Supervising and Improving Attentiveness in Human Computer Interaction

Dalila Durães
Department of Artificial Intelligence
Technical University of Madrid
Madrid, Spain
d.alves@alumnos.upm.es

Davide Carneiro
Algoritmi Center, Minho University
Braga, Portugal
CIICESI, ESTGF
Polytechnic Institute of Porto
Felgueiras, Portugal
dcarneiro@di.uminho.pt

Javier Bajo
Department of Artificial Intelligence
Technical University of Madrid
Madrid, Spain
jbajo@fi.upm.es

Paulo Novais
Algoritmi Center
Minho University
Braga Portugal
pjon@di.uminho.pt

Abstract— **The collection, storage, management, and anticipation of contextual information about the user to support decision-making constitute some of the key operations in most Ambient Intelligent (AmI) systems. The aim of this paper is to propose an AmI system to support and enhance the learning process by capturing and measuring the level of students' attentiveness in real scenarios and dynamically provide recommendations to the teacher based on an individual profile created by the system. These profiles are ideal for generating learning style-based instructional material in bigger classes, as they don't have the same limitations that human instructors have due to the lack of resources and time to focus on individual students.**

Keywords— Ambient Intelligence, Learning Styles, Innovative Scenarios, and Attentiveness.

I. INTRODUCTION

We live in a global and hyper connected world where technology is present in all spheres of life and is the backbone for the transformation of our society. Our society is in permanent change and it requires continuous adaptation of the human being to the surrounding environment.

It's crucial to improve the learning process and create AmI systems in order to mitigate problems that might occur in an environment with learning technologies. Learning theories provide insight into the very complex processes and factors that influence learning as well as and provide precious information to be used in designing instruction that will produce prime results. The learning models are design in order to provide the students a practice, evaluation and improvement procedures which will adjust the model. The teaching process first requires that the teacher create a pedagogical design of the objectives and determine the content to be taught. Second, a pre-assessment is used to determine learning abilities. Third, pedagogical procedures are used when teaching is initiated. Finally, assessment is applied to determine whether learners have achieved, and, according to the assessment results, teachers should use feedback to determine the cause of ineffective instruction [1, 2].

However, students, for various reasons, may not be predisposed to learning. Moreover, each student has its own particular way of assimilating knowledge, that is, his/her learning style. In this sense, and in bigger classes, it is necessary that the teacher have instruments, which indicate that a particular student is using other applications and he/she isn't predisposed to learning. It is important to refer that each learning styles specify a student's own way of learning. Someone that has a specific learning style can have difficulties when submitted to another one [3]. When the given instruction style matches the student's learning style, the process is maximized which guarantees that the student learns more and more easily.

This way, the target of this paper is to propose architecture of an AmI aimed to capturing and measuring the level of students' attentiveness in real scenarios and dynamically provide recommendations to the teacher. This are ideal for generating learning style-based instructional material in bigger classes, as they don't have the same limitations as human instructors due to the lack of resources and time to focus on individual students.

II. STATE OF THE ART

There is no universally accepted definition of attention because there is a diversity of disciplines that focused on it. In the past, only psychologists studied attention, however in present days attention is highly important for other fields like philosophy, chemistry, anatomy, and even computational science [4].

The concept of attention may be defined as the transforming of a huge acquired unstructured data set into a smaller structured one where the main information is preserved. This means that there is a filtering input space that selects the most important data in processing and this is a key mechanism of behavioral control for tasks, which is related to planning, decision making, and prevent new situations, however there are limited computation capabilities [4, 5].

As with the brain, computers should analyse more and more data, but unlike the brain they do not or, do rarely, "pay attention" [4]. That is why an AmI system appeared, not to replace the human being, but to complement it.

A. Learning Styles

Previous research suggests that, in the context of learning activities, different learning styles can influence learning performance. Learning styles are considered one of the most important factors influencing learning [6].

Learning styles specify a learner's preferred ways of learning. Some researchers have argued that learning style is also a suitable indicator of potential learning success because it provides information about individual differences in learning preferences and information-processing [7, 8].

