

Seamless Integration of Machine Learning Contents in Mechatronics Curricula

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Abstract—The topic of machine learning is becoming more and more important for mechatronic systems and will become ordinary part of today’s student life. Thus, it is obvious, that machine learning should be part of today’s student’s curriculum.

Unfortunately, machine learning seldomly is implemented into the curriculum in a substantial or linking manner, but rather offered as an elective course.

This paper provides an analysis of how machine learning can be integrated as a mandatory part of the curriculum of mechatronic degree courses. We consider, what the required minimal changes in fundamental courses should be and how traditional subjects like robotics, automation and automotive engineering can profit most of this approach. We will show, that only minimal reassignments within the classical curriculum and minimal changes in the mathematical fundamentals combined with a good link to control theory and simulation are necessary, which results in reassignments of only 8 European Credit Points (ECTS) in total. As a case study we utilize an existing German mechatronic degree course specialized on information technology, which covers most of the discussed aspects.

I. INTRODUCTION

Mechatronics is a multidisciplinary field, that includes parts of mechanical engineering, electronics and computer engineering. Typical application areas are industrial automation, robotics and automotive engineering. Especially for the latter two control theory has become a more important topic. Within mechatronic systems it is proven, that software and intelligent systems increase their importance, since they play a crucial role in the added value of modern intelligent mechatronic system solutions compared to classical approaches. Nowadays, also machine learning is a new major factor in this field, and it very often closely interacts with control theory. Some techniques will be or are already integrated in modern mechatronic systems as standard components, like e.g. image and speech recognition. Usually, these components are simply licensed from suppliers and integrated. Other aspects in parts of robotics, flexible manufacturing, vehicles and logistics will require some engineering performed by persons, who sufficiently understand the technical system the new technologies are designed for and/or applied to. This demand in mechatronic engineering practice gives rise to a demand for changing the current universitarian mechatronics and computer science engineering curricula: While machine learning is increasingly important for the mechatronic systems, the mechatronic degree courses at universities often lack integration of this subject,

and usually the different curricula are not ready to integrate this subject into fundamental courses of a degree curriculum. We will show, that with minor changes in the curriculum, a seamless integration of machine learning contents is achievable. In that way, a university can enhance the attractiveness of a degree course without additional expenses.

In the following sections of this paper we analyse the requirements for integrating machine learning into mechatronic degree courses based on an existing (example) degree course. In order to be able to choose a proper approach to integrate machine learning, it is essential to understand, which part of machine learning offers the strongest connections to the courses under discussion and therefore candidates are to be integrated into the courses. Next, the interaction to control theory and simulation will be highlighted; both topics have already (classically) a big influence on mechatronic degree courses. The subsequent section will show, which new requirements for degree courses have to be considered, and which already established approaches and topics can be utilized for this purpose by slight re-arrangements, e.g. in control theory.

II. MACHINE LEARNING AND MECHATRONICAL SYSTEMS

Machine learning enables predictions to be made based on data to elaborate knowledge and relationships out of experiences / data sets. For this purpose, it makes use of some mathematical fields, mainly regression, optimization and statistics.

A. Application areas

One area of application is Industry 4.0, also referred to as smart factory. In smart factory, production processes are connected and a lot of data can be collected in order to optimize the manufacturing process. In this context, machine learning supports e.g. process optimization by changing and adapting manufacturing settings or automatically improving quality assessment. In the application area of vehicle technology, machine learning can mainly be found as a tool to support autonomous driving and comfort functions or features. Furthermore, a lot of companies can make use of machine learning in maintenance and support services. By means of sensors the energy consumption of individual machines can be monitored, maintenance needs can be predicted, and maintenance cycles can be optimized. If a smart system is designed to continuously

learn, it is very likely that it will improve performance based on more accurate and actual predictions.

