

On the Cybernetic Arrangement of Feedback in Serious Games: a Systems-Theoretical Perspective

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Abstract

This paper explores the cybernetic regulation of complex human learning and teaching. It provides a theoretical description of the arrangement of adaptive, machine-generated learner feedback which relies on cybernetic principles. Cybernetics – today often referred to as control theory, or feedback control theory - involves the incorporation of self-establishing feedback mechanisms for optimal control in complex systems. Although feedback is considered a key element of any learning process, the arrangement of feedback by teachers and educators is under pressure because of the ever-growing complexity of learning environments which is being reinforced by open, online learning technologies and topical models of learning (competence learning, experiential learning, situated cognition, serious gaming). This paper explores how cybernetic principles could be implemented in complex learning environments, e.g. serious games, for the arrangement of self-regulating feedback loops for learners. The approach is based on a quantitative description of learning activities and learning performances. For the presentation of the feedback, a feedback decision procedure is suggested which is to be linked with pedagogical theories and assessment models. The proposed cybernetic approach is elucidated with a theoretical example. The paper provides a proof of principle and gives suggestions for further development.

Keywords

Learning, games, design, feedback, cybernetics, self-regulation

1. Introduction

This paper investigates the applicability of cybernetic principles for providing learner feedback in complex online learning environments. Cybernetics refers to a systems theoretical approach to keeping a complex system on target (Wiener 1948). The increasing complexity of online learning environments, which are readily associated with complex skills training, competency learning and game-based learning and the associated freedom of movement and ill-defined problems, hampers the provision of appropriate guidance and feedback to learners. Hence, the effectiveness and efficiency of learning are under threat. This calls for new approaches to supporting learners and keeping them on target.

The complexity of learning environments is amplified by new enabling technologies and new pedagogical insights. Contemporary pedagogies, e.g. constructivism, experiential learning (Kolb 1984) and situated cognition (Brown et al. 1986), stress the importance of active learner involvement. They all start from the premise that

learning is greatly fostered by the experiences we have in the world that surrounds us. This points at dynamic and ill-structured learning environments with lots of unstructured content and occurrences rather than well-established drills, instructions or tutorials (Westera et al. 2008). Also competences needed for the information age, which include information skills, self-regulation, networked cooperation, problem solving strategies and critical thinking, suggest an inherent richness and complexity of the learning environment. Serious games are a topical example of this trend, while these involve complex, multidimensional systems, which incorporate many aspects of real world complexity. Appropriate mechanisms have to be included for the arrangement of learner guidance and feedback: indeed, learners need to be kept on the right track and should be helped to avoid irrelevant and time-wasting activities. But the complexity of current learning environments systems, particularly online environments, produces severe barriers for this. In school practice teachers decide on when and how to give guidance and feedback to students (Hattie and Timperley 2007). In complex online learning environments such as games, however, teachers will not be able to tune these to the specific needs of the learners, unless they would spend all their time for tracking, analysing and understanding the whole game play and history of each individual learner. Also, much of the teaching expertise about when and how to support learners is implicit or hidden, which fairly matches the widespread idea that teaching is an art rather than a science. In recent years the learners themselves are increasingly assumed to be responsible for their own learning. Theories of self-regulation and self-determination (Zimmermann and Schunk 1989; Ryan and Deci 2000) are inherently based on the idea of continuous control loops that learners apply in their own learning. These are actually cybernetic approaches, be it that they are mainly qualitative in kind and focused on the mental processes of the learner rather than incorporating the systemic dimensions of the learning context. In this paper this context will be included as such, since the context of learning is widely considered the main determinant for effective learning (Dewey 1938; Roth 1995; Brown et al. 1989). Various approaches for creating responsive, adaptive systems are available, for instance, adaptive hypermedia approaches (Brusilovsky 2001), rule-editing approaches, standards-based instructional design (e.g. SCORM and IMS Learning Design) and semantic web approaches, but these all suffer from complexity of design (Westera et al. 2008).

Linking education with cybernetics is not a new idea (cf. Smith and Smith 1966), but there are no examples explicitly referring to feedback in complex or game-based learning environments. Kaburlasosa et al. (2009) applied cybernetic methods for the arrangement of adaptive assessments. However, these were based on Bayesian statistics involving a wide population of learners rather than single learner interactions. It is the challenge of the learning sciences to develop new scientific approaches for the improvement of learning and teaching, and dismantle the mystifying parts of it. So does this paper by exploring the opportunities of cybernetic theory for combining teaching, learning and the systemic properties of learning context.

The main aim of this paper is to elaborate the idea of the cybernetic generation of learner feedback in complex environments and provide a proof of principle for it. We will briefly outline the basic principles of cybernetics and elaborate the arguments for linking cybernetic theory with the system of human learning. We will then provide the quantitative description of cybernetics and explain how cybernetics can be implemented in complex learning environments. The approach is elaborated and illustrated with a serious gaming example. In conclusion we evaluate the outcomes of this analysis and suggest relevant research topics to be tackled.

2. Cybernetic principles

Cybernetics has been defined by its founder Norbert Wiener (Wiener 1948) as “the science of communication and control in animal and machine”. Cybernetics – today often referred to as control theory, or feedback control theory - involves the incorporation of self-establishing feedback mechanisms for optimal control in complex systems. The cybernetic approach can be illustrated by a simple and well-known example: cruise control. Suppose that we want to drive our car at constant speed, irrespective disturbing effects of wind changes, ascends or descents, bumpy roads, combustion temperature fluctuations. To achieve this we actually don't necessarily need detailed Newtonian calculations that describe the effects of wind force, rolling resistance and gravity on car speed. Instead, we carefully observe the speedometer and adjust our speed to the required speed simply by pressing or lifting the accelerator pedal. This approach reflects a cybernetic control loop which is depicted in generalised form in Figure 1.

