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GENERATING INITIAL DIGITAL TWIN MODELS FOR THE OPERATION OF ROAD TUNNELS

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Abstract

Ensuring the safe and uninterrupted operation of tunnels necessitates continuous monitoring and maintenance. Digital methods, including digital twins, have proven their effectiveness in reducing operating costs but require digital models that are often unavailable for existing tunnels. Therefore, this paper conceptualizes a deep learning-based approach to transform unstructured tunnel documentation into digital models through three core modules: (1) reconstructing the tunnel geometry from construction drawings, (2) analyzing inspection reports to create a damage model for structural condition assessment, and (3) analyzing point clouds, videos, and product data sheets to model the tunnel ventilation system.

Introduction

Tunnels are intricate structures that integrate components of civil engineering with complex Tunnel Electromechanical Equipment (TEE), including ventilation, lighting, and fire protection systems (Yu et al., 2021; Shen et al., 2022). Any failure of the tunnel or its installed TEE can have serious economic consequences or pose severe safety risks, potentially leading to catastrophic events. As a result, safety and reliability are critical priorities in tunnel operations. To ensure this, extensive monitoring and maintenance are necessary throughout the tunnel's operational phase. While these activities are crucial for maintaining functionality, they come with significant costs and must be carried out consistently over the long service life of a tunnel (Baji et al., 2017; Petroutsatou et al., 2021). Therefore, current research focuses on leveraging digital methods to enhance the efficiency of tunnel operations.

A method that has proven particularly effective in supporting tunnel operations and reducing operational costs is the Digital Twin (DT), as demonstrated in recent studies by Sanfilippo et al. (2023) and Diren and Althen (2023). According to Boje et al. (2020), a DT consists of a physical component and a virtual model connected by a data link that enables bidirectional data exchange. This connection facilitates a continuous flow of data between the physical object and its virtual counterpart, creating a mutually influential relationship between the two. Notably, this integration of real-time data is what distinguishes DTs from as-built models. In the context of tunnels, a DT contains comprehensive information about the tunnel structure, its condition, and the installed TEE while also providing real-time data. This enables the tunnel operator to closely monitor the tunnel, detect anomalies at an early stage, and implement targeted maintenance measures (Zhou et al., 2024).

Yu et al. (2021) present a digital twin-based framework for collecting and utilizing tunnel data to manage physical tunnel infrastructure. To support this framework, they extend the COBie[1] standard to incorporate inspection data and leverage semantic web technology to provide a comprehensive foundation for their data management system. This foundation enables their multilayered system to fuse and analyze the various types of data, generating recommendations for maintenance. The authors validate their proposed framework through a case study in a tunnel in China, demonstrating its ability to support tunnel managers by detecting faults in the tunnel's ventilation system. In a subsequent study, Yu et al. (2023) further extend their framework to incorporate domain knowledge and experience from prior maintenance activities, enabling proactive TEE management. This improved system supports effective strategies by prioritizing maintenance measures.

Zhou et al. (2024) also explore the application of DTs in tunnel management, proposing a platform for tracking and managing the performance of metro tunnels. The authors first develop a structured framework for the DT, integrating all the required data and accounting for tunnel defects.

Despite the advantages of DTs, many tunnels lack these systems and require retrospective implementation. A key element in the DT implementation is the virtual building model, which is often absent for existing tunnel structures. Consequently, these models must be created from available unstructured data sources, such as drawings, point clouds, images, and reports, a task that is both time-consuming and costly if done manually. Therefore, automating this process would assist the implementation of DT in tunnel operations.

Although previous studies such as Xu et al. (2025) or Ye et al. (2025) have presented various concepts, these approaches address only specific aspects of creating a digital tunnel model. In contrast, this study proposes a concept

[1]https://www.nibs.org/nbims/v3/cobie (Accessed: 30. April 2025)