B. Relevance of machine learning disciplines for mechatronics

Which aspects of machine learning are now the most important ones for mechatronics? One taxonomy for machine learning approach divides them into supervised, unsupervised and reinforcement methods. Supervised methods can be broadly divided into two groups of tasks: regression and classification. Regression is about estimating or predicting a continuous quantity, like e.g. the probability of a failure. Classification deals with assigning a given set of features into discrete categories, like e.g. animal or furniture. Furthermore, there exists a different class of algorithms referred to as unsupervised learning. While supervised learning is based on datasets of labelled answers to learn from – e.g. sensor data, which is annotated either as failure or as working correctly – unsupervised learning tasks identify patterns without labels. The main task here is clustering. Clustering refers to grouping things together in such a way, that members of a group are similar to each other. The last category is reinforcement. In order to be able to conduct reinforcement learning, it is essential to provide a signal suitable for rewarding and quantifying the amount of reward. Consequently, one does not in general know in advance, what the (final) solution will be. Thus, in general the result is usually of less quality than in the supervised learning case. Reinforcement learning is very useful in cases, where the algorithm can be thought of as an agent interacting with its environment. In mechatronics that can be a robot, a vehicle or even a whole factory.

As one can see, every category of machine learning approaches can be used in mechatronic products like robots, vehicles and factories. If one has to make a ranking, one might end up with reinforcement learning and supervised learning as most important categories, especially because modern approaches of reinforcement learning like Q-Learning require regression learning techniques like neural networks to represent the Q-Function [2]. Therefore, we will focus on the demands of reinforcement learning to illustrate connections and requirements, as an example.

C. Links to Robotics and Control Engineering

Machine learning approaches for robotic applications have grown quite popular in the last decade. Recent success in the fields of robotics vision and AI robotics showed the benefits in many applications. Prior to the increased popularity of machine learning in robotics, mainly control engineering approaches were used to ensure safe and autonomous operation of robotic systems. Nowadays, robotic platforms are getting more and more complex, including a variety of different sensors, increasing computational power and network capabilities. The challenge to achieve intelligent behaviour of the robot in an unknown and dynamic working environment leads to challenges combining recent machine learning approaches with traditional control engineering aspects in a neat manner. At first glance this seems quite difficult, as on the one hand

control loops require real time behaviour of the system and on the other hand machine learning approaches are often computationally expensive. A common model for the design of a robot control system in a layered structure is given in [1] and is illustrated in figure 1.

The layers of the control structure in figure 1 can be seen as complexity levels to be handled from the robot, ranging from obstacle avoidance to path planning:

- **Reflex:** Describes the lowest level of control and uses raw sensor data to immediately react to changes in the environment. This layer is often directly implemented in hardware.
- **Reaction:** Implements reactions that rely on filtered or fused data. Software modules process the sensor data and build the basis behaviour for robotics.
- **Task:** Controls the achievement of small tasks given to the robot. The task is only a small step to achieve a final goal.
- **Plan:** Creates a global plan to be executed from the robot. The global plan is divided in several tasks, which are executed from the layer below.

The execution frequency of the control cycles decreases with growing complexity. The lowest layer (reflex) directly uses the sensor data to react as fast as possible to changes in the environment, typically with a frequency of about 100 Hz. If an obstacle or hazardous area is detected, the system should stop its motion without any delays. It is highly required for security reasons that a real-time response of the system is possible, thus a direct implementation in hardware can be found in many systems. The frequency of the control layer above is already an order of magnitude larger. Reactions rely on fused sensor data, i.e. several sensors are used to derive more knowledge about the environment and to initiate a behaviour of the robot. For example, the robot could avoid an obstacle by detecting an alternative path with a variety of navigation sensors. The two lower layers, reflex and reaction, are closely related to the hardware of the robot. In contrary, the upper layers are independent of the robot hardware, they are responsible for the planning process. In this context planning is related to reaching a final goal or to solving a given problem. The planning process on global scale is performed from the highest layer (plan), which is only executed at minute intervals. The result of the global planning process is divided into several tasks, which are given to the task layer for execution. These upper layers are well suited to apply machine learning algorithms, as they are not time critical. The task and plan layers are commonly used for path planning and scheduling. This layered structure demonstrates, how the connection of control engineering and machine learning can be integrated in a modern robotic system.

