Towards an automatic approach to generating BIM models from digitized plans

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Abstract

This paper proposes a new approach to creating BIM models of existing buildings from digitized images. This automatic approach is based on three main steps. The first involves extracting the useful information automatically from the digitized plans (in .TIF, .JPG or .PNG image formats) by using image processing techniques (including segmentation, filtering, dilation, erosion, contour detection). This information will feed the knowledge base of an expert BIM model generation system. Secondly, using the knowledge base of the expert system, the information that will inform the BIM model can be deduced. Finally, an Industry Foundation Classes (IFC) model can be automatically generated with all the desired geometric, physical and technical information.

Keywords: Automation, Digitized Plans, Knowledge, Expert System, Artificial Intelligence

1. Introduction

A Building Information Model (BIM) is a database containing information relating to a built asset. It can represent not just the geometry of the building and its contents, but all its physical and technical characteristics (Aram *et al*., 2013; Doukari *et al.,* 2017). Over the last ten years, BIM has become, according to Celnik *et al.* (2014), the most discussed and utilised new technological tool in the field of construction. However, though its usefulness and benefits have been demonstrated in several fields of application (e.g. Ji *et al.,* 2013; Lee *et al.,* 2011; Kim *et al.,*2013; Kim *et al.,*2016) creating a BIM model can be a laborious task that requires the collaboration of several modeling teams over time. This is the case with a new asset: when it comes to modeling an existing asset (for example, retro-modelling an existing building to take advantage of a digital model for maintenance purposes) this can quickly become particularly expensive. First, there is the use of expensive technology, such as laser scanning equipment, post-processing and BIM modeling software. Then, expert intervention is required to identify certain information and characteristics of the various components such as types of materials (Zeibak-Shini *et al.*, 2016). On the other hand, the cognitive processes of the human expert might be reproduced automatically using artificial intelligence, using tools such as neural networks, expert systems, and genetic algorithms. The first step would be to represent human expertise in a machine-readable format, then to define reasoning operators that can, based on certain information, draw relevant conclusions (Gevarter, 1984). In this paper, we propose a new approach to creating BIM models of existing buildings from digitized images. This automatic approach is based on three main steps. The first involves extracting the useful information automatically from the digitized plans (in .TIF, .JPG or .PNG image formats) by using image processing techniques (including segmentation, filtering, dilation, erosion, and contour detection). This information will feed the knowledge base of an expert BIM model generation system. Secondly, using the expert knowledge base of the expert system, the information that will inform the BIM model can be deduced. Finally, an Industry Foundation Classes (IFC) model can be automatically generated with all the desired geometric, physical and technical information. We present a proof of concept as well as the conceptual model of an expert system for automatic generation of such BIM models. An algorithm for extracting information from digitized plans, developed in Python, together with a knowledge base, represented in the form of rules of production, are also presented. The successful application of such a system would overcome the constraints of time and cost when creating a BIM model of an existing built asset.

2. Methodology

Our approach is essentially based upon the use of programming and image-manipulation tools such as: Python, OpenCV, NumPy, SciPy, Skimage (scikit-image), and Matplotlib. The approach follows the stages that are shown in Figure 1, each of which is explained in the subsequent text.

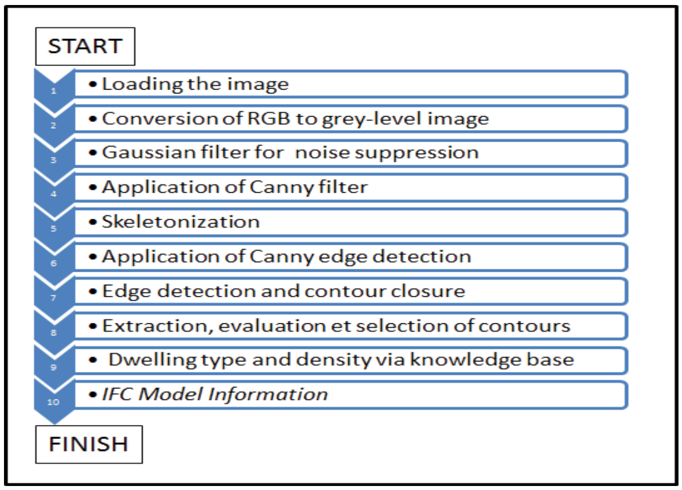

Figure 1: Stages in the algorithm for BIM model generation

2.1 Data

Two types of data were chosen, namely, cadastral sources (maps) and satellite images (see Figures 2 and 3, respectively) of a part of Nanterre, a suburb of Paris. The original format of the data is .TIFF, .JPEG or .PNG and each represents a surface area of 1 hectare.

