AC 2011-1400: CONNECTING THEORY AND PRACTICE: LABORATORY-BASED EXPLORATIONS OF THE NAE GRAND CHALLENGES

Lisa Huettel, Duke University

Lisa G. Huettel received the B.S. degree in engineering science from Harvard University, Cambridge, MA, in 1994 and the M.S. and Ph.D. degrees in electrical engineering from Duke University, Durham, NC, in 1996 and 1999, respectively. She is currently an Associate Professor of the Practice in the Department of Electrical and Computer Engineering at Duke University, where she also serves as the Director of Undergraduate Studies. Her interests include engineering education and applications of statistical signal processing.

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Abstract

This paper describes a pilot project, conducted during the Fall 2010 semester, that incorporated laboratory exercises inspired by the National Academy of Engineering (NAE) *Grand Challenges* into an introductory digital signal processing course. The Challenges were broadly interpreted and local expertise and resources were used to enhance the experience. In one project, students investigated environmental sensors in the local “SmartHome” and followed up by analyzing actual solar and electrical energy usage data. In another project, students learned about the process of collecting and analyzing electroencephalography data in a local neuroscience research laboratory. Basing these projects on the Grand Challenges – while integrating local researchers and technical experts – provided a societal context and supported deeper investigation by interested students.

The pilot study assessed effects of the new laboratory activities on three outcomes: improving student understanding of course material, increasing student interest in the course material and topic area, and broadening students’ perspective on applications of signal processing and the importance of interdisciplinary collaborations. Our assessment used a mixed-method approach, relying on both qualitative measurements (e.g., surveys of student opinions) and quantitative data (e.g., course performance). Baseline data (e.g., student surveys) were available from previous years for comparison. Students reported that the projects positively contributed to their understanding of course material. We also found that students’ awareness of the Grand Challenges and the role that signal processing can have in finding solutions increased. A number of students indicated that they plan to pursue more in-depth projects inspired by what they learned during the laboratory.

1. Introduction

The National Academy of Engineering (NAE) has identified a set of fourteen Grand Challenges for current engineering research and practice. These include such diverse topics as reverse-engineering the brain, improving access to clean water, and enhancing virtual reality. In its report, “Educating the Engineer of 2020,” the NAE contends that solving problems, such as those posed in the Grand Challenges, will require more than just providing students with technical training. An engineering education must, it is argued, produce graduates who combine technical excellence with a multitude of other skills including communication, teaming, ethical reasoning, and contextual analysis¹. Yet, without exposure to real-world applications in the context of a technical education, students may neither develop these important skills nor gain sufficient motivation to pursue careers in engineering. A key finding within the current engineering education literature is that exposure to real-world applications – especially when presented in an active, experiential learning environment – increases both student interest and pedagogical effectiveness²⁻⁵.

Since 2006, when our Electrical and Computer Engineering department instituted sweeping curriculum changes, incorporation of real-world problem solving has been increasingly emphasized. Consequently, the introductory digital signal processing (DSP) course had recently been modified to include an extensive hands-on laboratory component (effective Fall 2007). The series of laboratory experiments included Texas Instruments C6713 DSK-based hardware projects and complimentary MATLAB-based explorations. These labs included the following:

1. Echo Cancellation: Students implemented a simple audio processing algorithm on the DSK board to review how to use the board (which they had been introduced to in a previous class).
2. Comb Filter & Plucked String Synthesis: In this series of exercises, students first implemented a comb filter in MATLAB, and then applied and extended what they had learned by using low-pass and allpass filters to implement a model of a plucked string.
3. Biosignal Acquisition and Analysis: Students acquired electromyography (EMG) data in the laboratory and explored the use of MATLAB's filter design and analysis tools to analyze the data.
4. Notch Filter & Speech Recognition: Students first explored the design and implementation of a notch filter using MATLAB. Subsequently, they designed a real-time system (operating on the DSK) that analyzed spoken vowels and identified up to six different vowels.
5. Guitar Tuner: The culminating project asked students to use all that they had learned to design and implement a real-time electronic guitar tuner, which they tested using actual electric guitars.

