Calculating Least Risk Paths in 3D Indoor Space

Ann Vanclooster, Philippe De Maeyer, Veerle Fack and Nico Van de Weghe

Abstract Over the last couple of years, applications that support navigation and wayfinding in indoor spaces have become one of the booming industries. However, the algorithmic development to support indoor navigation has so far been left mostly untouched, as most applications mainly rely on adapting Dijkstra's shortest path algorithm to an indoor network. In outdoor space, several alternative algorithms have been proposed adding a more cognitive notion to the calculated paths and as such adhering to the natural wayfinding behaviour (e.g. simplest paths, least risk paths). The need for indoor cognitive algorithms is highlighted by a more challenged navigation and orientation due to the specific indoor structure (e.g. fragmentation, less visibility, confined areas…). Therefore, the aim of this research is to extend those richer cognitive algorithms to three-dimensional indoor environments. More specifically for this chapter, we will focus on the application of the least risk path algorithm of Grum (2005) to an indoor space. The algorithm as proposed by Grum (2005) is duplicated and tested in a complex multi-storey building. The results of several least risk path calculations are compared to their equivalent shortest paths in terms of path length, improvement in route description complexity and riskiness of the selected edges. The tests lead to the conclusion that the original least risk path algorithm has to be adjusted to be more compatible with the

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specificities of indoor spaces. Therefore, several adjustments and improvements to the original algorithm are proposed which will be implemented in future work, in an effort to improve the overall user experience during navigation in indoor environments.

Keywords Indoor • Navigation • Algorithms • Wayfinding • Cognition

1 Introduction and Problem Statement

Over the last decade, indoor spaces have become more and more prevalent as research topic within geospatial research environments (Worboys 2011). Past developments in the modelling and analysis of three-dimensional environments have already given us a better structural understanding of the use and possibilities of indoor environments (Becker et al. 2013; Boguslawski et al. 2011). These evolutions combined with the rapid progress in spatial information services and computing technology (Gartner et al. 2009) have put three-dimensional modelling and analyses more and more in the spotlight. Also, given the fact that as human beings we spend most of our time indoors (Jenkins et al. 1992), indoor environments have become an indispensable part of current geospatial research.

Within indoor research, applications that support navigation and wayfinding are of major interest. A recent boost in technological advancements for tracking people in indoor environments has led to increasing possibilities for the development of indoor navigational models (Mautz et al. 2010). Alternatively, several researchers have developed a wide variety of indoor navigational models ranging from abstract space models (Becker et al. 2009) and 3D models (Coors 2003; Li and He 2008) to pure network models (Jensen et al. 2009; Karas et al. 2006; Lee 2004). While these models might be useful in specific situations, a general framework for indoor navigation modelling has still to reach full maturity (Nagel et al. 2010). Far more recent is the commercial interest with public data gathering for navigation support in several indoor buildings (e.g. Google Maps Indoor), which demonstrates the current importance of this application field.

While a considerate amount of work is oriented to the abstract modelling and technological aspect of navigation, the algorithmic development to support navigation in indoor built environments has so far been left mostly untouched. Appropriate and accurate algorithmic support is nonetheless a necessary component for a successful wayfinding experience. In outdoor research, a wide variety of different algorithms exist, initially originating from shortest path algorithms, studied for over 50 years in mathematical sciences (Cherkassky et al. 1996). Many of them are based on the famous Dijkstra shortest path algorithm (Dijkstra 1959) with gradually more and more adaptations and extensions for better performance in terms of speed, storage and calculation flexibility (Zhan and Noon 1998). Over time, alternative algorithms were proposed adding a more cognitive notion to the calculated paths and as such adhering to the natural wayfinding behaviour in outdoor environments. Examples are hierarchical paths (Fu et al. 2006), paths minimizing route complexity (Duckham and Kulik 2003; Richter and Duckham 2008) or optimizing risks along the described routes (Grum 2005). The major advantage of those algorithms is their more qualitative description of routes and their changed embedded cost function, simplifying the use and understanding of the calculated routes and as such improving the entire act of navigation and wayfinding.

