POSTER ABSTRACT

Integrating Co-Robots and Machine Learning in Engineering Lab Environments to provide personalized feedback

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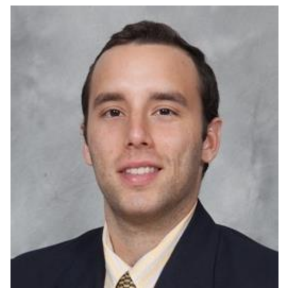
Biography



Christian Lopez is currently a Ph.D. candidate at Harold and Inge Marcus Department of Industrial and Manufacturing Engineering at the Pennsylvania State University. He holds a Master of Sciences in Industrial and Systems Engineering from the Rochester Institute of Technology, NY. He has worked as an Industrial Engineer in both the service and manufacturing sectors before pursuing his Ph.D. His current research focuses on the design and optimization of intelligent decision support systems and persuasive technologies to augment human capabilities. This through the acquisition, integration, and mining of large-scale, disparate data. He is an active member of ASME, ACM, ASEE, IISE, and SHPE.

Overview

Traditionally, instructors are able to provide personalized assistance and real-time feedback to students based on the facial or body cues they project, as well as their performance on a task. However, this personalized assistance might be challenging to achieve in engineering labs environments where the student to instructor ratio is high. As a result of these challenges, a machine learning method for predicting students' performance prior to the start of a task in an engineering lab environment is presented. The method employs students' facial expressions captured while reading the instruction of a task to predict their performance. A case study involving 40 students performing tasks in an engineering lab environment is used to validate the method. Furthermore, this work explores how this method could be implemented in a Collaborative-Robot (Co-robot) system to aid students towards the successful completion of an engineering assignment by providing students with real-time feedback. The Co-robot system could provide instructions to a student on how to perform an engineering task while capturing the student's facial expression that serves as input for the proposed machine learning model. Subsequently, based on the model's prediction the Co-robot system could potentially provide a personalized intervention or feedback to students (e.g., detailed instructions) with the intention of avoiding students' disengagement and failure. This personalized intervention and real-time feedback have the potential to improve students' performance and learning, as well as to improve the retention of students in STEM fields.

Motivation

Proper feedback can improve students' performance in a wide variety of tasks. Studies have shown that with systematic feedback students' can enhance their problem-solving and teamwork skills (Egan & Leduc, 2013). Similarly, appropriate and timely feedback has been shown to be a key component of a successful engineering design process (Bernal, Haymaker, & Eastman, 2015). Traditionally, instructors are able to provide personalized assistance and real-time feedback to students based on the facial or body cues they project, as well as their performance on the task. However, students' performance on a task is typically evaluated after it is completed. This approach limits the ability of existing systems to provide timely and systematic feedback to the students. Furthermore, this personalized assistance might be difficult to achieve in engineering laboratories where the student to instructor ratio is high, or online learning environments, where in-person interactions are challenging.

State of the Art

Thanks to the recent advancement of intelligent systems, researchers are starting to implement robots in educational settings. Robots have shown to improve students' performance and help in the learning process (Mubin, Stevens, Shahid, Mahmud, & Dong, 2013). A class of robots that have the potential to help students in engineering lab environments are Collaborative Robots (Co-robots). Co-robots are a class of robots that work in collaboration with humans towards the successful completion of a task. A Co-robot could observe a student while he/she performs a task and subsequently provide feedback on their performance, technique, and safety (Lopez & Tucker, 2017c, 2017b). Moreover, researchers have shown an increasing interest in the development of systems capable of providing feedback based on students' perceived affective state (Wu, Huang, & Hwang, 2015). The objective of these systems is to enhance students' performance by providing feedback during the learning process. This feedback is based on the students' inferred affective state (Ben Ammar, Neji, Alimi, & Gouardres, 2010). Affect-sensitive systems, such as Affective Tutoring Systems, have shown to improve student's learning performance (Mondragon, Nkambou, & Poirier, 2016). Fig. 1 illustrates how most of the current affect-sensitive systems could provide personalized intervention to a student while using engineering equipment (e.g., band saw). First, the system captures the students' facial expression with the use of an RGB sensor (i.e., video camera), and with the use of computer vision algorithms extract his/her facial keypoint data. This facial keypoint data is then used as input on a machine learning pipeline that infers his/her affective state (e.g., sad), based on the classification model employed. Based on the student's inferred affective state, the system provides an intervention (e.g., feedback) with the objective to improve his/her performance on the task.

