A 3D INDOOR PEDESTRIAN SIMULATOR USING A SPATIAL DBMS

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Abstract: Most crowd simulation models for pedestrian dynamics are based on analytical approach using experimental settings without being related to real world data. In order for the models to be adapted to real world applications such as fire evacuation or warning systems, some technical aspects first must be resolved. First, the base data should represent the 3D indoor model which contains semantic information of each space. Second, in order to communicate with the indoor localization sensors to capture the real time pedestrians and to store the simulation results for later uses, the data should be in a DBMS instead of files. The purpose of this paper is two folds. One is to suggest a DBMS-based 3D modeling approach for pedestrian simulations. The other is to improve the existing floor field based pedestrian model by modifying the dynamic field. We illustrated the data construction processes and simulations using the proposed DBMS approach and the enhanced pedestrian model.

1 INTRODUCTION

Many micro-scale pedestrian simulation models have been proposed for the last decade and applied to fire evacuation problems or building safety evaluation. Recent development in localization sensors such as RFID draws our attention to indoor spaces and real-time applications. In order for our pedestrian models to be applied to real world indoor applications, they need to use different data formats other than current experimental file formats. The data should include semantic and topological information of building 3D spaces. Also, to be able to communicate with the location sensors to capture the real pedestrian movement, the data should be stored in a DBMS. Once data are stored in a database, the simulation results can also be stored back in the DB for real time evacuation guidance.

In this paper we proposed a method to build a simplified 3D model which is suitable for pedestrian simulation. Instead of representing the complex details of indoor spaces, we used the floor surfaces focusing on the fact that pedestrian movements take place only on the surfaces. We showed the process to build the 3D model using a spatial DBMS.

We also developed a pedestrian simulator and tested using our proposed 3D model. In the model, we used the floor field model as our base model and revised the dynamic field strategy.

2 RELATED WORKS

3D models currently used in the 3D GIS are actually 2.5 dimensional CAD-based data types focusing on visualization purpose in realistic way. They have limitations for analytical purposes in indoor space applications due to its lack of topological and semantic structure. As a solution to this, topological models along with using DBMSs for 3D objects have been recently investigated by some researchers (Arens 2003, Stoter et al. 2002, 2003, Zlatanova 2000). 3D models suggested by those are generally categorized as follows:

A. SOLID – FACE – EDGE – NODE
B. SOLID – FACE – NODE
C. SOLID – FACE

The three types are data models for defining 3D volumes not for interior spaces. CAD-based models have been used widely and there is a growing interest in using IFC (Industry Foundation Classes) format especially for modeling and developing building information systems. Although these

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formats offer flexibility in modeling indoor spaces with various data primitives, they are file-based formats and, thus, have limitations in being used in indoor information systems as mentioned earlier. On the other hand, CityGML which was adopted as a standard by OGC (Open Geospatial Consortium) is a 3D model that provides different levels of details ranging from region to interior spaces (Kolbe 2008, Stadler et al. 2007). CityGML is based on XML format for the storage of data and has capability of storing complex semantic information. However, it has not provided fully functional data base implementation. One of the reasons is attributed to the fact that current commercial DBMSs do not fully support topological structure of 3D objects yet.

Evacuation models have been studied in various fields such as network flow problems, traffic assignment problems, and are generally categorized into two; macroscopic and microscopic models (Hamacher et al. 2001).

Macroscopic models appear in network flow or traffic assignment problems and take optimization approach using node-link-based graphs as the data format. They consider pedestrians as a homogeneous group to be assigned to nodes or links for movements and do not take into account the individual interactions during the movement. On the other hand, microscopic models emphasize individual evacuees' movement and their responses to other evacuees and physical environment such as walls and obstacles. Microscopic models are mainly based on simulation and use fine-grained grid cells as the base format for simulation. They have been used by experts in different domains including architectural design for the analytical purposes of the structural implications on the human movement especially in emergency situations.

