
Hey, Wake Up: Come Along with the Artificial Learning Companion to the e-Learner's Outcomes High!

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CHI'17 Extended Abstracts, May 06-11, 2017, Denver, CO, USA
ACM 978-1-4503-4656-6/17/05.
<http://dx.doi.org/10.1145/3027063.3053123>

Abstract

Compared to offline learners, online learners' attitude during the learning process is relatively poor, and a feeling of loneliness is entailed as they often study alone. This results in a low learning outcome. So far, no examples exist for the design of a learning companion to this end. Herein we present a pioneering work on a co-existing, artificial learning companion capable of improving the learner's attitude through sleepiness detection. We capture, analyze and estimate the level of sleepiness employing a machine learning technique with the pilot study data. Then, we propose a prototype called *LearniCube* using a sleepiness detection model with an experimental evaluation of *LearniCube*.

Author Keywords

Human-Robot Interaction; Artificial Companion;
Learning Companion; Design; Drowsiness Detection.

ACM Classification Keywords

K.3.1 [COMPUTERS AND EDUCATION] Computer Uses in Education, H.1.2. [MODEL AND PRINCIPLES] User/Machine Systems

Introduction

Online learning resources, such as Massive Open Online Courses (MOOCs), have received a lot of attention in

recent years [17]. One of the main challenges here is learning outcomes, especially a low completion rate (6.5%) [14]. The primary reason of this is a learning process without companions. According to Vygotsky [27], learning with companions is more effective than learning without them because social interaction plays a crucial role in the formation of an intrinsic cognitive structure. In addition, learning companions help students accomplish a continuing learning, in particular, by encouraging them to overcome their motivational deficit and to improve their attitude [9]. Furthermore, a feeling of being accompanied has a positive effect on the learner's level of comfort [3]. Therefore, there is a growing desire to design an artificial learning companion in HRI (Human-Robot Interaction) and HCI (Human-Computer Interaction), with the particular anticipation in the enhancement of the learning outcomes aforementioned [6, 8, 24].

Previous studies in artificial learning companions have usually focused on assistance. In other words, artificial learning companions are mostly involved in either the explanation of concepts contained in the subjects that the learners are studying, or becoming an internal part of the learning contents themselves, such as quizzes [24]. On the other hand, there are a few case studies where the artificial learning companions contribute to the attitude or behavioral aspects of learners during online learning. It is frequently observed that learners' behavior during online learning may not be as good as that of offline learners, since online learners are studying alone without the companions' intervention (or inspection) as mentioned earlier [21]. Actually, this becomes a critical problem in online learning that has rarely been resolved. To this end, we have conducted a research that improves learning attitude when the

online learner is less focused e.g. less concentrated when listening to online lectures.

In particular, this paper focuses on the prevention of sleepiness during online learning in order to improve online learning outcomes. Sleepiness significantly reduces both cognitive and behavioral functions [20]. It also reduces attention leading to attention deficit [15]. In effect, attention is a vital factor in learning [26], which in turn becomes a more important predictor of learning outcomes than other factors [28]. In this respect, sleepiness during the learning process should be resolved because of its negative effect on learning as seen above.

Therefore, we design and evaluate an artificial learning companion with the purpose of improving e-learners' attention when they get drowsy by detecting and alarming sleepiness in real time. We create a model to detect sleepiness through pilot test data, and then we propose the prototype, *LearniCube*. Afterwards, we present the empirical evaluation of the user experience through experiment. The evaluation of *LearniCube* is currently underway, so this paper focuses on the result of the pilot test and the prototype that has been carried out so far.

Related Works

Artificial Learning Companion

Past studies have shown the positive effects on learning when learning companions are designed in the form of a robot or an agent [2, 29]. The artificial learning companions are able to build trust with the learners, establish a mutually beneficial relationship, and help the learners in several learning activities [6, 24]. In addition, learners show a higher learning outcome with

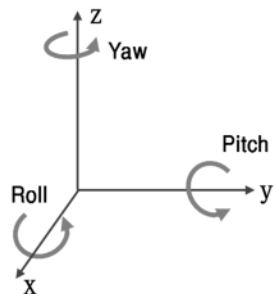


Figure 1: 3D rotation described as a sequence of yaw, pitch, and roll rotations.

Three-Stage Methods

1. Pilot test: First, a pilot test is performed to capture learners' data in a drowsy state through various devices, then to classify the data to form a system capable of detecting drowsiness.

2. Prototype: Then, we create an artificial learning companion prototype which serves as a learning companion and reflects the constructed system.

