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Review

Automatic Reconstruction of 3D Models from 2D Drawings: A State-of-the-Art Review

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Abstract: Among the methods of 3D reconstruction, the automatic generation of 3D models from building documentation is one of the most accessible and inexpensive. For 30 years, researchers have proposed multiple methods to automatically generate 3D models from 2D drawings. This study compiles this research and discusses the different methods used to generate 3D models from 2D drawings. It offers a critical review of these methods, focusing on the coverage and completeness of the reconstruction process. This review allows us to identify the research gaps in the literature, and opportunities for improvement are identified for future research.

Keywords: 3D reconstruction; design automation; Building Information Modelling (BIM); 2D architectural drawings; CAD to BIM; computational geometry; object detection; object recognition

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1. Introduction

As a spatial discipline, architecture's most accurate form of representation is through 3D models. Three-dimensional models are important design and visualisation mediums, allowing for an unambiguous and complete view of the building. With the introduction of Building Information Modeling (BIM), 3D models have become more than just geometric entities; they have become intelligent data-rich repositories of building information, containing all the information needed for the analysis, simulation, visualisation, navigation and clash detection of objects across multiple disciplines.

However, constructing a 3D model when none exists can be a complex, time-consuming manual process. For this reason, many researchers have proposed different methods to automatically generate 3D models from existing information. These can generally be categorised according to their method of data acquisition: On-site and off-site methods. On-site methods rely on collecting information on-site of an existing building and include a variety of photo-based methods, of both the inside and outside of the building, and point-cloud methods that rely on laser scanning. Off-site methods do not require the existence of a physical building and count on developing models from 2D drawings (scanned and in vector format) or other relevant documentation.

Gimenez et al. [1] offer a more extensive overview of these methods and analyse their strengths and weaknesses. They conclude that no one method is better than the others and that method selection will depend on the end users' objectives and constraints. While on-site methods like laser scanning are very reliable and produce accurate results, they require expensive equipment for data collection and can only capture limited semantic information. On the other hand, off-site methods are more complete and cost-effective but depend on the reliability and up-to-dateness of existing documentation for model accuracy. Such limitations can be complemented by mixing different methods of data acquisition [1].

As research on on-site methods is already abundant [2–6], this paper seeks to document the state of the art of off-site methods, i.e., the reconstruction of 3D models from existing documentation.

In this context, this review sets out to evaluate the level of information possible to extract from 2D drawings, more specifically the available 3D geometrical data and the semantical data for BIM enrichment.

The document is organised as follows: in Section 2, the work related to this study is presented, and the novelty of the study is discussed; in Section 3, an in-depth presentation of the theoretical concepts and techniques around the topic of 3D reconstruction is presented; next, Section 4 discusses the results extracted from the selected literature; and, finally, Section 5 concludes this study with the final remarks.

2. Related Work

Three-dimensional reconstruction is not a new area of research [7], and various researchers have proposed multiple methods, ranging from semi-automatic to fully automatic, to generate three-dimensional models of buildings. Some reviews and surveys attempt to compile all this information and compare different methods of reconstruction for easy browsing of the literature. Most of them, however, focus on the on-site methods of reconstruction, specifically laser scanning [2,8], photogrammetry [3,9] or both [4–6,10–12].

Only two surveys address 3D reconstruction for off-site methods. Yin et al. [13] discuss the pipeline for the generation of 3D models from 2D architectural plans, both scanned images and vector drawings, and review five reconstruction systems regarding their performance and automation capabilities. Gimenez et al. [1] give a more general overview of different reconstruction approaches available, including off-site and on-site methods, but only analyse methods for processing scanned paper plans. Of the two, only Yin et al. [13] address both scanned and vector plans, and with the rapid evolution of new methods and technologies, we believe an update might be in order.

3. Three-Dimensional Reconstruction

It is commonly accepted that to create valid and complete 3D digital models, three types of information are needed: geometric information, i.e., the shape and dimensions of each component; semantic information, i.e., component categories and additional characteristics and attributes; and topological information, i.e., the relationship between building components [14]. Figure 1 illustrates the methodology usually employed to acquire this information and create a 3D digital model of a building based on its existing documentation.

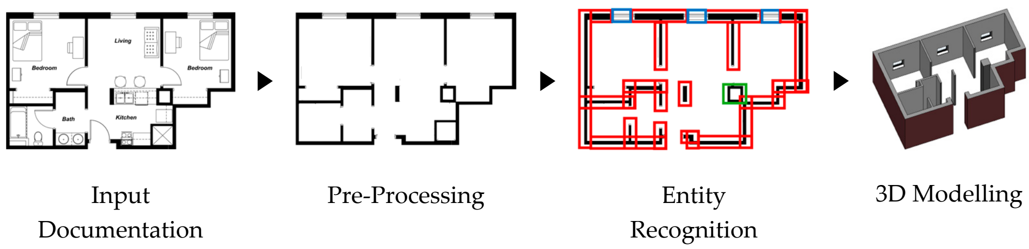

Figure 1. Methodology of 3D reconstruction.

Regarding topological information, Tang et al. [2] identified three categories of spatial relationships between components: aggregation relationships (e.g., part of), topological relationships (e.g., connectivity, inside or outside) and directional relationships (e.g., above or below). These relationships are typically represented by tree or graph structures.

The following subsections illustrate the methodology usually employed in the 3D reconstruction process of 3D models from building documentation.

