Health Monitoring Laboratories by Interfacing Physiological Sensors to Mobile Android Devices

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***Abstract*— The recent sensing capabilities of mobile devices along with their interactivity and popularity in the student community can be used to create a unique learning environment in engineering education. Android Java-DSP (AJDSP) is a mobile educational application that interfaces with sensors and enables simulation and visualization of signal processing concepts. In this paper, we present the work done towards building non-invasive physiological signal monitoring tools in AJDSP through hardware interfaces to both external sensors and on-board device sensors. Examples of laboratory exercises that can be introduced in classes are presented. The proposed software tools can be used to provide intuitive understanding in wireless sensing and feature extraction to demonstrate the application of DSP to health monitoring systems. The effectiveness of the software modules in enhancing student understanding is demonstrated with the help of preliminary assessments.**

Keywords—Android, DSP, Mobile Health Monitoring, Wireless Sensors, Physiological Signals

I. Introduction

Over the last decade computer based tools have created a great impact in engineering education. This has led to the development of several tools used in digital signal processing (DSP) courses that enable students to apply concepts in a variety of contexts. One such important tool is Java-DSP [1,2], a web-based visual programming environment consisting of various functions built to perform DSP simulations. Recently, mobile devices are being used to progressively engage students through their ability to provide enhanced visual representations of content with interactive user interfaces. This, in turn, brings a need to develop mobile applications (apps) that can augment a course curriculum in STEM education. Instead of using these devices as an alternative platform for content delivery, exploiting their interactivity can create a personalized learning environment that continues to move outside the classroom [3]. Wireless and mobile technologies can provide learning in multiple contexts [4] by connecting students with their peers and teachers, and introducing instant feedback in the learning process. Studies suggest that students feel more confident, develop critical reasoning and are able to retain their learning for longer when working in such an environment [5].

Current Android devices comprise sufficient memory, processing power and a rich set of on-board peripherals such as accelerometers, digital magnetometers, gyroscopes, GPS receivers, microphones, and cameras [6]. Together, these

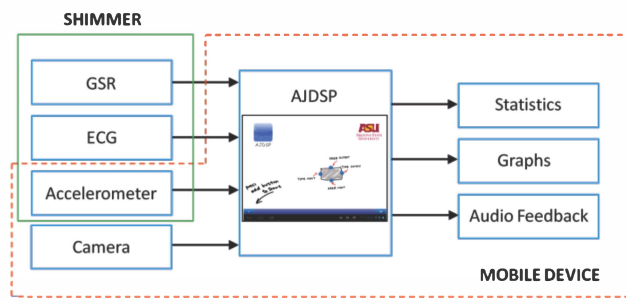

Fig. 1. Overview of the proposed mobile health monitoring system using android mobile devices.

sensors enable the development of a diverse set of applications, many of which can be used for research in mobile healthcare (m-Health). For instance, parameters such as pulse rate, blood pressure, oxygen saturation, and skin conductance, shown to vary based on physical activity and stress can be measured using mobile devices and sensors.

In this paper, we explore the trend of mobile sensing and adapt it towards improving digital signal processing (DSP) instruction by building interfaces to external and on-board sensors (Fig. 1), thereby providing a new scientific paradigm for teaching. Some of the popular Android apps available for learning DSP principles include MATLAB Mobile [7], WolframAlpha [8], and Octave [9]. Several of these apps typically have a command-line interface and require Internet connectivity to interface with the cloud. In addition, MATLAB Mobile and WolframAlpha also require an active license. Although these and other applications available in the market today are compelling, most do not provide a way to design and configure simulations and visualize results. To address these drawbacks, we have developed iOS and Android graphical programming apps (iJDSP and AJDSP) that can be used to complement instruction in graduate and undergraduate DSP courses [10-13]. The iJDSP app is available for free download on the iTunes App Store [14]. The AJDSP app will be available for download on the Google Play store by late summer 2013, and it can be run on all Android smartphones and tablets [15]. The apps support several DSP functions pertaining to topics such as filter design, convolution, multirate signal processing and the FFT. They also comprise an easy-to-use interactive design, numerous visualization tools, and a provision to create simulations of DSP systems.