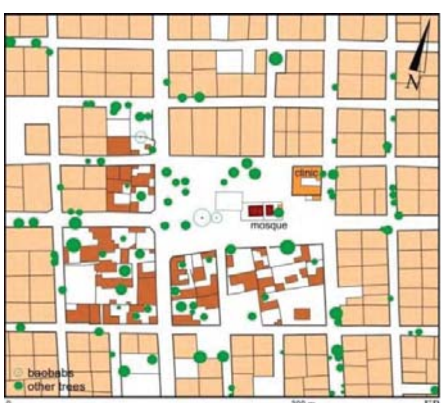

Figure 2: Section of a cadastral map

Figure 3: Satellite image (Google Earth)

2.2 Manipulation of the data

The application of the above algorithm to the cadastral map (Figure 1) produces the results shown in Figures 4 to 8, which are accompanied by a short description of the process.

Conversion of image from RGB to grey-scale: To simplify the data input we have chosen to work with monochromatic images. The RGB colour images are therefore converted to grey-level, as shown in Figure 4.

Gaussian filter: The occurrence of random noise information in the image reduces its sharpness. To reduce the noise an important step is to smooth the image using the Gaussian filter (see Figure 5).

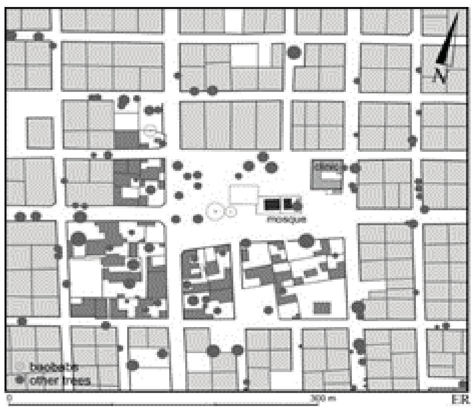

Figure 4: Source image converted to grey-level

Figure 5: Image after 'smoothing' using Gaussian filter

Canny filter application: The Canny filter is then used to: (i) minimize the error rate in edge detection, (ii) minimize the distance between the detected contours and the actual contours, and (iii) return a single response by contour. To draw only the contours, it uses a calculation of the intensity gradient followed by a hysteresis thresholding of the contours in order to have a binary image; with the outlines in white and the other points in black. This one is sensitive to noise and in order to avoid an increase in localization error, it is necessary to carry out a pre-treatment to suppress this. The detected contours also depend on the value of the thresholding. This varies from one image to another. There is no value in detecting all good outlines for all images.

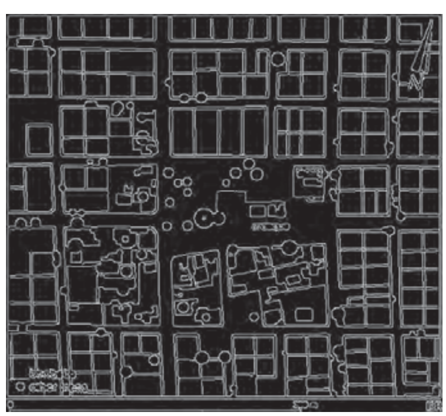

Figure 6: Image resulting from application of Canny filter

'Skeletonization': This stage may be necessary where there are shapes with irregular contours that require treatment by reducing and weakening their shapes into a curve called a skeleton. This enables an average contour to be obtained in cases where the size of the contours is not uniform. In the case shown in Figure 5, however, the process is not necessary and skeletonization had no effect.

Canny Contour Detection then detects all the contours of the previous image, in particular the coordinates of the points that make up the contours in a vector.