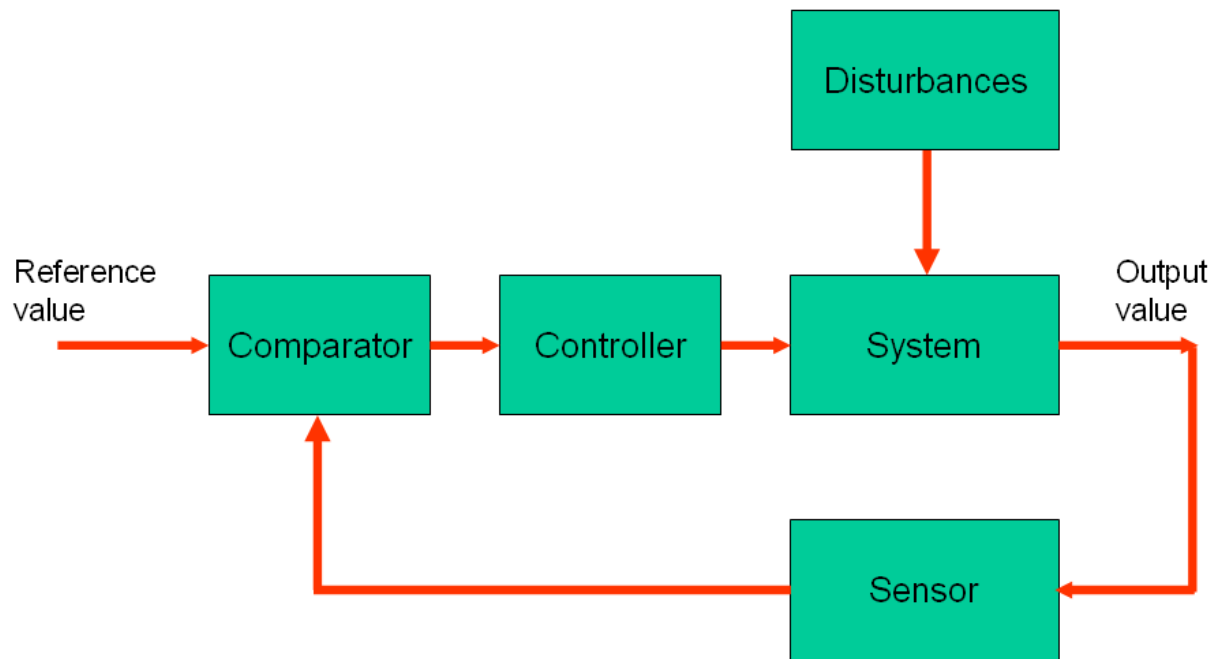


Figure 1. The principle of cybernetics: closed-loop feedback control.

The system S is our car which is driving under unclear conditions indicated by the disturbances which may affect the speed of the car. The output data of the system (car speed) is measured through a sensor (the speedometer), and is compared with the internal reference value (desired speed). The difference between the measured and desired speed is the input for a controller (the accelerator pedal) which counteracts the difference by adjusting motor power. When the speed is too high, we simply lift the pedal to reduce the difference; when the speed is too low we will press the pedal. Such regulation mechanism is essentially error driven, with the ultimate goal of achieving stable zero error, and robustness under unknown dynamics, disturbances and uncertainty of conditions. So, the cybernetic feedback control loop of figure 1 establishes the self-regulating capabilities of the system, without the need for detailed description of the system's internal structure and variables and without the need to understand and incorporate the mechanisms of disturbances. Cybernetic principles have been widely and successfully applied in a variety of systems like chemical plants, power plants or electronic circuits for the purpose of system optimisation and stability. Such complex systems are inherently difficult to describe, to understand or to forecast, but their performance can be greatly enhanced when we adopt a cybernetic perspective. Many complex dynamic systems (viz. a system that can be described mathematically by multiple variables that change over time), ranging from natural eco-systems to the system of blood circulation or the human immune system, can be accurately described and understood by cybernetic models.

3. The rationale of using cybernetics in education

There are various considerations in support of connecting cybernetics with (complex) learning. The arguments go beyond the concept of learning itself, while they also reflect visions of human functioning at large and the context of operation.

3.1 Human behaviour as the result of control loops

Some theories claim that all human behaviour is the result of internal control loops: Perceptual Control Theory (Powers 1973) and Choice Control Theory (Glasser 1986) claim that human behaviour is not caused by outside stimuli, but is the effect of keeping internal variables within survivable limits of internal references values. Living beings are thus considered to act upon their environment with the purpose of controlling perceptual inputs and minimise the differences with internal standards. The simple act of bringing a glass of water to our mouth without spilling, under whatever disturbing conditions (wind, or travelling on a bumpy road) is a highly adaptive operation, which can only be achieved by frequent control loop iterations. The theory is also framed as a theory of motivation, since it states that behaviour is the result of trying to satisfy internal goals, for instance survival, love and power. All human behaviour is thus interpreted as the result of internal feedback control loops.

3.2 Human-computer interaction as a control process

The interaction between human individuals and a computer program can be well understood by a cybernetic control loop, which continually provides feedback for adjusting the action. The human actor may have certain intentions when performing a action; the environment responds by changing its state. This, in turn, is evaluated by the user against some internal standard (intention) which may urge him or her to the next action. This highly cybernetic view is also reflected at a more general level in the execution-evaluation cycle of Norman's interaction theory (Norman 1988). Note that this interpretation of human-computer interaction is completely different from the single cause-and-effect relationship of actions. The latter is attractive for its simplicity, but also naïve and improper. Claiming that a player's action in a game is the cause of some effect in the game is not necessarily wrong, but it is only half the story. The player's action cannot be evaluated in isolation. Indeed, any action will be part of a complex, cohesive sequence of mutual interactions between the player and the game, which blurs the ideas of cause and effect. The player acts on the environment inasmuch as the environment acts on the player. The player itself cannot be isolated from the game, but is actually part of the game. Players do not act on the game, but act in the game: the player is part of the environment and adjusts its actions by means of a cybernetic feedback loop.

