Towards Real-time Ergonomics Feedback and Educational Content with the use of Co-Robots

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Abstract

Engineering students will play a major role in the process of improving the ergonomics in the workplace. Nonetheless, studies indicate that engineering students are not familiar with the Human Factors & Ergonomics (HF&E) methods used to improve these systems. Therefore, more emphasis should be given to advance HF&E education. However, in this pursuit hands-on activities that promote active learning need to be encouraged in order to maintain students' satisfaction and motivation. Moreover, the initial results from the case study presented in this work indicate that students' HF&E knowledge needs to be improved, and that they frequently use improper lifting techniques. In light of this, the recent advancements in technology, that could potentially allow a Co-robot system to provide real-time ergonomic feedback and HF&E educational content to students, are explored. Such a system has the potential to help students better understand and experience firsthand how HF&E can be applied to improve the workplace. Even though the method proposed is in its initial design stages, its capabilities are promising and future work will focus on implementing the system in engineering lab environments.

Keywords

Ergonomics, Co-robot, Biomechanics, Education, Musculoskeletal-disorder.

Introduction

Work-related Musculoskeletal Disorders (WMSDs) are a prevalent concern in today's work environments. In the U.S. alone, WMSDs caused the loss of more than 34 million man-hours in 2015[1]. According to the Bureau of Labor Statistics (BLS)[1], WMSDs were linked to 31% of all cases of work absenteeism related to nonfatal injuries and illnesses. These statistics indicate that there still exist numerous opportunities to improve the ergonomic design of the current workplace. Undoubtedly, engineering students will play a major role in the process of designing and improving these systems. Unfortunately, Human Factors and Ergonomics (HF&E) methods, which are intended to improve these systems, are not widely known among engineering students. As reported by Naeini and Mosaddad[2], 142 engineering students out of the 200 surveyed (i.e., 71%) did not have a "*fair*" understanding of ergonomics and its significance for their future careers. This might suggest that more HF&E courses and training are needed. Nonetheless, these courses need to be designed with hands-on activities that promote active learning (i.e., learning from experience) since research indicates that the lack of it can affect students' satisfaction and motivation[3,4]. Moreover, studies show that training that does not promote active learning, does not have a significant impact on the learning gain of individuals[5,6]. In contrast, real-time ergonomic feedback has been shown to have a direct impact on reducing the risk of WMSDs, as well as aid in knowledge transfer and long term behavioral change of individuals[7,8].

Even though students are faced with multiple circumstances throughout engineering lab environments that can serve as hands-on activities to apply HF&E principles, these events are not exploited to teach and improve their understanding of HF&E. This is mainly due to time and resource constraints, as well as the lack of systems that are able to identify circumstances in engineering lab environments that can serve as learning opportunities. Nonetheless, thanks to the recent advancement of intelligent system technology, researchers are starting to implement robots in educational settings. Robots have shown to improve students' performance and help in the learning process[9]. 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[10]. A Co-robot could observe a student while he/she performs a task and subsequently provide feedback on their performance, technique, and safety[11]. Moreover, studies have found that Co-robots that are simple in design (i.e., not humanoid-like) help individuals take accountability for the successful completion of a task[12]. This indicates that Co-robots' design appearance should be kept simple, which is beneficial to researchers since it would reduce the overall cost of the system. Their collaborative nature and capabilities make them suitable systems that could potentially provide real-time ergonomic feedback and HF&E educational content to students in engineering lab environments. Additionally, Co-robot systems could potentially personalize the feedback and the educational content provided to students by capturing their facial expressions[13]**.**

Due to the need to advance HF&E education, this work explores the recent advancement in non-wearable sensors, machine learning, and computer vision technology, which could potentially allow a Co-robot system to provide real-time ergonomic feedback and HF&E education content to students. Subsequently, quantitative data to support the need for real-time ergonomic feedback and the need to advance engineering students' HF&E knowledge is presented. Lastly, in the future work section, the authors introduce a method that integrates non-wearable sensors, machine learning, and computer vision technology to potentially allow a Co-robot system to provide real-time ergonomic feedback and HF&E education content to students.

