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WIP: A longitudinal study of students' conceptual understanding of signals and systems

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A longitudinal study of students' conceptual understanding of signals and systems

Abstract

This paper presents an initial literature review and methodology for a larger study on longitudinal conceptual understanding of signals and systems. We briefly discuss conceptual understanding, one way to measure it, and previous results in engineering-related disciplines. We then describe the Model of Educational Productivity as a framework for studying student, instructional, and environmental factors that may influence conceptual understanding and discuss results from previous studies that suggest additional influencing factors. Finally, we present our planned mixed methods approach, consisting of an exploratory qualitative stage to identify possible factors that influence conceptual understanding, a quantitative analysis to measure understanding and these factors, and an explanatory qualitative phase to add depth to our quantitative results. The purpose of this work-in-progress paper is to present our methodology for feedback from the community, our preliminary results from the initial Fall 2019 data, and to start a larger conversation about the importance of studying conceptual understanding from a longitudinal perspective.

1 Introduction

This work-in-progress paper outlines our planned study of students' conceptual understanding of signals and systems. Signals and systems (SS) is the focus of an electrical engineering (EE) science course at most universities, and topics in SS, such as filtering and Fourier transforms, are fundamental to control theory, signal processing, and machine learning. Despite the importance educators place on SS concepts, previous studies have shown that students understand few of the concepts at the end of a SS course [1]. Our planned study aims to determine if undergraduate students understand SS concepts, and, if they do, when they reach that understanding and what helps them reach it.

Few studies report on students' conceptual understanding of SS topics one or more semesters after a SS course. We aim to help fill this gap by examining student conceptual understanding over time. Our research questions are:

- RQ#1. How many and which concepts do students learn during their signals and systems class?
- RQ#2. How many and which SS concepts have students learned, retained, or forgotten as of their fourth year of undergraduate studies?
- RQ#3. What factors influence the answers to the first two questions?

This work-in-progress paper does not directly address these questions. Instead, it outlines our planned methodology, describes the theories that will influence our study, and presents preliminary data. Our goal is to receive feedback from the community on possible factors that influence long-term conceptual understanding to include on our surveys and to see if anyone else wants to add to the dataset for analysis.

2 Previous research on conceptual understanding

We define conceptual understanding as grasping the governing principles and *relations* between pieces of information in a discipline [2] (this definition is used in engineering education research by [3]). As an example, a student who conceptually understands Fourier transforms must know what low and high frequency mean and that a time domain signal can be described in frequency space using the Fourier transform - even if the student cannot remember the mathematical definition of a Fourier transform. Theorized benefits of increasing students' conceptual understanding include providing structure to help students recall and select the correct procedure, aiding in transferring procedures to new contexts, and developing more expert-like knowledge structures [3], [4].

To measure student conceptual understanding, we will use the signals and systems concept inventory (SSCI), a validated multiple-choice test that takes no more than an hour to complete [1]. The topics on the continuous time SSCI are background mathematics, linearity and time invariance (LTI), convolution, transform representations, and filtering. Despite their limitations [5], concept inventories are useful for testing a large number of students and comparing results across universities. Researchers typically give the 25-question SSCI in a pre/post-test format and calculate average gain statistics, $<g> = 100 \cdot \frac{\text{post}-\text{pre}}{25-\text{pre}}$, to measure how many concepts students learn as a percentage of how many that they did not know before taking SS. Across 29 courses at 6 schools, the average gain was $<g> = 22\%$ in lecture-based classrooms and 39% in active learning classrooms [6]. Similar results have been reported outside the U.S. as well, e.g., [7] found $<g> = 38\%$ after introducing hands-on projects.

2.1 Longitudinal conceptual understanding

The goal of most undergraduate courses (in addition to learning how to learn, collaborate, communicate, etc.) is to achieve long-term understanding that persists after the final exam. There are only a few studies that look at longitudinal conceptual understanding in SS, so this section includes results from other disciplines.

