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TEACHING MEASUREMENT DATA ANALYSIS

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Abstract: Education is one of the main tasks of universities. There are no universally best educational methods. Optimal practice and guidance depend on a number of factors, including the subject and the students. It is the teacher's responsibility to provide an advantageous environment for the students in order to maximize their learning results. In this paper we present the design of a course on measurement data analysis and how it complies with the pedagogical theories. We present the practical experiences from the first implementation with the summary of feedback from the students.

Keywords: data analysis, measurement information, discovery learning, teaching

1. INTRODUCTION

The eventual value of the measurements lies in the usage of the data produced by the measurement systems. The purpose of the measurements is to provide information about the target system under study in order to improve the decisions concerning that system. In many cases the optimal utilization of the measurements requires further processing and analyzing of the data. After studying data analysis in our department the students should be equipped with sufficient knowledge and skills to be able to perform such tasks in the endless number of different cases in real world applications.

Teacher's responsibility is to teach the required skills to the students. Or to offer the students a possibility to learn, which better complies with modern learning theories. Conventional teacher-directed teaching has been widely substituted with student-centered approaches that emphasize the learning process.

The contrast between the 'old' and 'new' approaches has often been exaggerated in the literature. Bereiter [1] presented juxtaposition, quoted in Table 1, exemplifying a prototype of common comparison in the literature. One column (left in Table 1) contains a caricature of conventional instruction and the other one the concepts related to the favorite approach of the author. Such comparisons tend to obscure differences that matter and bury real problems [1].

Table 1. Conventional and modern instructional approaches as often presented in literature [1].

Old	New
Knowledge Transmission	Knowledge Construction
Memorization	Reasoning
Teacher-directed	Learner-centered
Competitive	Collaborative
Tightly scheduled	Opportunistic
Fact-centered	Idea-centered
Etc....	Etc....

The approaches in the right column include knowledge building [1], discovery learning [2], constructivism [3] and collaborative learning [4]. All these approaches have their strengths and share many aspects that can be covered by principles introduced by Merrill [5]. They are well worth considering in all education, including measurement science and data analysis.

These new approaches may present a tempting idea that all you need to do as a teacher is to allow students to learn collaboratively, construct their knowledge by discovering. However that doesn't happen by itself and the teacher is still required [1]. Pure discovery learning as a general and global teaching strategy doesn't always work, especially for beginning and intermediate students, and sufficient guiding is needed [6].

Traditional education in technical university and engineering actually cover many features of the modern learner-centered approaches. Collaborative learning is provided for example by laboratory exercises in groups. Larger independent problem based projects require constructivist perspective and discovery learning. Naturally, it is always possible to fine tune our teaching and we must strive for providing more productive learning processes for the students.

In this paper we present the design of a data analysis course. We also discuss the relation of the implementation plan to the pedagogical theories or instructional approaches. We try to pick the best parts of both the conventional and modern approaches, keeping in mind Dewey's warning: "There is a danger of building a new education merely as a negation of the traditional" [7].

The paper is structured as follows. Section 2 discusses the relevant pedagogical topics, both instructional approaches and assessment of the learning results. Section 3 presents the contents and the implementation plan of the data analysis course including relationship to the pedagogical topics. Examples and experiences of the actual implementation are given in section 4, including a summary of the feedback from the students. The challenges and future improvements are also presented. Final section gives a brief conclusion.

2. TEACHING AND LEARNING

The most relevant instructional approaches regarding our data analysis course are constructivism, discovery learning, and collaborative learning. These and many others with a variety of terms include fundamentally similar principles [5].

From the constructivist perspective, learning is not a stimulus-response phenomenon and rote learning the “right” answers to solve problems [3]. Instead, the learners are supposed to actively construct their knowledge.

According to van Joolingen [2] discovery learning is a type of learning where learners construct their own knowledge by experimenting with a domain, and inferring rules from the results of these experiments. Thus discovery learning shares the common aspect with constructivism that the learners construct the knowledge. It is assumed that this allows them to obtain higher level of understanding than if the necessary information was just presented by a teacher.