Review of Ergonomic Feedback Methods

A common approach to reduce and control for musculoskeletal disorders is to evaluate the physical characteristics of the tasks (e.g., load, distances, frequency) and the exposures of individuals (e.g., body postures, joint angles, forces, moment arms). This analysis can provide valuable information to engineers that can be used to design tools, processes, and systems that improve individuals' performance and minimizes their risk of WMSDs. This reduction in risks of musculoskeletal disorders and improvement of individuals performance is the main emphasis of the HF&E discipline[14]. Existing methods to evaluate the risk factor of WMSDs can be categorized into self-reported, observational, or direct measurement methods[15]. Self-reported methods can be easily implemented in the way of questionnaires, surveys, checklists, or interviews; however, human bias can impact their reliability[16]. Observational methods, such as the RULA method[17], requires raters to quantify joint angles and displacement by visual inspection. Even though observational methods are practical and inexpensive to implement, their accuracy can be affected by the validity of the information collected. Direct measurement methods implement sensors to collect data of an individual while performing a task. To minimize bias and error during the data collection process, wearable sensors and hand-held devices are commonly used. For example, Battini *et al.*[8] proposed a method that implemented inertial sensors directly placed on an individual's body and provided real-time ergonomic feedback. However, these sensors can be affected by magnetic perturbations and require calibration that can take up to 10 minutes. Moreover, wearable sensors might restrict the motion of an individual and affect his/her posture [15]. An alternative for these systems is video-based systems. However, current video-based systems require the use of markers on the body for calibration purposes [18]. Lastly, both video and wearable sensor methods require complex and expensive systems to provide real-time ergonomic feedback, which limits their practicality[7].

In light of the limitations of current direct measurement methods, HF&E researchers have started exploring the use of low-cost non-wearable RGB-D sensors (i.e., Kinect) to capture data pertaining an individual's posture. Similarly, the Kinect sensor has been extensively used in the robotics community to sense objects, humans, and improve human-co-robot interactions[19–21]. Several studies have evaluated the accuracy of the Kinect in capturing individuals' posture data and have shown promising results [22–24]. This has promoted an increasing interest in developing systems that implement the Kinect sensor to provide real-time ergonomic feedback with the objective to reduce WMDSs [18,25,26]. Nonetheless, in current ergonomic feedback systems, the sensor's accuracy can be negatively affected by its placement, relative to an individual's body, and occlusions of the body itself. Moreover, contextual information (e.g., type of tasks, frequency, object weight) is commonly absent; even though, it is critical for appropriate ergonomic feedback[27]. However, the advancement of machine learning algorithms has made it possible for systems that implement RBG-D sensors (e.g., Kinect) to identify: (i) what type of task an individual is performing, (ii) if the task is performed properly, and (iii) predict if an individual will struggle in the task [28–30]. Similarly, advancements in computer vision and object recognition algorithms have made it possible for intelligent systems to recognize: (i) objects, (ii) their weight, and (iii) their dimensions, by using RBG-D sensors [31,32]. These technologies could be integrated into a Co-robot system, which could potentially make it capable to provide real-time ergonomic feedback and HF&E educational content to students while in engineering lab environments.

Case Study and Initial Results

A Co-robot system that could potentially provide real-time ergonomic feedback and HF&E educational content to students in engineering lab environments could help reduce their risk of WMSDs. Similarly, it has the potential to augment their knowledge of HF&E principles and methods, which can have a valuable impact on their future careers. Nonetheless, even though studies indicate there is a need to improve engineering student knowledge of HF&E, the need and potential benefits to students from implementing such a Co-robot system, needs to be further tested. Hence, the authors conducted an experiment to better understand if a discrepancy in students' understanding of HF&E exists (e.g., understanding of key terminology, understanding of proper lifting techniques). This experiment involved a case study where students performed two lifting tasks and completed a series of questionnaires. After the completion of the consent forms, the students were introduced to the experimental procedure. First, demographic, anthropometric, and physical activity data were collected. The participants were first required to lift a 14.0 lb. cardboard box from a 20" height table to the floor, then a 19.8 lb. wooden box from the floor to the 20" height table. Moreover, they were not given any specific instructions or feedback to avoid predisposing the participants towards a specific lifting technique or posture. During these lifting tasks, posture and joint location data was captured. Additionally, the participants were asked to subjectively estimate the perceived weight of the boxes before and after performing the lifting tasks.