Today, at first quite often simulated environments are being used. The reason is that for modern reinforcement approaches (e.g. [3]) using deep neuronal networks a lot of data is necessary for training purpose. This amount of data is typically hard to acquire just from real life tests. Thus,

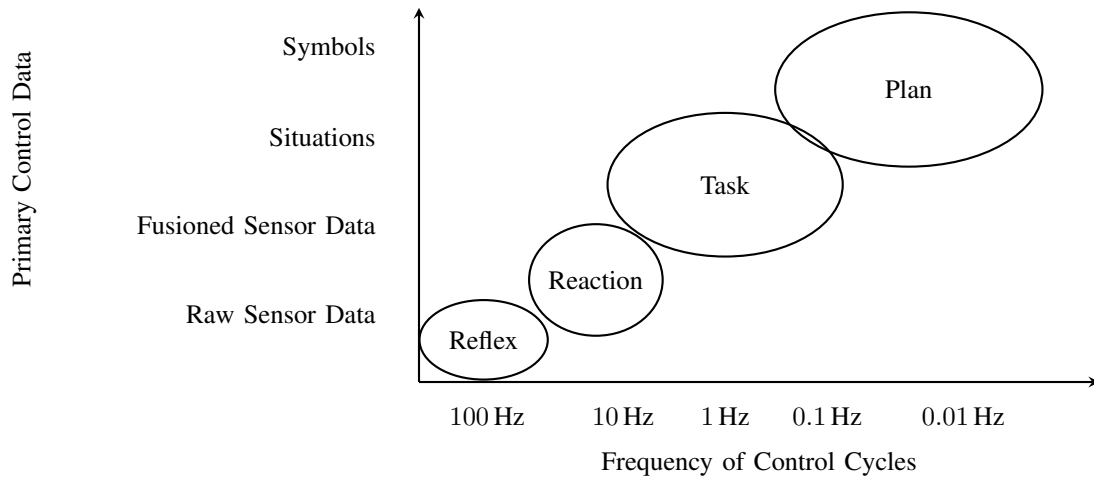


Fig. 1. Frequency range of control cycles, translated from [1, p. 262]

pre-training based on simulation is quite commonly found.

A similar challenging application area is automotive engineering / vehicles. As established state-of-the-art vehicle technology, many control tasks have to be performed on a millisecond calculation time basis performing on cost-optimized ECUs, while the environment sensing, classification and path planning performs on a different scale, still. In particular, in the context of fully automated driving, there are still many challenging aspects to provide suitable control structures and vehicle control architectures to cope with this challenge, though many OEMs and suppliers are working on these topics with very high effort and promising results.

III. IMPLICATIONS TO MECHATRONICS CURRICULA AND DEDUCTION OF A GENERIC FRAMEWORK

In this section we will discuss the implication of a successful integration of machine learning to the curricula of a mechatronic degree course plan; to the complete study plan as well as to individual existing modules. Even though today's European degree courses are based on the idea of modules, usually almost no module is separated from all other modules. Most courses base on fundamental courses and thus, rely on skills set up before.

A. Prerequisites and requirements for machine learning contents

Nowadays the availability of many easy-to-use machine and deep learning packages, such as scikit-learn [4](Python), Weka [5] (Java), Tensorflow [6] (Python) etc. makes it easier for engineers to use state-of-the-art machine learning algorithms in and for their products. Especially the Keras-API was a big step forward for the usage by different professions than mathematicians and computer scientists [7]. Nevertheless, machine learning is a field, that intersects statistics, optimization, computer science and algorithmic aspects. Despite the immense possibilities of existing tools, at least a rough mathematical understanding of many of these techniques is necessary in

order to obtain satisfactory or good results. Examples of this requirement are

- Selecting appropriate algorithms regarding aspects like e.g. the required accuracy, suitable training time, adequate model complexity, number of parameters and number of features.
- Choosing parameter settings and validation strategies.
- Identifying under- and over-fitting by understanding statistics, regression and function approximation.