Algorithms for 3D indoor navigation are currently restricted to Dijkstra or derived algorithms. The results of those shortest path algorithms not necessarily return realistic paths in terms of what an unfamiliar indoor wayfinder would need to navigate this building, i.e. using complex intersections, avoiding main walking areas etc. To date, only few researchers have attempted to approach algorithms for indoor navigation differently, for example incorporating dynamic events (Musliman et al. 2008), or modelling evacuation situations (Atila et al. 2013; Vanclooster et al. 2012). However, the need for more cognitively rich algorithms is even more pronounced in indoor space than outdoors. This has its origin in the explicit distinctiveness in structure, constraints and usage between indoor and outdoor environments. Outdoor environments are commonly described as continuous with little constraints, while the perception of buildings is strongly influenced by the architectural enclosures (Li 2008; Walton and Worboys 2009). Also, wayfinding tasks in multi-level buildings have proven to be more challenging than outdoors, for reasons of disorientation (due to multiple floor levels and staircases), and less visual aid (e.g. landmarks are less obviously recognizable; corners and narrow corridors prevent a complete overview) (Hölscher et al. 2007). As such, building occupants are faced with a deficient perspective on the building structure, influencing their movement behaviour (Hölscher et al. 2007). Algorithms developed to support a smooth navigation will have to consider these intricacies.

The main goal of this chapter is to translate existing outdoor cognitive algorithms to an indoor environment to provide in indoor route calculations that are more aligned to indoor human wayfinding behaviour. In a first phase, the original algorithm is implemented in indoor environments and tested in terms of its efficiency to reduce navigational complexity of the routes and as such improve the cognitive route instructions. The tests consist of comparing the paths suggested by the cognitive algorithm with those of the shortest path variant in indoor spaces. Also, the results indoor will be compared to the results obtained by the original algorithm. In this chapter, we currently focus on the implementation and applicability testing of the least risk path algorithm as described by Grum (2005). Later on, we are also planning to integrate the simplest path algorithm in indoor environments and develop a more general cognitive algorithm.

The remainder of the chapter is organized as follows. Section 2 elaborates on the definition of the least risk path algorithm and its relationship to other cognitive algorithms and the shortest path algorithm. In Sect. 3, the indoor dataset is presented in combination with the choices and assumptions made when developing the indoor network model. In the case study in Sect. 4, the outdoor least risk path algorithm is duplicated and implemented in an indoor setting with multiple analyses comparing its results. Section 5 discusses multiple improvements to be made to the original algorithm to be more compatible with the specificities of indoor environments. This chapter is completed with a conclusion on the discussed issues.

2 Least Risk Path Algorithm

The ultimate goal of cognitive algorithms is to lower the cognitive load during the wayfinding experience. Various cognitive studies have indicated that humans during navigation value the form and complexity of route instructions equally as much as the total path length (Duckham and Kulik 2003). This is the reason why several algorithms have been developed for outdoor space with the purpose of simplifying the navigation task for unfamiliar users. In this chapter, the least risk algorithm forms our focal point as it is implemented in a three-dimensional indoor environment (Grum 2005). More specifically, we want to investigate whether the results of the least risk path algorithm have the same connotation and importance in indoor spaces as in outdoor space where it was originally developed. Also, the least risk path algorithm is analysed for its applicability in providing route instructions that are more adhering to the natural wayfinding behaviour of unfamiliar users in indoor space.

The least risk path as described by Grum (2005) calculates the path between two points where a wayfinder has the least risk of getting lost along the path, by selecting all edges and intersections with a minimal risk value. The risk of getting lost is measured at every intersection with the cost of the risk calculated as the cost for taking the wrong decision at the intersection. This algorithm assumes (1) that the person taking the path is unfamiliar with its environment (and as such local landmarks). Also, (2) when taking a wrong path segment, the wayfinder notices this immediately and turns back at the next intersection (Grum 2005). While the algorithm assumes that an unfamiliar user immediately notices a wrong choice, Grum (2005) also acknowledges that the algorithm needs to be tested for its representativeness of the actual behaviour of users (Fig. 1).