A total of 17 students from the Pennsylvania State University, enrolled in engineering programs (i.e., Industrial Eng.: 8, Electrical Eng.: 4, and Mechanical Eng.: 2) and non-engineering programs (i.e., Statistics: 1, Communications: 1, and Human Development: 1) participated in the experiment. The participants' age ranged from 18 to 27 years old (μ=23, σ=2.5). From the 10-point familiarity scale questionnaire (e.g., 0: *not familiar at all*, 10: *very familiar*), 72% of participants reported a 7 or less when asked if they were aware of the term "*musculoskeletal disorders"*, which is a key term in the HF&E discipline. If we excluded the non-engineering students this percentage increased to 77%. Similarly, from the posture and joint location data analyzed, it was shown that students used a stoop lifting technique more frequently than a squat lifting technique, for both lifting tasks. Fig. 1 shows a representation of these two techniques and a breakdown of the number of students that implemented them. Additionally, Fig. 1 shows the estimated L5/S1 compressive forces for the average participant (i.e., Height: 65", Weight:178 lb.) lifting the 19.8 lb. box, calculated with the 3D Static Strength Prediction Program (3DSSP)[33]. In 58.8% of the cases, students used the stoop lifting technique. If only the engineering students were considered, this number increased to 71%. This lifting technique generates greater compressive forces in the L5/S1 disc and increases the risk of WMSDs, supporting why squat lifting is often recommended over stoop lifting[34].

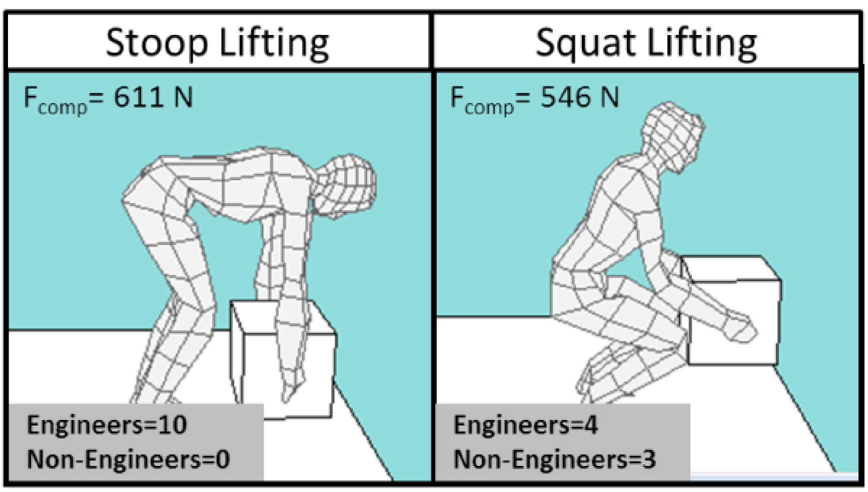

Figure 1. Simulation of participants lifting techniques, with 3DSSP[33]

