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► **To cite this version:**

Alex Pitti, Max Lungarella, Yasuo Kuniyoshi. Exploration of Natural Dynamics through Resonance and Chaos. International Conference on Intelligent Autonomous Systems (IAS-9), Mar 2006, Tokyo, Japan. pp.558-565. <hal-03516780>

HAL Id: hal-03516780

<https://hal.science/hal-03516780v1>

Submitted on 7 Jan 2022

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Exploration of Natural Dynamics through Resonance and Chaos

Alex Pitti, Max Lungarella, and Yasuo Kuniyoshi

Intelligent Systems and Informatics Lab

Dept. of Mechano-Informatics

The University of Tokyo, Japan

Email: {alex,maxl,kuniyosh}@isi.imi.i.u-tokyo.ac.jp

Abstract. Self-exploration of movement possibilities and exploitation of natural dynamics are two crucial aspects of intelligent autonomous systems. We introduce a dynamical exploration strategy which combines chaotic neural activity with feedback-induced resonance. The underlying mechanism satisfies three conditions: (1) resonant patterns are discovered even in the presence of noisy sensory feedback; (2) no preprocessing of the feedback signal is required; and (3) exploration is an integral part of the mechanisms. An embodied system endowed with our exploration strategy, can autonomously discover and tune into the intrinsic resonant modes most relevant to its body morphology. The mechanism not only allows to explore stable behavioral patterns, but also unstable ones. We demonstrate the role played by our exploration strategy on the emergence of movements through a simulation of a bipedal robot. We analyze with spectral and temporal methods the synchronicity of movements, spatio-temporal coordinations, and bifurcations in the couplings between neural, body, and environmental dynamics.

Keywords. Natural dynamics, feedback resonance, coupled chaotic fields, morphology, neural control

1. Introduction

The main question addressed in this paper is how an embodied system can autonomously discover modes of movement coordination which exploit the natural dynamics of the body. Traditional approaches to robot control [1] as well as soft-computing methodologies (e.g. reinforcement learning, neural networks, or genetic algorithms) conceive of the control of actions as a mathematical problem neglecting the importance of the interaction with the real world. The emphasis is placed more on precision, reproducibility, and planning of optimal movements guided by feedback. Although these approaches are successful in particular well-controlled application domains (e.g. industrial environments), they face considerable problems when the system's parameters are unknown, the number of sensor and actuators is subject to changes, or the robustness and adaptivity to unforeseen situations is of the essence.

The difficulties have not gone unnoticed, and there have been recent attempts at devising more adaptive control strategies grounded into dynamic systems theory (e.g. [5,10]). The focus of this research effort is on the coupling of brain, body, and en-

vironment, and the exploitation of the intrinsic dynamics of the individual components. The "control loop" explicitly and purposively exploits factors such as morphology, material properties, natural dynamics, and, more generally, the physical interaction with the real world. In this paper, building up on these ideas and on previous work [6,11], we present and discuss a framework for exploring and exploiting the bodily capabilities of a complex embodied system. The core intuition is that small but well-timed perturbations can be used to push the system into behavioral modes characterized by high behavioral flexibility and low energetic cost. For this purpose, we investigate neural and physical mechanisms involved in the emergence of actions that are driven by the interaction of brain, body, and environment, and propose several tools to quantify them. We focus on two key components governing such emergence: (1) feedback resonance (physical component), and (2) coupled chaotic fields (neural component).

In the following section, we detail how these two components affect the emergence of movements. We then describe our experimental setup and a set of methods aimed at shedding some light on the complex interplay between brain, body, and environment. We finally analyze the movement patterns produced by our system and discuss the results.

2. Exploration Mechanism

2.1. Physical component: feedback resonance

Feedback resonance is a mechanism to drive a nonlinear oscillator into resonance by varying the frequency of an external perturbation as a function of the oscillation amplitude [8]. The rationale is that such a perturbation destabilizes the system and induces it to move from its current orbit to another more stable one, potentially driving the system closer to resonance. In addition to external perturbations, changes of the system's global dynamics are also regulated through perturbations induced by the system's internal dynamics. Modulating the internal dynamics can therefore also provide clues about which external perturbations the system is sensitive to. This approach is inspired by the OGY-method [7] which demonstrates how a small time-dependent change of a control parameter of a chaotic system can significantly affect the behavior of the system, e.g. turn a chaotic behavior into a periodic one. It is also somewhat related to the notion of "intervention dynamics" which was introduced as a means of funneling the global dynamics of a system through particular characteristic via-points known as "focuses" [5].

