Modelling an Intelligent Tutoring System based on Supervised Behaviour Biometrics

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Abstract

The needs of skilled people have grown exponentially, which means that resources for education/training are significantly more limited. Intelligent Tutoring Systems (ITS) aim to enable users to improve knowledge and develop skills in a specific field. Moreover, the ITS offers individual and autonomously tutoring making each user progress at their capacity. In this paper, we present a new approach of an ITS to monitor users' biometric behaviour, learning style, and user's emotional state during e-learning activities to improve learning. So we develop a new framework to obtain emotional student state and learning style, based on a non-intrusive and non-invasive way.

1 Introduction

Education in the 21st century requires people applied continuous and lifelong learning. Learning environments, namely ITS, allow users to acquire knowledge and skills, which is oriented and adapted to the rhythm of each user. However, ITS is a complex learning platform, who contains intelligent algorithms. Yet, this platform should incorporate some basic activities like active user learning, interactivity, adaptability, and feedback.

The main objective of an ITS is to make these technologies adaptable to users, based on their individual characteristics and needs [DTGN19a]. Thus, an ITS provides individual benefits of automatic and autonomous tutoring, making each user progress at their own pace. To these systems, it is necessary to apply the concept of adaptive and interactive learning, to make it a powerful learning tool [Bru03].

The resources and expertise to build an ITS come from various areas of research, including Artificial Intelligence, Cognitive Sciences, Science Education, Human-Computer Interaction, and Software Engineering. Build this system is not an easy task. This multidisciplinary makes the process of building an ITS challenging, since

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the authors, who are from different areas, may have very different views of the system [PCNN15]. Consequently, some will be able to promote pedagogical precision, ensuring that the tutorial decision-making is based on pedagogical principles. Others may focus on the effective diagnosis of user errors, using the knowledge structure and appropriate algorithms to correctly interpret the user's decisions. So, ITS are complex computer programs that generate various heterogeneous types of knowledge [Mur99].

In this paper, we conducted a new proposed ITS framework in order to obtain data from behavior biometric, learning style, and user's emotional state during e-learning activities.

Consequently, this paper is organized as follows. After this introduction, section 2 introduces the definitions of the concepts of an ITS and affective computing. Then, section 3 presents a proposed ITS framework. Next, section 4 presents some application methods and results. Finally, section 5 concludes the study by performing a global analysis of the presented research.

2 State of Art

Currently, there are several types of tutors, however, these tutors have not completely achieved the desired objectives, since they are either autonomous or adaptable, but not both. Besides, they do not consider in real-time an important element that affects users' learning: their emotional state. There are some of these tutors who assess the user's emotional state only at the end of the work sessions, which is not enough to improve the learning environment [DTGN19b].

2.1 ITS

The typical architecture of an ITS has the following components: Expert Model, Student Model, Tutor Model, and Interface [AS13].

The Expert Model contains all the concepts, facts, rules, and strategies for solving problems in a given pedagogical domain. Also, it serves as a source of specialized knowledge, which is, a standard for assessing user performance and diagnosing their errors [AS13]. Finally, it performs data analysis and can also make predictions about the knowledge of a given user, as it observes the actions performed by that user.

The Student Model is an overlay of the Expert Model. This model contains the user's cognitive and affective states in association with their evolution as the learning process progresses. As the user works step by step in the problem-solving process, the system analyzes the user's interaction with the system [AS13]. This model contains the dynamic monitoring of the user's emerging knowledge and skills.

The Tutor Model is the part of the ITS that designs and regulates interactions with the user. This model accepts information from Student Model and Expert Model. Also, it is closely linked to the Student Model, since it makes use of knowledge about the user and its structure of tutorial objectives, to design the pedagogical activity to be introduced. It also monitors student progress, creating a profile of strengths and weaknesses concerning production rules [AS13].

The Interface is the front-end interaction with the ITS. This system integrates all types of information necessary to interact with the user, through graphics, text, multimedia, video, menus, etc. The Interface is the communication component of the ITS that controls the interaction between the user and the system. The interface translates the internal representation of the interface system to an understandable language for the user and vice versa [AS13].

2.2 Affective Computing

According to [HAN04], the evolution of affective computing is related to the need to put computers interacting, thinking, receiving and transmitting people's personalities.

Picard and Hassin [Pic99], [HAN04] highlight affective computing as a research area, which explores how computer systems can identify, classify and prove human personality.

