Topology of Learning and Correction in Dynamic Balance

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Submitted to the Program in Media Arts and Sciences,
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Abstract

"The discrepancy between [our personal experiences] and our idealizations of knowledge leads us into counterproductive strategies for learning and thinking" (Papert 1993). This discrepancy has driven most research towards understanding how people fail to accomplish a task, while few researchers have focused on looking at those instances where people have developed strategies for correcting their failure. This work has as its core belief that by identifying the strategies of correction we will develop better ways to assist in learning. However, to successfully assist in learning, we need to take into account both general rules of behavior and individual solutions. To explore this, we look at a concrete example from posture control, balance, to understand how learning modifies it. This research focuses on identifying an algorithm looking at the process of correction during dynamic balance. We outline an experiment whereby healthy subjects attempt to learn to balance on a two-degrees of freedom platform through external-focus feedback. The intent is to capture and analyze how the structure of old and new-learned body synergies for dynamic balance changes over time. The analysis we present offers a perspective of how subjects achieve kinetic coherence by building *strategy maps*.

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Con profunda admiración, esta tesis la dedico a quien me ha motivado a valorar lo que hago y a luchar por lo que no he hecho, mi esposo Bernardo.

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Chapter 1

Introduction

When it comes to learning, particularly learning a physical skill, the core dilemma is how fragmented motor responses come to be highly organized both in time and space to form a single-threaded program. What has been seen so far in brain research and motor control literature is that the brain acts not by seeking the ideal predictive information but rather the most useful one for coordinating the action (Berthoz 2000). To promote understanding of the organization dilemma, the focus of attention of this research is, thus, changes in movement coordination during the learning process attributed to the *process of correction*. That is, the study of movement will be attacked at the behavioral level of analysis, focusing on the changes in the learning process. Throughout this document, the reader will encounter the exploration of how movement patterns are acquired, corrected, and readapted during the execution of a specific balancing task.

1.1 Motivation

The interest in developing new theories and practices to support learning of physical skills is based on the MIT Media Laboratory's growing efforts to uncover new types of learning experiences in different domains by understanding the nature of human movement. Balance itself is interesting as one of the fundamentals of motion study. People are familiar with this concept and at the same time unaware of the complex processes that control posture. For these two reasons, the area of posture control is suitable for our research purposes.

In addition to the epistemological enterprise around posture and balance, the degeneration of the balance control system in the elderly and in many pathologies has posed this topic as relevant in healthcare research. According to the Center for Disease Control and Prevention (CDC), falls are the leading external cause of injury (cdc.gov 2001) and falls caused by changes in the somatosensory system are the most common cause of morbidity and mortality among the elderly (Collins, Priplata *et al.* 2003, March/April) (Dault, de Haart *et al.* 2003). Therefore, understanding more about how the system works and how to quantify its status at any point of time is the first step towards helping people to learn about learning to balance. The importance of learning about learning is pointed out not as a philosophical understanding but as a form to provide people with ways of discerning and choosing patterns or connections of balance strategies better than before.

New research done by using the concept of noise-enhanced sensation (boosting sensory feedback) could potentially speed up and enhance a patient's rehabilitation with somatosensory problems (Collins, Priplata *et al.* 2003, March/April) and increase the percentage of reduced falls. Nevertheless there is a pending issue that arises when people have posture deficits that require some durable benefit that no stochastic resonance-based device has proven to offer after the device has been removed. For these cases, the algorithm to be observed during the correction process will hopefully result in shareable models for unexpected perturbations that people can reflect on and learn about. After all, "anticipatory responses must be learned, but eventually they operate automatically, being triggered by specific intended movements" (Kandel, Schwartz *et al.* 2000).

1.2 Scope

This document seeks to understand and place in perspective the importance of *the process of correction* when learning a skill, in this case, when learning to balance on a board. Towards understanding the *process of correction*, readers must be clear that the goal of this research is not to develop a new method to assess balance problems nor to define a rehabilitation procedure, but identify an algorithm that potentially describes the learning process during balance. To do so, information captured by wearable sensors is analyzed through statistical procedures. Later, intuitions are offered about the two basic questions that arise in skill acquisition, namely, *what has to be learned?* and *how is it learned?*. And finally, a model and an algorithm that reflect aspects of the *process of correction* as learning is unfolding are presented.

Full investigation of how algorithms can be used for rehabilitation is beyond the scope of this project as well as exhaustive treatment of the various approaches to learning. The treatment here will be to provide a broad insight on what can be done to assist in learning based on the results of this research. Hence, the concept embedded in this research is of algorithms not as solution providers but as thinking catalysts.

1.3 Structure

The structure of this document is as follows. Chapter 2 serves as an introduction to relevant concepts and current research in postural control, balance assessment, and physical skill learning. In addition to the literature review, this chapter presents a description of the four major challenges to providing deep insights about the balance-learning problem. In Chapter 3, the design, implementation, and statistical analysis of the study are introduced. Chapter 4 presents empirical relationships and intuitions about learning, as well as common and useful measures in motor control. In Chapter 5, a model and an algorithm looking at the *process of correction* are introduced. Finally, Chapter 6 summarizes the most important conclusions of this work.

Chapter 2

Background

2.1 Terminology

The terminology used to describe balance depends on the perspective through which this phenomenon is approached. Throughout this document two different approaches will be presented. The most popular approach has to do with discrete modes of perception; the other with using pattern dynamics and attractors. Even though both lines of research differ, the following terminology for posture and balance pertain to both approaches:

1. Posture describes the geometric relation of the body parts relative to one another and to the environment.
2. Balance describes the dynamics of body posture due to postural disturbances.

In the present study, the focus is on posture and balance related to dynamic balance, which can be cast in terms of finding appropriate relations among body segments and defining what to do with those relations to maintain balance.

2.2 Postural control

Maintaining postural stability is a complex process that relies on the interaction of three components:

1. Combination of information from vision, the vestibular system and somatosensory system;
2. Motor responses coordinated among muscles of the feet, legs, and trunk;
3. Integration of the sensory and motor processes, previously mentioned, and the adaptation of these processes to changes in the environment (onbalance.com 2003).

This last component is particularly important because some of the information provided by the visual, vestibular or somatosensory systems can be inaccurate in certain environments. For this reason, the brain chooses sensory inputs according to the context to make the appropriate postural adjustments (Berthoz 2000). However, postural adjustments are not the only challenges met by the postural system. It also must be capable of generating responses that anticipate voluntary movement and capable of adaptive leaning.

Two different approaches of postural adjustment are seen in current research: discrete modes of perception and pattern dynamics and attractors. In the case of the discrete modes of perception, there appear to be two ways of perceiving these postural relations. One takes the head as reference and projects information in a top-down approach from the head to the trunk and then to the feet. The other takes the ground as a reference and projects in a bottom-up mode from the feet to the trunk and then to the head (Kandel, Schwartz *et al.* 2000). In contrast to the discrete approach, the pattern-dynamics approach suggests that postural synergies might not be discrete but functional synergies arranged in terms of pattern variables. This later approach deals with phase relations and attractors in a dynamic system (Kelso 1999) (Saltzman and Kelso 1985). In any case, postural and balance adjustments are characterized by a collective assembling of motor patterns. Their timing and amplitude are suggested as strategies or synergies (Winter 1995).

2.3 Balance assessment

A great variety of tests and instruments have been developed to qualify and quantify the status of the postural control system. Some of these instruments are administered under laboratory settings while others are not restricted to specific laboratory conditions. Some are qualitative while others are quantitative. But no matter their nature there is no single assessment technique that can truly indicate the efficiency of the balance control system (Winter 1990). Consequentenly, the selection of an instrument depends on the results aimed at.

The qualitative balance measurements are usually not restricted to laboratory settings because they are mostly designed to assess balance capabilities in various tasks related to everyday life (Berg, Wood-Dauphinee *et al.* 1989) (Tinetti 1986) (Whitney, Poole *et al.* 1998). They mostly measure the ability to execute coordinated movements. These tests do not require training to administer, last a couple of minutes, and are inexpensive. They are focused on capturing information related to typical balance problems, although because the assessment is usually based on scores, these tests do not provide detailed information about balance problems of the postural control system.

Thereupon a significant amount of research has focused on more elaborated balance assessment methods, such as optical motion analysis systems (Medved 2001), force platforms (Nashner 2001), and electromyography. These methods give more detailed information about postural balance than the qualitative balance measurements; nevertheless they are restricted to laboratory settings and are also much more expensive to perform than the qualitative methods.

An unconventional balance assessment method, although not new, is accelerometry. Accelerometry has been proposed as a useful gait analysis technique since the 1960's and more recently, it has been employed to:

1. Evaluate the effects of ageing and different walking surfaces as a measure of stability under real life environmental conditions (Menz, Lord *et al.* 2003);
2. Measure balance control during quiet standing (Moe-Nilssen and Helbostad 2001) (Mayagoitia, Lötters *et al.* 2002);
3. Diagnose and assist with therapy (Wall III and Weinberg 2003, March/April) (Sabelman 2002).

The need for low cost devices that fall within the two most common areas of balance assessment points towards accelerometry as an inexpensive alternative to optical motion analysis systems (Mayagoitia, Nene *et al.* 2002). These portable systems have the potential of enabling collection in everyday environments at low costs. Thus the data collection can be done frequently and therefore enable real-time feedback.

2.4 Physical skill learning

2.4.1 Theoretical frameworks

Motor learning and control are mostly being studied under two theoretical frameworks: a cognitive or information processing approach and a dynamic systems approach. The main difference between these approaches revolves around the learner. The cognitive approach and the dynamic systems approach conceive the role of the learner in different ways either as an integrator of information or as an explorer during the learning process. Consequently the learning process is rooted on a motor schema or an emerging design. This section briefly describes both theoretical frameworks.

Until the 1970s research on movement and skill learning was confined to a problem of motor control defined in terms of information processing and resource allocation. This research is well structured under the cognitive framework. Under the information-processing approach, learning occurs as an outcome of a motor program and its representation exists inside an entity that can be considered a central programmer. How well each person allocates processing and attention resources describes his/her ability to execute a motor skill (Magill 1998) (Schmidt and Wrisber 2000). Therefore, for the cognitive approach, the learner is the communication channel that processes information in different hypothetical scenarios to produce a motor action (Schmidt and Wrisber 2000). This same idea of being able to look into the future and consider various combinations of possible actions to predict a possible outcome is described by Minsky in his Five-Level Model of Mind with the difference that the scheme of control he proposes is decentralized (Minsky 2003).

In response to the argument that motor-learning understanding was not possible unless the processes of movement control were known, another approach to motor learning evolved. The dynamic systems approach suggests that the coordination patterns are not represented in motor programs but naturally emerge as self-organizing systems (Wulf, NcNevin *et al.* 1999). The key task for the learner is assumed to be the exploration of those patterns of movement that act as attractors. These attractors are first defined by each individual's intrinsic dynamics that represent their preferred modes of coordination and the environment's constraints (Corbetta and Vereijken 1999), but with practice, according to this approach, learners can destabilize those dynamics and search for more optimal attractors. Such process implies the optimal use of reactive forces in the environment. The principle of exploiting existing forces was already formulated by Bernstein in 1967 as the third and final stage of the skill-acquisition process. He stated that forces generated by the individual only worked as complement of those forces available in the environment (Vereijken, Whiting *et al.* 1992).

2.4.2 Dynamic balance studies

Learning is usually conceived as changes in motor behaviors to master the coordination of multiple degrees of freedom of a system (Bernstein 1967). Coordination can happen in two ways. It can happen by freezing and freeing joints to decrease the number of degrees of freedom to be mastered; or by the dissolution and emergence of task-specific couplings between oscillators in the system (Caillou, Nourrit *et al.* 2002). Both types of adaptations have been seen in previous research in balancing tasks and one of the basic conclusions of these studies is the confirmation that these adaptations are strongly constrained by the task. Task constraining becomes then an important issue to address in balance learning.

The most common way to study dynamic balance has been through the use of platforms and stabilometers to examine how people learn to coordinate redundant degrees of freedom (Ko, Challis *et al.* 2003) (Adkin, Frank *et al.* 2002) (Shea, Lai *et al.* 2000) (Shea and Wulf 1999) in laboratory settings. With the use of optical motion-analysis systems, force platforms and electromyography, researchers have recorded muscle anticipatory responses, forces and moments from force plates, and couplings between body parts to describe changes in practice and the learning process. The contribution of the majority of these studies is on global behavioral and motor trends that have enlightened the general panorama of motor control and learning.

In addition to what has been considered as the traditional and most reliable methods of analyzing motor trends, wearable inertial sensors have become an inexpensive option to measure movement. Body-mounted sensors, like accelerometers and gyroscopes, have and are being tested in different physical tasks to establish statistical reliability with laboratory measures (Mayagoitia, Nene *et al.* 2002) (Moe-Nilssen 1998) (Morris 2004). Balance studies using these systems have shown that they are useful for quantifying qualitative measures of balance (Sabelman 2002) and helpful for building discriminants (Moe-Nilssen and Helbostad 2001), but once balance-control measures are developed they also provide relevant quantitative data comparable to analogous optical data. Parameters such as angle, angular velocity, linear acceleration, and variability are representative examples (Mayagoitia, Nene *et al.* 2002). Nevertheless actual values of the parameters resulting from different systems are not directly comparable (Mayagoitia, Lötters *et al.* 2002).

2.4.3 Influences and effects on the learning process

When confronted with a motor task, the learner does not only deal with his/her physical constraints but also with other factors that might influence the learning process in positive or negative ways. Balance literature has reported factors that have an effect on learning and performance suggesting that skill execution can be modified by either controlling or enhancing such factors. A series of experiments have been conducted mainly with force platforms to measure the effect of the fear or falling or postural threat on the control of posture (Adkin, Frank *et al.* 2002), the effect of spacing practice sessions across days and within days on the learning of balance tasks (Shea, Lai *et al.* 2000) and the influence of external-focus feedback (Shea and Wulf 1999).