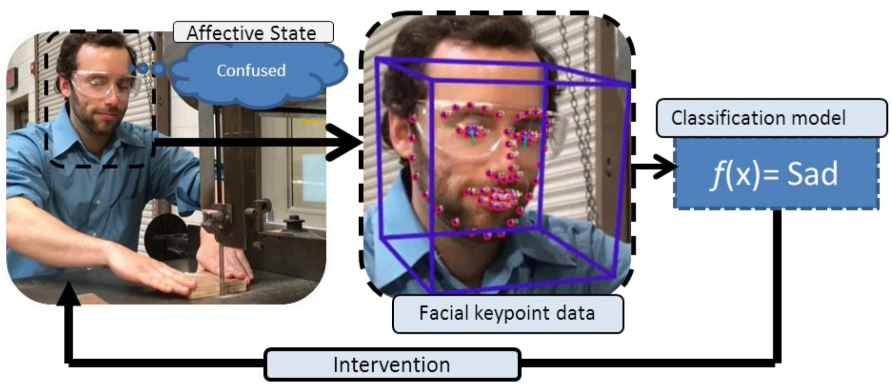


Figure 1. Representation of state of the art affect-sensitive system

Current affect-sensitive systems do not consider students' unique facial characteristics. These systems are often trained with data sets collected from a limited set of individuals. Thus, they implement general models (i.e., models trained with data of a general population) to infer a student's affective state. Hence, their capability to provide personalized feedback based on inferred affective states of a student it has not been trained is limited (Mondragon et al., 2016). In the example shown in Fig. 1, the student was not sad; instead, he was confused. Consequently, the intervention provided by the system was not optimal. Furthermore, these methods provide interventions based on predefined relations of affective state to students' performance. However, studies have indicated that based on tasks and individuals characteristics, the affective state that correlates to good performance could vary (Bezawada, Hu, Gray, Brick, & Tucker, 2017; Hu, Bezawada, Gray, Tucker, & Brick, 2016). Therefore, an intervention given to a student *i* on a task *t*, might not be ideal for the same student *i* on a different task *k,* or another student *j* on that same task *t.*

Intellectual Merit

Due to the limitations of current systems and the heterogeneity of students, this work presented a method to predict students' performance prior to the start of an engineering task. The method implements facial keypoint data of students captured while reading the instructions of a task. Thus, the authors' first hypothesize that a machine learning model, which employs student's facial expression data captured while reading the instruction of a task, can predict students' performance with accuracies greater than random change. In addition, this work presents how this machine learning model could potentially be implemented in a Co-robot system. This system could provide instructions to a student on how to perform an engineering task while capturing the student's facial expression that serves as input for the proposed machine learning model. Subsequently, based on the model's prediction the Co-robot system could potentially provide a personalized intervention to students (e.g., detailed instructions). Therefore, the main research question this work aims to address is: *What are the effects of implementing a Co-robot system, which can provide personalized interventions, on students' learning performance in an engineering lab environment*? The authors' hypothesize that implementing such a Co-robot system in an engineering lab environment can help improve students' learning and task performance.

Broader Impact

According to the National Academy of Engineering, the development of personalized learning systems is one of the grand engineering challenges of the 21st century (Vest, 2008). Personalized learning could improve students' engagement and performance on engineering tasks. Moreover, personalized learning could help improve the retention and recruitment of students in the STEM fields. Growth in the STEM fields can have a direct impact on the future economy and innovation capability of the nation.

Research Plan

This work implemented off-the-shelf hardware technology and open source software to assemble a co-robot system that will provide personalized intervention to students in engineering lab environments (Lopez & Tucker, 2017c, 2017b). Figure 2 illustrates the proposed system and how it will capture data from the students and subsequently implemented a machine learning model to predict their performance prior to the start of a task (Lopez & Tucker, 2017a, 2018). This will allows the system to provide personalized intervention with the objective to improve the students' learning and task performance. The figures also illustrate the process in which the system will validate its prediction model after the student complete the task at hand. This would be an iterative process in which the model will improve its performance as more data of the student is acquired. In other words, the Co-robot systems will learn from the students, while the student will learn from the Co-robot system. Similarly, Fig. 2 outlines the different components of the research plan, which include the **(1)** the data acquisition of facial expression and task recordings, as well as **(2)** the development of the machine learning pipeline that will employ students data to predict their performance on a task and iteratively validate its prediction model. Subsequently, **(3)** the machine learning pipeline will be integrated with the Co-Robot systems and employed in an engineering lab environment to provide personalized intervention to students. This step will allow researchers to **(4)** measure the effect of such systems on students' learning and task performance.