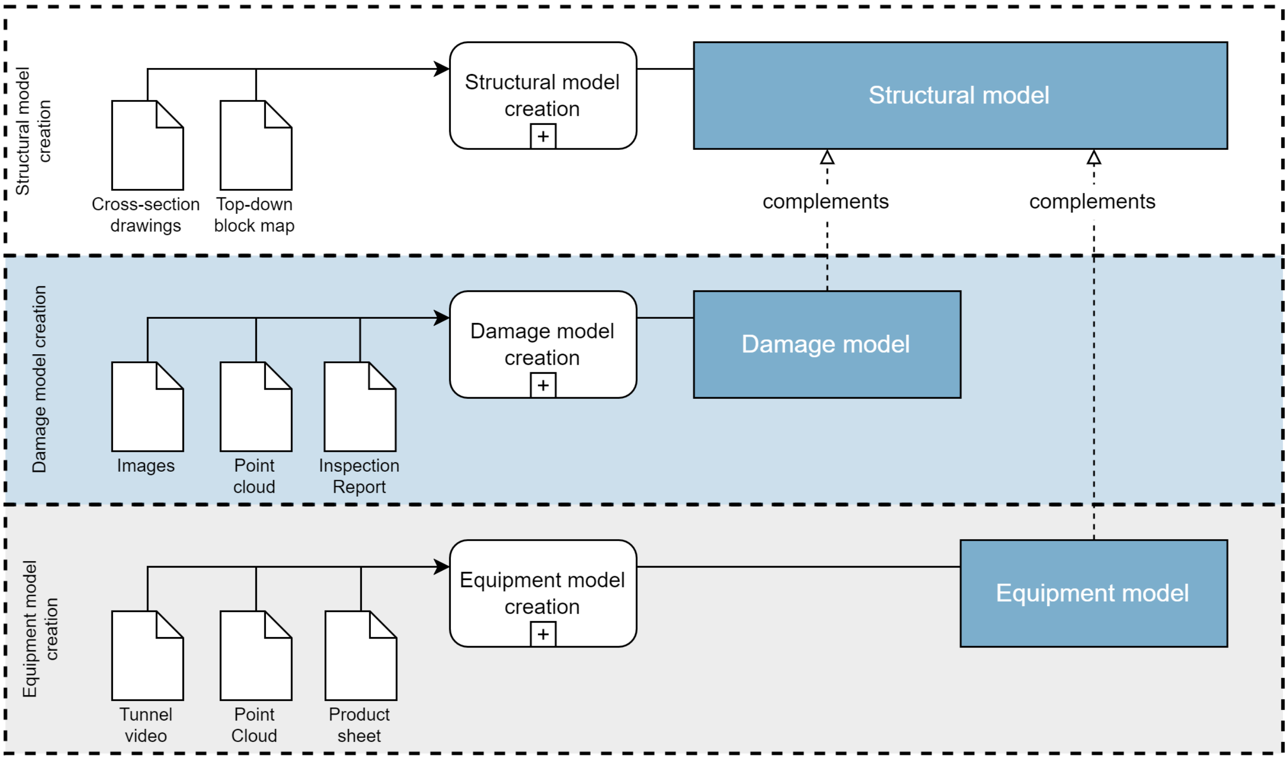

Figure 1: Illustration of the overall concept for the reconstruction of digital tunnel models as developed within the DIDYMOS project.

for automatically reconstructing tunnel models that comprehensively covers all key aspects. By integrating diverse data sources and leveraging deep-learning techniques from Computer Vision (CV) and Natural Language Processing (NLP), the proposed method enables the creation of detailed digital tunnel models that incorporate structural damages and TEE.

This concept is developed within the DIDYMOS research project[2], which is briefly introduced in the following section, along with an outline of the overall framework.

The subsequent sections detail the different aspects of model reconstruction, beginning with the tunnel structure in Structural Model Creation, followed by the identification of damages in Damage Model Creation, and finally, the technical equipment in Equipment Model Creation. The results are summarized in Conclusion and Outlook, along with suggestions for future research.

Conceptual Framework for Digital Tunnel Model Reconstruction

The DIDYMOS research project focuses on the use and implementation of DT for road tunnels. The research in this project is threefold: First, a deep learning-based concept is developed to automate the process of creating digital models for existing tunnels, with the results presented in the current study. These digital models form the basis for the DTs. Second, the project explores concepts for interacting with and visualizing DTs in tunnel management. Finally, the project aims to develop practical recommendations for operational and maintenance strategies based on these results.