Of main interest to this research is the use of feedback systems to aid in the learning process. The most common type of feedback system in the balance-learning literature is a visual display that provides real-time information about movement dynamics. Studies using stabilometers frequently design their feedback systems with lines that represent the deviations of the platform form the horizontal plane. The main purpose of this design is for subjects to visually identify how tilted the board is without looking at it directly. The criticism to this design is that it might be redundant with intrinsic feedback. Yet, according to Shea and Wulf (Shea and Wulf 1999), feedback, although redundant, can enhance motor skills if the given feedback refers to the effects of the participant's movements rather than the movements themselves (Shea and Wulf 1999). Nevertheless, some studies have indicated that feedback is ineffective if it is redundant with the performer's intrinsic feedback (Magill, Chamberlin *et al.* 1991) (Vereijken and Whiting 1990) or if learners become dependent on it. The degrading effects of frequent and immediate feedback are usually explained with the Guidance Hypothesis (Salmoni, Schmidt *et al.* 1984) according to which the learner develops a dependency on the feedback, if he/she is heavily guided by the augmented information. For this reason, the careful design of a feedback system is imperative to effectively help users.

Besides visual feedback, tactile feedback (in areas of the body other than the feet and the hands) has also proven to be effective in standing balance. Passive tactile sensory input on the shoulder and leg using a vibrator has demonstrated an improvement in stability during standing (Rogers, Wardman *et al.* 2001). Also, positive results have been achieved by tactile feedback on the torso through an array of vibration sensors that are activated by the outputs of an accelerometer and a gyroscope (Wall III and Weinberg 2003, March/April). A next step is to analyze the potential for tactile cues to modify postural reactions in dynamic tasks.

2.5 Lessons learned

According to Winter, balance is related to the acceleration involved in the dynamics of body posture and how the central nervous system (CNS) controls those accelerations (Winter 1995). For this reason, using accelerometers to capture balance information is thought to be a natural option for body sensing for this research study. However, choosing the movement-sensing system is not the only important decision to be made when designing a balance study. Balance studies face four major challenges when willing to provide deep insights about the balance-learning problem. These challenges will be next presented as well as the expectations and approach taken by this research study.

1. Balance studies with main interest in extrapolating their results to real life have to choose paradigms and design experiments that are representative of the kinds of disturbances experienced outside the laboratories (Winter 1995). In this research study, the experiment design is not likely to be representative of any disturbances experienced in real life, but it is expected that it will uncover stages of skill-learning that concern with the acquisition of movement coordination *per se* (which the authors of this research believe is closely related to the process of correction during task executions).
2. Measuring the dynamics of task executions and measuring the outcomes of those executions are two different things (Vereijken, Whiting *et al.* 1992). The skill-learning literature recognizes that a task can be interpreted in different ways, for example in terms of its final goal or the strategies carried out to achieve the goal.

However, it becomes apparent that to understand the underlying dynamics of task execution just looking at the final outcome is not sufficient. For this reason, this research will concentrate on an in depth analysis of the dynamics of task executions and the evolving strategy. Additionally, an overall analysis regarding to the final goal will be presented.

3. The design of the feedback system impacts the learning process. It has been well documented that "participants usually learn things that are different from those that the experimenter expected them to learn" (Perruchet, Chambaron *et al.* 2003). Therefore, careful design of the feedback system is essential. The feedback system used this research study will be based on the hypothesis that trying to fall within a range of what is considered close to being balanced achieves better performance than trying to perfectly balance (for details see section 3.2.2). This assumption has not been verified and might negatively affect the learning process if it is proven false. In such a case a recommendation of possible useful designs for a feedback system will be provided.
4. Learning and changes in variability are task dependent. It is frequently thought that decreases in variability are common in balance learning. Hence, variability should decrease if subjects learn to become more stable, and therefore become skilled at the balance task (Schmidt and Lee 1999). However, if subjects learn to move close to dangerous conditions, variability should increase (Patton, Lee *et al.* 2000). Because of the nature of the task and the duration of the research study, an inverse relationship between learning and variability is expected.

Chapter 3

Materials and methods

Healthy subjects attempted to learn to balance on a two-degrees-of-freedom platform with the intent to capture and analyze how the structure of old and new learned body synergies for dynamic balance changed over time. A balance fitness equipment was instrumented with a compact circuit board to measure linear acceleration about three axes. Two additional circuit boards placed on the subject's body provided information about acceleration dynamics. All data was wirelessly transmitted to a receiver connected to a computer through the serial port with 66-Hz full-state updates streaming directly from each circuit board.

3.1 Participants

Participants were recruited through flyers seeking research study subjects for compensation. Flyers were posted around the MIT campus. Thirty-one people volunteered to participate in the study. Each volunteer was asked to go to a website to download and answer a questionnaire, the Balance Self Test (see Appendix A), that helped the experimenters determine if the participant was at risk of falling. Exclusion criteria included any affirmative answer to the questions in the Balance Self Test. The study was conducted with twenty-four subjects (male to female ratio of 4:1, age (years) 27.19 ± 7.10, body mass (kg/m^2) 22.615 ± 2.73). Each participant, informed of the experimental procedures, provided written consent prior to each of three testing sessions. The MIT Committee On the Use of Humans as Experimental Subjects (COUHES) approved all experimental procedures (COUHES 2003).

3.2 Instrumentation

3.2.1 Accelerometers

Linear acceleration was collected via three 1.2” by 1” wireless circuit boards measuring three axes of acceleration. The circuit boards are instrumented with two 2-axis accelerometers from Analog Devices ADXL202/ADXL210, a microcontroller and wireless transceiver/receiver, and a 3-Volt power supply. For each board, one of the accelerometers is orthogonally attached to the side of the pane to achieve the third axis of sensing[1] as shown in Figure 3-1. These circuit boards are responsible for data collection and transmission to an additional board referred to as the receiver. The receiver, which can also be instrumented with two accelerometers, is connected to a computer through the serial port. The total sampling rate of the system is 200-Hz (Munguia Tapia, Marmasse *et al.*).

Figure 3-1 Transceiver with three axes of acceleration

Considering that the balance task might have harmonics as high as 12-Hz in terms of a load-upload mechanism for balance and taking into account that the suggested sampling rate in Movement Science should be four times the highest frequency (Winter and Patla 1997), four boards were appropriate for the study. Due to a last moment failure, the experimenter ended up using three boards instead of four, two of which measure linear acceleration in the ± 2g range and another one in the ± 10g range.

[1] Both accelerometers were soldered to the board by hand, so while the *x*-axis is expected to be close to perpendicular to the *y*-axis and the *z*-axis, the exact angle was unknown.

3.2.2 Feedback system

The main goal of the feedback system used in this study is to quantify what is not perfectly visible: a vicinity of balance. This is similar to answering the question *how close I am to be balanced?* To do so the system assumes that the minimum amount of data needed to provide this information is position and velocity (Kadkade, Benda *et al.* 2003).

Three different designs were tested with a small group of volunteers from MIT community to investigate the user experience and preferred real-time acceleration mappings. Several iterations of usability testing were conducted to find the form of data representation preferred by the group. The final outcome was a visual feedback system relying on two hypotheses.

Hypothesis 1. Trying to fall within a range of what is considered close to being balanced achieves better performance than trying to perfectly balance *(i.e.* $|\partial| \leq \varepsilon$, where ∂ corresponds to the tilt of the platform from the horizontal position, $\partial = 0$, and ε is a small number greater that zero).

Hypothesis 2. To efficiently balance, a person has to learn to respond to acceleration as opposed to the tilt of the board (Papert 2004).

The system built in Processing (Fry and Reas 2004) and interfaced with Java, consists of three squares, two of which move and change sizes according to the acceleration experienced by the board in two different axes: pitch and roll. Pitch, captured by the *x*-axis of acceleration of the circuit board (placed on the bottom of the board), controls the movement of the squares. While roll, captured by the *y*-axis of acceleration, controls the size of the squares. The frame of reference for the board seen from a top-view is depicted in Figure 3-2.

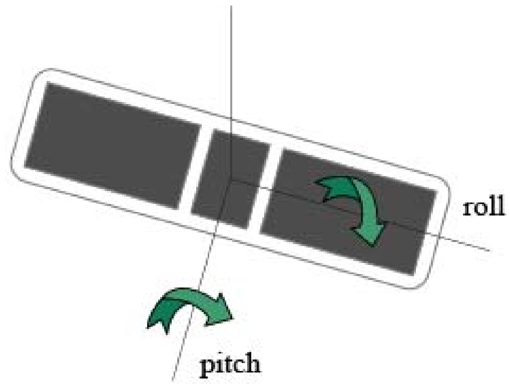


Figure 3-2 Frame of reference for the balance board

The acceleration, displacement, and size of the squares shown on a computer screen are not the result of a linear mapping of the acceleration onto the squares. The dynamic properties of the system are defined by a step function of the form:

$$f(x_1, x_2) = \alpha_1 f_1(x_1) + \alpha_2 f_2(x_2). \qquad \textbf{Equation 3-1}$$

Where α_1 and $\alpha_2 \in \mathbb{R}$.

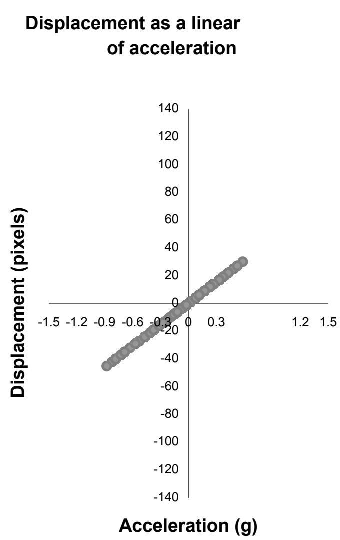
$$f_1(x_1) = \text{int}\left(\frac{\text{int}(x_1)}{\alpha_{1,1}}\right) \qquad \textbf{Equation 3-2}$$

is a noise-reduction function and

$$f_2(x_2) = \text{int}\left(\frac{\text{int}(x_2)}{\alpha_{2,1}}\right) \qquad \textbf{Equation 3-3}$$

is a noise-add function. x_1 and x_2 are multiples of a zero-mean transformation of the linear acceleration output from the sensors. x_1 takes its value from the acceleration output in the pitch axis of the platform and x_2 from the roll axis output from the same board. $\alpha_{1,1}$ and $\alpha_{2,1}$ are both constants.

The step-wise mapping is based on the hypothesis that trying to fall within a range of what is considered close to being balanced achieves better performance than trying to perfectly balance. This mapping is especially relevant when a subject is close to be balanced. Instead of watching the squares constantly moving due to common changes in acceleration when he/she is not perfectly balanced, he/she will watch no such changes. To provide with a graphical understanding of mapping functions, Figure 3-3 shows the horizontal displacement of the squares given two different mapping functions: a linear function and the actual step function used in the feedback system (Equation 3-1). In this case data was taken from a five-seconds sequence of movement on the balance board using a ± 10g accelerometer.



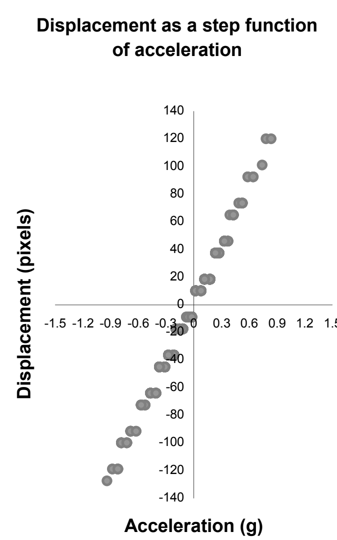


Figure 3-3 Horizontal displacement of the squares from the center to the edges of the screen as a function of acceleration

Movement and size variations are not the only important features of the system. Color was carefully chosen to enforce body symmetry and for easily searching the displayed information. The colors of the two external squares have the same hue distance from the central color. This helps the subject to avoid focusing on a single square and concentrate on the global information provided by the system (Bender 2004). Actual snapshots of the feedback system (Figure 3-4) show how the position of the platform is represented by the size of the squares and distance between them.

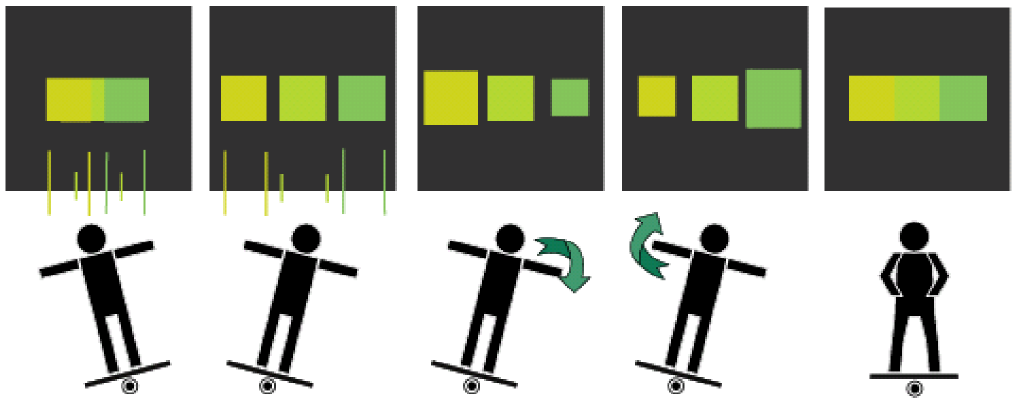


Figure 3-4 Feedback system mapping of movement

3.3 Protocol

3.3.1 The task

The study consisted of a balancing task. Participants were asked to wear two circuit boards placed on two different parts of their body (for details see section 3.4) and were asked to balance barefoot on a platform that moved in the sagittal and frontal planes. Participants were instructed to maintain the balance board as still and as horizontal for as long as possible. The study was divided into three sessions and performed under two conditions (with feedback and without feedback). Subjects were randomly assigned to one of these two conditions. The first two sessions of the study took place on two consecutive days and the last a week after the second session was held. In each session, subjects were asked to try to balance on a balance-fitness equipment called Extreme Balance Board^{TM} for 30 seconds and had eight trials to do so. The time interval between successive trials was 30 seconds. The total session time was of 45 minutes for the first session, 30 minutes for the second session, and 60 minutes for the last session. These inter-session and inter-trial spacing practices have proven to have a positive effect on performance and learning (Shea, Lai *et al.* 2000).

