Automatic generation of building information models from digitized plans

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Abstract

This paper proposes a new approach to creating Building Information (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 rasterized plans by using image processing techniques that include segmentation, filtering, dilation, erosion, and contour detection. This information feeds the knowledge base of an expert system for BIM model generation. In the second step, using the knowledge base of the expert system, the information required to inform the BIM model can be deduced. The range of information thus obtainable can be extended beyond the examples given. The paper concludes with a discussion of the final stage: the automatic generation of an Industry Foundation Classes (IFC) information model with all the desired geometric, physical and technical information. This can be accomplished by using one of the available open-source application program interfaces (APIs). This stage is currently work-in-progress and will be the subject of a future publication.

Keywords: Artificial intelligence; Automation; Digitized plans; Expert system; Knowledge base.

Highlights

- Proposes a new approach to the automatic creation of IFC BIM models of existing buildings from digitized images;
- The approach includes a Building Expert System to encode, represent and reproduce human expertise in order to help enriching BIM model with new information;
- An image-processing based algorithm to automatically calculate housing density is presented
- A case study approach is utilised to comprehensively test, evaluate and validate the developed method;
- The paper concludes with a discussion of the next stages in the work.

1- Introduction

A Building Information Model (BIM) is a database containing information relating to a built asset; more fully defined by the International Organization for Standardization as a "shared digital representation of a built object" and "the shared digital representation of the physical and functional characteristics of any construction works" (ISO, 2016). 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, as recently summarized by Zhao (2017) BIM has become the most discussed and utilized 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; Kim *et al.*,2013; Kim *et al.*,2016) the creation of 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 the purposes maintenance of facilities management) this can quickly become particularly expensive. First, there is the use of additional expensive equipment, such as laser scanning apparatus and post-processing and modeling software (Ding *et al.*, 2019; Prieto *et al.*, 2017; Volk *et al.*, 2018). Thereafter 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 with tools such as neural networks, expert systems, and genetic algorithms. Expert systems have for many years been used for different purposes and applied within several domain applications, for example: information retrieval (e.g. Waters, 1986), medical diagnosis (Heckerman, et al., 1992), help desk management (González, et al., 2005), performance evaluation (Lee, A.H., et al., 2008), loan analysis (Matsatsinis, et al., 1997) and computer virus detection (Sundaram, 1996). Construction-related applications include design optimization (Andersen et al., 2013; Chou and Thedja, 2016; Laptali and Bouchlaghem, 1995), logistical problems (Zhang et al., 2002) and the enrichment or validation of BIM models (Stuurstraat and Tolman, 1999; Lee, G. et al., 2006; Motawa and Almarshad, 2013; Lee, Y-C, et al., 2016).

In all such applications, the first step is generally to represent human expertise in a machine-readable format, then to define reasoning operators that can, based on certain information, draw relevant conclusions. In this paper, we focus our attention on the development of 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 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 the first stages in the automatic generation of such BIM models. An algorithm was developed using Python programming language and existing Python image processing modules (OpenCV, Numpy, SciPy, Scikit-image and Matplotlib) were used for extracting information from digitized plans. This process is presented in the next section together with a knowledge base, represented in the form of rules of production. The successful application of such a system would help to overcome the constraints of time and cost when creating a BIM model of an existing built asset.

2- Methodology

Many national and state governments have mandated the use of BIM for new buildings and infrastructure (Kassem and Succar, 2017) and have also recognised the advantages of having models of built assets that already exist (see, for example, Love and Matthews, 2019). However, the creation of models of the existing stock is a time-consuming and expensive exercise, currently requiring a significant amount of expert human intervention (Volk, *et al.,* 2014). The work described here concerns the automatic creation of IFC BIM models of existing buildings from digitized images. It was carried out in Paris and used test case buildings within the suburb of Nanterre. In France, as elsewhere, very few existing buildings enjoy the advantages of having digital models that can facilitate their operation, and fewer still have been originally modelled in BIM. In order to accelerate this digital transition and assist the modelling of existing buildings, automatic and fast approaches need to be defined and implemented. As with new buildings, arguably the most important information within such models is the semantic, non-geometric information required for auto-populating computerized facility management systems (Pishdad-Bozorgi et al., 2018). The human expertise that is required for providing this kind of information remains the most difficult part to automate, however, the use of artificial intelligence may ameliorate this situation.