The formula for the calculation of the risk value at a certain intersection and the total risk of an entire path p is as follows:

$$Total\_Risk(p) = \sum risk\_values(i) + \sum lengths \tag{1}$$

$$Risk\_Value(i) = \frac{2 * \sum length\_wrong\_choices}{possible\_choices} \tag{2}$$

Equation 2 indicates that the risk value is dependent on the number of street segments converging on the intersection, combined with twice the length of each individual segment (as it assumes the user will return through the same edge when going in the wrong direction). The risk value of an intersection increases with more extensive intersections and with many long edges that could be taken

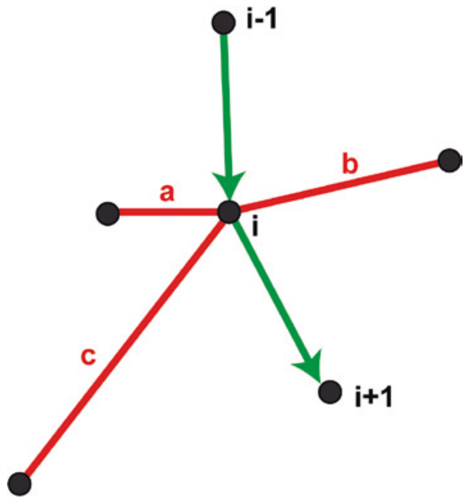

Fig. 1 Risk value calculation at intersection *i*. The *green* path depicts the chosen path, the *red* edges present wrong path choices at intersection *i*

wrongly. As such, the algorithm favours paths with combined long edges and easy intersections. The risk value is in this case a measure of the average length of a single edge that could be taken wrongly at that intersection. The formula for the total risk of a path (Eq. 1) balances the sum of all intersection-based risk values with the length of the actually taken edges. Both elements contribute in this case equally as much to the total risk of a certain path. Applied to indoor environments, it could be assumed that the least risk path might be quite similar to the shortest path and simplest path. Indoor spaces often consist of many decision points and short edges, along long corridors making derivations of the shortest path more difficult than outdoors. This will be examined in Sect. 4.

The algorithmic structure of the least risk path algorithm is similar to Dijkstra with a continuous loop over all nodes including three consecutive steps:

1. Detect the next smallest node
2. Change the selected node to the next smallest node
3. Adjust the cost values for adjacent nodes

It is only in the third step that the least risk path differs from the Dijkstra algorithm since the cost value is not only dependent on the length of the edge but also on the risk value of each intersection that is passed. This risk value is dependent on the previous route taken to reach the selected node and the length of its adjacent edges. The following steps in the 'adjust cost section' are consecutively executed:

Algorithm: **Adjust cost calculation in selected node**

//Algorithm which calculates and adjusts the costs for each edge leaving the selected node.

Input: *Costs in selected nodes and all endnodes of edges converging in the selected node*

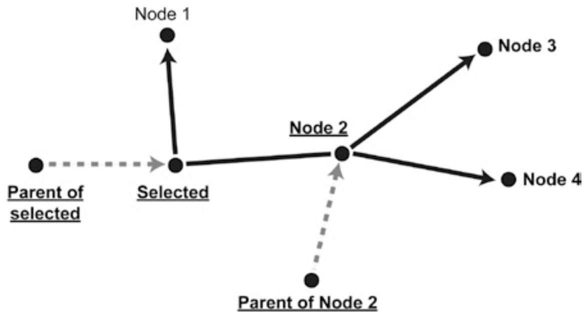

Fig. 2 Visual example of the implementation of cost adjustment in the least risk path algorithm. The *underlined nodes* have already been calculated and selected. *Bold nodes* have been calculated but not yet selected. Nodes 1, 3 and 4 will be (re)calculated starting in the selected node

Output: *Updated costs for endnodes of edges converging in the selected node*
Calculate the number of edges leaving from selected node and select each edge successively
Case a (Endnode of selected edge has not been selected):

- Calculate total risk values for endnode based on all possible routes arriving in selected node
- Store the minimal value by comparing it with the currently stored value in endnode

