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The use of artificial intelligence for a cost-effective tunnel maintenance

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ABSTRACT: Every year 4700km of new tunnels are built with an annual growth value of 7%. This results in the fact, that the total amount of tunnels which must be inspected will increase in the future. Furthermore, their operation reliability must be guaranteed with safe and cost-efficient means. Building upon Amberg Technologies' and Amberg Engineering's experience from several international tunnel projects, we have come up with a new platform which allow us to optimize the tunnel inspection process. Today, tunnel assessment is mostly based on a slow and subjective human inspection process. Automatic defect detection will provide a more objective and quantifiable approach to the task of tunnel inspection. By manual inspection it is difficult to assess anomalies objectively, especially cracks at an accuracy of 0.2 mm with random size and shape. It is also difficult to compare them to the historic state of previous assessment campaigns. Thus, it makes sense to aim at an automated detection procedure and a fully digitized workflow for tracking the defects over time. Recent developments in the field of big data and artificial intelligence can be applied to the field of tunnel inspection and bring it to a higher degree of automatization. Amberg is focusing on developing a computer-based and BIM-compatible implementation of the new methods for damage classification and tunnel assessment. This paper will explain the principle of the new platform and show some initial test projects.

1 INTRODUCTION/MOTIVATION

Currently tunnel inspections are carried out mainly by (visual) walking through inspections based on some input data available. This allows to focus on certain phenomena and locations which need special attention. These walk through inspections, which may also include some visual close-up inspections are carried out by experienced but sometimes not specially trained and educated staff. In often cases knowledge is missing on the severity of certain damages as such and of the relevance of their development.

During these walk through inspections notes, images and data in general are taken. After the inspection, this data is integrated into some kind of database, partly in digital form, partly still on paper. This data serves as an input for further inspection at regular intervals or as a trigger for additional inspections and measurements. As well as for immediate necessary maintenance and rehabilitation activities. Evaluation of the data for a holistic state assessment, damage development, maintenance etc. is done only to a limited extend and not in a digitalized manner.

The Project owner needs answers in real time to the following questions:

- What is the condition of my structure?
- What types of damages are present?
- Is there a threat to structural and operational safety?
- How much money must be budgeted for maintenance?

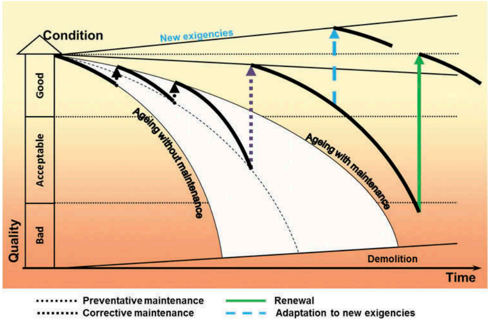

Figure 1. Aging process of an infrastructures.

To get answers to the questions above, project owners deploy systematic tunnel inspections. Periodical inspections should help to keep the overall costs low. It helps to identify the critical areas early and start with refurbishment work when the areas of damages are still small. Without regular inspections you can increase the risk of a big incident which ends up in bigger refurbishment work and also costs (Figure 1).

2 METHODOLOGY OF TUNNEL MAINTENANCE WORK

2.1 *State of the art today*

To maintain operational safety, serviceability and structural safety of tunnel infrastructure as economically as possible, a mature value preservation concept must be implemented.

The basis of the value preservation concept is regular monitoring, which means regular surveying and inspections each 5th year in most of cases (number of years can be different in each country and for each tunnel).

Preservation of tunnel infrastructures is divided into surveying measures and maintenance measures. Surveying measures consist of inspections, visual and measurement control, function and material tests. Maintenance measures are further divided into preventive maintenance, corrective maintenance and renewal measures. Maintenance measures are defined as the result of the condition assessment based on the surveying measures.

Maintenance management starts as soon as the tunnel is finished by the first inspection to document the as-built state. The survey measures serve both as initial documentation of the condition and as continuous or periodic documentation of the condition development.

Then each 5 year inspections are scheduled to register the tendencies of the state of the construction and to be able to define when a maintenance work is needed. After an intervention, the new state is also inspected.