Learning style not only specifies how a student learns and likes to learn, as it can help a teacher to adapt to individual students, so that they might teach successfully. When the teaching environment doesn't support a specific student learning style, he/she has difficulty to learn and to acquire knowledge. When students are doing learning activities using news technologies, it's extremely important that the teacher has some feedback from the students work in order to detect potential learning problems at an early stage so that he can choose the appropriate teaching methods.

Learning styles are define as cognitive, affective, and physiological features that serve as relatively stable indicators of how learners perceive interaction and respond to their learning environments [9].

B. Ambient Intelligent

The collection, storage, management, and anticipation of contextual information about the user to support decision-making constitute some of the key operations in most AmI systems.

An environment AmI system is where technology is embedded, hidden in the background, where technology is sensitive, adaptive and responsive to the presence of people and objects. This system also preserves security and privacy while using information when needed and an appropriate context [10].

In ours case adaptive systems aim at supporting and enhancing a student's learning process [11]. In their supply of adaptability, adaptive systems generally consider the student's knowledge, background, interest, goals, targets and/or choices [12].

III. Architecture

When students are affected by positive or negative states, they produce different kinds of thinking and this might hold important implications on the educational and training perspective. When that occurs it would be important to be able to notify and advice the teacher, so he can be able to dynamically modify the teaching style according to students' feedback signals which include cognitive, emotional and motivational aspects.

While the student conscientiously interacts with the system and takes his/her decisions and actions, a parallel and transparent process takes place in which the AmI system uses the information. The architecture of the AmI system (Fig.1) depicts the process through which the system operates. It is possible to be divided into three major parts.

The devices that generate raw data (eg. laptops) compose the lower level. These devices store the raw data locally until it is synchronized with the web server in the cloud, which occurs at regular intervals.

The middle level is composed by three layers: the storage, analytics, and classification profile. In the storage layer the raw data received from the lower level is stored in a data store engine. The analytic layer provides a powerful tools for performing analytics and statically analysis in real-time. This layer simplifies codes and limits resources requirements. It's important that in this process some values are filtered to eliminate possible negative effects on the analysis. The system calculates, at regular intervals, an estimation of the general level of performance and attention of each student. The classification profile layer is where the indicators are interpreted. For example, interpreting data from the attentiveness indicators and build the meta data that will support decision-making. When the system has sufficiently large dataset that allows making classifications with precision, it will classify the inputs received into different attention levels in real-time. This layer has access to the current and historical state of the group from a global perspective, but itcan also refer to each student individually creating each student learning styles.

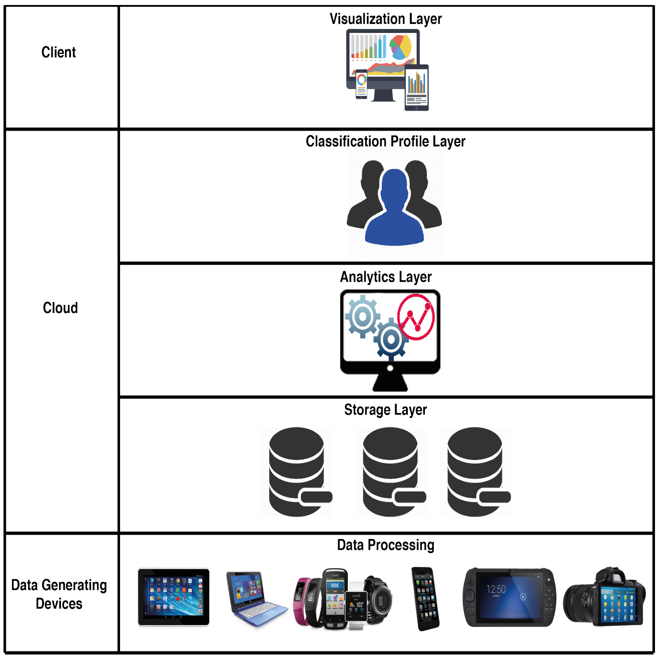

Fig. 1. Architecture of the system.

The classification profile is also a very important aspect to have control off. This possibility allows to analalises within longer time frames. This layer, whose function detect student's mood preserving those information (actual and past) in the mood database. This information will be used by another sub-module, the affective adaptive agent, to provide relevant information to the platform and to the mentioned personalization module.