Affective computing can increase the capabilities of conflict management with the customer, as well as increase the efficiency of recommendation systems. Affective computing is about: (a) understanding how emotions play vital roles in persons; (b) regulating our intention; (c) helping people make good decisions; and (d) changing the way we emphasize and prioritize things. Consequently, it is possible to build a personalized computer system with the ability to perceive and interpret the feelings of the human being, providing intelligent, sensitive and adapted responses to situations [PPB$^+$04].

3 Proposed Design

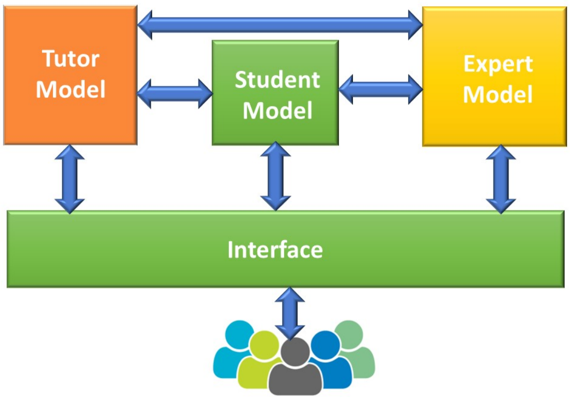

Figure 1: General Structure of an ITS.

Based on the state of the art section, the idea is to create an ITS adapted to each user, established on behaviour characteristics. In this first phase, a general structure of an ITS was developed, based on the traditional ITS general framework, which is shown in Figure1. The ITS is composed by 4 main parts: Expert Model, Student Model, Tutor Model, and Interface. With this general framework, we proposed a new framework for every four main parts.

The Expert Model, presented in Figure 2 contains the domains with program content. This domain its divide .in two parts: the content area and the performance area. The content area includes all concepts, facts, and problem-solving strategies for a given domain. Furthermore, the model contains the rules for each domain. The performance area has a standard assessment performance for evaluating user performance and allows diagnosing errors. Also, it is in the expert model that data analysis is performed and it is also possible to make predictions about the knowledge of a given user, as he observes the actions performed by that user.

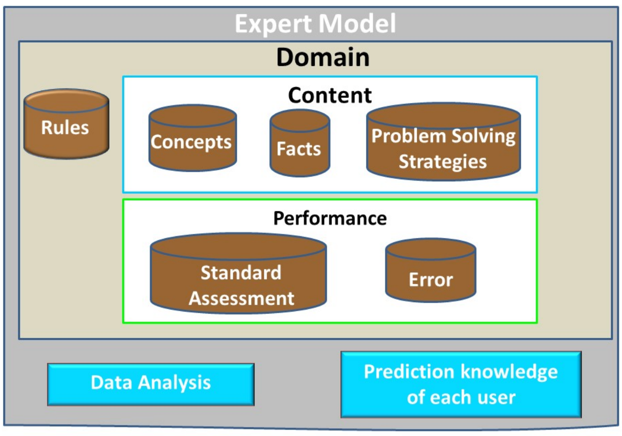

Figure 2: Structure of Expert Model.

The Student Model, presented in Figure 3 is subdivided into four levels: student style, student cognition, student emotion and monitor knowledge and skills. In the first level, student style is based on the user's learning style and user interaction with the systems, where type of learning is classified.

In the second level, student cognition, based on the users' cognitive states during learning, the user's cognitive state is classified. In the third level, student emotion, based on the user's emotions during learning, the user's current emotion is classified. Finally, at the fourth level, monitor knowledge and skills, the user's profile is

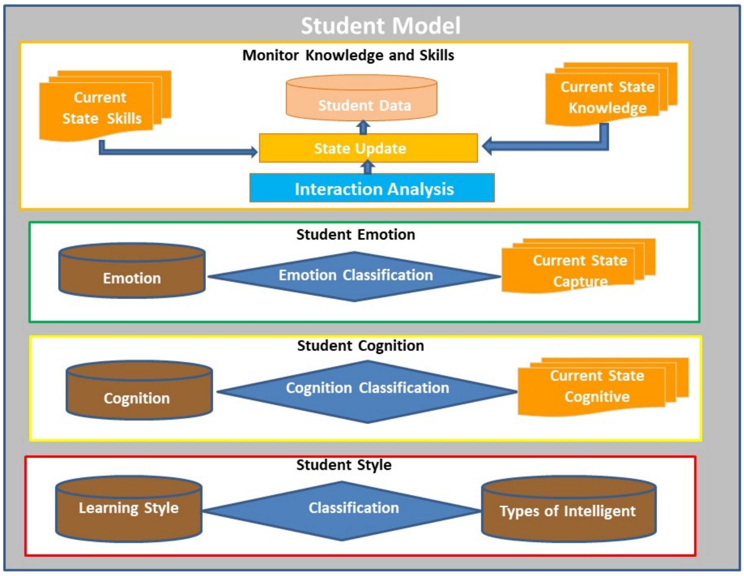

Figure 3: Structure of Student Model.

created concerning their learning evolution. All of this information is stored in its database. As the user works step by step in the problem solving process, the system analyzes the user's interaction with the system.

