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Complete Evidence-Based Practice: Analysis of Machine Vision in a First-Year Engineering Project

Dr. William Davis Ferriell, University of Kentucky

Dr. Davis Ferriell is a Lecturer at the University of Kentucky in the First Year Engineering Program and in Biomedical Engineering within the Pigman College of Engineering.

Analysis of Machine Vision in a First Year Engineering Project-Based Learning Environment

Abstract

This is a Complete Evidence-based Practice paper submission. Creating a team-based design project for a multi-disciplinary first year engineering class means meeting a variety of constraints and goals. At the University of Kentucky, projects are required to include content from a variety of engineering disciplines—such as mechanical, electrical, materials and computer science. Projects must also motivate student curiosity and enable students to meet learning objectives required for success in subsequent discipline specific coursework. These projects are designed to require all student team members to perform mathematical modeling to understand design constraints, computer programming, computer aided design, and prototyping to bring design concepts to reality. Working on the project also allows for professional skills such as practice of team interaction processes, communication skills, and basic project management skills. Another goal in project creation is to give students a design project that addresses aspects of engineering and computer science that: represent recent trends in engineering, are not normally covered in their high school background, are inexpensive to implement, and presents these in a way that is both challenging—yet attainable—to students with a semester or less of MATLAB programming. Machine vision uniquely fit this list of goals.

Vison systems are used by many engineering disciplines in an array of applications. For example, vision systems may be used by: manufacturing engineers for the inspection and monitoring of manufacturing processes; mining engineers for inspecting hazardous areas using remote/autonomous vehicles; biomedical engineers for medical imaging; and biosystems, environmental, and civil engineers for environmental monitoring. The decrease in camera hardware cost brought about by smart phones, the increase in image processing capabilities brought about by a combination of computer hardware improvements, and the rise of machine learning algorithms are opening new machine vision applications in nearly every area of society. Students are familiar with consumer uses for machine vision, such as sorting tomatoes and drones following skateboarders. The universality of machine vision across disciplines is evident to students; thus, the utility value of machine vision-related projects may be motivating to students.

This study seeks to evaluate the efficacy of machine vision-related deliverables as part of a 10-week project in a second semester first year engineering course. Similar to the goals of the first-year engineering sequence, the inclusion of machine vision in first year engineering projects is intended to: increase self-efficacy in first year engineering students by enabling students to learn and apply a new technical skill; improve the motivation of students by emphasizing the utility value of machine vision applications; result in successful student attainment of learning objectives; and result in the completion of successful semester projects. These metrics for success are evaluated by comparing student project submissions and teacher course evaluations from two course sections from the Spring 2023 semester. Additionally, the data presented include an analysis of student performance on project deliverables specific to machine vision which may suggest the attainment—or not—of course learning objectives. The methods may be used by engineering educators to motivate the design of similar activities in their programs.

Furthermore, educators may utilize a similar curricular framework to engage students. Future work will investigate the ways in which students later engage with machine vision concepts learned in the first-year program in their major-specific coursework. Additionally, two necessary improvements to the analysis methods are survey specific questions related to the machine vision portion of the projects and the inclusion of data from multiple instructors over multiple academic years, as the conclusions drawn in this study are limited.

Introduction

Creating a team-based design project for a multi-disciplinary first year engineering class means meeting a variety of constraints and goals. At the University of Kentucky, projects that require some content from a variety of engineering disciplines such as mechanical, electrical, materials and computer science and at the same time motivate student curiosity and meet current skill levels are targeted for development. These projects are designed to require all student team members to complete mathematical modeling to understand design constraints, computer programming, CAD work, and prototyping to bring design concepts to reality. Working on the project also allows for discussion and practice of team interaction processes and skills, as well as basic project management processes and skills. Another goal in project creation is to give students a design project that: addresses aspects of engineering and computer science that represent some of the more recent trends in engineering; covers topics that are not normally covered in their high school background; are inexpensive to implement; and enables faculty to manage the project in a way that is both challenging yet obtainable to students with a semester or less of MATLAB programming. Machine vision has uniquely fit this list of goals.

