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Design of a Self-Control Mechanism for an GDA-Based Tutor Module of an Intelligent Tutoring System

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Abstract

Cognitive control is often conceptualized as an opposite term to automaticity. Automaticity is related to the ability of a cognitive system to execute tasks with minimal effort using a streamlined well-practiced behavior. Cognitive control is a complement to automatic behavior when doing effortful biasing on unpracticed goal-directed behaviors. The objective of this paper is to present a first computational implementation of a cognitive control mechanism in a GDA-Based Tutor Module of an ITS (Intelligent Tutoring System) for the Personalization of Pedagogic Strategies using the theoretical approach of the theory of Koechlin & Summerfield. An overview of these authors' conceptual model of cognitive control is provided and how the quantitative aspect of this theory was implemented in the tutor module. This mechanism enables the ITS tutor module to incorporate additional techniques for responding to unforeseen situations. Moreover, an illustrative example about an ITS that facilitates healthcare protocols teachings for the early diagnosis of gestational and congenital syphilis is described.

Keywords: Self-control, cognitive control, GDA, Intelligent Tutoring System.

1. Introduction

Intelligent Tutoring Systems (ITS) provide a dynamic learning environment promoted by mechanisms of individualized teaching and feedback (Almurshidi et al., 2016). One of the main challenges in designing an ITS is instructional planning because planning plays a vital role in this system (Gómez et al., 2021). (Gomez et al., 2018; Gómez et al., 2021) state that the goal of an ITS is dynamically selecting and adapting these pedagogical strategies to the student's learning styles when inferring the pedagogical strategies based on the learner's performance and needs. This specific type of ITS presents some anomalies related to failures when pedagogical strategies are selected or loaded. For that reason, the amount and complexity of mechanisms that structure the personalization and adaptation of pedagogical strategies make this process a time-consuming and challenging task. Looking for necessary actions to reach a goal is one of the objectives of Planning (Dannenhauer & Muñoz-Avila, 2015). Also, triggering expectations, detecting discrepancies, and executing actions for achieving goals in the reasoning loop are necessary conditions in planning an autonomous system (Molineaux et al., 2012).

Goal-Driven Autonomy (GDA) is a goal reasoning method focused on formulating new goals through discrepancies explanation which enables the system to be more self-sufficient (Molineaux et al., 2010). Autonomous systems with this type of ability enable efficient self-regulation and self-control (Cox, 2013). Metacognition is one of the principal characteristics of goal reasoning (Samsonovich, 2014). Self-control makes part of the metacognitive abilities as self-regulation of an autonomous system (Samsonovich, 2012). (Anderson & Oates, 2007) present self-control as a metacognitive skill in intelligent systems that allow them to know when something is amiss, to evaluate and solve anomalies. (Coward & Sun, 2004) stated that self-control includes selecting reasoning methods, controlling the direction of reasoning, and assesing its progress. Also, (Sun & Mathews, 2012) affirms that self-control can include setting goals in processes of automatic responses or drives, setting essential parameters, interrupting, and changing ongoing processes. Cognitive control is often conceptualized as an opposite term to automaticity. Automaticity is related to the ability of a cognitive system to execute tasks with minimal effort using a streamlined well-practiced behavior. Cognitive control is a complement to automatic behavior for effortful biasing on unpracticed goal-directed behaviors. At this point, cognitive control can be presented as a complement of GDA mechanisms when the system faces novel situations or contexts that automatic behaviors of the system cannot address. Self-control has had many computational implementations aiming to give autonomy to intelligent systems (Caro et al., 2018; Dannenhauer et al., 2014; Grislin-Le Strugeon et al., 2005; Oh et al., 2021; Samsonovich et al., 2008; Sun et al., 2006, p., 2021), as well as theoretical approaches inspired from the human brain (Koechlin & Summerfield, 2007; O'Reilly, 2006; O'Reilly et al., 1999, 2010; Pezzulo & Castelfranchi, 2009; Verguts, 2017). However, current works in ITS that incorporate components of reasoning or techniques of GDA-based planning do not present mechanisms of self-control of pedagogical strategies used by the system. In previous research (Gomez et.al., 2020), we created the first ITS that used GDA mechanisms in its tutor module to personalize pedagogical strategies. However, the system lacked autonomy processes that allowed to increase its efficiency of selecting select a pedagogical strategy considering learner performance and preferences. Thus, self-control mechanisms are necessary for decreasing the system's automaticity when it creates its own goals.