Inspections are fundamental for all focused management processes for structural value preservation that must be based on detailed knowledge about the condition of the tunnels. During the surveying measures, technical data about the properties, characteristics and the condition of the tunnel must be collected:

- Construction materials and their properties.
- Geometry and profile of the cavity.
- Installations for operation and clearance profile.
- Damages and deficiencies.
- Additional data: Construction method and tunnel age, geology and geologically induced forces, hydrogeology and chemical characteristics of the rock water, climatic condition, rolling stock and operation types.

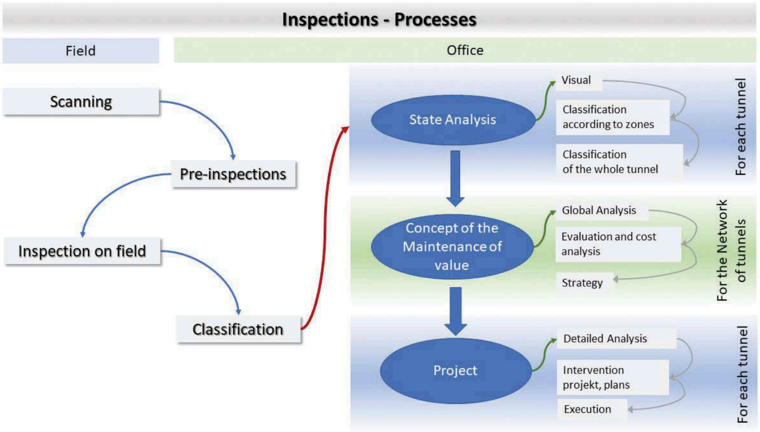

Figure 2. Inspection processes.

Inspection or surveying work is partly done in Field (Figure 2). For safety reasons, work in Field must be carried out in closure periods. These can be done usually only during night shifts and therefore it is very expensive. Therefore it is important to minimize time in the field as much as possible. This is facilitated by computer-aided tools for survey activities and data analysis. Carrying out a pre-inspection in the office using the scanned images as a background for the inspection software reduce the time needed in field. Accordingly, the tunnel structure, materials, installations and damages that have been already registered only needs to be checked, corrected or added, once the inspection is lead through the tunnel. The data collected and analyzed are the basis for the tunnel state assessment and future planning. Damage categories are for example deformations, cavities, cracks, water inflow, corrosion etc. or combination of these phenomena.

After a complete acquisition of the damages data and deficiencies of all tunnels on the network, it needs to be defined to which condition class each zone belongs to.

Each zone is assigned to a condition class. Classes are defined as follows:

– 1: Good.
– 2: Sufficient.
– 3: Insufficient.
– 4: Aggravating.
– 5: Alarming.

After classification the management approach has to be defined (preventive or corrective maintenance or renewal). This is going to be applied to the different condition classes 2 to 5.

Then this process needs to be done for the whole tunnel, then for the whole network in order to make a prioritization among the tunnels in function of the seriousness of the damages and the construction costs. The owner can organise finance plans and intervention schedules. Finally, a maintenance intervention project of the tunnel (or zone) is made according to the priorities defined for the whole network.

2.2 *Pros & Cons of used approach*

The assessment is carried out by experienced engineers but it is naturally subjective. The influence of subjectivity must be reduced without relieving the engineer from responsibility. Digitalization and working with artificial intelligence pushes the industry to work out an increasing amount of standards that makes the evaluation of the different phenomena easier, faster and more unified. This development is already an important factor to simplify, uniform, clarify the moreobvious results and to accelerate the communication between the different possible participants of the whole maintenance process.

Beside the fact that digitalization pushes the development of the standards, an important acceleration happens in each step of the inspection project. For example, scanning data can be transformed to action data of the maintenance project execution and then it's going to be the part of the as-built model. Later it can be used as a basis for further inspections/maintenance management tools. Firstly, the image data from the scanning is automatically analyzed by the software with image and object recognition tools. It accelerates the pre-inspection because it recognizes (semi-) automatically most of the defects. Due to its neural learning capacity, as the system get used, it detects more incidents more precisely and marks them on a layer over the scanning picture. This data must be checked and corrected if needed which implies much less work than drawing all the incidents by hand on the layer. The expectation is that the more this tool is used, the less corrections will be needed.