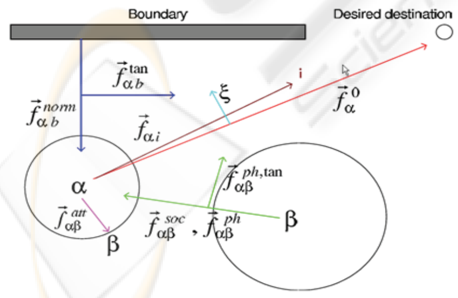


Figure 1: Helbing's social force model.

Different micro-simulation models have been proposed over the last decades (Schadschneider 2001) but two approaches are getting attention; social force model and floor field model (Kirchner et al. 2002). A frequently cited model of former type is advanced by Helbing and collegues (Helbing et al. 1997, 2001) and is based on strong mathematical calculation acted on agents to determine its movement to destination (e.g. exits). Helbing's model considers the effects of each agent upon all other agents and physical environment (Figure 1) leading to the computation of $O(n^2)$ complexity, which is unfavorable for computer-based simulation with many agents (Henein et al. 2005, 2007).

In recent years there is a growing interest to use cellular automata as the base of micro-simulation (Blue et al. 1999, Klupfel et al. 2002). Kirchner and colleagues (Kirchner et al. 2002) have proposed CA-based floor field model, where two kinds of fields—static and dynamic—are introduced to translate Helbing's long-ranged interaction of agents into a local interaction. Although this model considers only local interactions, they showed that the resulting global phenomena share properties from the social force model such as lane formation, oscillations at bottlenecks, and fast-is-slower effects. The floor field model uses grid cells as the data structure and computes movement of an agent at each time step choosing the next destination among adjacent cells. This makes computer simulation more effective.

In this paper we focus on Kirchner's model as our base model. We will later describe the limitation of his dynamic field computation strategy and how we revised it.

3 A SIMPLIFIED INDOOR 3D MODEL

In our previous study (Park et al. 2007) we had proposed a 2D-3D hybrid data model that can be used both in 2D-based semantic queries and 3D visualization. We used two separate models, 2D GIS layers and 3D models, and combined them using a database table as the linkage method.

Although the previous file-based approach was satisfactory in incorporating semantic and topological functionality into a 3D model, it has some drawbacks. First, two models are created separately and need additional table for linkage, which makes consistent maintenance difficult. Second, building a 3D model by separating compartments requires additional time and cost. Finally, such file-based models are not easy to store many buildings and, most importantly, they cannot be integrated with client/server applications such as sensor systems (i.e. RFID, UWB, thermal sensors).

To solve these problems, we proposed in this research a new approach that uses a DBMS instead of files. Because semantic information is now extracted from database tables and used for analyses and 2D/3D visualization, the new model does not require an additional table for linkage. This data model has a multi-layered structure based on 2D building floor plans as the previous file-based model. It retains 2D topology because building floor plans are converted into 2D GIS layers (shapefiles) and then are stored in a spatial database. Thus, it is possible to perform topology-based analyses and operations provided by the DBMS. Also, all records containing geometries can be visualized for 2D and 3D.

Indoor location-based application use locations and tracing information of pedestrians who move on the surface floors in the building. This means that it is possible to retrieve semantic data and perform analytical operations only using floor surfaces in such applications (i.e. indoor crowd simulation, indoor wayfinding). This is the reason that we choose to use building floor plans as the base data type. For the connection of floors, we also converted the stairs to a simple set of connected polygons and then stored in the DBMS. Figure 2 illustrates the process for storing indoor objects in a database. This shows that we used only the bottom part of a room polyhedron.

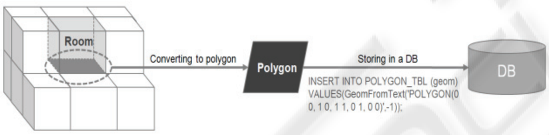


Figure 2: An example of storing rooms floors in a spatial DB.