The primary focus of this paper is to present AJDSP interfaces to wearable wireless sensors, developed by

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Shimmer Research Inc. The new sensing features are used to link concepts in DSP and wireless networks to applications in health monitoring. The proposed interfaces will enable students from the STEM program to perform laboratories that associate basic parameters estimated from bio-signals with bio-physical conditions. As part of this work, we have developed software modules in AJDSP to: (a) acquire data from on-board and SHIMMER sensors; (b) extract relevant features from the sensor measurements; and (c) compute and visualize bio-signal parameters. In addition, data acquired from these sensors can be processed using other AJDSP functions. Laboratory exercises and tutorials to be deployed in an undergraduate level DSP course (EEE 407) and a graduate level biosensors (EEE 598) course at Arizona State University (ASU) are being developed. The AJDSP app with its unique combination of sophisticated DSP functionalities, the proposed sensing features, and interactive workspace for performing block-based simulations make it a novel and valuable educational tool.

This rest of this paper is organized in the following manner. Section II provides a brief background on mobile apps for education and healthcare, and the SHIMMER sensor platform. Section III gives an overview of the AJDSP app. Section IV describes the proposed interfaces and the various physiological signals that can be monitored using AJDSP. In addition, it presents an overview of the learning opportunity using such interfaces. Section V presents a few sample laboratory exercises. Section VI discusses the assessment results, and concluding remarks are presented in Section VII.

II. MOBILE APPLICATIONS AND SENSORS

In this section, a brief overview of existing apps used in education and health monitoring are presented. Furthermore, a background on the SHIMMER sensor platform that is interfaced with the AJDSP app is also provided.

A. Apps in Education and Healthcare

A plethora of apps exist in the market today, many of which are geared towards assisting teachers and students in various tasks related to coursework. Some examples are Blackboard Mobile [16], Class Dojo [17], Calculus Tools [18], and Cram [19].

In addition, there exist several apps providing health related information based on measurements acquired using on-board device sensors. At times these can also connect to remote databases containing patient health records. A few examples are: (a) Endomondo which monitors users engaged in activities such as running, walking, and cycling [20]; (b) Instant Heart Rate Pro is an app that measures heart rate and allows sharing information via internet; (c) The Stress Check app measures stress levels of a person using their heart rate [21]; (d) Blood Pressure Journal that measures blood pressure, heart rate, custom medication doses, weight, and body mass index (BMI) [22]; and (e) FitBit, which automatically and wirelessly records data such as steps, distances, and calories burned, obtained from a FitBit tracker. It enables daily monitoring of food, activity, weight, water, and sleep [23]. However, these apps do not have the facility to allow users to perform tasks and analyses using DSP tools, and therefore have no scope to be used for DSP education and research.

B. SHIMMER Sensor Platform

Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability (SHIMMER) is a small wireless low-power sensor platform that can record and transmit physiological and kinematic data in real-time. This sensing platform has been adopted to increase the applications of sensor technology in healthcare, using open standards to achieve this goal. The platform focuses on integrating hardware and software components to allow for rapid prototyping of research in biomedical applications [24]. The SHIMMER baseboard forms the core component of this platform and comprises a microcontroller, a Texas Instruments™ MSP430 MCU, the advantage of which is that it consumes low power when inactive and is effective in medical sensing applications. The baseboard also consists of a Bluetooth or 802.15.4 low power radio transceiver, an accelerometer for activity monitoring, data storage using a micro SD card, and connection capabilities to different kinds of daughterboards (biosensors). The daughterboards extend the abilities of this platform by providing various kinematic, ambient and physiological sensing functionalities:

1) *Kinematic sensing:* Accelerometers, gyroscopes and magnetometers are included and utilized for inertial measurement applications.
2) *Physiological sensing:* Incorporates Galvanic Skin Response (GSR), Electrocardiogram (ECG), and Electromyography (EMG) sensors.
3) *Ambient sensing:* Comprises of temperature and light sensors.