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 1). 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.

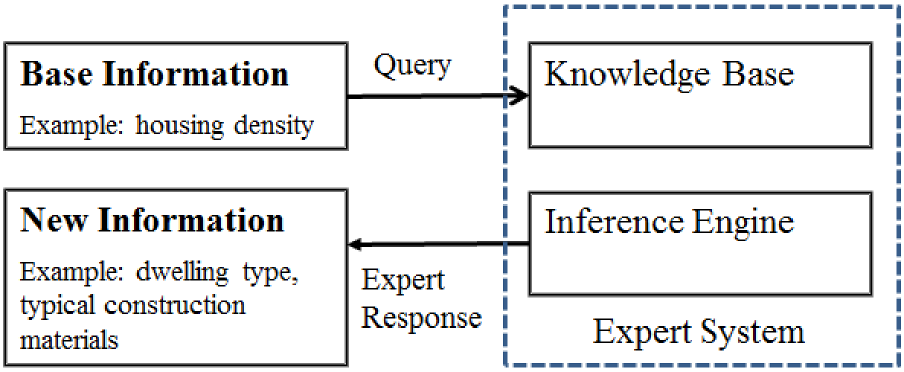

Figure 1: Conceptual view of an expert system

Expert systems are designed to solve complex problems by reasoning based on knowledge representation formalisms that involve various types of rules frames and ontologies (see, for example, Noy and Hafner, 1997). The approach that we adopted involves propositional logic encoding and is shown in Figure 2. and presented in the following text. As an example of semantic information that we are seeking, we selected the categories of ‘Dwelling type’ and (predominant) ‘Construction materials’ (e.g. ‘brick’ or ‘concrete’).

The functionality of the building expert system that we are aiming to build is based upon the process stipulated in Figure 2. Based on an expert knowledge base, it must be able to deduce useful information (for the present purposes, ‘Dwelling type’ and ‘Construction materials’) that would normally be provided by human experts for incorporation into the corresponding BIM model.

