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Capabilities and Challenges Using Machine Learning in Tunnelling

Thomas Marcher, Georg Erharter and Paul Unterlass

Abstract

Digitalization changes the design and operational processes in tunnelling. The way of gathering geological data in the field of tunnelling, the methods of rock mass classification as well as the application of tunnel design analyses, tunnel construction processes and tunnel maintenance will be influenced by this digital transformation. The ongoing digitalization in tunnelling through applications like building information modelling and artificial intelligence, addressing a variety of difficult tasks, is moving forward. Increasing overall amounts of data (big data), combined with the ease to access strong computing powers, are leading to a sharp increase in the successful application of data analytics and techniques of artificial intelligence. Artificial Intelligence now arrives also in the fields of geotechnical engineering, tunnelling and engineering geology. The chapter focuses on the potential for machine learning methods – a branch of Artificial Intelligence - in tunnelling. Examples will show that training artificial neural networks in a supervised manner works and yields valuable information. Unsupervised machine learning approaches will be also discussed, where the final classification is not imposed upon the data, but learned from it. Finally, reinforcement learning seems to be trendsetting but not being in use for specific tunnel applications yet.

Keywords: Big Data, TBM tunnelling, NATM, Automatic Classification, Machine Learning

1. Introduction

Digitisation in tunnelling is an ongoing process that draws on developments in Machine learning (ML) (a sub-field of artificial intelligence -AI) or advanced life cycle systems like building information modelling (BIM). While ML techniques have been used in other disciplines for some time, the demand for ML applications in geotechnics and tunnelling is growing more slowly. Many of the publications using ML for problem solving in geotechnical engineering or tunnelling rely on supervised ML; with [1–3] three papers are given that use artificial neural networks (ANN) to classify rock mass behaviour using tunnel boring machine (TBM) operational data.

The main drawback for those applications in geotechnical engineering is the limited availability of sufficient amounts of high quality data. To this day, only a small portion of the theoretically available data is in use during the design and construction process of tunnels (regardless of whether this data is stored for documentation purposes or is obtained as a by-product of construction works). Unfortunately, such data till now is never used to its full extent and a clear methodology for objective

and comprehensible data analysis is lacking. This applies specifically to geological and geotechnical applications, where many classifications are inherently semi-quantitative. Especially the bias introduced by man-made categorical classification presents a great challenge [2].

Great potential is therefore seen in unsupervised ML, where the final classification is learned from the data rather than imposed on it. ML techniques can be used to improve the efficiency and self-consistency of daily work in tunnel design and construction [4].

Finally, reinforcement learning (RL), another branch of ML, seems to be in vogue. To our knowledge, this form of ML has not yet been used for specific applications in geotechnical engineering and tunnelling. Basically, RL refers to the process of an agent learning to achieve a specific goal through interaction with its environment.

Two important prerequisites must be explicitly pointed out regarding data source and quality of the data:

- before processing data with ML techniques, the source of the data has to be verified and data preparation/pre-processing has to be performed (raw data must be separated from inaccurate or irrelevant parts of the data set).
- ethical use by all involved parties is imperative to provide the necessary safety required to get the most out of this technology [2].

Digital transformation in underground construction will be achieved through digital data, automation and networks. This transformation will affect both conventional and mechanised tunnelling. This change will influence payment and contract models, as well as software solutions for tunnel construction in general.

2. The future of digitised tunnel design and construction

The future of digitisation in tunnelling lies in a fully digitised project organisation linking different key technologies, e.g.:

- Machine learning (ML),
- Building Information Model (BIM),
- Augmented Reality (AR).

Through using machine learning techniques, it will mainly be possible to: (1) perform fully autonomous support installation, (2) elicit automatic rock classification, (3) update the geological forecasts in front of the tunnel excavation face (prior to arrive with the tunnel excavation), (4) overcome limitations in the definition of constitutive behaviour of soil and rock, explore the applicability of RL to fully automate different construction processes (self-driving TBMs).

The use of BIM will have an enormous impact on the design, construction and operation of tunnel projects. However, current developments in BIM for tunnelling are mostly focused on the basics of BIM: 3D geometries and corresponding data models /semantics. To fully implement the transition from “simple” semantically enriched 3D geometries to full digital twins, involving the above given technologies is imperative as only this allows for the necessary information exchange within the model. Digital transformation is achieved through systematic data collection

and automation and will influence both conventional (sequential) and continuous (TBM) tunnel constructions.

