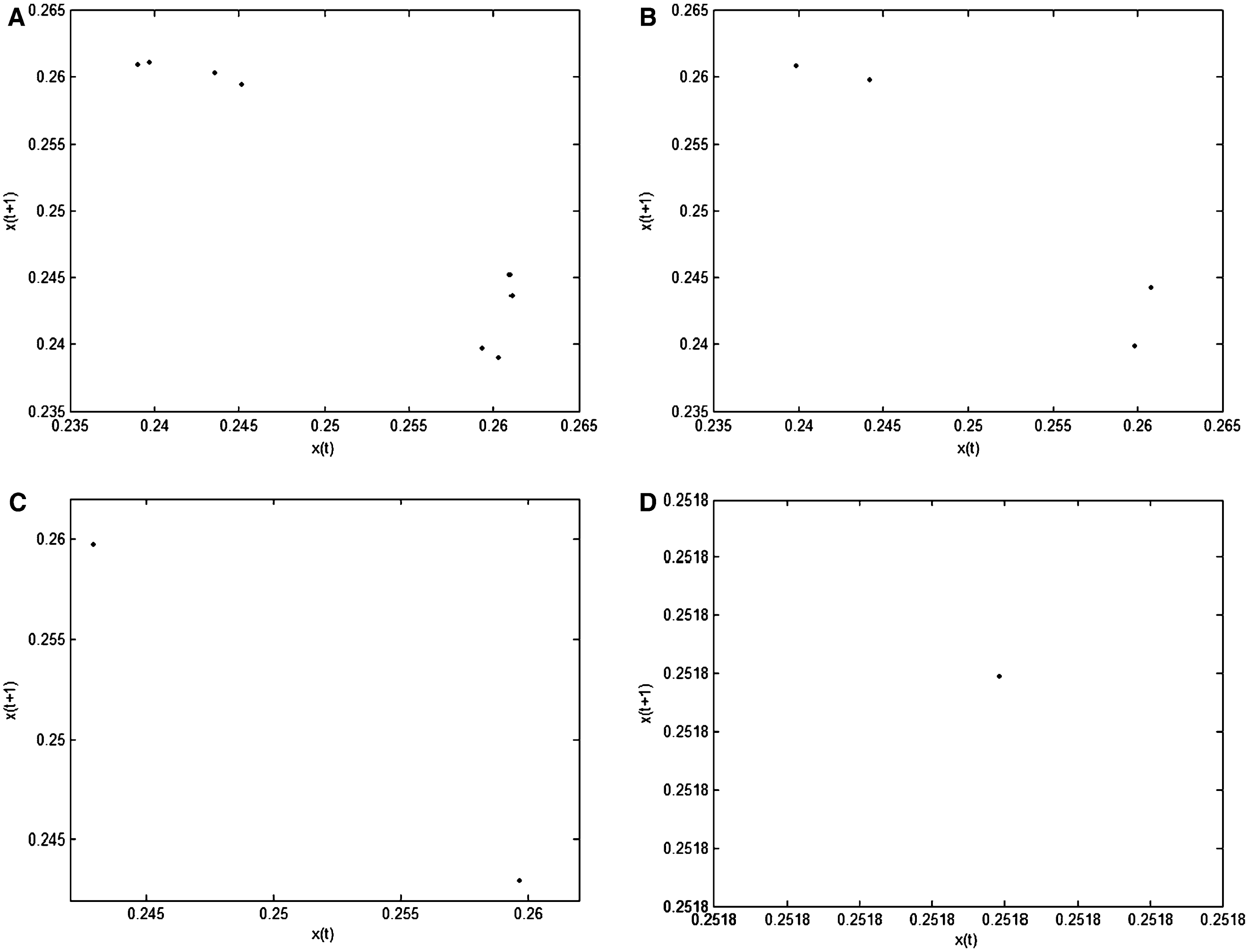

Fig. 4 Poincaré sections for the model while walking at $\gamma = 0.01823$ rad and $k = 0\ \mathrm{s}^{-2}$ (**a**), $k = 0.002\ \mathrm{s}^{-2}$ (**b**), $k = 0.01\ \mathrm{s}^{-2}$ (**C**), $k = 0.06\ \mathrm{s}^{-2}$

Perturbations were systematically increased for each simulation until the passive dynamic walking model fell down. The robustness was classified by how much of a perturbation the locomotive system could overcome with and without the presence of the ANN.