In the recent past, several m-Health applications have used the SHIMMER sensor platform to reliably obtain sensing measurements in real-time for signal monitoring and diagnosis. BioMOBIUS is an example where SHIMMER is used as part of a medical research platform [24]. Accelerometers have been used to study energy expenditure estimation in patients with Rheumatoid Arthritis [25]. ECG sensors have enabled a wavelet-based real-time delineation and compressed sensing-based compression of ECG signals [26,27]. Motion analysis of patients with Parkinson's disease, stroke, and epilepsy, using a wearable wireless sensor platform called Mercury has been developed in [28]. A combination of physiological sensors has been used to perform activity aware stress detection [29].

In the proposed interface, we employ the SHIMMER platform for real-time sensing, as it includes libraries for app development on Android devices. Moreover, the compact size, extensive sensing capabilities, wearability and light weight nature, make the SHIMMER ideal for creating mobile and nonintrusive physiological signal monitoring systems. The purpose of building this platform has primarily been for use in various biomedical and activity aware applications; however, it has not been used for demonstrative purposes in an undergraduate DSP course.

Fig. 2. SHIMMER interface to stream data in real-time. As an example, the accelerometer is chosen as shown in the options menu.

III. AJDSP OVERVIEW

In this section, we provide a brief background on the AJDSP app and its functionalities.

AJDSP is a standalone mobile graphical programming app designed to be used to aid in signal processing education. The app comprises of a block-based interface consisting of inputs and outputs that allow presentation of DSP concepts in an easily understandable manner. Using AJDSP, students can establish and run DSP algorithms with various configurations on their Android devices and can also perform undergraduate signal processing laboratories.

Signal processing functions, including signal generation, signal processing and signal display units are incorporated into the application. AJDSP has capabilities to generate deterministic and random signals, as well as MIDI and DTMF waveforms. Along with a rich suite of time and frequency domain signal processing functions, algorithms such as the fast Fourier transform, filter design and *z*-domain operations have been implemented. Furthermore, interactive demonstrations to teach concepts of continous-time and discrete-time convolution and relationships between the *z*-domain and the frequency-domain using the pole-zero placement method are provided.

IV. DEVELOPMENT OF AJDSP HEALTH MONITORING LABS

In this section, we describe the proposed sensing interfaces for AJDSP and highlight the concepts about which intuition can be provided by introducing health monitoring laboratories in DSP courses.

The proposed sensor interfaces allow access to both external SHIMMER sensors and on-board mobile device sensors. Data can be streamed in real-time from the SHIMMER-based electrocardiogram (ECG) sensor, galvanic skin response (GSR) sensor, and the accelerometer using the *Shimmer Signal Generator* block. It establishes a Bluetooth connection between the SHIMMER baseboard and the

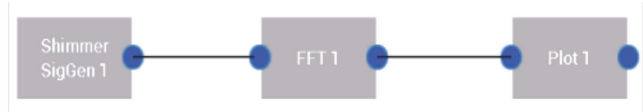

Fig. 3. FFT processing of SHIMMER sensor data.

Android device and data is acquired by configuring the required sensor to be turned on. Fig. 2 shows streaming data from a 3-axis accelerometer and Fig. 3 shows the FFT of the data. Changes in readings indicate movement of the sensor along each of the 3 axes. A brief description of the various sensor signals and the corresponding features that can be extracted using AJDSP is presented below. In addition, concepts that are intended to be taught using the proposed interfaces of AJDSP for in-class demonstrations and purposes of performing laboratory exercises are mentioned.

A. *Accelerometer*

The accelerometer can be used to measure instantaneous acceleration due to forces acting on the sensor. Analysis of accelerometer data requires extraction of features such as mean, standard deviation, and energy for each axis, and correlations between axes. Students can be provided with an insight on how physiological responses tend to be affected by physical activity. Examples inlude, displaying readings and waveforms of sensor measurements obtained while a person is at rest, in comparison to while a person is walking. Therefore, a need to incorporate accelerometer measurements in context-aware applications such as stress detection can be demonstrated. Furthermore, the appropriate placement and positioning of sensors for different appplications can be presented. For example, it can be shown that placing the accelerometer on the hip helps in classifying physical activity [30].

