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Approach to generate a simple semantic data model from 2D bridge plans using AI-based text recognition

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The digital twin is intended to serve as the basis for an improved maintenance management. However, in the case of existing bridges, a digital model of the physical structure rarely exists. Various research approaches are currently addressing this problem using advanced technologies (laser scan, AI, photogrammetry). An essential part of these efforts is the transfer of relevant semantic information from an analogue source into the digital model. This paper deals with the question of how textual information from 2D drawings of bridges can be recognised and translated into a semantic data model. For this purpose, an OCR algorithm was utilized to translate printed and handwritten textual information into machine-readable text. The information pertaining to the material properties of the examined component was subsequently assigned to its respective component and stored in a structured data table.
The choice of the OCR algorithm, the post-processing of the text recognition results, the identification of relevant information and the translation into a semantic data model are the key findings presented in this paper. It was shown that while the approach is operational, the reliable identification of information is highly dependent on the nature and form of its representation in the drawings. While text recognition has been shown to be reliable, further research is needed to process and interpret the extracted semantic information to enable a broader approach to semantic enrichment.

Keywords: Building Information Modeling, optical character recognition, bridge maintenance, construction / technical drawings, 2D-plans, machine learning.

1. Introduction

The utilization of Building Information Modeling (BIM) in the operation and maintenance of structures has gained considerable attention in recent years (Chan et al. 2016; Cheng et al. 2016). By storing findings from advanced imaging and data processing in the digital model, retrieval for future bridge assessments is facilitated, allowing engineers and bridge inspectors to make more informed decisions about the current condition of the structure. Hence, a well-structured, searchable and evaluable database provided by the digital model of a structure can serve as the basis for an effective maintenance management (Singer and Borrmann 2016).

Despite the numerous scientific contributions, the potential of BIM for engineering structures in the operational phase is rarely fully exploited, with one of the biggest obstacles being that digital building models, i.e. the actual BIM models, are seldom available for existing structures (Aengenvoort and Krämer 2021). Manually re-entering information or remodelling BIM objects based on technical drawings or point clouds is labour-intensive and error-prone (Borrmann et al. 2018). Thus, there is ongoing research on automating the generation of semantically rich as-built models. One approach is the use of multi-data-fusion (mdfBIM+), which integrates data from laser scanning and documentation (e.g., technical drawings) (Stemmler et al. 2022). By combining information from both sources, mdfBIM+ enables more accurate point cloud segmentation by reconstructing 3D models from 2D drawings, as described by Poku-Agyemang and Reiterer in their work (2023). For non-geometric information, a suitable approach is lacking. This paper aims to extract specific non-geometric information from 2D bridge plans, namely information in title blocks and material information in construction notes, and make it accessible for inclusion in a digital model.

2. Background

The relevant scientific literature can be divided into two main areas, covering the subject of semantic enrichment itself and the extraction of non-geometric information using machine learning techniques, optical character recognition, in particular.

The current research state of semantic enrichment has been systematized by Dinis et al. 2022. In their paper they identified several methods and tools for semantic enrichment, including semantic web technologies, machine learning, ontology mapping, custom plugins (e.g. Dynamo) and rule-based approaches. In a 2018 study, Bloch and Sacks compared the use of machine learning algorithms for semantic enrichment of BIM models with rule interference and concluded that the use of machine learning algorithms for semantic enrichment of BIM models can save time and effort compared to manual annotation and classification. Similarly Schönfelder et al. 2022 have argued for the adaptation of a data-driven approach. In their paper, they presented a holistic semantic enrichment process using natural language processing to extract textual information from semi-structured documents and feed structured object parameters directly into the BIM software using the Dynamo plugin. This approach differs significantly from others in that semantic enrichment is seen as something that presupposes an existing geometric model. Other researchers have worked to combine or integrate the semantic enrichment process with the BIM model creation process. For instance, Hichri et al. 2013 summarized different approaches to creating an as-built BIM model (including laser scanning, photogrammetry and terrestrial surveying) and propose an approach that directly assigns semantic features to historic objects during the survey and segmentation phase based on IFC classes. Belsky et al. 2016 developed a geometry- and topology-driven approach to create semantically useful building model files from the explicit and implicit information contained in building models exported by BIM tools.