5 Simulation results

With no added hip joint actuation (i.e. $k = 0$), the model had a cascade of bifurcations that led to a chaotic gait pattern as γ was increased (i.e. period-one, period-two, period-four, etc.) (Fig. 3). Period one locomotive attractors were present for $\gamma < 0.0150$ radians. A period one attractor indicated that the model selected the same initial stance leg angle for every step of the continuous locomotive pattern. At $\gamma = 0.0151$ rad, the locomotive pattern bifurcated from period one to period two. A period two indicated that the locomotive pattern alternated between two different initial stance leg angles. Additional increases in γ systematically resulted in further bifurcations in the initial stance leg angle chosen by the walking model. Positive Lyapunov exponents were present from 0.01839 rad $< \gamma < 0.0189$ rad (Lyapunov exponent range = +0.002 to +0.158).

Subsequently, we explored if hip joint actuation was a mechanism to control the locomotive pattern of the walking model. As the hip joint actuation was increased (i.e. k > 0), the order of the period-n gaits at the respective γ were decreased. For example, systematic increases in hip joint actuation applied to a period-8 gait drove the system to a period-4 gait, to period-2 gait and to a period-1 gait (Fig. 4). This type of joint actuation could be used to rapidly transition to any gait pattern in the bifurcation map (Fig. 3). For example, Fig. 5 demonstrates that the chaotic pattern present at $\gamma = 0.0189$ rad was rapidly transitioned to a period one gait when a hip joint actuation of 0.06 s^{-2} was applied at the 150th step of the model's gait. This should not be misinterpreted that hip actuation could only be used to transition to periodic gait. Hip actuation could be used to transition to any period-n gait, which included a lower level chaotic attractor that was embedded in the higher level chaotic system. We define a lower level chaotic attractor as a chaotic attractor with its largest Lyapunov Exponent closer to zero.

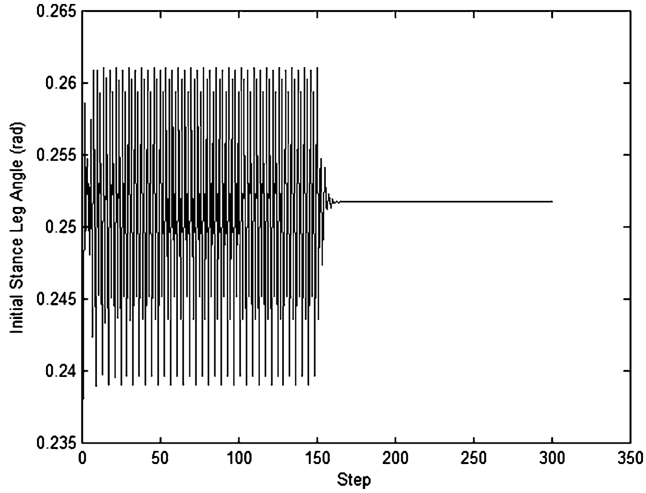

Fig. 5 A series of steps from the passive dynamic walker at a ramp angle of 0.0189 rad. No hip actuation was supplied prior to the 150th step and the model walked with a chaotic gait pattern. After the 150th step, a hip actuation of $0.06\,s^{-2}$ was applied which promoted the gait pattern to rapidly transition to a period one gait

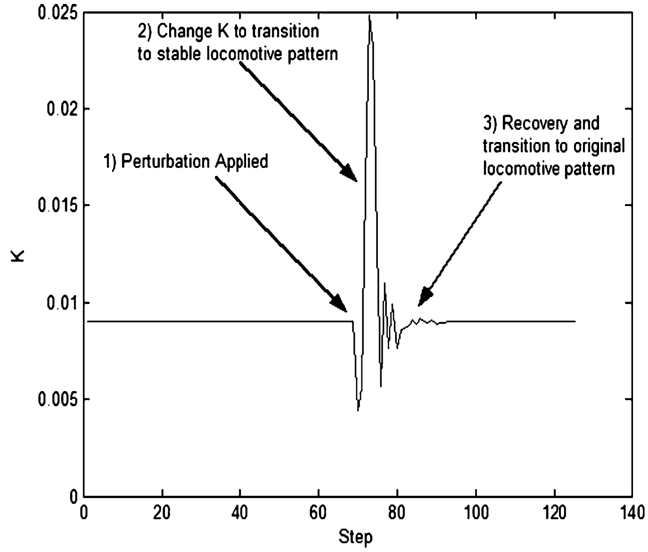

Fig. 7 Corresponding hip joint stiffness selected by the artificial neural network to transition to stable gaits embedded in the chaotic attractor when the unforeseen perturbation is encountered

Simulations of the ANN's performance indicated that it was capable of selecting a proper hip joint actuation that transitioned any period-n gait at a respective γ to a period-2 gait. Additionally, the ANN was capable of using hip joint actuations to induce locomotive stablity in regions where the model was not previously able to walk. Without the addition of hip joint actuation (i.e. $k = 0$), the model would fall down at ramp angles larger than 0.019 rad. However, employment of the ANN's chaotic control scheme resulted in the selection of hip joint actuations that allowed the model to walk with a stable gait at ramp angles that were previously considered unstable. Hence, the ANN was able to use hip joint actuations to induce stability in the model's locomotive pattern in uncertain environments.