Extraction, evaluation and selection of contours: After closing of the contours the next step is to select those that are of interest: i.e. those that are likely to represent buildings (as opposed to vehicles, natural spaces and other images that do not represent built assets). This is done by calculating the area and perimeter of the contours before selecting and distinguishing (using colour) those that appear to be of interest.

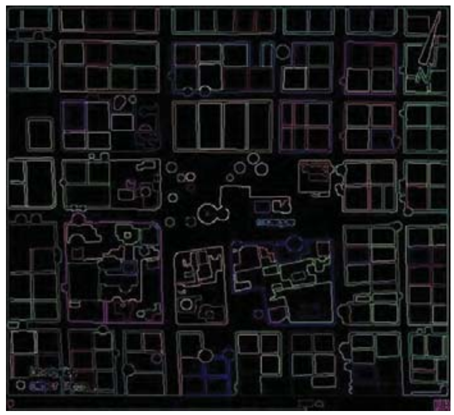

Figure 7: Image with highlighted contours of interest (338 contours detected)

Closing contours: The problem of unclosed contours remains (Figure 8). This distorts area calculations, counting, and contour selections. These are shown in close-up (zoomed) in the following Figure 8.

Figure 8: Image close-up showing unclosed contours

In order to solve this problem, a new algorithm was developed that can detect the ends of open contours and connect them to the nearest pixels in their vicinity. Some approximations were made during the tests. In its current state, this algorithm allows at least 70% open contours to be closed. As a result, a total of 588 contours are detected (Figure 9) as opposed to the original 338 contours.

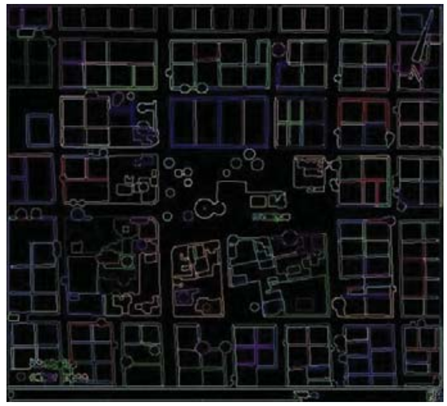

Figure 9: Image after closure of contours (588 contours detected)

In order to retain only the contours relevant to our study, i.e. contours potentially representing buildings, the results are again filtered to keep only contours whose area is between 30 m² and 1000 m². (Figure 10).

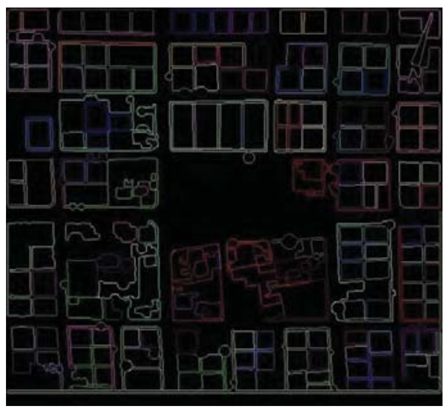

Figure 10: Image after selection of chosen contours (178 contours selected and coloured)

Following this, the results can be seen alongside the corresponding section of the original satellite image (see Figure 11, as an example).

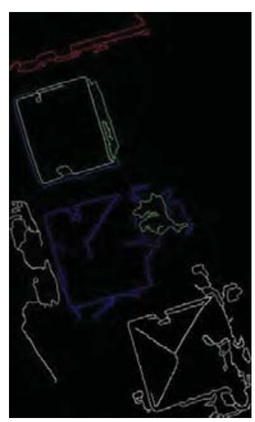

Figure 11: Section of the treated data (4 contours alongside original image of 4 individual houses).

Once the relevant contours have been selected, the useful and usable information is extracted into an Excel file, particularly the area and perimeter of the contours. It is also possible to extract the coordinates of the approximated points of the contours, that is to say, the edge points of each segment

2.3 Knowledge Base and IFC File Generation

In the realm of Artificial Intelligence, a knowledge base is a technology used to store complex structured and unstructured information used by a computer system. The first use of the term was in relation to the expert systems that were the first knowledge-based systems; computer systems that emulate the decision-making abilities of human experts. The term "knowledge base" was adopted to distinguish itself from the widely-used “database”, as by the 1970s, most large information systems managed their data stored in hierarchical or relational databases. An expert system is principally composed of two modules: an inference engine and a knowledge base (Figure 12). The knowledge base includes a set of defined rules that serve as a reference for extracted facts. The inference engine applies the rules to known facts to infer new facts and new information. In some cases, an inference engine can also provide explanations for the results obtained.