B. *Electrocardiogram (ECG)*

The ECG sensor detects small changes in electrical activity of the skin at every heart beat. The measurement is used to analyze the functionality of the heart based on the regularity of the heartbeats. An important processing step in ECG signal analysis is the extraction of the QRS-complex and detection of the R-wave peaks [31]. A few other features that can be extracted include the mean and standard deviation of heart rate and R-R interval, root mean square (RMS) value of the differences between successive R-R intervals, and percentage of heat beat intervals with a successive R-R difference in interval greater than 50ms (pNN50) [32].

Using these functions, demonstrations on the different configurations of electrode placement used to acquire the ECG measurements can be provided. Typical characteristics of ECG waveforms (Fig. 4) like the QRS-complex, P-wave and T-wave segments and their corresponding range of time intervals for normal and abnormal recordings can be understood. ECG signal artifacts such as low frequency baseline wandering and high frequency power line interferences that occur during signal acquisition can be observed.

Fig. 4. The ECG Signal Generator function block.

Concepts of signal denoising operations and the challenges faced can be highlighted. In addition, the time-domain and the frequency-domain visualization of extracted feature vectors such as, R-R interval and heart rate variability (HRV) can be associated with corresponding health conditions.

C. *Galvanic Skin Response (GSR)*

The GSR sensor measures the electrical resistance of skin based on the amount of moisture content present in it. This conductance varies based on skin and muscle tissue responses to stimuli. It is used to detect stress, fear or anxiety, all of which make sweat glands more active and cause a decrease in the skin resistance. Two signal characteristics that can be visualized from the GSR signal are: (a) Skin Conductance Level (SCL) – a slowly varying signal; and (b) Skin Conductance Response (SCR) – a fast varying signal. Important features extracted from this signal are the amplitude and latency of SCR and the mean and standard deviation of SCL. The distribution of the SCL peak and the SCR peak rate can be shown to carry information regarding the stress level of a person [29]. Using these features, classification of skin conductance into Tonic conductance and Phasic conductance can be demonstrated. The former is observed as a sharp transition in the signal values due to a stimulus and the latter is observed 1-2 seconds after the stimulus. Tonic conductance can further be shown to increase with stress levels or demanding mental activities. In addition to this, concepts of a startle response, which is the physiological response of the body due to a sudden stimulus, can be presented. The total number of startle responses in a windowed segment of GSR, the sum of the response magnitude and the sum of the response duration can be shown to characterize the startle response.

D. *Photoplethysmogram (PPG):*

In addition to acquiring physiological signals from SHIMMER sensors, the on-board device camera can be used to extract a Photoplethysmogram (PPG). The PPG signal is obtained by recording a video with the finger tip placed on the camera lens.

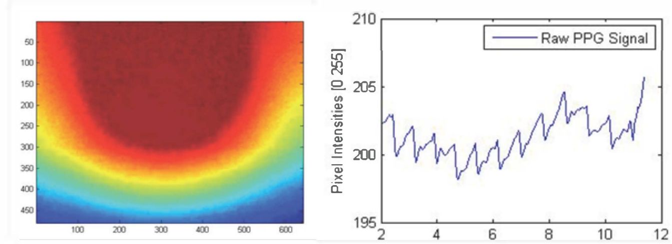

Fig. 5. The pixel intensities present in a single video frame (left) and the extracted PPG signal (right).

It provides a volumetric measurement of organs, such as the heart and the lungs. The PPG typically measures changes in light absorption by the skin. It can be used to monitor heart-rate and cardiac cycle, respiration, and hypovolemia and hypervolemia. The algorithm used to extract the PPG signal from the video was derived from [33] and an example signal is shown in Fig. 5.

V. SAMPLE LABORATORY EXERCISES

In this section, a few sample laboratory exercises designed for undergraduate students belonging to the STEM program is described.

A. *Undertanding QRS detection and Denoising of ECG*

Most physiological signals are non-stationary (frequency varies with time) and need to be observed in real-time to provide students a better perspective of its content. However, acquiring ECG signals from each student individually to work on an exercise can be cumbersome. Therefore, a few sample ECG recordings are provided internally within the *ECG Signal Generator* block. Fig. 4 shows the ECG signal generator interface with a normal sinus rhythm loaded into the block. It also shows the buttons provided to enable frame-by-frame processing of the non-stationary signal. The objective of this exercise is to provide hands-on experiences with AJDSP and a basic understanding of ECG signal characteristics, parameter estimation, and filtering.