Machine vision is a general term that refers to the integration of both hardware—typically a camera—and software—typically control code or other image processing operations—that interprets information from an image to inform decisions in many different applications [1]. These applications include—but are not limited to—manufacturing processes, control of autonomous vehicles, and medical imaging. With the advent of self-driving vehicles and other similar technologies, students are becoming increasingly familiar with consumer uses for machine vision. In turn, the application of machine vision in various engineering disciplines is becoming increasingly apparent to student; thus, the perceived utility of creating a machine vision system in a project-based learning environment may be motivating to students [2].

Previous work reported in the literature pertaining to machine vision in a first year engineering classroom can be divided into two main categories: machine vision—and related technical processes—incorporated into the learning environment [3-5]; and project-based learning in the undergraduate setting, the considerations of which is exhaustively documented [6]. In some instances, the literature can be categorized into both categories. The common theme for literature that implements machine vision elements within the project-based learning environment is that students are engaged due to the perceived utility of machine vision [2] and the challenge of applying and mastering the technique [7].

Although the use of vision systems in first year engineering projects is limited in the literature, elements of machine vision—as defined in this article—have been analyzed in the academic setting. For example, applications of machine vision have been analyzed in an engineering technology program [3], undergraduate classrooms [5] [8], and industrial training environments [1]. Some of these examples in the literature were published before smart phones were a part of daily life [3] [4] [8]; thus, the availability of the materials to employ accurate machine vision techniques in the classroom is greater now than when some of these articles were published.

In this paper, the implementation of machine vision within the first-year engineering project-based learning environment is detailed. Subsequently, the initial evaluation of machine vision within the classroom as well as the suggestions for future work are detailed. It is the goal of this paper to inform how machine vision was implemented within a first-year engineering class so instructors of similar classes may implement elements that fit their curricular needs.

Methods

This paper details the implementation of machine vision techniques within a primarily project-based learning class in a first-year engineering classroom taught to students of all engineering majors within the Pigman College of Engineering at the University of Kentucky: aerospace, biomedical, biosystems, chemical, computer, electrical, materials science, mechanical, and mining engineering, as well as computer science. The class is traditionally a second semester course in which all engineering students participate, although transfer students and other off-cycle sequences are accommodated during the first semester or third semester, depending on incoming credits. The first four weeks of the course is spent on a structural engineering-related project in which four- or five-person teams build a paper tower. In the remaining 10-11 weeks of the semester, student teams work on a constrained semester design project. It is within this semester design project that machine vision techniques detailed below are implemented as a subsystem. Each student is assigned a subsystem in which they have their own set of deliverables specific to that subsystem; therefore, approximately 20-25% of students in the class complete an entire subsystem using machine vision. Eventually, all subsystems must integrate to form a cohesive functional design. Some portions of the below information are specific to the machine vision subsystem within the semester design project; however, most of the provided information below was also included as individual homework assignments for all students to be introduced to machine vision as a technique. Although other project and teaching materials are provided for the completion of the semester design project, the implementation methods provided below focus on the machine vision techniques specifically.

There are a variety of tasks that can be incorporated within design projects using machine vision systems. These tasks include computer tools for image processing that find markers in a complex background or control a background to find an object in an image.

An example of the first type of task—find markers in a complex background—is used in a project where students create a semi-automated toy for a hypothetical child with a disability. The toy launches a ping pong ball at a target. The distance and angle to the target is found using machine vision, and then the launcher is turned and raised or lowered to reach the target. To determine the distance, fiducials are placed on the target and the students must write code to take an image of the target in a complex background and find the pixels in the image that correspond to the fiducials. The size and or distance in pixels between fiducials can be used to solve for distance to the target and the coordinates the angle with respect to the camera.

Figure 1: Example ping-pong ball launcher showing the webcam for finding the target so the launcher could be aimed.

