ASEE's 123rd Annual • Conference & Exposition • New Orleans, LA • June 26-29, 2016

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Paper ID #15212

Using Mounted Smartphones as a Platform for Laboratory Education in Engineering

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Using Mounted Smartphones as a Platform for Laboratory Education in Engineering

1. Introduction

Recent years have witnessed pervasive adoption of smartphones in our daily lives, accelerating the advancements in mobile technology to redefine the capabilities of these devices. Specifically, the sensing, storage, computation, and communication (SSCC) power of smartphones has reached an all-time high, creating a unique opportunity for the integration of smartphones as platforms in engineering laboratory education. The ubiquity of smartphones in today's world further supports their use in education since a vast majority of university level students already own smartphones. A recent study on mobile technology found that in 2014 64% of American adults owned a smartphone.[1]

With the availability of advanced sensors embedded in smartphones, applications that exploit measurements from such sensors have been developed.[2,3] Moreover, the multi-modal interactivity of the smartphone touchscreen facilitates intuitive interfaces that may improve user experience as s/he interacts with a physical system through the smartphone.[4] Thus, the embedded technologies of smartphones have a great potential to impact the experiences of educators, researchers, and students in laboratory settings. In fact, smartphones have already been leveraged in educational settings to sense parameters of physical systems such as the rotational energy of a pendulum by attaching the smartphone to a bicycle wheel and measuring the angular velocity through the embedded gyroscope.[5] Even as this application of rigidly mounting the smartphone to the system exploits the embedded sensing capability of these devices for measurement purposes, it does not explore the SSCC potential of the smartphone in a closed-loop feedback control setting.

In control engineering education, inquiry-based learning experiences can be made affordable and stimulating by integrating students' personal smart devices as platforms for closed-loop feedback control of laboratory experiments. In many applications, the multimodal sensing capacity of these devices allows the smartphone to act as a complete sensing platform, which can significantly reduce the cost and complexity of the system. In fact, smartphones have been investigated as the sensing and control platform in the wireless networked control of a DC motor test-bed, by rigidly mounting the device to the experimental test-bed.[6] However, Ref. 6 only investigated the effects of sampling rate and network delay on the closed-loop performance of the system, and did not explore its applications in education.

This paper investigates the potential of smartphone-mounted test-beds to perform closed-loop feedback control of a laboratory experiment as well as to facilitate an effective learning environment for students. We begin by presenting three examples that illustrate wireless control of a DC motor test-bed using different sensing modalities provided by a smartphone mounted on the test-bed. In each of the three examples, all sensing, filtering, and control computations required for commanding, monitoring, and controlling the test-bed are performed onboard the smartphone in the background of a mobile application. The different sensing approaches presented are intended to demonstrate the capability of smartphones to act as a sensing platform for laboratory test-beds. By integrating smartphones into the laboratory setting, an enhanced learning environment is developed that maintains student engagement through an interactive mobile application. To make this new class of educational systems more accessible to researchers and educators, an open-source library has been developed and is available for evaluation and adoption.[7]

To control the position of an arm driven by the DC motor, both the angular position and angular velocity of the arm must be known at each time step. To perform these position and velocity measurements, the smartphone is rigidly mounted to the motor arm. Next, the smartphone is used to measure these quantities using three approaches that employ two different sensing modalities: inertial measurement and vision-based measurement. In the first approach, the embedded inertial measurement unit (IMU) of the phone is used to measure both the angular position and angular velocity of the smartphone, and in turn, of the motor arm. The gyroscope provides raw measurements of the angular velocity, while sensor fusion from gyroscope and accelerometer measurements yields the angular position estimate. In the second approach, vision-based measurements of angular position are collected using the front-facing camera of the mounted smartphone. A platform is fitted with colored markers in the view of the camera and a color segmentation approach is used to determine the location of each marker in the image. Changes in the orientation of the phone are determined from the resulting changes in the location of each marker in the image. To obtain the angular velocity, a dynamic model of the system is used to estimate the state through the use of a Kalman filter.[8] Finally, in the third approach, a multi-modal sensing technique is used wherein inertial and vision-based measurements are fused to produce reliable estimates of the motor arm's motion. The variance in each measurement is considered in the data fusion technique implemented. Process and measurement noise are handled by implementing a Kalman filter that yields estimates of angular position and angular velocity. Both the Kalman filter and feedback control algorithms are implemented on the mobile application running on the mounted smartphone.

Smartphone-mounted experimental test-beds facilitate readily accessible, inquiry-based learning experiences, where standard control techniques such as pole placement controller design may be performed on the device and their effects on the system's response investigated in real-time. Starting with a given experimentally identified model of the DC motor dynamics students design and implement different controllers to investigate the system's response. A fundamental approach to full-state feedback controller design is the pole placement technique, where the locations of the poles in the s-plane determine the characteristics of the system's response.[9] In this case, the touchscreen on the smartphone is used to create an interactive s-plane, where students choose the desired poles of the system simply by tapping on the screen, and a new controller is designed on-the-fly. Students then study the effects that different pole locations have on the system and investigate phenomena such as overshoot, oscillations, and steady-state error. The real-time system response is also illustrated on the screen of the smartphone through colorful plots displaying both the angular position and angular velocity. The touchscreen display is used as a guide to help the user perform the experimental procedure by providing instructions and hints throughout the process.

The use of smartphone-mounted test-beds to teach students closed-loop feedback control concepts creates an opportunity to engage engineering students in new interactive ways to use the devices they bring to the laboratory. To validate and evaluate the proposed system, a group of 17 graduate level mechanical engineering students were asked to perform the experiment described in this paper. This methodology serves as an expert analysis wherein the graduate students performing the evaluation have experience with the control techniques covered in the lab, and are the ideal candidates to assess these types of experimental test-beds. In addition, the proposed system was implemented and assessed by a cohort of 38 undergraduate mechanical engineering students.

2. System Description

The test-bed used in this study is an educational geared DC-motor with attached incremental optical encoder and multi-turn potentiometer to measure the motor orientation, and a tachometer to measure its angular rate, as shown in Figure 1. Even as these attached sensors provide required measurements, they entail an additional cost. To illustrate the efficacy of smartphone's embedded sensors, all sensing in this study is performed by a smartphone rigidly mounted to the DC-motor such that the device is located at the center of its rotational axis. The smartphone is also used to filter the measurements and to compute the feedback control signals, which are wirelessly transmitted over a Wi-Fi network to a desktop computer running the MATLAB/Simulink environment. The desktop computer transmits the feedback control signals through a PC-based data acquisition and control (DAC) board to a power amplifier for driving the DC-motor. The use of vision-based measurements to obtain estimates of the state requires a marker platform, where the markers must remain in the view of the smartphone's front facing camera as the smartphone rotates with the motor.