Given two coupled systems A and B, we can formulate the principle underlying feedback resonance as:

$$F_i^A(t+1) = F_i^A(t) + \gamma F_i^B(t), \text{ with } F_i^A(t) \gg \gamma F_i^B(t), \quad (1)$$

where $F_i^A(t)$ denotes the "force" exerted on the i^{th} degree of freedom of system A at time t , and γ is a coupling constant. The term $\gamma F_i^B(t)$ represents the influence of system B on system A. Conversely, the same perturbation scheme can be applied to system B:

$$F_i^B(t+1) = F_i^B(t) + \eta F_i^A(t), \text{ with } F_i^B(t) \gg \eta F_i^A(t), \quad (2)$$

where $F_i^B(t)$ is the value of the i^{th} degree of freedom of B, and $F_i^A(t)$ indicates the influence of system A on system B modulated by the coupling constant η . Eqs. 1 and 2 establish a coupling between the two systems which allows internal dynamics and ex-

ternal perturbations to mutually entrain. Such mutual entrainment is typically accompanied by resonant modes. In our framework, A and B are the neuro-body and the body-environment sub-systems (Fig. 1 a).

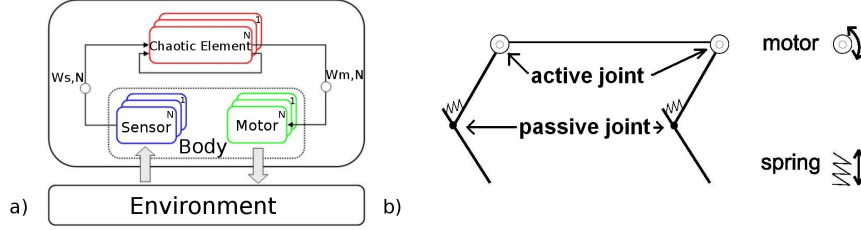


Figure 1. Our model: a) theoretical framework, and b) simulated bipedal robot.

2.2. Neural component: dynamically coupled chaotic field

We model the neural part of our system as a dynamical network of decoupled chaotic units. These units are connected through afferent connections to the sensors (input), and through efferent connections to the actuators (output). The chaotic system is coupled to the mechanical system (body) through feedback resonance (Eqs. 1 and 2). The effect of entrainment is the emergence of correlations and modes of coordination accompanied by an integrative field of neural units which can not be produced by a predefined and static coupling. We suggest that the interaction between brain and body-environment dynamics couples (or decouples) the chaotic units connected to the body parts involved in the movement. Each chaotic unit is modeled as a logistic map whose chaoticity is determined by the control parameter α :

$$x_i(t+1) = f_\alpha(x_i(t)), \quad (3)$$

$$f_\alpha(x_i(t)) = 1 - \alpha x_i(t)^2 + \eta F_i(t), \text{ where } 1 - \alpha x_i(t)^2 \gg \eta F_i(t).$$

In all our experiments and for all units: $\alpha \in [0.0, 2.0]$.

The use of chaotic units is partially justified by findings on human locomotion showing that variations between steps are not mere noise but have a chaotic structure [2]. Some evidence also indicates that chaos might occur at higher levels of the neuromuscular control system [2,3].

3. Methods

In this section, we introduce measures for quantifying movement patterns: the duty factor (DF), the spectral bifurcation diagram (SBD), the wavelet transform (WT) and a novel method derived from the wavelet transform, the wavelet bifurcation diagram (WBD).

The duty factor is typically used for quantifying and classifying different types of locomotive patterns [14]. It is defined as the fraction of time the legs are on the ground versus the duration of one locomotive cycle. In walking humans, for instance, each foot is on the ground for more than half of the time ($DF > 0.5$). In running humans, however,

γ	η	density	damping	stiffness	sampling time (s)
10	0.01	0.6	10	10	0.05

Table 1. Parameters used in our experiments.

it is on the ground for less than half of the time ($DF < 0.5$). The spectral bifurcation diagram is an attempt to analyze qualitatively the dynamics of high dimensional dynamical systems [9]. It superimposes the spectral density distribution of each variable relative to the current value of the control parameter of the system under study. The wavelet transform is a popular and powerful tool for time series analysis and signal compression [12]. It extends the Fourier representation to the temporal domain. An interesting property of the wavelet transform is that it can be used to identify short- and long-range temporal correlations in time series. We extended the wavelet transform to the analysis of correlations among the chaotic units composing the neural system and the individual body parts. In order to visualize the spatio-temporal patterns and the bifurcations at different scales, we added a dimension spanning the index of the units of the system. We call this measure the wavelet bifurcation diagram.