In addition to the considerations surrounding the methodology used, whether an existing model is enriched or weather the enrichment process is part of the model generation or is inferred from the model itself, there are varying categories and sources of information that are taken into account. One such approach is the enrichment of information from point clouds. For instance, Isailović et al. 2020 examined semantic information regarding spalling damage acquired from point cloud data and incorporated classified and reconstructed damage clusters into the as-built model. Xue et al. 2018 utilized 2D images, such as photographs, to generate semantically rich as-built models. Schönfelder et al. 2022 focused on leveraging existing building documentation, which is organized in a tabular format. Similarly, Faltin et al. 2023 used existing building documentation, i.e. construction drawings, albeit not for semantic enrichment, but rather for establishing building interconnections to reconstruct the geometry. Building on previous research, the present study focuses on the extensive, but primarily analogue, structural documentation in from of 2D plans as an information reservoir, as it contains a wide range of relevant data related to the operation and maintenance of bridges.

With regard to the extraction of non-geometric information from technical drawings, the literature offers various methods. Chai and Dori introduced a method to extract textboxes from engineering drawings without relying on pixel-level operations (Chai and Dori 1992). Lai and Kasturi developed a system to extract dimension sets conforming to ANSI drafting specifications (Lai and Kasturi 1994). Prabhu et al. proposed the AUTOFEAD algorithm to extract non-geometric information from manufacturing drawings using Natural Language Processing (NLP) techniques (Prabhu et al. 2001). Scheibel et al. described a method to extract dimensional information from pdf manufacturing drawings by clustering multiple text elements by position (Scheibel et al. 2021). In Kulkarni and Barbadekar 2017 and Lu 1998, a rule-based algorithm is developed for text and graphics separation from engineering drawings, followed by OCR-based text recognition. Jamieson et al. 2020 proposed a deep learning-based approach for text detection and recognition from engineering diagrams. A conceptual approach and prototype called DigiEDraw has been introduced to extract dimensioning information from engineering drawings and integrate it into the production process for quality control purposes (Chaudhuri and Pal 1997).

Previously conducted research on the extraction of non-geometric information from engineering plans has mostly concentrated on extracting large amounts of information, including all text in drawings or all text in title blocks, or entire sets of dimensions. However, challenges still persist when extracting more precise information, such as drawing titles in title blocks or material information in construction annotations. This study aims to tackle this issue through post-processing the results of text recognition from plans, obtained through optical character recognition algorithms (OCR-algorithms).

3. Methodology

This study focuses on the semantic information contained in 2D engineering drawings. Civil engineering technical drawings use a graphical language composed of lines, symbols, and annotations to depict objects intended for construction. They normally include title blocks, reference grids, orthographic views, section views, detail views, and notes to the construction. (Shah and Rana 2009). In addition, tables provide material properties or project-specific data. Although the plans are generally structured in a similar way, there can be variations depending on the owner, engineering firm or year of creation, and the quality can also vary. Older plans may also contain handwritten text. Because of this inconsistency, traditional programming approaches are impractical and a flexible machine learning based approach is preferred.

The plans are provided by the National Highways Agency, Regional Road Authority and National Rail as scanned pdf documents in A0 format or, for more recent plans, as pdf exported from CAD software.

The approach presented in this paper consists of two main steps. Firstly, an OCR algorithm is used to extract specific information about various parts of the building and their properties in combination with self-developed post-processing algorithms, tracing textual contents with the help of the corresponding coordinates (Chapter 4). Secondly, a building hierarchy is employed to allocate the extracted information to the corresponding building parts. Finally, a data file is generated that can be imported into a Common Data Environment (CDE) or Autodesk Revit via the Dynamo API to enhance a given geometric model (Chapter 5).

4. Information extraction

Optical character recognition (OCR) is a technology used to convert printed or written characters into digital format for computer processing (Mantas 1986). The field of OCR has diverse applications, including industries such as invoice imaging, legal, healthcare, banking, and others (Ganis et al. 1998). It is also utilized in areas like Captcha (Gossweiler et al. 2009), institutional repositories and digital libraries (Barwick 2007), optical music recognition (Singh et al. 2011), automatic number plate recognition (Chang et al. 2004) and handwritten recognition (Plamondon and Srihari 2000). Given the diverse applications of OCR technology, it is evident that it holds great practical importance in extracting, analyzing, and managing text-based information from engineering drawings.

The output of OCR-algorithms typically includes both the text and its associated coordinates. Post-processing involves tracing back the text using these coordinates. Depending on the features of the text components, different tracing methods are employed. This study concentrates on extracting information from title blocks and material information in construction annotations. The Handprint OCR-algorithm is employed to obtain the text recognition results.

4.1 *Semi-automatic extraction of specified information from title blocks*

Every technical drawing must have a title block. A reference grid is drawn around the edge of a drawing sheet with a minimum width of 10mm along all four edges, and the title block is located in the lower right-hand corner of the grid. The title block typically contains information such as the name, date, scale, title and drawing number, as well as the initials of those involved in preparing, reviewing and approving the drawing (Shah and Rana 2009).