The second type of task—finding an object in a controlled background—was used for both a water sampling project and a hydroponic design project. In both projects, the system was of the student's design so that the background in the image could be controlled. Students often chose to make the background in the image a solid color, such as white, by using poster board or an equivalent as a backdrop. In the water sampling project, the pipette lowered into the water sample needed to be at a few millimeters range above a sludge level, so that the system needed to find the level of the sludge and the bottom of the pipette and determine the number of pixels between the two. The tip of the pipette was covered with a colored tape and the sludge appeared dark at the bottom of the sample. For the hydroponic design students had to determine the height of plants in the growth area, and the pH of water from test strip color. In the case of the plant, the darker plant was found against a background and the number of pixels for the plant "blob" determined the height. The pH test strip was in a known location so pixel color could be found and read.

In these types of projects, the level of image processing that students do primarily involves logic statements to reduce images into areas of interest, a marker or a fiducial or a plant, vs a background that can be ignored. Software toolboxes then find the pixel blobs and return information about them, such as location and size. Students then use the data from these tables to answer the questions needed for the scaffolded project deliverables. Upon integration with other subsystems, this information is also used as inputs to other subsystems which require this information to perform actions. This includes motor or graphical user interface (GUI) subsystems which require these inputs to move system components or update a user interface, respectively.

Required Hardware and Software

To implement machine vision within the semester design project in a large first-year engineering class, affordable and effective hardware is required. Image processing can be done in images taken on any digital camera and saved as an appropriate image file such as .jpg. For a design project, it is also useful to have the students capture their own images and build image capture into the design; therefore, students were encouraged to utilize one of three hardware options: USB-connected webcam, their own smartphone or tablet camera, or a laptop camera. Autofocus was not required for the semester design projects which makes the webcam cost significantly less. Choosing a webcam with a variable focal range and the ability to manually focus on an object at a distance was sufficient for all projects. The biggest downside to utilizing a webcam was that these cameras were an added material cost to the project.

Students had the option to utilize a tablet as each student was provided one upon admittance to the University of Kentucky. To do this, the MATLAB Mobile App must be downloaded on the smartphone or tablet. Through the app, the camera can be controlled by a MATLAB script on a laptop to take images, process images, and return outputs to be utilized by other subsystems of the project. The greatest advantage to this is student access to these cameras is typically high, especially for tablets that are provided by the university to all students. A concern with utilizing a tablet or smartphone is that student teams needed to plan accordingly for integrating the camera within the design since students use these devices regularly throughout the day. This contrasts to a USB connected webcam that can typically be left in place since it is not regularly used throughout the day.

Another method for camera connection is to use the camera built into student laptops. Again, these can be controlled through MATLAB in both video and snapshot mode. The biggest advantage to using these cameras is the low cost to the project. The biggest disadvantage is that the laptop must be incorporated into the design using markers or physical stops so that the laptop can be moved into position when it is being used as part of the design but removed to be used for other instructional purposes in-between. This is similar to the concern described above with the use of tablet and smartphone cameras.

Instructional Methods

The semester design project is intended to balance rigor, student motivation, student abilities, and appropriate scaffolding of challenging technical topics. One method for appropriately scaffolding student skills for the required machine vision techniques was in-class demonstrations and programming walkthroughs. For example, instructors took an image using a smartphone or other camera and demonstrated how the image can be captured, stored in a programming environment as a variable, and post-processed as an in-class demonstration. All students were then tasked with an individual homework assignment where they were required to store an image file within MATLAB and perform post-processing techniques on the supplied image.

In addition to the homework assignments, students were supplied with modelling documents and modelling milestone deliverables. Over the course of five weeks, students worked towards a Model 1, Model 2, and Proof of Concept deliverable. Accompanying each of these deliverables was a walkthrough document. In this document, students were supplied with enough information to support progress while also requiring them to apply the provided material to their own situation. For instance, students were given an example for how to calculate RGB values of areas on interest and non-interest. Although the students were given many of the steps required, each design and environment would have different RGB values. This gave students the opportunity to practice techniques while requiring their understanding of the provided material in order for the information to be used properly. These documents scaffolded the necessary skills to be able to successfully complete the milestone deliverables.