Under the experimental condition of a trial, at an oral signal from the experimenter, the subject placed his/her feet on the platform and tried to remain in equilibrium for as long as possible. At any time, the subject could go to a stable position by placing one side of the board on the floor without stepping off the equipment. After the time was up, the experimenter gave an oral signal for the subject to stop and step off the platform. Under both experimental conditions, the study was restricted to the analysis of three stages in the learning process each represented by a session. (Session 1): People bring their balance knowledge (their constructions) of the physical world and try to apply that knowledge. (Session 2): The experiment design forces participants to try different strategies by providing specific instructions on where to place their feet on each trial. (Session 3): Participants are told to pick by themselves the strategy that would allow them to achieve best performance.

3.3.2 Conditions for the experiment

The experiment was held at the Media Laboratory in a space where a loss of balance would not result in contact with objects that could cause injury. This space was equipped with two mats (7 ft x 4 ft x ½ ft) to protect participants in case of a fall.

Initially, all subjects familiarized themselves with the balance board by moving it freely with their hands so that they understood its range of motion. In the case where a subject was placed under the feedback condition, the participant moved the board and watched the display at the same time so that he/she could understand how the feedback system worked. Once the subjects felt they had understood the limits and possibilities of the range of motion they were asked to leave the board still on the floor and stand barefoot close to the balance board.

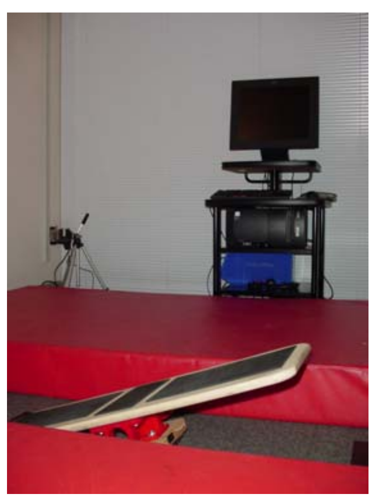


Figure 3-5 Experimental set-up

Subjects wore two circuit boards (previously described in section 3.2.1) to collect data from body movement. The boards were securely fastened on the forehead and over the T12[2] region using elastic bands and Velcro® straps as shown in Figure 3-6. A third circuit board was placed on the bottom of the board to collect the platform's acceleration. In the case where a subject was placed under the feedback condition this same circuit board controlled the visual display placed six feet away from the subject. This distance was appropriate for the visual system to control postural stability (Brandt, Paulus *et al.* 1986) and yet provide enough space for the subject to minimize any injury caused by a collision with an object.

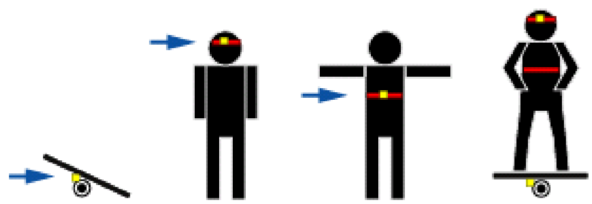


Figure 3-6 Placement of sensors

In addition to collecting data from the sensors, every session was videotaped. Anthropometric factors such as hip and knee joints, as well as the perimeter of the feet were measured for each subject.

3.4 Data collection

Linear acceleration was measured by three circuit boards. Two of the circuit boards were placed on the participant's body: on the forehead and over the T12 region. The third one was placed on the bottom of the platform. All data were wirelessly transmitted to a receiver connected to a computer through the serial port with 66-Hz full-state updates streaming directly from each circuit board. Data was recorded in a *.txt file that contained: the sampling times in milliseconds and the acceleration for each of the nine channels of information (three axes per board) in 10-bit samples. Data collection began before the first

[2] Originally, one of the circuit boards was to be placed over the L3 region which is close to where the center of mass (COM) is believed to be during quiet standing according to Moe-Nilssen, but pilot studies revealed that subject felt uncomfortable while trying to accomplish the task. Moe-Nilssen, R. (1998). A new method for evaluating motor control in gait under real-life environmental conditions. Part 2: Gait analysis. *Clinical Biomechanics* 13: 328-335.

trial started and after the sensors were correctly placed. Data collection ended approximately four to six seconds after the last oral signal to stop and step off the platform. Acceleration data for each subject was stored in files with the following naming convention: signal_s<subject no.>_t<session no.>. Where <subject no.> is an anonymous identifier for the participant from 01 to 31.

The beginning and end of each trial were recorded in a *.xls file that saved the computer clock time when a button was clicked. The starting time recorded for each trial corresponds to the moment in which the participant started to lift the board off the ground. This time was defined by the experimenter's action of clicking a button on the spreadsheet. The stopping time was automatically computed as 30 seconds after the starting time. Data for each subject was stored in files with the following naming convention: times_s<subject no.>_t<session no.>.

For each session, perceived confidence, satisfaction, performance, and expected performance measures were reported by the participant. Participants scored each item on a post-task questionnaire (one for each session) using a 7-point scale ranging from 1 (not at all/not well at all) to 7 (very confident/very well). Participants answered additional questions related to the strategies they used to balance during the first and last trials and the difficulty of the task in each session. In the last session all participants were asked to watch their own video recordings from Session 1 and Session 3 with the goal of comparing and contrasting their strategies and performances between sessions. Additionally, participants in the feedback condition reported levels of: usefulness; distraction; information; and intuition of the feedback system. Participants scored each item using a 7-point scale ranging from 1 (not at all) to 7 (very/ absolutely). By the end of the third session, each participant had answered a total of four questionnaires. For more detail about the questionnaires see Appendices B, C, D, and E.

3.5 Data analysis

3.5.1 Signal processing

Before statistical analysis of the data was done, a number of processing steps were applied to the data; data were truncated, adjusted, and filtered. MATLAB® was used for all signal processing.

Raw acceleration data were converted into MATLAB® files (*.mat) and then truncated into eight segments, 30-seconds each, corresponding to the eight trials. Data segmentation was computed in MATLAB® using a *.xls file that contained the beginning and end times of each trial. Once the data were divided into trials, the zero offset of the axes of the accelerometers was determined by the DC levels. Data were zero-meaned using the DC components and then transformed to units of [-2g, 2g] for the data collected by the on-body circuit boards and a range of [-10g, 10g] for the circuit board placed on the balance board. No further transformations were performed to accurately determine the static acceleration for each data point; determination of dynamic and static acceleration in the data could not be determined from measurement of acceleration alone according to Einstein's Equivalency Principle[3], hence the contribution of the gravitational component is still present in the transformed data. Determination of the dynamic acceleration could have been achieved by including a gyroscope on each board to record the orientation of the board with respect to the horizontal plane (Morris 2004).

After truncation, two types of adjustments were made to the data before the statistical analysis was done. Outliers were identified and replaced and some data was ignored due to a wireless transmission problem related to missing data packages. Values that were greater or equal than $\bar{x}_{(t_i,t_j)} + 3\sigma_{(t_i,t_j)}$ were considered as outliers; therefore they were replaced by $\bar{x}_{(t_i,t_j)}$. Where $\bar{x}_{(t_i,t_j)}$ is the estimate of the mean of a window of approximately six seconds of recorded data starting at time t_i and ending at time t_j for $i = 1,2,\ldots,8$ and $j = 1,2,\ldots,8$. The windows were overlapped by approximately three seconds. All data were low pass filtered[4] at a cutoff frequency of 20-Hz using a sixth-order Butterworth filter.

3.5.2 Descriptive statistics and performance metrics

The filtered acceleration data were used to extract descriptive statistics such as estimates for the mean ($\hat{\mu}$), median ($\hat{\mu}_{1/2}$), standard deviation ($\hat{\sigma}$), coefficient of variation (*CV*), and root mean square (*RMS*). These statistics were obtained for each of the nine channels of information of every subject's acceleration per trial, session, and experimental condition.

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[3] The principle states that no experiment can distinguish the acceleration due to gravity from the inertial acceleration due to a change of velocity.
[4] MATLAB® function butter.m was used.

Additional to the descriptive statistics, three *ensemble variables*[5] (*EV*) were derived as performance metrics: *ensemble variable* of the platform (EV_p), *ensemble variable* of the body (EV_b), and *ensemble variable* of the system (EV_s). These variables, *jointly* considered, were subsequently used to study how the task was learned and what types of strategies were used during the experiment. The *EV* variables were computed as follows:

$$EV_p = \sqrt{RMS_{x_p}{}^2 + RMS_{y_p}{}^2}\ . \qquad \textbf{Equation 3-4}$$

Where x_p corresponds to the pitch axis of the balance board, and y_p corresponds to the roll axis of the balance board.

$$EV_b = \sqrt{RMS_{x_e}{}^2 + RMS_{y_e}{}^2 + RMS_{x_h}{}^2 + RMS_{y_h}{}^2}\ . \qquad \textbf{Equation 3-5}$$

Where x_e and x_h correspond to the *x*-axes of acceleration of the back and the head; and y_e and y_h correspond to the *y*-axes of acceleration of the back and the head respectively.

$$EV_s = \sqrt{\sqrt{RMS_p{}^2} + \sqrt{RMS_b{}^2}}\ . \qquad \textbf{Equation 3-6}$$

3.5.3 Statistical analysis

After signal processing of the data was done, two major analyses were performed. The first compared all possible interactions between Session 1 and Session 3; and the second analysis was on the Strategies of Session 2. SPSS was used for all statistical analysis.

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[5] An *ensemble variable* is an informative and low dimensional dependent variable that reflects changes during the learning process. *Ensemble variables* have proven to be useful for explaining emerging movement patterns. Vereijken, B., H. T. A. Whiting, *et al.* (1992). A dynamical systems approach to skill acquisition. *The Quarterly Journal of Experimental Psychology* 45A(2): 323-344.

3.5.3.1 Session 1 *versus* Session 3

The experimental design consisted of a three-way design with one randomized group and two repeated factors for each channel of information. The randomized-groups independent variable was experimental condition (with feedback *versus* without feedback) and the dependent variables were $\hat{\mu}$ and *RMS*. Four trials were considered for the analysis (trial 3, trial 4, trial 5, and trial 6) either in Session 1 or Session 3. Session 2 was left out of this first analysis. Given the mixed design the statistical analysis was concentrated on the main effects of the experimental condition and its interactions as well as the main effects of the sessions, trials, and their interactions.

A 2 x 2 x 4 mixed randomized-repeated ANOVA procedure was performed for both $\hat{\mu}$ and *RMS* for each channel of information, resulting in a total of 18 mixed randomized-repeated analysis. Total N of 24 subjects (11 in the without-feedback condition *versus* 13 in the feedback condition) was reduced to 21 with the deletion of their corresponding data[6]. The subjects whose data was deleted from the analysis belonged to the feedback condition. Normality of sampling distribution and homogeneity of variance were evaluated. Two cells did not meet normality of sampling when the measure was $\hat{\mu}$ and six cells did not meet Normality of sampling when the measure was *RMS*. Large z scores in skewness and kurtosis ($z \geq 2.58$, $\alpha = 0.01$, two-tailed) were identified in some cells. In those cases, outliers were identified as a possible cause for the non-Normality. Outliers were adjusted to reduce their impact on the data set[7]. Homogeneity of variance was not met in channel 5 when the measure was $\hat{\mu}$ and in channels 4, 5, and 8 when the measure was *RMS*. Heterogeneity of variance in channel 5 and channel 8 were expected and were not worrisome because they corresponded to the vertical acceleration of the back and the head of the subjects. Heterogeneity of variance in channel 4, corresponding to the side-to-side acceleration of the back, ($F_{\max}$ for channel 4 was 16.14) needed treatment; therefore, α for testing all effects

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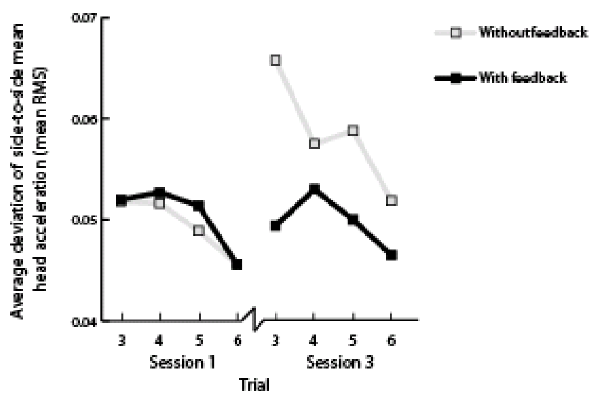
[6] One subject reported that he intentionally avoided looking at the display in the last session. Another subject reported that he had forgotten to watch the display during the last session. These two subjects had to be removed from the analysis because their data on Session 3 did not include any effect by the experimental condition. Another subject had an unusual posture during all the sessions that was not comparable to any of the postures adopted by the rest of the subjects.

[7] Given an ordered set of data points $\{y_1, y_2, \ldots, y_n\}$, if y_1 is identified as an outlier, the adjustment $\hat{y}_1$ for y_1 is $\hat{y}_1 = y_1 + (y_2 - y_1)$. If y_n is identified as an outlier, the adjustment $\hat{y}_n$ for y_n is $\hat{y}_n = y_n + (y_{n-1} - y_{n-2})$.

was set to 0.025 to compensate for any inflation of Type I error rate due to heterogeneity of variance.

The probability level for Maucheley's test of sphericity for trial and for session by trial interaction was smaller than 0.025 in channels 3, 7, 8, and 9 for $\hat{\mu}$ and channels 2, 3, 4, 5, 6, and 8 for *RMS*. This implied that sphericity assumption was not met. However, in some cases such as channels 4 and 6, the Huynh-Feldt corrections were used.

There was a significant three-way interaction between session number, trial number, and experimental condition in side-to-side *RMS* acceleration of the head, $F(3,57) = 3.127$, $p = 0.016$, partial $\eta^2 = .16$. Thus, 16% of the variance in *RMS* is attributable to the session, trial, and experimental condition interaction. For a graphical understanding of the interaction, means of the Simple Effects Analysis are plotted in Figure 3-7.



	Estimate for the Coefficient of Variation (standard deviation RMS/mean RMS)							
■	0.450	0.470	0.558	0.393	0.273	0.391	0.342	0.310
□	0.418	0.388	0.336	0.395	0.425	0.403	0.375	0.346

Figure 3-7 Average deviation of side-to-side mean head acceleration

Examination of Figure 3-7 confirms that on average, the variable *RMS* is affected in Session 3 by the experimental condition. It is not clear from these plots if the effect is due to the fact that all subjects in the feedback condition were looking at a fixed point in the room (the monitor with the visual feedback) or if it is attributable to the feedback.