Second, with a better quality of pre-inspection documents, the inspection can be done faster because fewer new damages have to be discovered on site. The inspection data can be registered in the cloud and be followed real-time.

On the other hand, the synergies of differing damages are quite complex. The same phenomena can have different importance according to:

- The geology.
- The building materials.
- Geometric position.
- The age of the damage, and the speed of change.

Even though the combination of most of these factors with the damage or deficiency types can be programmed into a software to support decisions, the human control factor cannot be excluded. For example, the possible complexity of the geology or a lack of information can cause individual cases.

Even though some decisions in the process of value preservation can't be 100% unmanned, still many steps can be standardized, digitalized, supported, optimized and finally accelerated by artificial intelligence. This kind of evaluation of data capturing, processing and analysis is a necessary must for integrating tunnel maintenance workflows in the world of the BIM. This is going to be more and more common in underground construction.

2.3 *Metric of today's solution, time needed for each step is compared later with the new system in the conclusion*

Based on the experience of 450 km of tunnels inspected by Amberg Engineering, we calculated the time needed when using a standard methodology used in the past 10 years in all instances, i.e. "Trolley and TunnelMap". Comparing this already computer-based methodology with the analog 2-dimensional CAD support indicates already significant improvements as shown in the first column of Table 1. The third column shows the time-saving effect of the use of artificial intelligence compared to Trolley and Tunnel Map.

Table 1. Potential time-saving on each steps of surveying/inspection, if by each step 100% is equal to the inspection method with TunnelMap and trolley.

Time needed for each step	Analog surveying-methods + CAD [%]	Trolley + Tunnel-Map [%]	Use of artificial intelligence [%]
Data capture (closing the tunnel)	0	100	100
Pre-inspections (analysis)	70	100	40
Field (closing the tunnel)	400	100	80
Field (Engineers work)	300	100	75
Documentation	300	100	60
Preparing the next insp.	200	100	70

While below shows that data capturing itself is not much faster, it could be further accelerated if combined also with GPR (Ground Penetrating Radar) data capture that would mean getting more information at the same time. The data capturing is going to be more detailed which contributes a lot to the clarity and precision of pre-inspection reports. A special case where digitally supported data capture is beneficial would be the use of drones for scanning in tunnels which are difficult or dangerous to enter. Related benefits depend on the individual circumstances.

The pre-inspections are going to be up to 60% more efficient thanks to the reasons described in detail in chapter 2.2 such as e.g. the fact that (semi-)automatic change and defect detection helps saving an encouraging number of working hours of engineers.

As for the inspection itself, working in the field is going to need less time as more detailed pre-inspections save detection work in the tunnel. Due to this fact less personnel is needed and the tunnel can be opened sooner. We consider that the time saving would be 25–30%.

An important aspect of the use of new technologies is that a part of the documentation of the inspection can be directly generated from the data capture itself. The data is going to be accessible in a cloud for everybody with a permission, so the owner of the tunnel can see the inspection results online in real time.

Finally, preparing the data for the next inspection happens automatically in the cloud as the previous inspection which helps accelerating the preparation process.

3 METHODOLOGY OF DATA CAPTURE AND DATA PROCESSING

3.1 *Data capture*

Data capture in the tunnel is very demanding due to low light, harsh conditions, usually very limited time for measurement, high expected accuracy and safety regulations. Data capture techniques have developed from visual inspection on sight to more automated technologies. Most common data acquisition method is laser scanning. The advantage is that light conditions do not influence the quality of results. On the other hand, the color information is lost. The opposite characteristic applies for photogrammetry.

Another parameter is the way how the measuring equipment is moved in tunnel. This varies from manually pushed trolleys, small robots up to big cars or locomotives. Obviously, the speed and purchasing cost vary. Lately drones are being tested for use in tunnels. The data capture methods are summarized in Table 2.

3.2 *Data processing*

Raw data processing starts with data import from measuring instrument and continues with positioning and exporting of files in formats needed for data analytics. These are usually pictures referenced in coordinate system of a tunnel axis.

Table 2. Evaluation of data capture methods.