(Koechlin & Summerfield, 2007) presents a theoretical approach of executive control as simple routines for selecting actions. The approach measures the amount of information required for each process using the statements of information theory. We implement the approach computationally with a goal-based system using the GDA mechanism. For this reason, the objective of this paper is to present a model of self-control for a GDA-Based Tutor Module of an ITS for the Personalization of Pedagogic Strategies using the theoretical approaches of (Koechlin & Summerfield, 2007). This paper is structured as follows: In the second chapter, we explain an overview of models of cognitive control. The next chapter shows the model of the self-control mechanism of GDA-based Tutor Module for the Personalized Adaptation of Pedagogic Strategies in ITS. The fourth chapter describes the Illustrative Example of the model. Finally, the conclusions of this study are presented.

2. **Models of cognitive control**

Cognitive control refers to a series of mechanisms to optimize cognitive processes oriented towards resolving complex situations (Roberds, 2015). These processes comprise various components, including working memory, such as the capacity of guidance and adequacy of attentional resources, inhibition of inappropriate responses in certain circumstances, and monitoring behavior of the organism's motivational and emotional states (Buehler, 2018). There are several formal theoretical investigations in the study of cognitive control useful for designing computational models that can simulate mechanisms of the human brain for executing this type of control. Many theoretical approaches attempt to explain the functioning of human cognitive control. (Shimamura, 2002), in his dynamic filter theory, states that four aspects of executive control characterize the information filtering process: selection, maintenance, updating, and redirection. According to the theory of cognitive complexity and control of (Zelazo et al., 1997), the development of executive control functions during childhood implies the appearance of a series of cognitive capacities that are necessary for the child to maintain, manipulate and act on the information self-regulate their behavior, act in a reflective and not impulsive manner, and adapt their behavior to changes that may occur in the environment. (Stuss et al., 1995) proposed a model on how the frontal lobe relationships operate that serve to control the functions of more basic schemas. These authors define a scheme as a network of interconnected neurons that can be activated by sensory inputs, by other schemes, or by the executive control system. (Christoff et al., 2003), in his theory, presents reasoning processes as information manipulation mechanisms at different levels of complexity. The proposal by (Koechlin & Summerfield, 2007) describes the anterior-posterior organization of the lateral prefrontal cortex (CPFL) in cognitive control, allowing an important advance in the understanding of the neuroanatomical substrate of executive functioning. The model postulates that the CPFL is organized as a cascade of representations extending from the premotor cortex to the most anterior regions of the CPFL. Based on information theory, this approach determines the total amount of information $H(a)$ required for selecting an action through the following equation: $H(a) = -log_2 p(a)$ where $p(a)$ is the relative frequency or probability that the action can be selected. The processing of stimulus is given by the mutual information $I(s,a)$ using the following formula: $I(s,a) = log_2[p(s,a)/p(a)p(s)]$ This mutual information is referred as sensorimotor or reactive control. This same author also considers the following quantity, usually referred to as the conditional information: $Q(s) = H(a) - I(s,a) = -log_2 p(s)$ This quantity $Q(s)$ corresponds to the cognitive control. Furthermore, total information *H(a)* for selection a is the sum of sensorimotor control $I(s,a)$ and cognitive control $Q(s)$ (Figure 1). A key feature of cognitive control is that it can be similarly broken down into two further terms, as follows: $Q(s) = I(s) + Q(s,c)$. The first term represents contextual control and the second term is the remaining information of past events. This study will emphasize Koechlin's theory of differential axes and his mathematical model of quantification of self-control.

3. Model of Self-control for a GDA-based Tutor Module of an ITS

One of the most important modules of an ITS is the tutor module (Rongmei & Lingling, 2009). Pedagogical model of the tutor module of an ITS executes the process of selection of the most adequate pedagogical strategy to facilitate the learning of students (da Silva, 2012). An ITS with capabilities of personalizing its pedagogical strategies can adapt its instructional plans in a personalized way considering the performance and interests of the learner. This process takes into account pedagogical theories, teaching strategies and pedagogical knowledge rules stored in the pedagogical model (Caro & Jiménez, 2014). Also, the pedagogical model contains instructional plans as resources of learning lessons generated by a GDA controller to promote achievement learner' learning objectives (Gómez et al., 2021).