This approach can well fit in DBMS-based applications due to less complex and simplified data construction process. Using a DBMS against file format gives many merits including data sharing, management, security, back-up and speed. It is also possible to integrate with sensor systems by storing the sensor information in the database. In this study, we used PostgreSQL/PostGIS for the DBMS. PostgreSQL is an open source object-relational database system, freely downloadable. To display indoor objects in 3D stored in the database, we used OpenGL library and it also interacts with the PostGIS database for the data retrieval and visualization (Figure 3).

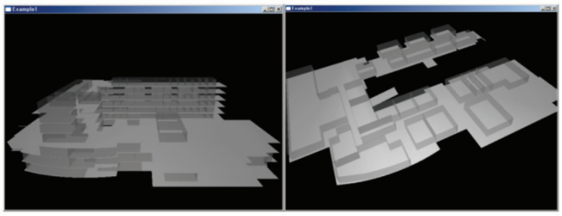


Figure 3: 3D visualization using data from a spatial DBMS.

4 FLOOR FIELD MODEL

We chose Kirchner model as our base model. His original model (Kircher et al. 2002) and some variations (Nishinari et al. 2005) have demonstrated the ability to capture different pedestrian behaviors discussed in the previous section while being computationally efficient. First, we will describe the basic features of the floor field model and, then, describe how we improved the model.

4.1 Two Fields in Floor Field Model

Floor field model is basically a multi-agent simulation model. Here, each pedestrian is an agent who interacts with environments and other pedestrians. The group of such agents forms a multi-agent system (MAS). The agents in MAS have some important characteristics as follows (Wooldridge 2002).

- Autonomy: Agents are at least partially autonomous. An agent reacts to environment and other agents with autonomous manner.
- Local View: No agent has a full global view of the system. Each agent has no guidance to exits, instead, it moves only by local rules.
- Decentralization: Each agent in the system is equal and no agent controls others.

These characteristics of MAS in pedestrian models are frequently implemented using cellular automata (CA) and Kirchner model is also based on CA. CA theories are introduced in many related works, thus we will not introduce them here.

The basic data structure of Kirchner model is grid cells and each cell represents the position of an agent and contains two types of numeric values which the agent consults to move. These values are stored in two layers; static field and dynamic field.

A cell in the static field indicates the shortest distance to an exit. An agent is in position to know the direction to the nearest exit by these values of its nearby cells.

While the static field has fixed values computed by the physical distance, the dynamic field stores dynamically changing values indicating agents' virtual traces left as they move along their paths. As an ant use its pheromone for mating (Bonabeau 1999), the dynamic field is similarly modeled where an agent diffuses its influence and gradually diminishes it as it moves. Without having direct knowledge of where other agents are, it can follow other nearby agents by consulting dynamic values.

It is possible to simulate different pedestrian strategies by varying the degree to which an agent is sensitive to static or dynamic field. For example, we can model herding behaviors in panic situation by increasing sensitivity to the dynamic field. Such sensitivity factors are described in the following section.

4.2 Floor Field Rule

An agent in the floor field model consults the scores of its adjacent cells to move. A score represent the desirability or the attraction of the cell and the score of cell *i* is computed by the following formula (Colin 2005):

$$Score(i) = exp(k_d D_i) \times exp(k_s S_i) \times \xi_i \times \eta_i \qquad (1)$$

where, $\boldsymbol{D_i}$: the dynamic field value in cell i

$\boldsymbol{S_i}$: the static field value in cell i

$\boldsymbol{k_d}$, $\boldsymbol{k_s}$: scaling parameters governing the degree to which an agent is sensitive to dynamic field or static field respectively

$\boldsymbol{\xi_i}$: 0 for forbidden cells (e.g. walls, obstacles) and 1 otherwise

$\boldsymbol{\eta_i}$: Occupancy of agent in the cell. 0 if an agent is on the cell, and 1 otherwise.