Some studies found that advanced students retained or gained conceptual understanding relative to newer students. For example, [8] found senior students had fewer misconceptions about circuits than freshman and sophomores, even though they had similar misconceptions regarding the physical aspects of circuits [8]. In physics courses, multiple studies found active learning helped students retain conceptual knowledge years after their course [9]–[11].

Many other studies saw declines in understanding after a relevant course. In a qualitative study, [12] found that 48% of students declined in their understanding of the Fourier representation of a signal one year after SS; ref. [13] saw a downward trend in SSCI scores over time if students did not take related upper-level courses; and seniors at MIT did 50% worse on conceptual physics questions than freshman (physics majors did "only" 23% worse) [14].

2.2 Factors influencing conceptual understanding

The mixed results on longitudinal conceptual understanding naturally lead us to ask what factors influence retention, forgetting, and learning of new concepts after a course. We did not find a unified framework for factors influencing longitudinal conceptual understanding. However, the Model of Educational Productivity (MoEP) offers a view on what factors affect learning [15]. Based on a national science achievement test given to 3,049 17-year-olds, Walberg, Pascarella, Haertel, *et al.* [15] found nine significant factors on test scores (summarized in table 1). Other authors, e.g., [16], have confirmed the model in the original high-school setting, and [17] found that the model (removing the mass media variable) transferred well to the higher education setting.

Category	**Factors**
Student factors	(1) Age, (2) ability, and (3) motivation
Instructional variables	(4) Quality and (5) quantity of instruction
Environmental variables	Social psychological environment of the (6) class and (7) home, (8) peer group environment, and (9) exposure to mass media

Table 1: Summary of MoEP factors that predict learning [15].

In addition to the factors predicted by [15], studies in engineering and physics have hypothesized (with varying amounts of evidence) that longitudinal conceptual understanding is influenced by: which courses students take as part of their major or as electives [13], [14], whether the SS course uses a graphical representation of systems (e.g., LabView's graphical interface might help student learn better than Matlab's text-based interface [18]), whether students view the concepts as important [19], and the instruction style of SS [9]–[11].

We can easily imagine many additional possible factors like student career goals, participation in extracurricular activities, repeated exposure to topics over several semesters, and whether labs require critical thinking. The methodology section discusses how we will use an exploratory qualitative approach to including additional potential factors.

3 Methodology

Fig. 1 overviews our mixed methods approach. First, we will use an exploratory qualitative approach (focus groups and interviews) to supplement our literature review about what factors might influence conceptual understanding. Second, in the quantitative piece (SSCIs and surveys), we will analyze data for a larger student population and compare our SSCI results to the literature. Students will complete our research instruments at up to three points in time: (1) the SSCI at the beginning of the course of interest, (2) the SSCI and survey #1 at the end of the course of interest, and (3) the SSCI and survey #2 when students are fourth years. Both surveys will measure factors that might influence conceptual understanding. Finally, we will have an explanatory qualitative phase (focus groups and long answer surveys) to add depth to the quantitative results. We use the terms "exploratory" and "explanatory" as described in [20].