3.3 The control loop of learning

Feedback is also considered a key element of any learning process (Mory 2004; Hatty and Timperley 2007). Contemporary views on learning, like constructivism, experiential learning and situated cognition, advocate the active involvement of learners in rich and complex learning environments that mimic or model part of the real world (serious games are a case in point). Such learning by experience involves a process of continued confrontation with the complexities of the environment, and the continued reconsideration of the decisions taken for achievement of learning goals. The impact of the learners' actions provide a natural feedback mechanism that may urge the learners to re-adjust and improve their actions and to develop alternative strategies for achieving their goals. Learning can thus be considered a continued self-regulation process which uses "error reduction" via feedback. The learning cycle can easily be mapped onto the cybernetic system of figure 1: the system is the environment where the learners carry out their learning tasks. The system output reflects the effects of the learning activities, which are registered by a sensing agent and assessed by comparing the signal with the reference output (which is somehow linked with the preset learning goal). The difference may reinforce the learners' approaches or may hint for the adjustment of activities or strategies. Indeed, learning itself is an inherently cybernetic process.

3.4 Increased complexity of learning environments

Since the 1980s computers have been used in education and training. Initially, this so-called courseware comprised programmed instruction and simple repetitive, quiz-like programmes for drill and practice exercises. Also educational games and simulations became available, be it that initially their user interfaces were still in text mode. Gradually courseware became more complex and supported multimedia presentation (graphics, sound and video). CD-rom and DVD became the main distribution carriers. The emergence of the internet enabled network options like multi-user games, user communities and collaborative computer-supported learning. It can be observed (Aldrich 2005) that digital learning environments and the associated learning tasks tend to become increasingly complex. Contemporary pedagogies call for authentic learning environments that provide safe experimentation with real-life tasks (Brown et al. 1989; Newmann et al. 1996; Gobert and Palant 2004; Jonassen 2004), as is the case in serious games, for instance. As a consequence, learners will probably not be able to control their learning to full extent, and will often need a hint or instruction for appropriate continuation. These hints may be provided by a teacher or a built-in facility, but the problem is to find the right metrics for generating advice. It is quite likely that teachers don't know how to continue either, due to the game's complexity. It doesn't make much sense to provide support that is no more than an improvised wild guess. So, the challenge is to define mechanisms that support the re-adjustments of learners' behaviours. This is of special importance because the growing proportion of e-learning in education and training that goes with restricted access to teachers. The top-down design of learner support mechanisms in these complex environments – say a serious game - is very intricate, because of the almost indefinitely large size of the system's state space (which is the multi-dimension space spanned by the values of all state variable, over time). It is very difficult, if not impossible to completely model the diverse student behaviours and the responses of the game environment in such a way that specific support interventions can be inferred. Alternatively, it seems to make sense to consider the complex environment as a "learning ecology", which only function is the development and survival of useful

knowledge and useful behaviours. Indeed, such learning ecology has many things in common with complex dynamic systems like populations of living creatures, a chemical plant or even a match of football, which all rely on cybernetic principles. Essentially, cybernetic theory requires that system outputs are evaluated against certain internal (or external) standards in order to apply the corrective feedback. Indeed, learning is a mostly and pre-eminently a goal-driven activity, motivated by learning goals, by learning content, or by reports to deliver. This complies with intentions and internal standards required for measuring progress or deviations from the standards set. As a (sub)system, the learning environment is supposed to help produce the right learning outcomes in an effective way in spite of unknown disturbances and without any instabilities or system failures. Hence, cybernetics is a promising candidate to explore.

4. Quantitative description of cybernetic theory

Cybernetics provides a systematic, theoretical approach for the analysis and design of complex systems by regulating system responses through closed-loop feedback control. The starting point of cybernetics is that complex systems do not possess the specific intelligence to respond to a variety of different stimuli and conditions, but instead respond by maintaining a subset of internal variables also called control variables within critical or often “survivable” limits from fixed reference values. To this end, it is important to have sensors and indicators available for the monitoring of the system’s relevant outputs, and, likewise, to have controllers for making adjustments to the inputs. The core idea of cybernetics is a negative system feedback loop as displayed in its classical form in figure 2 (similar to figure 1, but variables indicated).