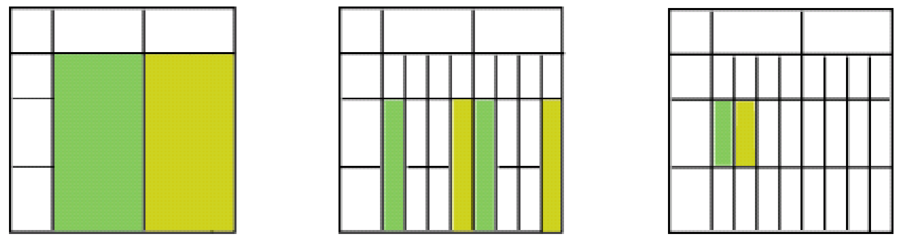
On each trial of Session 3, subjects in the feedback condition, on the average, successfully brought the head to oscillate with less variability than subjects in the without-feedback condition as shown by Figure 3-7. Nevertheless, this result does not imply that subjects in the feedback condition performed better on the task (*i.e.* maintain the balance board as still and as horizontal for as long as possible).

Additional and well-known effects approached statistical significance for both $\hat{\mu}$ and *RMS*.

1. Mean difference in $\hat{\mu}$ and *RMS* between trials was concluded for channel 1 (side to side $\hat{\mu}$ and *RMS* of the balance board), $F(3,57) = 3.350$, $p = 0.025$, $\eta^2 = 0.15$ and $F(3,57) = 3.977$, $p = 0.012$, $\eta^2 = 0.17$, respectively.
2. Mean difference in *RMS* between trials was concluded for channel 4 (side to side *RMS* of the back) and channel 7 (side to side *RMS* of the head), $F(3,57) = 4.066$, $p = 0.011$, $\eta^2 = 0.18$ and $F(3,57) = 3.621$, $p = 0.018$, $\eta^2 = 0.16$, respectively.
3. Mean difference in $\hat{\mu}$ between sessions was concluded for channel 6 (forward and backward acceleration of the back) with an $F(1,19) = 34.420$, $p = 1.19 \times 10^{-5}$, $\eta^2 = 0.64$
4. Mean difference in *RMS* between sessions was concluded for channel 1 (side to side *RMS* of the balance board), channel 4 (side to side *RMS* of the back), and channel 6 (forward and backward *RMS* of the back). The respective *F*-values, *p*-values and η^2 values are: $F(1,19) = 27.550$, $p = 4.57 \times 10^{-5}$, $\eta^2 = 0.59$, $F(1,19) = 8.514$, $p = 0.009$, $\eta^2 = 0.31$, $F(1,19) = 30.671$, $p = 2.42 \times 10^{-5}$, $\eta^2 = 0.62$.

A summary and graphical representation of the significant sources of variability of the within subjects effects is provided in Figure 3-8.

To conclude the statistical analysis of Session 1 and Session 3, three final analysis were performed on the *ensemble variables:* EV_p, EV_b, and EV_s. Statistically significant effects between sessions were concluded for the three *ensemble variables*, where 52%, 44%, and 52% of their variability is attributed to the session effect. Their corresponding *F* and *p*-values are: $F(1,19) = 20.799$, $p = 2.14 \times 10^{-4}$ for EV_p, $F(1,19) = 14.815$, $p = 0.001$ for EV_b, and $F(1,19) = 20.802$, $p = 2.14 \times 10^{-4}$ for EV_s.



	Between sessions		*Between trials*		*3-way interaction*	
	$\hat{\mu}$	*RMS*	$\hat{\mu}$	*RMS*	$\hat{\mu}$	*RMS*
Ch 1		59%	15%	17%		
Ch 2						
Ch 4		31%		18%		
Ch 6	64%	62%				
Ch 7				16%		16%
Ch 9						

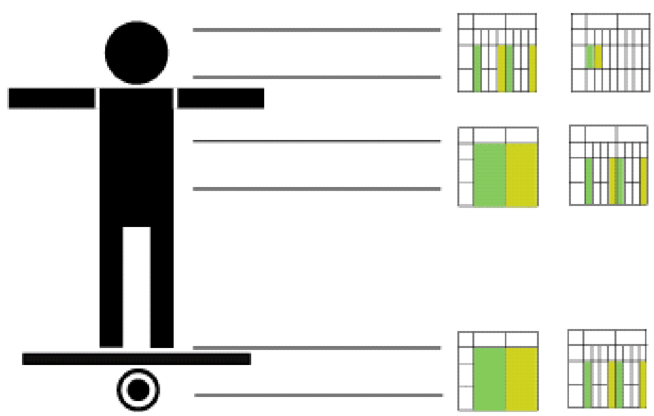


Figure 3-8 Significant sources of variability within subjects in Session 1 and Session 3

3.5.3.2 Strategies in Session 2

The design consisted of a three-way design with one randomized group and two repeated factors for each *ensemble variable*: EV_p, EV_b, and EV_s. The randomized-groups independent variable was experimental condition (with feedback *versus* without feedback) and the dependent variables were EV_p, EV_b, and EV_s. Three strategies corresponding to the placement of the feet were considered for the analysis (feet close to the center of the board (Strategy 1a and Strategy 1b), feet on the middle of the board (Strategy 2), feet close to the edges of the board (Strategy 3) either in trial 1 or trial 2. The sequence of eight trials was the following: (1,1,2,2,3,3,1,1)[8] where each number corresponds to a different strategy as shown in Figure 3-9. Given the mixed design the statistical analysis was concentrated on the main effects of the experimental condition and its interactions as well as the main effects of the trials, strategies, and their interactions.

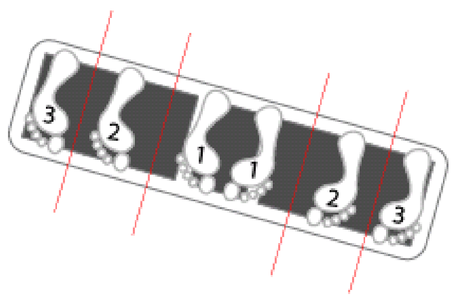


Figure 3-9 Strategy number corresponding to the placement of the feet during Session 2

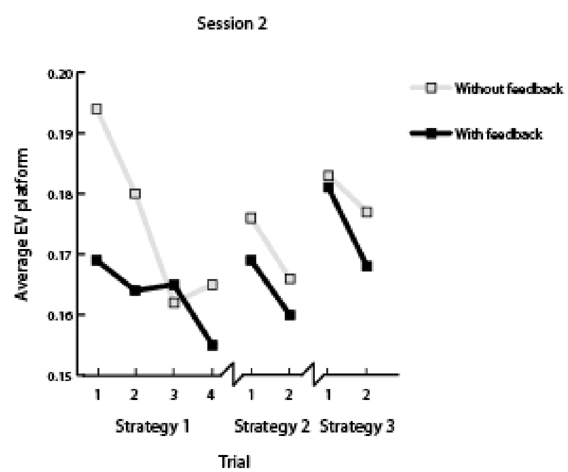
A 2 x 2 x 4 mixed randomized-repeated ANOVA procedure was performed on EV_p, EV_b, and EV_s, resulting in a total of 3 mixed randomized-repeated analysis. Total N of 21 subjects resulting from the previous statistical analysis (11 in the without-feedback condition *versus* 10 in the feedback condition) was reduced to 20 with the deletion of the corresponding data. Deletion occurred as a result of a wireless transmission problem related to missing data packages. The subject whose data was deleted from the analysis belonged to the without-feedback condition. Normality of sampling distribution and homogeneity of variance were evaluated. Two cells did not meet normality of sampling when the measure was EV_s and one cell did not meet Normality of sampling when the measure was EV_b. Large z scores in skewness and kurtosis ($z \geq 2.58$, $\alpha = 0.01$, two-tailed) were identified in

[8] In a difference with Strategy 2 and Strategy 3, Strategy 1 was performed four times instead of two. Subjects used Strategy 1 at the beginning of the session and at the end of the session. Data corresponding to Strategy 1 at the beginning of Session 2 is under the Strategy 1a factor. Data corresponding to Strategy 1 at the end of Session 2 is under the Strategy 1b factor.

some cells. In those cases, outliers were identified as a possible cause for the non-Normality. Outliers were adjusted to reduce their impact on the data set following the same conventions of the previous statistical analysis.

The probability level for Maucheley's test of sphericity for strategy and for trial by strategy interaction was smaller than 0.025 in the system analysis. This implied that the assumption of sphericity was not meet. However, the Huynh-Feldt correction was used.

There were significant effects between trials and between strategies in EV_p. $F(1,18)=15.371$, $p=0001$, partial $\eta^2=0.46$, and $F(3,54)=5.334$, $p=0.003$, partial $\eta^2=0.23$ respectively. This states that the variance in performance measure of the platform's control is mainly affected by practice (46%) and then, affected by the type of strategy (23%). Means are plotted in Figure 3-10.

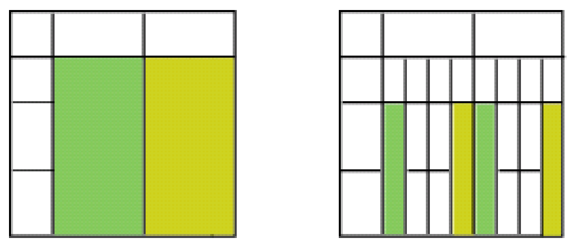


	Estimate for the Coefficient of Variation (standard deviation EV/average EV)							
With feedback	0.136	0.102	0.122	0.152	0.112	0.142	0.089	0.164
Without feedback	0.138	0.064	0.175	0.205	0.113	0.125	0.100	0.082

Figure 3-10 Average aggregate deviation of mean platform acceleration (EV_p) in Session 2

Strategies 1a and 1b when seen as a single strategy performed in four trials (Strategy 1a (Trial 1), Strategy 1a (Trial 2), Strategy 1b (Trial 1), and Strategy 1b (Trial 2)), shows the biggest reduction in mean EV_p in both experimental conditions, as shown by Figure 3-10. Strategy 1, in a difference with other strategies, incorporates the effects of practice and learning in one session because this strategy had not been used by most of the subjects during first session of the study.

Two additional effects between strategies approached statistical significance. First, mean difference in EV_b was concluded for the body analysis, $F(3,54)=14.967$, $p=3.28\times10^{-7}$, $\eta^2=0.45$. Second, mean difference in EV_s was concluded for the system analysis, $F(3,54)=13.631$, $p=9.78\times10^{-7}$, $\eta^2=0.43$. A summary and graphical representation of the significant sources of variability of the within subjects effects is provided in Figure 3-11.



	Between trials	*Between strategies*
	EV	EV
Platform	46%	23%
Body		45%
System		43%

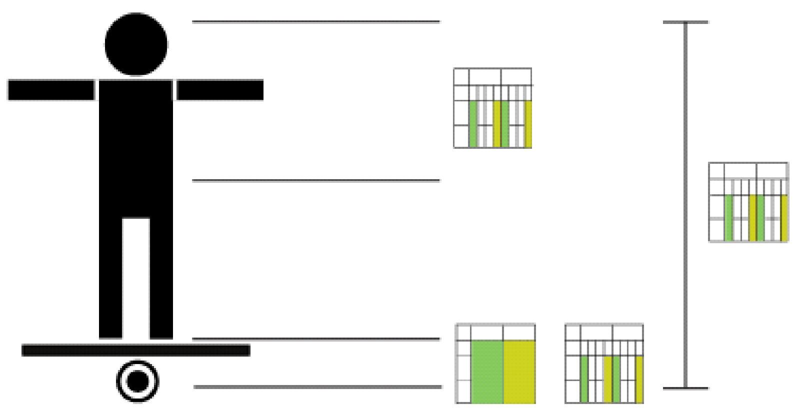


Figure 3-11 Significant sources of variability within subjects in Session 2

3.6 Summary

This chapter presented the experimental design and results from the research study. In the study, participants balanced on a moving platform with two-degrees of freedom, approximately half of them receiving external-focus feedback. The feedback, provided by a visual display and consisting of three squares, quantified how close a subject was to be balanced by using color, movement, and size variations of the squares. Data was collected from test subjects using a set of three-axis accelerometers: two accelerometers on the body and one on the platform. This last accelerometer affected the movement and size of each of the squares in the feedback system according to the acceleration experienced by the board in two different axes: pitch and roll. The collected data from the board and the body was processed in MATLAB® and analyzed in SPSS to determine the main effects of the experimental condition and its interactions. The main effects of the session, trials, strategies, and their interactions between experimental conditions were also analyzed.

In the analysis of Session 1 and Session 3 well-known effects approached statistical significance for both $\hat{\mu}$ and *RMS*. Mean differences between sessions and trials occurred. The most interesting result from this analysis was the significant three-way interaction between session number, trial number, and experimental condition in side-to-side *RMS* acceleration of the head, which showed that on average, the experimental condition affected the variable *RMS* in Session 3. On each trial of Session 3, subjects in the feedback condition, on the average, brought the head to oscillate with less variability than subjects in the other condition. The analysis of the strategies in Session 2 revealed that the variance in performance measure of the platform's control is affected by practice and the type of strategy used. However, the mean difference in the *ensemble variable* of the body was statistically significant only between strategies.

Chapter 4

How and what information is learned

Statistical results were presented in Chapter 3 regarding $\hat{\mu}$, *RMS*, and the *ensemble variables* (EV_p, EV_b, and EV_s). This chapter will present empirical relationships and intuitions about learning, as well common and useful measures in motor control by focusing on EV_p and EV_b. Although these *ensemble variables* are separately conceived as performance measures, when *jointly* analyzed, they unveil their dual nature to explain both performance and presumably learning. The approach is then to make inferences about learning on the basis of the changes in behavior that were *jointly* observed and directly reported by the participants. For most of the analysis presented in this chapter average performance curves and average changes will be the main sources of information. Careful attention needs to be drawn to these curves because they tend to obscure the variations that occurred within individual subjects across trials and sessions. To overcome this problem, detailed individual analysis is included in Chapter 5.

4.1 Intuitions about the task

When confronted for the first time with the balancing task, participants faced two major challenges: the understanding of the dynamics of the balance board and the discovery of appropriate movement strategies to cope with the board. More than thinking about balance, the task demanded a deeper insight into what was it that participants needed to control or not to control, and what could or could not be changed. The ability and the knowledge necessary to use their balance intuition and consciously or unconsciously modify them was expected to be encouraged throughout the study.