To ensure efficient tunnel operation, it is crucial to provide the tunnel operator with information regarding two key aspects: the tunnel structure and the TEE. This includes information on the tunnel geometry, the condition of the tunnel structure, and the position and specifications of the technical equipment. However, integrating all of these aspects into a single tunnel model may lead to excessive complexity, making it harder to manage, especially when changes are needed. Therefore, separate models for each aspect of the tunnel are proposed, with each complementing the others. In this study, three digital tunnel models are defined, as illustrated in Figure 1:

- A *structural model*, representing the tunnel's structural components, with a focus on the tunnel lining.
- A *damage model*, providing detailed information on the current condition of the tunnel lining, essential for assessing and addressing potential structural issues.
- An *equipment model*, allowing insights into the installed TEE.

The structural model is kept separate from the damage model due to the relatively static nature of tunnel geometry, which changes little over time. In contrast, the damage and equipment models are more dynamic, as the tunnel's condition may deteriorate, and technical equipment may be updated or replaced.

[2] https://didymos.blogs.rub.de/ (Accessed: 30. April 2025)

Dividing the tunnel model into individual aspects also enables the reconstruction process to be structured into three distinct sub-processes. For each sub-process, three questions must be addressed:

Q1: What information is required to generate the specific model?

Q2: Which building documentation or data sources must be analyzed to obtain this information?

Q3: Which methods can be applied to extract the necessary information from the available documentation?

The results of this analysis are summarized in Table 1.

The structural model focuses on the geometry of the tunnel lining, which can be reconstructed by combining the curvature and cross-section depicted in the construction drawings. Accurate digitization of these drawings requires the application of object detection and instance segmentation techniques, as detailed in Structural Model Creation.

The condition of the tunnel lining is documented through images and summarized in an inspection report at regular intervals. By applying instance segmentation to the damage images and NLP to the reports, a comprehensive damage model can be reconstructed. Additionally, a point cloud is used to pinpoint each damage's location within the tunnel, as described in Damage Model Creation.

Lastly, the equipment model requires the localization and semantic description of the installed TEE. Object detection is applied to videos, and the results are projected onto a point cloud to identify the equipment's location. Additionally, NLP is used to analyze product sheets and determine the equipment's technical specifications. A detailed process description is provided in Equipment Model Creation.

Structural Model Creation

The geometry of the tunnel lining can be derived from a point cloud or construction drawings. Point clouds provide accurate as-is geometric information, however, their acquisition is often costly and requires specialized equipment. Moreover, point clouds capture only the visible surfaces, missing critical information like the thickness of the tunnel lining. In contrast, as-designed construction drawings contain this additional information and are typically archived, and thus, available. Consequently, construction drawings are selected as the primary data source in the proposed methodology.

This study assumes that the drawings are pixel-based images, a reasonable assumption for several reasons: Older drawings, typically archived in paper form, are converted into pixel-based images when scanned. Additionally, vector-based drawings can be easily transformed into pixel formats. Moreover, deep-learning models designed for pixel images, such as the YOLO model family (Redmon et al., 2016; Yaseen, 2024), are well-developed and highly effective.

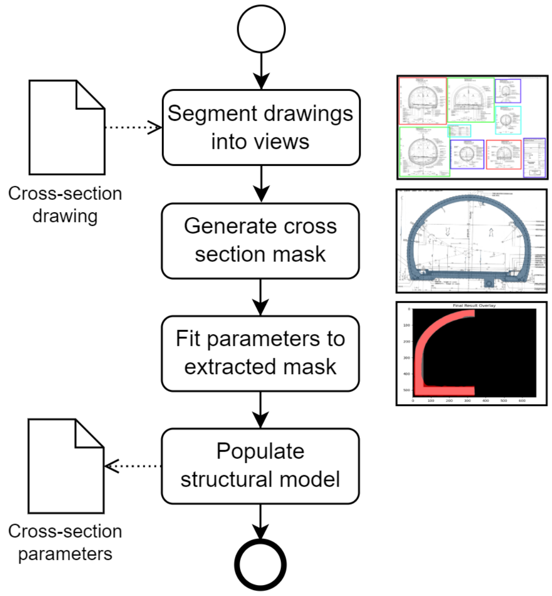

Figure 2: Cross-section geometry parameter extraction process.