3.1. Input Documentation

The most common type of building documentation used for 3D reconstruction is 2D drawings, specifically floor plans, as they are the most comprehensive and representative graphical documents of the entire building. However, floor plans do not contain all the building information, such as vertical information (e.g., the height of doors and ceilings), as this information is generally mapped to other types of drawings (e.g., sections and elevation drawings). Some researchers interpret the information from floor plans along with the information from other types of documentation to make up for this missing information. In [15], Riedinger et al. use elevations to map textures onto wall polygons through the triangulation of the elevation image and fix height information of the resulting 3D model. Lewis et al. [7] read the information of a reflected ceiling plan to define the spatial regions corresponding to room ceilings using a partitioning algorithm. Santos et al. [16], Lu et al. [17] and Vidanapathirana et al. [18] use photos to map material textures to building components. Lu et al. [19] use architectural tables to retrieve additional semantic information and component attributes and integrate them into the recognised objects. Byun and Bong-Soo [20] analyse structural member lists to retrieve the cross-sectional shape information and additional attributes of each structural member. D'Antoni [21] uses archaeological data found on-site of old archaeological buildings to estimate the volumetric of the elevations.

Reading information from technical drawings is a non-trivial problem. Firstly, there are no generalised drawing standards; different designers use different graphic conventions, as well as different symbols to represent the same objects. Secondly, drawing errors and inconsistent/incompatible documentation is an all-too-common part of the development process, making interpreting information a complex and difficult problem. Finally, hand-drawn or scanned drawings pose additional complications which include scanning or printing distortions, scanning noise, hand-written texts, inconsistent hand-drawn line weights, smudges, paper watermarks and folding.

The next sections will address some of the strategies developed to address these difficulties.

3.2. Pre-Processing

Before attempting to read any information from architectural drawings, these need to be cleaned and pre-processed to highlight important information, remove unnecessary information and maximise the chances of getting accurate results. As shown in Figure 2, these pre-processing steps vary according to the nature of the input documentation: raster drawings (e.g., .pdf, .png, .jpeg) or Computer-Aided Design (CAD) (e.g., .dwg, .dwf) vector drawings.

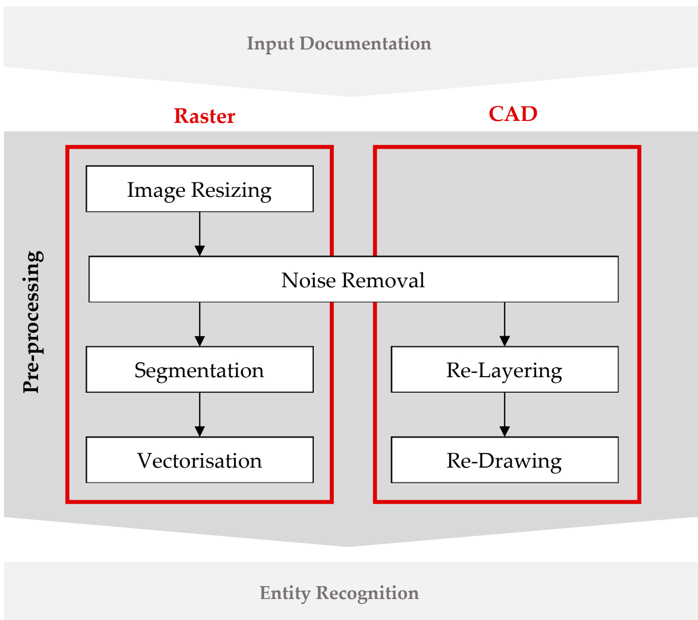

Figure 2. Pre-processing workflow for raster and CAD drawing comparison.

3.2.1. Raster Drawings

The pre-processing of scanned drawings often starts with (1) image resizing to transform the image into a manageable size, followed by (2) noise removal to remove all elements unnecessary to the recognition process, proceeded by (3) text and graphics segmentation, where texts and graphics symbols are separated for easier reading, and finally (4) vectorisation to convert pixels into readable vector geometry:

1. **Image Resizing:** Image resizing consists of reducing the size of the input image to reduce the amount of pixel information that needs to be processed when dealing with large input drawings. Image resizing techniques include downsampling and tiling/merging. Downsampling involves downscaling the size of an image to reduce dimensionality and the amount of information present in the image. For example, in Riedinger et al. [15], the input image is downscaled by sampling it on a $r \times r$ grid of pixels and keeping the darkest pixel of the sample. There are different implementations of downscaling [15,16,22]; however, these methods inherently result in some form of information loss. As an alternative, tiling/merging preserves all the original information, partitioning the input image into tiles, processing and analysing each tile individually and merging them back together after processing. In [23], Dosch et al. use tiling and merging to reduce image size and reduce memory strain on the computation workstation. This approach allows them to reduce processing time while maintaining a reportedly low error rate.
2. **Noise Removal:** Noise removal consists of reducing the amount of information from a scanned image while leaving only the relevant information for processing. Common sources of noise in scanned drawings include paper smudges, folding and printing and scanning noise. Removing or reducing this noise involves a series of image processing techniques such as binarisation, dilation and erosion. Binarisation, a popular method in scanned drawings [14,15,22,24,25], converts the input image into black-and-white pixels, eliminating unnecessary colour information and enhancing the contrast between black elements and white space. Horaud [26] and Ghorbel [27] differentiate between three binarisation types: global binarisation, i.e., applying a single threshold to the entire image; local binarisation, i.e., determining thresholds based on local pixel data; and dynamic binarisation, i.e., calculating thresholds per pixel based on neighbouring grey levels. Following binarisation, morphological operations like dilation and erosion refine the image further. For instance, Shinde et al. [28] utilise dilation to remove fine details and pixel noise, whereas Zhao et al. [25] use erosion to amplify black pixel areas, highlighting potentially important features. Opening and closing, combinations of dilation and erosion, are commonly employed to address salt-and-pepper noise [24]. Additionally, the Non-Local Means algorithm is widely adopted for noise removal [15]. This algorithm averages pixel values in similar neighbourhoods, obtaining the median value of the greyscale image and forming the binarised version by comparing pixel values against predefined thresholds.
3. **Text and Graphics Segmentation:** As opposed to discarding texts in a scanned drawing as noise, some researchers [14,22–24,29] choose to retain texts by separating pixels corresponding to textual information from pixels corresponding to graphical information into two different images—the text image and graphics image. In this way, textual information is preserved and can be used to introduce semantic information to the geometric information extracted from the graphics image. This segmentation is performed because information that is not required for a specific recognition process will just be noise and potentially lead to incorrect results. A popular algorithm for this process is the Hough transform-based approach by Fletcher and Kasturi [30]. Used in [22,23], the Hough transform-based algorithm is a technique used in computer vision for detecting shapes. In this context, it can be employed to identify lines representing architectural elements in floor plans. Furthermore, many authors [14,24,29] used the QGAR library. The now-discontinued QGAR project [31] introduced an open software environment, providing a common platform for applications and third-party contributions. Central to