Case b (Endnode of selected edge has been selected BUT adjacent nodes have not been selected):

- Calculate the number of edges leaving from endnode and select each edge successively
- Calculate total risk values for endnode based on all possible routes arriving in selected node and the connection between the selected node and its adjacent node
- Store the minimal value by comparing it with the currently stored value

Figure 2 shows that starting in the selected node, first Node 1 and Node 2 will be checked. Node 1 has not yet been selected nor calculated (case a) and will be calculated as a path coming from selected node and its consecutive parent node. Node 2 has already been calculated and selected as next smallest cost node with a path connecting through its parent. When Node 2 was selected, Node 3 and Node 4 were consecutively calculated with [Node 2—Parent of Node 2] as previous path nodes. Although Node 3 and Node 4 were previously calculated with Node 2 as their immediate parent node, the path coming from [Parent of Selected-Selected-Node 2] could possibly be shorter than through [Parent of Node 2-Node 2]. This will be checked through case b of the algorithm. This section also forms the increased computational complexity compared to the Dijkstra shortest path algorithm.

For each path, the total length and risk values for the intermediate nodes are calculated in both the shortest path and least risk path algorithm. Given the fact that the only difference with the Dijkstra algorithm is in the cost calculation, and there the additional calculations only affect the amount of edges in the selected node, the computational complexity is similar to Dijkstra, being $O(n^2)$.

3 Indoor Dataset

The algorithms developed require to be thoroughly tested in an extensive and complex indoor environment to be a valid alternative for outdoor algorithmic testing. Although the authors realize that using a single specific building dataset for testing can still be too limited to generalize the obtained results, we tried to map a building with several features that are quite common for many indoor environments. The dataset for our tests consist of the 'Plateau-Rozier' building of Ghent University. It is a complex multi-storey building where several wings and sections have different floor levels and are not immediately accessible. It is assumed that the mapped indoor space is complex enough with many corners and decision points to assume reasonable wayfinding needs for unfamiliar users. Previous research executed in this building has shown that unfamiliar users can have considerate difficulty recreating a previously shown route through the building (Viaene et al. 2014).

The dataset is based on CAD floor plans which are transformed to ArcGIS shapefiles for additional editing and querying. For application of the least risk and shortest path algorithm, the original floor plans are converted into a three-dimensional indoor network structure. Automatic derivation of indoor networks has long been focused on as one of the problematic areas for indoor navigation applications. Recent efforts have shown possibilities of automatically assigning nodes to each room object and connecting them when they are connected in reality (Anagnostopoulos et al. 2005; Meijers et al. 2005; Stoffel et al. 2008). However, the development of a comprehensive methodology for automatic network creation requires a thorough foundation and agreement on the appropriate and optimal (i.e. user friendly) network structure of indoor environments which supports the user in his navigation task (Becker et al. 2009). Therefore, in most existing indoor navigation applications, the data is still mostly manually transformed into graph structures. As such, we decided to manually create the network based on the subdivision into separate rooms (Fig. 3).

The network structure is chosen to be compliant to Lee's Geometric Network Model (Lee 2004) as this is one of the main accepted indoor data structures. In this model, each room is transformed into a node, forming a topologically sound connectivity model. Afterwards, this network is transformed into a geometric model by creating a subgraph for linear phenomena (e.g. corridors), as such enabling network analysis. The position of the node within the rooms is chosen to be the geometrical centre point of the polygons defining the rooms. This premise implies that the actual walking pattern will sometimes not be conform to the connectivity relationships in the network inducing small errors in the calculations of shortest and least risk paths. We will need to verify whether or not this error is significant in the total cost of certain paths. The selection of corridors to be transformed into linear features is based on the map text labels indicating corridor functionality. These areas also appear to be perceived as corridors when inspecting the building structure itself in the field. Obviously, this topic is depending on personal interpretation