Finally the higher level is developed as a web app with an intuitive and visual representations (diagrams and graphical) of the attentiveness states and learning styles of each students', abstracting from the complexity of the data level where they are positioned. At this point, the system can start to be used by the people involved, especially the teacher who can better adapt and personalize his teaching strategies. With a focus on individual and group performance real time analytics, the visual representation tools are intuitive, suggesting and facilitating the decision-making and human resources management. The actual students' mood information is displayed in the visualization layer, and can be used to personalize instruction according to the specific student, enabling the teacher to act differently with different students, and also to act differently with the same student, according to his/her past and present mood.

A. Data Acquision

Once information about the individual's attention exists in these terms, it is possible to start monitoring attentiveness in real-time and without the need for any explicit or conscious interaction. This makes this approach especially suited to be used in learning activities in which students use computers, as it requires no change in their working routines. This is the main advantage of this work, especially when compared to more traditional approaches that still rely on questionnaires (with issues concerning wording or question construction), special hardware (that has additional costs and is frequently intrusive) or the availability of human experts.

It is possible to collected data that describes the interaction with both the mouse and the keyboard [13]. Previous work on this data collection tool and analysis can be found in [14,15] where a deeper analysis about this process is explained in detail.

The data collected by the logger application, characterizing the students' interaction patterns, is aggregated in a server to which the logger application connects after the student logs in. This application runs in the background, which makes the data acquisition process, non intrusive and a completely transparent one, from the point of view of the student. At regular time (around 5 minutes) the server receives a new set of raw data about each student.

With this new data, the server has access not only to the exchanges with the mouse and keyboard, but also to the application switched for each student at a given timestamp. The new raw data received at regular intervals is a follows: (Id, Username, Timestamp, [AppName, Timestamp]).

The Mouse and Keyboard collected data captured information describing the behavioral patterns of the students', and receiving data from events mouse and keyword students'. This layer encodes each event with the corresponding necessary information (e.g. timestamp, coordinates, type of click, key pressed). These data are further processed, stored and then used to calculate the values of the behavioral biometrics. Mouse movements can also help predict the state of mind of the user, as well as keyboard usage patterns.

The Analytic layer is responsible to process the data received from the storage layer in order to be evaluated those data according to the metrics presented. It's important that in this process some values are filtered to eliminate possible negative effects on the analysis (e.g. a key pressed for more than a certain amount of time). The system receives this information in real-time and calculates, at regular intervals, an estimation of the general level of performance and attention of each student.

B. Extraction of Behavioural Features

After the server received the data described in previous subsection, the AmI system needs to filter and depict all the information. Data was analyzed in two different ways. First, a general analysis was carried out with the aim of searching for group trends, i.e., behaviors common to a significantly large slice of students. Secondly, an individual analysis was made, in order to compare the different moments.

In the first step, the AmI system counts the number of interactions with the keyboard and the mouse in order to determine each data length student in each class. This data are the general activity that each student has with the keyboard and the mouse. Fig.2 and Fig.3 present respectively the keyboard and mouse interactions of each student in each class. The data collected from the keyboard and mouse are specified in a previous work [13]. The features measure is: for the keyboard kdt and tbk; and for the mouse mv, ma, cd, tbc, dbc, ddc, edbc, aedbc, ssdbc, asdbc, tdc, dplbc, and adplbc.

$$\begin{pmatrix} \mathrm{T2210001} & \{10, 10\} \\ \mathrm{T2210002} & \{11, 11\} \\ \mathrm{T2210003} & \{10, 10\} \\ \mathrm{T2210004} & \{6, 6\} \\ \mathrm{T2210006} & \{10, 10\} \\ \mathrm{T2210007} & \{9, 9\} \\ \mathrm{T2210008} & \{9, 9\} \\ \mathrm{T2210009} & \{11, 11\} \\ \mathrm{T2210010} & \{9, 9\} \\ \mathrm{T2210012} & \{11, 11\} \end{pmatrix}$$

$$\begin{pmatrix} \mathrm{T2230001} & \{13, 13\} \\ \mathrm{T2230002} & \{11, 11\} \\ \mathrm{T2230003} & \{13, 13\} \\ \mathrm{T2230004} & \{9, 9\} \\ \mathrm{T2230011} & \{9, 9\} \\ \mathrm{T2230013} & \{7, 7\} \\ \mathrm{T2230014} & \{11, 11\} \end{pmatrix}$$

Fig. 2. Number of keyboard interactions for each student in each class. The features are: username, kdt, tbk.