During the planning phase, digital data acquisition, data management and 3D modelling techniques will improve the way geological models or rock mechanics prediction models are created for tunnel projects [5]. This change will influence payment and contract models and will require the systematic implementation of software solutions for construction in general.

Finally, AR can be expected to become more widespread throughout the field of tunnelling. It gives a view of the real world where elements and layers are superimposed by computer generated files such as graphics, sounds, videos, or other digital information. This computer technology offers significant benefits through simulation and visualisation in the construction industry, e.g. by allowing the user to directly immerse him-/herself in specific information of the environment. Users can interact with both actual and virtual objects and monitor construction progress by contrasting the planned (target) state with the actual state of the project [6]. The users of AR may experience the enhanced world while digital information, including virtual models and contextual information, is presented and augmented with the real world [7]. In areas such as engineering, entertainment, aerospace, medicine, military, and automotive industry, AR technologies have been used as a frontline technology to meet visualisation difficulties in their specific domain [8]. These technologies still have considerable need for research. Their full potential is not fully reached yet [9].

3. Machine learning

3.1 Overview

Machine Learning is a sub-field of the research for AI and deep learning is itself a sub-discipline of ML (**Figure 1**). Where AI research in general focuses on understanding and synthesising intelligence, deep learning is a specific field that uses multilayer computational frameworks such as artificial neural networks (ANNs) to learn from data. The tremendous advances of ML in the past years (e.g. object

Figure 1. The fields of artificial intelligence, machine learning and deep learning in a topical context to each other as well as possible applications of the three sub-branches — supervised, unsupervised and reinforcement learning — of ML in tunnelling (modified after [4]).

detection, speech recognition etc.) are mostly based on this technology as it provides a high performing way of establishing input – output connections. However, downsides of deep learning are for example its “data hungry” nature (the impressive functionalities of deep learning are only possible through tremendous datasets) and the “black box” characteristics of the algorithms themselves, where the learned reasoning and logics are still poorly understood. ML itself is comprised of three main branches — supervised learning, unsupervised learning, reinforcement learning — which are described below.

3.2 Supervised learning

Supervised learning is the most widely applied type of ML with common applications being regression and classification tasks. To train supervised learning algorithms labelled datasets are required. Therefore, the input and the output values have to be known before the algorithm is trained (for further information see [10]). If such sufficient datasets are provided, state of the art algorithms can achieve great performance and are theoretically able to learn almost every possible relationship. The dependence on datasets with predefined input and output is however also a downside of supervised learning, as many real world datasets are inherently unlabelled and labelling them is either impossible or very expensive (see next chapter for more information).

The input can usually be imagined as a vector quantity [11] consisting of multiple features. These features are consigned to the learning algorithms together with the corresponding output and during training the algorithm learns to establish an input – output function. For evaluation of the training progress, the whole dataset is divided into several parts where one is used for model training, one for model validation during the training and in some cases a third independent dataset is split off for the sake of testing after the training process is finished. This partitioning of the dataset is necessary as supervised learning algorithms have a tendency of overfitting the data, they are trained on which ultimately leads to a bad generalisation performance if the algorithm is confronted with unseen data.

During training, the model learns a function that is able to map the given input to the corresponding output [11] (**Figure 2**). Supervised learning has already been applied for various geotechnical applications and in tunnelling (e.g. [1–3] natural hazards (e.g. [12]) and constitutive modelling (e.g. [13])).

Figure 2.
Basic principle of supervised learning (modified after [4]).

Figure 3.
Basic principle of unsupervised learning.

3.3 Unsupervised learning

Unsupervised learning is a sub-category of machine learning for which the algorithms receive only inputs but no labelled data. The aim of unsupervised ML is for the machine to build representations of the data [14] that in the end helps the operator to gather new information about the dataset. In the course of unsupervised ML, almost all steps can be viewed as learning a probabilistic model of the data [15] (**Figure 3**). The main methods of unsupervised learning and possible geotechnical applications are outlier detection (e.g. for monitoring works), clustering (e.g. to identify structure within data [16] or applying K-Means clustering to recognise rock mass types within TBM operational data) and dimensionality reduction to visualise high dimensional space in a more comprehensible way [14] (e.g. for improving the performance of geophysical log data classification).