Kirchner and his colleagues used probability *P(i)*, the normalized value of *score(i)* against all nine adjacent cells including itself. However, it turns out that using *score(i)* and *p(i)* has same effect since they are always proportional to each other in the adjacent nine cells.

The static field is first computed using a shortest distance algorithm such as the famous Dijkstra's algorithm. Then, all agents decide on their desired cells and they all move simultaneously. We converted Kirchner's rule to a pseudocode. The following pseudocode represents the movement of an agent.

After an agent has moved to one of its adjacent cells except its own, the dynamic value at the origin is increased by one: $D_i \rightarrow D_i + 1$ (Burstedde 2001, Nishinari 2005). Then a portion(α) of D_i is distributed equally to the adjacent cells (diffuse) and a portion(β) of D_i itself becomes diminished. α and β is the input parameters to the model. This diffuse and decay process follows the analogy of ant pheromones which are left for a while and decayed gradually. Agents consult dynamic and static values at the same time. The scaling factors($\boldsymbol{k_d}$ and $\boldsymbol{k_s}$) are used to control the degree to which an agent react more to one of two fields. The ratio k_d / k_s may be interpreted as the degree of panic. The bigger the ratio, the more an agent tend to follow others.

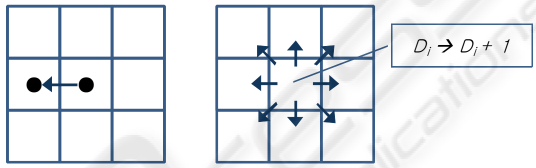


Figure 4: Diffuse and decay of the dynamic value.

5 REVISED DYNAMIC FIELD

The dynamic field is believed to be an effective translation of the long-ranged interaction of Helbing's model (Helbing et al. 1997, 2001) to local interaction. However, Kirchner model do not differentiate an agent's dynamic value with ones of others. The model simply adds the diffused and decayed values to the existing values.

It is reasonable that we consider that an agent should be able to avoid its own influence as an ant uses its pheromone. Kirchner's dynamic field does not cause a significant problem when an agent moves to one direction. However, as shown in figure 5, there may be cases when an agent comes back to its own trace area. Then, the agent has no choice but to get influenced by its own dynamic value if not much.

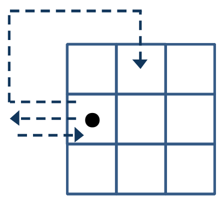


Figure 5: A problem of using the dynamic value when returning to the own dynamic area.

We modified the Kirchner's dynamic field such that an agent can exclude its own dynamic value when computing equation (1). To make it possible, the model should have a data structure that allows each cell to store a list of dynamic values of agents that have chance to leave their values to that cell. If we put the dynamic value of agent p as d(p, k), then a set D(k) having a list of dynamic values can be given by

$$D(k) = \{d(p, k) : p=1, 2, \ldots, n\}$$

Here, n is the number of agents that have the dynamic values that are greater than zero. We might easily presume that maintaining such set makes the model $O(n^2)$ complexity which are computationally unfavorable. However, D(k) does not contain the entire agents' values and, instead, keep only those agents' values that pass k's nearby areas and keep non zero dynamic values. Thus, each cell keeps relatively small number of entries compared to the whole number of agents. For the implementation of the simulator, we used .NET C# language, and the data structure called Dictionary. The dictionary keeps a list of (*key, value*) pairs, where the *key* represent an agent while the *value* is its dynamic value.

If an agent p happens to leave any portion of its dynamic value to cell k more than once, d(p, k) maintains only the maximum value among them. This makes sense if we imagine that the decaying scent get again maximized when an ant returns to that area.

$$d(p, k) = \max\{d(p, k): p=1, 2, \ldots, m\}$$

Here, m is the number that an agent p leaves any portion of its dynamic values to cell k. Eventually, when consulting the score(i), agent q at cell i is able to exclude its own dynamic values in the adjacent cells and only takes the maximum one from each D(k) into account.

$$D(k)_q = \max\{d(p, k): p \neq q\}$$

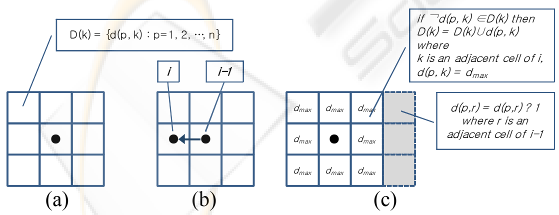


Figure 6: The list of dynamic values at cell k(a), an agent's movement, and diffusion and decay(c).