Method	Speed	Data capture	Accuracy	Personnel
Manual inspection	Walking speed	Camera images, Test results of material behavior	0.1m	2
Trolley based inspection	Kinematic laser scanning (profiler), 3 - 5 km/h	Gray scale image, RGB image,	0.005m	1
Train based inspection	Kinematic laser scanning (profiler), operating speed (40 – 60km/h)	Gray scale image, RGB image, Ground penetrating radar information, thermal image, ultra-band width	0.01m	-
Unmanned robot	Kinematic data capture, autonomous inspection in walking speed 3 – 5 km/h	Kinematic scanning (profiler), camera image, thermos image, GPR, . . .	0.1m	-
UAV	Kinematic data capture, autonomous inspection	Kinematic scanning (profiler), camera image, thermos image, GPR,. . .	0.5m	-

As the table in previous chapter shows, there are many ways how to capture data. What matters in the end is the quality of data. When it comes to data processing, low quality data is inefficient because the inspected phenomena are usually not visible and the repetitive tunnel visits are needed.

When there is good quality data the second important factor is to be able to effectively use and reuse this.

3.3 *Data analytics*

Having good quality data is a promising start. But the real value is still missing. Equally important as the quality of the data is good data processing. Just the grayscale images are futile. Grayscale images with the ability to add features drawing is proving advantageous. But the aim is to have an intelligent system where each picture and phenomena relates to database where all the additional information is organized. This connection makes it easy to analyze the data and reuse them in the future.

To analyze the collected data, referenced grayscale pictures are used as a background and tunnel features are drawn on it. All the feature drawings are stored in a database. The common coordinate system provides connection between drawings, pictures and the real tunnel. Experienced engineers evaluate state of the tunnel based on feature drawings and determine condition class of each block.

3.4 *Motivation of our development project*

Currently used software TunnelMap (Figure 3) provides the functions to create database from phenomena drawing. But the whole software has its limitations caused mainly by the age of the software. It was developed roughly two decades ago when data synchronization, ideas about BIM and possibilities of smart construction were on a completely different level (if existed at all).

Nowadays the gap between the old software and modern inspection demands reached the size when using it is not effective and therefore unsustainable any more. It is time for modern web based platform that will keep pace with today technology and market expectations.

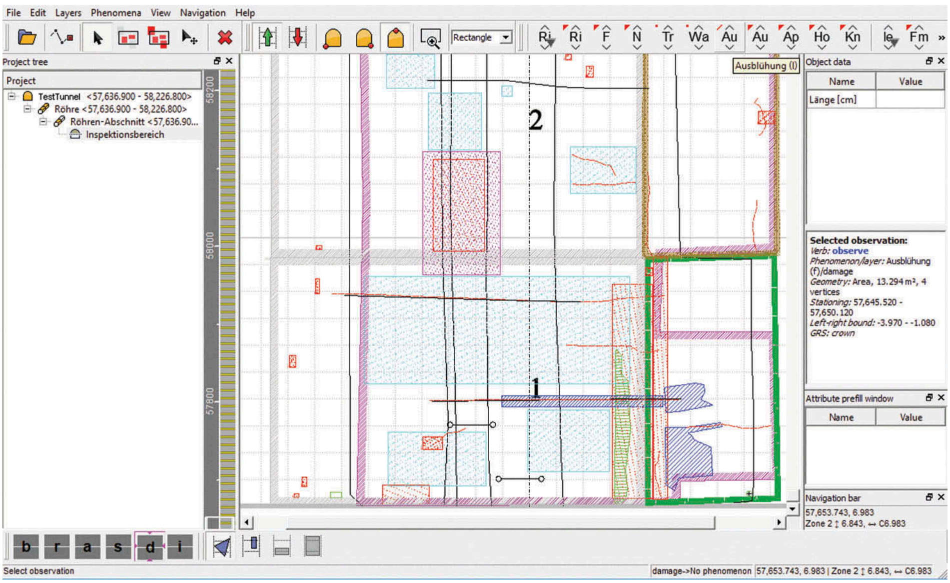

Figure 3. TunnelMap software - drawing page.

