

Adaptivity through Physical Immaturity

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Abstract

Given a neural control structure, what would be the impact of body growth on control performance? This question, which addresses the issue of the interaction between innate structure, ongoing developing structure and experience, is very relevant to the field of epigenetic robotics. Much of the early social interaction is done as the body develops and the interplay cannot be ignored. We hypothesize that starting with fewer degrees of freedom enables a more efficient exploration of the sensorimotor space, that results in multiple directions of stability. While not necessarily corresponding to optimal task performance, they will guide the coordination of additional degrees of freedom. These additional degrees of freedom then allow for optimal task performance as well as for more tolerance and adaptation to environmental interaction. We propose a simple case-study to validate our hypothesis and describe experiments with a small humanoid robot.

Keywords: Developmental robotics, embodiment, adaptive behavior, entrainment, incremental learning, sensory morphology.

1. Introduction

Twenty years ago, (Turkewitz and Kenny, 1982) pioneered the theoretical position that limitations in sensory and motor systems early in life may play an adaptive role in ontogeny. Their main hypothesis was that constraints in the sensory system and biases in the motor system would lead to a reduction of the complexity of the environmental information that impinges on a learning system, while increasing the adaptivity of the system.

Several researchers have argued along similar lines, claiming that processing limitations of young learners stemming from the immaturity of the neural system, can actually be beneficial to learning itself (Newport, 1990), (Elman, 1993), and (Westermann, 2000). (Elman, 1993), for in-

stance, describes neural networks which are only able to learn the task of processing complex sentences when handicapped by being forced to begin with severe memory limitations. These limitations are released during the learning process. In other words, certain aspects of children's immaturity seem to be adaptive in their own right (see also (Bjorklund and Green, 1992)), and lead to a greater flexibility. These limitations or *ontogenetic adaptations*, i.e., unique adaptations to the environment throughout development, are not simply incomplete versions of adult characteristics but serve a specific purpose, since learning is facilitated by them.

Environment, body, and mind have to work together in order to simplify the learning problem. (Pfeifer and Scheier, 1999) calls it the *principle of ecological balance*. This principle states that there has to be a balance of the complexity between the agent's task environment, and its sensory, motor, and neural system. (Bushnell and Boudreau, 1993), two developmental psychologists, talk about *motor development in the mind*, i.e., in human infants there seems to be a co-development of the sensory and motor system, and specified motor abilities must be executed in order for corresponding perceptual abilities to emerge.

In this paper we attempt to characterize how developmental changes in the body structure affect control performance. After a short review of the relevant literature, we describe our framework and the experiments carried out with a small-sized humanoid robot. After discussing the meaning of our results, we derive conclusions and outline future directions for research.

2. On Physical Immaturity

(Kirby and Hurford, 1997) associate the term incremental learning with the *idea of some learning-related resource (e.g., memory, or attention span), starting at a low value, which then gradually increases while (but not necessarily because) the organism matures*. An essential point of incremental learning is the fact, that the initial immature (low)

value of this resource actually facilitates, or even enables, the early stages of learning. Later stages of learning are in turn enabled by higher-valued settings of the resources concerned. In other words, the temporal sequence of different developmental stages can lead to tractable incremental learning tasks.

Here are a few telling examples of initially limited resources. These examples show that there are limitations in the sensory and motor apparatus as well as in the neural system:

- Newborns are not able to see an object as of its actual size. Size constancy, when it appears (at between 4 and 6 months), is initially restricted to very near distances (probably not greater than 70cm) (McKenzie et al., 1980).
- The infant's accommodative system is fixed, and objects that are approximately 10 inches away, are most clearly in focus (Turkewitz and Kenny, 1982).
- Working memory and attention span in young children are initially restricted, and increase over time (Elman, 1993).
- The postural control of trunk, head and arms is limited (Thelen and Smith, 1994). Movements are inefficient and jerky.

There have been a few attempts to address such developmental issues in robotic systems.