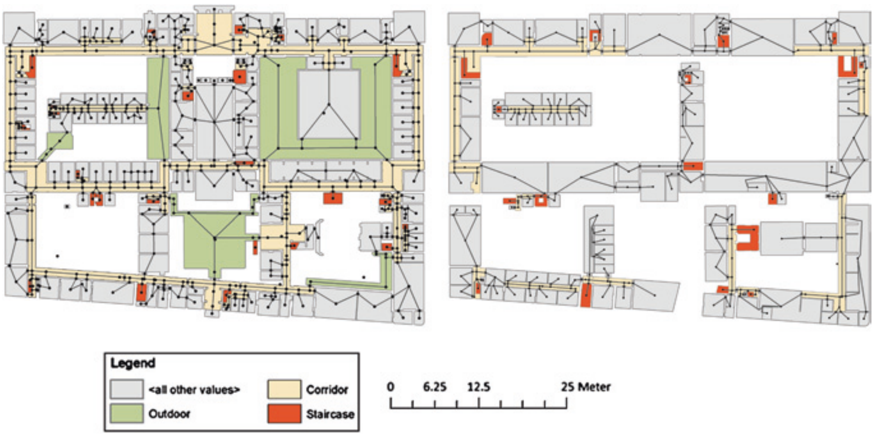

Fig. 3 Floor plan of the ground floor (*left*) and first floor (*right*) with their 3D indoor network

and choice. Therefore, in a future part of this research project, the dependency of the performance of cognitive algorithms on the indoor network topology will be investigated.

4 Implementation and Analysis of Least Risk Paths in Indoor Space

4.1 Analysis of Least Risk Paths Within Indoor Space

In the next section, the results of our analyses of the least risk path algorithm in indoor space are presented. The analyses are performed on two distinct levels: first, a general overview of the entire dataset is compared to the results of the original least risk path algorithm; second, a subset dataset is selected for more in-depth analyses. The main question interweaving the entire analyses section remains to investigate whether least risk paths have a similar advantage to shortest paths in terms of navigational complexity as is the case in outdoor space.

4.1.1 Analysis of the Entire Dataset

The entire dataset consists of more than 600 nodes and more than 1,300 edges which required a computation of almost 800,000 paths to exhaustively calculate all possible paths between all nodes for both the shortest as well as the least risk path algorithm.

As stated before, we would like to investigate whether least risk paths have the same connotation as in outdoor space, i.e. minimizing the overall risk of getting

Table 1 Summary of the entire dataset

	Total cost difference (m)	Length difference (m)	Risk value difference (m)
Average	11.13	−4.48	15.61
Min	0.00	−74.63	0.00
Max	135.48	0.00	145.73

Table 2 Classification of path lengths

Length increase	Number of paths	Percentage of total paths
Equal path lengths	160,984	46.64
0–5 %	87,681	25.40
5–10 %	50,773	14.71
10–25 %	41,196	11.94
25–50 %	4,363	1.26
>50 %	159	0.05
Total	345,156	100.00

lost by taking a slightly longer route. Given the definition of least risk paths, we put forward the following hypotheses. First, the length of a path described by the least risk path algorithm is expected to be equal or longer than its equivalent shortest path. As such, it provides a measure of detour a wayfinder would need to take when using a path that is less easy to get lost on. Second, the risk values of the shortest path will be equal or larger than for the least risk path. The least risk path algorithm will more likely calculate routes with fewer intersections, away from the major corridors where many choices appear. It will also take longer edges while the shortest path will go for the most direct option ignoring the complexity of the individual intersections. Third, the total risk value for the shortest path will be equal or higher than for the least risk paths as this is the minimization criterion for the least risk algorithm. Above aspects are analysed in the following paragraphs by comparing paths calculated by the least risk path algorithm and those calculated by the Dijkstra shortest path algorithm. These results aim to provide an indication of the balance struck by the different algorithms between the desire for direct routes versus less risky routes.

Table 1 shows that on average, the difference in path length for least risk paths is around 4.5 m with a decrease in risk value of 15.6 m. The values comparing the Dijkstra algorithm with the least risk path algorithm (total risk value minimization) align with the hypothesis stated before, with an increase in risk values for shortest paths and an increase in length values for least risk paths.