Although the individual homework assignment introduced students to the skills necessary to successfully complete the machine vision subsystem, significant troubleshooting and persistence was also required. To support student efforts while troubleshooting, undergraduate teaching assistants staffed “Open Lab” time in which students could attend to receive help. These occurred over the course of three days of the week and 11-13 hours total. This provided students with direct feedback on their subsystem progress, as well as aid in understanding of the modelling documentation.

Image Processing Methods

The student’s goal for image processing is to develop code that will separate the object of interest from the background and return the required information about that object. The process of writing this code starts with determining the code necessary to do this for a single example, and then working to generalize the logic so that it works with all examples that the design might generate.

MATLAB, like most high-level languages, has toolboxes to help work with images, as well as tools based on machine learning to find objects and return data. Since the process of developing a strategy for finding objects requires some trial and error, a command to display what the processed image looks like is very useful in the development of code. In MATLAB with the image processing toolbox loaded, that command is imshow(imagename) where “imshow” is the toolbox command and “imagename” is the variable storing the data for the image that is loaded into the MATLAB workspace.

The first step in developing a method to separate background from object(s) of interest is to look at the pixel values of different areas in an image. The imtool(imagename) in MATLAB produces an interactive version of the image that lets students see the values for the RGB (Red Green Blue) levels as well as the X and Y coordinates of a pixel in the image. The figure below shows an example image using imtool.

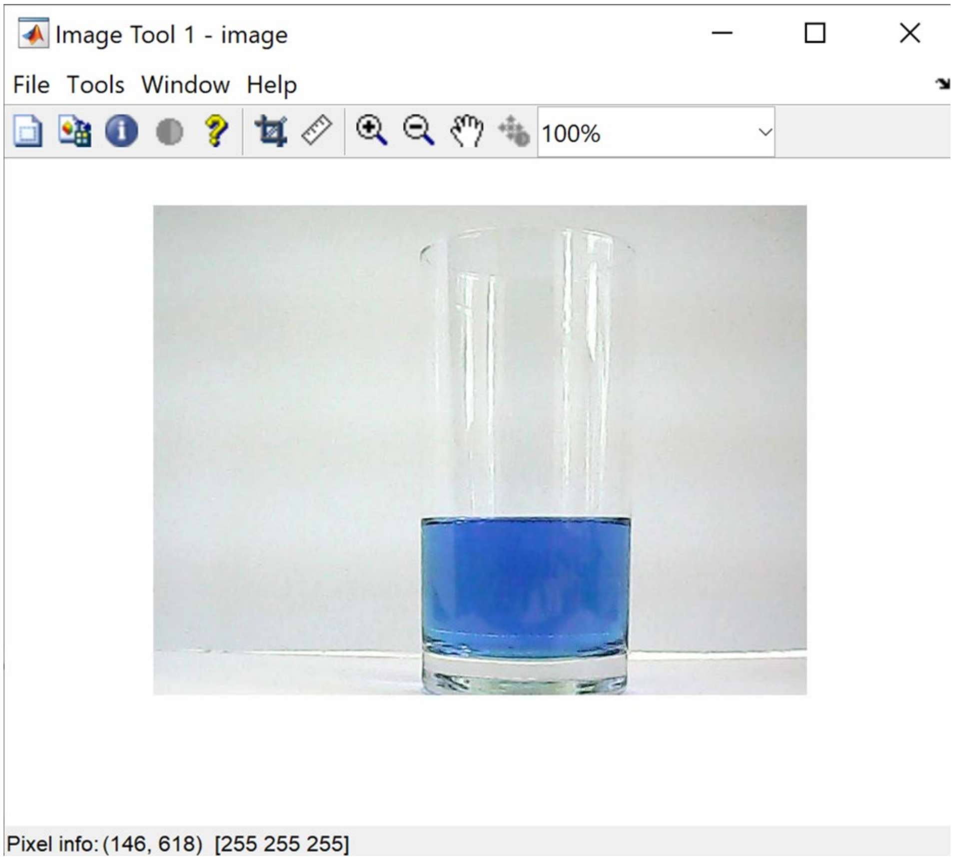

Figure 2: An image of a glass of colored water against a white background. Using the imtool() command in MATLAB, the curser location (146,618) and the RGB values [255,255,255] are shown.