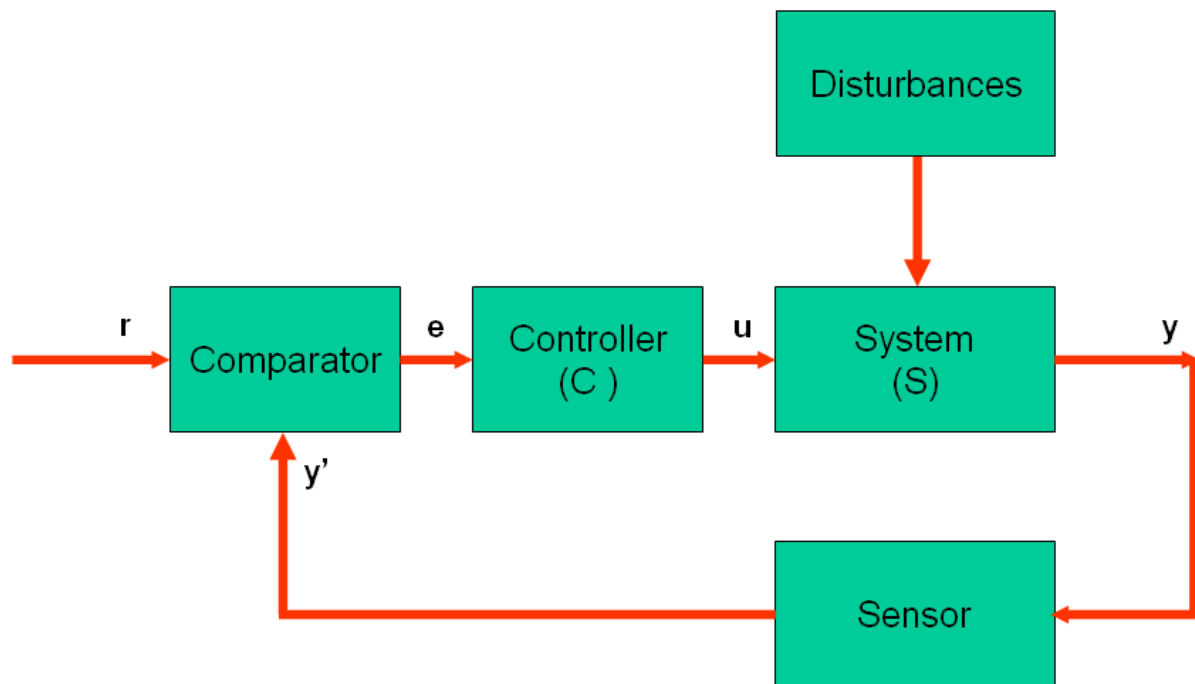


Figure 2. Cybernetic loop with variables indicated.

Here S is the system that covers the learning process. It is perturbed by unknown dynamic disturbances, which may have external or internal origin. The output of the system S at time t is denoted $y(t)$, while $y'(t)$ is the observed output that is measured by the output sensor, $r(t)$ is the reference value indicating the desired output, $e(t)=r(t)-y'(t)$ is the error function, $u(t)$ is the input function of the system as produced by the controller C . In case of multiple inputs and multiple outputs these variables represent vectors rather than scalars and their mutual relationships are described by matrices rather than single coefficients. For reasons of simplicity it is assumed here that the sensor produces the exact and noiseless value of the output, so

$$y'(t) = y(t) \tag{1}$$

When C and S are the transfer functions of the controller and the system, respectively, it follows that the system’s closed loop transfer function H reads (Leigh 2004):

$$H(s) = \frac{y(s)}{r(s)} = \frac{C \cdot S}{1 + C \cdot S} \quad (2 \text{ in})$$

where s is the complex frequency and $y(s)$ and $r(s)$ are the Laplace transforms of $y(t)$ and $r(t)$, respectively. The Laplace transform is a mathematical procedure that transforms an equation from the time domain (in which inputs and outputs are functions of time) into the frequency domain (where the same inputs and outputs are functions of complex angular frequency, in radians per unit time). In many cases the Laplace transform simplifies the mathematics and eases the finding of valid solutions to the equations, while maintaining the full functional qualities of the original time-based equation set.

The main idea of cybernetics is that when we have sufficient information about the system transfer function S , we need to define an appropriate control function C for optimal performance to achieve perfect and stable transfer of $H=1$, viz. the output $y(t)$ perfectly matches the reference value $r(t)$. When the system is malfunctioning, the control function C should compensate for this by reducing the error $e(t)$. Note, however, that by the nature of error reduction, the control action is always lagging behind the system output: indeed, an error can only be compensated for after its appearance. As a consequence unwanted time effects in system performance may occur like oscillation, drift, cumulative delays, chaos, explosion and breakdown. For optimal functioning the control function should not just be a function of the present output $y(t)$, but also take into account system history by incorporating previous system outputs $y(t')$ and previous system inputs $u(t')$, with $t' < t$.

In a variety of technical applications generic solutions for the controller function have been developed. The Proportional-Integral-Differential controller algorithm (PID) is built on 3 separate components, which appear on the right side of equation (3):

$$u(t) = K_p \cdot e(t) + K_i \cdot \int_{\tau=1}^t e(\tau) d\tau + K_d \cdot \frac{de(t)}{dt} \quad (3)$$

The first term on the right hand side represents proportional control: the corrective input is proportional to the current error $e(t)$. Its response is fully determined by the current error and aims to directly compensate for it. The second term reflects integral control by taking into account the history and duration of the error. The third term represents differential control, which reduces transient overshoot by accounting for the rate of change of the error. Transformation of equation (3) to the frequency domain produces the PID controller transfer function C :

$$C = \frac{u(s)}{e(s)} = K_p + \frac{K_i}{s} + K_d \cdot s \quad (4)$$

The PID controller function is well documented and instrumented, but still requires careful tuning of its parameters K_p , K_i and K_d to avoid system instability (Leigh 2004; Ziegler and Nichols 1942).

5. Applying cybernetics in an educational context

Applying cybernetics to the process of learning is equivalent with arranging an effective controller function. In most cases, however, we have to deal with two separate controller functions exercised by: 1) an educational agent (e.g. a teacher, an instructor or an instructional system such as a book or a serious game) who aims to guide and support the learner toward predefined learning goals, and 2) the learner as an autonomous individual who exerts self-regulation in order to satisfy his or her personal needs. This means that the cybernetic system is composed of two interlinked cybernetic cycles (cf. figure 3).

