CAD2GRAPH: Automated Extraction of Spatial Graphs from Architectural Drawings

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Abstract. A significant obstacle in spatial epidemiology is the absence of computationally amenable spatial maps of the underlying space (e.g., a large hospital). Spatial data for built spaces are typically stored in computer aided design (CAD) architectural files which are difficult to parse, query, and combine with other data sources. To alleviate this difficulty we design a tool CAD2GRAPH, which automatically extracts spatial maps from CAD files. To ensure that the spatial map is easily amenable to computations, we represent it as a graph whose vertices represent spatial units of a uniform size and whose edges represent obstacle-free, walkable paths of uniform length connecting pairs of spatial units. CAD2GRAPH extracts key information such as walls, doors, and room labels from the CAD file and through a series of geometric transformations, extracts the above-described spatial graph from it.

Keywords: spatial graphs · graph extraction · architectural drawings.

1 Introduction

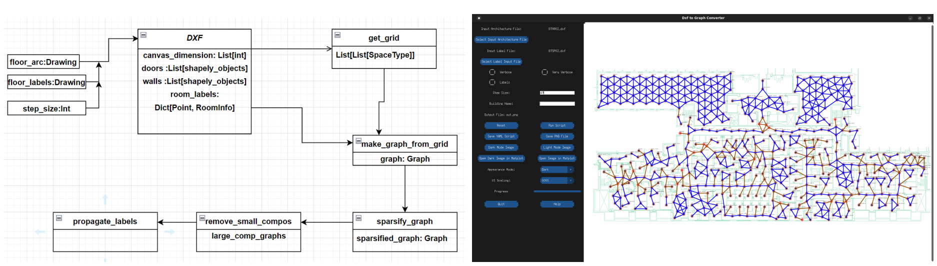
Spatial epidemiology at the scale of healthcare facilities is critical for modelling and combating healthcare associated infections. Some example include spatio-temporal clustering of *Clostridioides Difficile* (CDI) infections in hospitals [8], characterizing spatial distribution of healthcare professionals (HCPs) [4, 5], swabbing locations for outbreak detection [1], and non pharmaceutical interventions to combat such as CDI and *Methicillin-resistant Staphylococcus Aureus* (MRSA) [3, 7]. A major obstacle in spatial epidemiology at the healthcare facility level is the lack of spatial maps of the architectural layout of the facilities. While many healthcare facilities have spatial data, it is often stored as computer aided design (CAD) files. It is non-trivial to analyze these together with other datasets often required for spatial analysis such as healthcare professionsals login data, patient transfer between rooms, and patient-room-doctors interactions [2, 6]. On the other hand, if the data present in CAD files could be extracted as a spatial graph, it could easily be stored in the same database as other data and be analyzed together. In our prior works [5, 6], we have been using hard crafted spatial graphs. Generating hand crafted spatial graphs for the entire University of Iowa Hospitals and Clinics took many months of work by many undergrads, a couple of masters students, and 3 faculty members. This is a significant effort that not all healthcare facilities can afford.

To address the issues mentioned above, here we develop and demonstrate cad2graph, a novel tool to automatically generate location-location graph between physical spaces within hospitals given an input CAD file. cad2graph carefully reads the outline of the architectural drawing and extracts spatial graph via a series of careful transformations. Our target audience include data mining researchers, especially those who focus on large networks, who are seeking to apply their work on spatial epidemiology applications and epidemiologists/practitioners who are seeking to apply data mining techniques.

Note: Our demonstration and source code is designed to work for CAD files in the dxf format. Note that there are many open source tools to convert files from one CAD format to another.

2 System Overview

Input to cad2graph is a CAD file representing a specific floor in a specific building. We first extract the external layout of the floor and structure of the walls and doors. We then construct a two dimensional grid with a pre-defined spacing and overlap the grid and walls assign label to each grid node based on whether the given grid is part of a wall or not. We then repeat the same process and label the door nodes. We then add edges between the grid nodes in eight-directions. Finally, we sparsify the grid and extract spatial graph. We implemented a tool with graphical user interface in python. The overview of the system and GUI are presented in Figure .



(a) (b)

Fig. 1: (a) Overview of cad2graph. (b) The interface of the tool implemented in python. The left panel consists of interactive elements and the right panel visualizes generated graph on top of the architectural layout.

The system presented here automatically extracts spatial graph $G_L(L, E, W, X)$ from CAD files. The graph is defined between the locations L within healthcare facilities including patient rooms, hallways, and so on. Each edge $e(l_1, l_2) \in E$ between two locations l_1 and l_2 indicate that they are in close proximity. The corresponding edge-weight depends on whether l_1 and l_2 are within the same closed space or are connected via doors, stairs, and elevators. We provide a high-level summary of the steps involved in CAD2GRAPH next.

1. Canvas construction. We read the CAD file and extract the architectural layout and room labels, positions of walls and doors, and the dimension of the outer most walls. We then construct a 2-d canvass and assign (x, y) co-ordinates to each label read from the CAD file.