T2210001	{10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10}
T2210002	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}
T2210003	{10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10}
T2210004	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}
T2210006	{10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10}
T2210007	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T2210008	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T2210009	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}
T2210010	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T2210012	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}

T7110061	{10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10}
T7110062	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}
T7110064	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T7110066	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T7110068	{9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9}
T7110072	{11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11}
T7110073	{10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10}

Fig. 3. Number of mouse interactions for each student in each class. The features are: username, mv, ma, cd, tbc, dbc, ddc, edbc, aedbc, ssdbc, asdbc, tdc, dplbc, and adplbc.

In the second step, the AmI system calculated the time spent for each student in each class with the mouse (Fi.4). In this step it is possible to verifying the mouse activity of each student in the class. This mouse activity depends on the subjects that are applied in the class.

T2210001	50.0026 min
T2210002	55.0297 min
T2210003	50.011 min
T2210004	55.0029 min
T2210006	50.0025 min
T2210007	50.0023 min
T2210008	45.0024 min
T2210009	55.0017 min
T2210010	50.0011 min
T2210012	55.0025 min

T2230001	69.978 min
T2230002	64.9661 min
T2230003	64.983 min
T2230004	64.9835 min
T2230011	59.9824 min
T2230013	59.9943 min
T2230014	59.9881 min

Fig. 4. Time spent interacting with the mouse for each student in each class.

In the third step, the AmI system goes through the list of pairs and measures the time during which a window was active. Often there are cases in which the student doesn't change applications for a large extended period of time. In this case, which are represented by a pair with an empty AppName, the time is added to the last known AppName (since this means that the student is still interacting with it). Fig.5 presents an example of the output of the process.

In the four steps, it quantifies the compute level of attention of each student. In this sense it is necessary to measure the amount of time in each interval, that the student spent interacting with work-related applications. However it's necessary that the algorithm has knowledge about the field in order to classify each application as belonging or not to the set of work-related applications. The knowledge is provided by a team administrator and is encoded in the forms of regular expressions. The team administrator uses a graphical interface to set the rules such "start with Google" or "Contains the word Code" which are then translated to regular expressions that are used by the algorithm to determine which applications are work-related.

By default, applications that are not considered work-related are marked as "other" and count negatively towards the quantification of attention. However when one application does not match to any of the known rules for a specific subject that is found, the application name is saved so that the team manager can decide late, if a new rule should or should not be created for it. The team manager determines the regular intervals that attention is calculated.

Several interesting functionalities can be implemented with this approach, which provides valuable information to improve the team manager's decision-making process. Fig.6 presents the evaluation of attention of a specific student. These results consider the entire session time and give for each student the percentage of time spent in work-related or other applications.

Application	End Date	Use Time
record	Mon 7 Dec 2015 08:51:21 GMT	7.936 s
Iniciar	Mon 7 Dec 2015 08:51:22 GMT	1.152 s
Java Auto Updater estÃ¡ a pedir permissÃ£o	Mon 7 Dec 2015 08:51:22 GMT	0.00300026 s
Iniciar	Mon 7 Dec 2015 08:51:24 GMT	1.34 s
Iniciar	Mon 7 Dec 2015 08:51:25 GMT	1.085 s
google - Pesquisa Google - Google Chrome	Mon 7 Dec 2015 08:52:05 GMT	40.448 s
Anybody can learn | Code.org - Google Chrome	Mon 7 Dec 2015 08:58:06 GMT	6.01968 min
MEO Cloud - Home - Google Chrome	Mon 7 Dec 2015 08:58:15 GMT	8.159 s
Microsoft Word	Mon 7 Dec 2015 08:58:20 GMT	5.939 s

Fig. 5. Sequence of applications switched by a specific student and the time spent interacting with it.