(Berthouze and Kuniyoshi, 1998) describe experiments with a nonlinear redundant four degrees of freedom (DOF) robotic vision system, where in order to reduce the risk to get trapped in *stable but inconsistent minima*, the introduction of two of the four available DOFs is delayed in time. The advantage of the adoption of this *developmental strategy* is a reduction of the complexity of learning for each joint and a faster stabilization of the adaptive parameters of the controller.

In a similar vein, (Metta, 2000) describes a robotic system called Babybot, which *in order to acquire the correct information for building sensory-motor and motor-motor transformations follows a precise developmental course*. Again, development consists of the release of the various mechanical degrees of freedom according to a developmental schedule.

Another instantiation of this idea is due to (Taga, 1997). Results of simulations of the development of bipedal locomotion of infants show, that by means of freezing and freeing DOFs of the neural-musculo-skeletal system, the *u-shaped changes in performance* typical in the development of the stepping movement can be generated.

3. Exploring Physical Maturation

In this paper, our focus is on the exploration of the impact of body growth on control performance for a given neural control structure. Accordingly, a research platform (system plus environment) should be used that offers enough complexity that controlling it is not trivial, and qualitative (or even quantitative) discrimination of the mechanisms supporting the developmental process is possible. In this respect, various requirements have been discussed in the field of developmental robotics. Namely, the existence of multiple degrees of freedom, redundancy, presence of environmental forces (e.g. friction, gravity), the ability of the system to explore its sensorimotor and control space. Additionally, in this particular study, it is desirable that an external observer can assess the behavior of the system. The human body and its natural environment provide an appropriate platform, however, the interaction between innate structure, ongoing developing structure and experience is difficult to characterize (by lack of an access to the control structure).

We chose the exploration of swinging behavior (brachiation style) in a small-sized humanoid robot as case-study. Swinging is a very natural behavior (a form of circular reaction) and favors the exploration of control parameters. It seamlessly integrates environmental dynamics, physical dynamics and neural dynamics (control structure). Optimal control is not trivial to achieve. In the field of control theory, various control schemes have been proposed. It is beyond the scope of this paper to present a theoretical survey. More appropriately, the work of (Inaba et al., 1996) and (Williamson, 1998) are worth pointing out as they correspond to both extrema of the spectrum. (Inaba et al., 1996) utilize visual feedback to servo the oscillatory behavior, whereas (Williamson, 1998) focusses on exploiting the dynamical properties of the neural control structure, without modelling either the system or its environment. Similarly to (Williamson, 1998), we suggest the use of neural oscillators as they are well-understood and appropriate control structures for oscillatory behavior. With the use of such control structures, there is no need for an *a priori* model of the body (or the environment). Proprioceptive information (torque resulting from lower limbs for example) is physically embedded in the system. Distributed control is possible, allowing for a developmental view of control, via the freezing and un-freezing of degrees of freedom for example.

3.1 Experimental platform

Our experiments have been performed with a small-sized 12-DOF (degrees of freedom) humanoid robot - see Figure 1. Two thin metal bars were attached

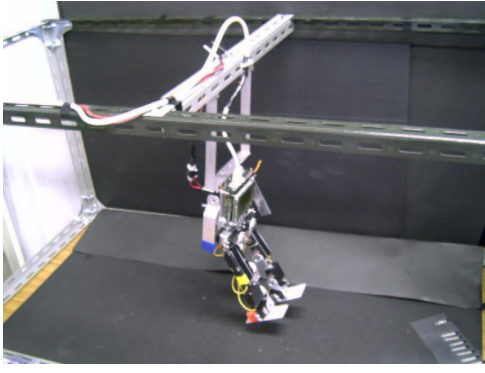


Figure 1: Picture of the humanoid robot used in our experiments.

to the robots shoulders and the robot was fixed in a supportive metallic frame, where it could freely oscillate in a vertical (sagittal) plane.