The broadest definition of collaborative learning is that it is a situation in which two or more people learn or attempt to learn something together [4]. Each element of this definition can be interpreted in different ways. What is the number of ‘two or more’ learners, and what is meant by ‘learning’ and ‘together’? Dillenbourg [4] summarizes the 'collaborative learning' as a situation in which particular forms of interaction among people are expected to occur, which would trigger learning mechanisms. Generally there is no guarantee that the expected interactions will actually occur. Hence, it is teachers’ interest to develop ways to increase the probability that some types of interaction occur.

Pure discovery learning with minimal guidance as a general and global teaching strategy for beginning and intermediate learners doesn't work. See Kirschner et al. [6] for a good overview. Mayer [8] presents examples from 3 decades, 1960s, 1970s and 1980s where guided discovery is generally more effective than pure discovery in promoting learning and transfer to new problems. The debate on how much guiding is needed is somewhat open.

Merrill introduced five general principles that cover a wide variety of instructional theories [5]. He named them the first principles which are quoted in the following list

1. Problem-centered: Learning is promoted when learners are engaged in solving real-world problems.
2. Activation: Learning is promoted when relevant previous experience is activated.
3. Demonstration (Show me): Learning is promoted when the instruction demonstrates what is to be learned rather than merely telling information about what is to be learned.
4. Application (Let me): Learning is promoted when learners are required to use their new knowledge or skill to solve problems.
5. Integration: Learning is promoted when learners are encouraged to integrate (transfer) the new knowledge or skill into their everyday life.

The principles can be used as a guideline in designing education.

One important part of education is assessment, measuring the learning. One has to differentiate between Intended Learning Outcomes (ILO) – written statements in a course syllabus; and Achieved Learning Outcomes (ALO) – those results that students actually have achieved [9]. These two can be brought closer to each other by using constructive alignment [10]. It is based on twin principles of constructivism in learning and alignment in the design of teaching and assessment. It is ‘constructive’ because it is based on the constructivist theory. The ‘alignment’ reflects the fact that the learning activity in the intended outcomes needs to be activated in the teaching in order to achieve the outcome. Furthermore, the assessment task has to verify that the outcome has in fact been achieved.

Such alignment is very desirable but not always easy to achieve, even though Biggs admits it should be obvious [10]: “The idea of aligning assessment tasks with what it is intended that students should learn is very old – and very obvious. It’s called ‘criterion-referenced assessment’ in the jargon and it’s what anyone outside an educational institution does when teaching anyone else anything.”

Ideas of constructive alignment are structured as an educational framework for engineers in the CDIO™ INITIATIVE [11, 12]. It provides students with an education stressing engineering fundamentals set in the context of Conceiving — Designing — Implementing — Operating real-world systems and products. More than 50 collaborating institutions in over 25 countries worldwide have adopted CDIO as the framework of their curricular planning and outcome-based assessment.

3. COURSE ON DATA ANALYSIS

Name of the course is *Introduction to Systems Analysis*. It is targeted to students from 3rd year onward.

Prerequisites for the course consist of basic mathematics, including probability and statistics. Additional advisable prerequisites include two courses: *Systems and Control* and *System Models and Identification*. Mandatory courses from two first years include *Practical Systems Thinking* [13] followed by *Applied Automation*. These courses use small groups and problem based learning.

3.1. Contents of the course

There are two general higher level intended learning outcomes [14].

1. Inferring measurement information from data with inverse (Bayesian) method
2. Understanding the difference between the real system (state) and the thinking process (beliefs about the system)

Overall picture of the data-based management of the target system is illustrated in Fig.2. Vertical line separates the real system (on the left) from the thinking process. We acquire data from the real system through measurements. The information can be inferred from data for two purposes: to improve decision about actions on the system and to update the models of the target and the measurement systems. The real system can be affected by actions that are decided on the basis of the available information (provided by measurements and other knowledge about the system) and the required performance criteria.