2. Grid extraction. We then construct an evenly spaced 2-d grid on the generated canvas. The number of rows and columns on the grid is determined by the size of the canvas and a use-specified parameter ρ. We then assign numeric labels to each point on the grid. Points on walls and doors are labelled 1 and 2 respectively. Others are labelled 0.

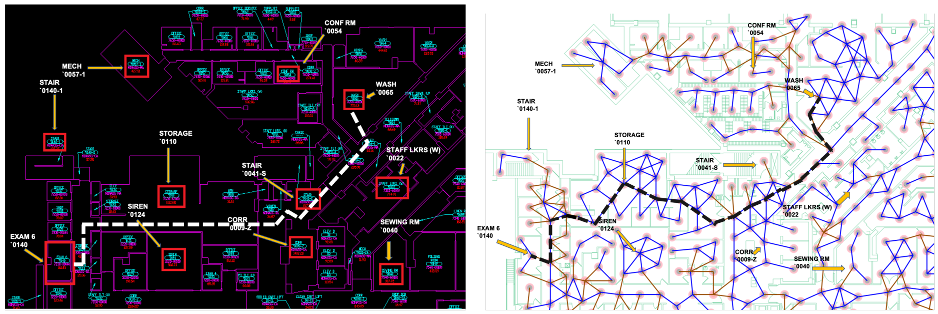
3. Graph extraction from the grid. The next step involves creating a spatial graph $G'(L', E', W', X')$ from the grid defined above. First we go over the labels extracted in step 1 and assign them as nodes L' (note: each room has a single label in the underlying CAD graph). We then add edges E' between the newly added nodes L'. Since the nodes were extracted from the grid, they too are organized in a 2-d space. We connect nodes in horizontal, vertical, and diagonal directions and assign weights depending on whether an edge crosses a door.

5. Graph sparsification. $G'(L', E', W', F')$ could be very dense for small values of ρ. This would imply that even a small room could have multiple nodes inside it, which is not ideal. Therefore, we sparsify $G'(L', E', W', F')$ to obtain a sparse spatial graph $G(L, E, W, F)$ using K-nearest neighbor search [9] and finally we remove small disconnected components. We then add edges between disjoint connected components while ensuring that the newly added edges are between the nodes which are geographically close. Note that only very few edges are added in the post processing step.

3 Demonstration

We run CAD2GRAPH on CAD files obtained from the University of Iowa Hospitals and Clinics (UIHC). We have CAD files for a total of 6 buildings and 71 floors. We ran CAD2GRAPH on all of them. Here we present a subsection of the visualization of a CAD file for a floor in Roy Craver building [3] for demonstration (See Figure 2). Figure 2 (a) visualizes the input CAD files. The red rectangles represent a subset of labelled rooms. Figure 2 (b) shows spatial graph extracted by CAD2GRAPH on top of the architectural layout. Here, we are only showing some of the labels and subsection of the floor for legibility. First, we notice that CAD2GRAPH is able to assign the labels to the correct nodes. As observed, the

[3] `https://www.facilities.uiowa.edu/building/0359`



(a) (b)

Fig. 2: (a) Visualization of a subset of CAD file showing one of the floors of the Roy Craver building in the University of Iowa Healthcare and Clinics.(b) Spatial graph extracted by CAD2GRAPH from the CAD file shown on the left.

stairs, storage rooms, mechanical rooms, and staff's rooms are all assigned in the right place. Next, we observe that the cross door edges (in brown) and non-cross door edges (in blue) have been correctly identified. As clearly visible, none of the blue edges cross any doors and all brown edges cross a door. Finally, we see a reasonable number of nodes within each open space and only one node in small rooms. Next, we also observe that the hallways are represented by single chain of blue edges, which is what we desired.

The dashed white line in Figure 2 (a) shows obstacle free walkable path from the room EXAM 6 to the room WASH 0065. The dashed black line in the 2 (b) is drawn over the edges along the shortest paths between the two rooms. As observed in the figure, the spatial graph extracted by CAD2GRAPH is actually able to infer edges which correspond to meaningful obstacle-free walkable paths between physical spaces. Moreover, the pearson's correlation between the euclidean distances between rooms and the shortest hop distance on extracted spatial graph was 0.83, further validating that the spatial graphs extracted by CAD2GRAPH do capture the underlying architectural space well.

4 Conclusion

In this paper, we presented CAD2GRAPH, an automated approach which extracts spatial graphs from CAD files. CAD2GRAPH lays a 2-d grid on top of a canvas created from the outlines of the walls read from the CAD file. It then carefully constructs a sparse graph from the grid. We demonstrated a subsection of spatial graph generated from a CAD file obtained from University of Iowa Hospitals and Clinics. Additional demos along with out source code are publicly available. Our results show that the generated graphs are meaningful. Once generated, these graphs can be stored in relational databases along with other datasets obtained from hospital operations and can be easily leveraged for spatial analysis of epidemics within healthcare facilitates.

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