Each leg of the robot has five degrees of freedom (DOF), but only three of them have been used for the experiments described in this paper. In other words, our system consists of two 3-DOF legs, which have a hip, a knee, and an ankle joint, and two 1-DOF arms (not used in our experiments).

Each joint of the humanoid is actuated by a high torque RC-servo module. Since these modules do not provide any form of feedback, proprioceptive feedback (on joint position) was simulated by an external camera, which was used to track colored markers placed on the robot's limbs.

3.2 Control architecture

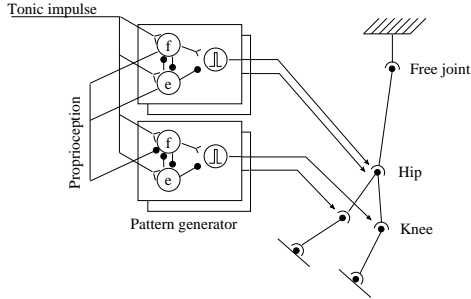


Figure 2: Control architecture.

A schematic of the control architecture is shown in Figure 2.

Each neural oscillator is modelled by the following set of differential equations, derived from (Matsuoka, 1985):

$$\begin{aligned}
 \tau_{u_f} \dot{u}_f &= -u_f - \beta[v_f]^+ + \omega_c[u_e]^+ + \omega_p[F_{eed}]^+ + te \\
 \tau_{u_e} \dot{u}_e &= -u_e - \beta[v_e]^+ + \omega_c[u_f]^+ + \omega_p[F_{eed}]^- + te \\
 \tau_{v_f} \dot{v}_f &= -v_f + [u_f]^+ \\
 \tau_{v_e} \dot{v}_e &= -v_e + [u_e]^+
 \end{aligned}$$

where $u_{f,e}$ is the inner state of the neuron f (flexor) or e (extensor), $v_{f,e}$ is a variable representing the degree of adaptation or self-inhibition effect of the neuron, te is a tonic excitation (external input), β is an adaptation constant, ω_c is a coupling constant controlling the mutual inhibition of neuron e and f , ω_p is a variable weighting the feedback F_{eed} . τ_u and τ_v are time constants of the inner state and adaptation effect. The operators $[x]^+$ and $[x]^-$ return the positive (respectively negative) portion of x .

The following simulation parameters were kept constant throughout the study: $\beta = 2.5$, $\omega_c = 2.5$, $\omega_p = 3.0$. Other parameters were set as discussed in the text.

Similarly to (Taga, 1991), each neural oscillator is used as a neural rhythm generator. Its output activity y is given by $y = u_f - u_e$, i.e. by the difference between the activities of the flexor and extensor neurons. This value is then fed to a pulse generator, whose activity at time t is given by:

$$pg^t = te(\text{sgn}(y^t) - \text{sgn}(y^{t-\delta t}))$$

where $\text{sgn}(x)$ is the sign function and te is the tonic excitation defined above. The kicking motion pg^t is finally used to control the servo motor of the corresponding joint.

4. Experimental Discussion

The experiments are organized so as to provide the basis for a comparative analysis of different learning strategies, from a physical point of view. In all experiments, the neural structure is kept unchanged and neither exteroceptive nor proprioceptive information is fed back to the controller unless specified otherwise, i.e. $F_{eed} = 0$. Movements are analyzed via the recording of hip, knee and ankle positions. Same initial conditions are used in all experiments, with the humanoid robot starting from its resting position.

Our experiments can be divided into three categories:

- 1-DOF exploratory control. Left and right hip servo motors are fed with identical motor commands (from a single oscillator unit). Other joints are stiff, starting from their resting position.
- 2-DOF exploratory control. Each pair of joint (hip, knee) is controlled by its own oscillator unit. Other joints are kept stiff, in their reset position. Two cases are considered. In the first case, oscillator units are perfectly independent and their respective parameter space is independently explored. In the second case, local feedback is used between hip and knee control unit, possibly leading to local neural entrainment between the oscillatory units. From a control point of view, the

former case is a particular instance of the latter with the gain of the proprioceptive information set to null.