In a previous research, (Gómez et al., 2021) presented a GDA controller that facilitates the selection of new goals in each learning lesson of the ITS. The ITS presents the following structural characteristics: An initial goal g_0 given to the *Planner* by the *Metacore Package.* This *Metacore Package* links the components of the system through information traces. The *Planner* using Domain D, the problem P, and g_0 to generate a plan, $\pi = < a_i, a_{i+1} \dots a_n >$, where a_i is an action that is stored in the *Metacore Package* to be later executed by the ITS Graphic User Interface. At this moment, the *Planner* generates expectations, x, which are given to GDA Controller *Discrepancy Detector.*

This *Discrepancy Detector* uses an ontology to compare ITS world facts and inferences from these facts to the expectations x. The ITS world current state, S, is a set of facts f,which are represented as triples $f = < S_p, C_s^s, R_s >$ where R_s is a **Selected Resource** in a given time, S_p and C_s^s will be explained later. This matching process allows us to detect if exists a discrepancy between the current state and the expected state. Thus, in this research, an expectation x consists of in the activated resource and completed activity *(the completion of an activity consists of the achievement of an expected minimum score).* A discrepancy d, is the contradiction of the previously described *(Deactivate resource and uncompleted activity)*.

The *Explanation Generator* gives an explanation for the detected discrepancy. This GDA component generates a hypothesis as explanation e that describes d, taking into account an ITS world current state, S and a discrepancy d.

The *Goal Formulator* uses this explanation to build a new goal g_n to pursue, with $g_n \in G_p$, where $G_p$represents the pending goals of the ITS GDA Controller (the ITS first pending goal is the initial goal g_0). This goal g_n constitutes from the response to an explanation e and a discrepancy d in the ITS world current state S.

Then the *Goal Manager* update G_p adding g_n which may also ensure other edits (e.g., to remove and to modify goals). The Goal Manager will select g_n and turn it into g_c to be given to the Planner.

In this study, a self-control mechanism is proposed to improve this selection process so that it can be less automatic. It can be regulated considering the performance and interests of the students determined by the interaction history with the system. In a previous research, (Gómez et al., 2021) presented a GDA controller that facilitates the selection of new goals in each learning lesson of the ITS. Thus, just before creating new goals using the GDA controller, the ITS will have the possibility of self-regulating this process considering previous episodes of performance and interest of the learner.

According to the model proposed by (Koechlin & Summerfield, 2007), self-control can be fractioned in a temporal framing of actions and events involved in the selection process. In this way, considering a stimulus s which in the model proposed is the Student Profile $S_p = < S_i , S_s^l, S_d, S_s^p >$ which is a 4-tuple where S_i is the student identifier, S_s^l is the Student Learning Style, S_d is the Pedagogical Dimension assigned to the Student by the system and S_s^p is the Pedagogical Strategy assigned to the Student by the system. The initial goal of the ITS g_0 is received by the *Planner* from the *Metacore Package.* Also, *Planner* receives vital information for generate a plan constituted by D and P. Both S_p and C_s^s make part of D and $C_s^s =< C_i , C_l^c , C_l^s >$ it is the selected course by the student where C_i is the Course ID, C_l^c is the Current Course Lesson and the C_l^s is the structure of the Current Course lesson. The Planner generates a plan, $\pi = < a_i , a_{i+1} \dots a_n >$. Where a_i is an action that is stored in the *Metacore Package* to be later executed by the ITS Graphic User Interface. This plan π comprises the principal action regulated by the self-control mechanism.

Algorithm 1 shows the main actions of self-control of ITS. Lines 1 and 2 specify actions and stimulus managed by the self-control mechanism. Reactive functions of the system.

Algorithm 1 The *SelectAction* procedure describes the reactive control of the system. Also, the cognitive control procedure shows the code that uses the system for processing the cognitive control conditions.

1. **global** $K_b = [\ ]$ $I_m = [\ ]$ ⇒ The Knowledge base contains all plans created by the system
2. **procedure** *SelectAction* (S_p)
3. i ← 0
4. While i < EOF (K_b) ⇒ All case base is examined
5. $R_c \leftarrow log_2[p(S_p, K_b[i].\pi)/p(K_b[i].\pi)p(S_p)]$ ⇒ Reactive control between S_p and π is inquired
6. $I_m[i] \leftarrow R_c$
7. i++
8. $o \leftarrow pos\ (max\ (I_m))$
9. $return(K_b[o].\pi)$ ⇒ The plan with the highest mutual information is selected
10.
11. **procedure** *CognitiveControl* (δ, s^π, h, S_p) ⇒ δ is performance, s^π is score, h is interaction history
12. $t \leftarrow$ *SelectAction* (S_p) ⇒ Reactive behavior of the ITS is invoked
14. $Q_c \leftarrow -log_2 p\ (t) - max\ (I_m)$ ⇒ Key feature of cognitive control: contextual control plus remaining information conveyed by past events.
15. $Q_f \leftarrow Q_c + p(\delta) + p(s^\pi) + p\ (h)$
16. $return\ (Q_f)$

4. Illustrative example

The previously described mechanism of cognitive control was implemented in an ITS called Fichas y Protocolos en Salud. This ITS is used in the nursing program of the Universidad de Córdoba-Colombia for the teaching process of healthcare protocols for the early diagnosis of gestational and congenital syphilis.