QGAR is the QGAR library which offered an extraction mechanism for sets of characters in images [24]. The methodology revolved around identifying geometry primitives that play a crucial role in depicting architectural components like walls and openings as sets of points, such as segments or arcs [14]. However, in this method, there is an underlying assumption that these primitives adequately capture the essential architectural elements targeted by the project [14]. Once graphics and texts have been separated, the graphics image can optionally be further divided into two other images, containing thick and thin lines, respectively, to separate walls (thick lines) from other symbols, such as doors and windows (thin lines). This can be achieved with further morphological filtering [22,23].

4. **Vectorisation:** Vectorisation is the process of converting a raster image, consisting of pixels, into a vector image consisting of lines, arcs and other geometric shapes. Vectorisation methods can be categorised into transform-based methods [14,17,29,32], thinning-based methods [15,23,24], contour-based methods [22,33], sparse-pixel-based methods [34,35], run-graph-based methods [36,37], mesh-pattern-based methods [38] and, more recently, neural-network-based methods [39–42]. Each of these categories, except for neural-network-based methods, is thoroughly reviewed and compared by Wenyin and Dori [43]. They conclude that vectorisation methods should be chosen according to the needs of the system. Good vectorisation methods should preserve shape in formation, including line width, line geometry and intersection junction, and should be fast to be practical.

3.2.2. CAD Drawings

CAD drawings are produced digitally and in vector format and thus do not need to be vectorised. However, they still need to be cleaned and sometimes reworked before they can undergo the recognition process. The pre-processing of CAD drawings often includes noise removal, re-layering and re-drawing:

1. **Noise Removal:** In the context of CAD drawings, this stage involves simplifying the drawings to enhance recognition accuracy, akin to the process used for scanned drawings. CAD drawings may contain vector elements, such as dimensions, grid lines, hatches or drawing borders, that are unnecessary for and can hinder the recognition of other geometric entities. Additionally, problematic or redundant geometry, such as segments with zero length or duplicate lines, needs to be addressed. In the literature, this step is mostly executed manually, with a designer manually deleting unneeded elements. Exceptions include Domínguez, García and Feito's iterative checker [44], which automatically loops over geometric primitives, removing duplicate segments and segments with zero length and replacing partially overlapping segments with unique segments, until no more problematic geometry is found.
2. **Re-Layering:** CAD drawings use layers to group geometric primitives representing building elements of the same type and, in this way, map semantic information to those primitives. This is one of the easiest ways to classify information in CAD drawings and, in some cases [45,46], almost entirely dismisses the need for the recognition process altogether. Unfortunately, there is no universal standard way to organise information in layers in CAD drawing, and each designer can have their own system of layer organisation. Moreover, during project development, some geometric primitives may be mistakenly placed in the wrong layers, further complicating this process. Thus, a common approach to re-layering in CAD drawings often involves the manual re-layering of geometric entities into component-specific layers, e.g., categorised by element types, such as walls, doors and windows [7,44–46], according to the semantic information that designers wish to assign to those primitives.
3. **Re-drawing:** Sometimes, as-designed drawings may contain drawing errors or too much information that complicates the recognition process. Thus, some researchers opt to re-draw parts of the drawing to simplify or fix problematic geometry before recognition. This process can include the reduction in the level of details of specific objects, such as doors and windows [7], grouping geometric primitives corresponding to the same

building component into single entities, such as blocks [44,45], the contour outlining of difficult-to-detect building elements, such as floors, ceilings and walls [45,46], and primitive uniformisation—some researchers prefer to group lines into polylines [46], while others prefer to separate polylines into singular lines [47–49]. Unlike raster drawings, problematic geometry in CAD can be readily identified and excluded from the recognition process. While predominantly manual, some researchers use error detection mechanisms [50], while others have developed algorithms to automatically address minor geometry issues, such as Lewis and Sequin's coerce-to-grid algorithm [7] for fixing gaps between lines and overlapping line edges or Xi et al.'s rule-based merging of overlapped lines and arcs [47].

3.3. Entity Recognition

Entity recognition is the core of drawing analysis and consists of identifying semantically distinct building elements from a set of unlabelled geometric primitives or pixels.

Entity recognition approaches can be layer-based, rule-based, graph-based, grid-based and learning-based. Each of these approaches addresses the specific needs of the recognition problem, and they are often used together to yield different types of information.