The first part of the exercise provides an overview of various signal characteristics in relation to the corresponding health conditions diagnosed from the patient data. Students are asked to use the *ECG Signal Generator* block to load the sample synthetic waveform obtained from Physionet's ECGSYN toolkit [34]. They observe the P-wave, the QRS-complex and the T-wave of this artificially synthesized normal ECG and understand concepts of atrioventricular (AV) ratio, and the required ordering of the wave segments for a normal heart. The sampling rate of this signal and number of samples comprising the R-R time interval are provided to enable students to estimate the heart rate.

Next, real ECG recordings, normal sinus rhythm, arterial fibrillation (AFB) and ventricular tachycardia (VT), and the corresponding waveforms are observed for these abnormalities. Furthermore, signals obtained using a lead VI configuration with and without baseline wandering (noise) are also provided and visualized [35].

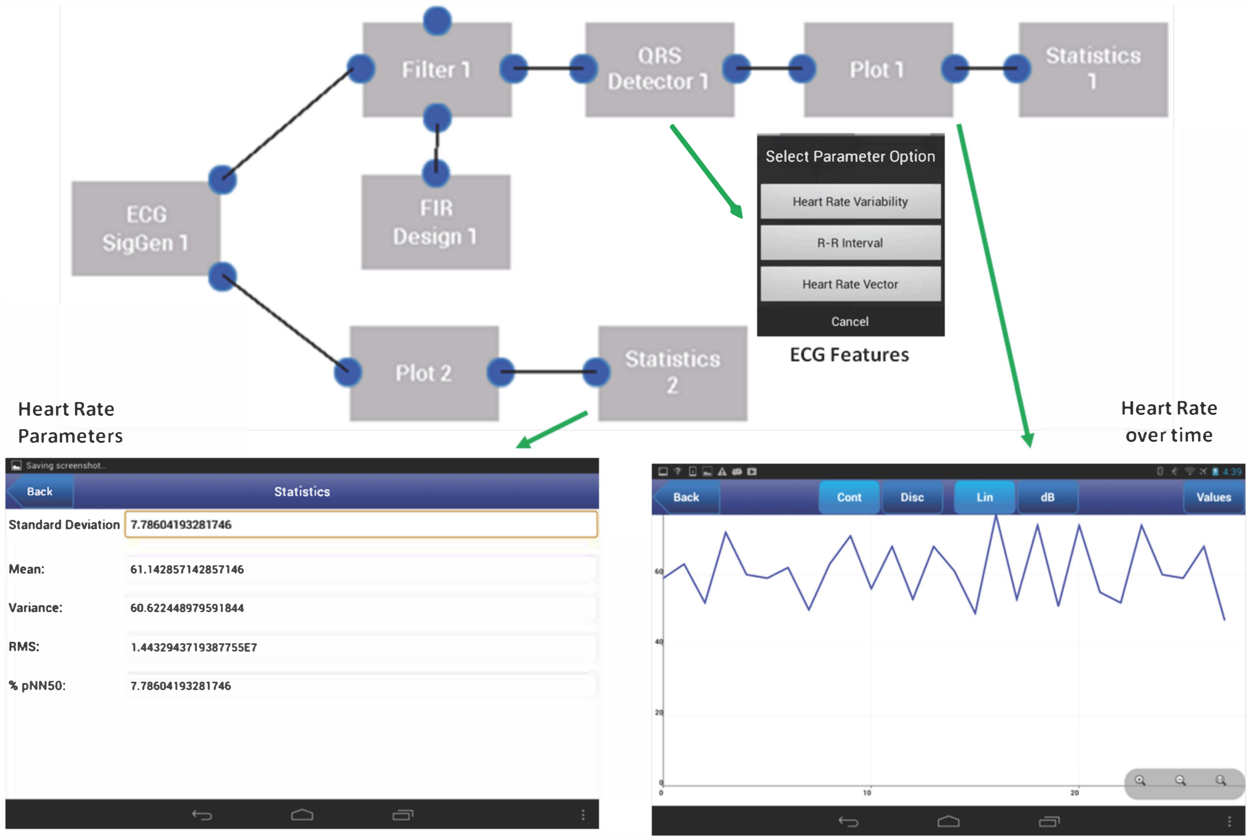

Fig. 6. Sample laboratory simulation exercise using ECG signals.