4 THE SYSTEM

4.1 *Workflow*

The paper drawings are rather old fashioned. Working on the computer is a main stream nowadays. Looking in the future we need to go further. Move the data to the cloud to make these available everywhere, every time, from all types of devices and for all users.

In this chapter the new platform called Amberg Inspection Cloud will be described. Mainly the new methodology and advantages for tunnel inspection will be discussed.

4.2 *Workflow optimization*

The basic workflow remains identical as described in the *Chapter 3*. The main goal is to make the whole inspection process easier, more automated and therefore less time consuming and cheaper.

Our focus is on the data processing and data analysis itself. There are many ways how to collect data efficiently in automatic or semi-automatic way. But the inspection and damage drawing itself has always been tedious and time consuming manual work.

The workflow optimization can be done in two steps. The first step is helping users with manual drawing by highlighting areas with high crack (damage) probability. This way users do not have to see the whole tunnel in detail and can focus only on problematic areas.

The second step is an automatic phenomena drawing. It means that inspected damages or utilities are found and drawn fully automatically. Users can then perform a quick visual check. This second level of the workflow optimization is expected to save ¾ of the inspection data processing time.

In both above mentioned steps an artificial intelligence (deep neural network) is used for damage highlighting and automatic drawing. The deep neural network will be trained either by your own work (manually inspecting tunnels) or by the community (all users of the platform).

4.3 *The new platform – Why artificial intelligence?*

The evolution of the artificial intelligence and machine learning started already in the middle of the last century. Recent findings in this field and powerful hardware enabled us in the last years to transfer this technique from academic field to business use. The hardware development was especially important for so called deep neural networks. These networks are based on the same principle as a human brain. The power and weakness of these networks lie in millions of parameters that need to be adjusted during the network training. The learning process may take from a few minutes up to several days. But with a suitable network structure, very complicated phenomena can be extracted from pictures. Various studies have already been conducted on this topic. The biggest effort was probably done in a medical field. But some investigations were already done in road, rail and concrete damage detection [Yokoyama et al. 2017, Cha et al. 2017, Faghih-Roohi et al. 2016, Yang et al. 2017, Eisenbach et al. 2017]. In these studies, we can find many similarities with tunnel damages. But up to this date we are not aware of any work on this topic in tunnel environment.

Using the previous research dealing with damage detection and available tools (Keras, TensorFlow™) we tested LeNet and VGG-16 network. The tools Keras and Tensorflow are common used in this field of development and have a huge community of users. The networks (LeNet & VGG-16) promised good results in reasonable computation time.

The main limitation in the first development stages was a limited amount of a training data. Therefore, we excluded very deep networks from testing. Even VGG-16 ended up overfitting the training data. After this observation we fine-tuned the LeNet network for searching cracks or wet areas on tunnel walls and ceiling. As an input for the network training we used gray scale images created from laser scanning data. Detailed results are described in more detail in *Chapter 5.* The visual results (Figure 4) are presented in more detail on the new web-based platform Amberg Inspection Cloud.

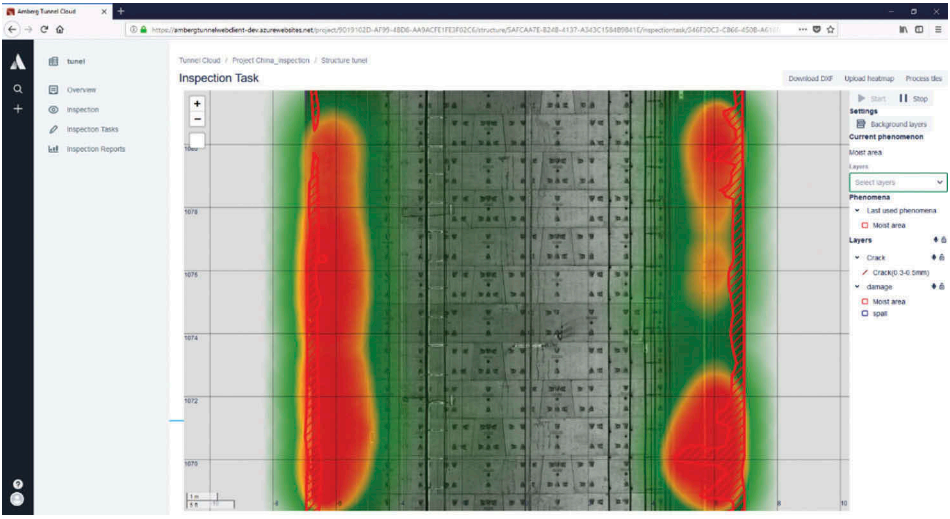

Figure 4. Color map showing probability of wet area in tunnel.