1. **Layer-based approaches:** Entity recognition in CAD drawings typically falls under this category [7,44–46,51]. In layer-based approaches, geometry recognition is simplified using layers, which semantically identify geometric primitives belonging to building elements of the same type. In some cases, combined with prior re-drawing, wall polylines in the wall layer can be extruded, and symbol blocks' information in the door and window layers can be read, requiring no further recognition [45,46]. This results in more manual pre-processing and less automated recognition. In other cases, authors seek to combine the information extracted from layers with other recognition methods to develop more automated alternatives to identify building elements from disjointed lines. For example, Dominguez et al. [44] combine a rule-based wall-prone pair strategy with a Wall Adjacency graph data structure to keep track of the hierarchical and topological relations between line segments in the wall layers and find pairs of lines that constitute a wall. By combining these methods, different types of information can be extracted and combined to achieve a more complete 3D model.
2. **Rule-based approaches:** Rule-based approaches, or template-matching approaches, seek to recognise geometric entities or symbols by describing them through the geometric and topological rules that define them and comparing them to predefined rules or templates. These methods are predominantly used in symbol recognition, where drawing symbols, such as doors and windows [16,24,52], dimensions [53] or other mechanical, electrical and plumbing (MEP) symbols [47], are compared to databases of symbol templates to find a match based on similarity. These databases can be dynamically adapted as new symbols are discovered [19]. Rule-based methods can also be used for the recognition of structural elements such as walls. These can generally be divided into wall-driven methods and room-driven methods. Wall-driven methods focus on finding the parallel pair lines representing a wall [19,29,44,46]. Room-driven methods focus on finding closed room contours by its boundary walls [7]. Horna et al. [50] formalise some of these rules by proposing a set of consistency constraints to define the geometry, topology and semantics of architectural indoor environments and automatically reconstruct 3D buildings.
3. **Graph-based approaches:** Graph-based approaches seek to represent building elements as a network of connected nodes. They focus not only on the identification of building elements but also on the geometric and topological relationships between them. A graph-based approach is the most topological-centric approach of them all. For example, in [7], Lewis et al. use a spatial adjacency graph to map the relationships between rooms and discover the location of doors and spaces in the floor plan. Dominguez et al. [44] develop a Wall Adjacency graph, where nodes represent the line segments from a floor plan, and edges represent relations between those segments.

This allows them to identify walls from the topological relationships between their composing line segments. Gimenez et al. [14] develop a topological wall graph, where each node represents a relationship between two walls, to aid in the contour-finding of each room. Xi et al. [47] develop a global relationship graph for finding beams by mapping the relationship between beams and their load-bearing columns.

4. **Grid-based approaches:** Typically used in engineering drawings, this method uses grid lines to locate and identify structural entities in floor plans. It assumes columns are located around the intersection points between grid lines and that beams extend as parallel lines between columns. Lu et al. [48] pioneer this method with their Self-Incremental Axis-Net-based Hierarchical Recognition model, which progressively simplifies the drawing by removing objects that have already been recognised [54]. This offers an alternative recognition method for CAD drawings, not reliant on layers. Y. Byun and B.-S. Sohn [20] developed an automatic BIM model generation system that relied on the grid lines of structural CAD drawings and a list of information containing cross-sectional shape data of structural elements (including, columns, beams, slabs and walls) to automatically create an Industry Foundation Classes (IFC) file containing structural elements. In a similar study, Q. Lu et al. [20] created a semi-automatic system to generate geometric digital twins from CAD drawings. Their method used optical character recognition technology to extract symbology from CAD drawings to create grids and blocks to define the location of each structural component.
5. **Learning-based approaches:** Learning-based approaches have been gaining popularity in the field of entity recognition in scanned drawings and consist of the use of deep learning for training a network to identify building components in technical drawings. Different types of networks have been used throughout the literature, including Graph Neural Networks (GNN) [18,39], Generative Adversarial Networks (GAN) [39,55], Convolutional Neural Networks (CNN) [56–58], Global Convolutional Networks (GCN) [59], Fully Convolutional Networks (FCN) [60], Faster Region-based Convolutional Neural Networks (Faster R-CNN) [25], Cascade Mask R-CNN [61,62] and ResNet-50 [63–65]. These networks rely on datasets containing large quantities of floor plans to train the network to produce reliable results. Floorplan datasets include the Rent3D dataset [66], a database of floor plans and photos collected from a rental website; the CubiCasa5K dataset [67], a vectorisation database containing geometrically and semantically annotated floor plans in SVG vector graphics format; the CVC-FP dataset [68], a floor plan database annotated with architectural objects' labels and their structural relation; and the SESYD dataset [69], a synthetic database for the performance evaluation of symbol recognition and spotting systems, among others. Other learning-based approaches include the use of clustering techniques to group geometric primitives representing building components of the same type [52].

3.4. Three-Dimensional Modelling

Once the input data have been properly cleaned and recognised, they need to be converted into 3D. In the 3D reconstruction literature, there are four main ways to represent a 3D model: (1) polygonal modelling, (2) solid modelling, (3) wireframe modelling and (4) BIM modelling.

Polygonal modelling makes up most literature attempts at 3D reconstruction and consists of modelling objects through their polygonal faces. Earlier research [7,45] relied on polygonal modelling to model building objects by extruding 2D vector lines to form 3D polygonal faces. Extrusion soon became the most popular modelling technique for walls [15,23,46,50,51], which requires finding the closed loop of lines that represents the wall section, verifying the orientation of each line normal (this is done so that the resulting face will face outwards) and extruding to a specified height. Triangulation can also be used to model more complex geometric shapes, such as floors and ceilings [45] and walls of historic buildings [15].