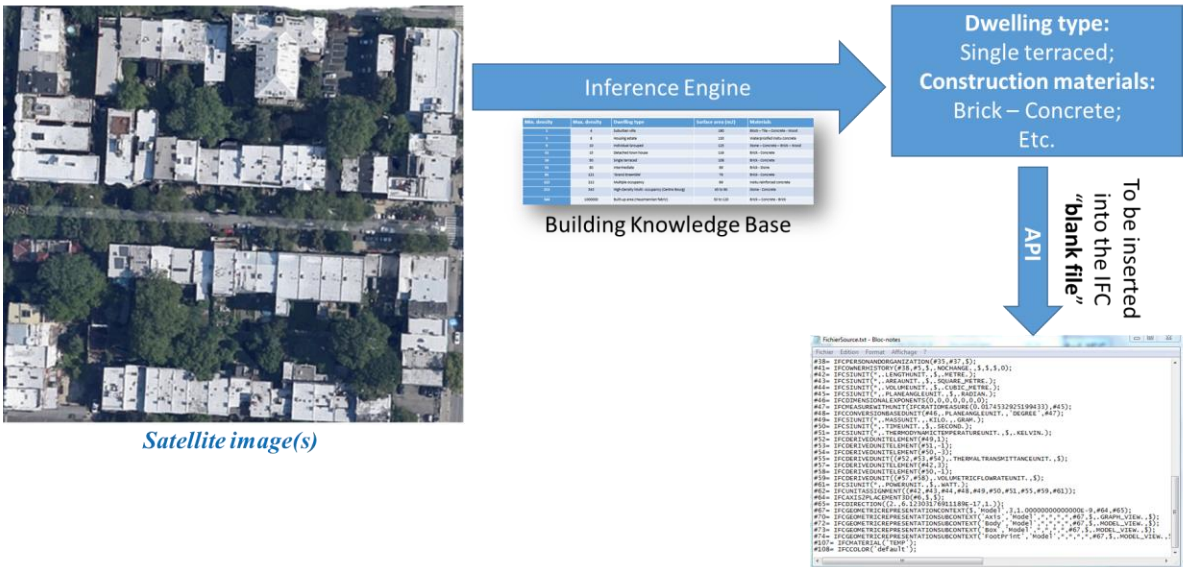

Figure 2: Building Expert System

2.1 Building the Knowledge Base

As noted by Hayes-Roth (1984) the knowledge base of any expert system is its most important component and building this component represents a fundamental step in creating the expert system. In this paper, we present a simplified prototype version of the knowledge base that simply allows it to deduce information, for incorporation into a BIM model, relating to ‘Dwelling type’ and ‘Construction materials’ (see Table 1). We intend subsequently to develop and enrich this initial proof-of-concept version to take into account other types of information. In France, buildings are classified by geographical zone (urban, suburban, rural, etc.) and according to dwelling type (see Steiniger, et al., 2008). In order to simplify automation, we have here classified the different dwelling types (e.g. as ‘detached’, ‘semi-detached’, ‘terraced’, ‘dense housing complex’, etc.) in line with the types that commonly occur throughout the regions of France.

Table 1 shows a simplified version of the knowledge base as far as it currently extends. For these purposes ‘Housing density’ is defined as Number of dwellings / Site area in Hectares (Ha).

Table 1: Knowledge base of dwelling types with typical surface areas 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.

The most used representation of knowledge-based reasoning is propositional language. Representing human expertise with propositional language takes advantage of the simplicity of expression of this language and, from a computational point of view, of its decisiveness. In addition, most of the reasoning and inference operators defined in the area of knowledge representation are defined in propositional calculus (Doukari *et al.*, 2007).

Consider the statements (derived from Table 1):

a) The Building (B1) is situated in Region R;
b) If the Housing density observed is between 5 and 8, then:
Dwelling type = Housing estate and
Construction materials = Waterproofed Insitu concrete.

A very simple representation in propositional language can be:

– To calculate the Housing density of Region R: such as c) R_6 (The Housing density of Region R is 6). R_x (The Housing density of Region R is x).
– To infer consequences from rules (a), (b) and (c), on this list: B1 is a Housing estate and B1 Construction materials is Waterproofed Insitu concrete.

To enable this, we must first address 'Housing density' and its means of calculation as explained in the next section.

2.2 Base Information: Housing density

The information base of our expert system consists of a set of satellite images taken on regions, building facades, etc. in .TIFF, .JPEG or .PNG formats. To enable us to extract information that can be used by the expert system (example: 'Housing density') it is necessary to carry out image processing.

Thus, our approach is essentially based upon the use of programming and image-processing tools such as: Python, OpenCV, NumPy, SciPy, Skimage (scikit-image), and Matplotlib. The approach follows the stages that are shown in Figure 3, each of which is explained in the subsequent text.

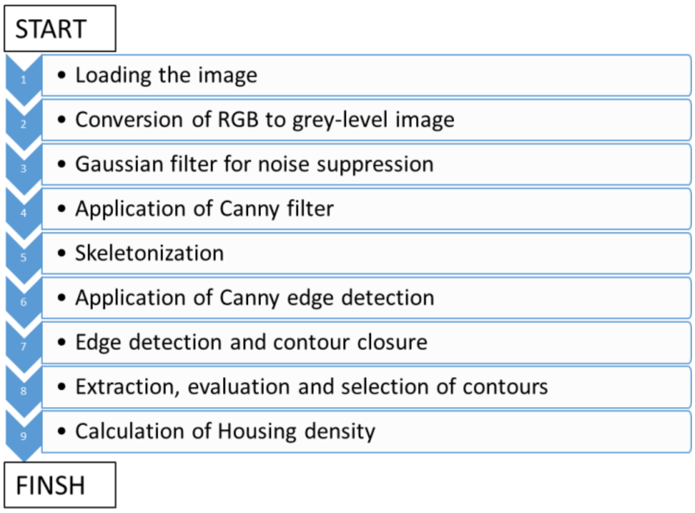

Figure 3: Stages in the algorithm for Housing density generation

To illustrate how this algorithm works, in the following sections we apply it step by step on a real-life example with data taken from Nanterre City (France).

2.2.1 Data

We selected two types of data, namely, cadastral sources (maps) and satellite images (see Figures 4 and 5, 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.