The smartphone used in this study is an Apple iPhone 6 Plus, which has a 5.5 inch (140 mm), 1080×1920 pixel multi-touch display, 1.4 GHz dual-core processor, an InvenSense MP67B six-axis MEMS IMU, and 1.2 megapixel front-facing camera. The advanced embedded technologies of these types of devices make them a feasible platform for SSCC in many embedded control applications. Currently, two of the most powerful sensors integrated into smartphones are the IMU and the cameras, which can provide physical measurements of orientation and motion.

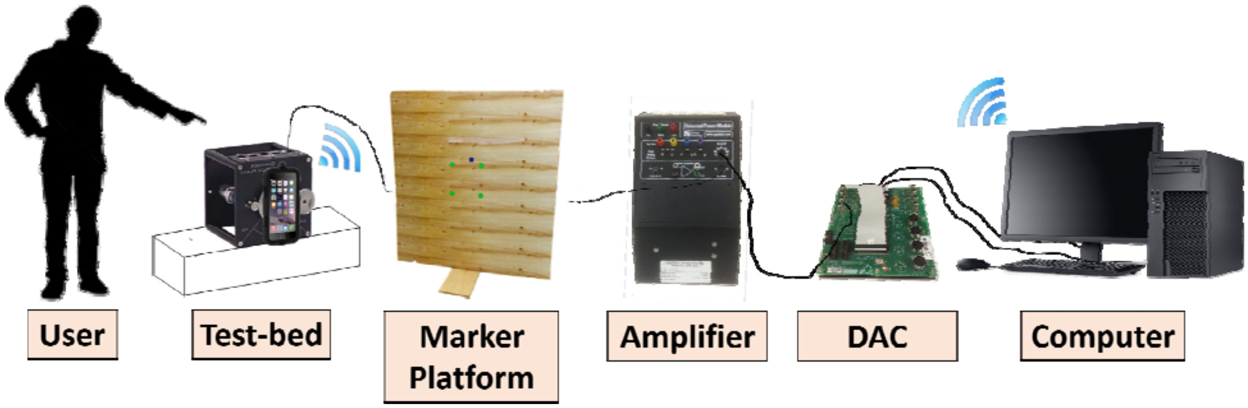

Figure 1: Schematic diagram of DC-motor test bed with a mounted smartphone (marker platform is only used in vision-based sensing applications).

2.1. IMU Specifications

The iPhone 6 Plus is equipped with both an InvenSense IMU and Bosch BMA280 three-axis accelerometer. The IMU can be configured to operate in a six-axis inertial sensor mode, three-axis gyroscope mode, or a three-axis accelerometer mode, with rated current consumption of 3.4 mA, 3.2 mA, and 450 uA, respectively. The IMU is also capable of sampling data at rates of up to 100 Hz. An onboard digital motion processor (DMP) located on the chip is responsible for full six-axis integration of the motion data. The DMP provides 16-bit readings that are critical in applications, such as gaming, requiring accurate and responsive inertial sensing. The IMU also provides significantly higher sensitivity than the Bosch accelerometer, however at significantly higher power consumption. For applications that do not require full six-axis readings and can tolerate lower sensitivity, such as estimating screen orientation and pedometer functionality, the BMA280 is utilized to reduce power consumption. Both the BMA280 and the accelerometer of the IMU can sense accelerations of up to 16g. For the purposes of this study, the InvenSense IMU is used to gather high-resolution inertial measurements.

2.2. Camera Specifications

The front-facing camera of the iPhone 6 Plus, which is most popularly used for applications such as video conferencing, supports frame rates up to 60 frames per second (fps). The quality of the image ranges from the lowest image resolution of 192×144 pixels to the highest resolution of 1280×960 pixels. Apple software development supports the use of open source and third-party libraries, such as Open Source Computer Vision Library (OpenCV). Computer vision techniques are often computationally expensive and require long processing times. Moreover, for closed-loop feedback control, a sufficiently fast sampling rate is required to ensure that the system remains stable. Thus, the processing time of vision-based measurements must be minimized to maximize the sampling rate. Minimizing the processing time can be accomplished by decreasing the image resolution, however this increases measurement noise and reduces the resolution of vision-based measurements.

3. Sensing Approaches

The high-tech sensors and impressive processing capabilities of smartphones can enable yet untapped applications that can benefit students and researchers in the laboratory setting. As indicated previously, these devices are capable of sensing many properties of physical systems. Specifically, in this paper, we explore the use of inertial- and vision-based sensing of rotational motion of a DC-motor to create an activity focused on feedback control as well as an effective learning environment for engineering students. The different sensing approaches illustrate multiple ways for measuring the DC motor motion using the mounted smartphones. These different methods of sensing also create opportunities to teach students other concepts such as computer vision techniques and sensor fusion. The three sensing methods described below are intended to demonstrate the value of utilizing the variety of sensors embedded in smartphones. However, practical constraints introduced in each laboratory experiment may require the use of different sensing approaches. For example, the use of computer vision techniques demands a clear view of key features (marker platform) in the image to estimate the orientation of the smartphone. Obstructing the view of the camera diminishes the ability of mounted smartphones to perform vision-based sensing. For the mobile application piloted and tested with students, only the inertial sensing approach is used to control the DC-motor test-bed. This sensing approach is selected because the experiment involves students iteratively modifying system characteristics and evaluating the system's performance, which could cause students to obstruct the camera's view of the marker platform. However, each sensing approach is described in detail to demonstrate the vast capabilities of the smartphone to act as the sensing platform in an emerging class of smartphone-mounted laboratory test-beds. Additionally, the description of each sensing approach provides users of the open source library the ability to integrate IMU-, computer vision-, and data fusion-based techniques into their mobile applications.

3.1. Inertial Measurements

In contrast to the high-priced laboratory sensing equipment, the use of student-owned smartphone's inertial sensors and onboard DMP offer a low-cost alternative. For this application, the onboard IMU is only responsible for estimating device attitude, i.e., orientation in space, from measurements of the device's angular velocity. However, there are several other features of the sensor, such as motion-based gesture recognition and measuring user-applied accelerations, which are not being utilized in this experiment. Apple's software development kit provides a class for central access to either the raw data from each axis of the inertial sensors, or measurements of device attitude and rotational rate after the raw data has been processed by the DMP using a sensor fusion algorithm. In this study, the iPhone is oriented in the vertical plane, such that only the pitch data from the iPhone is used to estimate the orientation of the motor arm. Measurements of angular velocity are captured directly from the iPhone's gyroscope, while estimates of the device orientation are extracted after the motion data has been processed by the DMP.

To investigate the noise characteristics of the angular measurements provided by the IMU, raw data is obtained from the smartphone while it is mounted to the DC-motor in static equilibrium. The static noise characteristics of each measurement are shown in Figure 2. The data is collected over a course of 20 seconds at a sampling rate of 30 Hz. Although the measurements from the IMU can sample at rates as high as 100 Hz, the data fusion technique described in subsection 3.3 requires both IMU and vision measurements to be sampled at the same rate. Because images are being captured by the front facing camera of the iPhone at 30 fps, the sampling rate of the IMU is also constrained to this value. The angular position and angular velocity data obtained from the smartphone (see Figure 2) is found to have a variance of 0.0118 deg^2 and 0.0037 $(deg/sec)^2$, respectively. The variance of the angular position measurement reported by the IMU is used in the data-fusion technique to combine inertial and vision-based measurements.