Alternatively, solid modelling relies on simple 3D geometric primitives (e.g., cuboids, spheres, cylinders) to create more complex geometries by combining and subtracting said primitives. For example, Park and Kim [37] model walls as boxes separated by wall junction solids, representing each major type of wall junction (X, T, L, I). Doors and windows are modelled by subtracting a hole in the wall and placing a pre-modelled door/window object at that location [36]. Similarly, Lu et al. [48] reconstruct the model component by component by modelling each component solid individually according to their shape coordinates and 3D attributes. Zhang, C. et al. [70] developed a pattern-matching technique capable of reconstructing 3D CAD solid models from 2D orthographic drawings, effectively capturing the complex curvature of solid objects. While initially applied to individual solid objects, their methodology shows promise for broader implementation across entire buildings, addressing the challenges encountered by previous methods when dealing with curved geometries.

Wireframe modelling can be used in structural 3D models to represent the building's structural framing through its edges. For example, Xi et al. [47] use a wire frame algorithm to match vertices and edges and reconstruct the 3D wireframe model of the building's structural framing through its 2D projection (floor plan) data.

Finally, more recently, BIM modelling has been used to not only model the geometric 3D model but also to retain semantic and topological information. Instead of directly modelling a 3D model, this approach focuses on identifying and storing geometric, semantic and topological information in an IFC file so that it can be read by any BIM proprietary software [17,20]. This is a tool-independent, information-centric approach that yields the most complete 3D model.

4. Discussion

In the following discussion section, key findings identified in the reviewed literature are discussed regarding the type of input data and the type of information extracted, among others. This section aims to uncover the broader implications of the reviewed literature to achieve a deeper understanding of the state of the art concerning 3D modelling from 2D drawings.

4.1. Type of Input Data

Regarding the input data, Figure 3 shows that most of the reviewed literature on 3D reconstruction (n = 27, 56%) uses scanned drawings as input for the recognition process, with CAD drawings (n = 21, 44%) not far behind.

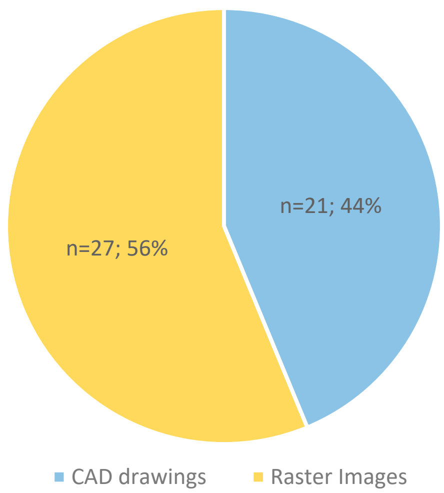

Figure 3. Input data type of the 3D reconstruction process in the literature.

Regarding the type of input files used, as highlighted by Figure 4, the revised literature shows that the majority of studies used raster images of technical drawings (n = 23). The second most used input strategy was using CAD drawings exclusively (n = 16). After these two categories, which account for 83% of all the analysed studies, there are a series of studies that combine one of these two input methods with other types of documentation, such as photos (n = 3), member lists (n = 1), laser scans (n = 1) and architectural tables (n = 1). Moreover, Pan, Z. et al.'s [61] methodology was capable of scanning through CAD and raster files (n = 1).

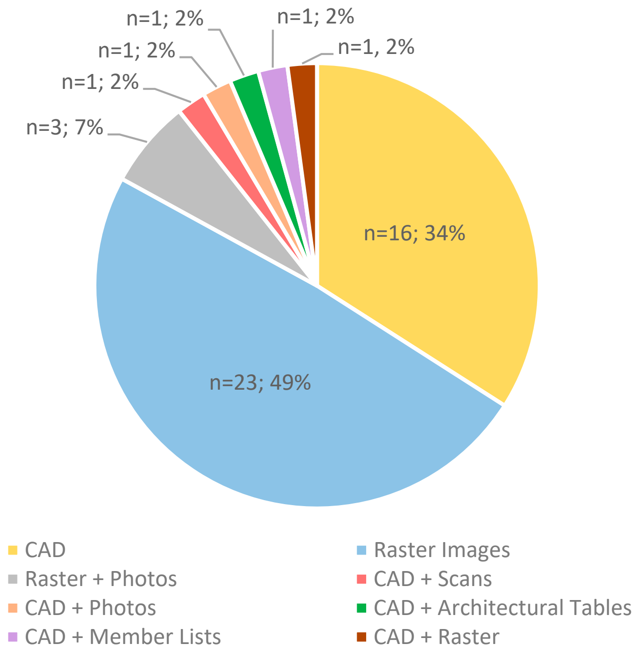

Figure 4. Combination of input data types for the 3D reconstruction process in the literature.

All of them use floorplans as the main source of information (Figure 5), but some researchers use other technical drawings [7,15,19,20], photos [16–18], laser scanning [71] or archaeological data [21] to complement the missing information in floor plans.

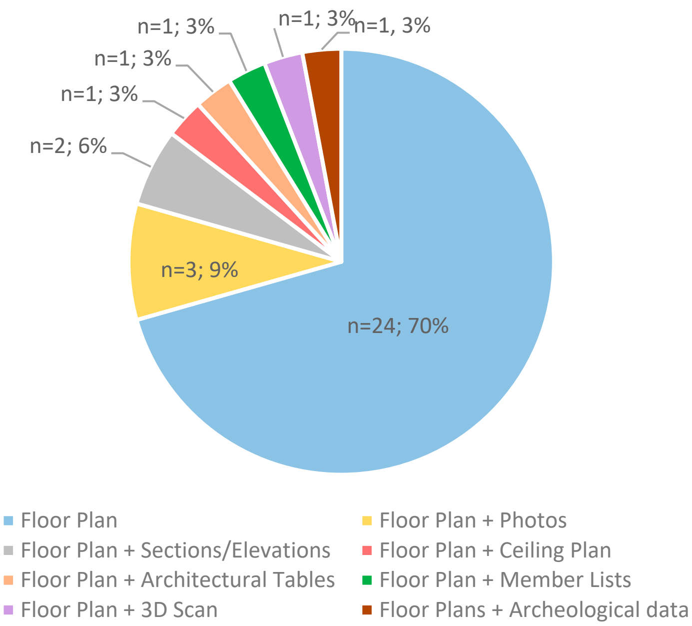

Figure 5. Input documentation type used for the 3D reconstruction process in the literature.