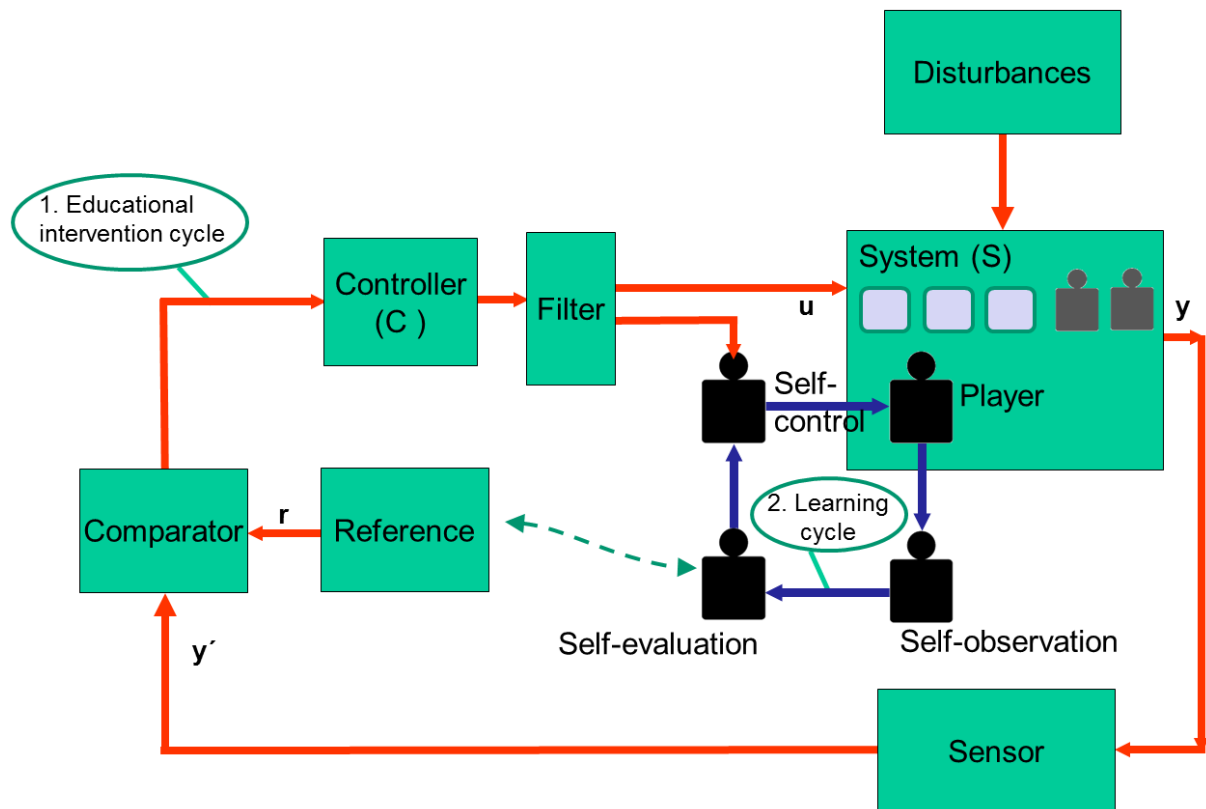


Figure 3. The two cybernetic cycles required for the learning system.

For the sake of convenience these are labelled as 1) the educational intervention cycle, which refers to teaching agency, and 2) the learning cycle, which is controlled by the learning individual.

The educational intervention cycle reflects the observations, considerations and actions of teachers or tutors to guide and support the learner toward the learning goals. In general the system S, e.g. containing the learning context, including materials, the learner and fellow-learners, will be described by multiple dimensions, which means that $u(t)$, $y(t)$, $y'(t)$ and $r(t)$ are essentially vectors. The output vector $y(t)$ and the measured sensor outputs $y'(t)$ are supposed to cover the observable effects of these actions, viz. the various dimensions of the learner's performance (corresponding with learning outcomes) or manifest effects in the game. The reference values $r(t)$ – also a vector – reflect the pursued learning performances, which act as the standards for system control. Deviations between the observe values $y'(t)$ and the reference value $r(t)$ indicate suboptimal learning performance and call for adjustment of the system input vector $u(t)$, which adapts the conditions for learning.

The learning cycle reflects the personal nature of the learning process. It comprises the learner as the actor performing learning activities in the learning environment S, but also the learner as an observer of self-performance, the learner as a self-comparator (evaluation self-performance against personal goals and intentions) and the learner as a self-controller (adjusting behaviours on the basis of controller inputs). From figure 3 it can also be read that on the one hand the learner is an intrinsic and active part of the system S and its associated learning activities, while on the other hand the learner acts as a self-observer, self-evaluator and self-controller, who is (by its nature and role) located outside this system. This dual role of the learning individual has been made quite explicit in theories of metacognition, reflection and self-regulation (Butler and Winne 1995). Note that exactly at the meta-level interface the teaching cycle and the learning cycle are interconnected. The system controller C (the teaching agency) may also directly address the self-controlling learner and give direct instruction at a meta-level to the learner.

In the next section we will explain how the cybernetic approach is applied to an educational setting, say a serious game.

6. System elaboration

We will explain the various system components of figure 3 in more detail. For the purpose of illustration we refer to an exemplary context that uses a (fictitious) serious game. Consider a serious game, for instance a business game that puts the learner in the position of a business manager running a plant. Assume that the game

is a multi-player role-play game: fellow players have adopted relevant roles either as business staff, customers, suppliers or competitors in the same market. Generally in this type of games, players learn to optimise their business performance under the constraints of imperfect and/or asymmetric information. Also the game could include a real-time simulation model of the production process, generating the dynamics of supplies, orders, processing capacity, staff, sales and so on.

The system S

The main system S represents the full learning context, including both the player and all game objects and other game attributes (e.g. game rules, game processes, tools, aids, simulation engines). Game play, which is equivalent with learning activity, reflects the interaction between the player and the other system components. In the game the player adopts the role of business manager and aims to run the business in a favourable way. In case of a multiplayer game, then fellow-players adopting similar or complementary roles are part of the system as well (cf. figure 3). Player actions may include buying supplies, hiring staff, designing a marketing plan, buying advertisements, tuning the business process logistics, negotiating with fellow players, deciding about investments, reorganising business, and many more.