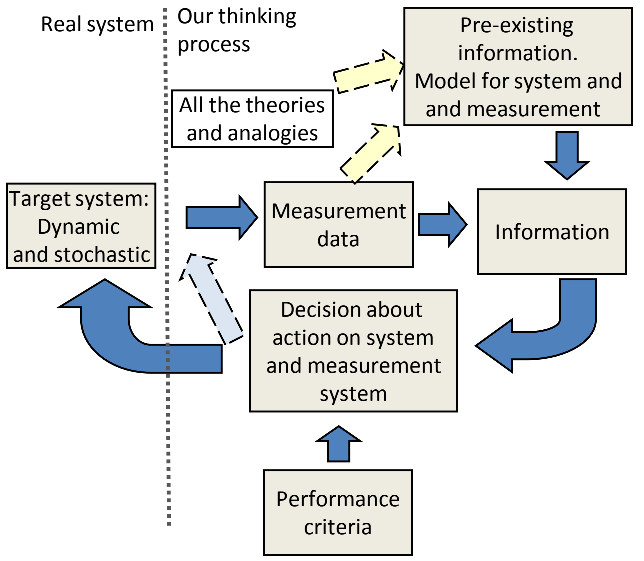

Fig. 1 Reference models and double use of measurement data [14].

We assume that the system can be conceptualized with mathematical objects chosen on the basis of background knowledge about the system and what we aim to achieve. The information about the past, present and future state of the system is uncertain and the system itself has a touch of randomness. Data about the target system is uncertain (incomplete). Thus we can only have beliefs about the system concepts. One can compute with beliefs as with probabilities.

Detailed topics of the course include

1. Interpreting measurement data
2. Predicting system state
3. Modelling (Markov process models)
    - general principles,
    - maximum likelihood,
    - observation model
4. Fourier transform and signal reconstruction
5. Power and cross spectrum, coherence

This course focuses on Markov process models. This provides a clear concept for the state of the target system. Also the connection between the state and the belief is straightforward and easy to understand. Thus, Markov model is not an objective as such, but a tool for simplifying the thinking process.

Fig. 2 shows an example of using measurement information for predicting in discrete-time case. The measurement system provides information on the real system. Y(n) is the measurement about the actual system state X(n) of the target system at current time instance n. The measurement system also includes two more components that are omitted from Fig. 2: data acquisition by measurement devices (part of the real system) and data analysis (part of the thinking process) that provides the information inferred from the data. The measurement information is used to update our belief about the system state, depicted as b(n-) before and b(n+) after the measurement.

The beliefs are represented by probabilities and updated using the Bayes formula

$$P(X(n+)=i \mid Y(n)=j) = \frac{P(Y(n)=j \mid X(n)=i)\cdot P(X(n-)=i)}{P(Y(n)=j)} \qquad (1)$$

The real system state at the next time instance, X(n+1) is determined by the current state X(n) and our action a(n). The prediction of X(n+1) is the belief b(n+1-). It is formed from all the knowledge about the system, current belief b(n+) and the current action a(n).

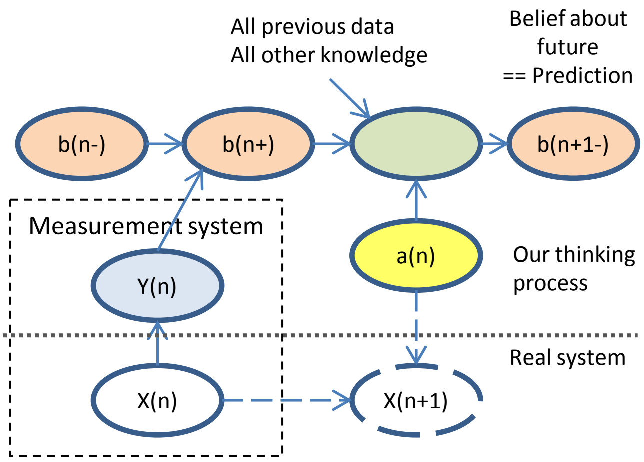

Fig. 2 The measurement system provides information about the real target system for prediction [14].

General purpose of modeling is to “package” modeling data into a few numbers characterizing information about model parameters θ. The measurement data set is $D=\{y_k\}_{k=1}^{K}$ consisting of observations about the state of interest X. In general the observations can be exact or uncertain, incomplete or complete.

If observations are mutually statistically independent, obtained with identical ways of observing the system and if the observations are complete and exact, the parameter information (probability distribution) is

$$f_{\Theta|y_1,\ldots,y_k}(\theta \mid y_1,\ldots,y_K) = E\cdot\left[\prod_{k=1}^{K} f_{X|\theta}(y_k \mid \theta)\right]\cdot f_{\Theta}(\theta) \qquad (2)$$

where E is a normalization constant and $f_{\Theta}(\theta)$ is any other prior information about the parameters, known without the data.