3. Evaluation: Finally, we evaluate the user experience through experiments using the prototype.

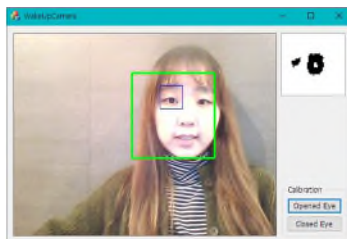


Figure 2: PC application screen to record pupil size data.

an artificial learning companion than without them [24]. On the other hand, few studies on artificial learning companions that improve learning attitude have been carried out [1]. Furthermore, there is a lack of user studies on interaction with companions during online-learning. In this study, we would like to design a learning companion that improves learning attitude of learners under the same situation. Especially, we present a hardware product that is capable of communicating in nonverbal ways, since nonverbal expression usually has a greater indicator of favorability than verbal expression [19]. We believe that a well-designed physical form of the artificial learning companion is able to facilitate the level of natural interactions, since the physical shape of a robot substantially enhances the level of comfort in the user perception and interaction with the robot [11].

Detection of Sleepiness

As mentioned earlier, it is very important to detect drowsiness and appropriately set an alarm, as drowsiness has a negative effect on attention [15, 26, 28]. In addition, arousing feedback (e.g. alarms, alerting) to learners shows the good effect in improving the performance of the subject immediately [13]. Nevertheless, sleepiness detection which in turn gives rise to feedback with respect to attention during the learning process has not been well addressed in previous studies. It is rather actively discussed in the driving domain since drowsiness is directly connected to drivers' safety during the operation of vehicles [30]. The existing systems herein have focused more on the accuracy of detection, and the user experience evaluation is insufficiently performed [30]. Different from this, we believe both the accuracy in sleepiness detection and the evaluation of the user experience when receiving an alarm upon detection are

required in the learning situation, since both the accuracy of detection and the adequacy in alarming can improve learner's attitude. Otherwise, low accuracy and bad user experience can lead learners to be annoyed easily.

Pilot Test

This study consists of three stages (see the sidebar).

Data Collection

Capture System: In order to detect sleepiness, we place two capturing systems: *TrackIR* and Webcam. First, we use *TrackIR* to measure the head position. It is an infrared camera that tracks the head position and orientation. *TrackIR* is installed at the same position as the webcam on a laptop computer, and the participant wears a baseball cap with a *TrackClip* attached. *TrackClip* has three retro-reflective markers which directly shoot infrared lights back to the *TrackIR*. *TrackIR* tracks all six directions in which a player's head can move in a 3D space (Fig 1) [22, 25]. In order to record the head position data in real time into a file at 30Hz, we develop the OpenCV application written in C++.

Next, we use a built-in webcam on the laptop to measure the pupil size. While the video is played on the laptop, the webcam tracks the pupil size of both pupils of the participants' eyes, and captures and records the participants' images simultaneously. Like above, we use OpenCV application written in C++ to record pupil size data in real time into a file at 20Hz (Fig 2).

Study Design: We establish the experimental environment in order to (i) collect the physical data when participants are falling into sleep and (ii) to perform the inference on drowsiness. Participants are

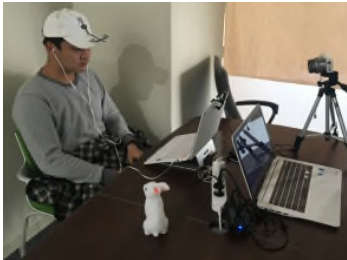


Figure 3: Pilot test setting. All experiments are conducted in the same room between 1 pm and 5 pm. To keep constant distance between all participants and the monitor, the distance is fixed at 94 cm. The laboratory temperature is kept constant at 23-25°C.

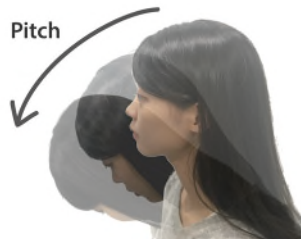


Figure 4: Pitch refers to the direction when nodding head forward or backward. Sleepiness can generally be described by the pitch value.

given the task of watching a BBC Earth documentary, which creates a boring atmosphere and leading participants to feel drowsy during the experiment (Fig 3). In order to collect natural sleepiness data, participants are instructed not to fall asleep immediately with the assumption that a teacher will accompany them during the experiment. Finally, to make the eye detection easier, participants wearing glasses are requested to wear contact lenses. Six participants ($M=29.33$, $SD=6.501$, Male=4) take part in the pilot test. The pilot test takes 30 minutes in average. The reward for the participation is \$5.