Although these projects have generally been very well-received, we continued to search for projects that would highlight even broader applications of signal processing. The introduction of the Grand Challenges, and subsequent development of the Grand Challenge Scholars program⁶, served as the inspiration for illustrating to students how a specific field of study, such as signal processing, could contribute to the solution of global and societal challenges.

The fundamental characteristics of the DSP course were unchanged during the pilot period: The course is typically taken by about 25 students and is offered in the fall semester. There are two 75-minute lectures and one three-hour laboratory session each week. Laboratory exercises are typically completed in groups of two. In an effort to balance existing hands-on experiences with the new Grand Challenge-inspired explorations, the pilot project, implemented in the Fall 2010 semester, adapted the Comb Filter project into a homework exercise and retained the Notch Filter & Speech Recognition project while adding two Grand Challenge-themed experiences (described in the next section).

2. Grand Challenge-inspired Project Descriptions

Two Grand Challenges were selected for the pilot project: *Making Solar Energy Economical* and *Reverse Engineering the Brain*. These were chosen for two reasons: they were likely to appeal to our students and they could take advantage of specialized resources available at the university. We broadly interpreted these Challenges to best fit the resources available.

2.1 Making Solar Energy Economical: The Duke University SmartHome

This project used the Grand Challenge of *Making solar energy economical* as a foundation. To take advantage of available resources, this Challenge was interpreted more broadly to allow for the exploration of energy usage and efficiency in the context of the Duke University SmartHome. The SmartHome contains a broad variety of sensors that monitor many energy systems; e.g., city electrical consumption, self-generated solar energy, etc. By developing an understanding of these systems, students would gain new insight into how signal processing can play a role in addressing the Grand Challenge.

The project had two components. First, there was a physical tour of the SmartHome led by a local expert who discussed the sensors installed in the house, the data these sensors provide, possible analyses that could be performed on that data, and limitations of the data collection systems. Then, students analyzed actual data collected by the solar and electrical energy system monitors in the SmartHome. This project was assigned early in the semester concurrent with topics such as difference equations and the Z-transform. Its objectives included:

Component 1:

1. To better understand the nature of the NAE Grand Challenges, generally, and Making Solar Energy Economical, specifically.
2. To identify input and output signals of real-world systems in the context of the SmartHome.
3. To characterize signals and systems in the SmartHome in terms of important parameters and properties (e.g., sampling rate, quantization, stability, causality).
4. To understand how data is collected and the implications of various parameters (e.g., sampling rate) on signal and system analysis.
5. To formulate questions that can be answered using existing data.
6. To propose additional research questions and to identify the data (and new or modified sensors) needed to answer those questions.

Component 2:

1. To examine several theoretical concepts (e.g., LCCDE's, pole-zero plots, impulse response) in a realistic context.
2. To model an energy-related system in the SmartHome, using MATLAB tools.
3. To explore the relation between impulse response, pole-zero plots, and system properties.
4. To analyze real data and to discover issues that can arise when processing real data.

The first component of the project required students to read some background material on the NAE Grand Challenges⁷ and on the specific Challenge *Making solar energy economical*⁸. A pre-tour exercise encouraged students to brainstorm the type of information they would need to obtain during the tour in order to collect enough information to perform an analysis of energy efficiency for the house. The written assignment for this component required students to submit a document with three parts:

- 1) a brief, qualitative summary of the current state of energy usage in the SmartHome, demonstrating their understanding of how the SmartHome functions, in terms of energy sources and sinks.
- 2) a discussion of the current state of data collection and possible analyses, demonstrating their understanding of the existing data collection processes/parameters, as well as suggesting possible questions that could be answered based on an analysis of this data.
- 3) a proposal for further analyses/experiments (e.g., defining what data should be measured, the parameters of those measurements, how the data could be analyzed) that could/should be conducted to further their understanding of current energy consumption and the impact of possible modifications to the house.

Collectively, these activities illustrated the global context of this Grand Challenge, so that students could subsequently focus on how signal processing could contribute to the solution.