Two core features are needed to reconstruct the geometry of the tunnel lining: the cross-section and the overall curvature of the tunnel's axis, along which the cross-section is extruded (Amann et al., 2013). The process for reconstructing the cross-section is detailed in Figure 2. The initial input to this process is a drawing that contains views of the cross-section. Since the cross-section can vary along the tunnel's curvature, e.g., to incorporate service bays, a single drawing may include multiple cross-section views. These views must be isolated from the construction drawing, a task that can be performed manually by an engineer or through automated methods, such as the approach proposed by Mafipour et al. (2023).

A segmentation network such as U-Net by Ronneberger et al. (2015) can then identify the tunnel cross-section in each isolated view. The network may be trained on synthetic drawings generated from a parametric tunnel model. Once trained, it is expected to predict pixel-level labels that approximate the geometric mask of the cross-section.

Subsequently, the parameters defining the cross-section, such as height, width, and thickness, can further be estimated by fitting a parametric template to the mask. To determine the parameter configuration that achieves the best overlap between the template and the mask (see Figure 3), a global grid search over the parameter space is proposed. The overlap metric combines the Intersection over Union (IoU) and an area penalty, which is calculated as the difference between the area of the parametric template and the area of the mask. This process yields a parameter configuration that best describes the tunnel's cross-section.

The process for extracting the tunnel axis from construction drawings is depicted in Figure 4. Assuming minimal variation in the tunnel's elevation profile, the elevation is considered negligible, reducing the process input to the

Table 1: Overview of used tunnel documentation and utilized extraction methods for reconstructing the individual tunnel models.

Module	**Task (Q1)**	**Data source (Q2)**				**Extraction method (Q3)**		
		Image	Video	Point Cloud	Document	Object Detection	Instance Segmentation	Natural Language Processing
Structural model creation	Axis Reconstruction	✓				✓		
	Cross-Section Extraction	✓					✓	
Damage model creation	Damage Detection & Localization	✓	✓	✓			✓	
	Inspection Report Analysis				✓			✓
Equipment model creation	Equipment Tracking & Localization		✓	✓		✓		
	Product Sheet Analysis				✓			✓

top-down view only. In conventional tunnel construction, the tunnel consists of multiple sections called blocks, each representing a straight segment of fixed length. Consequently, the tunnel axis forms a polyline, with each segment corresponding to a tunnel block, as shown in the top-down block map. In this map, each polygon point is

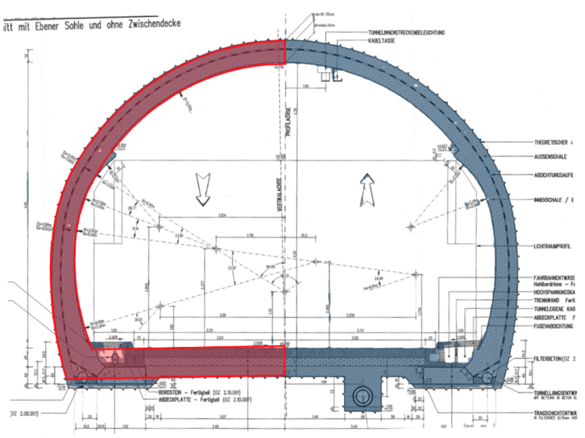

Figure 3: Example of a fitted parametric template overlaid with the predicted pixel mask.

marked by a circle and assigned a unique number. The Circle Hough Transform (Hassanein et al., 2015) can be employed to detect circular shapes, while the corresponding numbers may be identified using PaddleOCR (Du et al., 2020). Spatial proximity serves as the basis for associating each number with its corresponding circle. Connecting the individual circles results in a polyline that represents the tunnel axis. By combining this axis with the cross-section parameters, a comprehensive structural model of the tunnel is created.

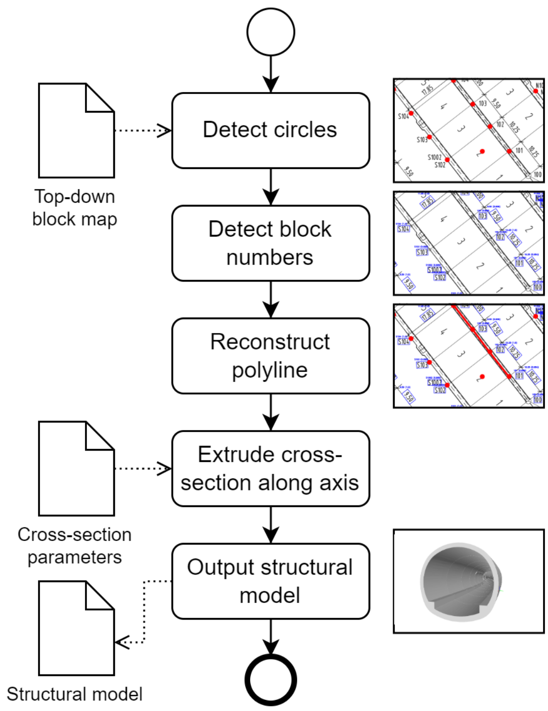

Figure 4: Tunnel axis reconstruction process.