Date	% Work	% Others
Mon 7 Dec 2015 08:58:06 GMT	87.4223	12.5777
Mon 7 Dec 2015 09:03:24 GMT	34.9715	65.0285
Mon 7 Dec 2015 09:16:05 GMT	73.1357	26.8643
Mon 7 Dec 2015 09:21:07 GMT	77.2261	22.7739
Mon 7 Dec 2015 09:26:38 GMT	93.2369	6.7631
Mon 7 Dec 2015 09:33:26 GMT	100.	0.
Mon 7 Dec 2015 09:43:10 GMT	100.	0.
Mon 7 Dec 2015 09:48:10 GMT	99.3287	0.671286
Mon 7 Dec 2015 09:53:23 GMT	100.	0.
Mon 7 Dec 2015 09:56:10 GMT	100.	0.

Fig. 6. Detail of evaluation of attention for a specific student.

IV. Validation

A system with these characteristics is a powerful tool in very different spheres, including administrative, academics or any environment in which people operate with computers.

In order to validate the proposed system, we have implemented it for the last past months in Caldas das Taipas Higher School, located in northern Portugal. In the Portuguese academic context, this system gains increased importance as current policies move towards the creations or bigger classes, which make it increasingly difficult for the teacher to individually address each student.

This created AmI system shows several tools that facilitate the decision-making. When at disposal of the teacher, this AmI system allows:

- Identifying in real time oscillations in attention level, improving decision-making concerning aspects like breaks or when the student leaves the class.
- Deciding in real time in which student the teacher must focus, according to their level of attention.
- Evaluating, a *posteriori* which contents are more likely for the students and which contents are predisposed to create distractions, providing a change for improvement.

In order to validate this system, we are following several subjects of students during their computer academic learning activities. All these data collection processes allow us to assess the influence on attention of aspects such as time of the day, breaks, classes' contents, classes' objectives, and learning styles.

As an example, we briefly analyzed the data collected for two different classes' objectives. In the first class a bells-letters class (12F) and in the second class a vocational class (12I). The subjects applied to each class was the same, an application gamed with provide to learning algorithm concepts. Apart from the aims the conditions were the same: the same cohort of studying working on similar tasks, which required the use of application game named "code.org" and the Microsoft Word.

Fig.7 allows the teacher to analyze at the end of the class, the amount of time that each student spent at the computer (Task Duration) as well as the amount (and percentage) of time that each student devoted to work and to other activities. This is important for the teacher to perform a self-evaluation of how the each class took place. Note that student username of a belles-letters class are named between T2230001 and T2230014, and student username of a vocational class are named between T2210001 and T2210012.

Student	Task Duration	Interaction Duration	Interaction Duration %	Work	Work %	Others	Others %
T2210001	50.0026 min	3000.2 s	100.002	2347.41 s	78.2417	652.793 s	21.7583
T2210002	55.0297 min	3304.7 s	100.088	2071.97 s	62.6977	1232.73 s	37.3023
T2210003	50.011 min	3001.03 s	100.012	1564.75 s	52.1404	1436.28 s	47.8596
T2210004	55.0029 min	3300.22 s	100.001	2709.18 s	82.0908	591.043 s	17.9092
T2210006	50.0025 min	3000.21 s	100.002	1487.39 s	49.5761	1512.82 s	50.4239
T2210007	50.0023 min	3000.24 s	100.003	22.1258 min	44.2481	1672.69 s	55.7519
T2210008	45.0024 min	2700.28 s	100.005	2340.92 s	86.6918	359.359 s	13.3082
T2210009	55.0017 min	3300.18 s	100.002	3260.52 s	98.7981	39.666 s	1.20193
T2210010	50.0011 min	3000.16 s	100.003	47.1176 min	94.3469	169.602 s	5.65309
T2210012	55.0025 min	3300.18 s	100.001	1826.02 s	55.3309	1474.16 s	44.6691

Student	Task Duration	Interaction Duration	Interaction Duration %	Work	Work %	Others	Others %
T2230001	69.978 min	4196.08 s	99.938	2518.52 s	60.0207	1677.56 s	39.9793
T2230002	64.9661 min	3894.16 s	99.9022	2010.09 s	51.6181	1884.07 s	48.3819
T2230003	64.983 min	3896.87 s	99.9459	3340.72 s	85.7284	556.147 s	14.2716
T2230004	64.9835 min	3897.08 s	99.9505	3104.17 s	79.6538	792.909 s	20.3462
T2230011	59.9824 min	3597.16 s	99.9505	1170.88 s	32.5502	2426.28 s	67.4498
T2230013	59.9943 min	3598.78 s	99.9755	1325.93 s	36.8439	2272.85 s	63.1561
T2230014	59.9881 min	3597.79 s	99.9584	997.912 s	27.7368	2599.88 s	72.2632

Fig. 7. The task duration and the amount of time that each student class spent interacting with the computer and the amount of actual work versus the amount spent interacting with other applications.