4.2. Type of Information Extracted

As stated previously, the validity and completeness of a 3D model resulting from a 3D reconstruction process are determined by the types of information that can be extracted from the input data. To assess the quality of the generated models, we consider three types of information: geometric information, semantic information and topologic information. Figure 6 shows the different types of information that different publications on 3D reconstruction can extract from the input documentation. As the main goal of 3D reconstruction, geometric information is the most important and always covered in 3D reconstruction research. Topologic information is the least covered type of information in 3D reconstruction, with only eight of the covered papers offering any kind of strategy to uncover this data from the input documentation. Semantic information is covered in about half of the reviewed papers, with different levels of completeness.

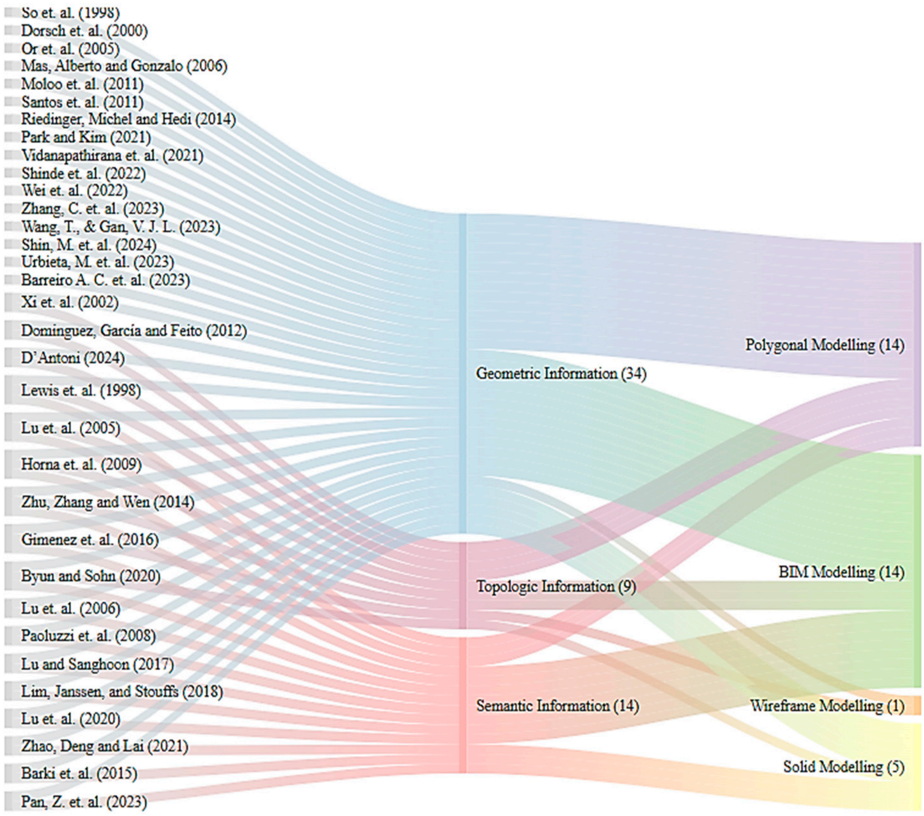

Figure 6. Semantic richness of the reviewed literature [7,14–21,23–25,28,37,44–52,54,61–65,70–73].

4.3. Scanned Drawings vs. CAD Drawings

Three-dimensional reconstruction in CAD vector drawings and raster images brings different challenges and opportunities. While 3D reconstruction using scanned drawings requires more complex pre-processing techniques to clean and vectorise pixels into readable geometry, available research is more mature regarding semi-automated processes to deal with these challenges.

CAD drawings, on the other hand, are typically reliant on extensive manual pre-processing labour, especially in the re-layering and re-drawing stages, ultimately making them more labour-intensive approaches. The existence of layers, although laborious to set up, ultimately simplifies the recognition processes, by imbuing geometric primitives with semantic information.

4.4. Geometric Coverage

Figure 7 shows the geometric coverage of the researched papers, i.e., the range of different building components covered by the solution. Most papers focus, first and foremost, on the structural elements, i.e., walls, columns, beams, floors and ceilings, followed by transitional elements, i.e., doors and windows, between spaces. Papers that focus on semantic information extraction are also concerned with extracting information regarding spaces, including room labels and other attributes. Beams are specifically only addressed in structural drawings as they are usually not present in architectural drawings. Structural drawings also have the information needed to generate rebars, and a small percentage of papers (7%) address that. Finally, other elements include the recognition of annotative floorplan symbols such as dimensions, grids and other MEP symbols. Overall, articles tend to focus on a narrow scope of building components, depending on the research's objective; for example, for 3D visualisation and walkthroughs, only visual and geometric elements are considered, and thus, spaces and MEP are often neglected. However, in the last two years, there have been two studies on the automatic reconstruction of MEP structures [61,74] that suggest that there are methodologies in development to retrieve this building information.