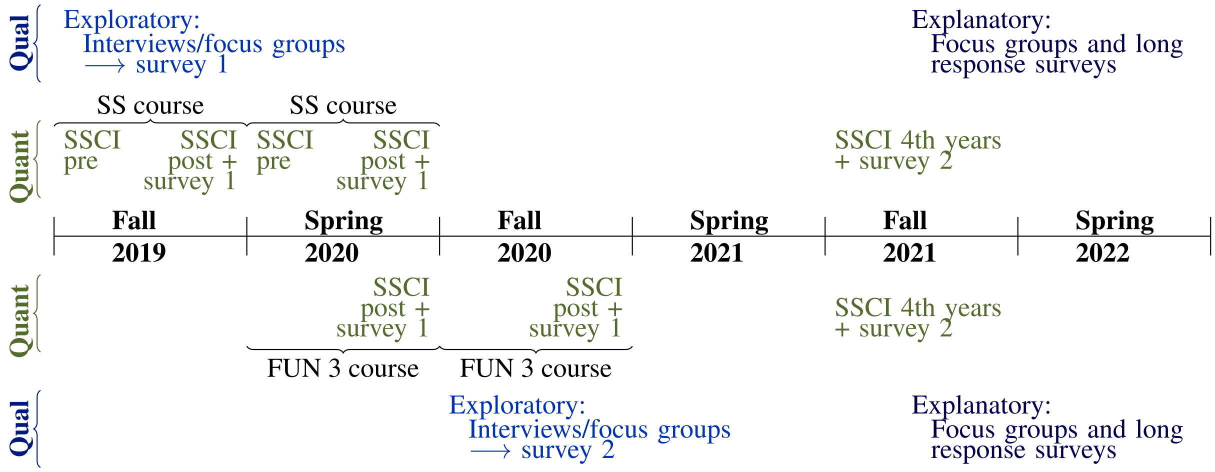

Figure 1: Summary of our data collection. The top half of the diagram is for UM and the bottom half is for UVa. The data from the exploratory focus groups and interviews will influence survey design; the SSCI pre/post data will help answer RQ#1; and the SSCI post and 4th year data will help answer RQ#2. All of the data will help answer RQ#3.

3.1 Study population

We will study undergraduates at University of Michigan (UM) and University of Virginia (UVa) during their second through fourth years. At UM, there is a single SS class aimed at second year students. The class emphasizes continuous time analysis and has an associated lab section that meets roughly five times a semester. At UVa, there is a series of three Fundamentals courses (abbreviated FUN 1-3) that intermix the curriculum typical in Linear Circuits, Electronics, and Signals and Systems courses. The classes emphasize connections between the subjects and mix lectures and labs. For more information on the course design at UVa, see [21].

The primary sample population for this study is students in their second year in Fall 2019-Spring 2020. These students will have paired SSCIs from their SS course (or last FUN course) and as fourth years. We expect to include roughly 200 students at UM and 75 students at UVa. The secondary sample population is students who will only take the SSCI as fourth years (without paired data). This group includes roughly 500 past and current fourth years at UVa and an estimated 150 current third and fourth years at UM. For simplicity, we only describe the data analysis on the primary sample population, but results from the secondary sample population will help support the data analysis.

Students will be incentivized by a mixture of course credit for completing the SSCI, free food for being in focus groups, and raffle prizes for completing surveys and consenting to participate in the research.

3.2 Phase 1: Exploratory qualitative design

In Phase 1, we will make a list of potential factors which influence longitudinal conceptual understanding. In Fall 2019, we reviewed previous studies, conducted two focus groups (one each with undergraduate and and graduate students), conducted an instructor interview, and informally spoke with instructors. Much of the data from our focus groups aligns with our literature review. For example, students mentioned "interest" as a factor that helped them learn:

> If your first lecture is super well-motivated and we're going to say 'oh, we're going to learn how the TV works,' then you will be interested in learning the electronics. [If] I'm going to tell you you're going to learn op amps and transistors, and I haven't heard of them, you're like 'okay, good luck. I'm not going to learn this.'

We also noted factors not emphasized in our literature review, such as the importance of students designing systems instead of following written instructions:

> They would just tell us, like 'build an ECG' and we got to design everything and choose whatever we did with it. So I think that really helped me figure things out. But, [in signals and systems it] kinda just felt like we didn't have that opportunity.

We planned to conduct additional focus groups, instructor interviews, and interviews with engineers working in industry in Spring 2020, but will now collect that data in Fall 2020 due to the move to online courses. Although we had to design survey #1 before analyzing our qualitative data, we will use the results to design survey #2.