In the second part of the exercise, the baseline wandering artifact is removed by designing filters using the *FIR Design* block. The R-wave peaks are detected and relevant features are extracted using the *QRS Detector* block. The algorithm to detect these R-R peaks and extract features is based on multiresolution wavelet transform as described in [36]. The simulation diagram and expected outputs for this part of the exercise are shown in Fig. 6. Students can also visualize the frequency spectra of both the noisy and the de-noised ECG signals using the *FFT* block. Heart rate variability (HRV) analysis is conducted and feature vectors such as difference in successive R-R interval, mean and standard deviation of heart rate and R-R interval are calculated in the time-domain using the *Statistics* block.

B. Accelerometer Data Acquisition for a Step Counter Application

The objective of this exercise is to demonstrate a wireless DSP sensor system, to understand remote data acquisition, and to learn simple concepts about accelerometers and their role in context aware applications.

In the first part of this exercise students are asked to use the *Accelerometer* block and select the option to connect to Shimmer sensors. The sensors are either held in their hand or strapped around their waist/ankle. They then establish a Bluetooth connection between the mobile device and the sensor through the app user interface. Data is streamed from the accelerometer and the signal from each of the 3 axes is observed. The change in the axis experiencing the gravitational-force and the corresponding signal transitions based on different orientations of the sensor and activity of the subject is noted. In the second part of the exercise, students stream data from the accelerometer built-in-to the mobile device. They are asked to simultaneously stream data and calibrate the step counter by performing a predetermined activity, such as walking for five steps. Once calibrated, they then perform one of three activities: standing, walking and running. On stopping the data streaming, the total number of steps taken and the duration of each of the listed activities are displayed. By observing the frames of the signal, students learn that each step corresponds to a peak in the accelerometer magnitude and sharp signal transitions mark a change in activity.

C. PPG Extraction and Bio-parameter Estimation using a Camera

The objective of this exercise is to demonstrate a non-invasive health monitoring system by using the camera to extract a physiological signal.

In the first part of this exercise students record a video of their finger tip using the *Health Meter* block. A preview of the video is observed during the recording to understand the optical principle behind the PPG signal. A pulsating light ring within the preview can be visualized with care to understand the physiological property of the signal obtained as every pulsing ring corresponds to a heartbeat [33]. After about 15 seconds, the recording stops and a meter displays the estimated heart rate. The extracted PPG waveform can be observed along with parameters such as oxygen saturation and respiratory rate. In the second part of the exercise students learn about extracting the frequency band that corresponds to the respiratory information in the PPG signal using the *Wavelet Transform* and *Inverse Wavelet Transform* blocks. The different bands can be observed by selecting the low frequency detail coefficients to be preserved during reconstruction of the transformed signal. Concepts on the relationship between scale, wavelet width and frequency can be understood using the wavelet blocks. The significance of approximation and detail coefficients and their relationship to signal energy can also be understood. In addition, a brief idea on the different family of wavelets that exist and choosing the right one in relevance to the application is provided.

Performing laboratories using these sensors provides an overview of the procedure of collecting sensor measurements from the different sensors, and the abilities of mobile devices to act as computational signal analysis platforms. Additionally, the AJDSP block functionality of processing signals in a frame-by-frame manner gives a better intuition of the processing operation that takes place, and a way to closely observe important signal characteristics. The interface between sensors and mobile apps can be used to present students with the diverse applications of DSP.

VI. ASSESSMENTS AND OUTREACH

Preliminary assessments were conducted for AJDSP in general DSP and how students receive it in class. Two workshops were held, one comprising graduate students and the other, undergraduate students. A detailed evaluation methodology was designed to test various aspects of the AJDSP app such as educational value, robustness, and improvement in conceptual understanding.