At the beginning of Session 1, participants were asked to move the balance board with their hands to understand its range of movement and familiarize themselves with the board; however, most subjects did not seem to fully explore or understand the dynamics of the balance board before the first trial of Session 1. Other experiences related to balance came to their minds before creating new models for the task. In this way, the task was first approached as transitions from other balance experiences.

4.1.1 Placement of the feet

Out of 20 subjects[9], 80% of the participants reported to having an initial thought of where to place their feet on the board before the first trial. Their intuitions were based on four ideas:

1. What they had seen in other balance tasks such as surfing, skating or acrobatics (one subject reported "he thought of the guys that use a long pole in the circus".);
2. What they conceived to be the most natural position for balance (*i.e.* wide stance);
3. Physics concepts (one subject reported that he thought about "using the moment $M = F \times d$ from Statics".);
4. What they thought was a good exploration strategy (close to the middle to know if the task demanded moving the feet inward or outward).

Based on their initial thoughts of how to approach the task, subjects, on the average, placed their feet either close to the edges or on the middle of the board and found that the task was more challenging than what they expected. Progressing through the eight trials of Session 1, subjects either *consciously* or *unconsciously* changed the placement of their feet. Although 75% of the subjects reported *consciously* exploring the dynamics of the platform by changing the position of their feet on it[10], the rest of the participants reported no doing so.

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[9] Subjects correspond to those that were included for the analysis presented in Chapter 3.
[10] Four participants reported that changing the placement of their feet was useful all the time and six reported it was useful most of the time.

4.1.2 Focus of control

Half of the subjects reported that during the first trials of Session 1 their effort was put into keeping the balance board from moving instead of trying not to interfere with the natural movement of the platform. This is the same as dominating the system *versus* adapting into it. From these people, 30% stated that the strategy was useful to maintain balance. But the results differed for the last trials. The number of participants who explicitly chose to control the balance board from moving was reduced to 20% of whom all of them agreed on the usefulness of trying to dominate the system for maintaining balance.

It becomes apparent that the starting point for most of the subjects is to think that, for this task, learning to keep the board as horizontal as possible has to do with learning to enforce their own movements onto the board. But once subjects actually try to balance, their intuitions change. The reflected change (from 50% to 20%) provides empirical support to say that by the end of the Session 1, participants not only did not fully trust their original intuitions but some even explored the impact of the placement of the feet on their reaction time as well as on the amount of force required to perform the task.

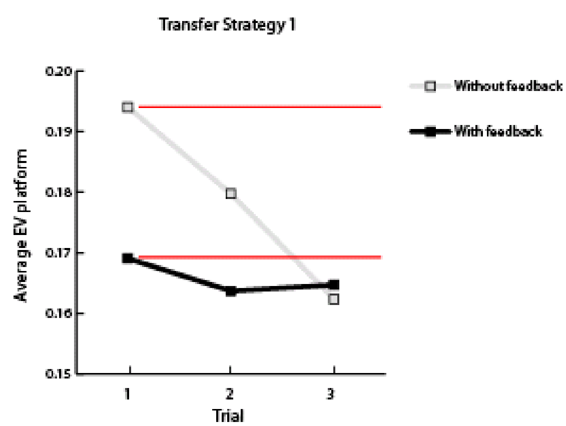
4.2 Assumptions and memories of balance

During the Session 1 of the study, participants self-explored the task based on assumptions that were not unreasonable in other contexts and then adopted different ways to approach the task. Nevertheless, Session 2 saw an increase in the set of strategies related to the placement of the feet on the board. For most of the subjects, at least one of the strategies of Session 2 had not been used during Session 1, hence it was expected that during this session participants would identify one strategy to be the most appropriate for the task and consequently use that same strategy during Session 3.

On the basis of the predictions of this study, results related to the persistence of the acquired capability for performance under the experimental conditions are next presented. Acquired capability refers to how well the balance skill was retained over time (retention) and how useful was it to practice any strategy before asked to perform a specific one (transfer). To evaluate retention and transfer, common methods and measures in motor control and learning were used. On the one hand, transfer was measured by the percentage of gain or loss of improvement in one strategy that was achieved by practice on another strategy. This measure is known as Percentage Transfer (Schmidt and Lee 1999). On the other hand, relative retention was evaluated using the Savings Score measure that corresponds to the number of trials required for the subjects to reach the level of proficiency achieved in previous practice. Both retention and transfer occurred in terms of the performance measure EV_p (an aggregate measurement of error for the platform) previously described in Chapter 3.

4.2.1 Changes within one day: Transfer of learning

Given that all subjects first practiced balancing on the board in Session 1, Session 2 was used as a transfer test. Recall that during Session 2, subjects were indicated where to place their feet on each trial with the goal of introducing them to three different strategies related to the placement of their feet (Strategy 1: feet close to the center of the board, Strategy 2: feet on the middle of the board, Strategy 3: feet close to the edges of the board). In 10% of the cases (two subjects) participants tried all three strategies during Session 1, but for most of the subjects, at least one of the strategies presented in Session 2 was new.



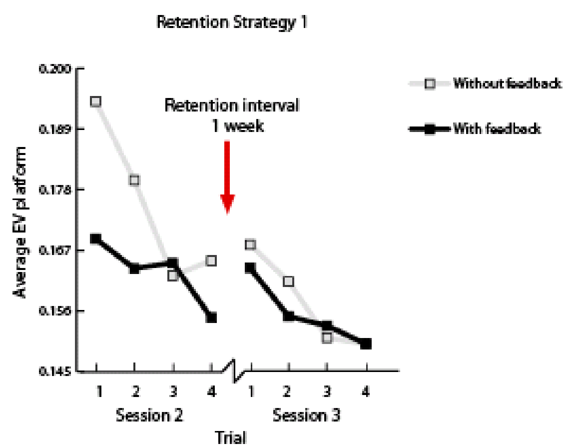
	Estimate for the Coefficient of Variation (standard deviation EV/average EV)		
■	0.136	0.102	0.122
□	0.138	0.064	0.175

Figure 4-1 Transfer test

Under the feedback condition the group's experience with other strategies in Session 1 provided for more than 80%[11] of the improvement for the first three trials of Strategy 1 in Session 2, as seen in Figure 4-1. Therefore, although it is not possible to infer the percentage of learning from this data, it is possible to conclude that the skills involved in the first session under the feedback condition have transferred to the skills involved in Strategy 1 as if something that was learned in Session 1 was possibly applied to Strategy 1.

4.2.2 Changes within one week: Retention of skill

Session 3 served as a retention test, which was performed after a one-week retention interval. During Session 3, subjects were asked to achieve best performance, and therefore chose the strategy they thought was going to help them accomplish that goal. 90% of the subjects (18 subjects) chose Strategy 1.



	Estimate for the Coefficient of Variation (standard deviation EV/average EV)							
■	0.136	0.102	0.122	0.152	0.136	0.135	0.157	0.138
□	0.138	0.064	0.175	0.205	0.131	0.122	0.151	0.169

Figure 4-2 Retention test

[11] This percentage describes only the outward manifestations, *i.e*. performance, that resulted from the habit transfer.

Although the results show that performance in the first trial of Session 3 was not as good as the last trial of the previous session, suggesting memory loss as possible reason for this, recovery occurred immediately in the next trial (savings score of approximately 1 trial). This fast rate of relearning suggests that retention was more or less complete; therefore, instead of a memory loss the decrement in performance was possibly caused by the loss of non-memory adjustments (bodily adjustments) critical to performance[12].

4.3 The know how

As seen before, Session 2 played an important role during the study because it introduced those strategies that participants had not tried in Session 1. Provided that no additional information was given to the subjects but the placement of the feet, a big leap in the learning process occurred as a result of being exposed to all the different strategies. Without doubt, this session was a carrier of knowledge.

By the end of Session 2, 80% of the participants reported that they were planning on using Strategy 1 in the next session. According to the accelerometer data, subjects seem to *unconsciously* choose Strategy 1 as the best strategy based on its impact on upper body control although they reported *consciously* choosing that strategy mainly according to one of the following two reasons:

1. Good lateral control/ more control of the board/ ability to control methods and movements;
2. How fun the task was with Strategy 1[13].

---

[12] The Set Hypothesis states that "the loss of skill is related to the loss of set (one or more temporary internal states) that underlie and support the skill " Schmidt, R. A. and T. D. Lee (1999). Motor control and learning a behavioral emphasis. Champaign, Human Kinetics.

[13] One subject reported that he had chosen Strategy 1 because the task was more fun when using that strategy.

Average results for each condition show that EV_p scores were similar between Session 1 and Strategy 1 in Session 2 while scores differed for EV_b. Results from Table 4-1 suggest that although the task was focused towards keeping the balance board as horizontal as possible, after Session 2 subjects *unconsciously* hypothesized that by reducing body oscillations they could perform better. Average results of EV_p for Session 3, where the main strategy used by all subjects was Strategy 1, were the following: EV_p for the feedback condition was 0.149 and EV_p for the without-feedback condition was 0.148. The immediate effect was on the body and then, that effect was translated onto the board. Their strategy was, thus, to ride the system and exploit the reactive forces. Hence, learning to keep the board as horizontal as possible did not mean learning to control the board from moving, but learning to reduce body oscillations.

Table 4-1 Ensemble variable scores for Session 1 and Strategy 1 in Session 2 of the platform and the body

	Average EV_p		*Average EV_b*	
	Session 1	Session 2	Session 1	Session 2
With feedback	0.169	0.163	0.228	0.163
Without feedback	0.176	0.175	0.230	0.178

With these results, the importance of Session 2 is again highlighted. It is not clear if three sessions (structured like Session 1) would have been enough for people to hypothesize and try different strategies to discover an appropriate movement coordination pattern. The introduction of Session 2 as a hands-on-experience of movement strategies and modeling encouraged participants to recognize and choose among different styles the way to approach the task. It is probable that Session 2 *unconsciously* helped people to understand some of the mechanical properties of the task that did not only include the platform, but the platform and the body as a system. By doing so, people had at their disposal additional rules necessary to perform the task. There are, however, marked individual differences that were not analyzed.

4.4 Visual feedback

Having identified that visual feedback could have positively benefited the transfer of kinesthetic learning from one strategy to another, the next question to be addressed is if participants in the feedback condition perceived it in the same way or not. Although in the present study no data were collected about the subject's perception of the feedback system in each session, a few notes can be devoted to the results collected on the final session.

4.4.1 Learning and performance

In terms of learning, 60% [14]of the subjects believed that the system helped them to learn to balance faster than if they did not have had a display. Except for the data represented in Table 4-1, the there is no evidence that the learning rate was significantly different between experimental conditions. It is possible that participants might have perceived characteristics in their own learning process that the sensors were not able to capture. That is, they experienced a gain in the capability to think about learning while evident gains in performance did not appeared. Sensors captured the output, but they missed to capture the changes that happened on the inside.

Having described the perceived importance of the feedback system on the learning rate, a surprising finding happened during the last session of the study. 20% of the participants expressed belief that they would have performed better without a display. According to the statistical analysis, no matter to which group they were assigned, participants, on the average, showed similar performance results along the study, except for the lateral acceleration of the head. As no further tests were performed in which people under the feedback condition were asked to balance without feedback, this study cannot offer additional details about performance when the display is removed.

4.4.2 The balance meter

Finally, a particular issue related to metrics of performance needs to be pointed out. In the without-feedback condition, 40% of the subjects measured their performance based on a metric present in the environment (*i.e.* the number of times the board touched the floor),

[14] Using a 7-point scale ranging from 1 (not at all) to 7 (absolutely), that percentage corresponds to the fraction of participants that chose numbers 5, 6, and 7 as their answer.

while half of the subjects measured their performance based on personal levels of confidence, frustration, and effort. For feedback condition subjects, in addition to the number of times that the board hit the floor, the display brought up a metric that was not perfectly visible in the environment: how close people were to be balanced (one of the participants called it the "balance meter"). A third of the participants measured their performance based on this new metric while 50% used the number of times the board touched the floor as a way to evaluate their performance. Realizing that subjects under the feedback condition did not use any measures regarding levels of confidence, frustration, or effort, this outcome empirically suggests that the feedback system was partially able to represent the effects of the participant's movements rather than the movements themselves.

4.4.3 Effectiveness of the feedback system

A couple of factors might have impacted the effectiveness of the feedback system on performance such as: the modality of the feedback and the mapping between the sensors and the output. It might be possible that other modalities of feedback, such as tactile feedback might prove to be more effective than the visual feedback in this type of tasks. Just like researchers have studied how passive tactile feedback while standing improves balance (Clapp and Wing 1999) (Rogers, Wardman *et al.* 2001), currently a more sophisticated technology is being tested as a balance prosthesis that provides self-motion cues (Wall III and Weinberg 2003, March/April). The benefit of tactile feedback in dynamic balance still needs to be examined. In terms of the mapping, additional studies might be required to experiment with several ways of mapping the sensor data to the feedback system as well as to develop personalized mappings. In any case, careful consideration is needed to account for how noisy the sensors are by nature.

4.5 Perceived confidence and satisfaction

Critical to the performance and learning of the task, confidence and satisfaction levels needed to be evaluated to see if they might have negatively impacted the task. Participants reported their perceived confidence and satisfaction levels in each of the sessions using a rating scale ranged from 1 (not confident at all/not satisfied at all) to 7 (very confident/very satisfied).

By the end of the Session 1, perceived confidence levels, on the average, dropped for both experimental conditions, presumably as a result of the wrong intuitions subjects had about the task (see Figure 4-3). In the following sessions participants adopted a conservative approach to rate their confidence level, once they had a more clear understanding of the task constraints, as a way to ensure rewarding satisfaction levels. In fact, on average, after Session 1, the perceived confidence levels (reported before the first trial of each session) and the satisfaction levels (reported after the last trial of each session) followed similar increasing trends as seen in Figure 4-4.