Figure 1 presents a screenshot of the lesson plan presented to a student according to his profile using the automatic response mechanisms of the system when the learner is logged in the system for the first time. This information, solicited by the planner, is complemented by intern codification in PDDL language used to build the domain and the problem in the reasoning process of the ITS. In this way, four topics are presented to the student related to the course Maternal and child health.

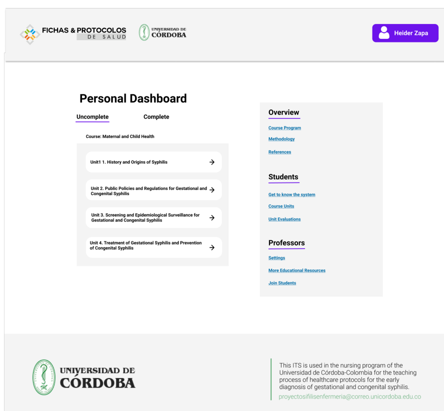

Figure 1. Lesson plan created with automatic mechanisms of the system.

Figure 2 presents the result of the cognitive control mechanism in the ITS reasoning process. The pedagogical strategies selection process has been developed considering the performance and other control conditions. These control conditions are related to loading and selection of resources. Thus, the resources are shown to the student for the third time. At that moment, the system is waiting for the response of the student to use the GDA mechanism. Finally, the data are saved in the trace of the student.

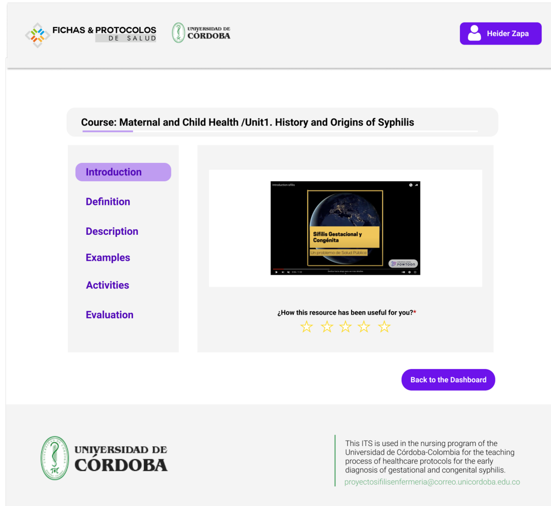

Figure 2. Cognitive control mechanism in the ITS reasoning process presenting resources to the student.

5. Conclusions and Future Work

This paper presented the computational implementation of a theoretical approach of control cognitive in a GDA-based tutor module of an ITS. The study allowed the integration of the cognitive control mechanisms into a GDA controller component in the ITS tutor module packages. The GDA controller enables the tutor module to determine when new goals should be selected and decide which goals should be pursued at each learning lesson. The GDA controller enables the tutor module to determine when new goals should be selected, and to decide which goals should be pursued at each learning lesson. For this, the tutor module must know the student profile, and courses in which the student is enrolled and associated with the resources of these courses. Also, GDA controller enables the ITS tutor module to incorporate additional techniques for responding to unforeseen situations. However, the system presented anomalies related to failures when pedagogical strategies were selected or loaded. The cognitive control mechanism improves this process, adding autonomy to the system's decisions when choosing pedagogical strategies. This mechanism facilitated the selection of pedagogical strategies considering the student’s performance, score, and interaction history. An illustrative example regarding an ITS facilitates the healthcare protocols teachings for the early diagnosis of gestational and congenital syphilis. This ITS will allow solving the existing problems in learning the protocols of early detection of the infection, in the timely identification of the contacts, to improve the efficiency in the evaluation time of medical consultations and the ignorance of public policy by part of health professionals.

The ITS *Fichas y Protocolos en Salud* has a limited set of algorithms of decision. In future research, we will develop a cognitive system that will use deep learning algorithms to improve this process of decision-making. Also, this cognitive system will have introspective monitoring procedures that will significantly improve the system's performance.

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