We also modified the diffusion and decay strategy in our model. As shown in Figure 6, right after an agent p moves, d(p, k) values of the adjacent cells of cell *i-1* is decreased by one, and then d(p, k)s of the adjacent cells of the current cell *i* are newly assigned the maximum dynamic value. Then, what is the maximum dynamic value? Let us first take an example before describing it.

Figure 7. shows a building floor plan that has a main exit and a room inside with a door. We assume Agent A and B are located as in the figure. The numbers on the cells indicated the static field values computed from the main exit.

In Kirchner's model, the dynamic values are assigned regardless of the static values of the current location. In a simple rectangular space as those used by the author, such strategy may not cause much problem since the static values lead the agents to the exit eventually even though the dynamic values are much greater than its static counterparts at the current location.

However, in using real building plans where multiple rooms are located inside, such strategy can cause a problem. If static values are gradually assigned from main exit(s), inner rooms can have very low values depending on the size of the building. Let's suppose Agent B reaches the room door. If there are multiple agents in the room and they happen to leave bigger dynamic values in the back of agent B than the static values in that area, then the agent can get stuck in the door because one or more empty adjacent cells in the back may be bigger than that of forward cells.

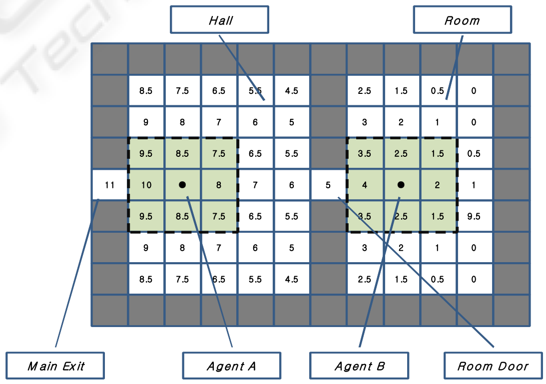


Figure 7: The problem of initializing the dynamic values in a building having multiple compartments.

To solve this problem, we changed the diffuse and decay strategy by letting an agent choose the maximum value of the adjacent static values as its initial dynamic value. This way, any agent inside the space can have the initial dynamic value which is proportional to the corresponding static values. The static and dynamic values are of different units; one is distance and the other is an abstract interpretation for attraction force. In order for a model to control the sensitivity to these two field values, two values should be comparable to each other at any cell. That is the reason we synchronizes the initial dynamic values with the static values every time an agent moves. Following is a pseudocode with the modified dynamic value computation.

```
i = b                 // Set i to the beginning node
O=Φ                   // Set the open list to empty set
D(k)=Φ for k∈N        // Set the Dynamic list for each node to empty set
P(i) = null           // Set the parent node of node i to null
s(i) = 0              // Set the score of the node i to 0
O = (i)               // Add the node i to the open list
While (i ≠ E)         // Iterate while node-i is not the destination node
{
    // Choose the maximum score node among the open list.
    Let i ∈ O be a node for which
     s(i) = max{ s(i) : i ∈ O } and s(i) > 0

    // If the agent- i has moved to a node other than itself
    if( i ≠ P(i) )
    {
        // For each node in the open list, if the node contains
        // the agent p's dynamic value, decrease it by one
        for each k ∈ O
            if d(p, k) ∈ D(k) then d(p,k) = d(p,k) - 1

        O=Φ        // Reset the open list to empty set
        // For each of searchable adjacent nodes of i
        // (i.e. excluding those obstacles as walls and furniture and
        // including i and) set parent, and add to the open list
        // j: Adjacent nodes of i including i itself
        for each ( i, j ) ∈ A(i)
        {
            // If not in the open list, add j to it
            if j ∉O then O = O ∪(j)
            // Set the parent node of j to i
            P(j) = i
        }
        // Get the maximum static value among those
        // in the open list nodes (t(k): static value in cell k)
        d_max = max{ t(k) : k ∈ O }
        // For each node in the open list, if the dynamic list does
        // not contain the dynamic value of node k, add it to D(k)
        for each k ∈ O
        {
            d(p, k) = d_max
            if d(p, k) ∉ D(k) then D(k) = D(k) ∪d(p, k)
        }
    }
}
```