3.4 Reinforcement learning

While in supervised and unsupervised learning the data is the main focus and algorithms either learn from or about it, reinforcement learning (RL) is about algorithms that improve their performance from interaction with the environment [17]. Algorithms/models are often called “agent” in this case and can be thought of as players of entities that can take certain action to influence the overall state of their surroundings. The environment on the other hand is the agents’ battleground which changes as a response to their actions and provides feedback to them by sending an updated state back to the agent and a reward signal that allows the agent to assess its own performance (**Figure 4**). The agent initially begins with performing random actions and over time starts to learn a “policy” for completing a task by

Figure 4.
Basic principle of reinforcement learning (modified after [4]).

analysing the current state of the environment and whether or not its past actions were successful.

Classical applications are board-games (e.g. chess, GO), but there is growing interest in RL for industrial applications (e.g. process optimization).

4. Examples for machine learning tunnel applications

4.1 Automatic rock mass classification approach for TBM excavations

The Brenner Base Tunnel (BBT) which is currently under construction, is a railway tunnel between Austria and Italy, connecting the cities Innsbruck and Fortezza. Including the Innsbruck railway bypass, the entire tunnel system through the Alps is 64 km long and is therefore the longest underground rail link in the world. The BBT consists of a system of two single-track main tunnel tubes, 70 meters apart, that are connected by crosscuts every 333 meters.

A service and drainage gallery lies about 10–12 meters deeper and between the main tunnel tubes (**Figure 5**). During construction the service tunnel serves as an exploratory tunnel, which is driven in advance to gather relevant information about the geology and the expected rock mass behaviour for the main excavation.

The present chapter focuses on 15 km of TBM – operational data from the exploratory tunnel “Ahrental – Pfons”, which is part of the construction lot “Tulfes-Pfons”. This tunnel section is driven with an open gripper TBM. Throughout the tunnel, the “Innsbrucker Quartzphyllite” and units of the “lower-” and “upper Schieferhülle” are the dominating lithological units. The rocks consist of low grade metamorphic phyllites to medium grade metamorphic schists with isolated bodies of gneiss, marble and greenschist. During excavation, the rock is mostly of good quality, however, friable and squeezing behaviour as well as large discontinuity driven overbreaks have occurred.

Efforts are undertaken to correlate the data from the exploratory tunnel with the encountered geology with the aim of deriving the rock mass behaviour from the TBM

Figure 5.
Overview of the tunnel arrangement of the BBT [18].

Figure 6.
 Exemplary section of TBM data between chainage 2000 and 2750 m; several features show a distinctive response to the encountered fault zone (taken from [2]).

operational data of the main tubes [19]. The TBM data comprises different recorded parameters such as advance force and cutterhead torque or computed parameters like the specific penetration or the torque ratio (after [20]). A corresponding classification of the rock mass behaviour – called the Geological Indication [21] – was also developed and shows the rockmass’ quality based on a traffic light system (**Figure 6**). Treating TBM data as input and the rock mass classification as output is a classic application of supervised machine learning. In [1], two different ANNs are given the job to automatically classify TBM operational data into various rock mass behaviour types. In [2], the applicability of a long short term memory networks [22] - a certain type of ANN for sequential data - for the classification of rock mass into behaviour types based on TBM data is shown. In [3], it is shown how an AI system can be misused to get either an optimistic or a pessimistic rockmass classification that might be in favour of one or another party at a specific construction site.

The labels of the geotechnical documentation have been altered to represented a binary form (one-hot encoded vectors), e.g. green = class 1 = [1, 0, 0, 0] (see [1]). Succeeding results show the outcome of applying such a network to the task of automated classification of TBM data (for details see [1]). Between 10,000 and 12,000 tunnel metres of TBM data has been used for training in the above given studies. **Figure 7** shows a result for chainage 1000 to 2000 m. In the upper row, the TBM data (normalised torque ratio) is given, the second row shows the “ground truth” which is the human classification. The third row shows the respective categorical classification of the LSTM network. The resulting output of the final layer (i.e. represented by the probability values for individual classes) is shown in the last row and displays an indication of how “sure” the model is about its assigned classes. This implementation of an LSTM shows adequate accuracies and good consensus between the model and the classification done by humans on site. Where the categorical classification makes the output directly comparable with the human classification more in depth information can be obtained from the probability values resulting from the direct output of ANN.