Over the entire dataset, a least risk path indoor is on average 4 % longer than its respective shortest path (using both the calculations of Duckham and Kulik (2003) as well as those from Jiang and Liu (2011)). Although 53 % of least risk paths are longer than their equivalent shortest paths, the majority (almost 99 %) of the paths are less than a quarter longer (see Table 2). This indicates that even though half of all the paths seem to deviate from the shortest path to obtain a theoretically less risky route (otherwise their lengths would be equal), those deviations are mostly limited

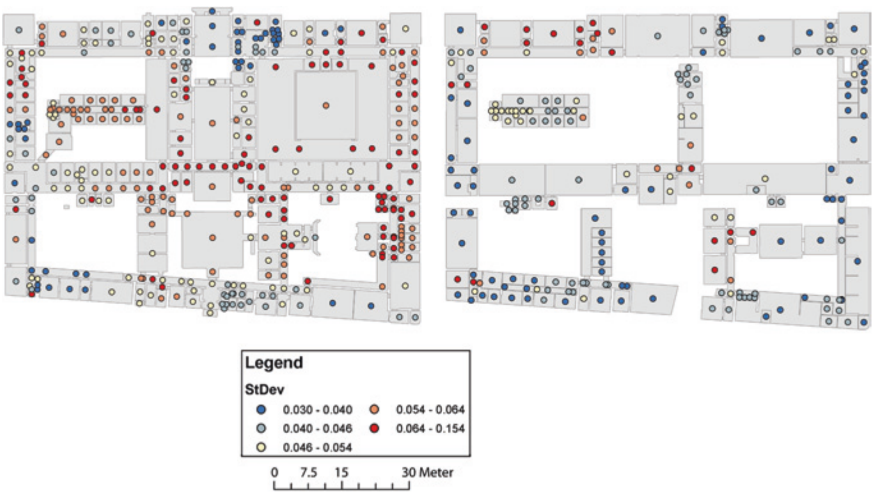

Fig. 4 Spatial distribution of the standard deviation of normalized least risk path lengths

in size. Taking into consideration that the total path length of both shortest and least risk paths in indoor space are already quite short (109.22–113.69 m with standard deviations of 45.89 and 48.74 m respectively) due to the restricted building size, the found limited differences are even more intensified as a whole. These results point to an at first sight equivalent path choice by both algorithms, implying that (1) either the shortest path algorithm is already selecting paths that are least risky to get lost on or (2) these results could also be a first indication that the least risk path algorithm is actually not calculating routes that are less risky and as such might not be well defined for use in indoor spaces. This will be investigated in the following paragraphs.

A second analysis focuses on the internal variability of the results over the entire network. More specifically, we want to analyse whether certain areas in the building return a significantly different result compared to the average. Figure 4 visualizes the spatial distribution of the standard deviation for all least risk paths starting in that point. The standard deviations have been classified in five quintiles (five classes with equal cardinality), similar to Duckham and Kulik (2003) analysis. Low standard deviations (i.e. blue data points) indicate starting points with little variation between their least risk and shortest paths in terms of total path length. Figure 4 shows that these points with low standard deviations can mostly be found on the first floor and in lesser connected areas of the building. The higher standard deviations (red data points) generally occur on the ground floor in denser connected areas and around staircases both on the ground and first floor. This greater variability can be interpreted as a result of the deviations of the least risk path from the shortest path being more pronounced at rooms with many options like around staircases where paths can be significantly different in the final route. Starting locations within isolated areas (e.g. on the first floor) have no option but to traverse similar areas to reach a staircase and deviate from there onwards.

The ground floor standard deviations are generally larger due to a network with higher complexity and connectivity. This trend can also be detected in the classification of the paths and their respective increase in length by choosing a less risky road. 80 % of the longest paths (compared to the shortest path) with an increase of 50 % or more are found on the ground floor, while half of the paths on the first floor are equal to their respective shortest path.