The characteristics of title blocks can be succinctly described as follows: (1) they are located at the bottom right-hand corner of the reference grid; (2) in a given set of technical drawings, the arrangement of each drawing page is identical. (3) in a given set of technical drawings, the absolute dimensions of each corresponding sub-block are uniform.

When the origin of coordinates is set in the bottom right-hand corner point, the absolute coordinates of the four corner points of every corresponding sub-block are the same for every page of the drawings. With this rule, a semi-automatic extraction of specified information from title blocks is achieved. An example extracted results is illustrated in Figure 1.

The pipeline can be explained as below:

(a) The coordinate origin of each plan is set at the bottom right-hand corner. The four vertices of sub-blocks containing specific information, such as the drawing title or scale, are defined manually by mouse clicks. The result is the coordinates of the four corners of the defined sub-blocks.

(b) The contents in the locations of defined sub-blocks for each drawing within a set of drawings can be searched in the OCR results using the coordinates obtained in step (a). This step results in the contents in the defined sub-blocks for each drawing.

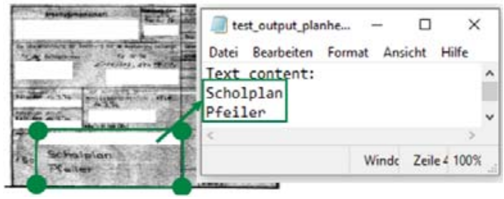

Figure 1: An example of the extracted title block contents saved in a txt file.

4.2 *Semi-automatic extraction of material information*

The characteristics of material information are different from those of title blocks and it can appear in the form of text fragments or tables. This study deals specifically with material information in the form of text fragments and starting with special character strings such as "Baustoff", “Ausfuehrung”. The distinguishing features of all such material information are: (1) the presence of the special character string such as "material", "instruction", etc., (2) the fragment starts horizontally from the smallest ordinate of the line element with the special character string, and (3) there is an apparently large line spacing when the material information ends and another textual annotation begins. Therefore, the retrieval of material information is based on these three features. An example of the extracted results is shown in Figure 2.

The pipeline can be explained as below:

(a) The origin of the coordinates of each drawing is set at the bottom right-hand corner. For each technical drawing, the coordinates of the line elements containing the special character string are automatically extracted from the handprint text recognition results. The maximum horizontal coordinate can be obtained.

(b) All line elements in the handprint text recognition results of the drawing with left horizontal coordinates near the maximum horizontal coordinate obtained in step (a) are identified and extracted. The output of this process is a collection of line elements

(c) Within the collection of line elements obtained in step (b), the minimum horizontal and vertical coordinates of the line elements can be determined by comparing the coordinates of all corner points. The top left corner coordinates of the line element containing the special character string are then used in combination with these minimum horizontal and vertical coordinates to define the bounding box of this collection of line elements.

(d) A search is performed using the four corner points of the bounding box from step (c) to find line-elements starting within the bounding box range. This results in a new collection of line-elements.

(e) The line spacings between the first few line elements in the collection of line elements generated in step (d) are measured to determine the largest line spacing, which is used as a reference. The line spacings of the collection of line elements in step (d) are then checked one by one from top to bottom. If a line spacing is greater than the reference, this line element and all other line elements below this line element are eliminated. The remaining line elements are output as material information.

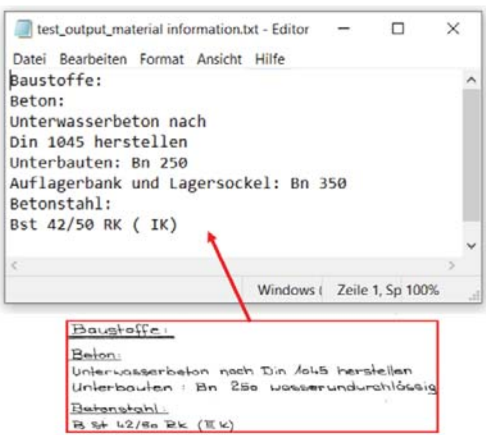

Figure 2: Example of the extracted material information.

5. Information mapping and sorting

The extracted information subsequently is to be organized so that that it can be assigned to the correct component of the digital model.

For the purpose of this study, it is assumed that the components of the digital building model are unknown, and therefore no information about object classes is available. The challenge is to match the extracted information to the corresponding component in the geometry model, taking into account the varying granularity or level of detail of a preexisting digital model. For example, the abutment may be broken down into the components of wing walls and bearing bench, or the superstructure into carriageway slab and foundation slab. To meet these challenges, the component tables of the ASB-ING (Road Information Database for Engineering Structures) are used as a blueprint. These tables list all components in a hierarchical structure and allow the assignment of features, via the hierarchical chain of components, so that they correspond to the level of detail used in the digital model. The identification process uses the information extracted from the title blocks as keywords, which serve as input for the algorithm described in the following sections.