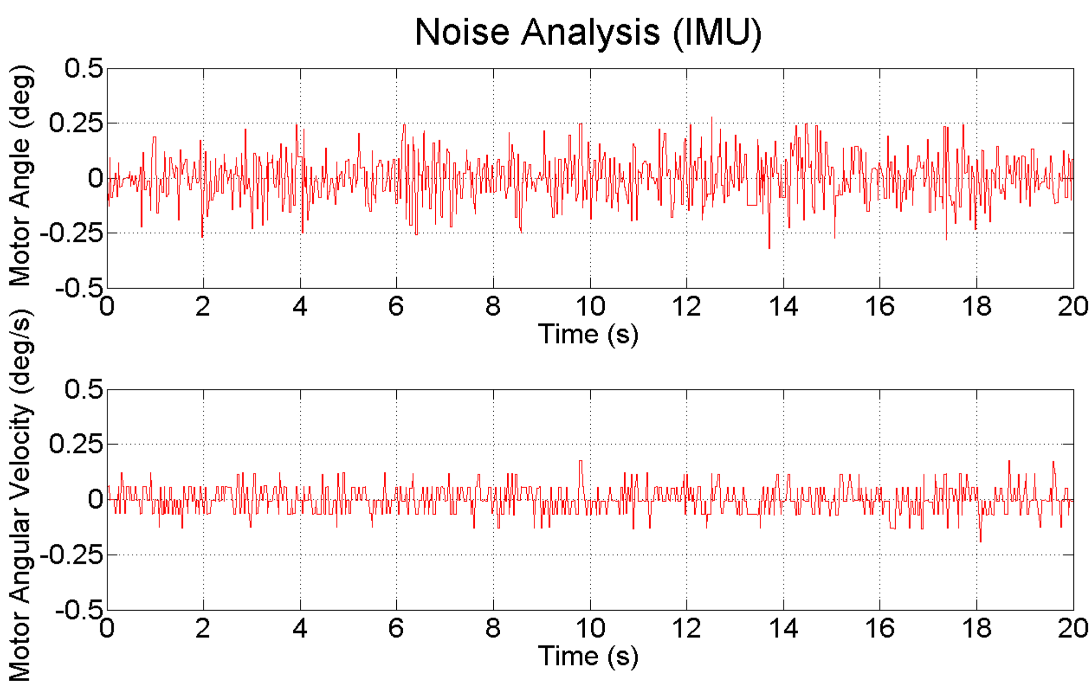

Figure 2: Raw sensor data collected from the IMU of the smartphone while the system is at rest.

3.2. Vision-based Measurements

In front of the DC-motor test-bed, and in view of the smartphone's front-facing camera, a vertical platform is fitted with colored markers. These markers are used to estimate the orientation of the mounted smartphone as the smartphone rotates with the motor, by determining the location of the center of each marker, in image coordinates, through a color segmentation approach. This approach involves thresholding the image in the hue-saturation-value (HSV) space and performing morphological filtering operations to remove small amounts of noise.[10] Constraints on the stability of the closed-loop system require a computationally efficient image processing routine. Therefore, to minimize the processing time, regions of interest are used in the computer vision algorithm.[11]

Attached to the marker platform, in front of the test-bed, three green markers and one blue marker are configured such that each green marker is identified by its relative position from the other three markers, as shown in Figure 3. To estimate the orientation of the mounted smartphone, two views of the marker platform are used. The first view is obtained from a still image while the smartphone is mounted to the test-bed and pointed approximately normal to the marker platform. The coordinates of the four markers in the first view are used as reference coordinates. The second view is captured from images streaming from the front-facing camera of the iPhone while the experiment is running. Since the markers are configured in a 2-D plane in 3-D space, a projective homography matrix can be calculated using the image coordinates of the markers in the two different views.[12] However, to properly estimate the homography between the two sets of image coordinates, the correspondence of the markers between frames must be solved. To sort the markers, the image coordinates of each green marker are used to create two sets of ordered triplets of points using the location of the blue marker and each of the remaining green markers in the image. For example, marker 4 is used to construct two sets of ordered triplets of points using marker 1 and 3, as well as marker 1 and 2. Then the orientation of each ordered triplet of points is classified as either clockwise or counterclockwise. Each green marker can uniquely be identified by its two resulting orientations. Once the homography between the two sets of image coordinates has been calculated, the orientation of the smartphone can be obtained. This is accomplished by decomposing the homography matrix into a rotation matrix and a translation vector in Euclidean coordinates.[13] The angle of the motor's lever arm can then be found as the rotational component of the transformation between the current image and the reference image.

To examine the noise characteristics of the vision-based measurements, raw estimates of the pose of the camera are collected from the mounted smartphone while the system is at rest. The raw data is displayed in Figure 4. Images are captured at a frame rate of 30 fps, at an image resolution of 640×480. To achieve this frame rate, the computation time of the computer vision algorithm is constrained to 33.33 milliseconds. The mean computation time of the computer vision algorithm is 12.32 milliseconds, with a standard deviation of 2.34 milliseconds. The vision-based angular position measurement obtained from the smartphone (see Figure 4) is found to have a variance of 0.0017 deg^2. These noise characteristics are also used in the data fusion algorithm. Although the vision-based approach does not provide measurements of angular velocity, a dynamic model of the system is used to estimate the angular velocity using a Kalman filter. All of the computation to accomplish this task is performed on the smartphone.

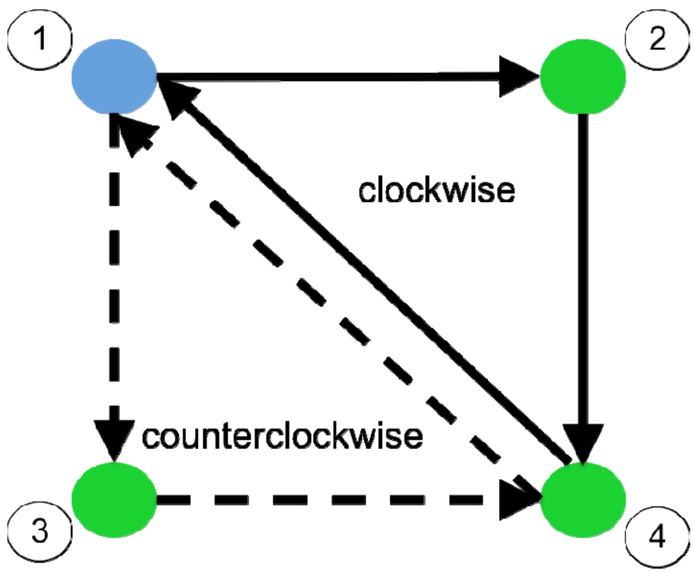

Figure 3: Diagram of markers used to perform vision-based measurements, indicating the orientation of both ordered triplets of points for marker 4.