This course covers identification of the maximum likelihood estimate (point-based approximation) as well as the Laplace approximation, which provides information on the uncertainty of the parameters.

The rest of the course deals with Fourier transform and signal reconstruction. The topic includes the effect of windowing and Welch spectrum estimation. Identification of transfer function is covered by using power and cross spectra including the coherence function for evaluating the reliability of the identified frequency response.

3.2. Implementation plan

The course is designed to be a functional trade-off between well instructed lectures and sufficiently guided discovery learning. The implementation consists of 29 learning events, each of which is 2*45 minutes.

Lectures are planned for 14 events and guided computer exercises for 4 events. 8 events are reserved for guided problem based exercises in small groups. 3 of these exercises consist of handing out homework exercises and providing guidance for solving them. The remaining 3 events are dedicated to returning the homework and working out the exercises together. The returned homework exercises are evaluated and provide bonus for the exam. One computer exercise and two other ones before that are dedicated to a small project work which integrates the contents of the course to the on-going research at the department.

The plan covers the Merrill's first principles [5]. The lectures contain motivation and activation of the previous knowledge (principle 2). Demonstrations are presented during both, the lectures and the computer exercises (principle 3). The problem based exercises engage the students with real world problems and require them to use their new knowledge (principles 1 and 4). The homework exercises transfer the knowledge to new problems (principle 5). Principles 1, 4 and 5 are involved especially in the project work. Some exercises in small groups include an opportunity to publicly present the acquired new skills, which is included in principle 5.

4. IMPLEMENTATION AND EXPERIENCES

The theoretical foundations were provided in the lectures. They contained also understandable examples for motivating and to demonstrate the connection of the theory with the real life.

The computer exercises were done either in pairs or alone. MATLAB [15] with the Symbolic Toolbox was used for numerical and analytic calculations in computes exercises.

The type of the rest of the exercises varied from lecture-like instruction to discovery learning in small groups. Typical exercise consisted of several independent problems. In some exercises each group worked with different problems, presenting their results at the end. This turned out to be the one that the students liked best. As the homework exercises were evaluated, their guidance events were not supposed to give the answers. In those events each of the small groups had different problems but instead of solving them, they listed further questions that would help to solve the problems. The problems were then rotated to the next group which could add further questions or hints to the problem.

Working with the small groups enabled continuous discussion with the students and revealed the most severe challenges that would hinder their learning. We collected also anonymous written feedback in the middle of the course. These were used to detect topics to revise and to provide additional material along the course to support the students. Another set of feedback, collected at the end, will be used for improving the course in future implementations.

4.1. Mobile robot simulation project

The course included one small project that was worked on during three events. The project provided the students an opportunity to apply the theories on a real problem, which is related to the research at the department. Fig 3. shows a car-like mobile robot that is involved in research projects.

Fig. 3 A car-like mobile robot used in the departments research projects.

The project involved a simpler car which is steered by the front wheels only. A commonly used bicycle model of such a car is presented in Fig 4. [16].

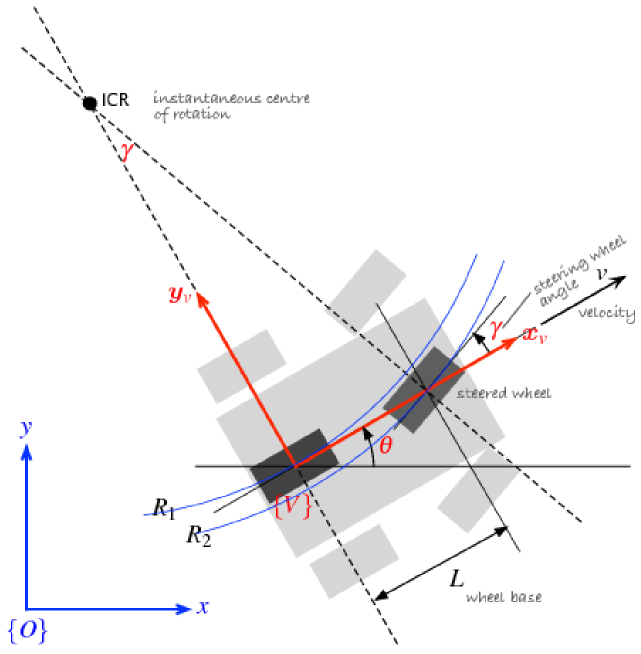

Fig. 4 The bicycle model for a car-like mobile robot [16].