4. Experiments

For our experiments we used a simulated bipedal (two-legged) robot moving in the sagittal plane (Fig. 1 b). Each leg was composed of two limbs linked by a damper-spring joint and had two active and two passive joints. The legs were actuated at the hip by two motors controlled by a neural system consisting of two chaotic units. The input to the chaotic units was provided by angle sensors located in the passive joints (the sensors measured the angle between upper and lower limb). The parameters used for the simulation are given in Table 4. All our simulations were performed with Matlab.

By changing the control parameter α , we observed many different movement patterns. For $0 < \alpha < 0.7$, the dynamics of the chaotic system and of the body were weakly coupled and perturbed each other only slightly. The small perturbations transmitted by both systems, however, were not strong enough for any movements to occur.

For $\alpha = 0.7$, the system started to rock slowly back and forth without actually changing its position. By increasing α up to 0.8, the robot had enough energy to balance but not enough to lift its legs and locomote, that is, the system began to "crawl" and then from time to time returned to its initial (balanced) position (Fig. 3 a). For $\alpha = 0.85$ the system had finally enough inertia to lift one of its legs and started moving. The external perturbations, and the speed increased too. This change is reflected by a drop of the duty factor from about 0.65 to 0.40 for speeds $v < 0.3 m/s$.

For $\alpha = 0.9$, the internal excitations of the chaotic system fed to the motors had enough energy so that both legs could move separately. The system coordinated its legs alternatively by hopping (Fig. 3 b; duty factor $DF < 0.20$ and speeds $v < 0.5 m/s$), walking (Fig. 3 c), and jumping (Fig. 3 d; $DF < 0.20$, $0.5 m/s < v < 1.0 m/s$).

Note that for $\alpha < 1.0$ hopping was a more stable and reproducible behavior compared to walking and jumping which require a more precise synchronization between the legs. Systems with hard ($k = 50$) and soft ($k = 10$) springs displayed the same stable behaviors (Fig. 2). For $\alpha > 1.0$ we observed a change of the dynamics depending on the spring stiffness. In the case of hard springs, the mechanical system moved in the

same stable fashion quite immune to changes of the chaoticity of the neural system. The system with soft springs was able to perform faster coordinated movements but as the control parameter increased the movements were less stable. Its dynamics allowed it to run and jump at $v > 1.5 \text{ m/s}$ for $DF < 0.20$. For $\alpha > 1.4$, the system was highly unstable and did not display any coordinated movements. The perturbations of the chaotic system strongly affected the body movements. External perturbations due to the body-environment interaction had no measurable influence on the neural system.

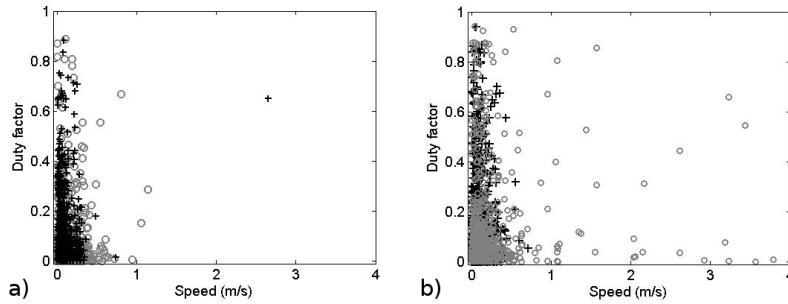


Figure 2. Duty factor for different values of α and for joints with different stiffness. (a) Hard springs ($k = 50$); and (b) soft springs ($k = 10$). $\alpha < 1.0$ (circles); $\alpha > 1.0$ (crosses). 600 samples for each category.

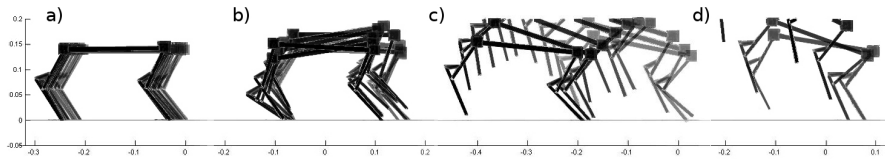


Figure 3. Gaits for different values of the control parameter: a) crawling, b) hopping, c) walking, and d) jumping.