The goal for the graduate student workshop was to assess the robustness and the accuracy of the software while the undergraduate student workshop was conducted to assess the ability of the application to foster understanding of signal processing concepts. The concepts tested in the workshop with the help of exercises consisted of filter design, FFT, z-transforms and convolution. A total of thirty-three students participated in the assessment workshops. Fig. 7 shows the results obtained. Most students were satisfied with the robustness and speed of the AJDSP app. Based on this exercise, an overall improvement in understanding was observed to be about 11 percent (Fig. 8). From these results, we can substantiate that mobile learning introduced into the curriculum improves conceptual learning. Detailed assessments on using the proposed functions for m-health applications will be provided at the conference.

As part of outreach, the AJDSP app was displayed at the Engineering Open House event conducted at ASU. The event was designed to showcase engineering and technology, in a creative and interactive fashion to students from K through 8th Grade.

VII. CONCLUSIONS

The ability to experience how sensors measurements are acquired and signals are processed will help students relate textbook knowledge to applications and creatively conceptualize their understanding. By depicting the challenges faced in the healthcare domain, students can be guided to innovate in these areas. In particular, the role of DSP in tackling problems in such real-world contexts can be presented along with its diverse applications. Furthermore, the AJDSP app helps to serve as a platform to visualize physiological signals such as PPG, ECG and GSR. In addition, function blocks to extract features and compute parameters such as heart rate, oxygen saturation and step count were developed. These functions were used to create laboratory exercises, samples of which were provided. Preliminary assessments show promise in improving students' understanding of DSP concepts when using the AJDSP app as part of the curriculum. Detailed assessments will be conducted and the results will be presented at the conference.

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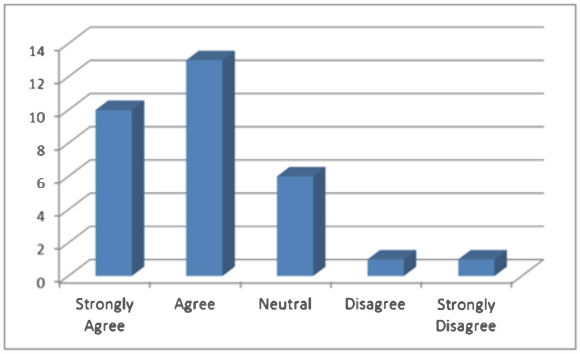
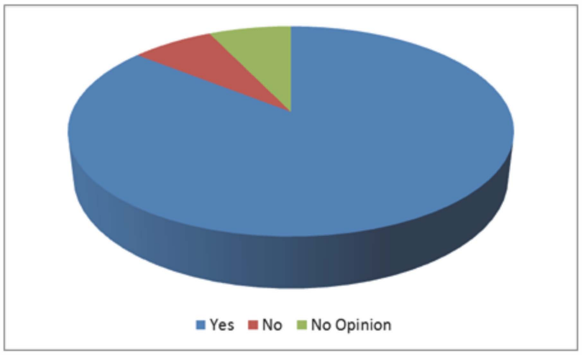


(a) Response of students when asked if the AJDSP app is stable.



(b) Response from students if they found the speed of the app satisfactory.

Fig. 7. Preliminary assessments obtained from graduate students on the AJDSP app robustness and speed.

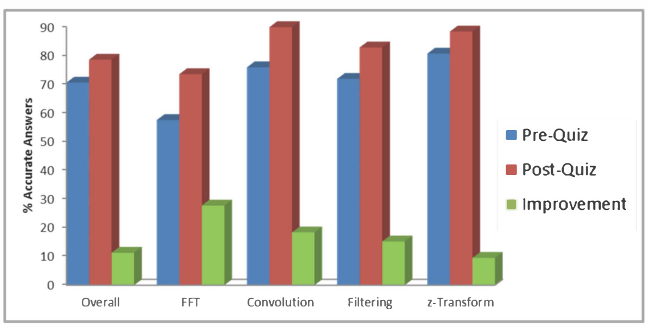


Fig. 8. Improvement shown in student understanding of different DSP concepts.

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