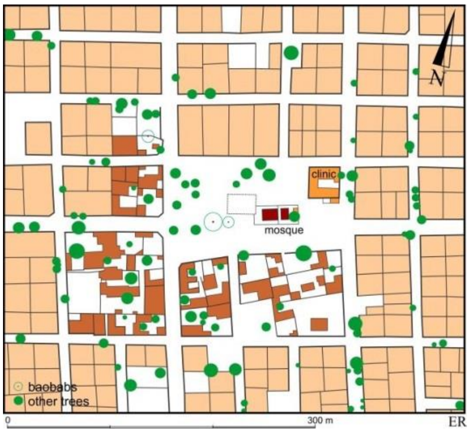

Figure 4: Section of a cadastral map

Figure 5: Satellite image (Google Earth)

2.2.2 Manipulation of the data

By applying the above algorithm to the cadastral map (Figure 3) we obtained the results shown in Figures 6 to 12. These figures 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 6.

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 (Figures 6 and 7).

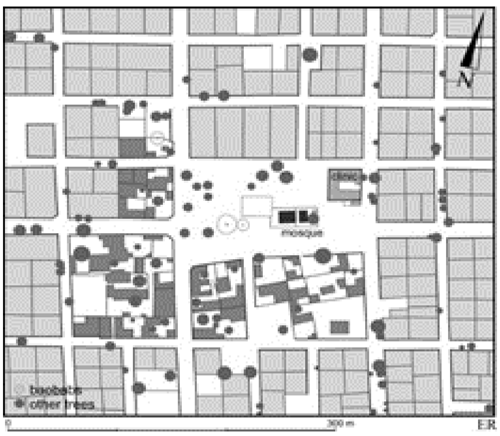

Figure 6: Source image converted to grey-level

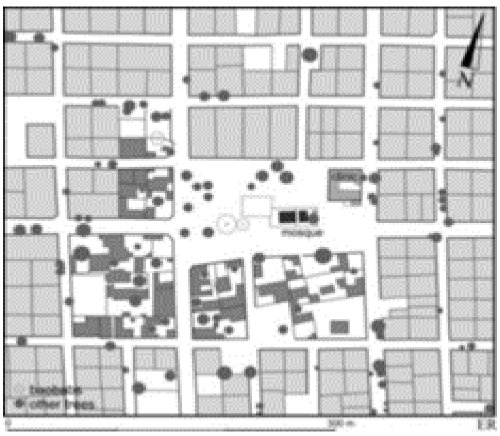

Figure 7: Image after 'smoothing' using Gaussian filter

Edge detection using Canny filter application: The Canny filter algorithm (Canny, 1986) 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 (Figure 8). Unwanted electronic visual 'noise' is suppressed by the hysteresis thresholding. This typically requires the input of two user-defined threshold levels, namely: minValue and maxValue. Pixels with an intensity above the maxValue threshold are retained; while those below minValue are removed. Where intensity falls between the two values, a further criterion is applied: pixels are retained if they are connected to other pixels classified as 'accepted' edges. The minValue and maxValue threshold values may need to be varied depending upon the data input quality and data acquisition method in order to get reliable edge recognition results.

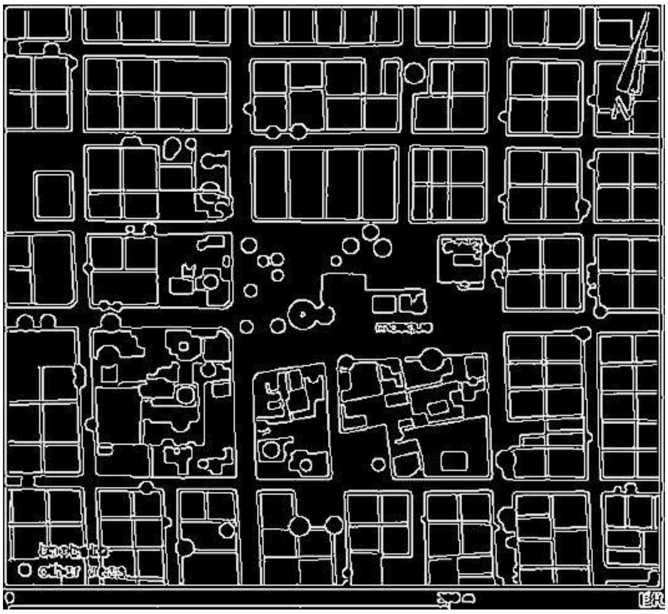

Figure 8: Image resulting from application of Canny filter

'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 7, however, the process is not necessary and skeletonization had no effect.