3. Bootstrapped 2-DOF exploratory control. The second degree of freedom is released and controlled while the system is in the stationary regime obtained in a 1-DOF configuration. Again, the same two cases are considered: independent exploration of the parameter space of the second DOF or exploration under proprioceptive feedback. Such process is intended to model the un-freezing of degree of freedom suggested by developmental psychologists.

4.1 Natural frequency

For control purposes, the natural frequency of the freely swinging humanoid robot is measured. After a manual push, the robot is let swing freely and the position of 3 markers (hip, knee and ankle) is tracked. The frequency is experimentally found to be $0.905Hz$ (period of $1105ms$). This value is confirmed by a power spectral analysis of the hip position time series (sampling frequency of $33Hz$). Figure 3 shows the solutions in the space of parameters τ_u and τ_v for a Matsuoka unit to oscillate at the resonant frequency. It can be observed that a small variation in the parameters results in a significantly different frequency. If we make the premise that in this study, optimal performance is the robot sustaining oscillations at the resonant frequency, then, in the case of one DOF only, optimal performance will necessarily require fine tuning. However, the continuity in the neighborhood of the optimum should also make it possible for various configurations to implement the task, and eventually help bootstrap the emergence of higher-order coordinated behavior when additional degrees of freedom are added. This hypothesis is confirmed with our next experiments on 1-DOF and 2

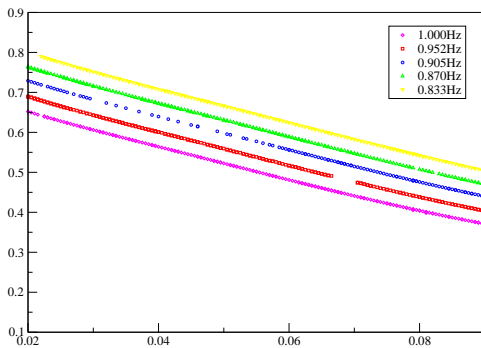


Figure 3: Oscillator parameters corresponding to the resonant frequency ($0.905Hz$) and other frequencies. The horizontal (resp. vertical) axis denotes τ_u (resp. τ_v).

4.2 1-DOF exploratory control

Explorative behaviors have been shown to play an important role in the development of cognition in infants and animals. Such behaviors are not necessarily goal-oriented and bodily motion is seldomly constrained (apart from physical constraints). Properties of the body are actively explored while performing movements so that the system can sustain that motion and create new forms of it. As indicated by (Goldfield, 1995), *the goal of exploration by an actor may be to discover how to harness the energy being generated by the ongoing activity, so that the actual muscular contribution to the act can be minimized*. In this study, exploration of the control parameters is realized by a stochastic exploration of the parameter space: $\tau_u \in [0.02 : 0.09]$ and $\tau_v \in [0.1 : 0.9]$. Spontaneous motion is realized in the form of kicking movements.

A full spectrum of oscillatory behaviors is observed, ranging from exact anti-phase ($\tau_u = 0.04$, $\tau_v = 0.65$) to in-phase ($\tau_u = 0.09$, $\tau_v = 0.65$) oscillations of the legs with respect to the body motion. The amplitude of the oscillations varies largely, from 23 units in the case of anti-phase oscillations to up to 100 units in the case of in-phase oscillations. In all cases, the stationary state was obtained without external intervention. Figure 4 shows the temporal series of the hip and ankle positions (along with the corresponding motor commands) for the two extreme cases described above. Figure 5 shows the stability of the stationary regime to environmental perturbations. These experiments are quite valuable with re-