In this experiment, the weights used in the lifting tasks generated L5/S1 compressive forces that were below NIOSH limites[35]; hence, it did not represent any threat to the participants. Nonetheless, from the estimated box weight questionnaire, it was clear that participants were not aware of the weight of the boxes since they could not accurately estimate their weight after a visual inspection and in some cases even after performing the lifting tasks. The average response for the estimated wooden box weight before the task was 13.41 lb. and 12.65 lb. after the task. These were statistically significantly different than the true box weight of 19.8 lb. at α=0.05 (i.e., before: *t-test*= -11.49, *p-value*<0.001; after: *t-test*= -11.80, *p-value*<0.001). Similarly, the average response for the estimated cardboard box weight before the task was 9.18 lb. and 13.11 lb. after the task. In this instance, only the average estimated weight response before the task was statistically significantly different than the true box weight of 14.0 lb. at $\alpha=0.05$ (i.e., before: *t-test*= -10.23, *p-value*<0.001; after: *t-test*= -1.12, *p-value*=0.28). In summary, the results from the case-study are in line with previous studies[2], which indicate that engineering students' knowledge and understanding of HF&E needs to be improved. Additionally, they indicate that engineering students tend to implement a lifting technique that increases their risk of WMSDs. Probably as a result of their lack of HF&E principles understanding. Nonetheless, as previous studies[7,8] indicated, real-time ergonomic feedback can help reduce this risk. Moreover, the results suggest that after visual inspection students struggle to accurately estimate the weight of objects, which could impact their ability to choose a proper lifting technique. Therefore, the results support that students might benefit from a Co-robot system capable of providing real-time ergonomic feedback and HF&E educational content.

Conclusions and Future Work

The prevalence of Work-related Musculoskeletal Disorders (WMSDs) in today's workplace calls for an improvement of existing systems in regards to proper ergonomics. As expected, engineering students will play a major role in this process, once they enter the workforce. However, previous studies indicate that engineering students are not familiar with the HF&E principles and methods, which will allow them to improve the systems currently used in the workplace. Moreover, although the case study presented in this work had a relatively small sample size, the initial results indicate that students HF&E knowledge could be improved and that they frequently use improver lifting techniques. Furthermore, researchers advise that HF&E education needs to be improved and encouraged; while taking into consideration the need for hands-on activities that promote active learning and increase students' satisfaction and motivation.

In light of current technological advancements and the need to improve engineering student HF&E knowledge, this work presents a method that could potentially implement a Co-robot system to provide real-time ergonomic feedback and HF&E educational content to students. The system has the potential to identify and exploit scenarios throughout engineering lab environments that could serve as learning opportunities to apply HF&E principles. Fig. 2 presents a visualization of the proposed method and the potential steps required for a Co-robot system to provide real-time ergonomic feedback and HF&E educational content to students. In Fig.1 an example of a Co-robot system consisting of a processing unit with a display (i.e., Microsoft Surface), an RBG-D sensor device (i.e., Kinect), and a motor unit system that provides mobility is illustrated. First, in the proposed method the Co-robot could capture RBG-D data (i.e., image, and depth data) while the student performs a task in an engineering lab environment, using a Kinect as its vision system. With this data and the use of image recognition algorithms, the Co-robot could recognize the location of the student[19,36]. Once the Co-robot recognizes the student, it could move to an appropriate location that would not interfere with the student but still accurately capture his/her posture and joint data. Similarly, the Co-robot could potentially identify the type of object the student is interacting with, as well as its weight and dimensions with the use of image recognition algorithms[31,32]. Once the Co-robot is positioned in an appropriate location, the Kinect SDK algorithms could accurately identify the locations of the student's joints[36]. Subsequently, the Co-robot could implement machine learning algorithms to recognize the type of task the student is performing, and even identify if the student is performing the task correctly[29]. The object, task type, and student's joint data could allow the Co-robot to assess the risk factor of the task by generating a biomechanical model of the student or by completing a risk task assessment. The biomechanical model could be generated using a software such as the 3DSSP [33]. While, a risk task assessment, such as the RULA[17], could be completed online to provide additional real-time ergonomic feedback to the student[7].