Figure 8: Pseudocode for an agent movement.

6 SIMULATION

6.1 3D Data Model Construction

For the simulation, we constructed a 3D model of a real campus building following the proposed approach described in the previous section. The building has two main exits; the one in the front is wider than the side exit. We first simplified the CAD floor plans for the test purpose and they were converted to shapefiles, then stored into the PostGIS. The stairs were simplified and decomposed into several connected polygons and also stored in the DBMS. Once all data are stored, all connected floor surfaces now can be retrieved simply by SQL queries. Finally, the queried surface data were then converted to grid cell data for simulation. We set the cell size to 40cm × 40cm considering the human physical size.

We developed a simulator using the C# language and the OpenGL library. Figure 9 shows the interface of the simulator and the 3D model used in the simulation. The simulator reads in the data from the PostGIS or the cellularized surface data. Once the data are read in, they can be visualized in 2D or 3D in OpenGL-based display module. In the simulator, we can input parameters such as k_s, k_d, d_{max}, time step, the number of agents, the number of iterations and the increments of the agents number in the iterations.

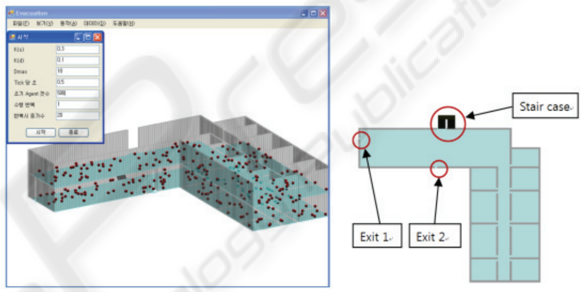
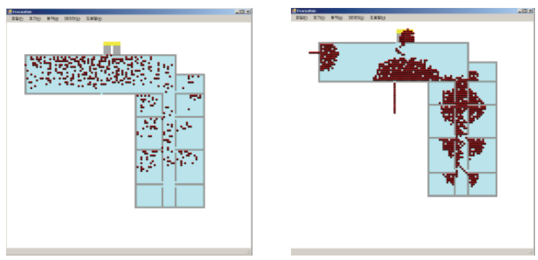


Figure 9: The pedestrian simulator and the 3D model used in the test.

6.2 Results

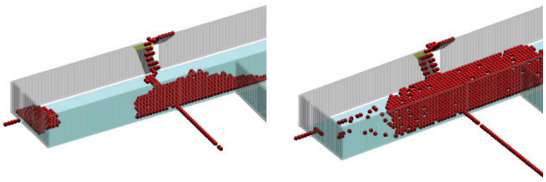
The simulator first constructs the static field computing the shortest distance from the two main exits to each cell in the building. We used varying numbers for the parameters. Figure 10 shows the two extreme cases; k_s = 0 and k_d = 0. As can be easily guessed, k_s = 0 makes the agents wander around the space herding towards nearby agents without any clue of direction to exits. On the other hand, K_d = 0 causes the agents flow directly towards exits without any herding behaviors.



(a) (b)

Figure 10: Snapshot of two extreme cases; k_s = 0(a) and k_d = 0(b).