The Tutor Model, presented in Figure 4 accepts information from the Student Model and the Expert Model. Besides, it is closely linked to the Student Model, since it makes use of knowledge about the user and its structure of tutorial objectives, to design the pedagogical activity to be introduced. It also monitors user progress, creating a profile of strengths and weaknesses concerning production rules.

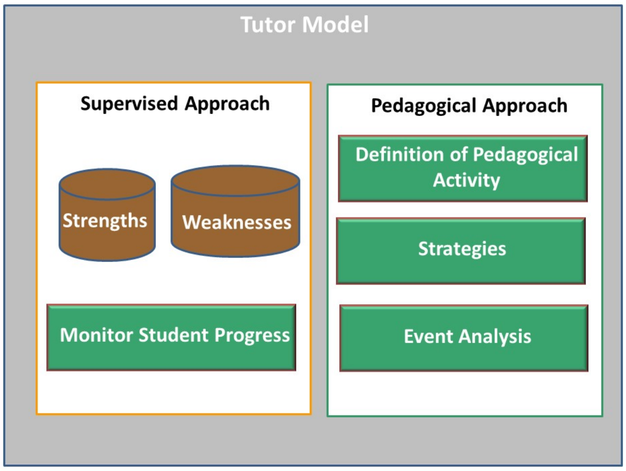

Figure 4: Structure of Tutor Model.

The Interface, presented in Figure 5 is the front-end interaction of an ITS. This system integrates all types of information necessary to interact with the user, through graphics, text, multimedia, video, menus. The Interface is the communication component of the ITS that controls the interaction between the user and the system. The Interface captures data from the user's interaction with the ITS. Data capture is done using a non-invasive and non-intrusive approach. There is a log application that runs in the background, saving the user's necessary events with ITS. This application has a device that generates raw data that describe the user's interaction with the system: mouse, keyboard, and activity. There are also flexible sensors that use the information available from other measurements and process parameters to calculate and estimate the amount of raw data. The raw data generated is stored locally until it is synchronized with the web server in the cloud at regular intervals, usually every 5 minutes.

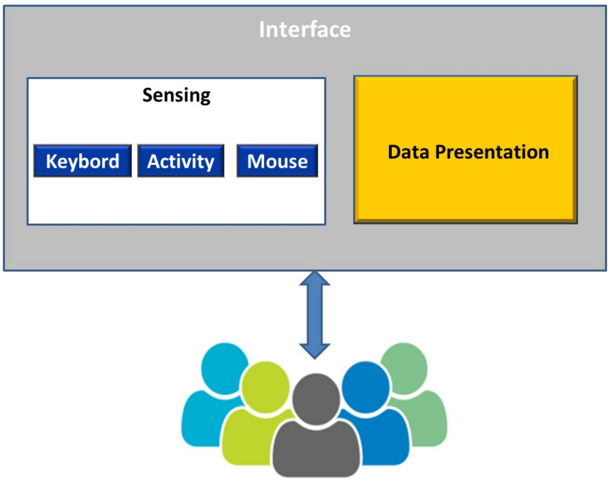

Figure 5: Structure of Interface.

4 Methodology and Results

In the present study, we only experimented the ITS to monitor the patterns user' behaviour. This is behaviour patterns based on mouse dynamics, keystroke, and user's activity. The idea is monitoring biometric behavioural variations for each activity and bases the set of attributes relevant and machine learning classifiers obtain user' learning preference. This approach used a non-intrusive method to assess the preferences of user while interacting with the computer.

4.1 Features Extraction

All involved participants presented computing proficiency and the rooms were equipped with similar computers, where each participant was randomly assigned to a computer. Information regarding each assessment's duration is presented in Table1.

Table 1: Summary of the characteristics of each assess activity.