An image of a glass of colored water against a white background using the imtool() command in MATLAB is shown in Figure 2 above. The curser has been moved to pixel position (146, 618) with (0,0) being the upper left-hand corner, and the RGB values of the pixel are pure white or 100% of each value (255, 255, 255).

The imtool() command allows the student to take data from representative pixels in the image, which they can record on paper or preferably on an Excel spreadsheet. The student then looks for patterns in the RGB values, or ratios of those values, to separate objects of interest from areas of no interest. Ratios of pixel values are preferred as they are more robust against lighting changes than absolute color values. This procedure is included as both an individual homework assignment for all students, referenced earlier, as well as a part of the scaffolded documentation for the students responsible for the vision subsystem.

Images can be cropped and resized as shown in the figure below. The imcrop() command allows for an interactive cropping or can be automatic if the X and Y coordinates of the upper left and lower right hand corners of the new image is given. If a strategy of location within the image is used, this can be a useful way to accomplish tasks. Scaling the image can be used to reduce the computational complexity of an image and can help with the speed that an image is processed or can be used by instructors for creating smaller files for web instructions or student downloads.

```
% This command reduces the image to 25% of what it used to be in all
% dimensions.
ScaledImage=imresize(image,.25);

% this command will set the number of rows and columns for the image, I
% selected 200 x 200 which is intentionally not the same proportions as
% before.
RowColumnImage=imresize(image,[200,200]);
```

original　　Scaled 25%　　Scaled to 200x 200 pixels

Figure 3: The original image scaled (maintains aspect ratio but drops resolution) and scaled to fit a given pixel by pixel template (aspect ratio is not maintained)

In Figure 3 above, the original image of a glass of oil and colored water is scaled using the MATLAB commands shown above. Note that the resize command maintains the original aspect ratio. The imresize() command reduces resolution and forces the image to match a specified pixel number by pixel number size, which generally does not maintain the original aspect ratio. While they appear smaller in the images above, they will appear normal when presented on a screen but will have a much smaller file size.

The final steps are to separate the pixels associated with an object of interest from those that are not of interest using the data collected from these two regions referenced above. To do this, the student creates an image using a logic statement, so that the image will contain only black (not of interest) and white (of interest) pixels. A logical array can be created that will do this. An example command in MATLAB would be:

finalImager=(gr_ratio>=3.0 & gb_ratio >= 3.0);

where the *gr_ratio* variable is a number representing the green to red pixel value ratio at each spot in an image. This creates a logical array the same size as the image, but at each pixel point there is only a single color value and that value is either black (0) or white (1). It is important to note that the values in the example code above are hypothetical. As stated earlier, students and instructors will need to tailor these values to the project purpose, design, and enviornment. The figure below shows two versions of a student image of a prototype target with green fiducials. After processing, only the fiducials are visible as white blobs in the image.