3.3 Phase 2: Quantitative design

We will use the SSCI data to answer RQ#1-2. Students who participate in the research will take the SSCI up to three times: at the start of their SS course (at UM only), at end of their SS course or FUN 3, and during their fourth year. The SSCI will be tied to students' names to allow us to pair surveys across time. The latter two times the students take the SSCI, they will also take a short survey to measure factors that may predict their conceptual understanding.

We designed survey #1 based on the MoEP. For the motivation variable, we asked seven Likert style questions about how likely students are to major in EE, if learning SS in interesting, and if students think learning LTI, convolution, Fourier transforms, pole-zero plots, and filtering will benefit their career. We use individual student opinions on instructional quality and quantity to help account for students having different learning styles and study habits. For the instructional quality variable, we use responses to a Likert style question that asked students to rate the overall quality of instruction. For instructional quantity, we asked students how many hours they spent on homework in a typical week and what percentage of lectures they attended. Following [17], we do not include the mass media variable. We use the highest educational status of students' parents/guardians to measure home environment, a Likert style question on if the learning environment made students feel comfortable to measure classroom environment, and a Likert style question on if peers helped students understanding of SS material to measure peer environment. All Likert style questions had 5-options and followed the design principles suggested by [22].

Survey #2 will include additional factors from our phase 1 qualitative analysis. We will also use transcripts to see which elective courses students took and use this information and their grades in relevant classes as factors in our analysis. We will use standard quantitative techniques on the resulting dataset to create a hypothesis for RQ#3.

3.4 Phase 3: Explanatory qualitative design

The final phase of our project will be explaining the quantitative results. One benefit of qualitative research is that it can draw (or rule out) causal connections where quantitative results suggest correlations. We will use focus groups with a small subset of the primary student population to discuss how well they think the quantitative results reflect their experiences. We will also give a short-answer survey with similar questions to reach more students.

4 Preliminary results and discussion

From the Fall 2019 semester, we have N=92 pre/post-tests and N=79 complete surveys from students at UM in SS. The average class SSCI pre-test score was 49.6%, the average post-test score was 72.7%, and the class gain was $<g> = 45.8\%$. The pre-test scores and gain are higher than typically reported for a lecture-based SS course, possibly because many students entering SS at UM are junior or senior level in terms of number of credits, while the typical data is for sophomore-level students.

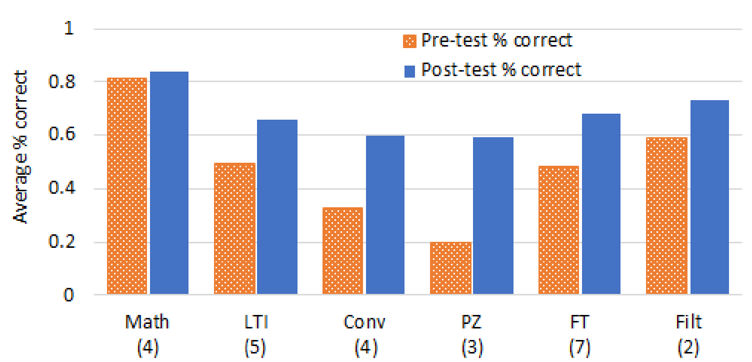

Figure 2: SSCI results by sub-test (and number of questions per sub-test). We split the transform representations sub-test into Fourier transforms (FT) and pole-zero plots (PZ).

Fig. 2 shows how students did on the pre/post-test for each of the topics on the SSCI. Average student scores improved for all topics. Unsurprisingly, students scored highest on the four background mathematics questions on both the pre- and post-test. Surprisingly, only 57% of students got question #3 correct on the post-test (which requires students to recognize a plot of a shifted and flipped signal), while students averaged 96-99% on the other three background mathematics questions.