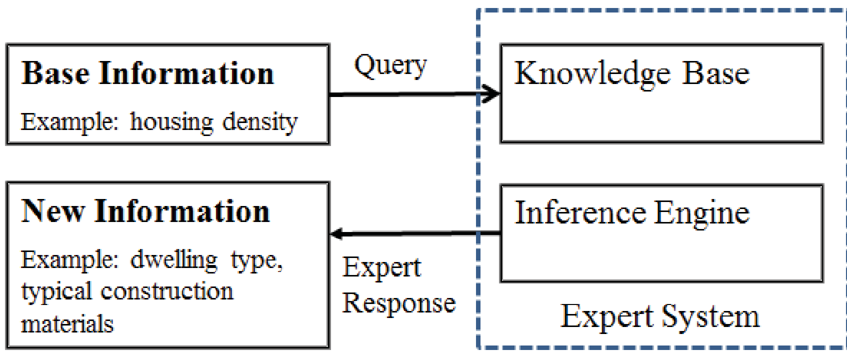

Figure 12: Conceptual view of an expert system

Expert systems are designed to solve complex problems by reasoning on knowledge, represented in a given formalism: logical, ontological, production rules, etc. The latter is the one adopted as part of this study. Since we are working on images whose area is 1 hectare then the number of buildings detected will correspond directly to the density of housing. Thus:

Housing density = Number of dwellings / Site area (Ha)

Given that we are working on images whose area is 1 hectare then the number of buildings detected will correspond directly to the density of housing. In France, buildings are classified by geographical zone (urban, suburban, rural, etc.) and according to type. In order to simplify automation, the different types of housing are also variously classified (e.g. as detached, semi-detached, terraced, dense housing complex, etc.) according to types that commonly occur throughout the regions of France.

The following table (Table 1) is a simplified version of the knowledge base as so far as it currently extends.

Table 1: Knowledge base of dwelling type, surface area and construction materials

Min. density	*Max. density*	*Dwelling type*	*Surface area (m2)*	*Materials*
1	4	Suburban villa	180	Block – Tile – Concrete - Wood
5	8	Housing estate	130	Waterproofed Insitu concrete
9	10	Individual Grouped	125	Stone – Concrete – Brick – Wood
11	15	Detached town house	116	Brick - Concrete
16	50	Single terraced	108	Brick - Concrete
51	80	Intermediate	89	Brick - Stone

81	121	‘Grand Ensemble’	78	Brick - Concrete
122	212	Multiple occupancy	69	Insitu reinforced concrete
213	343	High-Density Multi-occupancy (Centre Bourg)	45 to 90	Stone - Concrete
344	1000000	Built-up area (Hausmannian fabric)	30 to 120	Brick – Concrete - Brick

From the knowledge base created, the type of housing and the type of materials that it is typically composed of can be readily deduced. In the case of the previously discussed satellite image, the resulting inference is that the dwelling is part of a collective housing complex and the material of construction is brick and concrete (see Figure 13).