Therefore, one can conclude, that the fundamentals for understanding machine learning are mainly programming skills and knowledge about algorithms and mathematics. Fortunately, a lot of the necessary concepts are already part of the mathematical education of e.g. mechanical engineers. Let's have a look at the list of the main mathematical aspects needed for machine learning:

- 1) Ordinary one-dimensional basic calculus
- 2) Basic Linear Algebra, especially vector spaces, Projections, Eigenvalues & Eigenvectors, norms and metrics
- 3) Some parts of higher dimensional calculus, especially how to determine or estimate gradients and derivatives
- 4) Basics in optimization approaches like Gradient descent, Newton's Methods and similar methods
- 5) Curve fitting and basic regression like least squares methods
- 6) (Basic) Mathematical statistics

While the first five aspects are usually part of the mathematical education of engineers – maybe optimization sometimes needs slightly more attention – the last point is only rarely taught in engineering mathematics. Consequently, the question has to be answered, how deep and how much of this new aspects are needed? The answer to this question can not uniquely be given and depends on the choice, how machine learning is presented. If one chooses a more algorithmic approach in teaching of machine learning like in [8] in contrast to a quite probabilistic perspective as in [9], the topic of machine learning fits quite well to common fundamental engineering

mathematics courses. The basics for an engineer can be handled in between three and five weeks during a semester. Therefore, 2 European Credit points (ECTS) are somehow a lower boundary for the additional statistics needed. Of course, more ECTS would allow for a broader basis, such as also up to 4 European credit points could be reasonable.

From fundamental computer science courses some other subjects including the following are required:

- 1) Procedural and Object-Oriented Programming
- 2) Practical skills in Python and/or Java
- 3) Basics in Algorithm analysis
- 4) From Physics, some newton mechanics and advanced topics like friction models are useful in order to understand some important effects within the simulated environments.
- 5) For a Simulation and Modelling course the concept of models in simulation is important as well as some basic practical skills in this topic.

The first two items are mainly covered in typical mechatronic degree courses as part of programming courses. The third topic, basics in algorithms, is not necessarily covered in a mechatronics curriculum. Nevertheless, it can be easily integrated in any computer science related lecture. From our perspective, reinforcement learning is one of the most relevant machine learning disciplines for mechatronics students (compare Section II. B), therefore items number four and five become mandatory. To understand the physics behind a system is especially important, when reinforcement learning is applied to a real world system.

B. Placing of machine learning contents in a generic curriculum framework

The analysis of the requirements necessitates mathematical fundamentals as well as programming skills to be taught prior to any machine learning module. As discussed, it makes sense to focus on reinforcement learning in mechatronics, since it is helpful to be able to rely on basics in physics, simulation and control theory before the machine learning module pops up in the study curriculum. Control theory is not really mandatory but very useful, since many standard problems, like e.g. the inverted pendulum, are being used as examples in control theory courses. These application examples from control theory courses can then be adopted in machine learning as well in order to illustrate to the students, how reinforcement learning approaches may achieve similar or equal results based on completely different approaches. A machine learning module can be sped up significantly, if the students have already participated in such control engineering experiments and have prior knowledge in application examples.

Nevertheless, machine learning is by no means a separated degree course in mechatronics, and it makes most sense if it is integrated into advanced courses of application areas like robotics, intelligent or automated driving or automation. Consequently, there should be still sufficient time following the machine learning course to integrate this approach into those fields of application.

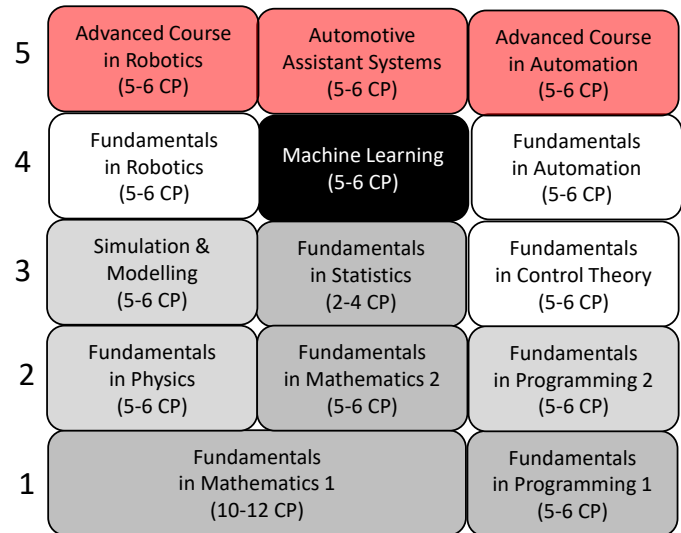


Fig. 2. Generic Curricula Framework for 6 semester degree courses with application areas