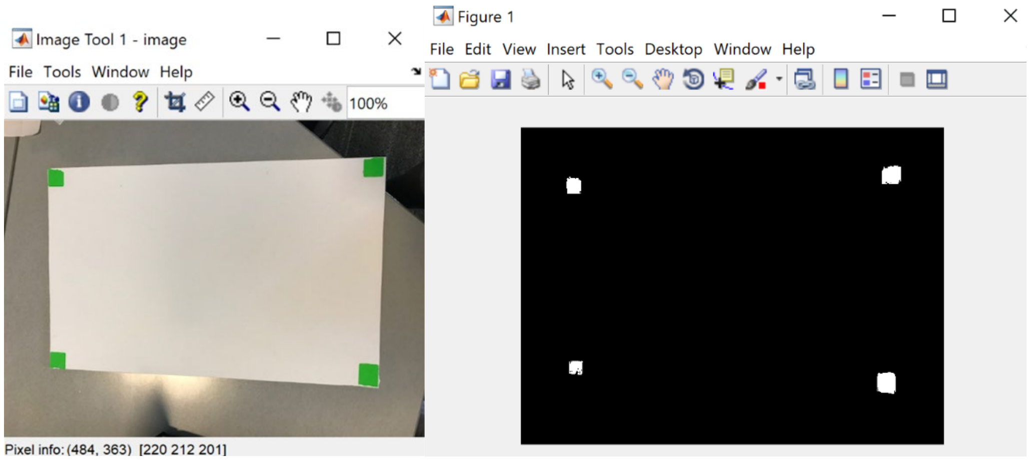

Figure 4. Isolating the green fiducials (seen in leftmost image) from various background pixels to produce a binary image of regions of interest and non-interest on the right, with white regions representing green fiducials.

The final step is to convert the isolated white groups of pixels into information in a table that can be pulled out and used to control movement or give information. For this step the regionprops() command is recommended as it has a variety of options for the types of shapes being found and the information provided back to the user. An example command would be:

TableofPropWater = regionprops('table', waterMask, 'BoundingBox');

where "waterMask" is the name of a black and white image with the objects of interest being white pixels as in figure X. This command returns a MATLAB table, and the "Bounding Box" command returns a table with the X and Y values of the upper left-hand corner of each rectangle—or what MATLAB has recognized as a rectangle—and the width and height of each.

To evaluate whether the inclusion of machine vision increased student motivation, end-of-semester student evaluations were analyzed from an instructor of two sections of the course from the Spring 2023 semester. In this semester, students were required to automatically locate a target—similar to Fig. 4 above—and eject a projectile from a spring-loaded mechanism—similar to project example in Fig. 1 above—into a target receptacle. To evaluate the extent to which student learning objectives were attained in the course, student project deliverables were analyzed. The end-of-semester functional design was analyzed for each student team. Additionally, an earlier assignment in which isolated machine vision subsystems were evaluated was used to demonstrate the attainment of learning objectives. For this assignment, functional machine vision subsystems were considered to demonstrate attainment of the machine vision related learning objectives, whereas non-functional vision subsystems were considered to demonstrate a lack of attainment of learning objectives. Learning objectives related to the success of the machine vision within the project include: "Evaluate results of their own creative endeavors and, using that evaluation, reassess and refine their work" and "Apply the logic, laws, or constraints of the area of study [as part of the design process]". Although students are evaluated in the course on professional and project management skills, those learning objectives were not considered to be represented by the success rate of machine vision-related project deliverables.

Results

The student course evaluation comments were not specific to the inclusion of machine vision; however, two student comments mentioned bolstered self-efficacy as a result of successfully completing the project.

> "I thought that this class was helpful in improving my adapting and overcoming of challenges."

> "I found this course very challenging. It was great for gaining actual project experience, even if it is such a small–scale project. While we were given several resources to help with our design process, most of it was ultimately left up to us. This pushed me to learn skills like 3D modeling…"

Additionally, one student comment stated their perceived utility value of the course.

> "Having experience with teams and letting students create something. It gives students a small understanding of what engineering is like."

Other comments discussed negative feelings toward the course or assignments.

> "The course had nothing to do with what I will be doing after graduation. This course is mostly mechanical and computer engineering principles which have nothing to do with my major."

> "I often struggled to figure out what the assignments were asking me to do because the directions were long, wordy and vague."

There were also multiple comments regarding perceived exorbitant workload that warranted an increase in credit hours.

Student learning objectives for the final device were mostly met. 94.6% of students from 20 student teams were successful in each aspect of their final device. One team (5.4%) was inconsistently successful.

In an earlier assignment in which subsystems were tested independent of other subsystems, student learning objectives were mostly met for the machine vision subsystems. 70% of the machine vision subsystems were functional, whereas 10% of students did not complete a functional vision subsystem. The remaining 20% of students submitted vision subsystems that were inconsistently functional. All students at least partially met the machine vision-related learning objectives.