4.1.2 Analysis of Selected Paths

In this section, the authors dilate upon an example shortest and least risk path, visualized in Fig. 5, to examine whether the least risk path calculations actually result in the selection of less risky routes compared to the shortest path calculations. As shown in the example in Fig. 5, there is a significant visual difference in path choice of the example route with both the starting and the end point located on the ground floor of the building. In this example, the least risk path is 43 % longer than its shortest path equivalent, which minimizes its total length. This example shows a 'worst-case scenario' as it has one of the biggest differences in total path length of the entire dataset. While the shortest path takes the direct route following main corridors, the least risk path avoids certain areas to (theoretically) prevent wayfinders from getting lost as easily. However, from this figure alone, it is not entirely visible why the least risk path deviates from the shortest path in favour of using its calculated route.

In Vanclooster et al. (2013), several benchmark parameters were identified which objectively quantify the risk of getting lost based on research of wayfinding literature (both in indoor and outdoor space). These parameters can be used to understand whether the theoretically calculated least risk paths are selecting edges that actually reduce the navigational complexity and as such lower the risk of getting lost. Table 3 enumerates on the parameters used in the algorithm itself (first 3 lines) and on the selected benchmark parameters. The values show a lower total risk value for the least risk path with a considerable lower risk value at the individual decision points, by choosing a longer route. This is in line with the original definition of the algorithm. The other parameters, however, show a different side of the coin, with better results for the shortest path algorithm in terms of reducing the risk of getting lost. For example, the shortest path has 7 turns in its description, while the least risk path requires 12 turns. Wayfinding experiments have extensively shown that more turns on a certain path considerably increase the risk of disorientation making users more inclined to take wrong decisions at decision points. The chosen corridors in the least risk path algorithm are also generally less integrated, with less visibility towards the next decision points (4.68 vs. 5.17) and a higher route complexity (more decision nodes passed on the total route, more curves and more spatial units passed).

Above results indicate a less comfortable (and much longer!) route traversing for unfamiliar users compared to the shortest path. It can be concluded that the least risk path algorithm performs worse in terms of choosing less risky edges which completely undermines the initial intentions of the algorithm.

Fig. 5 Comparison of a typical shortest and least risk path

Table 3 Parameter results for an example least risk and shortest path

	Least risk path algorithm	Shortest path algorithm
Risk values of decision points (average; m)	166.36	274.27
Risk value of the entire path (m)	411.79	445.07
Total path length (m)	245.43	170.80
Number of turns	12	7
Number of spatial units passed	13	6
Number of curves	3	0
Width of corridors (m)	3.2 and 2	3.2
Number of decision nodes passed	37	29
Number of visible decision nodes at each decision node (average)	4.68	5.17

The suggested shortest path will in this case probably be closer to the natural wayfinding behaviour of unfamiliar users. Therefore, we are inclined to say that up to this point the least risk path algorithm indoor calculates alternative routes between two points, without necessarily reducing navigational complexity. This shows a need to adapt the original algorithm to be more compatible to the implementation in indoor environments (see also Sect. 5).

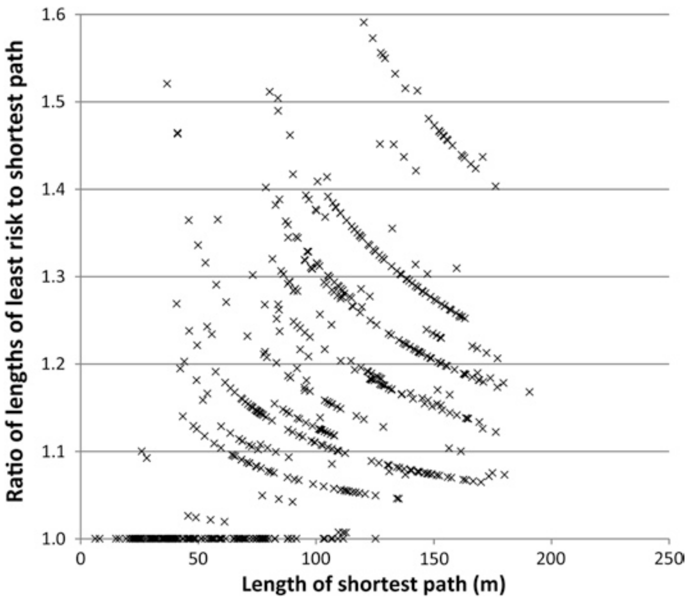

Fig. 6 Graph of the ratio of least risk on shortest path length to the shortest path length

A comparison of the lengths of the least risk and shortest paths for one set of paths from a single source to every other vertex in the data set is shown in Fig. 6. The figure provides a scatter plot of the normalized least risk path length (the ratio of least risk to shortest path lengths), plotted against shortest path length. In this example, more than 98 % of the least risk paths are less than 50 % longer than the corresponding shortest path.