4.2 Investigation of rock loads via TBM operational data during standstills

Remote rock load monitoring allows TBM operators, engineering geologists and geotechnical engineers to collect, store and process information about the load

Figure 7. LSTM network classification from chainage 1000 to 2000 m (taken from [1]).

acting at the interface between TBM shield and the surrounding rock mass, a region that cannot be observed by other expeditious means. Its importance not only lies in the consideration of squeezing ground conditions [23–25], but furthermore in terms of the deformation behaviour and stress redistribution of the surrounding rock masses in hard rock tunnels. To gather relevant information from the collected TBM operational data application of digital systematic data analysis is inevitable.

Many open gripper TBMs are equipped with a roof support shield directly behind the cutterhead which is extended against the tunnel wall during standstills. TBM specifics vary between manufacturers, one example on data logged during the operation of an Herrenknecht open gripper TBM is presented in this chapter. On this machine the roof support shield is driven by two independently movable left- and right cylinders [26]. Sensors separately record the pressure that acts on both sides of the TBM's roof support shield. This provides the unique opportunity to analyse differential rock-loads that are applied to each side of the shield.

Before analysing, the raw data is passed through a pre-processing pipeline with the goal to filter out continuous periods of uninterrupted loading of the shields. Problematically, these loading periods do not simply occur before and after each complete stroke of the TBM, but due to intermediate stops during the excavation process, each stroke is (seemingly) randomly divided into sub-strokes of unequal length. **Figure 8a** gives an example of one stroke, which is separated into five sub-strokes. A blurred analysis would result if the whole stroke was treated as one instead of separating it into sub-strokes.

As throughout the whole tunnel excavation thousands of these sub-strokes would need to be separated, data pre-processing has the goal to achieve a best fitting separation in a fully automated way as manual filtering would be infeasible. A pre-processing pipeline for this problem would consist of the following steps: 1. arranging raw data (e.g. in a database), 2. Filtering out non-advance periods, 3. Checking for and correcting of possible systematic errors, 4. Separating sub-strokes via cluster analysis.

Figure 8.
Plot of a single complete stroke, in the upper row the pressures in the RSCs left and right have been plotted against each other, whereas in the lower row the pressures were plotted against time (“p_rsc_r” and “p_rsc_l” denotes the pressure in the right and left cylinder respectively). The left column shows (Figure 8a) all pressure increases during the stroke and the right column (Figure 8b) only shows the longest increase [27].

After pre-processing, continuous pressure increases for each roof supporting cylinder (RSC) per sub-stroke during standstills of the TBM are isolated (e.g. in **Figure 8b**). In order to do a proper comparison between both RSC’s and to take qualitative statements about the stress redistribution/direction in the interface between shield and rock mass, the Line of Isotropic Pressure (LIP) concept [27] is considered.

Plotting the pressures of the left and the right RSC against each other for an isolated sub-stroke (e.g. **Figure 8** upper row), an isotropic pressure increase would represent a straight line of 45°, indicating an equal pressure increase in both cylinders (**Figure 9**). In other words, when fitting a linear regression to the aforementioned plot, the LIP would compare to a regression line with a slope equal to 1. Deviations from the LIP towards the horizontal, corresponding to a decrease in slope equal to values <1, indicate that the pressure increase in the right RSC exceeds the pressure increase in the left cylinder. Same concept applies to deviations from the LIP towards the vertical, corresponding to an increase in slope equal to values >1, indicating that the pressure increase in the left RSC exceeds the pressure increase in the right cylinder. Hence, to assign a slope value to every cluster an extension to the cluster analysis code has to be adapted, fitting a linear least squares regression to every cluster/isolated sub-stroke. At the end of the analysis the data is clustered into significant sub-strokes assigned with a slope value describing the relation of pressure increase between the two RSC’s.

Following the approach that the pressure in the RSC’s increases with the same extend as the rock load increases, one can state that the rock load acting on the one side of the shield with the higher pressure reading, exceeds the load applied

Figure 9.

