In-building Coverage of Automated External Defibrillators Considering Pedestrian Flow

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Abstract:

Automated external defibrillators (AED), which are used as an emergency medical device for heart attacks, are required to be set in the critical transportation facilities such as metro rapid transit (MRT) stations or high speed rail (HSR) stations. However, location performance of current installations should be evaluated for appropriateness. In this paper, we aim to evaluate the accessibility of in-building AED coverage. To achieve our goal, we retrieve building geometry from Building Information Modeling (BIM) models for network construction and further modeling. We then incorporate pedestrian flow from video clips for the calculation of passage capacity in the target building. Finally, we determine if coverage of AED is appropriate based on the constructed network and attributes collected.

Keywords: Building Information Modeling (BIM); Medial axis transform; Human detection; Set covering; Automated external defibrillator (AED)

1. INTRODUCTION

Automated external defibrillator (AED) is a piece of equipment for emergency medicine for heart attacks. AEDs are installed in critical transportation facilities like Metro Stations, High Railroad Station and Airports. According to research in the domain of medicine, the survival of cardiac arrest patience is related to the response time .The optimum time for defibrillation is three to five minutes after the occurrence of cardiac arrest (U.S. Dept. of Labor, 2001). In other words, AED should be used as soon as possible when a cardiac arrest occurs. The utility of AED increases monotonically with the numbers of AEDs but there would be marginal utility appeared (Dao, T. H. D. et al, 2011).

In order to analyze the amount of time it will take for people to acquire the AED during an emergency, we need a graph to form the basis for route analysis. A graph is a geometric network composed of vertices and edges. Given a Building Information Modeling (BIM) model, such a graph could be constructed. There are many graph construction methods, among which two methods potentially suit our purpose best: visibility graph (VG) (Chu & Yeh, 2012) and medial axis transform (MAT) (Mortara & Spagnuolo, 2001). The Straight MAT algorithm (S-MAT) (Lee, 2004) constructs the medial axis by using the specific geometric relationship in typical buildings.

We utilized BIM in our research to retrieve geometric data, to automatically construct the network. BIM has been developed rapidly in recent years. There are research efforts focused on BIM and emergency rescue (Chen and Chu, 2015), evacuation simulation (Mayer et al., 2014), or network construction with BIM models (Chen and Huang, 2015; Taneja et al., 2015; Ruppel et al., 2010).

To determine the performance of in-building AED placement, we propose to form the problem into a set covering problem, which has been used as a model for designing evacuation guidance systems (Chu & Yeh, 2012) in complex building spaces. We believe AEDs should be distributed for maximum coverage of people.

In additional, we propose to consider pedestrian flow in our work. Human detection and tracking should be involved to retrieve the information of pedestrian flow. There are many studies in the domain of feature descriptor in computer vision. Haar-like features were used in the real-time human face detection (Viola & Jones, 2001). Scale-invariant feature transform finds a special point which can perceiving objects (Lowe, 1999). Histograms of oriented gradients (HOG) was extensively applied in human detection (Dalal & Triggs, 2005). For pedestrian tracking, HOG and Kalman filter (Li, C. et al., 2010) for video-based human detection and tracking were applied and there is also video-based detection for small groups (Ge, W. et al, 2012).

2. METHOD

This section presents the methodology proposed by this research, which includes data subtraction from BIM geometric data, construction of a graph for network analysis, and human detection via visual sensing.

2.1 Geometric Data from BIM Model

In the beginning, geometric attributes of objects from BIM model were retrieved automatically by using the Revit API through the C# programming language. Revit API was used for filtering objects of interest such as walls, doors, and stairs. After 3-D coordinates of each selected objects were taken from BIM model, they were read into Matlab for network construction. The process for data retrieval is shown in Figure 1.