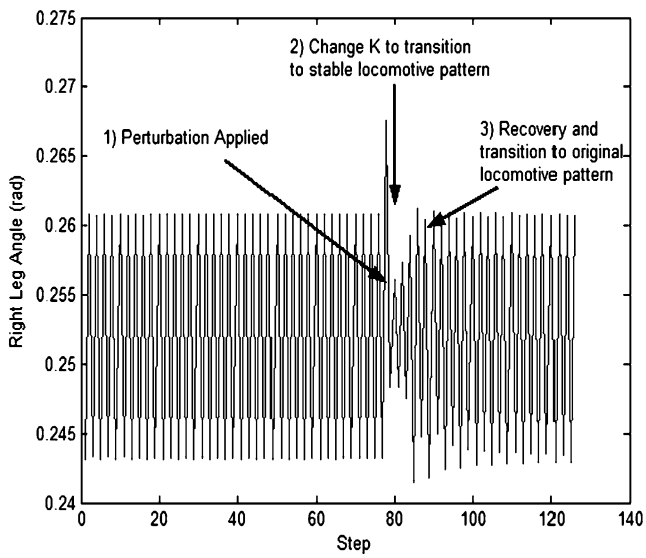

Fig. 6 An exemplar gait pattern where an unforeseen perturbation was applied to the passive dynamic bipedal walking model. The artificial neural network utilized the hip joint actuator to rapidly transition to a stable gait embedded in the chaotic attractor

The results from the perturbation analysis further demonstrated the robustness of the ANN. When the ANN was not used for control, the model was able to use passive dynamics alone to stabilize a perturbation of $P = 0.0007$. However, with the use of the ANN, unforeseen perturbations that were 73% larger were stabilized by rapidly transitioning to a stable gait embedded in the chaotic attractor. Figures 6 and 7 depict the robustness of the ANN where a perturbation was applied during stable locomotion. The ANN rapidly selected a hip joint actuation that transitions the locomotive system to a stable pattern. Upon stabilizing the disturbance, the ANN quickly transitioned the locomotive system back to the original stable gait pattern.

6 Discussion

Chaos is a central feature of human locomotion (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1997, 1998, 1999, 2000; Stergiou et al. 2004a,b; West and Griffin 1998, 1999). The origin of such complex physiological rhythms in locomotion has come under closer examination because it has been suggested that they are linked to the control mechanisms of the neuromuscular system (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1997, 1998, 1999, 2000; Stergiou et al. 2004a,b; West and Griffin 1998, 1999). In this investigation, we explored how the principles of chaos can be used as a control scheme for bipedal locomotion. With no hip joint actuation (e.g. $k = 0\ s^{-2}$), our passive dynamic bipedal walking model was capable of producing a chaotic locomotive pattern when the ramp angle was $0.01839\,\text{rad} < \gamma < 0.0190\,\text{rad}$ (Lyapunov exponent range =

+0.002 to +0.158). When hip joint actuation was added to the model, it provided a mechanism to control bifurcations and the presence of chaos. Hip joint actuation allowed the model to transition to other stable gaits embedded in the chaotic attractor. These simulations suggest that humans may use well-timed joint actuations to transition to stable locomotive patterns available in the chaotic attractor when instabilities are encountered in the walking environment. These simulations build on Garcia et al. (1998) concept that the basin of stability may be larger for chaotic gaits compared to the basin of stability for periodic fixed point gaits. It is theoretically plausible that hip joint actuations could be used to ensure that the locomotive system remains within the basin of stability of the chaotic attractor. The advantage of remaining in the chaotic region is that there are many different step length combinations available for a stable gait pattern. Once in the chaotic basin, further hip joint actuations can be used to select a stable gait that meets the changes in the environment.