The movement of the car can be described by the following equations.

$$\begin{aligned} x(n+1) &= x(n) + \Delta t \cdot v(n) \cdot \cos\theta(n) \\ y(n+1) &= y(n) + \Delta t \cdot v(n) \cdot \sin\theta(n) \\ \theta(n+1) &= \theta(n) + \Delta t \cdot \frac{v(n) \cdot \tan(\gamma(n))}{L} \end{aligned} \tag{3}$$

The velocity $v(n)$ and the steering angle $\gamma(n)$ are both controlled, but include additive Gaussian noise.

$$\begin{aligned} v(n) &= v_C(n) + \varepsilon_v(n) \\ \gamma(n) &= \gamma_C(n) + \varepsilon_\gamma(n) \end{aligned} \tag{4}$$

The car is assumed to be able to perform a measurement that determines its orientation $\theta(n)$ and position by choice either in x or y direction. All the measurements contain additive Gaussian noise.

The first task was to deduce the equations for predicting the state (position and orientation) of the car, assuming that the information of the current state has Gaussian distribution. This included linearization of the state transfer equations. The next step was to deduce the equations to update the state information after a selected measurement provides data.

The final part of the project was the computer exercise. The task included "driving" the car by giving control values for the velocity and the steering angle and to predict its state. The main code for the simulation and crude visualization were given. The students were required to code the functionality for predicting the state and updating it with the available measurement data. Finally the students were able to play around and see how the selection of the measurement and the variances of the additive noises affect the predictions and the uncertainty of the state.

4.2. Feedback from the students

We collected written feedback both in the middle of the course and at the end. The following list includes feedback on what was considered to work well and should be maintained. Some items are followed by our response comments.

+ Lots of good exercises, answers available
+ Nice project exercise, starting with theoretical part and final results analysed at the computer exercises
+ Exercises in the smaller groups and ending with analysing together
+ Good summary at the end
    - o Initiated by the feedback in the middle

The following lists feedback on issues that could be improved.

➢ More examples and connection to real life
➢ Collection of the very basics
  - o Provided and updated along the course
➢ Too much to do in the computer exercises
➢ complicated notations hard to understand
  - o Additional summary on notation for the next implementation
➢ More time needed for exercises, especially computer exercises
  - o More intermediate steps and ready code provided towards the end

4.3. Challenges and future improvements

We expected to encounter the biggest challenges in motivating and linking the subject to existing understanding of the students (principle 2). That also showed in the feedback. Donovan et al. [17] also emphasize the need to draw out and work with the pre-existing understandings that students bring with them.

Another challenge is to limit the amount of content to learn. Superficial coverage of all topics in a subject area should be replaced with in-depth coverage of fewer topics that allows key concepts to be understood [17]. Keeping the number of topics low allows us to introduce multiple views of the covered topics. The goal is to avoid looking at the subject from just one perspective which is one serious kind of oversimplification that often leads to learning failures [18].

The students attending the course play an important role in the large level of these challenges. It is essential to maintain constant dialogical connection with the students and adapt the both, the contents and the didactic methods. The written feedback provided very valuable information in this implementation.

5. CONCLUSION

In this paper we have presented an overview of a course on measurement data analysis. We have connected the implementation plan to learning theories, especially the *first principles* that act as an umbrella for a number of instructional approaches as well as guidelines to designing education. We also discussed the most potential challenges in the implementation.

The first implementation of the course in this form was taught during the spring semester 2012. Collaborative learning in small groups was well appreciated by the students and considered educational. The course included a project of several learning events working with the theory and simulation of a vehicle, similar to the one we have for research purposes. These exercises were widely considered the best part of the course, connecting the studies to concrete real problems.

Feedback was actively collected along the course. That allowed us to adapt to the students' experiences and to provide additional material to support the mathematically challenging issues. Motivation and connection to existing knowledge turned out to be challenging as expected. More practical example cases that are familiar to the students will be planned for the next implementations.

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