Achieving this is more demanding within a six semester degree course, though these are quite common in traditional universities as bachelor degree curricula. Of course, it is much easier to realize it in a seven semester curriculum, which is often being chosen by most universities of applied sciences. Figure 2 sketches some possible solutions to set up a curriculum for a six semester version of a bachelor study programme. Dark grey filled elements highlight mandatory prerequisites for the machine learning module depicted in black. Light grey filled courses are highly desirable, while white filled courses are needed for the advanced machine learning courses filled in red.

Of course, the statistics fundamentals need to be integrated in the general mathematics fundamentals. They are displayed separately, because this is in general the only really new aspect next to machine learning itself required in the degree courses. On the one hand, it is very encouraging that this new topic fits in so well. Still, on the other hand, these are at least seven or eight credit points that need to be re-assigned in the existing bachelor courses. Beyond this, it only fits in easily, if the existing degree course comes up with sufficiently integrated credit points for mathematical fundamentals and focus on principals and ideas rather than training to solve more complicated integrals by hand or handle conic sections. Therefore, the integration of machine learning shifts the focus in mathematics from human computation to more general principals and more linear algebra and statistics. In the whole degree course plan, it shifts the course plan more into the direction of computer science, because the total amount of credit points is limited and transferred from mechanics and/or electronics.

TABLE I
STUDY PLAN BACHELOR MECHATRONIC & INFORMATION TECHNOLOGY FROM THE BOCHUM UNIVERSITY OF APPLIED SCIENCES

1.	2.	3.	4.	5.	6.
Analysis 1 Linear Algebra Fund. Programming 1	Analysis 2 Physics 1 Fund. Programming 2		System Analysis & Simulation Fund. Control Theory	Machine Learning Fund. Robotics Fund. Automation	Advanced Robotics Advanced Automation

IV. PERSPECTIVES AND BENEFITS OF LINKING MACHINE LEARNING, AUTOMOTIVE, ROBOTICS AND AUTOMATION

In this section we discuss, why in our option it is worth to integrate machine learning to keep mechatronic degree courses up-to-date and to satisfy the demands of the typical mechatronics application areas. Of course, the benefit strongly depends on the seamless integration of machine learning contents on module level and the cooperation of different lectures across module borders.

Especially in the field of robotics, machine learning plays an important role. Thus, the students of mechatronic courses strongly benefit from integrated machine learning contents in their curriculum when working on robotic-related projects. Machine learning had a big influence in many computer vision approaches. Camera systems are standard equipment of any mobile robot platform, they are available as low-cost commercial of the shelf components. These camera systems in combination with machine learning are often used for the identification of objects in the robot environment or for obstacle detection in navigation task. Another important application field of machine learning is mobility of robots. The control of challenging robot kinematics, such as humanoid robots or mobile platforms with legged locomotion, is quite demanding. Control software development for unknown terrain or noisy environments is very sophisticated. Here comes reinforcement learning into play to achieve a stable and adaptive behaviour of the robot. This is particularly challenging, when the scenario involves multiple agents acting and learning [10].

Similar developments to the ones just discussed within the fields of robotics can be observed in automotive engineering, too. Machine learning techniques have played crucial roles, in particular in the area of systems trying to investigate the environment of vehicles. Examples are camera systems for speed sign recognition, radar, lidar or ultrasonic sensors in addition to mono and stereo cameras. They are used to detect possible paths to follow for the car or to identify obstacles within or near to the planned paths as part of advanced driver assist systems of manual driven cars. Beyond this, they can be used as part of vehicle controllers for trajectory tracking of (partly) automated driving vehicles; see e.g. [11] as an introduction to these topics. The impact of machine learning techniques even become more important due to the very manifold development challenges, validation tasks for components, systems and full vehicles and also for the driving tasks of the individual vehicle to be engineered and during life

time of each vehicle making use of modern driver assist systems or future (partly) automated driving. Thus, summarized, machine learning will get increasingly important as enabler for functions or features for vehicles to be engineered as part of components or systems, and machine learning is being investigated to support the tuning and validation processes of these functions or features, as well.