The primary objective of this task is to assign text fields to their relevant context within the ASB-ING, which is challenging due to the occurrence of several component names under different parent categories. Correct assignment is only possible with knowledge of the categorisation. However, since the input consists of individual keywords, creating this context is challenging. Therefore, the idea is to decide which categorisation fits best, based on all the recognised keywords in the plan.

The initial assumption is that each keyword has only one correct categorization for all instances found in the plan. In the second step, a list of component names without duplicates is created by disregarding the hierarchical arrangement in the ASB-ING. Each recognized text field is then compared to this list, and the field is assigned to the component with the highest similarity value, provided that it exceeds a certain threshold.

Subsequently, a complete list of keywords and their respective positions in the plan is obtained. In the third step, the most appropriate superordinate categorizations for keywords that appear multiple times in the ASB-ING are selected. Each possible path leading to each keyword in the ASB-ING is examined individually. The layers are analyzed, keyword by keyword, to determine the number of different paths of other recognized keywords that match the available categories for selection. The category with the most included keywords from the plan is selected. This step is performed separately for each keyword, and only one path per keyword remains at the end. All instances found in the plan, including their positions and similarity values from step 2, are then stored.


```
{
    "name": "Rahmen",
    "number": 130011711500000,
    "occurences": [
        {
            "accuracity": 0.9991896186052855,
            "bbox": [
                [
                    4230,
                    2520
                ],
                [
                    4308,
                    2520
                ],
                [
                    4308,
                    2549
                ],
                [
                    4230,
                    2549
                ]
            ],
            "plan": "30.jpg",
            "similarity": 0.9090909090909091,
            "text": "Rahme"
        },
```


Figure 3: Example of matching an identified title to the corresponding component in the ASB-ING hierarchy.

However, this method is not infallible, given the assumption of only one correct categorization per keyword. Additional information should support the categorization, so an optional input is added to provide a preferred path with arbitrary depth. In step 3, if available, this preferred path or parts thereof are preferentially chosen.

5. Discussion

The proposed method was tested using a dedicated dataset, and the results have shown that the extraction and organization of semantic information can be achieved without a pre-existing geometric model. This is a notable advantage compared to other approaches that rely on such models. The use of JSON or CSV formats also facilitates easy transfer of resulting files into the CDE used for the asset, or via the Dynamo API into the authoring tool Revit. In the long term, however, the application of the IFC schema should be extended in a process-accompanying manner in line with the Open BIM concept. A first step would be to create a standardised IFC object catalogue for bridge components, monitoring technology and damage according to national requirements.

The accuracy and quality of the extracted information remain a significant challenge for future research. Although a predefined hierarchical structure such as the ASB-ING provides a useful framework for assigning and localizing unstructured extracted information, the accuracy of the mapping is subject to the level of detail and quality of the geometric model. The mapping algorithm may also need to be modified to support English-based categorisation, which would broaden its application beyond German-speaking countries, as the success of the mapping process depends on the alignment between the components of the geometric model and the hierarchical structure set by a national standard for bridge components (e.g. ASB-ING).

6. Conclusions and outlooks

In this study, the authors demonstrate the feasibility of using OCR technology and backtracking techniques for semi-automatic extraction of textual material information and structural component names from 2D technical drawings. However, the accuracy of the semi-automatic extraction can be further improved by training object detection algorithms like Yolo and detectron2 and integrating them into the pipeline.

The versatility of OCR technology is evident from the study, which shows that it can be applied to various types of structures beyond bridges. However, organizing and assigning the extracted information to the correct component in the geometry model can be challenging due to varying granularity or level of detail of the model. The

ASB-ING tables provide a hierarchical structure for all components, which serves as a blueprint for assigning features based on the recognized keywords from the plan.

The proposed algorithm in this study outlines a process for assigning the most appropriate superordinate categorizations for keywords and storing all instances found in the plan, using a similarity value. Although there are challenges in correctly placing identified keywords, the proposed pipelines and algorithm provide a framework for the semi-automatic extraction of information from 2D technical drawings, which can significantly reduce manual efforts.

In conclusion, the study emphasizes the critical task of information mapping and sorting in creating a digital building model. The findings suggest that OCR technology can be leveraged for semi-automatic extraction of information from structural documentation beyond bridges. The proposed pipelines and algorithm provide a promising framework for automating the extraction of construction drawing annotation information, which is a significant step towards reducing manual efforts and providing digital models for existing structures for improved maintenance management.

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