Figure 10 shows the effect of varying k_d values. While $k_d = 0$ correctly leads the agents to exits where the agents are belonged to based on their static values, $k_d > 0$ begins to show the herding behaviors. When a few agents happen to leave the group, others begin to follow them, leading to increasing the use of the side exit.



(a) (b)

Figure 11: The effect of varying k_d; $k_d = 0$(a) and $k_d/k_s = 0.5$.

We further investigated the effect of the dynamic term k_d using varying values. Table 1 shows the effect of K_d on the evacuation time and the use rate of the side exit (Exit 1). 2000 agents were used for the test. We observed that the use rate of the side exit gets increased in proportion to k_d. However, using k_d>0 slightly decreased the total number exited and then didn't change it significantly thereafter. This was because Exit 2, the main exit, is wider around twice as much as Exit 1. This indicates that using wider second exit can help decreasing the number exited.

Table 1: The effect of Varying K_d on evacuation time and use of the side exit.

	k_d=0	k_d=0.05	k_d=0.1	k_d=0.25	k_d=0.5	k_d=1.0
Exit1	120	351	422	484	566	689
Exit2	1880	1649	1578	1516	1434	1311
evactime	945	723	702	688	670	632

Another experiment was carried out to measure the time escaped with increasing agents and varying k_d/k_s. The results are provided in Figure 12 showing the number of outgoing agents and the time taken with 6 sets of k_d/k_s. The (k_d, k_s) value pairs in the test were (0, 0.3), (1, 0.1), (0.25, 0.5), (0.1, 0.1), (0.05, 0.1), and (0.1, 1). The number of agents used were 500~5000. We observed that $k_d = 0$ made the curve almost linear increase while using different k_ds that are greater than 0 did not cause significant differences. However, the result shows leading people to alternative exit definitely decrease the overall escape time.

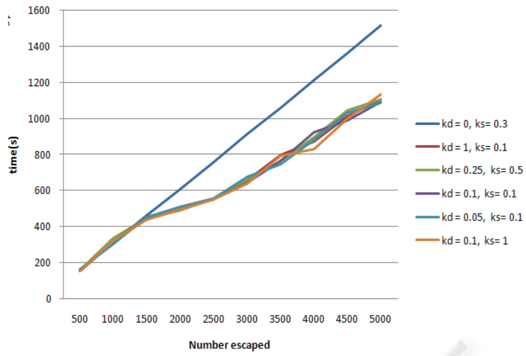


Figure 12: Time take for escape of varying number of agents with different sets of k_d/k_s.

7 CONCLUDING REMARKS

In this study, we suggested a process to develop a 3D evacuation simulator instead of trying to improve the scientific investigation of crowd behaviors. In order to be able to integrate our system with real-time evacuation or rescuers' guidance, we suggested a less complex 3D indoor model focusing on the semantic information and navigation taking place on the floor surface. We also implemented the proposed model using a SDBMS and 3D visualization.

We also suggested a modified floor field pedestrian model using Kirchner's model. His model has demonstrated the ability to represent different pedestrian situations while maintaining basic MAS(multi-agent system) rules of autonomy and localization. However, his model is unable to capture the differences in dynamic values of different agents.

We have improved the floor field model in order for an agent to be able to exclude the influences of its own dynamic values by changing the data structure of dynamic field, which better conforms the analogy of ant pheromones. Also, by turning his constantly increasing and decreasing dynamic term D into dynamically changing term around agent's nearby static values, our model has shown the flexibility to more complex indoor configurations.

We currently keep improving the model by incorporating visibility effects and multiple velocities. Also, we focus on relating our model to real world applications. In this paper, we briefly introduced the use of spatial DBMS and 3D structures. However, with some refinements, we believe that our model can be adapted to real world 3D indoor applications equipped with indoor localization sensors. Then, we will be able to use the real distribution of indoor pedestrians captured by sensors instead of using randomly generated agents.

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