5. Analysis

Movement patterns have spatio-temporal structure resulting from changes in the coordination dynamics of both body and neural system. The spectral bifurcation diagram illustrates the spectral distribution of the coupling between the neural system and the body as a function of the control parameter α (Fig. 4). The frequencies with high density correspond to those of synchronization between the two dynamical systems. They represent the inner resonant states for which perturbations (or moments of energy exchange) between the two coupled systems are significant.

Interestingly, for $\alpha < 1.0$, the body dynamics has little effect on the neural dynamics and vice versa. We can distinguish the fundamental mode at a frequency of 10 Hz , and harmonics at regular intervals from the fundamental with an harmonic mode around 256 Hz . This corresponds to the excitation of the passive dynamics of the damped springs (the low frequencies) by the chaotic system (the higher frequencies) when the mechanical system balances, crawls, and starts walking and hopping. These frequencies

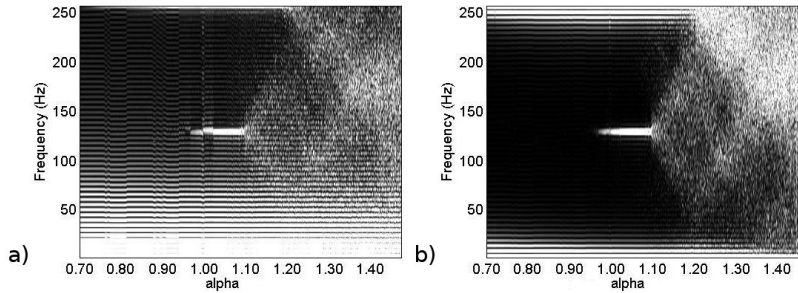


Figure 4. Spectral Bifurcation Diagram: (a) sensors, and (b) chaotic units.

represent the lowest energetic cost required by the system to move and locomote and at the same time the maximum amount of external perturbation that the system can absorb while performing the required actions. The wavelet transform for different values of α for the time series extracted from the sensor located in the knee of the rear leg is plotted in Fig. 5 (a). This figure also illustrates the stability and low complexity of the behavior when the robot is poised in balance. Note that for $\alpha < 1.0$ every scale lacks long-range temporal correlations.

Conversely, for $\alpha = 0.97$, a qualitative change occurs in the interaction between the two dynamical systems. As a result a spectral bifurcation at frequency 128 Hz appears in the SBD indicating more powerful hopping and walking patterns. The wavelet transform in Fig. 5 (a) shows this qualitative change for $s = 128$ and for $s < 50$. Temporal correlations are formed by the appearance of long almost single-scale (i.e. periodic) temporal patterns. The wavelet bifurcation diagram (WBD) in Fig. 6 (a) allows to visualize the emergence of rhythmically stable spatio-temporal coordinations of the two legs (units 1 and 2) when the system starts to walk and hop (appearance of stripes at scales 1 and 2). When α increases a little, these dynamical patterns become more unstable (Fig. 6 b).

For $\alpha > 1.13$, the spectral bifurcation at 128 Hz diffuses and gradually activates all the surrounding frequencies. This new modulation affects the stability of the coordination between the chaotic system and the body producing fast walking and running behaviors in addition to hopping and crawling. These frequencies represent the amount of energy that the system can actually absorb to perform these behaviors with regard to internal/external perturbations. These irregular harmonics are characteristic of the change of stiffness in springs as observed in [13], giving the property of the system to "harden" or "soften" its springs, and thus to have higher flexibility. As can be seen in Fig. 5 (c) short-lasting unstable motions for scales $s < 25$ form stable and repetitive long-range temporal patterns at higher scales ($s > 25, 128, 155$ and higher). The stability of the dynamics has changed scale with α implying that stability is scale-dependent. The same result is observed in the case of the WBD (Fig. 6 c). For scales $s > 2$ the embodied system performs stable "long-range" movements which are accompanied by short-range perturbation-like movements at lower scales. The structure of the spatio-temporal patterns is fractal as in human locomotion [2]. The patterns are formed at the lowest scales and are integrated and coordinated in time at higher scales. Long-lasting movements are thus composed of movements of smaller duration.