On the post-test, the hardest question for students was question #15, which requires students to recognize the output of an LTI system given plots of the input and the impulse response. Only 33% of students selected the correct answer, while 55% selected the answer that did not correctly scale the output due to the non-unit width of the input signal (this was the most popular wrong answer on the post-test). Students did better (72% correct) on a very similar question that used a unit-width input signal.

Question #10, which asked students to find a plot of the Fourier transform of a signal convolved in the time domain, had the second-most common wrong answer. Only 49% of the students answered correctly, with 45% selecting the distractor answer corresponding to convolving frequency responses instead of multiplying them.

4.1 Factors influencing conceptual understanding

The students have not yet taken the second survey, which will contribute to the factors in the Model of Educational Productivity. Therefore, we present simple descriptive statistics and correlation results rather than testing the full model at this time. Table 2 summarizes the way we measured the MoEP factors, as well as the correlation results for the N=79 complete surveys. Following [17], we do not include the mass media variable, nor to we include the age/maturation variable, as all students are roughly the same age. All questions are coded such that we predict a positive correlation between the factors and post-test score.

All of the correlations have the expected positive sign (i.e., an increase in that factor is related to an increase in end-of-course SSCI score) except that of instructional quantity and peer group. Our survey question for peer group asked if peers helped with learning. A more typical question is whether schooling and grades are important to friends [16], which we will ask in survey #2. For instructional quantity, our research instrument was ambiguous, and some students may have counted time spent on pre and post labs toward homework time while others did not. It is also possible that students who struggled with SS spent more time on the homework, without learning more than students who understood and did the homework quickly.

We found a statistically significant, positive correlation ($p<0.01$) of post-test score with ability and motivation, and a slightly significant correlation ($p<0.10$) with instructional quality and home environment. These preliminary results suggest that the factors in the MoEP are worth investigating. However, we have yet to perform a statistical analysis of the full regression model due to our current low sample size and lack of data from survey #2. Therefore, we caution against any strong conclusions based on the data presented.

Factor	**Measurement**	**Descriptive statistic**	**Correlation**
Ability	Score on the pre-test	12.5	0.52**
Motivation	Average of 7 Likert questions	3.8	0.29**
Instructional quality	5-point scale on quality of instruction in SS	5	0.20*
Instructional quantity	Number of hours spent on SS homework in an average week	7.40	-0.28**
	Self-reported attendance	63.8%	-0.02
Home env.	Highest educational status of parent(s)/gaurdian(s)	Bachelors	0.21*
Classroom env.	5-point scale on if the learning environment was comfortable	4	0.09
Peer group	5-point scale on if peers helped with their understanding	3 and 4	-0.12

*significant at $p< 0.10$, **significant at $p< 0.01$,

Table 2: Correlation between factors in the MoEP [15] and the SSCI post-test score. For continuous dependent variables (ability and instructional quantity), the descriptive statistic is the mean value. For variables measured by 5-point Likert response questions (instructional quality and the three environmental variables), we report the mode value and Spearman correlations.

5 Conclusion

Our goal is to understand which SS concepts undergraduate students learn, retain, and forget and why the answer might differ between students for each concept. Based on longitudinal results from previous work in other subject areas [14], and results over the course of the signals and systems class [1], we expect students to struggle learning and retaining

SS concepts. However, we do not know which concepts will prove the hardest to retain or what causes some students to retain a concept while others do not. While we have chosen to study SS conceptual understanding, we anticipate our study will provide insights into the conceptual understanding over time in other engineering disciplines.

Embedded in our research questions are answers to other interesting questions like: Are there any SS concepts students never learn? Do upper-level courses impact which concepts a student retains? Do results differ between UM and UVa (possibly due to the very different course structures)? The answers to these questions can help instructors and curriculum designers decide which concepts need more focus, which are sufficiently covered, and how to best help students learn challenging concepts.

We welcome feedback on factors that may influence conceptual understanding, especially from areas of the literature we might not be as familiar with. We also invite others to give the SSCI to their students to add to the data-set!

6 Acknowledgements

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