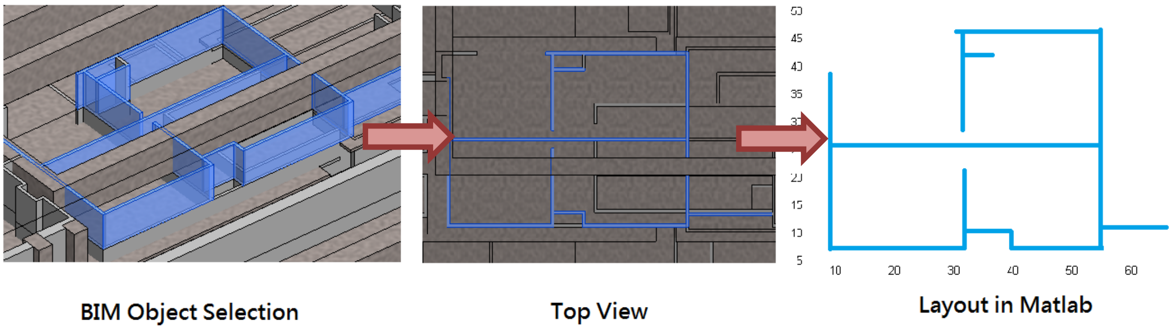

Figure 1. Process of constructing network directly from BIM model

2.2 Route Network Construction

In this research, we modified S-MAT in order to adapt the algorithm for our work (Chen and Huang, 2015). First we defined the data structures used in our network construction algorithm as follows. To construct our graph G represented the final route network, obs to be the set of obstacles' coordinates, such that $obs = \{V,E\}$, which V is the set of the two ends vertices that $V=\{ V_1, V_2,..., V_m\}$ of walls' and the set of obstacles edges $E = \{ e_1, e_2,...,e_m \}$ with $e_i = (V_i, V_{i+1})$. Vertices of door sets $d =\{ V_{d1}, V_{d2},..., V_{dm}\}$. Set $LL =\{L,V'\}$, L represent the set of links formed by concave vertices and convex vertices which showed in Figure 2 , which $L_i = (V_i, V_j)$, V_i, $V_j \in obs$. The mid points of links $V'=\{ V'_1, V'_2,..., V'_m\}$ are stored in the LL set.

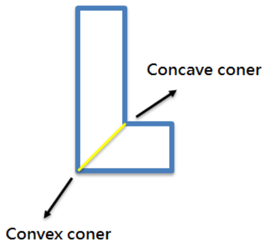

Figure 2. Definition of concave and convex in the polygon and the links formed by convex and concave vertices

However, the previous statements can only be used to deal with planar cases, so we defined a new matrix s which record the set of stairs $str = \{ V_s,R\}$, V_s is the set of ending vertices representing top and bottom runs of stairs as shown in Figure 3. $V_s = \{ V_1, V_2,.... ,V_m\}$. $R =\{ r_1, r_2,..., r_m \}$ would be set of stair linkage with $r_i = (V_i, V_{i+1})$, V_i, $V_{i+1} \in str$.

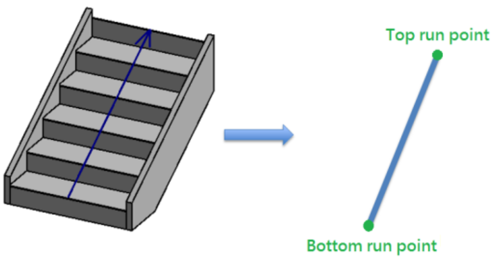

Figure 3. The schematic diagram of stairs representation.

Then, we used previously defined data structures for network construction, as described in the following.

(1). Define the vertices type (convex or concave) in *obs*. Produce the bisectors of the interior angles of convex vertices in *obs*, put them into *L1*.

(2). Extend the bisectors rays in *L1* to seek for intersections but extended rays couldn't penetrate any edge e_i. Pick up the intersection point which is closest to the origin vertex of ray and put them into set *L2*.

(3). Make bisector rays of concave corners formed by parent rays from *L2* where intersection points are used as starting points. Save the new points and rays into *L1*.

(4). Check the rays in *L1*. If it meets other rays in *L1* or points in *L2*, link and save them into *L4*.

(5). If any of rays in *L1* cannot find end point to form a link, then check whether origin point of the ray can connect to the center points of links between pairs of convex and concave vertices (in *LL*). If it could save them into *L4*. The connection segments between the mid points of links in *LL* are also stored into *L4*.

(6). Reconstruct *L4* by deleting repeated segments to the new list *L5*.