In the second component of the project, students performed analyses of actual data collected by the electrical and solar system monitors which they had previously viewed on the SmartHome tour. These analyses include examining the time- and frequency-domain data and relating the parameters to the physical signals, estimating a model (in the form of a difference equation) based on a set of input-output data, and examining the resulting system properties and other characteristics (e.g., impulse response, poles and zeros). Much of this analysis was done using the MathWorks System Identification Tool. A sample data set is presented in Figure 1, showing total electrical energy used (pulled from the grid) and total solar power generated (fed back to the grid). Note that the SmartHome does not itself use the solar power generated, thus subsequent analyses assumed that the generated solar power was used internally to offset electrical power consumption.

Figure 1: Sample data set used in SmartHome energy usage analysis

Students began their analysis by loading the dataset into MATLAB and examining the data in both the time and frequency domains. The goal was for students to make the connection between the real parameters of the system (e.g., oscillations in the data due to position of the sun or house occupancy, the sample rate) and the observed data (in both domains). The next step was to use the MATLAB System Identification Toolbox to estimate a linear model of the system using solar usage as input and net electric usage as output (see Figure 2a for a screen shot of the tool). This involved partitioning the data in to “training” and “testing” data and then using the estimation capabilities of the tool to generate a model capable of simulating the data. There are a number of different options for model estimation. Given the background of the students and the goals of the project (to illustrate course concepts), the students were instructed to use the linear parametric model estimate which resulted in a linear, constant coefficient difference equation of the form:

$$y[n] = -\sum_{k=1}^N a_k y[n-k] + \sum_{k=0}^M b_k x[n-k],$$

where the output of the model was a set of coefficients, a_k and b_k , and a delay. The tool also evaluated the fit of each model, a sample of which is shown in Figure 2b.

Figure 2: (a) MathWorks System Identification Tool screenshot, (b) Sample model output using best-fit ARX model.

The model generation, described in the previous paragraphs, was treated as somewhat of a black box since students had no background in model estimation. Ultimately, the goal was to obtain a difference equation related to the data, so that students could analyze the system using techniques and concepts recently covered in class. Thus, once students generated a suitable model, they exported the model parameters into the MATLAB workspace for further analysis. Their analysis began by writing out the resulting difference equation and attempting to interpret the equation in terms of the physical parameters of the system. Subsequently, they were asked to determine whether the system was FIR or IIR (based on the difference equation), then to verify their conclusion by generating the impulse response of the system. Finally, students were instructed to generate the corresponding pole-zero diagram and to draw conclusions about the properties of the system (e.g., stability, causality).

To conclude the project, students were asked to consider whether or not this was a good model of the energy usage system, taking into account factors such as how easy it would be to break the model (e.g., what happens if the input is modified to simulate cloudy days or different durations of daylight in summer versus winter). Despite not having any background in modeling, students could use this approach to consider the relations between the mathematical model and real system parameters.

2.2 Reverse-Engineering the Brain/EEG Data Analysis

The second project was based on the Grand Challenge of *Reverse-engineering the brain*. This topic was a natural choice given local expertise (e.g., the Biomedical Engineering department in which several faculty conduct research closely related to the challenge topic, the Duke Institute for Brain Science which brings together researchers from across the university with an interest in better understanding the brain) and the perceived strong interest of students, generally, in this topic area. The project took place near the end of the semester, concurrent with the introduction of topics such as the Discrete Fourier Transform and filter design.

For this project, the principal investigator of a research laboratory based in the Duke Center for Cognitive Neuroscience gave a lecture to the class and conducted a tour of his research laboratory. This researcher, who has a primary appointment in the Department of Psychiatry, runs a laboratory in which various techniques (e.g., electroencephalographic recordings, EEG; functional magnetic resonance imaging, fMRI) are used to study human attention and perception. The researcher also has an undergraduate degree in Physics and Applied Mathematics and could, therefore, naturally relate signal processing concepts to his research.

The lecture was given during a regular class period. In preparation for the lecture, students read a handout describing the nature of EEG signals and some background material on the Challenge itself⁹. The lecture provided an overview of the collection of EEG and event-related potential (ERP) data, depicting the experimental set-up and illustrating typical signals that are recorded. Sources of noise in the data were discussed (e.g., eye blink artifacts, head movement, background brain activity), as well as signal processing that can correct for such distortions (e.g., amplification and filtering). Issues related to sampling and aliasing were discussed in terms of the experimental system parameters and expected information contained in the data. The discussion next focused on data analysis and visualization, illustrating how techniques such as time-locked averaging could be used to improve the signal-to-noise ratio. Throughout the presentation, students had the opportunity to ask questions, which they did quite frequently.