Extraction, evaluation and selection of contours: The next step is to select those contours 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, as shown in Figure 9.

Figure 9: Image with highlighted contours of interest (338 contours detected)

Closing contours: There remains the potential problem of unclosed contours. This distorts area calculations, counting, and contour selections. An example of this is shown in close-up (zoomed) in Figure 10.

Figure 10: Image close-up showing unclosed contours

In order to solve this problem, we have developed a new algorithm 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% of open contours to be closed. As a result, a total of 588 contours were detected (Figure 11) as opposed to the original 338 contours.

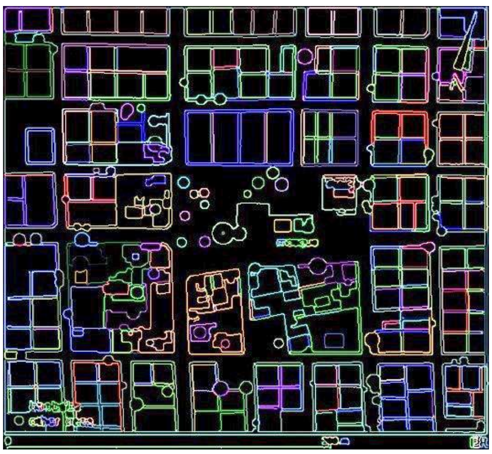

Figure 11: Image after closure of contours (588 contours detected)

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. (see Figure 12).

Figure 12: Image after selection of chosen contours (178 contours selected and coloured)

An example of the results following this stage is shown in Figure 13 alongside the corresponding section of the original satellite image.

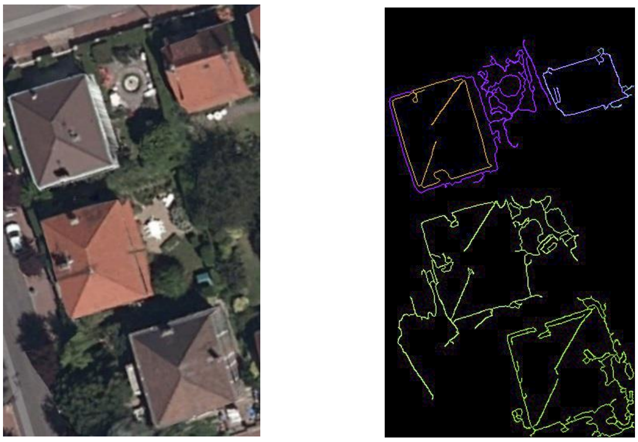

Figure 13: Section of the treated data (4 contours alongside original image of 4 individual houses).

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.

Calculation of housing density: the housing density represents the number of dwellings (or detected buildings) per site area (Ha). 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.

2.3 Generation of further information

From the knowledge base presented in Table 1, 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 (Figure 12), 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 14).