(7). Add links between doors (matrix *d*) and segments in *L5*, save them into *Ld*. Then combine *Ld* and *L5* as the temporary 2-D network *LT* which represented the floor it belongs.

(8). Add links between vertices of the stairs (V_i in matrix *str*) and *LT* where V_i and *LT* are on the same floor, save them in to *LS*. Then combine *LS* and *LT* into final 2-D network *L2D* which represents the floor it belongs.

(9). Add linkage of the stairs (*R* in each *str*), then combine all of 2-D network of the entire building into final 3-D network *L*.

(10). Remove repeated segments in *L*, then the final network *G* was finished.

2.3 Human Detection and Counting

To retrieve pedestrian flow information from videos in the buildings, first, we train a classifier.

(1) Train classifier

HOG is the selected feature descriptor. Images from the training dataset were divided into positive and negative sets. The training dataset were composed of images from the INRIA and MIT human database (INRIA, 2005; MIT, 2010). In addition, we add five hundred images of Metro station in Taiwan as negative examples into the training dataset. After HOG were computed for each image of the training dataset, they were input into a linear support vector machine (SVM), for training of the human detector. The process is shown in Figure 5.

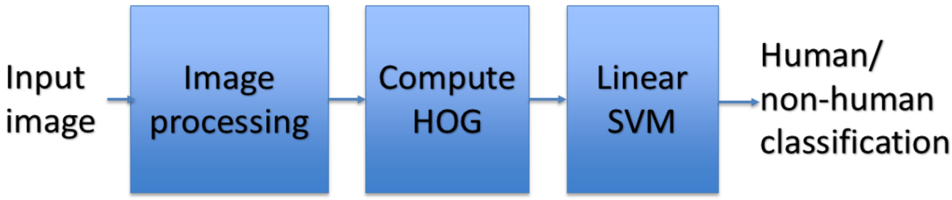

Figure 5. Processing of training classifier from training dataset.

(2) Detection

After the classifier was trained, each frame of input videos captured by in-building cameras were scanned by a sliding window on foregrounds. The classifier was used to determine if the scanned frame contains human image. The process is shown in Figure 6.

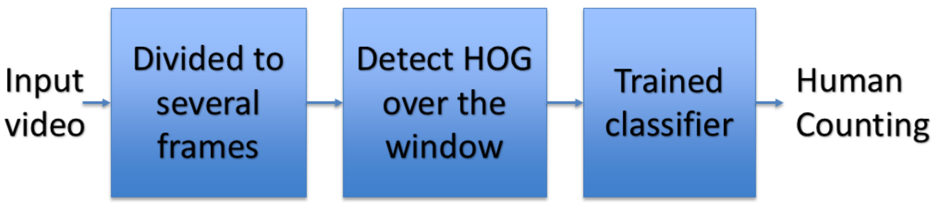

Figure 6. Processing of human detection from video.

2.4 Scenario

(1) Guiding

In our work, we suggest to provide a shortest cost route for people in the building to get AED and back. The information of existing AED from BIM would be considered here and the information of pedestrian flow would be the independence of the network. Then, when there is someone who got sudden cardiac arrest, other people in the building would be known a shortest path to get AED for the victim.

(2) Planning

In planning, we would set number of the AED we wanted. The location of candidate AEDs would be considered. We proposed a maximal set covering model to let the model choice where we should put the AEDs.

(3) Evaluate

In order to evaluate the utility of existing AED, first we would set a threshold of time which we accepted for people get and back AED. For the variation of time, the distribution of people in the building would not be the same. At last we would decide on an overall service efficiency indicators for existing AED in the respective threshold.

3. RESULTS

We used a 4-floors building to be our input BIM model for the geometric data. All floors of the testing building was consisted of the same deployment of doors and walls but different stairs between floors. Our network construct algorithm is implemented in Matlab. Figure 7 depicts the 2-D network of one floor of the building. The red lines denote the 2-D route network of this floor, and the green dots denote the doors on this floor.