Damage Model Creation

To give the tunnel operator an overview of the tunnel's condition, the damage model must include the location of each damage instance along with descriptive information such as damage type and severity. Currently, this information is fragmented across inspection reports and infrastructure management systems (Ou et al., 2025). In Germany, standardized guidelines, such as DIN 1076[3] and RI-EBW-PRÜF[4] define the structure for both inspection reports and infrastructure management systems. Since both contain the same information, this study focuses on inspection reports, which are more easily accessible.

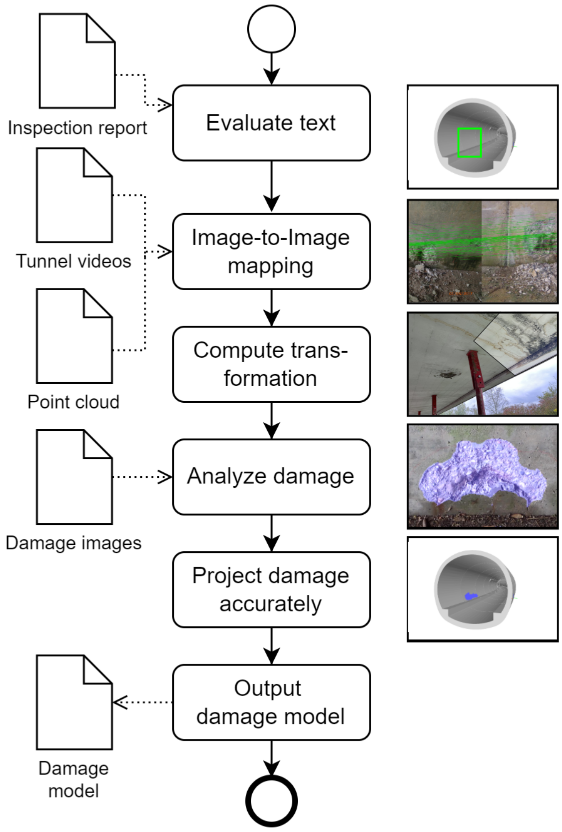

Figure 5: Damage model creation process.

Each damage instance in the report is typically described with an image, a brief textual description, and an assessment of its severity. Since inspections are conducted at regular intervals, a historical record of each damage and its progression is also available.
The process for reconstructing the damage model is illustrated in Figure 5. Textual descriptions in the reports can be used to estimate the approximate location of each damage and to extract semantic information. Given the standardized report structure, rule-based methods provide a way to retrieve key information, such as the damaged component or the damage type (Heise et al., 2024). For free-text fields, string-matching can support the detection of relevant keywords. This approach enables the identification of the tunnel block where the damage has occurred, along with additional information about its relative position within the block (e.g., left, right, top, or bottom).

[3]https://www.dinmedia.de/de/norm/din-1076/23474630 (Accessed: 30. April 2025)

[4]https://www.bast.de/DE/Publikationen/Regelwerke/Ingenieurbau/Erhaltung/RI-EBW-PRUEF-Erhaltung.pdf (Accessed: 30. April 2025)

Point cloud data can further be incorporated to improve localization accuracy within each tunnel block. This data may be recorded using a vehicle-mounted mobile mapping system[5] equipped with multiple cameras and a LiDAR scanner. Such a system is capable of capturing both video footage from each camera and point cloud data during a single pass, without the need for a full tunnel closure. Aligning the point cloud with the structural model allows objects positioned relative to the point cloud to be indirectly registered to the structural geometry. Consequently, each damage image should also be positioned relative to the point cloud, ensuring accurate placement within the damage model and proper alignment with the structural model. This alignment may be achieved through an image-to-image mapping process that links detailed damage images from the reports with frames positioned within the point cloud. These frames can be extracted from video footage synchronized with the point cloud, for example, by using the forward-facing camera installed in the scanner.
Each video frame can be processed using a two-step approach: keypoint detection followed by image matching. Keypoints in both the damage image and the video frame may be detected using XFeat (Potje et al., 2024) and matched with LightGlue (Lindenberger et al., 2023), resulting in the matching shown in Figure 6. To significantly reduce the search space for the matching algorithm, the rough position obtained from the textual evaluation can serve as a spatial constraint. Once the keypoints are matched, a transformation may be computed to align the damage image with the point cloud.