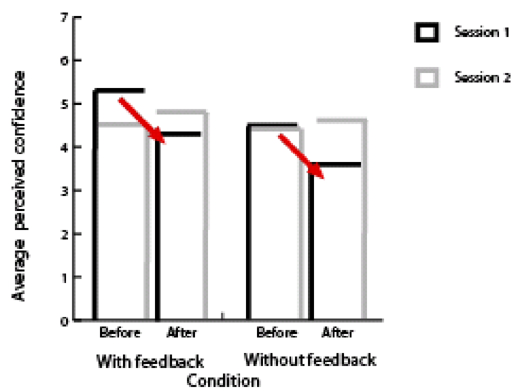


Figure 4-3 Average perceived confidence in Session 1 and Session 2

A remark must be made about the satisfaction level reported by the end of Session 1. The low satisfaction reported by subjects could have affected both performance and learning in further sessions. However, it appears that the decision to not overestimate confidence allowed participants to focus on the action planning process rather than on possible failures.

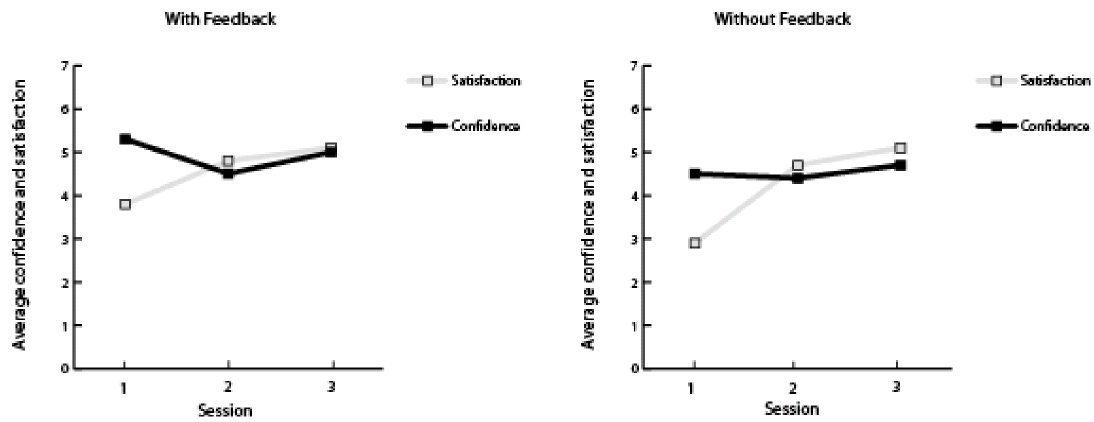


Figure 4-4 Average perceived confidence and satisfaction by experimental condition

4.6 Summary

The most salient results for explaining *how* and *what* was learned during this study were presented throughout this chapter. On the one hand, at the beginning of the first session *all* participants had the wrong intuitions about balancing. They balanced with their feet wide apart (which is possible, but requires much more practice) and tried to impose correcting mechanisms solely based on the tilt of the balance board. Throughout the rest of the sessions and trials participants developed new ways to approach the task by riding the system and exploiting the reactive forces. Hence, learning to keep the board as horizontal as possible did not mean learning to control the board from moving, but learning to reduce body oscillations.

On the other hand, the visual feedback system, although it did not significantly impacted performance, might have impacted the learning process according to the participants' perspective. However, none of the variables analyzed were able to capture that learning-support. What was in fact captured was the partial success of the system to become a "balance meter". The display brought up a metric that was not perfectly visible in the environment and although it was not the most natural way to measure performance, 30% of the subjects adopted it.

Chapter 5

Model and algorithm

So far the discussion has been focused in fragmented results from the research study. To fuse everything together, this chapter presents a formal model of relationships and choices in the balance-task domain of the study. The algorithm emerges from an agent-based model grounded on the abstract framework of choices of Anigrafs™ (Richards 2003). This framework allows for the construction of a useful topology that is consistent with the constraints of the task and the subjects themselves. The degree to which the model and the algorithm explain, or have the potential to explain the observed phenomena is partially explored through an individual analysis.

5.1 Model and algorithm specifications

Modeling of the experimental paradigm (emerging strategies as a result of a *process of correction*) is particularly convenient to understand and represent the learning process, as the strategies used during the three sessions varied between subjects. Various models have been developed for task specific studies to analyze control schemes, but none of them has as its particular goal to develop an algorithm to articulate the *process of correction*. Therefore, the model and the algorithm presented in this chapter will attempt to provide such a relationship between strategies and their transitions in time. To do so, the model and the algorithm must be able to account for well-known biomechanical, control, and task constraints that play a role in forcing the selection of strategies (Kuo 1995). On the one hand, the model must be able to: 1) account for a scheme that is sufficient to reproduce major characteristics of human responses similar to that observed experimentally and 2) simulate the two most common strategies in balance control: ankle and hip strategies. In other words, the model should be able to represent a one-segment inverted pendulum (ankle strategy) or a two-segment inverted pendulum (hip strategy). On the other hand, the algorithm must be able to: 1) describe controls in the strategy space and 2) consider subject differences. With these principles in mind, a model and an algorithm to describe the process of correction are next introduced.

5.2 Description of the model

Let the following map be a reduced-order six state system of the body. Where each node represents the following body parts: node H is the head, nodes R and L are the right and left arms respectively, node T corresponds to the torso, node P are the hips, and node F represents the feet.

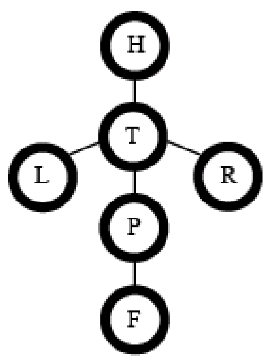


Figure 5-1 Graphical representation of a six-order state system of the body

Nodes are linked to each other in a non-arbitrary way just like body parts are related to each other. H, R, and L are connected to T; T is connected to H, which is connected to F. The bi-directional connections among nodes in this graph (see Figure 5-1) represent feasible interactions and allows for the existence of a top-down or a bottom-up flow of information as suggested by the discrete modes of perception approach to postural adjustment (Kandel, Schwartz *et al.* 2000). In this way, this rough and simple representation of the body is the topology of the model to be used in this section: an Anigraf™.

An Anigraf™ is a graphical representation of a network of agents that have preferences for a set of different actions (Richards 2003). It is abstracted as a map consisting of nodes (agents), edges (preferences), and weight variables (voting power) that represent the system as a whole.

> The vertices (nodes) of the graph correspond to the different actions, and the edges of the graph show the similarity relations between the set of actions. The agent's second choice(s) will be those actions most similar (*i.e*. adjacent nodes in the graph.) Weights or nodes reflect the numbers, or strengths of each type of agents. These weights, together with the preference ordering on actions for each type of agent are used to determine which particular action the system will take place (Richards 2004).

Because each agent has preferences, agents use their vote-power to define the next stage in the social system. Hence, after all actions are compared paired-wise, the agent who wins drives the action.

> In some cases there will be no unique winner. Both the topology of the graph, as well as the voting strengths play the principal role in whether or not the group of agents can reach an agreement, or will suffer a settlement, which often may lead to chaotic series of outcomes for the system (Richards 2004).

Therefore, useful topologies are needed in order to achieve consensus.

5.2.1 The control structure

In this model that will be further referred as the *Balancer*, controls are described in strategy space, where strategies are defined as the collective assembling of motor patterns of the different agents (parts of the body) while trying to balance. Hence, the strategy space consists of all the possible voting power (weight) combinations of the $n = 6$ agents H, T, L, R, P, and F that are constrained by the task. Although it will be assumed that the voting power can take any number in the interval [0,10], as seen before, not every combination of weights will result in consensus nor will represent a strategy that is biomechanically feasible.

To deal with that, the topology of the system will define the instabilities and the video recordings will be used to construct similar models to the ones observed during the study.

Since the model is driving the system, if the system fails (*i.e.* there is no winner or there are ties), this implies that the model is not an adequate controller. Therefore, the model has to be updated. The approach taken here to update the model consists of assigning new weights to each agent in the same way subjects rely on different parts of the body to balance on the board. Other alternatives are possible, such as building a model with additional free agents that can be assigned into a similarity relation to the current model[15]. Nevertheless, to keep the model as simple as possible, this last alternative is not explored in this document.

5.2.2 Finding the winner: The tally machine

Once an Anigraf™ is built, there are several ways to incorporate information available about the preference orderings of agents. In this document, the method that is used to aggregate choices and find the winner is the one proposed by Marquis de Condorcet in 1785 (Richards 2003). The Condorcet tally is conducted like a tournament where all actions are compared pair-wise. Every agent emits a vote for each of the comparisons according to its preferences. An agent will vote for the member of the pair who is directly connected to it by assigning a positive or negative weight depending on whether an agent chooses the first or second member of the pair[16]. Two important characteristics make this method suitable for finding the winner. First, it uses all the information available in the graph, and second it is a maximum likelihood method (Richards 2003). Although, the drawback is that as the topology grows, the computations become complicated because there are too many $\binom{n}{2}$ pairs to choose from.

[15] Before the free agents are assigned into a similarity relation they might be hooked-up either by random connections or weak connections.
[16] For more details about how the tally is computed see Richards, W. (2003). *Anigrafs: Mind games.* Retrieved May 30, 2004 from http://www.ai.mit.edu/people/whit/contents.html

5.2.3 Simulation

In previous chapters it was seen that learning to balance on the board had to do with learning to reduce body oscillations. Both accelerometer data and video recordings support that, on average, in Session 3 the focus of control was in the upper body. But is the *Balancer* a good model to simulate the overall finding of the study? To answer that question, two simulations were ran for a 100 trials using the Condorcet tally. In one of the simulations random weights[17] between 0 and 10 were assigned to each agent, while in the other one a constraint was set to assign the arms equal weight. The results from both simulations are summarized by a winner distribution that shows how many times each of the agents drove the action.

For the case in which weights were randomly assigned without constraints, the distribution was $\{1,82,5,3,5,0\}$ where the first number in the set represents the number of times H drove the action, the second number represents the number of times T won, and thereafter, when P, F, L, and R were the winners. From this distribution it is seen that 82 times out of a 100, the torso (T) drove the action, which means that the focus of control was in the upper body. Similar results were obtained when L and R were constrained to have the same weight. The winner distribution was the following: $\{2,82,10,0,0\}$. Again, 82 times out of a 100, T drove the action, but in a difference with the other winner distribution, no arm ever drove the action.

From both distributions it is seen that between 94% and 96% of the times the model was an adequate controller, but the times when it was not may reveal useful information about strategies that ended up in chaos. For those instances, the algorithm will play an important role to understand the learning process.

5.3 Description of the algorithm

As pointed our by Kelso, "learning may take the form of instabilities […] depending on the relation between what is to be learned and the [subject's] existing coordination tendencies" (Kelso 1999). This suggests that if a task requires subjects to modify some of their coordination tendencies, the learning process can be interpreted by taking a look at those

[17] Random weights were assigned because it was expected that they were going to closely represent the different strategies subjects used to achieve the same goal, and in fact they did.

times when the instabilities occurred. The relationship between the stabilities and the instabilities (mentioned by Kelso) is what this research describes as *the process of correction*.

5.3.1 Understanding zones of chaos

From the *Balancer* perspective, instabilities occur when the voting process results in no-winner due to the combination of the agents' voting power. Therefore, to create an algorithm, there is a need to understand if, in fact, the changes in movement coordination happened as a result of an unstable strategy selection that ended up in a no-winner according to the *Balancer* model. To do so, the approach will be to define the individual learner as the unit of analysis.

5.3.1.1 Strategy A

Let the following set of weights be the voting powers of each of the agents defining a balance strategy in the *Balancer* model, namely Strategy A:

$$\{w_H, w_T, w_P, w_F, w_L, w_R\} = \{0,0,5,9,6,6\}. \qquad \textbf{Equation 5-1}$$

Where w_H is the voting power of agent H, w_T is the voting power of agent T, and so forth. Voting power in the *Balancer* model is assigned according to how much participation the agent shows in the social system, in this case, the balancing task. Therefore, a weight of 0 represents null participation, and a weight of 10 represents the maximum involvement. Hence, Equation 5-1 states that the feet are heavily involved in Strategy A, while neither the head nor the torso are. Once an individual learner is defined, and weights are given to every node of the *Balancer* model, the Condorcet tally takes place.

Based on these weights the Condorcet procedure did not yield a winner (i.e. the model was not an adequate controller), and according to the video recordings, the subject was not able to balance using this strategy. Since the system failed the model had to be updated, from the *Balancer* perspective, or a different strategy needed to be explored, from the perspective of the subject. In fact, that is what happened. In the next two trials of Session 1 the subject slightly modified Strategy A by exploring new ways of incorporating the head into the strategy and modifying the participation of the arms.

To represent the impact of such modifications suppose that from the six agents only two of them could accept modifications to their original voting power, say H and L. Therefore, it would be useful to have a map that could depict unstable zones such that one could know which combination of weights would result in appropriate controllers for the *Balancer* model. Using a color-coded representation of multiple Condorcet procedures (Purtell 2004), a *strategy map* was built to show the regions of chaos (textured areas) and stable regions (full-colored areas) of the *Balancer* with weights $\{x,0,5,9,y,6\}$.

A *strategy map* is a modeled representation of stable and unstable zones of coordination tendencies described by the set of weights of the *Balancer* model. When a set of weights (strategy) falls in an unstable zone then it is said that the *Balancer* is not and adequate controller of the system. Both *x* and *y* can take any value in the range of [0,10] and each node is represented by a color. For this model the color-coding is: $\{red, yellow, green, cyan, blue, magenta\}$ each of which represent $\{H, T, P, F, L, R\}$ respectively.

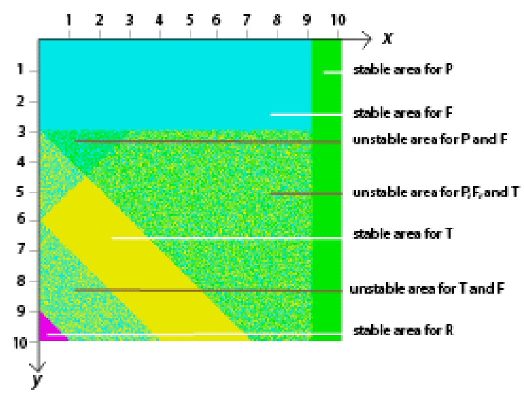


Figure 5-2 Strategy map for the Balancer model: $\{x,0,5,9,y,6\}$

As seen in Figure 5-2, although the map shows that there are some areas of stability for T, P, F, and L, it is easy to imagine that if weights for H and L are randomly chosen from a uniform distribution, about 65% of the times the combination will be placed in a chaotic zone. The rationale behind this is the following: approximately 65% of the total area corresponds to unstable zones of T, P, and F; T and F; and P and F. Although certain combinations of H and L make the *Balancer* an adequate controller, there might be better strategies than Strategy A. That was exactly what the subject being analyzed thought of.