Increasing α beyond 1.25 gives rise to a second spectral bifurcation at frequency 256 Hz leading to chaotic interaction dynamics between the coupled systems. In this

mode, the embodied system is highly sensitive to any kind of perturbations and is unstable (almost all the perturbations give rise to resonance). This result seems to contradict the ones obtained with the wavelet transform (Fig. 5 d) and with the WBD (Fig. 6 d). The movements, although unstable and dynamic for scales $s < 25$, are highly correlated at the higher scales presenting stable movement patterns with long-range temporal correlations. On other words, the stability of the dynamics has changed scale.

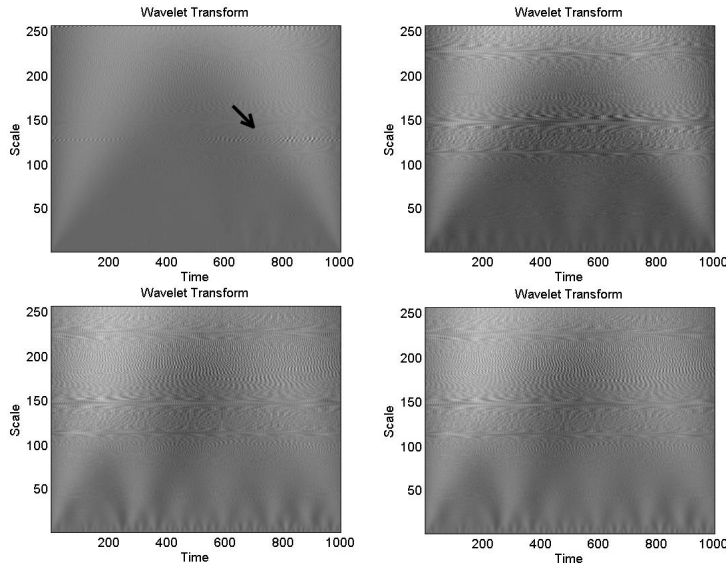


Figure 5. Wavelet Transform. From top-left to bottom-right the intervals of the control parameter α are: $[0.90; 1.00]$; $[1.00; 1.10]$; $[1.10; 1.20]$; and $[1.20; 1.30]$. The arrow indicates a spectral bifurcation.

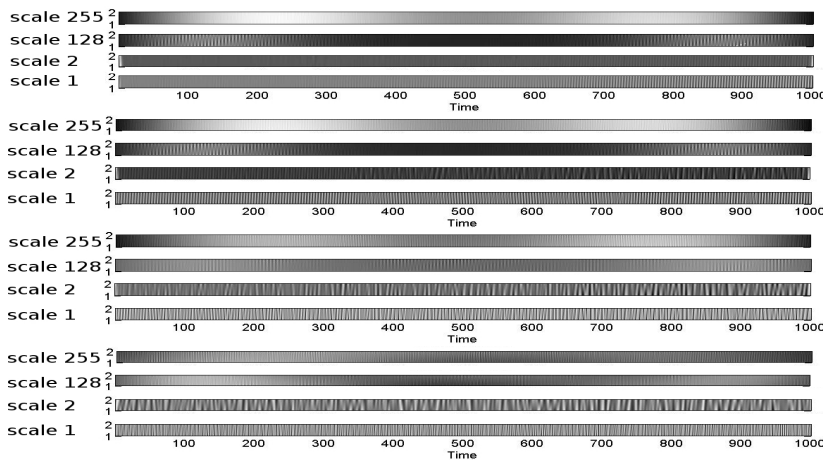


Figure 6. Wavelet Bifurcation Diagram. From top to bottom the intervals of the control parameter α are: $[0.90; 1.00]$; $[1.00; 1.10]$; $[1.10; 1.20]$; and $[1.20; 1.30]$. The horizontal axis denotes time, the vertical axis denotes the index of the chaotic unit. The individual graphs have different time-scale resolutions.

6. Conclusion

In this paper, we addressed the question of how an embodied system can autonomously explore its movement possibilities and exploit its natural dynamics. We proposed a general framework based on two core phenomena: resonance and chaos. We also introduced a set of quantitative measures to analyze the dynamics of coupled nonlinear system. We observed that the stability of the emergent movement patterns in a simulated bipedal robot is scale dependent and present a spatio-temporal fractal structure. Our future work will be aimed at exploring how our framework might be combined with learning, planning, and intentional behavior.

7. Acknowledgments

The authors would like to thank Fumiya Iida for kindly providing the simulation of "Puppy – the dog robot", and the Japanese Society for the Promotion of Science (JSPS) for supporting this research.

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