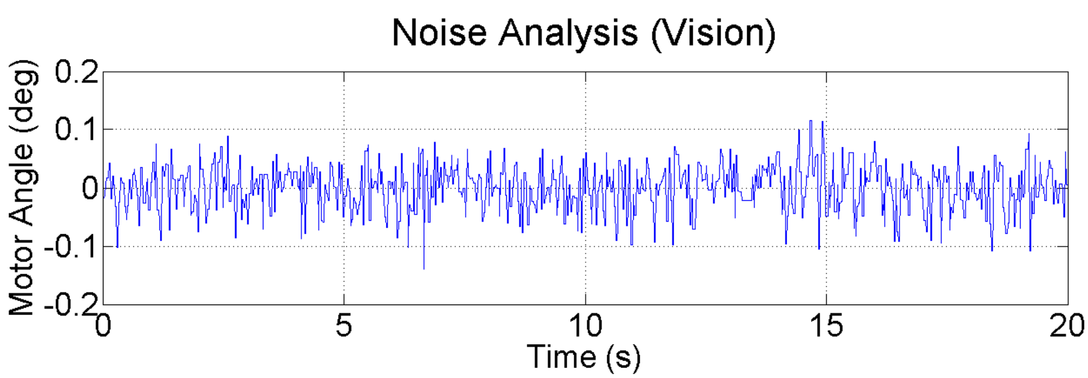

Figure 4: Noise data collected in static test for vision-based measurements.

3.3. Fused Data

The wide range of embedded sensors available on smartphones creates an opportunity to make use of data collected by different sensing modalities to produce a more reliable fused signal. This is a common technique applied to many sensing and control applications to improve system state estimates. Specifically, the Kalman filter can be used to produce a linear combination of two redundant measurements that minimizes the variance of the final signal.[14] This is achieved through weighting the measurements according to their individual variances as follows

$$\hat{x} = \omega_1 x_1 + \omega_2 x_2$$

where ω_1 and ω_2 are the weighting factors, and x_1 and x_2 are the inertial- and vision-based measurements, respectively. Optimal values for the weighting factors are calculated as a linear combination of the variances in each measurement,

$$\omega_1 = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

and

$$\omega_2 = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}$$

where $\sigma_1{}^2$ is the variance in the inertial-based measurements and $\sigma_2{}^2$ is the variance in the vision-based measurements. From the noise analysis performed in the previous sections, it is seen that the variance in the inertial-based measurements is an order of magnitude larger than the variance in the vision-based measurements. Thus, this approach yields a final measurement that favors the measurements obtained from the front-facing camera of the iPhone over the IMU. From the experimental data obtained in the noise analysis, the weighting factors, ω_1 and ω_2, are calculated to be 0.1234 and 0.8766, respectively. As a result, the variance in the measurement from the fused data can be represented as follows

$$\hat{\sigma}^2 = \frac{(\sigma_1 \sigma_2)^2}{\sigma_1{}^2 + \sigma_2{}^2}$$

where $\hat{\sigma}^2$ is the variance of the fused data measurement. From the variances calculated in the noise analysis for inertial- and vision-based measurements, the fused data exhibits a variance of 0.0015.

3.4. System Response

To validate the use of each sensing method described above, the smartphone is mounted to the DC-motor test-bed and is controlled using each sensing approach. A controller is designed such that the system exhibits a critically damped behavior. This behavior is characterized as the system reaching the desired set point quickly, without exhibiting oscillations. During the performance test, the system is first controlled using the motor's onboard optical encoder and tachometer. The system response using these sensors provides a reference performance against which the system response obtained using the smartphone-based measurements can be compared. It is seen from Figure 5 that the smartphone-based measurements demonstrate a system performance that adequately resembles the performance of the system while it is controlled using the motor's onboard sensors. Discrepancies between the system responses using different sensing method arise due to computation and communication delay. The results of this performance test validate the use of the smartphone-based measurements to control the DC-motor test-bed.

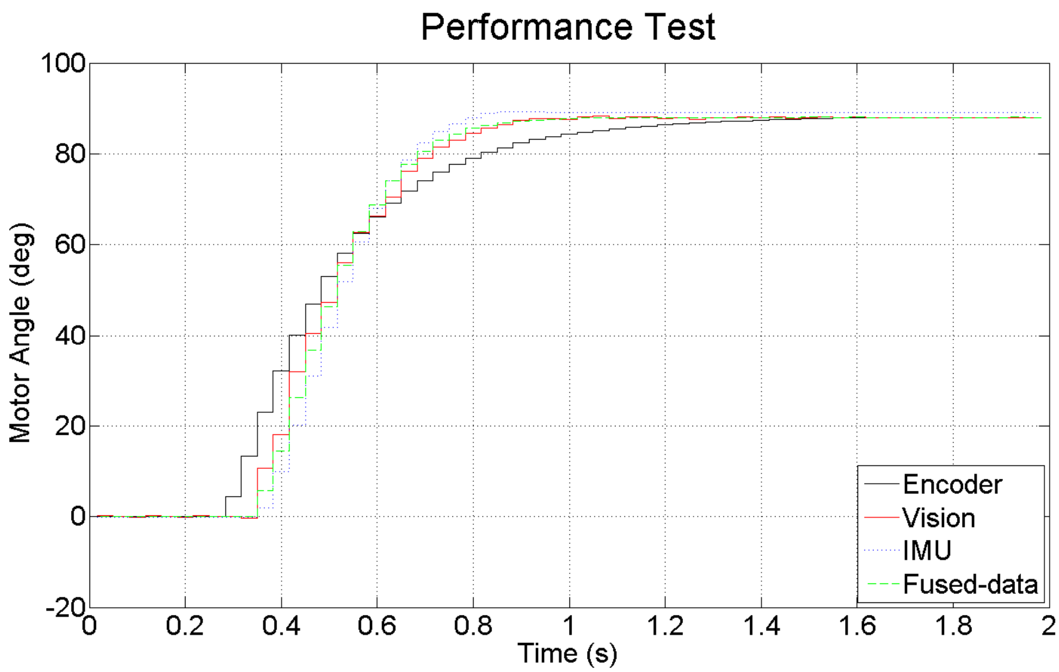

Figure 5: Performance test for each sensing approach using the mounted smartphone.

The architecture of the mobile application is depicted in Figure 6, where the inputs are retrieved from sensors embedded in the device and user interaction detected by the touch screen.

4. Lesson Description

In undergraduate courses on automatic control, students are exposed to fundamental theory of system modeling, analysis, and design. However, many of the topics taught through lectures, e.g., selection and design of controllers through a pole placement technique and the resulting performance characteristics of the system, can be more deeply understood by students through hands-on laboratory experiences.