5.3.1.2 Strategy B

In trial 5, the subject adopted a new strategy. Let the following set of weights be the voting powers of each of the agents defining a balance strategy in the *Balancer* model, namely Strategy B that can be represented as follows:

$$\{w_H, w_T, w_P, w_F, w_L, w_R\} = \{3,4,4,9,2,2\} \qquad \textbf{Equation 5-2}$$

Strategy B resulted in an unstable system, but some times the subject made minor modifications to the strategy and was able to balance occasionally. This time, the subject mainly modified the participation of T and F to explore for more useful strategies. To graphically show viable modifications of T and F that allowed the subject to balance, a *strategy map* was built. This map shows stable and unstable areas of a *Balancer* with weights $\{3, x, 4, y, 2, 2\}$

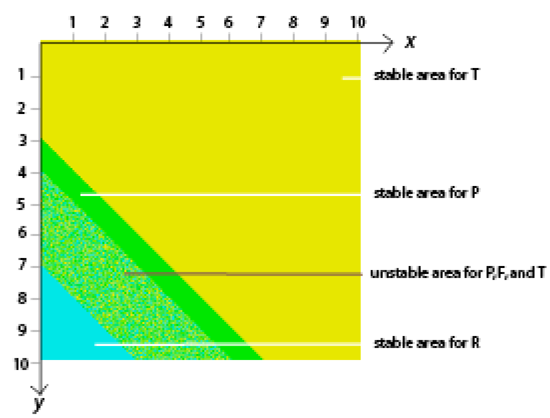


Figure 5-3 Strategy map for the Balancer model: $\{3, x, 4, y, 2, 2\}$

As seen in Figure 5-3 the chaotic area has greatly decreased while the area where T is stable has considerably increased with the new set of weights. Once again, instabilities occur between T, P, and F but with less probability. Hence, this research will assume that Equation 5-2 represents a set of strategies that are more suitable for the task, than the ones represented by Equation 5-1. By comparing the different strategies and the regions of chaos in Figure 5-2 and Figure 5-3 it can be conjectured that changes in movement coordination happened as a result of an unstable strategy selection that ended up in a no-winner according to the *Balancer* model.

5.3.1.3 Strategy C

While Strategy A and Strategy B were not adequate controllers for the *Balancer*, a new strategy used in Session 3 was an adequate controller. This strategy, Strategy C with weights: $\{0,9,5,9,2,2\}$, heavily involved the torso during the balancing task. In fact, the Condorcet procedure found that in this system T was driving the system. This result was not surprising as previous analysis presented in this document had suggested that learning to balance had to with learning to reduce body oscillations. However, finding that the *Balancer* could represent actual strategies seen during the study suggests that the model proposed accounts both for individual differences and average behavior.

Like with previous strategies, the subject made minor modifications to Strategy C during the last session of the study, but this time most of them were appropriate controllers for the *Balancer*. It appears that Strategy C allowed the subject to make adjustments to the original strategy without loosing control. Which presumably suggests that the vicinity of strategies close to Strategy C contained good controllers as well. Further explanation of the role of a vicinity of appropriate controllers (*i.e.* a vicinity of balance) is explored through a proposal of how subjects might discern between strategies until they discover the vicinity that satisfies the property of allowing for modifications without loosing control.

5.3.2 Balance conjectures

Let ${}_t\varepsilon_{\partial}^{s,stg_k}$ be the value that corresponds to subject's *s* threshold of displacement from the balance board's current position that will allow him/her to maintain balance at the time $t+\partial t$, where stg_k denotes the strategy used at time *t*, in this case Strategy *k*. Let ${}_t r_{\partial}^{s,stg_k}$ be a function of ${}_t\varepsilon_{\partial}^{s,stg_k}$ such that ${}_t r_{\partial}^{s,stg_k}$ represents the radius of a two-dimensional sphere in a *strategy map* that encloses adequate controllers for the *Balancer* model of subject *s* in the time interval $(t,\ t+\partial t]$

1-1 Conjecture 1: If ${}_t r_{\partial}^{s,stg_k} > 0$, then subject s will be able to balance at time $t+\partial t$ whenever changes to Strategy *k* originate a Strategy *k* + 1 that falls within the border of the sphere defined by ${}_t r_{\partial}^{s,stg_k}$.

Let $stg_1, stg_2, \ldots, stg_m$ be *m* strategies each of which are adequate controllers for the *Balancer* model at time *t* such that $\{X_1, X_2, \ldots, X_m\} = \{{}_t r_{\partial}^{s,stg_1}, {}_t r_{\partial}^{s,stg_2}, \ldots, {}_t r_{\partial}^{s,stg_m}\}$ are their respective radiuses.

1-2 Conjecture 2: If the radiuses of a set of adequate controllers for the Balancer at time t are reorder so that $Y_1 < Y_2 < \ldots < Y_m$, where $Y_1 = \min_j X_j$ and $Y_m = \max_j X_j$, then the best balance strategy is given by Y_m.

Conjecture 1 postulates a relationship between when the tilt is too much to actually be able to control it and the boundaries of stable regions in a *strategy map*. The conjecture claims that a subject will be able to balance if the new strategy chosen lies within the boundaries of a stable sphere as shown by Figure 5-4. There might be cases in which the new strategy might lie outside the sphere defined by ${}_t r_{\partial}^{s,stg_k}$ and the subject might be able to balance. In those cases, it is expected that the new strategy will lie within another stable region. However, there is no way to ensure that outside the stable sphere are non-chaotic regions. In this way, it seems that subjects define ${}_t\varepsilon_{\partial}^{s,stg_k}$ by exploring different alternatives during the learning process, and once they find a strategy that suits the task purpose, they concentrate on exploring strategies similar to the one they have discovered as useful.

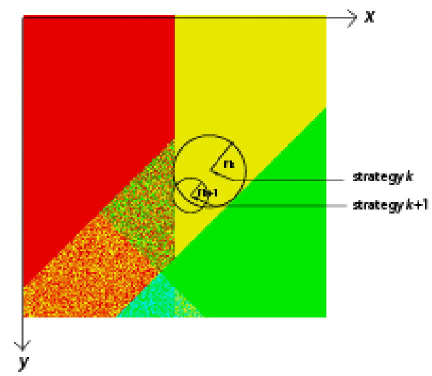


Figure 5-4 Graphical representation of Conjecture 1

Subjects build *strategy maps* just like they build imaginary maps of cities and routes. They all start with a first strategy and explore its vicinity. By doing so, they build a map in their minds about possible stable and unstable areas. Some subjects drastically change strategies, which means that they build a completely new *strategy map*. Hence, by having a collection of different maps, given a strategy subjects are capable of defining ${}_t\varepsilon_{\partial}^{s,stg_k}$ that allows them to change their strategy according to the task and the environmental demands. Based on Conjecture 2, which claims that given *m* strategies the one with the largest radius is the best strategy, the final goal might be to adopt the strategy that allows for the greatest number of changes in the agents' voting power and at the same time satisfies the subjects' expected performance.

5.3.3 Learning conjecture

1-3 Conjecture 3: Thinking about innate abilities for performance and learning, map-building mechanisms that evolve from building own maps in real space are translated into building maps in a balance-strategy space.

What this conjecture suggests is that, considering what is natural to people (*i.e.* building maps), looking for correctibility and restorability of stability is related to learning boundary conditions. Therefore, by using the Euclidian space, maps that result from the *Balancer* are bringing continuity and the concept of a metric. They depict how much of the deviation of the conditions a subject is adapted to can be tolerated by himself or herself. This concept connects to genetics and the evolution of species theory. This theory states that survivability occurs when there is sufficient diversity in the gene pool so that if conditions change they can adapt and survive. In this sense, learning to balance is related to surviving and adapting to changes.

5.4 Summary

A model and an algorithm were presented to explain how subjects in this study discovered and chose between appropriate strategies for balance. The approach taken was to build an Anigraf™, namely the *Balancer*, to build the framework for a description of the *process of correction* by using *strategy maps*. To a first approximation, the representation problem was constrained to a reduced-order six state system of the body. Despite this reduced dimensionality, the model successfully represented individual and average behavior.

On the theoretical side, three conjectures were postulated to explain how subjects were involved in building and exploring the *strategy maps* to determine how they chose which strategy to use at the right time. In principle, the conjectures rely on subjects building their own maps, just like they build imaginary maps of cities and routes, but one can imagine aiding the learners in this construction process.

Chapter 6

Conclusion and future work

6.1 An overall summary

Now is time to sum up the ideas and results presented in this work. The first part of this document (Chapter 3 and Chapter 4) analyzed the dynamics of trying to balance on a two-degrees of freedom balance board under two experimental conditions: with feedback and without feedback. The feedback system, which consisted of a visual display that was controlled by the acceleration of the board in the pitch and roll axes, had no significant impact in performance. Nevertheless, it positively affected the transfer of learning between strategies and most importantly, it brought up a performance metric that was not perfectly visible in the environment: *how close people were to be balanced*.

In this study, the experimental design allowed subjects to explore different strategies in a constrained amount of time. Although real-practice time was limited to 12 minutes total, the structure of the experiment allowed for the learning process to unfold progressively and fully to the expected levels of performance. At the beginning of the study, subjects had the wrong intuitions about balancing. But during practice, and as a result of the exploration of different strategies, subjects learned not to counteract the dynamics of the board but rather exploit them. Participants evolved from having fragmented constructions of the task to engaging mechanisms that synthesized all the multiple executions allowing them to seek the most useful information for regulating the action. Although all the mechanisms of selection have yet to be deciphered, the study revealed at least one that was simple and efficient: reducing body oscillations to balance on the board.

The second part of this study documented a model and an algorithm to describe the *process of correction*. The approach taken was to build an Anigraf™ (Richards 2003), namely the *Balancer*, which allows, in principle, for a personalized study of the learning process since the weights for each node can be assigned according to the strategy used. Although the *Balancer* is a simplified model of the task and the strategies, it demonstrated to account both for individual differences and average behavior. The fact that as seen by the data the effect of the difference on the control of the platform was through the body, leads to believe that that *Balancer* is a good model for the task.

The novel approach taken in this document was describing the *process of correction* by focusing on vicinities of balance in *strategy maps* (which is closely related to the concept of attractors). The explanation of how subjects build *strategy maps* and therefore decide on which strategy to use, was given by three conjectures which are the core of the algorithm. The first one postulated a relationship between when the tilt is too much to actually be able to control it and the boundaries of stable regions in a *strategy map*; and the second conjecture defined a rule for choosing the best strategy from a set of *n* strategies. The final conjecture postulated how learning boundary conditions in the strategy space evolve from our innate ability to build maps. Hence, this work claims that thinking in terms of vicinities in *strategy maps* is useful because, similar to what Peper *et al*. said in Catching Balls (Peper, Bootsma *et al.* 1994), this information does not specify when to [chose what] but how to [chose] the right [strategy] at the right time without worrying about [what combination] it will be (Berthoz 2000).

Defining suitable strategies, should comprise more than comparing regions of stability or sets of weights. However, the approach presented in this document helped in understanding how a subject achieved kinetic coherence. What this work has done is understand the process of learning a physical skill from a map-like perspective. By building *strategy maps* that capture the strategies' consequences, the searching pattern for adequate controllers (optimal combinations of motor patterns) can be clearly represented and could be predicted.

6.2 Two questions that remain unanswered

During the development of this thesis two main questions arose:

1. What would have been the effect in the chosen final strategy if subjects were told to reduce body oscillations instead of asking them to change the placement of their feet?
2. Did the feedback provide with information that people could handle and manipulate?

Although no further studies were conducted to provide conclusive answers to these questions, a couple of insights about possible answers can be extracted both from the data collected and from the researchers' thoughts.

It might be possible that what people learned so easily (to re-frame the objective to balance their own body instead of the board itself and to reduce body oscillations as a result of the placement of their feet) can become complicated if they are asked to do so consciously. Changing the placement of the feet to improve stability is somehow intuitive, but thinking about what to do with the torso for posture or balance is not. A deeper probe into how people use deliberative and conscious strategies is needed in order to understand how the conscious and unconscious play together in this particular balancing task.

Balance is a non-stationary process in which responses might be different whether the feedback provided is about the platform or the body. Recall that the feedback system used in the study provided error information about the board and not about the body. The visual system was expected to generate a temporary visual map of the task by guiding the learner through the action planning process. Unfortunately, there is only a weak statistical link that supports this in terms of performance. In terms of learning, participants agreed on the usefulness of the system but none of the ensemble variables was able to reflect this impact. Therefore there is a need to run further studies to analyze the impact of corporal feedback in this particular task.

6.3 Suggestions for further work

The study showed that learning to balance on the board was characterized by an important development in the coordination of the system which included the platform and the body. The torso became progressively involved in the coordinative structure that allowed a finer control of the oscillations of the board. During the study, participants might have learned a new skill, but more than that, they acquired new ways to use what they already knew about balance.

For a better understanding of the learning process expansion of the research presented in this thesis may proceed along two fronts: conducting studies to test different mapping functions and different feedback modalities and/or incorporating indices or methodologies for assigning weights to the *Balancer*. In the current feedback system there was no additional way to control for the ability of the feedback to give localizing information; therefore other researchers should pursue finding ways to control it. Doing so, performance might be affected. In addition, the use of tactile or musical feedback as well as other mapping functions should be investigated in this balancing task. Along the lines of the second suggestion for further work, researchers might want to consider the use of anchoring indices (Assaiante and Amblard 1993) to assign weights to the *Balancer*. The current model does not provide a methodology to compare the stabilization of a body part with respect to the space or with respect to another body part. The weights given to the model of one of the participants in the study were based on interpretations of the recorded sessions. By using anchoring indices, the assigned weights will be sensor-based and will not require subjectivity.