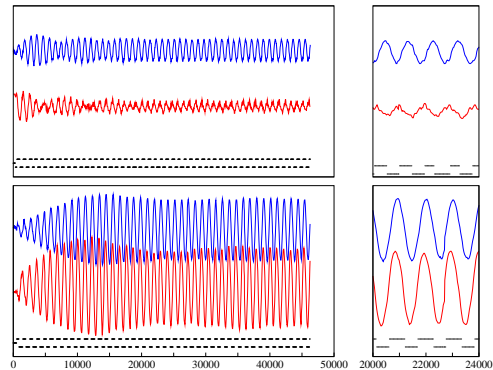


Figure 4: Anti-phase oscillations for $\tau_u = 0.04$ and $\tau_v = 0.65$ (top). In-phase oscillations for $\tau_u = 0.07$ and $\tau_v = 0.65$ (bottom). In each graph, the time-series denote motor impulse (bottom), ankle position (middle) and hip position (top). Right-hand windows are close-ups on the time-series. The horizontal axis denotes time in ms .

spect to embodiment and physical interaction. They show that physical entrainment takes place. While the physical system exhibits a natural swinging frequency of $0.905Hz$, the oscillators settings used to produce Figure 4 would theoretically produce a con-

trol pattern with a frequency of $0.71Hz$, $0.89Hz$ respectively. Experimentally however, the corresponding frequencies were found to be $0.77Hz$ and $0.96Hz$ respectively. Such variations could be attributed to either the inaccuracy inherent to servomotor control and/or the additional torque induced by gravity. Frequencies measured after the system reaches its stationary regime, i.e. after the system has entrained, appear to be significantly different from either the natural frequency or the control frequency, which is the definition of entrainment. Numerically, in the case of anti-phase oscillations, the resulting frequency was found to be $1.075Hz$, while $1.15Hz$ was the frequency observed in in-phase oscillations. Frequencies measurements made on other oscillator settings were found to range between $0.93Hz$ to $1.22Hz$. These extrema were actually found in two different experiments with the same parameters ($\tau_u = 0.07$, $\tau_v = 0.65$).

4.3 2-DOF exploratory control

Independent control

Provided that in this study, the behavior of an oscillator is controlled by two parameters τ_u and τ_v , an exhaustive exploration of the parameter space for two independent controllers is not plausible. Again, a random sampling of the space was performed. A resulting behavior is evaluated in terms of the presence (or not) of a stationary regime, the amplitude of such regime, its smoothness (qualitatively), the relative configuration of hip and knee motor commands as observed in a hip-ankle phase plot and its robustness to external perturbations (a manual push, as in

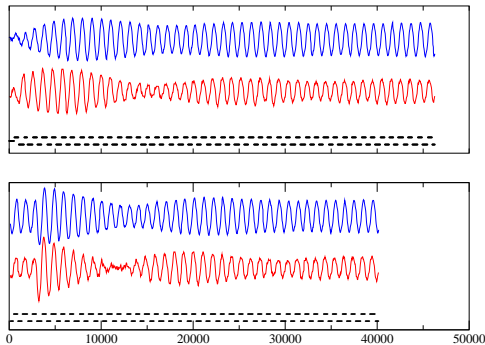


Figure 5: Stability of the stationary regime to initial condition and environmental perturbation for $\tau_u = 0.06$ and $\tau_v = 0.65$. Horizontal axis denotes time in ms . The top window depicts the convergence of the physical system to stable oscillations from a "zero" initial condition. The lower window depicts the "return" to the stationary regime after an external perturbation (the robot was manually pushed $3000ms$ after having reached its stationary regime).

ploration of the control parameters ($\tau_u \in [0.02, 0.09]$ and $\tau_v \in [0.1, 0.9]$) for both hip and knee controllers, a very rugged sensorimotor configuration space was observed. To illustrate this, a more exhaustive analysis was made for neighboring parameters. Parameters for the hip oscillator are kept in the range $\tau_u^h \in [0.055, 0.065]$ and $\tau_v^h \in [0.55, 0.65]$ while $\tau_u^k \in [0.025, 0.35]$ and $\tau_v^k \in [0.25, 0.35]$ for the knee oscillator unit and the space is regularly sampled with 7 experiments. The ratio between hip and knee amplitude is 1.4 for all experiments.