4.4 *The new platform – From tunnel to cloud*

Amberg Inspection Cloud is a brand-new web-based platform specialized on tunnel inspections. It is open for data from different sources and measurement methods. As long as the inputs are good-quality, high-resolution images the measurement method is not important.

Tunnel design and the high-resolution images are uploaded to a cloud. Pre-trained neural network can automatically detect damage probability in each area and draw a damage probability color map. Experienced operator then just looks at the highlighted areas and draw the exact tunnel damages. In case of bigger project more operators can work independently without tedious data transfer and synchronization.

When the drawing is finished the analysis can be accessed directly in Amberg Inspection Cloud. That includes comparison of the tunnel state in different years, visualization of damages along the tunnel and the standard DXF export.

In the future, automatic phenomena drawing will be introduced. When Amberg Inspection Cloud is fully developed, the inspection engineer only checks the automatic drawings and potentially make some small changes if needed. That will save enormous amount of time compared with manual drawing.

4.5 *Outlook*

The final goal is to eliminate manual work from tunnel inspection as much as possible. Nowadays it does not seem possible to skip manual input and expert knowledge completely. In the future experts will still need to decide on some unclear cases. But the tedious manual marking of all the clear cases will be replaced by the artificial intelligence. Automatic crack detection and drawing is on the horizon.

Not only is the inspection evaluation itself an issue. Other time-consuming aspects are the result evaluation and data transfer. The goal in this area is to be fully BIM compatible. That is somehow restrained by the fact that BIM standard for tunnels is not yet defined. The Amberg Inspection Cloud already combine position information (3D), feature info (1D), time (1D) and powerful data analysis. The missing part of the chain is a BIM format that allow easy transfer to other programs.

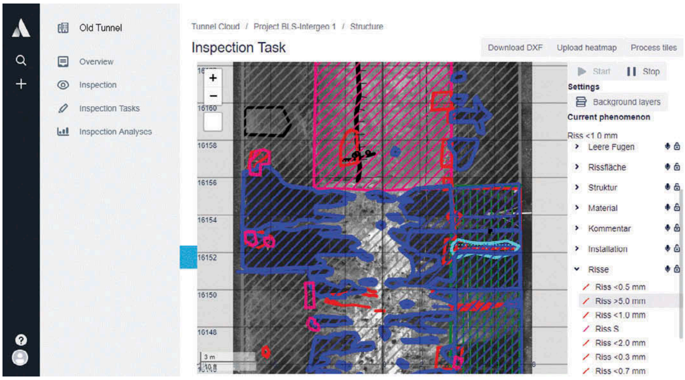

Figure 5. Finished phenomena drawing of masonry tunnel.

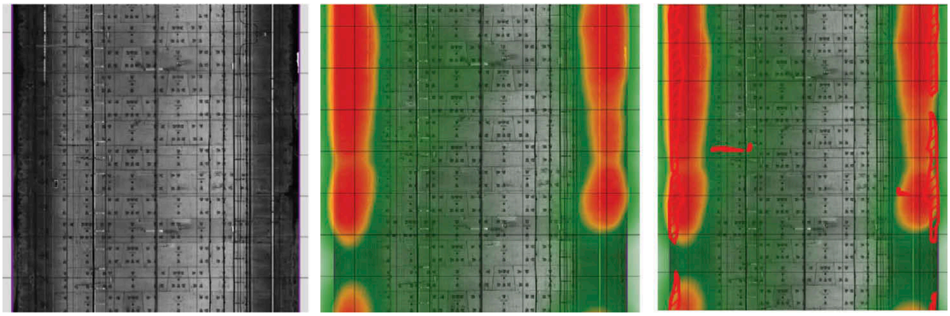

Figure 6. Workflow with wet area probability predicted by neural network.