Procedures: In the experiment, after brief instructions are given, participants wear a cap with the *TrackClip* attached (Fig 3). After running the application, we measure the baseline pupil size. Then, participants are asked to find a comfortable posture when they take a seat, and head position and pupil size are detected afterwards. As the video starts recording and playing the documentary, the researchers leave the room. After 25 minutes, we go back to the room and the pilot test is finished. The confirmation of the data labelling with the participants is carried out in a separated meeting afterwards.

The Data

Data Preparation: For the prediction of drowsiness, we first extract the features to use for the data analysis. Since people nod their heads when they feel sleepy (Fig 4), we use the pitch value only. After the feature extraction, we perform a smoothing operation for all data captured from various systems to align the data on each single time axis by averaging the data over a 5-second window. During the pilot test, some participants are completely asleep, a few participants

are slightly asleep, and the rest are not. Two peer-to-peer analysis methods are used to compare the collected data with the three levels (0: Alert; 1: Slightly sleepy; 2: Very sleepy) inspired by Karolinska sleepiness scale [23]. Finally, we show the recorded video to the participant once again, and the ground truth is secured by confirming the actual sleeping point.

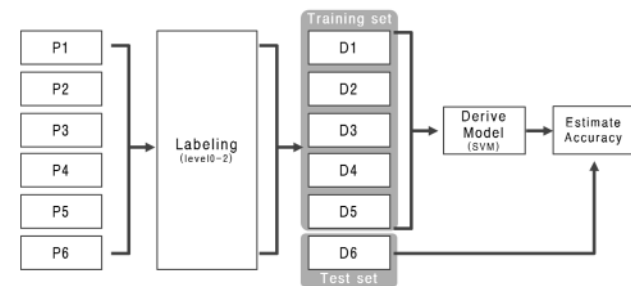


Figure 5: Computation procedure used in the study.

Data Classification: We use six labeled data sets in total - five for training, one for test. We use K-Nearest Neighbors, Gaussian Naive Bayes, RBF SVM (Radial Basis Function Support Vector Machine), and linear SVM in *scikit-learn* python package for the prediction. The linear SVM shows the highest score of 0.93. Therefore, the level of sleepiness is inferred by the trained Linear SVM (Fig 5).

Prototype

We propose a prototype called "*LearnICube*" in conjunction with the sleepiness detection model aforementioned. The prototype is developed in the form of *Android* mobile applications capable of communicating with capturing systems, and the appearance is created using 3D printing. The prototype is designed to provide visual and auditory signals

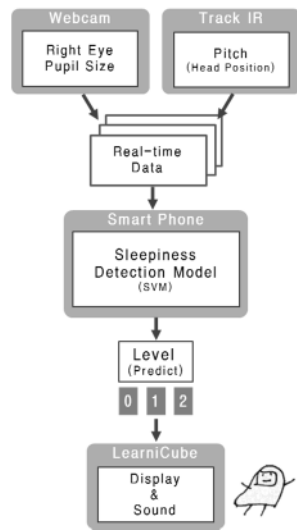


Figure 6: Main algorithm of our sleepiness detection system.

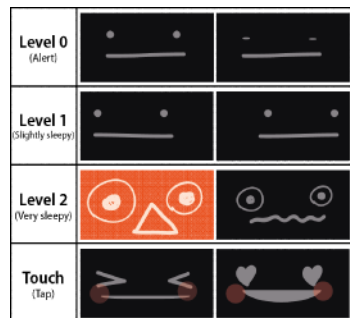


Figure 7: Changes in facial expression of *LearnICube* according to predicted sleepiness level and touch interaction.

whenever any learner's drowsiness is detected by the sleepiness detection model.

System

We develop an *Android* mobile application for both perceiving and analyzing user data from each sensor in real time in the prototype (Fig 6). Each sensor and mobile application communicates using TCP/IP sockets on a WiFi network written in Java. When the mobile application is executed, the PC applications composing the capturing system access the mobile device and periodically transmit the head position and the pupil size data. On the mobile application, extracting pitch and eye's pupil size from the received data –a smoothing task- is performed by averaging every five seconds. The preprocessed data predicts the sleepiness level through the sleepiness detection model based on the linear SVM implemented in java using the open source library LIBSVM. Moreover, we develop the emotional expression to display different interactions towards the users according to predicted values by the sleepiness detection model (Fig 7).