		Duration (min)		
Class	Date	$\bar{x}$	$\tilde{x}$	S
Video	21/05/2018	7.31612E+15	8.4653E+15	3.00389E+15
Image	24/05/2018	9.99167E+15	1.21798E+16	4.7135E+15
Text	25/05/2018	6.19021E+15	7.29301E+15	2.64201E+15
Audio	29/05/2018	7.0459E+15	8.95808E+15	3.55391E+15

When the Tutor Model receives the data from sensing Interface, it transforms it so its features can be extracted. Specifically, it goes through the list of pairs and computes the time during which each window was active (Figure 6). When a user does not change applications for a large amount of time, which are represented by a pair with an empty AppName, the time is added to the last known AppName (since this means that the user is still interacting with it).

4.2 Dataset

The biometrics features captured of each case study were labeled with the respective activity. Besides, based on the biometric features recorded from different soft sensors, the distribution of each feature (e.g. mean, median, standard deviation, etc.) are displayed in different scales. To solve this problem, it was important to

Data:
p - A list of pairs of the type (AppName, Timestamp)
ft - the finishing time of the task
Result: durations - A list of triplets of the type (AppName, Timestamp, Duration)
durations ← [];
i ← 0;
while $i < Size(p)$ **do**
    task ← $p_{i,1}$;
    time ← $p_{i,2}$;
    i++;
    while $i < Length(p)$ *and* $StringLength(p_{i,1}) = 0$ **do**
        i++;
    end
    if $i = Length(p)$ **then**
        AppendTo(durations, task, ft, ft - time);
    else
        AppendTo(durations, task, $p_{i,1}$, $p_{i,1}$-time)
    end
end

Figure 6: Creating triplets with the duration and timestamp of each application.

apply features scaling (i.e. normalisation techniques). In this study, the two methods adopted were max-min normalisation and Z-score normalisation.

Max-min normalisation technique is a normalisation strategy which linearly scales feature value to range [0,1], based on the minimum and maximum values of the set of observed values [TGDN18]. In other words, the minimum value of the feature value is mapped to 0 while the maximum value is mapped to 1. As for Z-score, this technique is a stand-in for the actual measurement, and they represent the distance of a value from the mean measured in standard deviations [TGDN18]. This distribution technique is useful when relating different measurement distributions to each acting as a ‘common denominator’. With this, several machine learning categorisation methods were used to predict the user’s activity, through the analysis of his/her behaviour.

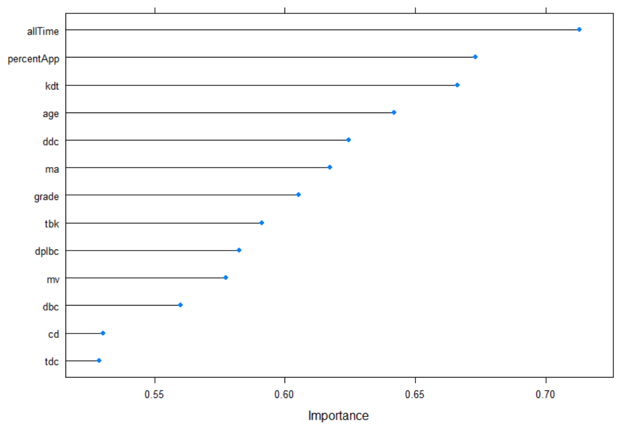

Figure 7: Random Forest: Features Relevance in Activity Classification.

Several classifiers were trained and tested to determine the most efficient method to categorise the student’s activity. The set of classification methods trained and tested were: Support Vector Machine, Nearest Neighbour, Naive Bayes, Neural Network and Random Forest. As for the validation method, a split validation method was used to determine the classification performance, where 2/3 of the study cases were used for training the classifiers while the remaining 1/3 was used to test it [TGDN18].

In the end, the model with the lowest error rate was the selected one. Figure 7 presents the set of results from this process, where it shows that the model displays an average minimised error when the number of decision trees is 80.

5 Conclusions

This paper presents the first approach to ITS. The approach aims to make the ITS non-invasive and non-intrusive. The entire ITS scheme is proposed, from the Expert Model, through the Student Model, through the Tutor Model to the Interface. Besides, it presents a lot of detail of the modules that make up each model.

It was also presented some results made from real tests that were applied to a group of students in a real context. These tests analyzed the biometric part of the behavior of different students with different learning styles. The system monitors and analyzes the dynamics of the mouse, keyboard, and tasks to determine the student's interaction with the computer.

In the future, we will continue to develop ITS, namely the Student Model, where we intend to create a system that aggregates all the information.

5.0.1 Acknowledgements

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