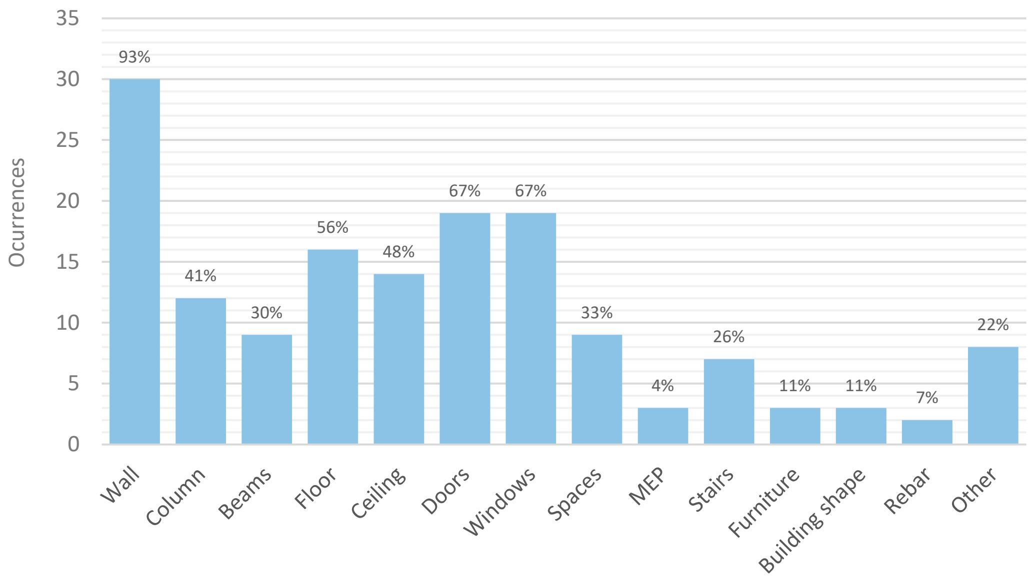

Figure 7. Geometric coverage of literature publications.

4.5. Two-Dimensional vs. Scan-to-BIM vs. Photogrammetry

The conventional approach to 3D reconstruction has revolved around the scan-to-BIM and photogrammetry methods, where 3D models are created through a field survey employing laser scanners or through photos. The scan-to-BIM method involves the generation of a point cloud that serves as the foundation for developing 3D models, employing various techniques. In the context of this study, it is important to analyse the differences between the widely used scan-to-BIM method and the approach from 2D drawings.

The reviewed literature highlights that the scan-to-BIM process achieves the most precise results for the 3D reconstruction of infrastructure [72,75,76]. The precision offered by laser scanners and the latest developments of these devices allow for easier point-cloud pre-processing, making this method yield very reliable results [1]. However, the relatively high cost of laser scanners makes the implementation of this methodology in the industry more difficult. In this sense, photogrammetry offers a good compromise between precision and cost-effectiveness, relying on photographs that may be taken using everyday items such as smartphones.

The literature review reveals that while the 3D reconstruction from 2D drawings may not yield results as precise as those achieved through the scan-to-BIM methods, it offers notable advantages in terms of cost-effectiveness, coverage and execution speed [20]. Moreover, this method is more convenient concerning data availability, given the decades-long prevalence and widespread use of 2D drawings in the field [20]. Additionally, while scan-to-BIM can only be applied to existing buildings, 2D drawings offer the advantage of applicability for both new construction projects and pre-existing structures since this approach only requires access to the final drawings. Despite the more accurate results of scan-to-BIM, the potential trade-offs in accuracy, efficiency and economic benefits of reconstructing 3D models from 2D drawings make it a compelling alternative, especially in scenarios where rapid, cost-efficient representation of buildings is paramount.

4.6. Comparison of Entity Recognition Approaches

The different entity recognition approaches presented in Section 3.3 have their own set of advantages and disadvantages. A discussion highlighting them is relevant to help future researchers choose suitable approaches for their practical applications.

The literature shows that layer-based approaches allow for simplified recognition in CAD drawings through semantic identification using layers and can result in accurate recognition by focusing on specific layers for different building elements. However, the reliance on manual re-layering and re-drawing can transform this approach into a time-consuming, labour-intensive and error-prone one, especially in complex geometric cases. Researchers should be aware of this and apply layer-based approaches in simpler cases that may require minimal manual pre-processing, leading to faster recognition.

The clear rules and templates of rule-based approaches allow for the precise recognition of specific geometric entities or symbols. Rule-based approaches are meant to recognise components with standardised symbols (e.g., doors, windows, MEP symbols), where a database of symbols with only small variations can be inferred and used to recognise similar symbols. If these databases are too wide-ranging, the similarities that define a component might be lost and lose meaning. Non-standard components might be more suited to be recognised with other recognition methods.

Graph-based approaches excel in structuring building elements and their relationships, offering valuable insights into the topological connections between elements. They prove effective in deciphering intricate relationships and facilitating comprehensive 3D model reconstructions. However, their implementation demands substantial computational resources for graph construction and interpretation, with complexity escalating alongside drawing size and intricacy. Furthermore, their success hinges on the precise segmentation and parsing of input drawings to derive meaningful graphs.

Grid-based approaches offer a direct method, using grid lines for identification, making them ideal for engineering drawings where elements align perfectly with grid intersections. They are a viable alternative to layer-based recognition methods, especially in CAD drawings. However, they struggle with irregular or non-standardised layouts, lacking the flexibility to adapt to various drawing styles or formats without manual adjustments or pre-processing.

Finally, learning-based approaches can adapt to various drawing styles and formats through training on diverse datasets and can potentially achieve high-accuracy results, especially with deep learning techniques and large training datasets. While the same dataset that contributes to their high accuracy demands substantial amounts of annotated data for training, the acquisition process can be both costly and time-consuming. Moreover, the training and fine-tuning of deep learning models entail significant computational resources, adding to the complexity. To the best of our knowledge, no learning-based approaches have been used with CAD drawings, making this a potentially unexplored area of research for learning-based approaches.