Disturbances

Many games use random generators for triggering unexpected, critical events. Likewise, fellow players in the game may behave in highly unpredictable ways and thus cause unforeseen system disturbances. In principle these two factors are system-internal disturbances, rather than external noise. In addition, a wide range of external factors (e.g. room temperature, internet connection speed, time, player's mood or fatigue, interrupting phone calls) may influence the system.

System output $y(t)$

The output variables $y(t)$ reflect the relevant observable parameters of the system S. These may include content-related indicators such as investments made, stock volumes, sales, vacancies, energy waste, new contracts, customer satisfaction rates etcetera. But output may also include the learner's behavioural patterns that could be easily tracked by game engines, such as time spent to certain activities, number of documents consulted, peer-assessed scores of reflection reports, visits to different game locations and so on. A main challenge is to assess observed activities in terms of learning gains. For the assessment in game-based learning Shute et al. (2009) propose a combination of Evidence-Centered Assessment (ECD: Mislevy et al. 2003) and Bayesian score models (e.g. Pearl 1998). Its ingredients are 1) a competency model, which describes the competencies, skills and knowledge of the variables to be assessed, 2) a task model, which describes features of situations that will be used to elicit performance, 3) an evidence model, which explains how aggregated interactions and behaviours (observables in the task model) provide evidence to performances, and 4) the learner model, which expresses the learner's scores of the assessment variables, indicating to what extent the competencies, skills and knowledge are mastered (Shute 2009). Note that for the sake of simplicity we assume that no observational losses occur, which means that $y(t)=y'(t)$.

Reference standards $r(t)$

The reference values $r(t)$ reflect the anticipated growth of the system S over time. It covers the same parameters as $y(t)$ and thus may include both the game's business performances and behavioural metrics of the learner. This is where pursued competences or learning goals come into play. The references $r(t)$ not just indicate final goals but also cover the time-dependent trajectory toward these goals. They are thus linked with the intended, most favourable learning and development scenario. Reference criteria to be met will be closely linked with the game play and may be based on population metrics derived from previous runs or on any other available theoretical, logical, social, historical or formal standards. The reference values may in principle be different for different learners because of personal characteristics, personal goals or personalised preferences, and may change over various episodes of learning.

Comparator

Deviations of $y'(t)$ from the reference value $r(t)$ indicate suboptimal performance and call for adjustment of the system input vector $u(t)$. For instance, if a player requires too much time to complete a task (e.g. defining mile stones or solving a delivery problem) as compared with the standard scores a deviation is reported to the controller, which prepares a system intervention.

Controller

In turn, the controlling system C makes adjustments to system inputs $u(t)$, which are aimed at influencing the system in the most favourable way. Here several options are possible. First, the controller may directly intervene in the system's process by changing the process parameters. For instance, if the business is about to go bankrupt,

the simulation parameters may be set to reduce the financial load by raising sales figures or sales margins, or by reducing costs of supplies or personnel, other reveal relevant clues in the game that may guide the learner toward better performance. These interventions would all be part of the game play and can in many cases be regarded natural feedback (Dewey 1938), which is feedback that is reflected in observable changes of the environment. Second, the controller could directly address the learner and provide feedback, hints or instructions, such as “please try to spend less money on marketing, because...”, or “...it seems that you require too much time defining concrete financial targets, please consult the example in your task description”. Such interventions directly address the meta-level process of learning, which means that they transcend the game play, in contrast with natural feedback. Although such meta-level intervention is the most dominant mode of teaching, it should be noted that generally the controlling power over learners is quite limited: forcing people to learn is counterproductive, if not impossible. The human subject, viz. the learner, is in all cases an autonomous agent, who may be reluctant to adopt the controllers intervention, or simply fails to understand the significance of the controllers instruction.

The learner’s refusal to adopt the feedback doesn’t mean that the feedback loop itself is interrupted. Actually, the learner’s contrary behaviour within the control loop can be regarded as a temporary disturbance of the system, which may challenge the loop’s robustness. The learner runs the risk of worsening his or her performance, which in turn will produce an even more rigorous controller advice. If the learner keeps neglecting the controller’s hints, either the learner’s self-regulation abilities will produce sufficient system performance to continue learning, or the learner’s performance will keep going down, which will eventually lead to system breakdown. This is exactly why feedback is supposed to be a key factor of learning.

Feedback strategies

The controller system need not necessarily pass the generated feedback signals on to the system or the learner. Indeed many teachers use a pedagogical strategy, which may sometimes use direct feedback, while in other cases delayed feedback or even no feedback is preferred. Pedagogical feedback strategies have been extensively researched (Hattie and Timperley 2007; Mory 2004; Shute 2009) . It means that the cybernetic cycle should include a feedback strategy filter, which defines what feedback is passed on and under what conditions this occurs.

The learning cycle

Analogous to the education cycle the learning cycle includes four components: the learner as an actor in the system S, the learner as a self-observer, the learner as a self-evaluator and the learner as a meta-cognitive agent who adapts the learning strategy. Essentially the process of learning is fully owned by the human individual, be it that in many respects it is a continuous and implicit process that learners can only partly control (metacognitive skills).

7. Multivariate systems

The approach illustrated above can be extended to multivariate system descriptions. When the system S can be subdivided into a number of independent subsystems which all have there own sets of input variables and sets of output variables, each subsystem can be treated independently, much like the example given above. However, when no independent subsystems can be identified and multiple input variables are connected to multiple output variables, the mathematics becomes more complex. A wide class of first order multivariate systems is covered by a matrix algebra approach which is commonly known as the time-domain state space representation (Leigh, 2004). Input variables $u_i(t)$ and output variables $y_j(t)$ are preferably linked via a linear, time-invariant system model, which yields a set of coupled linear differential equations. Having established an appropriate controller model, for instance using the PID mechanism, we are able use the output signals $y_j(t)$ and generate the controller outputs $u_i(t)$. These, in turn, can be used as an advice to the learner for prioritising some learning actions above others by indicating what action would procure desired outputs $y_j(t)$. This means that the calculations would allow for guiding learners to certain activities that would compensate flaws in their learning achievements. To ensure more subtle feedback messages multiple trigger levels can be used. The technical explanation of the state-space approach is beyond the purpose of this paper.