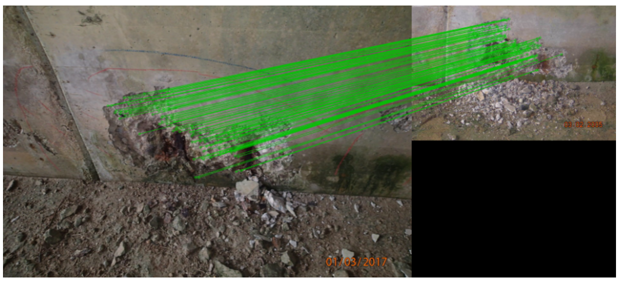

Figure 6: Example result of the image matching step in damage localization. The images show the same damage at different dates of inspection.

Subsequently, the damage can then be segmented using a custom segmentation network designed to capture features at multiple scales, following the approach of Çelik et al. (2022). The model cloud be trained on images of different concrete damages to predict a pixel-level damage mask supporting two key applications: Firstly, the pixel mask can be projected onto the point cloud to identify the corresponding points. A sphere placed at the center of these points could geometrically represent the damage within the 3D model. Secondly, if the camera distance and im-

[5]https://leica-geosystems.com/de-de/products/leica-pegasus-trk/product-overview/evo-mobile-mapping-system (Accessed: 30. April 2025)

age resolution are known, the damage size can be precisely measured in real-world units, as demonstrated by Awadallah and Sadhu (2023). This process results in a precise damage model that contains the lining condition state.

A major advantage of the proposed approach is that the video footage and damage images do not need to be taken simultaneously. Since the tunnel's appearance remains largely consistent over time, even historical damage images can be mapped accurately to video frames and, consequently, to the point cloud. This distinguishes the proposed method from other approaches (Ni et al., 2024; Xu et al., 2025), which require simultaneous recording of point clouds and detailed damage images. Moreover, if historical images are successfully mapped and damages are precisely located in the model, the progression of each damage can be visualized over time. Operators can then compare damages visually, enabling size progression analysis and historical evaluations.

Equipment Model Creation

The equipment model provides information about the TEE system and their characteristics. Additionally, it can serve as a linkage point in the DT for integrating real-time data from the physical system. This study focuses on the tunnel's ventilation system for simplicity, but the proposed process can be easily extended to other equipment types.

To create the equipment model, multiple data sources may be combined, including video footage recorded during tunnel traversal, point cloud data, and product data sheets of the ventilation systems. The point cloud and the synchronized video footage can be obtained from the approach described in Damage Model Creation. As an alternative approach, structure from motion was considered for generating point clouds from the video footage but appeared to be unsuitable due to the poor lighting conditions in the tunnel and the self-similarity of the tunnel interior. Consequently, tunnel fans may be localized using the LiDAR-captured point cloud and enriched with product information, as illustrated in Figure 7.

In the first step, the YOLOv8 (Yaseen, 2024) object detection network may be employed to identify ventilation fans within the video footage. The network could be trained on video recordings collected during similar tunnel traversals. The trained model can detect and track individual ventilator fans across video frames, enabling it to distinguish each fan and associate it with specific frames, as shown in Figure 8. This makes it possible to link the tracking results with the point cloud data.

The simultaneous capture of video and point cloud data allows for the precise positioning of each video frame along the point cloud. The detection bounding box can be mapped onto the corresponding point cloud for video frames containing fans, identifying and marking the points associated with the detected fan. This multi-modal approach eliminates the need to train a point cloud segmentation algorithm specifically for fan detection, a task considered more labor-intensive than image-based processing.