Subsequently, students were given a tour of the research laboratory. On this tour, they were able to observe the experimental set-up and see a real-time display of the EEG recordings from a 128-channel system. As they watched, the experimental subject was instructed to blink, clench her teeth, look left/right/up/down, and to shift visual attention in response to such cues. Students could clearly see artifacts in the EEG signal introduced by events such as a blink.

After the lecture and laboratory tour, students were asked to write a report discussing challenges associated with reverse-engineering the brain, using the research laboratory and research questions discussed as context, and ways in which collaboration between engineers and non-

engineers can be mutually beneficial and intellectually stimulating. Specifically, students were asked to address the following questions:

- What are some applications of signal processing in this general research area/research modality? For example, what are some of the challenges faced and how can expertise in signal processing contribute to the solution of these problems. Provide specific examples, if possible.
- How can this be generalized into opportunities for signal processing to contribute to the advancement of the Grand Challenge of *Reverse-Engineering the Brain*?

3. Assessment

Assessment of the pilot project focused on the following outcomes: impact on student understanding, student engagement and interest, and students' perspective of signal processing. We used a mixed-method approach that measured both qualitative markers of student opinions (e.g., surveys of student opinions) and quantitative data about student outcomes (e.g., course performance). Data collected following the pilot project course were compared to baseline data from previous years of the same course.

3.1 Analysis of Learning Objectives and Measurable Outcomes

Learning objectives and measurable outcomes were defined for this course in the Fall of 2007 in advance of the ABET accreditation process. As part of our ongoing ABET self-assessment, we regularly calculate achievement scores that estimate how well each course meets its curricular objectives. These calculations are based on student performance (grades) on specific exam questions and laboratory reports. For each of those assignments, students are rated as non-proficient (0), proficient (1), or highly proficient (2). Although the specific questions and assignments on which the students are evaluated vary from semester to semester, the process has been designed so that data can be compared across terms. Thus, historic data from the Fall 2007 and Fall 2009 semesters provide a comprehensive baseline to which Fall 2010 student performance can be quantitatively and directly compared,.

The seven Measurable Outcomes (MOs) for this course include:

- MO1. Determine the transfer function of a discrete-time system and analyze it to determine characteristics such as pole and zero locations, Region of Convergence, or associated frequency response.
- MO2. Find the impulse response and/or difference equation relating the input and output of a discrete-time LTI system.
- MO3. Determine the system properties (e.g., linear, time-invariant, stable, causal) of a discrete-time system.
- MO4. Compute DTFT, DFT, Z, and inverse Z transforms using methods such as the defining equations, tables of standard transforms and properties, or Partial Fraction Expansion.
- MO5. Generate a discrete-time signal via sampling, determine if aliasing occurs and its impact on the time- and frequency-domain representations of the signal, and reconstruct a continuous-time signal from the samples.
- MO6. Design a digital filter to meet specifications.

MO7. Determine the overall system response (in time- and/or frequency-domain) of a system of interconnected, discrete-time, LTI systems.

These outcomes are then each mapped to a set of Learning Objectives (LOs), which are aligned with a subset of the ABET a-k criteria, specifically Criteria a, b, c, e, and k.

A two-tailed Student's *t*-test assuming unequal variance was performed on the data, with individual student achievement scores from the Fall 2007 and Fall 2009 semesters (N = 31) constituting one sample and the individual student achievement scores from the Fall 2010 semester (N = 22) constituting the other sample. The results are presented in Table 1.

TABLE 1. Statistical analysis of Measureable Outcome data.