Conceptual diagram explaining the line of isotropic pressure (LIP): Plot of the pressure in the right RSC on the x-axis vs. the pressure in the left RSC on the y-axis. The LIP corresponds to a linear regression line with a slope of 1 and represents an isotropic increase in pressure in both cylinders [27].

to the shields other side. Plotting the distribution of the slope values in histogram plots either for the whole tunnel, for certain tunnel sections or even parallel to the tunnelling process would hence give a qualitative indication on the rock load distribution in the interface shield to rock mass. In addition to the site characterisation mapped by engineering geologists the pressure in the RSC's provides a vital parameter contributing to the understanding of the overall system behaviour of a tunnel drive.

4.3 Interpretation of monitoring results

Geotechnical monitoring is an integral part of the life cycle of a tunnel structure. The observation method is described in detail in [28]. The observation method is used, on the one hand, to check the design during construction and on the other hand, to check the condition of the tunnel lining during the operational life of the tunnel.

From the technical side, the observational method addresses tunnel surface deformation methods (absolute geodetic measurements, distometers), deformations of the surrounding ground (extensometers) and monitoring of ground support (anchor forces), pressure cells implemented in the shotcrete liner [29].

There are different methods of evaluation and interpretation. The first step is typically the evaluation of a time-displacement diagram. More sophisticated approaches involve the interpretation of displacement vector orientations [29].

Unsupervised ML can be used to develop a warning system for monitoring tunnelling data as it is used today for several other cases of outlier detection (see Section 3.3). This applies to both conventional and machine tunnelling methods. This warning system would consist of a multi-stage pipeline that takes the raw displacement measurements as input and provides an indication of whether a measurement point is behaving 'normally' or not.

4.4 Tunnel maintenance

Many railway and roadway tunnels around the world are ageing. Maintaining works for these tunnels are becoming a major issue. To this day, inspection work is done by visually examining the surface of the lining while walking and through the tunnel and tapping with a hammer on suspicious surfaces (often during night times on temporally closed roads or tracks). Collected data is laborious to process after the inspection.

Digitisation aids this process in terms of making it easier and less subjective. Lately images obtained with different technologies (i.e. laser scanning, slit cameras and line-sensor cameras) find increased usage. These techniques are not only non-destructive, they can also be applied in an automated manner. Especially, vision-based automatic inspection techniques are used to detect damages at the concrete surface of the tunnel lining. In order to recognise and distinguish various types of structural damage of the tunnel lining automatic methods have been introduced [30].

5. Conclusions

Digitisation in general and ML in particular are adding value in tunnelling by improving efficiency of operational processes and quality assurance as well as increasing the safety for on-site personnel by replacing humans with sensors in highly hazardous areas. Nevertheless, these improvements come at the cost of an increasing demand of personnel that is not only skilled in the geotechnical disciplines, but also brings knowledge of ML technology.

The examples given in the previous section show that training ANNs in a supervised manner works and provides valuable information. Nevertheless, today's AI systems – especially the ones based on supervised learning - should only be used as an aid and not as a replacement for geologists or geotechnical engineers on site. The immediate benefit of this technology is the improved classification efficiency and self-consistency but results still need to be critically checked before they are used for decision making. Additionally, ML based automation of the above given processes also increases the safety for human lives and there are also economic advantages that should not be underestimated.

The vision of the “tunneller of the future” who will control the whole construction site and operate all the machines from the comfort of his office chair, with keyboard, joysticks and monitors is still several years ahead of us. To realise this vision, full automation of mechanical underground processes is imperative and to achieve this, great potential is seen in RL technology. The rapid advances in mobile control and navigation technology are giving a sustained boost to automation and robotics in underground mining.

Looking at “evolutionary line for digitalisation in tunnelling” (e.g. [4]), the following developments are foreseeable in the medium term: autonomous machines such as e.g. automatic shotcrete application, autonomous drilling and grouting and driverless dumpers, excavators and loaders for drilling and blasting sequences, real-time adjustments of driving parameters for TBM drives, automatic rock classification procedures, automatic geological updating before the face and e.g. optimised prediction models for sequencing and support quantities. The withdrawal of workers from the most hazardous zones in the active areas of tunnelling is an important aspect of increasing the safety and comfort of underground workers.

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