Appendix A

Balance Self Test

1. Have you fallen more than once in the past year due to an unexplained reason? **Yes No**

2. Do you take medicine for two or more of the following diseases: heart disease, osteoporosis, hypertension, arthritis, anxiety, and depression? **Yes No**

3. Do you feel dizzy or unsteady if you make sudden changes in movement such as bending down or quickly turning? **Yes No**

4. Do you have black-outs or seizures? **Yes No**

5. Have you experienced a stroke or other neurological problem that has affected your balance? **Yes No**

6. Do you experience numbness or loss of sensation in your legs and/or feet? **Yes No**

7. Do you use a walker or wheel chair, or do you need assistance to get around? **Yes No**

8. Are you inactive? (Answer yes if you do not participate in a regular form of exercise, such as walking or exercising 20-30 minutes at least three times a **Yes No**

week.)

9. Do you feel unsteady when you are walking, climbing stairs? **Yes** **No**

10. Do you have difficulty sitting down or rising from a seated or lying position? **Yes** **No**

The previous test is by no means a substitute of any diagnosis test for balance disorders. We are using this test as an inclusion/exclusion criteria for our experiment.

Appendix B

Post-task questionnaire Session 1

I. YOUR STRATEGY

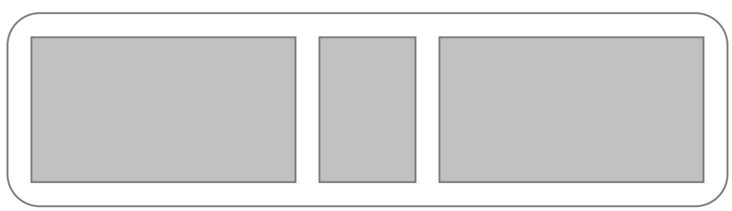
1. When you first saw the board, did you have any **initial thought** on where would you place your feet?
   a. No
   b. Yes

If yes, please explain why did you think this would work.

____

____

2. Where did you place your feet on the **first trial**? Please sketch.



3. Did you **consciously** change the placement of your feet along the board during the trials?
   a. Yes
   b. No
   c. I don't recall

If yes, please explain why

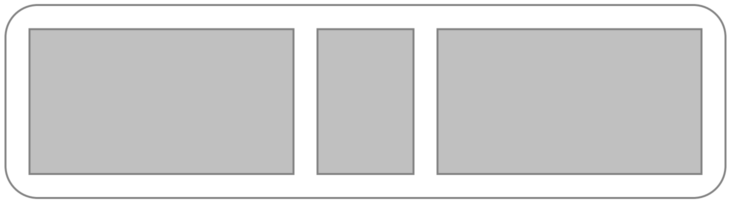
____

____

If yes, was it **useful**?

All the time	Most of the time	Sometimes	Rarely	Not at all

4. Where did you place your feet on **later trials**? Please sketch.



5. Besides the position of your feet on the platform, what other parts of your body do you remember using to control and maintain balance? Please circle all the body parts you used. If any part is not listed, include it.

   a. Head
   b. Shoulders
   c. Arms
   d. Pelvis
   e. Knees
   f. Ankles
   g. Other_________________________
   h. I don't recall

6. Try to explain your strategy during the **first trials**.

   6.1 What were you looking at (where were your eyes focused on) during the first trial?

      a. My feet
      b. The floor
      c. The platform
      d. A spot in the room
      e. I was not looking at any specific place
      f. Other ____________________________
      g. I don't recall

   6.2 What were you trying to control during the **first trials**?

a.	The platform	Yes☐ No☐	Did you succeed?	No, never	Sometimes	All the time
b.	My body	Yes☐ No☐	Did you succeed?	No, never	Sometimes	All the time
c.	Both	Yes☐ No☐	Did you succeed?	No, never	Sometimes	All the time

   6.3 Was this strategy useful to maintain balance?

      a. No
      b. Yes

   Please explain why.

   ____

   ____

7. Try to explain what was your strategy during the **last trials**.

7.1 What were you looking at (where were your eyes focused on) during the **last trials**?

a. My feet
b. The floor
c. The platform
d. A spot in the room
b. I was not looking at any specific place
c. Other ___________________________
d. I don't remember

7.2 What were you trying to control during the **last trials**?

a. The platform	Yes☐	No☐	Did you succeed?	No, never	Sometimes	All the time
b. My body	Yes☐	No☐	Did you succeed?	No, never	Sometimes	All the time
c. Both	Yes☐	No☐	Did you succeed?	No, never	Sometimes	All the time

7.3 Was this strategy useful to maintain balance?

a. No
b. Yes

Please explain why.

____

____

8. In General, what was easier to control?

a. The lateral movement of the platform
b. The back and front movement of the platform
c. Both of them were easy
d. Neither of them were easy

Please explain why.

____

____

II. THE TASK

1. How **difficult** was the task in this **first session**?

1 very easy	2	3	4	5	6	7 very difficult

2. How **confident** were you about a good performance **before the first trial**?

1 not at all	2	3	4	5	6	7 very confident

3. How **confident** are you **right now** about your ability to maintain balance on the platform?

1 not at all	2	3	4	5	6	7 very confident

4. How well did you **perform** on the task?

1 not well at all	2	3	4	5	6	7 very well

5. How **satisfied** are you with your performance?

1 not at all	2	3	4	5	6	7 completely

6. How **afraid** are you about trying different strategies to maintain the balance?

1 not at all	2	3	4	5	6	7 very afraid

7 How do you **expect** to perform on the next session?

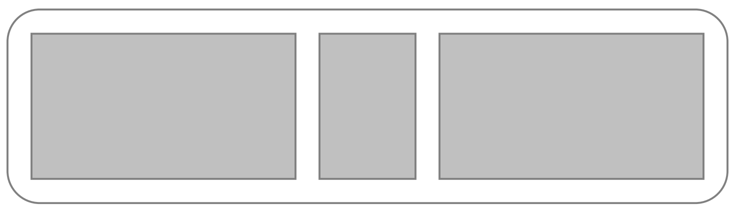
1 not well at all	2	3	4	5	6	7 very well

Appendix C

Post-task questionnaire Session 2

I. YOUR STRATEGY

1. Where on the board was the placement of your feet that allowed you to better maintain balance?



2. Besides the position of your feet on the platform, what other parts of your body do you remember using to control and maintain balance? Please circle all the body parts you used. If any part is not listed, include it.
   a. Head
   b. Shoulders
   c. Arms
   d. Pelvis
   e. Knees
   f. Ankles
   g. Other________________________
   h. I don't recall

3. What was easier to control when you placed your feet **on each end of the board**?
   a. The lateral movement of the platform
   b. The back and front movement of the platform
   c. Both of them were easy
   d. Neither of them were easy

Please explain why.

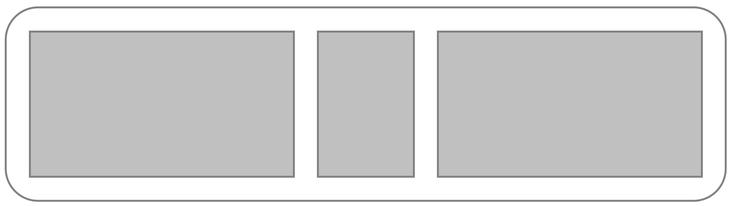
____

____

4. What was easier to control when you placed your feet **close to the middle**?
    a. The lateral movement of the platform
    b. The back and front movement of the platform
    c. Both of them were easy
    d. Neither of them were easy

Please explain why.

5. After this session, where do you think you will be placing your feet in the **next session**?



Please explain why.

II. THE TASK

1. How **difficult** was the task in this **second session**?

1 very easy	2	3	4	5	6	7 very difficult

2. How **confident** were you about a good performance **before the first trial**?

1 not at all	2	3	4	5	6	7 very confident

3. How **confident** are you **right now** about your ability to maintain balance on the platform?

1 not at all	2	3	4	5	6	7 very confident

4. Did you experience any **improvement** on your performance?

1 not at all	2	3	4	5	6	7 a lot

5 How well did you **perform** on the task?

1 not well at all	2	3	4	5	6	7 very well

6 How **satisfied** are you with your performance?

1 not at all	2	3	4	5	6	7 completely

7. How **afraid** are you about trying different strategies to maintain the balance?

1 not at all	2	3	4	5	6	7 very afraid

8 How do you **expect** to perform on the next session?

1 not well at all	2	3	4	5	6	7 very well

Appendix D

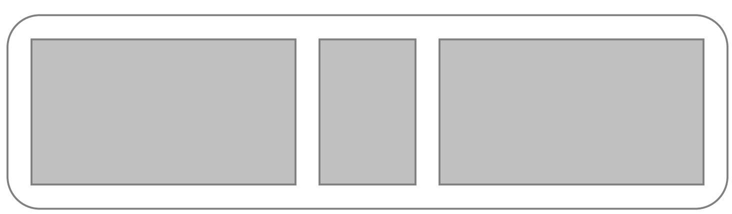
Post-task questionnaire Session 3 part I

1. Age : ___________
2. Height: ______________Weight: _______________
3. Do you have an arch or flat feet? Circle one.
4. Gender : Male____ Female____
5. What type of sport do you practice? _______________________________________
6. Have you ever tried to balance on a similar platform like this one before? (e.g. Bongo board, Weeble boards, BOSU balance board, etc.) Yes ___ No ___

If yes, did you try during the first session of this study to use the same balance strategy that you previously used with other boards? Yes ___ No____

II.YOUR STRATEGY

1. Where did you place your feet on the **first trial** of **this session**?



2. What was your reason to do so? Please explain.

____

____

____

3. Did you **consciously** change the placement of your feet along the board during the trials?
   c. Yes
   d. No
   c. I don't recall

If yes, please explain why.

____

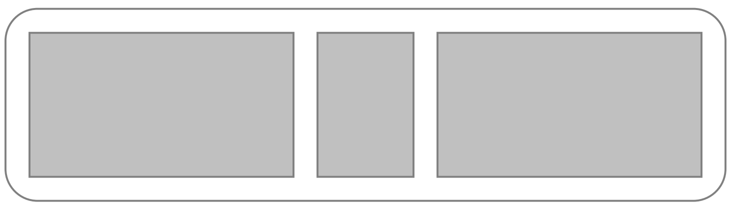
____

____

If yes, was it **useful**?

All the time	Most of the time	Sometimes	Rarely	Not at all

4. Where did you place your feet on **later trials**?



6. Besides the position of your feet on the platform, what other parts of your body do you remember using to control and maintain balance? Please circle all the body parts you used. If any part is not listed, include it.
   a. Head
   b. Shoulders
   c. Arms
   d. Pelvis
   e. Knees
   f. Ankles
   g. Other_________________________
   h. I don't recall

II. THE TASK

1. How **difficult** was the task in this **third session**?

1 very easy	2	3	4	5	6	7 very difficult

2. How **confident** were you about a good performance **before the first trial**?

1 not at all	2	3	4	5	6	7 very confident

3. Did you experience any **improvement** on your performance?

1 not at all	2	3	4	5	6	7 a lot

3.1 Please, explain how did you measure your own improvement.

____

____

____

4. How well did you **perform** on the task?

1 not well at all	2	3	4	5	6	7 very well

5. How **satisfied** are you with your performance?

1 nothing	2	3	4	5	6	7 completely

6. How **afraid** are you about trying different strategies to maintain the balance?

1 not at all	2	3	4	5	6	7 very afraid

7. Was the task **challenging** enough throughout the sessions?

1 not at all	2	3	4	5	6	7 very much

Appendix E

Post-task questionnaire Session 3 part II

YOUR STRATEGY ON SESSION 1 AND SESSION 3

You will be asked to watch the videos we have recorded from you on Session 1 and Session 3 of this study. You will be required answer some questions related to them. Please read the following questions before you watch the videos.

1. What parts of your body, you saw you were using to balance during **Session 1**? Please circle all the body parts you used. If any part is not listed, include it.
   a. Head
   b. Shoulders
   c. Arms
   d. Hip
   e. Knees
   f. Ankles
   g. Feet
   h. Other___________________________

2. Were you **consciously aware** you were using **all** of them?
No Yes

3. What parts of you body you saw you were using to balance during **Session 3**? Please circle all the body parts you used. If any part is not listed, include it.

   a. Head
   b. Shoulders
   c. Arms
   d. Hip
   e. Knees
   f. Ankles
   g. Feet
   h. Other___________________________

4. Were you **consciously aware** you were using them?
No Yes

IV. THE TASK: comparison between sessions

Based on the information on the video that you just watched:

1. Did you observe any **improvement** on your performance?

1 not at all	2	3	4	5	6	7 a lot

2. How well did **you** perform on the task on **Session 3 compared to Session 1**?

1 not well at all	2	3	4	5	6	7 very well

3. After watching the video would you **change** your strategy if you had **another chance** to balance?

1 not at all	2	3	4	5	6	7 definitely

4. Did you find the video **useful**?

1 not at all	2	3	4	5	6	7 very

V. THE DISPLAY

1. Did you find the display **intuitive**?

1 not at all	2	3	4	5	6	7 very

2. Did you find the display **informative**?

1 not at all	2	3	4	5	6	7 very

3. Did you find the display **useful**?

1 not at all	2	3	4	5	6	7 very

4. Did you find the display **distracting**?

1 not at all	2	3	4	5	6	7 very

5. Do you think you would have **performed better without a display**?

1 not at all	2	3	4	5	6	7 absolutely

6. Do you consider that the presence of the display helped you to **learn** to balance **faster** than if you didn't have a display?

1 not at all	2	3	4	5	6	7 absolutely

7. Please select all the phrases that you consider are true.
   a. Trying to fall within a range of what is considered close to being balanced achieves **better performance** than trying to perfectly balance
   b. Trying to perfectly balance achieves **better performance** than trying to fall within a range of what is considered close to being balanced.
   c. It is **easier** to balance when you try to control the platform from moving.
   d. It is **easier** to balance when you try not to interfere with the natural movement of the platform.
   e. To **efficiently** balance, a person has to learn to respond to acceleration as opposed to the tilt of the board.
   f. To **efficiently** balance, a person has to learn to respond to the tilt of the board as opposed to the acceleration experienced.

V. THE TRIALS

1. The number of trials per session (8) were: Please circle one.
   a. Not enough trials. How many trials per session would you suggest? ______
   b. The right number of trials
   c. Too many trials. How many trials per session would you suggest? ______

2. 30 seconds of balancing time was: Please circle one.
   a. Not enough time. How much time would you suggest? ______
   b. The right amount of time
   c. Too long. How much time would you suggest? ______

Thank you for your participation in the Balance Study!

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