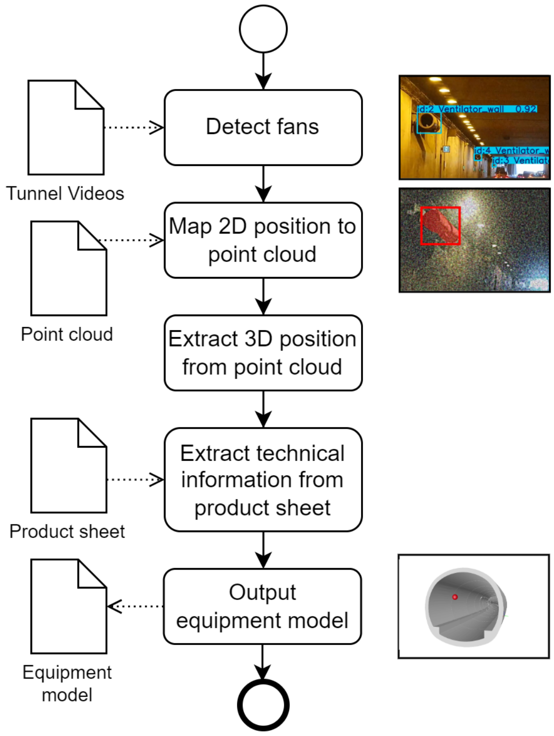

Figure 7: Fan localization and object enrichment process.

However, simply mapping all pixels in the detection bounding box to points in the point cloud may incorrectly assign background points, such as those from the tunnel lining, to the fan. To address this, post-processing steps need to be applied to filter out points that appear to be part of the fan but are spatially distant in the three-dimensional point cloud. This filtering process results in a cleaner point cloud for each detected ventilator fan. For simplicity, each fan can be represented by a spherical blob located at the averaged position among all associated points. However, if the fan product type is known, it is also possible to fit a predefined geometric object into the segmented point cloud, providing a more accurate representation of the fan.

Figure 8: Example tracking result, indicating the fan's positions in the video frame.

To semantically enrich each fan object, product data sheets can further be analyzed when available. These sheets usually contain a table listing the product specifications. Using PaddleOCR, these tables may be extracted, and the contained information retrieved. Pre-trained language models like BERT have been successfully applied to similar extraction tasks (Schönfelder et al., 2022). Ideally, a comprehensive database of all available fan types would be established to streamline the process. With such a database, only the type of fan would need to be extracted from the data sheets, significantly reducing the effort required for semantic enrichment.

The outcome of the process is an equipment model that contains fan objects precisely localized relative to the structural model and richly described with product specifications.

Conclusion and Outlook

This study proposes a comprehensive concept for the automatic reconstruction of tunnel models from unstructured documentation. It demonstrates the feasibility of fully automating the process and provides a basis for DT-based operations. The concept consists of three deep learning-based modules, each of which produces a distinct digital tunnel model that captures a critical aspect of tunnel operation: the structural model, the damage model, and the equipment model. To validate the effectiveness of the proposed processes, they will be applied to two tunnels as part of the DIDYMOS project.

While this concept is a significant step forward, several opportunities for future research remain. One important direction is the integration of the currently omitted elevation profile along the tunnel axis. Existing work by Bayer et al. (2023) may serve as a foundation for extending the current framework. Another promising direction is to enhance the structural model by incorporating semantic information, such as material properties, to enrich its descriptive power. In addition, validation of the model against point cloud data would provide an accurate representation of the as-built geometry, complementing the current reliance on as-designed drawings.

Beyond the structural aspects, the equipment model offers an opportunity for expansion. Currently focused on the ventilation system, future work could incorporate other critical components, such as fire protection systems, to create a more comprehensive digital representation.

Furthermore, the proposed approach relies on deep learning networks that require training on tunnel-specific datasets. This dependency limits the adaptability of the trained networks to other tunnel types, documentation standards, or variations in data quality. To improve generalization, future work could explore the application of foundation models, such as SAM (Kirillov et al., 2023) for image segmentation or LLaMA (Touvron et al., 2023) for document understanding, which offer broad capabilities without specific training.

Lastly, future research should explore how the resulting digital tunnel models can be utilized for DT applications, identifying operational processes that stand to benefit most from this technology. By addressing these aspects, future studies can build on the foundation established in this work and continue to improve the management of tunnels through digital innovation.

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