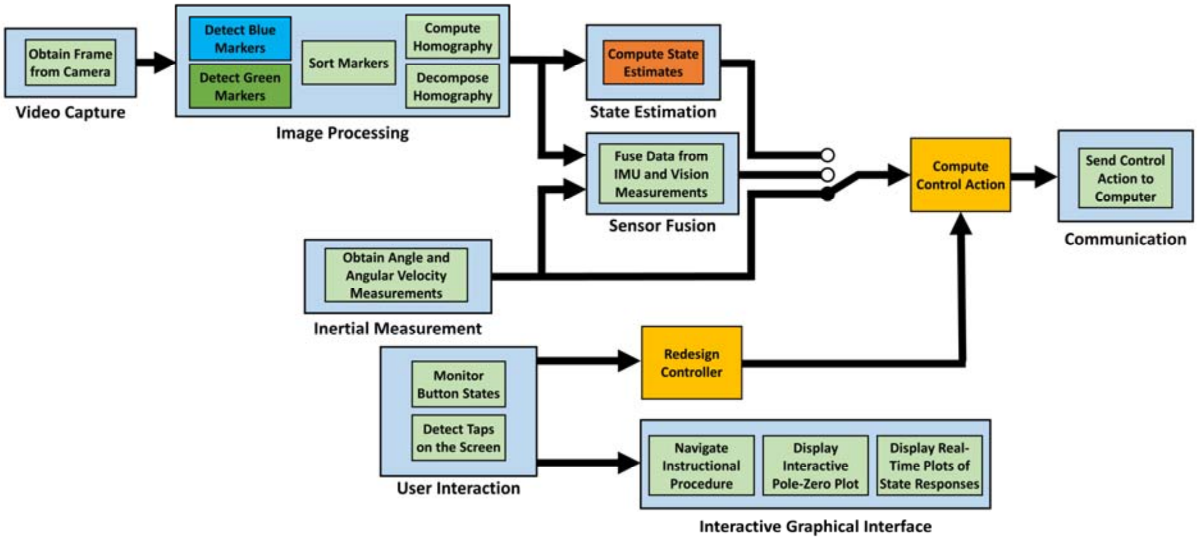

Figure 6: Architecture of the mobile application used during the experiment, including all three sensing approaches.

To enhance the students' exploration of these concepts, a mobile application is developed that allows students to sense, control, and even design the closed-loop system response of a DC-motor test-bed by using a smartphone mounted on the test-bed. The smartphone performs all necessary measurements and computations in the background of the application. Through this immersive application, students study the effects of s-plane location of system poles on its response. Effects such as overshoot, oscillations, and stability are examined and demonstrated through the closed-loop control of the test-bed. In one feature of the mobile application, an interactive s-plane allows students to change the location of the system's poles. In turn, the controller is re-designed and students can command the test-bed to a desired position to examine changes in system response. Students then participate in a design challenge in which they must place the poles in locations that will yield a system response with specified performance criteria.

4.1. User Interface

The integration of smartphones as SSCC platforms in closed-loop feedback control creates an opportunity to leverage their touchscreens to render an immersive user interfaces for interacting with the test-bed (see Appendix A, Figure A). Instructions can be incorporated to guide the student through the complete laboratory procedure. For this application, the user interface is divided into two segments: instruction and experimentation. The instructional component of the user interface guides the student through the development of an understanding of the effects that different pole locations have on the system response. Specifically, students gain an understanding of damping, oscillations, and stability conditions of the system. The experimentation section allows students to interactively modify the locations of the system poles through taps on the touchscreen, and to examine the changes in system response that result from these modifications. This component of the lab allows students to guide their own learning through trial-and-error while observing trends in the responses. Colorful plots of the system responses are included in both segments of the lesson to allow students to visually inspect the states of the DC-motor test-bed.

4.2. Instruction – Overshoot, Oscillations, and Stability

In order for students to transition to practicing engineers who can effectively design controllers using pole placement techniques, a sound understanding of the effects of pole locations on the system response is essential. To begin this lesson, students are introduced to four fundamental classes of system responses: underdamped, overdamped, critically damped, and unstable. This is accomplished through a descriptive content that defines each of these different types of behavior. Included with each definition is a plot of simulated data that illustrates the behavior of the system, as shown in Figure A.2-A.5. Through this experience, students gain the conceptual understanding necessary to characterize system responses, however they have not yet related response characteristics to the corresponding pole locations. To relate the system characteristics to the pole locations, the smartphone-mounted test-bed is controlled. Specifically, each of the four characteristic responses defined at the beginning of the instruction is explored further. For each case, a controller is designed such that the DC-motor test-bed demonstrates the response under investigation. Additionally, the locations of the poles in the s-plane are displayed on the screen, and colorful plots display the response of the system, as shown in Figure A.6-A.9. Students have the opportunity to control the DC-motor to investigate the system response by observing the motion of the smartphone, as well as the plots generated on the interface.

4.3. Experimentation - Controller Design Challenge

While the instructional component of the lesson provides guided learning, the experimentation component is focused around students exploring the s-plane with freedom (Figure A.10). In this section of the mobile application, an interactive pole-zero plot is provided to students, where they can modify the pole locations by tapping on the pole-zero plot, as shown in Figure A.11. Now, students have the opportunity to investigate the effects of pole locations anywhere in the s-plane, and are not restricted to only examining the four characteristic responses investigated in the instructional component of the application. This procedure allows students to gain valuable experience designing controllers in the s-plane, and provides them with the ability to observe the effects on the response of the system.

To verify that students have gained the knowledge necessary to characterize the response of a dynamic system and intuitively place the poles in the appropriate location in the s-plane, students are presented with the design challenge (Figure A.10). In this challenge, students are responsible to place the poles of the system in the s-plane such that the system exhibits no more than 10% overshoot and settles in less than 1.5 seconds. This exercise requires students to make use of the knowledge they gained in the previous components of the lesson and take away valuable design skills in the area of feedback control.

5. Assessment

To validate the usefulness of smartphones as a SSCC platform in control engineering education, an expert analysis and content knowledge assessment were conducted. The expert analysis was performed with graduate mechanical engineering students who have experience in feedback control. These students possess domain knowledge and skills needed to effectively analyze the performance of the smartphone-mounted test-bed, and can provide valuable insight regarding its educational value. The content knowledge analysis was conducted with undergraduate mechanical engineering students enrolled in an automatic control course. These students did not have prior experience with control design, however in the previous semester they were enrolled in a measurement systems course, which taught them how to characterize the response of a dynamic system. These students performed the laboratory experiment using the mounted smartphone, and their content learning outcomes were evaluated through a pre- and post-assessment of content knowledge, as well as their performance during the design challenge.