If necessary, the teacher may also click on a student in order to analyzed temporal evolution of the attention of a specific student in a class. Fig.8 shows the evolution of attention for two specifics students of each class described previously.

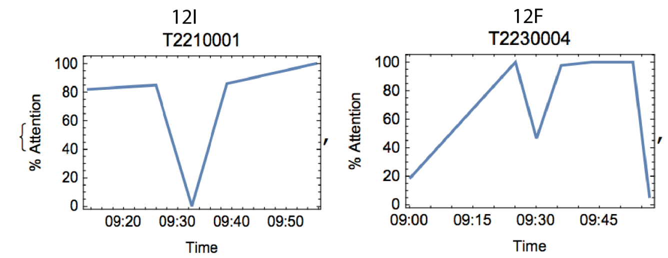

Fig. 8. Temporal evolution of attention in two different students in different class.

The teacher may also find very important to see in real time or a *posteriori*, the evolution of attention of the entire class. In order to obtain this visual representation, the teacher may select which group compares and which class.

Fig.9 presentes the global evolution of attention in a bells-letters class (a) and vocational class (b). Combining data from all students' class and computing a running average construct this visual representation.

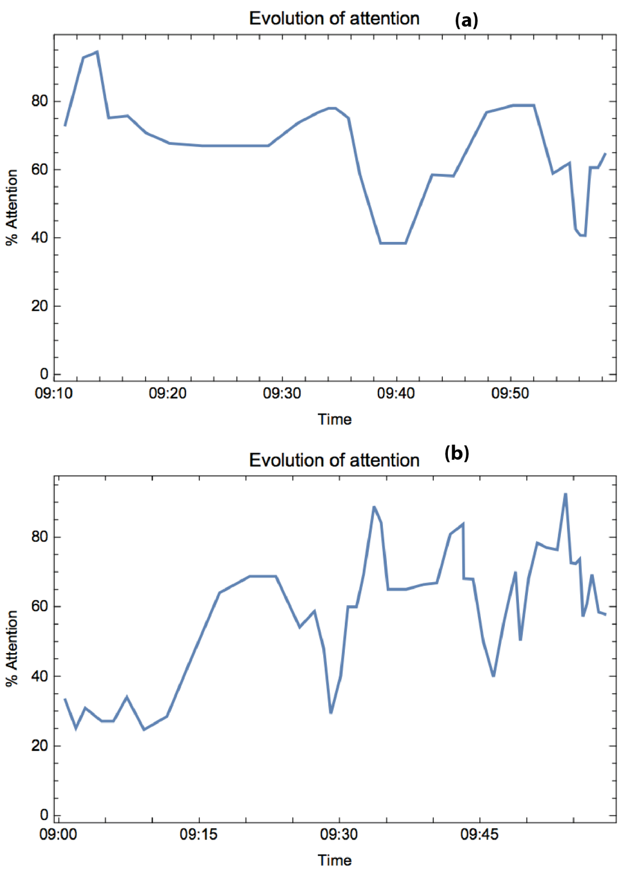

Fig. 9. Temporal evolution in two class in the same situations. (a) vocational class 12I and (b) belles-letters class 12F.

It is also possible to provides several summarization techniques with the aim of providing the teacher with simple and intuitive visions of the data. Fig.10 shows the distribution of the values of attention group in the vocational class (12I) and belles-letters class (12F).

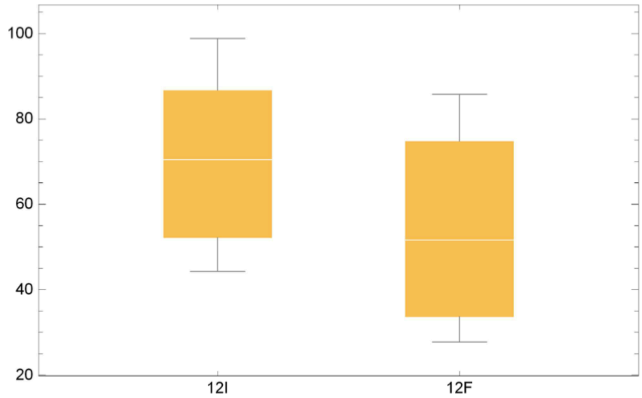

Fig. 10. Comparing the overall attention of the both class.