5 TEST PROJECTS

As test data we have some old masonry tunnels in Switzerland where the inspection is done regularly. The second type of the tunnel that was used for testing is significantly newer rail segmental lining tunnel.

We realized that it is important to distinguish between different types of the tunnels. Obviously, the tunnels and the damages in them are very different. Therefore, it seems impossible to train one neural network that is applicable for all tunnel types.

5.1 *Old masonry tunnel*

Obviously, the inspection of old tunnel (Figure 5) is much more demanding because significantly bigger amount of damages is found here. Moreover, different types of materials (for example: bricks, shotcrete) makes automatic recognitions even more difficult.

5.2 *Segmental lining tunnel*

Segmental lining tunnels are in general not so old. Therefore, less damages can be found in these tunnels. The most frequent are wet areas. Sometimes small cracks can be found.

That means on one hand that the damage data are rarer and it is more difficult to gather enough pictures with damages to train the network. On the other hand, the damages are much more uniform so it is easier to recognize them automatically even with smaller training dataset.

In detecting the wet zones in segmental tunnel, we achieved accuracy over 90% (Figure 6). This can be further improved by adding more training data and tweaking the network model.

6 CONCLUSION

Artificial intelligence is not a new technology, but the change of access to powerful processing engines changed the usage of these technologies dramatically. The transfer from academic field to business area started in the last few years. The construction industry is nowadays also transferring many operations and applications with neural networks approach. Our industry can now profit from applications and learnings from different industries - for example the medical industry.

Our challenge for the future requires safe, predictable and adaptable tunnels which help us to optimize the costs for the entire life-cycle of a tunnel infrastructure. Thanks to the digitalization of our industry we will collect more data from our infrastructure. However, the challenge will be to increase the data analytics. Artificial intelligence helps to automate this process. The usage in this paper for artificial intelligence for defect detection has shown that these technologies will change the way tunnel inspection will be done in the future. However, for the time being there is still some work to do and to collect some more reliable training data. First test project shown that the time saving is up to 60% of the initial time. However currently we reached with the actual state of the software around 30%. We're optimistic that with improving our neural network and training the system with existing project, which has been already carried out with our previous software TunnelMap, we can increase the degree of automation.

Once we can automate the data processing for defect detection we can also increase the data capturing cycle. The data capture process is currently also in a big change. New sensors and platforms are developed which allow an automated data capture of the entire tunnel infrastructure. Combining this data, we can then build up a digital tunnel twin. With these technologies, it then should be possible to start changing the periodically inspections to event driven inspections. Which means that the owner of an infrastructure can plan their inspections based on the real conditions and the changes in certain sectors of the tunnel.

REFERENCES

Cha, Young-Jin, et al. 2017. "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks." *Computer-Aided Civil and Infrastructure Engineering*, vol. 32, no. 5, pp. 361–378, doi:10.1111/mice.12263.

Eisenbach, Markus, et al. 2017. "How to Get Pavement Distress Detection Ready for Deep Learning? A Systematic Approach." *2017 International Joint Conference on Neural Networks (IJCNN)*, doi:10.1109/ijcnn.2017.7966101.

Faghih-Roohi, Shahrzad, et al. 2016. "Deep Convolutional Neural Networks for Detection of Rail Surface Defects." *2016 International Joint Conference on Neural Networks (IJCNN)*, doi:10.1109/ijcnn.2016.7727522.

Winkler N. & Ackermann A.W., 2011, "Value Preservation of underground infrastructure through focused conceptional planning", *Amberg Engineering Ltd.*, *Switzerland*

Yang, Liang & Li, Bing & Li, Wei & Zhaoming, Liu & Yang, Guoyong & Xiao, Jizhong. 2017. "Deep Concrete Inspection Using Unmanned Aerial Vehicle Towards CSSC Database." *Conference: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems*

Yokoyama, Suguru, and Takashi Matsumoto 2017. "Development of an Automatic Detector of Cracks in Concrete Using Machine Learning." *Procedia Engineering*, vol. 171, pp. 1250–1255, doi:10.1016/j.proeng.2017.01.418.