Design

Emotional expressions play a vital role in interactions. It can increase the importance of the interactions or regulate the interactions of engaged people [7] by conveying people's emotions visually [10]. On top of this foundation, the prototype is designed to deliver different facial expressions according to several scenarios (Fig 7). If the predicted sleepiness level is 0, we conclude that the learner is concentrating on the lecture and thus *LearnICube* displays a blinking, neutral look. If the level is 1, *LearnICube* expresses a worrying look. When the level is 2, *LearnICube* shows a surprised look, a red light with an announcement sound. In

addition, *LearnICube* is designed to show a happy emotion when the participant taps the screen, since a touch requires a close physical contact and is able to communicate a distinct emotion [12].

The purpose of the study is not to simply create a system to detect drowsiness, but to create a better learning companion for the learner. Appearance design is also important because it affects the intimacy with the companion [16]. We choose animal-like form based on the previous research which indicates that users give more positive feedback and show higher preference when using pet-like robots rather than humanoid robots [4]. Thus, the prototype is made in the form of an anthropomorphized animal which is able to enhance interactivity while giving a cute feeling [28] (Fig 8). We design *LearnICube* in the posture of sit-down intending to be recognized as an artificial companion that will listen to online lectures along with the learner.

Evaluation

We attempt to confirm that *LearnICube* helps the attitude and gives a positive impression in the real online learning situation by experiments. Participants listen to an online lecture "Service Design", a Korea-Massive Open Online Course (K-MOOC) lecture. While listening to the lecture, *LearnICube* detects the learner's sleepiness and sends an alarm (Fig 9). After listening to the lecture, the participants evaluate *LearnICube* through questionnaires in 7-point Likert scale and we evaluate the user experience as high and low based on the median value of 4. Also, we conduct interviews to obtain additional comments. Five participants are recruited to participate in this experiment ($M = 28$, $SD = 5.050$, Female = 4). As a



Figure 8: Actual prototype, *LearnICube*.



Figure 9: Experiment setting.

result, Familiarity ($M = 5.80$, $SD = 0.371$), which asks whether *LearnICube* is accessible, favorable, or friendly, and Academic Support ($M = 5.13$, $SD = 0.558$), which asks whether it supports learning attitude and overall learning, are rated higher than the median value. On the other hand, Annoyance ($M=3.70$, $SD=1.605$), which assesses whether *LearnICube* is annoying to notice sleepiness, is rated below average. In the interview, participants mentioned that the presence of *LearnICube* influences their attitude, especially when they just see *LearnICube*'s face. Participants responded that *LearnICube* is not interfering during the learning process and their evaluation of *LearnICube* is generally positive.

Discussion and Future Works

Implications

Artificial learning companion studies have focused on assisting learning contents and not much on contributing to the attitude and the behavioral aspects of learners in spite of its importance. Therefore, we designed a learning companion to help learners increase their attitude by detecting sleepiness in real time. Since the sleepiness detection studies have mainly investigated in the driving field, this study can be seen as a pioneering work in the education field. In addition, we develop a system to detect and analyze drowsiness in real time in a situation where people watch online lectures for a long time, in conjunction with the presentation of a classification result well fit to the learning situation. We believe *LearnICube* will be able to provide the social support to solve the most persistent problems in online lectures, such as low concentration problems and a high level of loneliness. In other words, it will serve as both instrumental and emotional support by the provision of (i) audio-visual

expressions when detecting the drowsiness and (ii) interactions with learners who feel lonely in online learning situations. Indeed, our *LearnICube* will be used for a relatively longer time than many other wearable devices that are also available to help learners improve their attitude, as it also plays the role of a companion for the user [5].

Future Works

We are currently investigating how *LearnICube* can provide a positive effect on academic support or cognitive learning when providing a signal, and how learners actually feel about *LearnICube*. We will look at the effects of *LearnICube* and improve the design through the investigation of the differences between groups with and without *LearnICube* (alarm present / absent). In addition to the questionnaire, the experiment will be conducted through various objective measures. We will measure: 1. the academic support through the number of times the learner actually corrected the posture or showed a change of behavior when an alarm sounded, and 2. the actual learning through the quiz score. We will also look at the preference and annoyance of *LearnICube* through distance and the number of times the learner interacted with it. We believe that this research will greatly contribute to the design of human-companion interaction in the future.

Acknowledgements

We thank Jioon Park and Mincheol Shin who provided helpful comments on the prototype. This research was supported by the MSIP, Korea, under the G-ITRC support program (IITP-2017-R6812-15-0001) supervised by the IITP. This research was supported by the Ministry of Education(NRF-2016R1D1A1B02015987).

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