To mitigate the limitations of these approaches, researchers can combine different entity recognition methods. For instance, layer-based methods, paired with rule-based approaches may leverage semantic information and rules for accurate recognition, while reducing manual pre-processing (especially aimed at standard geometry components). Another example could be pairing grid-based methods that excel in identifying elements aligned with grid intersections and learning-based techniques that can adapt to various drawing styles and formats, providing flexibility and robustness in recognition. Future studies incorporating hybrid systems may exploit the strengths of each technique, yielding more adaptable and accurate recognition systems across diverse drawing complexities.

4.7. Limitations and Future Research Paths

The authors of the reviewed literature identified different limitations in their work and in 3D reconstruction from 2D drawing overall. L. Gimenez et al. [14] reveal that their methodology relied on manual input for critical parameters, such as building height and openings, which allowed to expedite the process, but the assumption that all components share equal height proves inadequate when confronted with the inherent variability in real-world scenarios [25]. Relying solely on floor plans makes obtaining complete elevation data challenging, leading to default height values in IFC BIM creation [25].

The authors also confirm that their model confines itself to identifying walls with straight lines and homogeneous textures, potentially limiting its adaptability to evolving drawing conventions, a struggle felt by many researchers [14,36,55]. In fact, most of the authors assume that walls are straight and connected elements are perpendicular to wall lines, making complex structures, such as curved and non-perpendicular walls, difficult to detect [14,25,55]. Furthermore, simplifications involving text elements and polygonal shapes tend to be implemented leading to unrecognised spaces in intricate geometries [14]. Enhanced algorithms, potentially utilizing machine learning, could overcome these limitations and broaden the automation's applicability to handle more complex buildings and diverse scenarios [46].

A noteworthy algorithm type that remains unexplored for entity recognition in 3D reconstruction is Natural Language Processing (NLP). The existing literature demonstrates the success of NLP algorithms in entity and keyword extraction, which involves identifying crucial information from textual data [77,78]. Future studies should focus on augmenting entity recognition techniques by integrating NLP algorithms into previously employed approaches.

Additionally, researchers can explore diverse combinations of entity recognition techniques to address the limitations of individual methods. By adopting hybrid systems in future studies, the advantages of each technique may be leveraged, leading to recognition systems that are both adaptable and accurate across a broad spectrum of drawing complexities.

Raster images are also susceptible to additional errors, such as when addressing photo-wide colour shifts and illumination issues, leading to inaccuracies [18].

There is a need for continued research on the performance and accuracy of 3D modelling across different image types due to identified limitations in performance, accuracy and scalability [36]. Lastly, it is essential to conduct further research aimed at automatically recognizing all building information [20]. This should encompass a broader range of building elements beyond just structures and facades.

Despite being a difficult challenge, a solution should look at a tool capable of identifying all elements within a 2D drawing, instead of focusing on a reduced number of elements to improve accuracy which masks the tool's effectiveness.

5. Conclusions

This paper performs an in-depth literature review on the methods for the creation of 3D models from 2D drawings.

Despite 3D reconstruction not being a new area of study, only two surveys on off-site 3D reconstruction have been performed. Yin et al. [13] is the only review that covered both scanned paper plans and vector plans; however, an update may be needed due to rapid advancements in this subject.

This review performs a thorough examination of the 3D reconstruction process from 2D drawings, from the type of data input to pre-processing, entity recognition techniques and 3D reconstruction techniques.

The type of input data is very important as there are no generalised drawing standards, and these documents are susceptible to errors, making the pre-processing of data of the utmost importance. To this end, despite the acknowledged difficulty in standardising drawings, there is a need for the standardisation of these documents to facilitate efficient 3D reconstruction processes and reduce the manual pre-processing step. However, the authors believe this to be a short-term issue, to be corrected by the ongoing standardisation efforts in the architectural, engineering and construction sector.

This article highlights the key pre-processing steps for raster and CAD drawings. Raster drawings need to be resized to reduce processing time while maintaining a reportedly low error rate and cleaned through noise removal techniques such as binarisation, dilation and erosion, and their relevant information needs to be separated through text/graphics segmentation. These steps prepare files for the conversion of raster to vector images, aiming for efficient vectorisation while maintaining shape details.

CAD drawings, on the other hand, require less pre-processing; nevertheless, they still need to be cleaned and sometimes reworked before they can undergo the recognition process. CAD drawing pre-processing commonly involves tasks such as noise removal, re-layering and re-drawing.

Entity recognition is a crucial aspect of 3D reconstruction as it allows for the identification of distinct building elements from a set of unlabelled geometric primitives or pixels. In this study, five types of approaches to this process are presented: rule-based, learning-based, grid-based, graph-based and layer-based. These approaches cater to different needs in the entity recognition problem and are often used together to provide comprehensive and accurate results in entity recognition for CAD drawings. The choice of approach depends on the specific requirements and characteristics of the drawings being analysed.

When it pertains to 3D modelling, the literature identifies four possible methods: polygonal modelling, solid modelling, wireframe modelling and BIM modelling. In this study, despite polygonal modelling making up most literature attempts at 3D reconstruction, it is concluded that among all methods, BIM modelling yields the most complete 3D model.

Furthermore, this review highlighted the main techniques used and the limitations faced by the authors.

While no method has yet been able to fulfil the promise of comprehensive semantically rich 3D models, we are not far from that goal. Continued investigation is necessary to improve the performance of 3D modelling. Subsequent efforts should focus on automating the generation of building information beyond structures and facades. The development of a tool capable of accurately identifying all elements in a 2D drawing is crucial for enhancing usefulness.

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