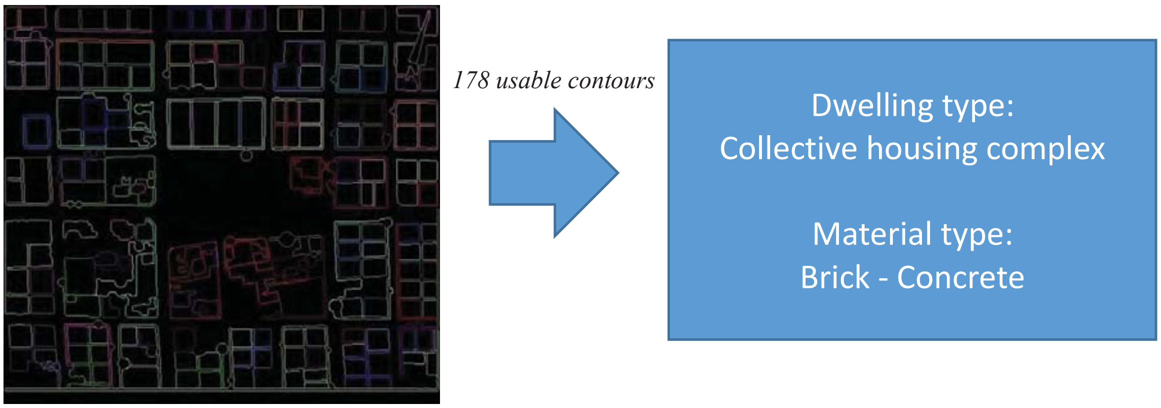

Figure 13: Results of expert system query

Generation of IFC model: This stage of the process is, as yet, in its development stage. The aim is to develop a program that allows the population of a model ("blank IFC") with all the information derived from the image processing at the urban scale, as exemplified in this article, together with the images of the facade of the building of interest, i.e. the one for which we wish to generate the BIM model. New information such as the number of levels, openings, doors, rooms, etc. could easily be derived from this second category of images and inserted into the "IFC blank" file. The APIs offered as part of the "IFC TOOLS PROJECT" project (see Doukari *et al.,* 2017 and the website http://www.ifctoolsproject.com). which include IFC object class development libraries, would be utilised for the completion of this stage.

3. Conclusion and perspectives

The use of BIM in the construction and property sectors is increasing, and as it does so, further benefits are becoming evident. However, the creation of a BIM models can be expensive and time-consuming, particularly in the case of the existing stock of built assets, where the required information (both geometric and non-geometric) needs to be retro-fitted into a model using a variety of scanning and other techniques. Thereafter human expert intervention is required to fully develop the information in the model. Here, the possibility is explored of automating the modelling process by developing artificial intelligence that replicates and replaces certain of the cognitive processes that are elements of the human expert intervention.

In this article, we have illustrated an algorithm that automatically retrieves information about the area, the perimeter of a building, and the housing density of a region (limited to 1 hectare). We have also demonstrated the creation of a knowledge base with an expert system able to deduce new information such as the type of housing or the type of materials used. The final step of generating and populating an IFC BIM model based on information already derived is currently under development.

This task will be based on the tools developed as part of the 'IFC TOOLS PROJECT' (see Doukari et al., 2017 and the website http://www.ifctoolsproject.com).

References

Aram, S., Eastman, C., & Sacks, R. (2013). Requirements for BIM platforms in the concrete reinforcement supply chain. Automation in Construction. 35 (0) (2013) 1–17.

Celnik, O., Lebègue, E., & Nagy, G. (2014). BIM et maquette numérique pour l'architecture, le bâtiment et la construction. 1ère ed. Paris: Eyrolles & CSTB.

Doukari, O., Naudet, B., & Teuilier, R. (2017). « Merging IFC-Based BIM Models: A new paradigm and co-design support tool ». International Journal of 3-D Information Modeling (IJ3DIM), 6(1).

Gevarter, B. W., (1984). Expert systems: Artificial intelligence applied. Telematics and Informatics. Volume 1, Issue 3.

Ji, Y., Borrmann, A., Beetz, J., & Obergrießer, M. (2013). Exchange of parametric bridge models using a neutral data format, J. Comput. Civ. Eng. 27 (6) (2013) 593–606.

Kim, H., Anderson, K., Lee, S., & Hildreth, J. (2013). Generating construction schedules through automatic data extraction using open BIM (building information modeling) technology. Automation in Construction 35 (0) (2013) 285–295.

Kim, H., Shen, Z., Kim, I., Kim, K., Stumpf, A., & Yu, J. (2016). BIM IFC information mapping to building energy analysis (BEA) model with manually extended material information. Automation in Construction 68 (2016) 183–193.

Zeibak-Shini, R., Sacks, R., Ma, L., Filin, S. (2016). Towards generation of as-damaged BIM models using laser-scanning and as-built BIM: First estimate of as-damaged locations of reinforced concrete frame members in masonry infill structures. Advanced Engineering Informatics, Volume 30, Issue 3.