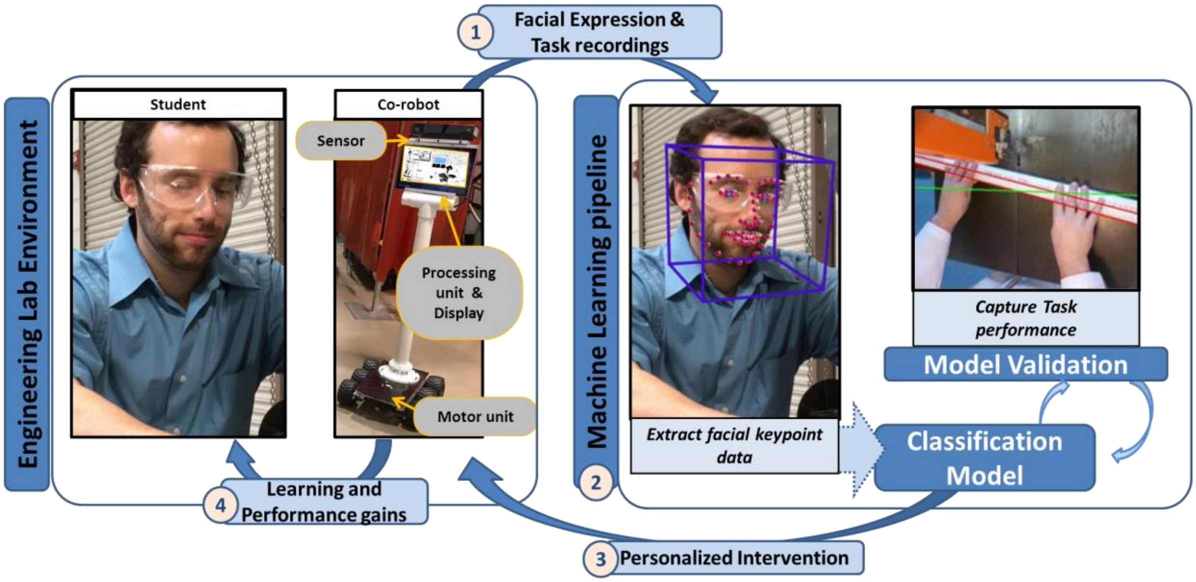


Figure 2. Illustration of the proposed Co-robot system and research plan components

The four components outlined in Fig. 2 will allow the authors' to address the research question and hypotheses presented in this work. This will help advance the grand engineering challenge of the development of personalized learning systems. The timeline for this project is summarized in Table 1 below:

Table 1: Statement of Work and Project timeline

Task	Description	Time (month)	Fa17 (4.5)	Sp18 (4.5)	Su18 (3)	Fa18 (4.5)	Sp19 (4.5)
1	Data acquisition: Facial expression and Task recordings	12.0					
2	Development of the machine learning pipeline to predict students' performance	12.0					
3	Integrate machine learning model in Co-Robot system to provide personalized intervention	12.0					
4	Implement in engineering lab environments to measure students learning and performance gains.	9.0					

Conclusions

In this work, a machine learning method for predicting students' performance prior to the start of a task in an engineering lab environment is presented. Furthermore, this work explores how this method could be implemented in a Co-robot system to aid students towards the successful completion of an engineering assignment by providing students with real-time feedback and personalized intervention, which has the potential to improve students' performance and learning. While the first and second components of the research plan have already started (see Table 1), the acquisition of a larger dataset and the refinement of the machine learning pipeline will continue.

Furthermore, the research plan will follow with the integration of the machine learning pipeline in a Co-robot system in order to provide personalized intervention and feedback to students in engineering lab environments. Finally, the effects that implementing such a Co-robot system will have on students' learning and task performance is assessed. The findings of the refinement of the machine learning pipeline, its integration with a Co-robot system, and the effects of implementing the systems in students' learning and task performance will be published and presented in research venues related to engineering education and the use of computer and intelligent systems in engineering.

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