Measureable Outcome	μ_{nonGC}	μ_{GC}	<i>t</i> stat	<i>p</i> value
MO1	1.12	1.33	1.17	0.25
MO2	1.27	0.98	-1.80	0.08
MO3	1.29	1.40	0.56	0.58
MO4	1.11	1.27	0.94	0.36
MO5	1.02	0.73	-1.13	0.27
MO6	1.32	0.70	-4.15	2.30E-04
MO7	1.23	1.47	1.01	0.33

Of note, there was little evidence that the new Grand-Challenge themed approach to projects had direct, positive effects upon these measurable outcomes. Only one of the seven outcomes (MO6) yielded a significant difference between the two groups – and that effect was negative (i.e., the Grand-Challenge students had lower achievement in digital filter design). This result reinforces the idea that including additional content, in the form of background information to provide context for the exercises, requires some sacrifices and tradeoffs in course content. Performance on the other criteria was roughly similar in the two sets of courses, suggesting that both the previous projects and the new Grand-Challenge projects significantly contributed to students' understanding and ability to apply course material.

We emphasize, however, that this particular set of outcomes would be unlikely to capture positive contributions results of the changes made to the laboratory projects. In other words, the five criteria to which the MOs and LOs are mapped – *a) apply knowledge of science, mathematics, and engineering, b) design and conduct experiments and analyze and interpret data, c) design a system, component, or process to meet desired needs, e) identify, formulate, and solve engineering problems, and k) use techniques, skills, and modern engineering tools necessary for engineering practice* – neither motivated the change in the laboratory experience nor reflect the goals of our pilot project. Rather, one would expect to observe greater differences between the groups on criteria such as *h) understand the impact of engineering solutions in global and society context* which, unfortunately, is not measured using this specific tool. Fortunately, the complete set of ABET criteria were included in student surveys, as discussed in the following section, so a qualitative comparison between groups is possible.

3.2 Analysis of student surveys: ABET criteria

As part of our standard end-of-class evaluation process, students complete surveys in which they rate how well each course met specific ABET a-k objectives on a scale from “1: Strongly Disagree” through “5: Strongly Agree”. We performed two-tailed Student’s *t*-tests (assuming unequal variance) comparing individual student responses to each question from the Fall 2007, Fall 2008, and Fall 2009 semesters (N = 41, 84% response rate) to the individual student responses to each question from the Fall 2010 (Grand Challenge) semester (N = 18, 82% response rate). Mean ratings and statistical comparisons are provided in Table 2.

TABLE 2. Statistical analysis of end-of-semester student survey data: ABET criteria.

ABET criteria	μ_{nonGC}	μ_{GC}	<i>t</i> stat	<i>p</i> value
<i>a) apply knowledge of science, mathematics, and engineering</i>	4.74	4.65	-0.64	0.53
<i>b) design and conduct experiments and analyze and interpret data</i>	4.29	4.20	-0.41	0.68
<i>c) design and conduct experiments and analyze and interpret data</i>	4.65	4.45	-1.02	0.31
<i>d) function on a team</i>	3.90	3.44	-1.81	0.08
<i>e) identify, formulate, and solve engineering problems</i>	4.42	4.11	-1.50	0.15
<i>f) understand professional and ethical responsibility</i>	2.98	3.33	1.00	0.33
<i>g) communicate persuasively, in writing and orally</i>	2.90	3.39	1.39	0.17
<i>h) understand the impact of engineering solutions in global and society context</i>	2.93	4.11	3.68	1E-04
<i>i) recognize the need for engaging in life-long learning</i>	3.36	4.06	2.27	0.03
<i>j) know and understand contemporary issues</i>	3.19	4.00	2.55	0.02
<i>k) use techniques, skills, and modern engineering tools necessary for engineering practice</i>	4.51	4.71	1.24	0.22

This analysis revealed that the Grand Challenge version of the course was judged significantly better on three of the ABET criteria – *h) understand the impact of engineering solutions in global and society context*, *i) recognize the need for engaging in life-long learning*, and *j) know and understand contemporary issues* – all at a probability level, *p*, of less than 0.05. None of the results for any other question met the threshold for significance. Thus, the new course was judged to better meet the three ABET criteria that are most related to the goals of the Grand Challenge projects program, while more general criteria (e.g., “Apply knowledge of math, science, and engineering”) showed no significant difference between course versions. Furthermore, the selective results of the statistical analysis eliminate the possibility that the students in the Grand Challenge version of the course simply were more generous in their ratings than students in the previous version of the course.