5.1. Expert Analysis – Graduate Student Evaluation

The expert analysis conducted in this study was designed to leverage the experience of graduate engineering students in evaluating the functionality and educational effectiveness of the proposed smartphone-mounted system. To conduct the evaluation, graduate students performed the experiment (Figure 7) presented in this paper, and then responded to a survey in which they provided their feedback. The survey given to the graduate students consisted of two components: i) a set of statements with which the graduate students were asked to agree or disagree according to a five-point Likert scale (with 1 representing strongly disagree and 5 representing strongly agree), and ii) a space to provide comments, suggestions, or criticisms. The statements included in the survey (see Table 1) were designed for the evaluators to report their assessments of the usability of the mobile application, the performance of the system, and the usefulness of the application in transferring conceptual knowledge to undergraduate students.

The results of the expert analysis indicate that the graduate engineering students found the smartphone-mounted experiment enjoyable and useful in demonstrating the feedback control content. Specifically, they indicated that all four characteristic responses investigated in the experiment were demonstrated well using the mounted smartphone test-bed. The interactive pole-zero plot was also deemed an effective tool for investigating relationships between the closed-loop pole locations and response of the system, and overall the graduate students highly recommended the application in feedback control education. In fact, one student wrote "as a former student of the class, I must say that this is quite an innovative and interactive approach to the lab; a very useful tool to learn about damping and poles". These responses suggest that the graduate students support the use of the smartphone-mounted test-bed to teach undergraduate controls concepts, and the system performance adequately captures intended content in the experiment.

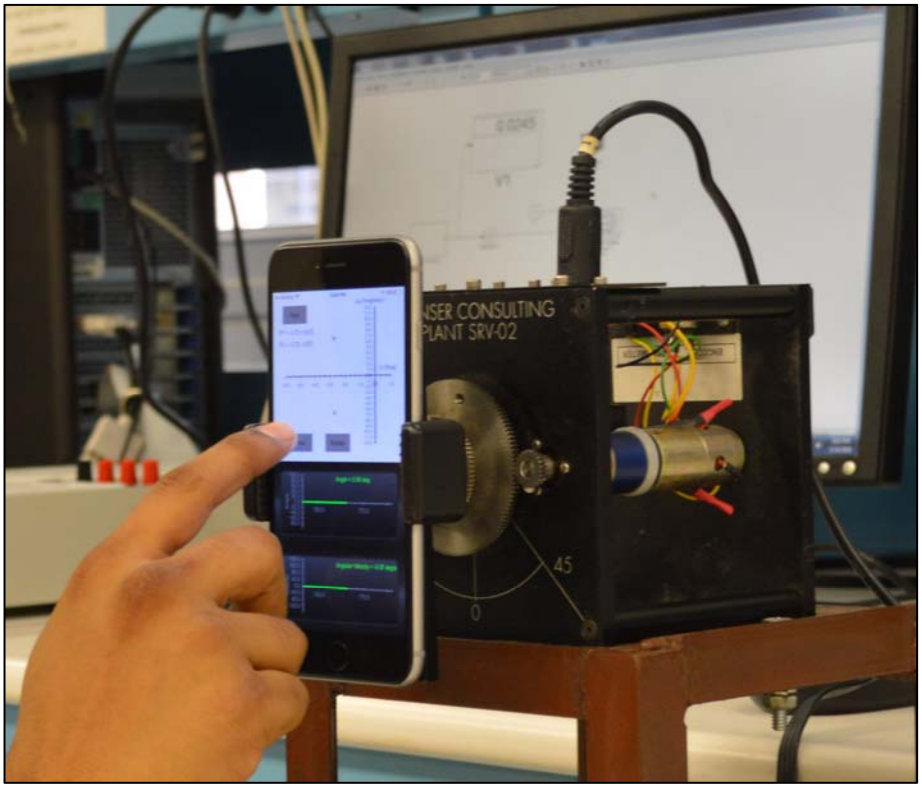

Figure 7: Graduate student interacting with the smartphone-mounted experimental test-bed.

5.2. Content Knowledge Assessment – Undergraduate Student Evaluation

The content knowledge assessment conducted with undergraduate students consisted of three components: a pre-assessment, an experimental procedure, and a post-assessment. The pre-assessment began by asking the students to report their level of understanding of damping, stability, and the poles associated with dynamic systems. Then, students were asked to answer a set of 12 questions that determined their knowledge of these concepts. Specifically, they were asked to characterize the four different dynamic responses being investigated in the experiment from plots of simulated data, and relate these responses to the location of the closed-loop poles. Students were also asked to match plots of simulated data with the corresponding pole-zero plot that would result in a similar response.

After the pre-assessment was completed, students performed the same experimental procedure as the graduate students, following the instructions provided by the mobile application while commanding the test-bed to a desired position, observing the response of the test-bed, and selecting new locations for the poles of the closed-loop system. Through this experience, students had the ability to learn the intended concepts through descriptive content, investigation of each characteristic response individually, and an interactive pole-zero plot. After completing the application, students were expected to be able to intuitively place the poles of the closed loop system to design a desired system response. To assess the degree to which students can accomplish such a task, the design challenge was used. Specifically, we aimed to determine if students with little to no prior understanding of effects of closed-loop pole locations could successfully design controllers given certain system constraints after performing the experiment. The researchers present during the experiment were responsible for observing the response of the test-bed to validate that the controllers designed by the student satisfy the design criteria.

To evaluate the content learning outcome of the experiment, students finished their participation in the study by answering the post-assessment that posed the same questions as the pre-assessment. Changes in students' content knowledge can be attributed to their experience with the smartphone-mounted experiment.

The results of the content assessment conducted with the undergraduate students indicate that the students were capable of learning the material covered in the laboratory exercise. The mean score on the pre-assessment was found to be 43.85% (s.d. 23.78), while the mean score on the post-assessment was 81.14% (s.d. 22.65). The significant increase in the scores between the pre- and post-assessment suggests that the application was successful in teaching the students the damping, stability, and pole-location concepts presented in the experiment. To test the statistical significance of the increased scores, a paired t-test was conducted. The paired t-test gives a t-value of 6.99719 yielding $p \ll 0.0001$, which indicates a statistically significant increase in test scores. Moreover, the number of students who answered each question correctly improved between the pre- and post-assessment, as seen in Figure 8. Therefore, the content assessment demonstrates that the smartphone-mounted experiment improved student content knowledge, and was an effective tool for teaching undergraduate feedback control students.

The design challenge conducted at the end of the experiment provided students with the opportunity to place the poles of the closed-loop system to produce a desired system response. Interestingly, all of the students were able to intuitively place the poles to develop a system response that satisfied the design constraints. However, these poles were placed in an iterative manner, in which the majority of students made use of a trial-and-error technique. With more advanced design constraints, and limited attempts to obtain the correct solution, students may be provided with a more difficult challenge.