Discussion

In this paper, methods for instruction of machine vision-related design projects in a general engineering first-year design class were detailed. Course evaluations were utilized to evaluate the effectiveness of machine vision to positively influence student motivation. Two components of student motivation—self-efficacy and perceived utility—were identified in student comments on the end-of-semester course evaluations. Although the identified comments did not specifically mention how the machine vision portion of the design project bolstered these vectors, the completion of the project in general resulted in improved motivation. Students also commented on the perceived utility of the project and course, specifically mentioning the relationship of the project and course to their perception of what engineering is in industry.

Despite the generally positive comments, some students were frustrated with the perceived emphasis on disciplines that they are uninterested in. The Pigman College of Engineering at the University of Kentucky offers 11 undergraduate engineering programs. The class served students from all disciplines; therefore, many students were required to work on aspects of the design project that they were unfamiliar or uninterested in. It is possible that the inclusion of machine vision subsystems in the project exacerbated this effect. Although machine vision has broad applications in many disciplines [8], the underlying technical skills are heavily reliant upon programming. As such, many students from disciplines such as chemical or civil engineering may have struggled to be motivated to work on the machine vision aspect of the project.

The lack of motivation of students from disciplines that do not have significant programming emphasis could be for a few reasons. First, students could have a diminished self-efficacy as it pertains to programming due to comparisons they may draw about their skills with the skills of their peers that have extensive programming experience from high school. One way that this could be addressed in future semesters is to encourage students that are primarily responsible for the machine vision subsystem. Additionally, providing more appropriate scaffolding for students of all programming skill levels could be helpful. Although an attempt at this was made with other course assignments, the provided materials intended to scaffold required programming skills should be refined to be more accessible to students of all programming skill levels.

Second, students may be generally uninterested in programming and perceive this technical skill as unrelated to their discipline. Although interest can be challenging to address, making a more concerted effort to provide clear and compelling arguments for the utility of programming in all disciplines is essential. One method for this could be in-class video examples of how programming can be used in industry for each discipline.

Team success in the completion of the project was high. All teams completed the project demonstration successfully at least once; however, 94.6% completed the project demonstration successfully each of four times. This shows the machine vision elements can be included in a multi-subsystem design project in a first-year engineering class and not impede student success. Furthermore, the individual assignment in which machine vision subsystem performance was evaluated demonstrated an ability of a majority of students to successfully complete their subsystem requirements. Despite the 70% successful attainment of all requirements, 20% of the students completed only 60% or less of the assignment successfully. This is an indication that while some students were unable to complete their subsystem by an initial due date, most teams eventually had a functioning machine vision subsystem—as shown by the rate of success on the final project demonstrations.

Conclusion

In this paper, methods for implementing machine vision elements within a first-year engineering 10-week design project in the Pigman College of Engineering at the University of Kentucky were detailed. Results showed the students had mixed attitudes toward the project and course in general; however, there were no specific comments that mentioned the machine vision portion of the course. Students did express bolstered self-efficacy and perceived utility of the coursework; however, these comments were also general and did not directly refer to the machine vision portion of the design project. The students primarily responsible for the machine vision subsystem were generally able to complete the machine vision portion of the project. Additionally, student teams were mostly successful; thus, it is unlikely that the inclusion of machine vision within the project deliverables impeded student success. Further conclusions cannot be drawn from this study for a few reasons. First, the end-of-semester survey did not specifically ask students about their perceptions of the machine vision portions of the project. Future work should include a survey that asks students about the influence of the machine vision portion of the project on their self-efficacy and motivation. This could result in more detailed responses from students about the machine vision portions of the project which may support more substantive conclusions. Secondly, the learning objectives for the course were not specific to the learning objectives of the machine vision portion of the project. Future work should include learning objectives that are specific to each subsystem to enable comparisons between subsystems. The results could be used to inform changes to the course to make the experiences of students completing different subsystems more similar—equally challenging—and may also provide insight into the impact each subsystem has on student self-efficacy and motivation to continue in engineering.

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