Though the parameter space now considered is very narrow, a small variation in parameter selection leads to very different behaviors. Qualitatively, the following states are observed. With $\tau_u^h = 0.060$, $\tau_v^h = 0.60$, $\tau_u^k = 0.03$, $\tau_v^k = 0.3$, our reference configuration for this experiment, a smooth stationary regime of the hip oscillation is observed, with an amplitude of 80 units. While being in phase with the hip oscillation, the ankles do not reach a true stationary regime which leads to the ankle-hip phase plot of Figure 6(left). This phenomenon can be attributed to a dampening effect resulting from this particular morphological structure. The system was found to return to its stationary regime even in the case of external perturbations.

Slightly changing the hip control parameters ($\tau_u^h = 0.065$, $\tau_v^h = 0.65$) but leaving the knee parameters unchanged results in a qualitatively very different behavior. While the ankle position quickly reaches a smooth stationary regime, an overall oscillatory behavior cannot be found (overall amplitude of less the 20 units), as illustrated by the phase plot on Figure 6(right).

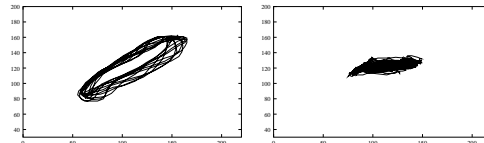


Figure 6: Ankle-hip phase plots for $\tau_u^h = 0.060$, $\tau_v^h = 0.60$, $\tau_u^k = 0.03$, $\tau_v^k = 0.3$ (left) and $\tau_u^h = 0.065$, $\tau_v^h = 0.65$, $\tau_u^k = 0.03$, $\tau_v^k = 0.3$ (right).

When keeping the knee parameters unchanged, yet another behavior is obtained if the hip control parameters are set to ($\tau_u^h = 0.055$, $\tau_v^h = 0.55$). In this case, the overall oscillatory behavior is smooth and reaches a stationary regime. Interestingly, the ankle behavior exhibits several transitions to different stationary regimes, the succession of which is depicted in Figure 7. Transitions between stationary regimes are very rapid. (Goldfield, 1995) reports that it is a characteristics of spontaneous activity in infants that it enters preferred stable states and exhibits abrupt phase transitions. After perturbation, the hip returns to its former stationary regime. The pseudo-

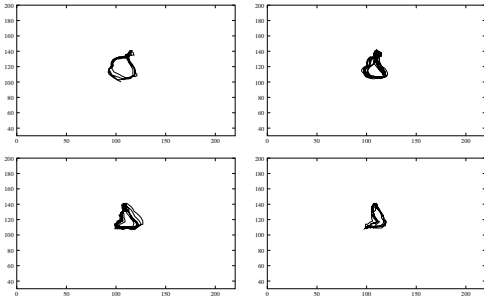


Figure 7: Successive pseudo-stationary regimes obtained with $\tau_u^h = 0.055$, $\tau_v^h = 0.55$, $\tau_u^k = 0.03$, $\tau_v^k = 0.3$. From top, left to bottom, right, the regimes occurred roughly at time 12s, 21s, 44s.

stationary regimes in the motion of the ankle only partially overlap with the ones observed earlier.

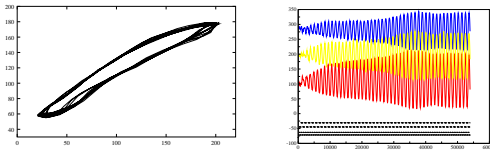


Figure 8: Phase plot (left) of a large amplitude smooth performance after a long transient (right) with $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.025$, and $\tau_v^k = 0.35$.

Finally, with $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.025$, $\tau_v^k = 0.35$, seemingly optimal performance is achieved. An amplitude of 120 units (larger than any amplitude obtained during the 1-DOF experiment) is reached and sustained. In-phase smooth oscillatory behavior is obtained both at the hip and ankle level. The hip-ankle phase plot is given in Figure 8(left). The time series provided in Figure 8(right) shows that this stationary regime was achieved only after a smooth transient of about 50s. This regime shows a good robustness to external perturbations.