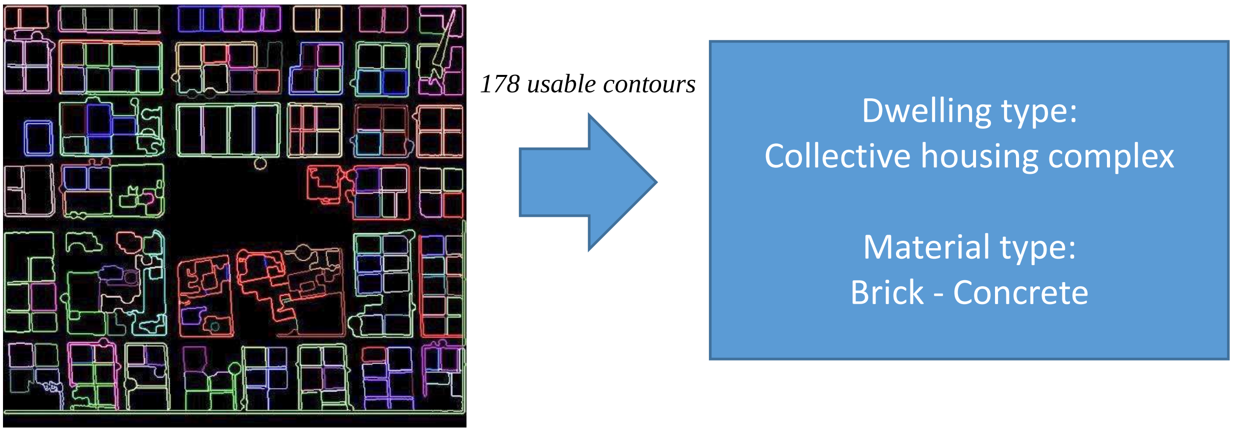

Figure 14: Results of expert system query

Using the techniques exemplified above more information may be derived from image processing at the urban scale; for example, the images of the facade of a building of interest (see, for example, Figure 15).

Figure 15: Building facade image processing

More detailed information such as the number of levels, openings, doors, rooms, etc. could readily be derived from this second category of images and the Building Knowledge Base can be completed with new expertise as shown by the examples in Tables 2 & 3.

Table 2: Knowledge base of window types

Windows standard size: Height x Width (metre)	*Window type*
0.75 x 0.60	Simple window:1 door wing
1.15/1.25/1.35 x 1	Simple window: 2 door wings

1.25/1.35 x 1.20	Simple window: 2 door wings
2.15 x 0.60 / 0.80	French window: 1 door wing
2.15 x 1 / 1.20	French window: 2 door wings
2.15 x 1.80 /2.10 /2.40	Sliding bay: 2 door wings

Table 3: Knowledge base of maximum storey height of building types

French building level height (metre)	*Building type*
2.66	Parking; Hotel
3	Older residential building
3.3	Office building; Hospital
4	Station; Exhibition hall; Superstore
> 4	Cathedral

The final step in the process, namely the incorporation of automatically generated information into an IFC BIM model is discussed in the next section.

2.4 Creation of an IFC BIM model

The work described is aimed towards the ability to generate and populate an IFC BIM model of an existing building using information that has been automatically generated from images. The attractiveness of such an approach for modelling existing assets, and its efficiency and cost-effectiveness, have long been recognised (see, for example, Arayici, 2008). As a result, several open-source application program interfaces (APIs) have become available for this type of operation. One of the most highly-regarded of these is the eXtensible Building Information Modelling (xBIM) Toolkit (Lockley et al., 2017). The xBIM Toolkit platform (at https://docs.xbim.net/examples/proper-wall-in-3d.html) gives a simple example of how to generate a 3D parametric *IfcWall* using its programming functions. Using basic information (e.g. length, width, height, materials) about a wall, all of which could be deduced using the Building Expert System described, a compliant IFC model can be created that contains a parametric 3D wall object. Iterations of the same process would result in the creation of other 3D parametric objects (e.g. windows, doors, roof) and their integration within the same IFC model. This last step, the integration of parametric IFC objects, can also be readily accomplished using the framework for merging IFC-Based BIM Models presented in Doukari et al. (2017). This process also allows checking the overall consistency of the resulting IFC parametric model. If any inconsistency is detected, the wrong parameter and its value are highlighted in the model tree, facilitating its correction.

3- Conclusions, discussion and future work

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 retrofitted 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. In this paper, we have explored the possibility of automating the modelling process by developing artificial intelligence that replicates and replaces certain of the cognitive processes that are elements of human expert intervention. We have illustrated a set of image-processing algorithms that automatically retrieve information about the area and perimeter of a building, and the housing density of a one-hectare sample of a region. 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.

This building knowledge base can be automatically enriched using new machine learning techniques, thus enhancing the inference engine. Furthermore, better building image processing could be obtained by using new generation deep convolutional neural networks like those described in Cevallos *et al.* (2019) and Mayya *et al.* (2016). Image pre-processing to remove noise and unwanted features could also be useful to enhance contour closure and building component results (see, for example, Vinay *et al.*, 2018). Using the same methodology our intention is to extend this system to a much wider range of information that could then, using available APIs, be used to populate semantically-rich IFC BIM models in a quick and inexpensive way. Ultimately, we aim to develop an interactive graphical user interface for the proposed expert system to assist architects, engineers and construction project managers in executing advanced BIM-creating tasks.

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