Our biologically inspired ANN was capable of utilizing the principles of chaos as a control scheme. Remarkably, the ANN selected a hip joint actuation that rapidly transitioned the locomotive system to a stable gait embedded in the rich chaotic attractor. Additionally, our simulations demonstrated that the chaotic control scheme employed by the ANN was very robust. The ANN was capable of using hip joint actuations to accommodate unstable environments and to overcome unforeseen perturbations. Insights from our simulations are quite striking and provide a foundation for further understanding of the advantage of having chaotic walking pattern. We suggest that chaos may provide ultimate flexibility in the gait pattern by allowing the nervous system to select a stable gait pattern that is embedded in the chaotic attractor. This type of control may be highly desirable in the ever changing environment. By having a chaotic locomotive system, the controller can match what type of gait pattern is necessary for the given environment. This may include various types of period-n locomotive patterns. Based on these insights, it was quite evident that the ANN provided additional benefit beyond the natural stability of the chaotic attractor. The ANN could use the properties of the chaotic attractor to select a hip joint actuation that transitions the locomotive system to a gait that is stable for the given perturbation or environmental circumstances.

Several investigations have indicated that gait is controlled by a central pattern generator (e.g neuronal group) located in the spinal cord (Grillner 1981; Rossignol et al. 2000; Forssberg et al. 1980a,b; Barbeau and Rossignol 1987; Harkema 2001; Suster and Bate 2002; Marder 2002). The central pattern generator provides neural timings necessary for locomotive patterns. Even in the absence of higher brain center influences, the central pattern generator is capable of producing viable gaits in spinalized animals (Rossignol et al. 2000; Forssberg et al. 1980a,b; Barbeau and Rossignol 1987) and humans with spinal cord injuries (Harkema 2001). Since there is extensive evidence that steady state human locomotion has a chaotic structure (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1995, 1997, 1998, 1999, 2000; Stergiou et al. 2004b; West and Griffin 1998, 1999), it is possible that chaos may actually be embedded in the dynamics of the central pattern generator. However, neural signals from the higher brain centers may be necessary for altering the behavior of the chaotic central pattern generator. Possibly neural signals from higher brain centers may initiate well-timed joint actuations that cause the central pattern generator to alter its neural firing pattern to a new stable gait patterns embedded in the chaotic system. Such a control scheme may be advantageous because it will reduce the need for continuous commands to be sent to the multiple degrees of freedom present in the musculoskeletal system during locomotion. Additionally, it would allow the central pattern generator to rapidly switch to the multiple stable gait patterns available in the chaotic attractor as environmental circumstances change. To further explore this hypothesis, we are experimentally investigating and modeling the influence of higher brain centers on chaotic locomotive dynamics in clinical populations with isolated disorders of the central nervous system (i.e. Parkinson's, stroke and spinal cord injuries).

Based on the results of our simulations, we suggest that how the nervous system takes advantage and utilizes the properties of the chaotic locomotive attractor may be a source of the previously observed differences in chaotic dynamics of abnormal locomotive patterns (Buzzi et al. 2003; Dingwell et al. 2000; Hausdorff et al. 1997, 1998, 2000; Stergiou et al. 2004a,b). As stated previously, the nervous system may be able to select a desired gait pattern from among the infinite number of behaviors naturally present in the chaotic locomotive attractor. The ability of the nervous system to capitalize on the properties inherent to the chaotic system may allow for a healthy and flexible locomotive system. An example of this notion is provided in a recent investigation where it was determined that the elderly have altered chaotic locomotive dynamics (Buzzi et al. 2003). Since it is well known that the elderly have abnormal hip joint mechanics (Winter et al. 1990; Winter 1991; Judge et al. 1996; Kerrigan et al. 1998), it is possible that the altered chaotic dynamics may be related to an inability of the elderly nervous system to champion the use of hip joint actuation for the control bifurcations and chaos. In a sense, the elderly may not be able to supply joint actuations that are necessary for transitions to stable locomotive patterns when instabilities are experienced in the gait pattern. Such instabilities may arise from slight changes in the walking environment or local changes in the performance of the musculoskeletal system (Dingwell et al. 2000). Currently, we are using our passive dynamic bipedal walking model to further explore the influence of other lower extremity joint actuations on the control of bifurcations and chaos in locomotive patterns.

7 Conclusions

In this investigation, we have demonstrated that hip joint actuation can be used to control bifurcations and chaos in a bipedal locomotive pattern. Based on our simulations, it appears that having a locomotive system with a chaotic pattern provides an advantageous control scheme. As long as the locomotive system remains within the basin of the chaotic attractor the nervous system can select from among the many different step length combinations. Our simulations indicate that hip joint actions selected by the nervous system allow the locomotive system to rapidly transition to stable gaits embedded in the rich chaotic attractor. Chaos may be embedded within the locomotive central pattern generator. Further exploration of how chaos is used as a control scheme will enhance our understanding of the neural control of locomotion.

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