8. Conclusion and outlook

In this paper we have explored how cybernetics in principle can be used to generate learner feedback in complex learning environments. By constructing a (dual) cybernetic control loop, error-correcting performance feedback can be generated, which can in principle be used for supporting learners. But this achievement is not without conditions. It assumes the readiness to capture learning activities as well as learning performances in quantitative metrics. Many testing and assessment procedures in education already make use of quantitative standards, either in manifest or in implicit ways. Qualitative learner assessments (verbal feedback, portfolios, reflection blogs) or

qualitative overall judgements (e.g. “poor”, “sufficient”, “good”, “excellent”) reflect ordinal scales, which allow for the easy and justified conversion into numerical values (e.g. marks).

For being able to generate feedback to learners, the relationship between activities (input variables) and performances (output variables) should be made more explicit, be it that detailed understanding of disturbances and noise is not required. Various mathematical techniques like Laplace transformations as well as matrix algebra can be used to determine optimal control outputs. Best solutions can be calculated in linear processes, or processes that can be linearised easily. Although the description in this paper used continuous variables, discrete time variables can be treated likewise. An important mechanism that has been explained also is the use of feedback decision criteria, which are based on pedagogical theories and models.

Further research is needed to establish the interconnections between cybernetics and existing pedagogical theories and models for feedback and self-regulated learning. Also theories and heuristics for the design of input and output metrics are required, that produce valid and useful representations of the learner’s functioning and performances, and that cover the underlying mental processes and learner characteristics. Educational feedback control mechanisms should be validated with respect to system accuracy, reliability, stability and responsiveness, but also with respect to their appropriateness and effectiveness for learners. The research should also aim at developing design guidelines and collecting empirical evidence, both in controlled experiments and educational practice.

Emerging technologies create new leads for cybernetics in education. For instance, web-based learning, social software services and serious gaming provide a range of accessible user tracking and tracing services that enable the capturing and monitoring of learner behaviours and performances. Hence, data collection needed so urgently for the appliance of activity metrics and performance metrics is much better supported. New modelling approaches based on intelligent agents and multi-agent systems also aim at system optimisation, but in addition to cybernetics these techniques also lend themselves for logical inference and computation which are needed for problems in areas such as vision and language. Yet, the agent concept exactly represents a cybernetic system, since all agents are equipped with sensors and actuators that are linked via a feedback control loop. Also, the topical domain of learner analytics enlarges the opportunities for implementing cybernetic loops that can guide learners to their learning goals. Finally, we point at the trend towards mixed reality solutions, involving the entanglement of virtual spaces and physical reality, for instance by including mobile devices, remote controls and sensor technologies like location tracking, movement tracking, gesture recognition or bio-sensing, which amplifies the interest in cybernetic principles and demonstrates their topicality and viability.

Cybernetics is not a new branch of science. It actually goes back to the nineteen-forties, and many areas of technology and industry rest on its principles. A general observation is that cybernetics is especially useful when open loop approaches fail because of complexity. Closed-loop approaches like cybernetics can handle complicated processes even when no detailed knowledge of the system is available. In view of the ever-growing complexity of learning environments, the tuning of cybernetics to learning processes is a promising journey.

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Appendix: Mathematical elaboration

To demonstrate the mathematical procedure we will elaborate an example. Suppose we have a learning context S, say a serious game, where students have to carry out certain activities, expressed in activity metric $u(t)$ to achieve a certain performance metric $y(t)$. Let the dynamics of S be described by a first order differential equation:

$$\frac{dy(t)}{dt} + a_0 \cdot y(t) = b_0 \cdot u(t) \quad (5)$$

with a_0 and b_0 time-invariant coefficients.

After Laplace transformation of equation (5) we obtain the system transfer function $S(s)$:

$$S(s) = \frac{y(s)}{u(s)} = \frac{b_0}{a_0 + s} \quad (6)$$

Assume proportional-integral control, so that the control function $C(s)$ is given by (cf. equation (4)):

$$C(s) = K_p + \frac{K_i}{s} \quad (7)$$

According to equation (3) we obtain the following expression for the closed loop transfer function H:

$$H(s) = \frac{C(s) \cdot S(s)}{1 + C(s) \cdot S(s)} = \frac{(K_p + \frac{K_i}{s}) \cdot (\frac{b_0}{a_0 + s})}{1 + (K_p + \frac{K_i}{s}) \cdot (\frac{b_0}{a_0 + s})} = \frac{K_p \cdot b_0 \cdot (s + \frac{K_i}{K_p})}{s^2 + (a_0 + b_0 \cdot K_p) \cdot s + b_0 \cdot K_i} \quad (8)$$

This formula can easily be rewritten into the form:

$$H(s) = \frac{K_p \cdot b_0 \cdot (s + \frac{K_i}{K_p})}{(s - p_1) \cdot (s - p_2)} \quad (9)$$

where p_1 and p_2 are the poles of the equation, given by:

$$p_{1,2} = -\frac{1}{2}(a_0 + b_0 \cdot K_p) \pm \frac{1}{2} \cdot \sqrt{(a_0 + b_0 \cdot K_p)^2 - 4 \cdot b_0 \cdot K_i} \quad (10)$$

In order to examine the system output response $y(t)$ to a sudden input change $u(t)$, we set $u(t)$ to a unit step function (Heaviside), which produces $u(s)=1/s$ in the Laplace domain. This yields the following expression for the output spectrum:

$$y(s) = u(s) \cdot H(s) = \frac{K_p \cdot b_0 \cdot (s + \frac{K_i}{K_p})}{s \cdot (s - p_1) \cdot (s - p_2)} \quad (11)$$