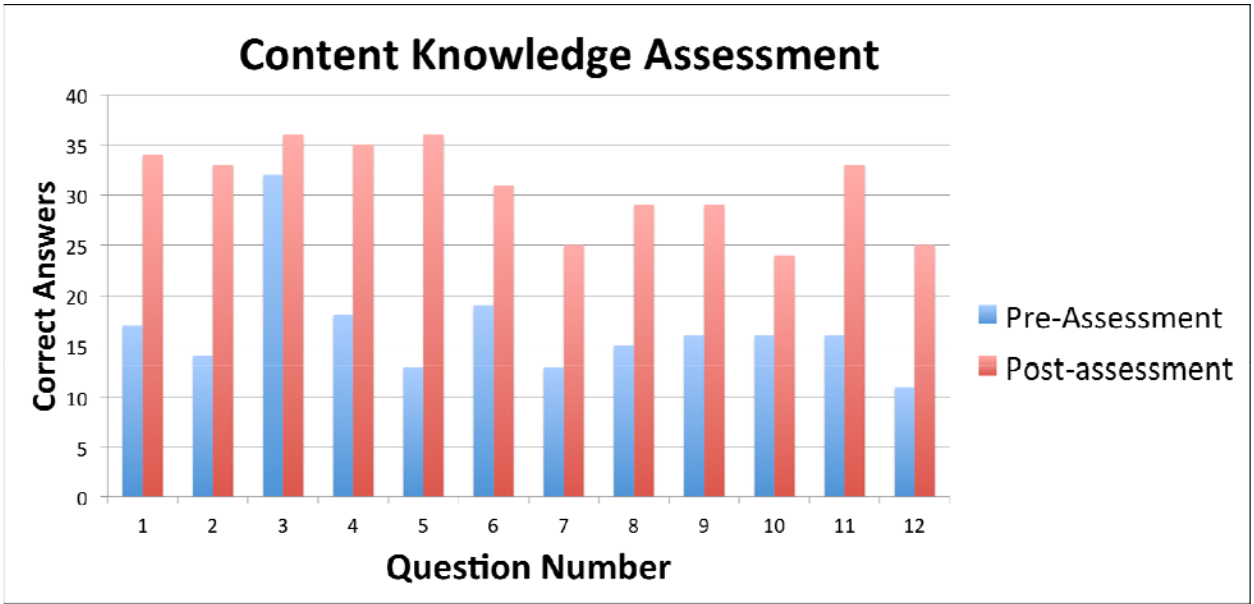

Figure 8: Diagram showing the number of student who answered each question correctly for the pre- and post- assessment.

To capture the undergraduate students' response toward the smartphone-mounted experimental test-bed a survey was conducted using the same five-point Likert scale used in the expert analysis (see Table 1). Responses from the undergraduate students indicate that the experiment was useful in demonstrating the concepts presented. Moreover, a majority of the undergraduate students would like to see similar applications that make use of smartphones developed and applied to other laboratory experiments in the future.

6. Open Source Library

In an effort to make these types of laboratories more accessible to researchers and educators, an open source library has been developed and is made accessible online.[7] Included in this library is a sample Xcode project for developing iOS applications, a C++ library including functions used to perform filtering, sensor fusion, image processing, and control algorithms, as well as instructions for implementation.

7. Conclusion

This paper presented a novel method of integrating smartphones into the laboratory setting as an educational tool to teach undergraduate students feedback control concepts. Three different sensing methods were presented for measurement and in turn to close the loop on a DC-motor test-bed. A mobile application was developed to help teach engineering students four characteristic responses of a dynamic system and the affect that changing the location of system closed-loop poles has on its behavior. To validate the system, an expert analysis was conducted in which 17 graduate engineering students evaluated the performance and potential educational value of the system. The results of the expert analysis suggest that the graduate engineering students recommend the application for educational purposes and validate the systems ability to demonstrate the topics investigated through the experiment. Moreover, a content knowledge assessment was conducted to evaluate the content learning outcomes of a group of 38 undergraduate students who performed the laboratory. The results of the content knowledge assessment indicate that the students' understanding of closed-loop poles and their effects on the system response significantly improved after using the mobile application.

Table 1: Statements provided to the graduate students for expert analysis and to undergraduate students for post-assessment, including the mean and standard deviations (S.D.) of student responses for each question. The five-point Likert scale was used with 1 representing strongly disagree and 5 representing strongly agree.

	Graduate		Undergraduate	
Statement	Mean	S.D.	Mean	S.D.
a. It was easy to navigate the smartphone application.	4.63	0.50	4.80	0.47
b. It was easy to work with the interactive plots in the application.	4.50	0.52	4.63	0.81
c. The underdamped response of the system was easy to observe.	4.75	0.58	N/A	N/A
d. The critically damped response of the system was easy to observe.	4.75	0.58	N/A	N/A
e. The overdamped response of the system was easy to observe.	4.69	0.87	N/A	N/A
f. The unstable response of the system was easy to observe.	4.88	0.34	N/A	N/A
g. The plots of the system response generated on the screen were useful visual tools.	4.56	0.73	4.89	0.32
h. Using the smartphone as a mounted sensor felt comfortable.	4.25	0.68	4.51	0.66
i. I would like to see more experiments that use the smartphone as a sensor.	4.50	0.89	4.34	0.97
j. Overall, the application made it easy and fun to interact with the motor test-bed.	4.31	0.70	4.57	0.78
k. I required assistance from the researchers to use the application.	2.44	1.15	2.77	1.09
l. It took a long time for me to become comfortable using the application.	1.69	0.87	1.86	0.94
m. The interactive pole-zero plot was useful in investigating the effects of closed-loop pole location on response of the system.	4.13	0.72	4.26	0.89
n. Overall, the application was useful in teaching the effects of closed-loop pole location on response of the system.	4.44	0.51	4.49	0.70
o. Overall, I would recommend this application to students for learning about damping, stability, and closed-loop poles.	4.50	0.63	4.70	0.62
p. I would like to see applications like this introduced into the engineering lab curriculum.	4.63	0.62	4.51	0.92

Acknowledgements

This work is supported in part by the National Science Foundation grants DRK-12 DRL:

1417769, GK-12 Fellows DGE: 0741714, and RET Site EEC-1132482, and NY Space Grant Consortium grant 76156-10488. In addition, it is supported in part by the Central Brooklyn STEM Initiative (funded by the Black Male Donor Collaborative, Brooklyn Community Foundation, J.P. Morgan Chase Foundation, Motorola Innovation Generation Grant, NY Space Grant Consortium, Xerox Foundation, and White Cedar Fund), Fred and Joanne Wilson, and Siegel Family Endowment. The authors thank graduate and undergraduate students who participated in the expert analysis and content knowledge assessment, respectively.