Joint synergy

In the human motor system, joints receive two different types of sensory information: proprioceptive and exteroceptive. Proprioception is the sense of the positions and movements of different parts of the body. As stated by (Taga, 1991), possible kinematic state variables are anatomical angles and inertial angles. Inertial angles require both proprioceptive and exteroceptive information. Information on the proprio-extero relationship seems to be crucial for adaptation to the environment however in our case, since the environment is mostly static, we focus on the anatomical angles which may be sensed only by proprioceptors. In this study, we specify, a-priori, the representations of sensory signals of anatomical angles. The flexor unit of the knee oscillator is fed with

the output of the flexor and extensor units of the hip controller. Namely the factor $\omega_s([u_f^h]^+ + [u_e^h]^+)$ is added to the term $\tau_{u_f} \dot{u}_f$ in the flexor unit of the knee oscillator. u_f^h and u_e^h are the inner states of the flexor and extensor units in the hip oscillator. (Taga, 1991) reports typical settings for the frequencies of the knee oscillators based on observations made on serial angular patterns of movements in humans. In our study however, we leave it to the exploration process to find (or not) such "optimal" settings.

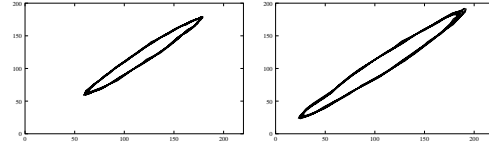


Figure 9: Phase plots of hip motion (left) and ankle motion (right) with $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.025$, $\tau_v^k = 0.35$ and $\omega_s = -1.0$.

The gain ω_s plays a crucial role. With too low a value (absolute value), the coordination between hip and knee oscillators is very loose and we only observe similar results as in the previous series of experiments, i.e. the independent case ($\omega_s = 0$). With too high a value (here, -1.0), a strong coupling occurs and the system essentially becomes a flexible 1-DOF system. From a qualitative point of view, such strong coupling leads to the most natural looking oscillatory behavior. Figure 9 shows the phase plots for hip and ankle motions. Ankle and hip are in-phase and the ankle motion follows a sinusoid of very large amplitude 160 units.

When intermediate values of coupling are considered, i.e. between -0.25 and -0.50 , two important observations are made: (a) transients are shorter (the duration of the transient is reduced by a factor 2 in the configuration previously discussed) and (b) abrupt phase transitions (when existing) disappear (settling into one of the pseudo-stationary regimes). Such result is not surprising. With an appropriately chosen coupling gain, neural entrainment is achieved between the control units. Similarly to the physical entrainment discussed earlier, neural entrainment will see two units with their own distinct time constants (or frequencies in this case) pull each other towards a new common time constant (here, a new frequency). Because the control units tend to smoothly converge towards a stable configuration, the ongoing physical entrainment is also stabilized, by entrainment effect. Thus abrupt phase transitions which demonstrate a global instability of the control do not occur and the transient are shortened. Further analysis of this interaction between neural and physical entrainment is underway and will be published elsewhere.

4.4 Bootstrapped 2-DOF exploratory control

The relationship between learning somewhat related but distinct skills, such as standing and walking, has caught the attention of developmental psychologists on the concept of freezing and releasing of degrees of freedom. The idea is that learning will be characterized by alternating freezing and release of degrees of freedom. At first, the inability to control excessive degrees of freedom might push infants outside the limits of stability. The number of degrees of freedom will be then reduced till a controlled release of the degrees of freedom takes place. (Woollacott and Sveistrup, 1992) found support for such theory in changes of coordination during the transition to independent stance and walking between 7 and 14 months.