Finally its possible to compare in the two classes, various features from the keyboard and form the mouse. For example, in Fig.11 and Fig.12 presented a comparison is presented between the mouse velocity and the mouse acceleration for the mouse, and key down time for the keyboard and in the two classes. In this example, the vocational class has the higher values for these features, because it's vocational classes of electronics and computer system.

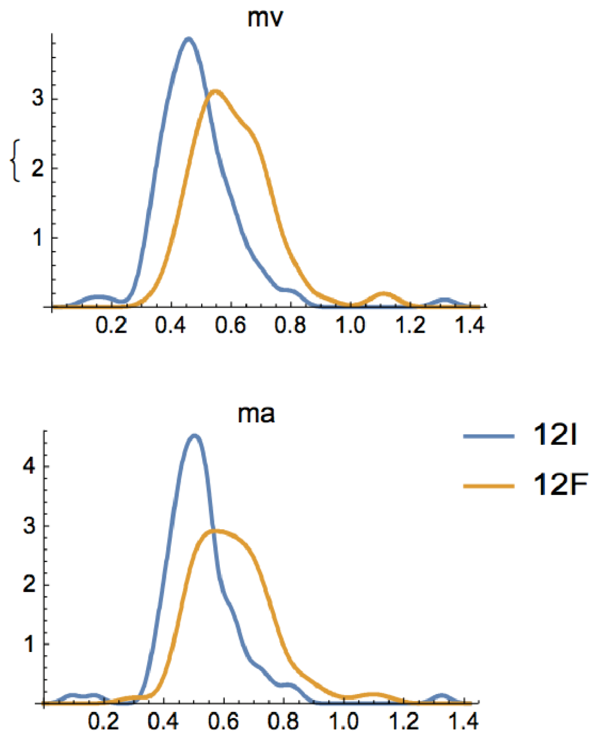

Fig. 11. Comparing the overall moviment of the mouse in each class.

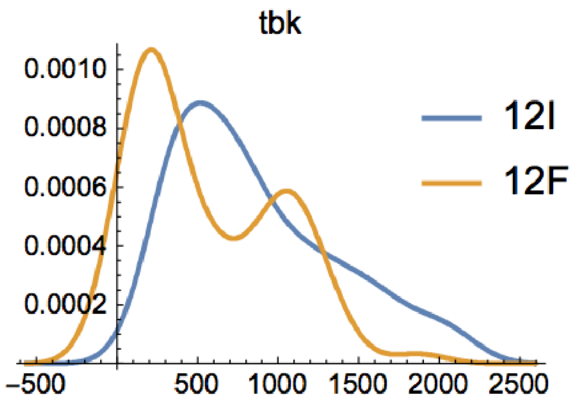

Fig. 12. Comparing the overall moviment of the keyboard in each class.

V. Discussion and Future Work

AmI systems make possible the enhanced of learning/teaching processes. The architecture of an AmI system is proposed to address these issues, especially to monitor the students' attentiveness students in learning activities, through the use of a developed log tool. With this AmI system it is possible to detect those factors dynamically and non-intrusively, making it possible to foresee negative situations, and taking actions to mitigate them. In this case the door is then open to allow to analyze students' profile, taking into account their individual characteristics, learning styles, and to propose new strategies and actions, minimizing issues such as stress, anxiety, and new environments, which can influence students' results and are closely related to the occurrence of conflicts. Moreover its possible to maximized the performance and attentiveness since the teacher is informed about the behavioral of each student.

Enlarging this study to the use of smartphones and tablets, taking advantage of their new features such as several incorporated sensors, and high resolution cameras, is the next step that may allow a wider characterization of the student, making it possible to enhance the learning experience, though better recommendation and personalization.

Acknowledgment

This work has been supported by COMPETE: POCI-01-0145-FEDER-007043and FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2013.

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