V. CASE STUDY ON THE BACHELOR DEGREE COURSE MECHATRONIC & INFORMATION TECHNOLOGY

The considerations mentioned above provide a theoretical approach to cover relevant machine learning contents into a curriculum. Now, it will be shown in a case study, how this has been achieved in an existing mechatronics degree program. The main issue with new content is, that existing study plans are quite often fully packed and there is no further degree of freedom to place new contents. In general, there are two approaches to this: On the one hand, the establishment of a suitable specialisation subject or on the other hand, the development of a specialised degree programme. The framework described in section III.B places the machine learning lecture in the fourth semester of a six-semester course. In this way, a specialisation subject in machine learning can be implemented. In the presented case study, we look at a seven-semester bachelor's degree program in mechatronics and information technology, which belongs to the genre of specialized degree programs. Table 1 shows an excerpt of the study plan, which only shows the contents related to the framework of Section III. B. The third semester contains lectures such as electrical engineering and mechanics. These are not contents of our framework, thus it is kept blank in Table 1. This is possible because it is a seven- and not six-semester degree course. The module *System Analysis & Simulation* mainly covers the required skills in modelling and simulation. The machine learning module will be followed by two specialisation subjects. First of all, this shows that integration is possible in the sense of the framework. At the same time, however, there are also challenges that make a seamless integration difficult, which will be similarly found in other degree programmes. The first challenge lies in teaching the subject of machine learning with regard to the available mathematical basics. Mathematics in the degree programme is sufficiently represented with 18 ECTS credits and further expansion is not possible without going at the expense of other subjects. However, the mathematical courses are already filled with traditional engineering subjects and are under increasing pressure to deal with the heterogeneous admission requirements of the students. Therefore, statistical basics are only discussed in terms of the equilibrium calculation as they

are necessary for the fitting of measurements. Corresponding contents are therefore first and foremost imparted in machine learning and partly in *System Analysis & Simulation*. This is accompanied by a reduction in the amount of the core substance, which has been minimized by an algorithmic orientation of machine learning.

The second challenge concerns the application areas. As it is often the case in modular degree programmes, these are also used as compulsory or optional subjects in other degree programmes. Therefore, the lecturers cannot assume that all participants have dealt with machine learning beforehand. This prevents integration as an integral part of the course, although the majority of participants are familiar with it. The chosen solution for this is the integration of modern teaching concepts which are especially suitable for advanced students. These events are partly enhanced by aspects of problem and project-based learning. This differentiation allows the integration of machine learning in selected projects and problems as well as a stronger practical activation of the advanced students. In general, problem-based learning has shown itself to be an excellent integration option, which offers interested students opportunities and at the same time takes the individual interests of the students into account. Focusing on the students as initiating partners leads to more active learning, better understanding and stronger anchoring of what has been learnt. In addition, this learning approach promotes the acquisition of interdisciplinary skills – important for mechatronics – and soft skills, see e.g. [12] discussing this for medicine. The most common difficulties in implementation, which [12] also mentioned, are the need for more personnel and, in certain areas of expertise, for more equipment per student. Therefore, it is in general a good approach to use this technique in higher semesters. Nevertheless, the open design of problem-oriented learning scenarios as well as in social aspects such as group dynamics are still aspects of research [13], [14], [15]. In our work we focussed mainly on machine learning contents to be integrated into the curriculum. It should be mentioned, that there is a strong demand to include in modern engineering curricula additional contents like personal and professional skills, like proposed in the CDIO approach [16]. These additional qualifications were not covered in this work, but a number of different courses (e.g. english classes, scientific writing courses) are available and are mandatory for all bachelor students in our engineering department.

VI. CONCLUSION

This work introduced a framework to integrate machine learning contents in a modern mechatronics curriculum. The relevance of machine learning disciplines for mechatronics applications has been discussed, and a framework with required course contents has been derived. The framework has been formulated in a modular way to enable a seamless integration in any engineering degree program. The successful integration has been demonstrated with a case study at the University of Applied Sciences Bochum. Benefits and drawbacks of this solution have been presented and discussed.

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