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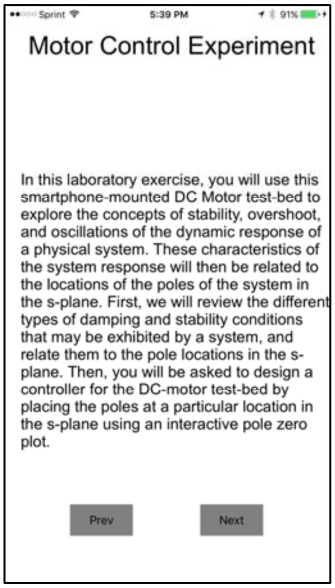
Appendix A



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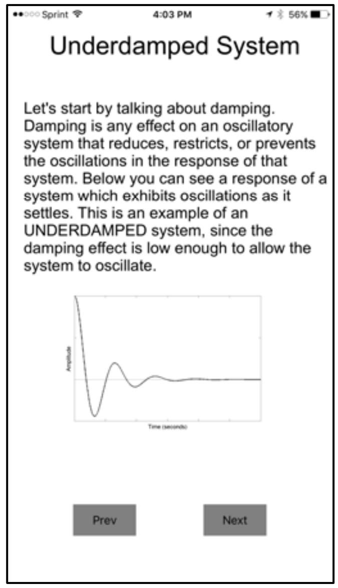

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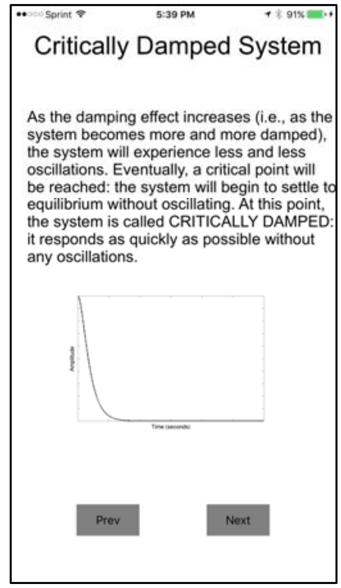

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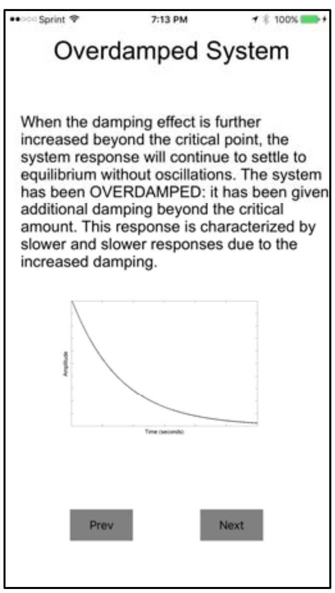

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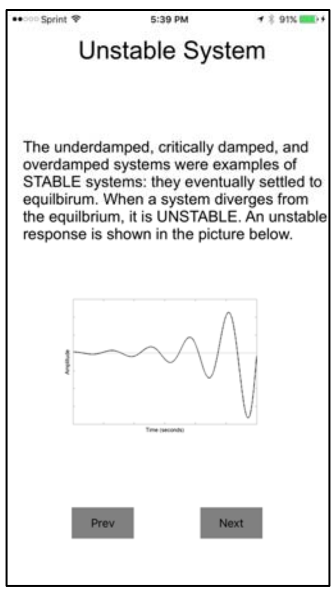

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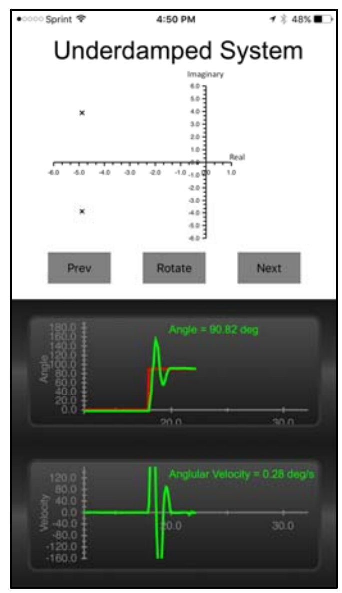

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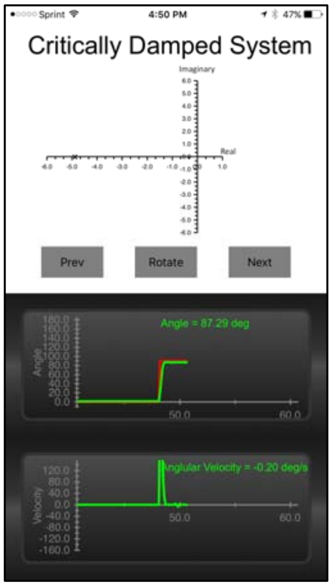

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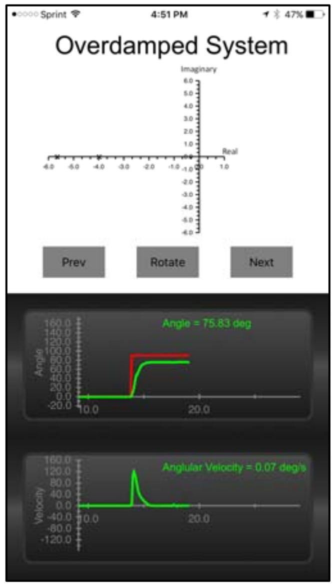

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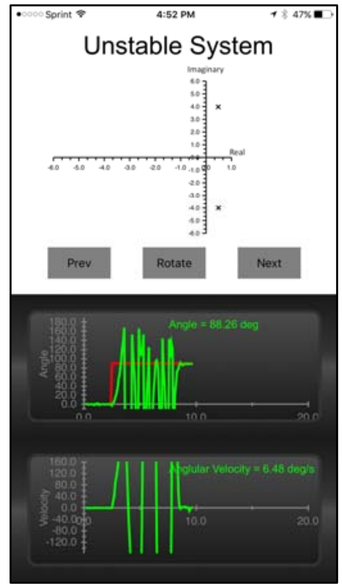

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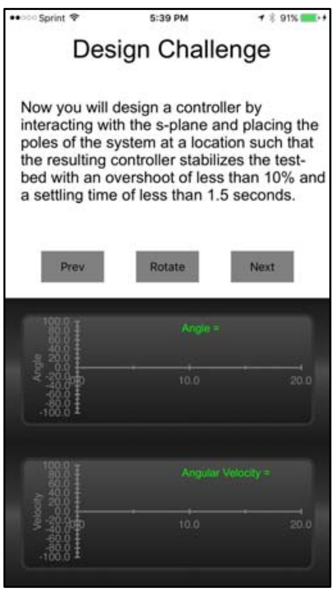

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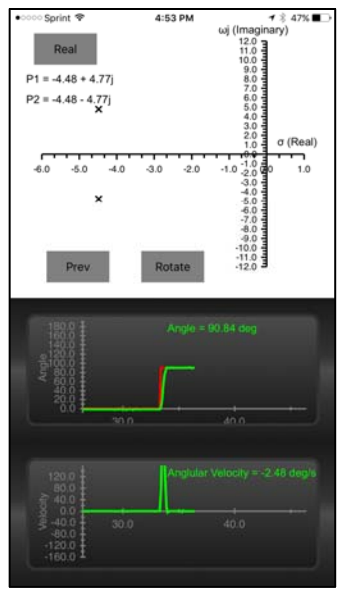

A.11

Figure A: Screenshot of each page of the mobile application.