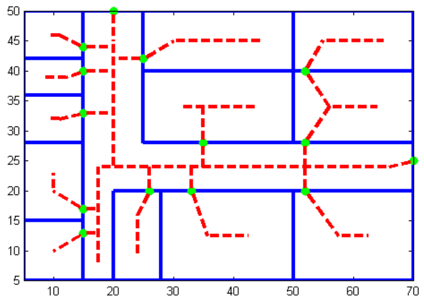

Figure 7. The top view of 2-D network of our testing example of floor 1

The result of elevation view of the 3-D network is shown in Figure 8. The blue lines in the figure represent the 2-D network from each floor and the green lines are the stairs connecting the floors in the building. Figure 9 shows the 3-D view of the resulting network.

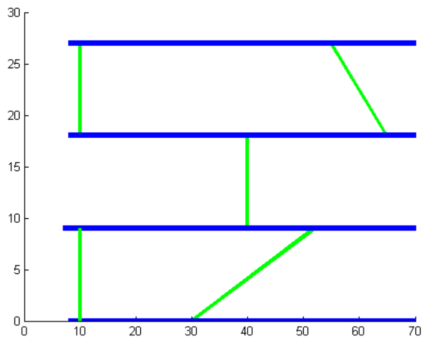

Figure 8. The side view of 3-D network of our testing example

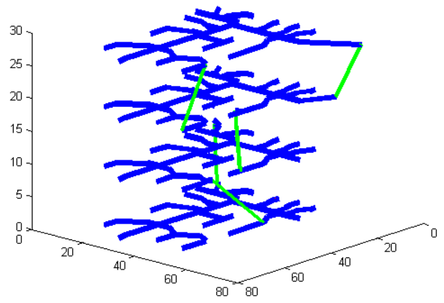

Figure 9. The 3-D view of our 3-D network for our testing network

Table 1 shows results for human detection.

Table 1. Tracking and counting results

	Dataset 1	Dataset 2	Dataset 3
Ground Truth	149	157	296
System Counting	167	120	188
Recall (%)	87.92	73.31	63.51

4. DISCUSSION

In our research, we automatically retrieving geometry data from a BIM model to construct in-building graph for network analysis. There were special geometries design for an existing MRT station in Taiwan, and the network construction is not well behaved under exceptions. The way BIM models are built may vary from people to people. We suggest a standard model building protocol for BIM model building for less number of exceptions. Given the constructed network and the statistics that could be derived from human detection, decision making through network modeling is possible. The evaluation of AED locations for pedestrians is to be modeled through classical models such as facility location. A potential formulation of the facility location is as follows.

The following formulation (P) is the Binary Integer Program (BIP) formulation of the capacitated facility location problem. The parameter K indicates the allowed number of AEDs to be placed. The decision variable x_{ij} is binary, and it represents assignment of demand i to AED j, and y_j is whether to place an AED at j. The parameter d_{ij} is the assignment cost such as travel distance or time from node i to node j, and p_j is the cost for establishing an AED at j.

$$\min \sum_{i=1}^{N} \sum_{j=1}^{M} d_{ij}\, x_{ij} + \sum_{j=1}^{M} p_j y_j \quad (1)$$

s. t.

$$\sum_{j=1}^{N} x_{ij} = 1 \qquad \forall i \in \{1,2,\dots,N\} \quad (2)$$

$$\sum_{i=1}^{N} x_{ij} \leq N y_j \qquad \forall j \in \{1,2,\dots,M\} \quad (3)$$

$$\sum_{j=1}^{N} y_j \leq K \quad (4)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in \{1,2,\dots,N\}, \forall j \in \{1,2,\dots,M\} \tag{5}$$

$$y_j \in \{0,1\} \qquad \forall j \in \{1,2,\dots,N\} \tag{6}$$

5. CONCLUSIONS

This paper proposes a modified method for constructing 3-D in-building route network that mainly considers geometry from a given BIM model. The route network would be used to analysis the coverage of AED. Apart from this, the pedestrian detection would be considering as the people being covered by the AEDs in different travel costs and also potentially the link cost between nodes to model dynamic behaviors such as congestion in the network.

The possible direction of ongoing research is to optimize the numbers of AED to minimize the cost for the operator or to optimize the locations for AED in fixed numbers of them to maximize the coverage of potential pedestrians.

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