We experimented with a controlled release of the second degree of freedom after the system has reached stationary regime in a 1-DOF configuration. Random 1-DOF configurations were selected, not necessarily close to the optimal solution. The reaching of the stationary regime was visually evaluated by the experimenter. The second degree of freedom was then released. The main result is that all configurations lead to a stable, in-phase stationary regime with large amplitude (from 105 to 115 units), as depicted by the phase plot in Figure 10 (right). Note that this behavior is qualitatively similar to the optimal behavior observed in Section 4.3, see Figure 8(left) for example.

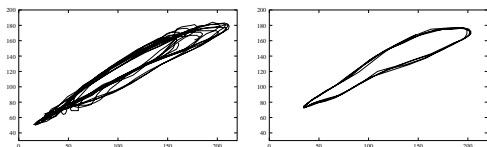


Figure 10: Ankle-hip phase plots for $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.065$, $\tau_v^k = 0.55$ with physical entrainment only (left) and neural entrainment (right).

Two configurations were of particular interest. With $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.065$, $\tau_v^k = 0.55$ and $\omega_s = 0.0$ (independent case), the oscillatory behavior in stationary regime is in-phase but pseudo-periodic. Using neural entrainment ($\omega_s = -0.285$), the behavior settles for the large amplitude (110 units), smooth sinusoidal behavior observed in all other configurations. This transition from pseudo-periodic to periodic behavior is depicted in Figure 10. Similarly, with $\tau_u^h = 0.055$, $\tau_v^h = 0.65$, $\tau_u^k = 0.065$, $\tau_v^k = 0.80$, whereas a two-kick like movement is observed in the ankle movement with physical entrainment only, the introduction of a loose coupling between hip and knee oscillators ($\omega_s = -0.285$) results in the reference behavior.

A power spectral analysis performed on the stationary regime obtained in all experiments shows that the system oscillates with a frequency of $0.877Hz$ (negligible standard deviation), no matter what the control frequencies are set to. This confirms our hypothesis that entrainment takes place between physical and neural entrainment processes.

5. Conclusion

Given a neural control structure, what would be the impact of body growth on control performance? We hypothesized that physical limitations inherent to body development could be beneficial to the emergence of stable sensorimotor configurations and allow for more tolerance to environmental interaction. Using experiments with a small-sized humanoid robot, we proposed a comparative analysis between outright use of the full body for exploration and progressive exploration using a mechanism of developmental un-freezing of the degrees of freedom. Experiments on 1-DOF exploratory control showed that through physical entrainment, stable performance (if not optimal) is achieved even for a wide range of parameters. Optimal performance is unlikely to occur however because it would require very fine tuning.

With the outright use of two degrees of freedom, the space of control parameters to explore is very large. Furthermore, it is shown that continuity in a neighborhood of control parameters does not guarantee consistent behavior. When coupling between control units is introduced (which can be seen as some sort of innate knowledge of the morphological structure), more stable behaviors are observed. It is attributed to the neural entrainment between control units. When the coupling is strong (strong innate knowledge), the system essentially becomes a flexible 1-DOF system and achieves near optimal performance.

Our last set of experiments corresponds to a developmental release of an additional degree of freedom after the system has stabilized into a stationary regime in 1-DOF control. It is shown that independently of the choice of control parameters, the system converges into a unique smooth, in-phase swinging behavior with maximal amplitude. We attribute the convergence of the entire control space onto this unique attractor to an entrainment effect between physical and neural entrainment processes. The frequency of the resulting behavior is slightly less than the natural frequency of the freely swinging system, which is consistent with theoretical predictions. In other words, the system converges to optimal performance, in a very robust manner.

A natural follow-up of this work is the study of neural entrainment and its interplay with proprioceptive information, in particular inertial angles. (Goldfield, 1995) suggests that coordinative struc-

tures with attractor dynamics emerge from spontaneous dynamics. As a consequence of producing variable trajectories under specific constraints, the microscopic components of actions become assembled into coordinative structures which exhibit attractor dynamics (a process of self-organization). Collective variables exhibit entrainment, whereby the system enters preferred stable states and exhibit abrupt phase transitions, both being characteristics of spontaneous activity in infants.

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