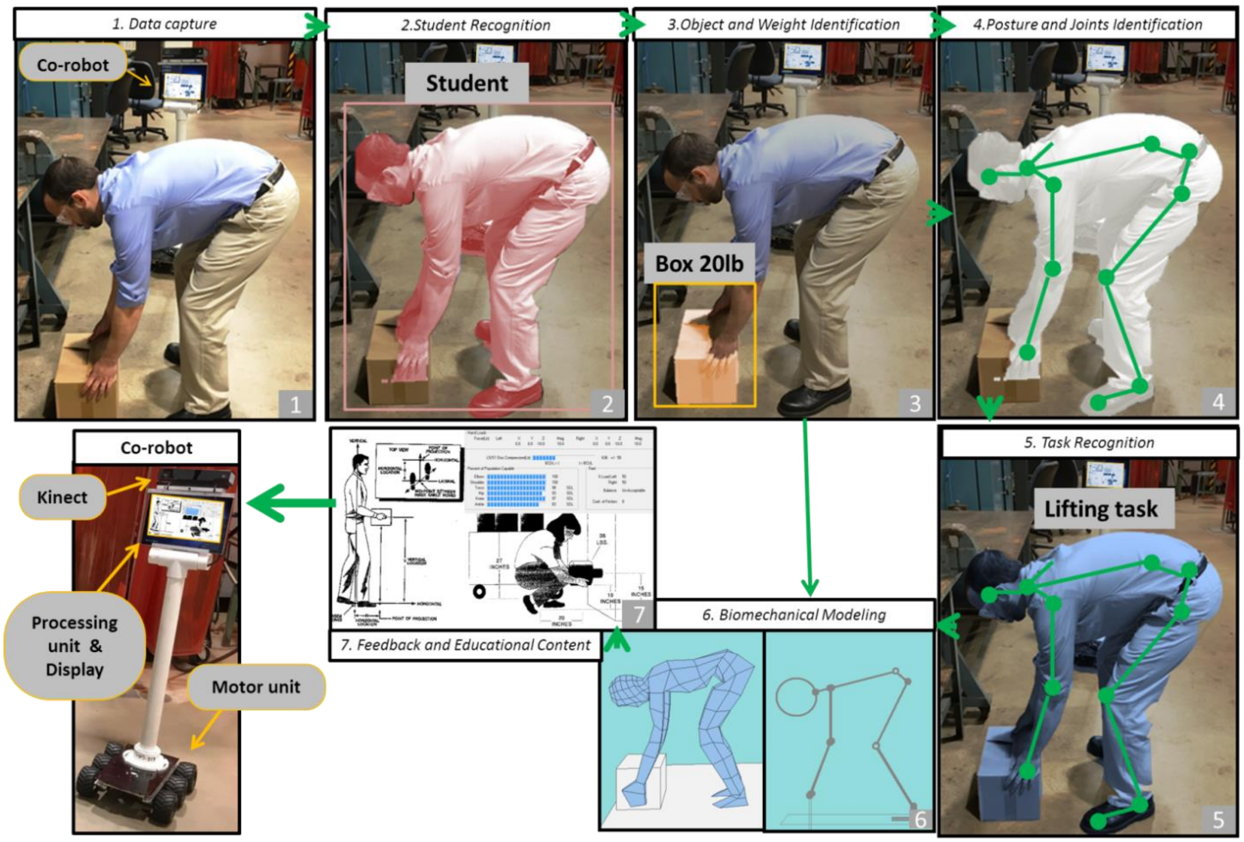

Figure 1. Visualization of Method outline.

Once the Co-robot evaluates the risk factor of the task the student is performing, it could potentially provide ergonomic feedback to the student, as well as educational content that shows: (i) how the assessment was generated, (ii) how it could be implemented in other tasks, and (iii) how HF&E principles could be used to reduce the risk factor of the task (e.g., *use a squat lifting instead of a stoop lifting technique*). Even though this method is in its initial stages of design and needs to be further tested, its potential capabilities are promising and needed based on the results of the case study presented. Future work should strive towards an application of the proposed method that provides real-time feedback, and further test the advantages and limitations of implementing it in an engineering lab environment. Nonetheless, this Co-robot system has the potential to help students better understand and experience firsthand how HF&E principles and methods can be applied, as well as how they could reduce the risk of WMSDs and improve the ergonomics of a task. This has the potential to improve and expand engineering student knowledge of HF&E, which is essential for their future career.

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