By reversed factorisation, equation (11) can be rewritten as:

$$y(s) = Q_0 + \frac{Q_1}{(s - p_1)} + \frac{Q_2}{(s - p_2)} \quad (12)$$

where Q_0 , Q_1 and Q_2 are constants given by:

$$Q_1 = \frac{b_0 \cdot K_i}{p_1 \cdot p_2}$$

$$Q_2 = \frac{b_0 \cdot (K_p + \frac{K_i}{K_p})}{p_2 - p_1} \quad (13)$$

$$Q_3 = \frac{b_0 \cdot (K_p + \frac{K_i}{K_p})}{p_1 - p_2}$$

Taking the inverse Laplace transform of equation (12) yields the output response $y(t)$:

$$y(t) = Q_0 + Q_1 \cdot e^{p_1 t} + Q_2 \cdot e^{p_2 t} \quad (14)$$

Figure 4 displays the output response function $y(t)$ of equation (14) for the case $a_0=7$ and $b_0=5$ and various sets of controller variables K_p , K_i .

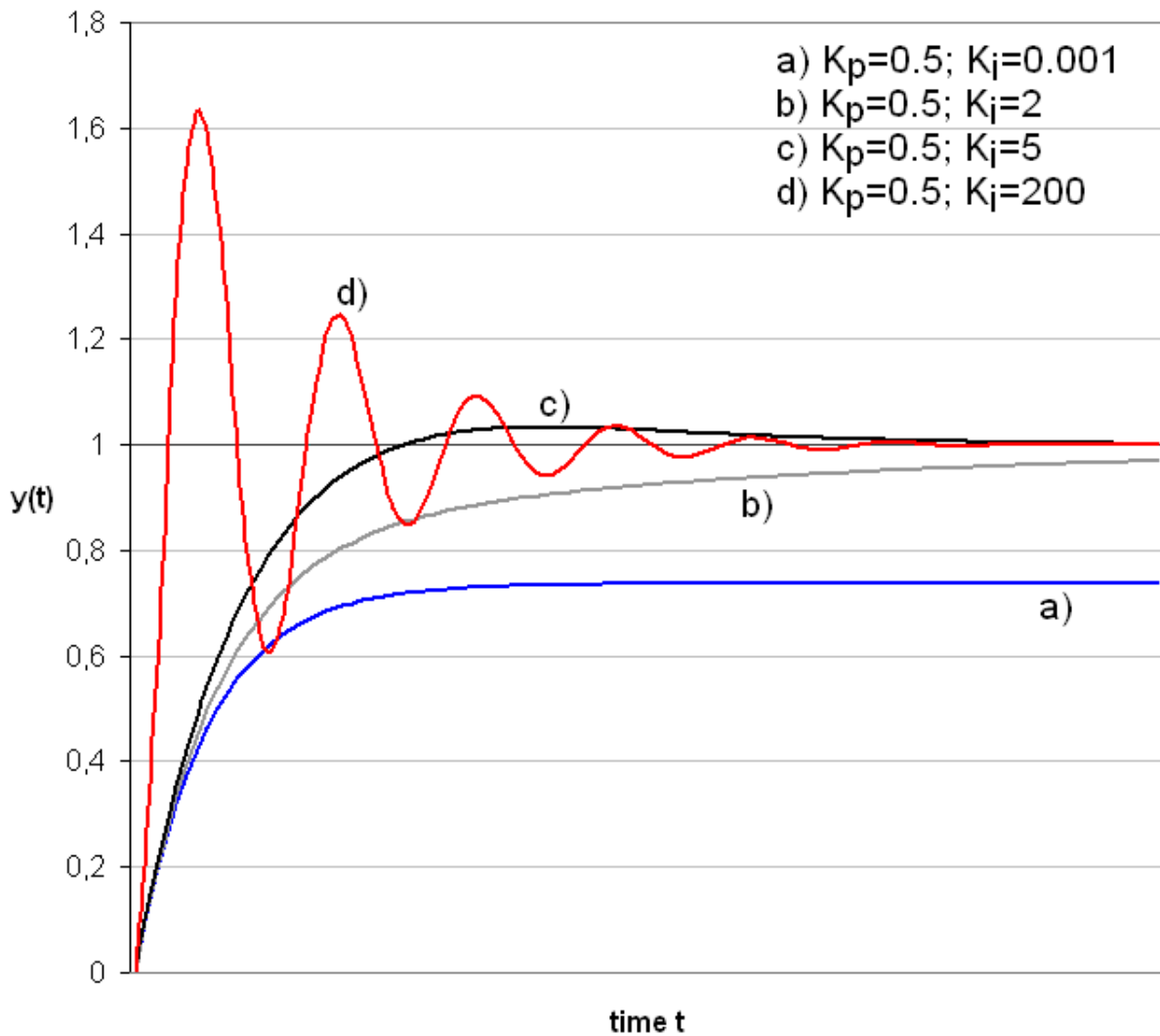


Figure 4. Three different closed-loop time response functions for $a_0=7$ and $b_0=4$.

Curve a) in figure 2 is dominated by proportional control. It produces a large settling time because error correction gradually decreases with decreasing error. The long term behaviour saturates well below unit value. Such steady state tracking error signifies structural loss of system performance. In curve d), which is greatly dominated by integral control, the response is much faster response, but as a side effect prolonged oscillations are visible. These are due to the large weight function K_i , which accumulates the errors of the past that can only be compensated for by creating errors with opposite signs. Intermediate curves b) and c) balance between the two control mechanisms and show a more gradual approach towards the ideal response value $y(t)=1$. Optimisation of the response function requires careful tuning of the controller parameters K_p and K_i .