3.3 Analysis of student survey: Grand Challenge project-specific feedback

In an anonymous survey administered at the conclusion of the course, students evaluated how well each Grand Challenge project successfully illustrated real-world applications of signal processing concepts, increased the students’ understanding of the course material, and the extent to which the project increased their interest in signal processing more generally. Students also answered several questions about whether the projects affected their awareness of the Grand

Challenges and their perspective on applications of signal processing. Of the 22 students enrolled in the course, a total of 12 responded to the survey.

TABLE 3: Student assessment of Grand Challenge projects: Percent of responses (N = 12)

	Strongly Agree	Agree	Neither	Disagree	Strongly Disagree
The SmartHome/Economical Energy project...					
...illustrated real-world applications of signal processing.	8.3	66.7	16.7	8.3	0.0
...increased my understanding of the course material.	0.0	41.7	33.3	25.0	0.0
...increased my interest in signal processing as a field of study or career path.	0.0	33.3	41.7	25.0	0.0
The EEG/Reverse Engineering the Brain project...					
...illustrated real-world applications of signal processing.	25.0	75.0	0.0	0.0	0.0
...increased my understanding of the course material.	8.3	75.0	16.7	0.0	0.0
...increased my interest in signal processing as a field of study or career path.	16.7	75.0	8.3	0.0	0.0
OVERALL ASSESSMENT					
As a whole, the Grand Challenge projects broadened my perspective on applications of signal processing and/or electrical engineering.	0.0	83.3	16.7	0.0	0.0
	None	Minimal	Somewhat familiar	Very familiar	Extensive
My level of awareness of the Grand Challenges BEFORE this class was	0.0	33.3	58.3	8.3	0.0
My level of awareness of the Grand Challenges AFTER this class was	0.0	0.0	41.7	50.0	8.3

Based on these responses (Table 3), both projects were judged to successfully illustrate real-world applications, with 75% and 100% positive responses (Strongly Agree or Agree) for the SmartHome and EEG projects, respectively. This point was echoed in the student feedback; e.g., a student who stated that the best aspect of the projects was “*being able to go outside of lab to see how signal processing was used in the real world.*” The two projects differed, however, on how well they contributed to students’ understanding of course material and to increasing students’ interest in signal processing, with the EEG project receiving very positive ratings and the SmartHome project tending toward more neutral responses. Based on anecdotal student comments, it was not as apparent to the students how signal processing could be applied to the SmartHome as in the EEG project. This is an area for future improvement.

Key pilot project goals were to demonstrate the need for interdisciplinary work in solving grand problems and to show how signal processing, in particular, could contribute to such exercises. Thus, the fact that 83.3% of the students indicated that the projects broadened their perspective on applications of signal processing and/or electrical engineering is a very positive outcome. One student commented:

I enjoyed not only understanding the signal processing techniques used in the different settings but also coming up with solutions to Grand Challenge problems by combining different techniques I had learned and discussed in class.

Another student commented:

Sometimes example problems all start to sound the same--all sound idealized, simplified, and trivial--but here we got to learn about big, complex questions of

obvious importance and how the material we were learning about can be used to answer those questions--generally in much more creative ways than we were ever using in class (which gave us a taste of where you could go further with the field).

4. Conclusions

In conclusion, the integration of Grand Challenge-inspired projects into the introductory digital signal processing class had significant positive impact on students' perspective of the importance and use of signal processing to solve important interdisciplinary problems. Students were very enthusiastic about the opportunity to meet with experts from other areas of campus and to learn how the fundamental concepts studied in class could be applied to real problems. Although students reported that the projects positively contributed to their understanding of the course material, objective measurement of their understanding showed a slight decrease in comparison to the performance of students in the non-Grand Challenge version of the course. This may be attributable to the fact that the Grand Challenge projects were not as technically detailed as some of the pre-existing laboratory experiences and thus students did not have as much opportunity to put theory into rigorous practice. Therefore, future offerings of the course will attempt to strike a better balance by incorporating more of the traditional laboratory exercises and/or increasing the technical rigor of the Grand Challenge projects.

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