Most paths are (almost) similar in length to its shortest path equivalent. Often only a small change in path choice can be found with a difference of only a couple of nodes compared to the shortest path. On the other hand, the strongly correlated stripes going from top left to bottom right in the graph exhibit blocks of correlated paths with very similar path sequences throughout their entire route. These occur because many adjacent nodes are required to take similar edges to reach their destination. This can also be seen in Fig. 5. The nodes within the dashed rectangle all take the same route for both their least risk and shortest path, resulting in connected ratios in Fig. 6.

4.2 *Analysis of Indoor Least Risk Paths Compared to the Results in Outdoor Space*

In this section, several of the data obtained before will be compared with the results obtained by the calculations of least risk paths by Grum (2005) and simplest paths by Duckham and Kulik (2003). We mainly want to investigate whether we can draw the same conclusions from our results of the calculations in indoor space as those from outdoor space. Also, the question is raised if the size of the difference is equivalent to outdoors.

A comparison with the result obtained by Grum (2005) is difficult as the author only calculated a single path in outdoor space. In both cases, the total risk value for the least risk path is minimal and the length is longer than its shortest path. The outdoor least risk path is 9 % longer than the shortest path, while in our dataset an average increase of 4 % is detected. However, the number of turns in our example path (Fig. 5) is higher for the least risk path compared to the shortest path. Other paths in our dataset have less turns than their shortest path equivalent. This does not seem to match with the results from the outdoor variant. An explanation could be that the author only works with a limited outdoor dataset. Also, the least risk path indoor might have a different connotation because of the description of the indoor network. Due to the transformation of the corridor nodes to a linear feature with projections for each door opening, the network complexity is equivalent to a dense urban network. However, the perception for an indoor wayfinder is totally different. While in outdoor space each intersection represents a decision point; in buildings, the presence of door openings to rooms on the side of a corridor is not necessarily perceived as single intersection where a choice has to be made. Often these long corridors are traversed as if it were a single long edge in the network.

Simplest paths have similarly to least risk paths the idea of simplifying the navigation task for people in unfamiliar environments. The cost function in both simplest and least risk paths accounts for structural differences of intersections, but not for functional aspects (direction ambiguity, landmarks in instructions…) like the simplest instructions algorithm (Richter and Duckham 2008). However, the simplest path algorithm does not guarantee when taking one wrong decision that you will still easily reach your destination, while the least risk path tries to incorporate this while at the same time keeping the complexity of the instructions to a minimum. Several of the comparison calculations are similar to the ones calculated for simplest paths (Duckham and Kulik 2003). At this point, we cannot compare actual values as it covers a different algorithmic calculation. In the future, we plan to implement the simplest path algorithm also in indoor spaces. However, it might be useful at this point to compare general trends obtained in both.

With regard to the variability of the standard deviations (Fig. 4) similar conclusions can be drawn. At the transition between denser network areas and more sparse regions, the variability tends to increase as a more diverse set of paths can be calculated. The sparse and very dense areas have similar ratios showing similar network options and path calculations. The worst-case example can also be compared to a worst-case dataset of the outdoor simplest path. A similar trend in 'stripes' as found in the graph in Fig. 6 is also found in the outdoor simplest path results, also due to sequences of paths that are equal for many adjacent nodes.

5 Discussion on Adjusting the Least Risk Path Algorithm

The previous analyses have shown multiple times that only limited differences can be found in terms of length and risk value between the least risk path algorithm and the shortest path algorithm. This indicates that both algorithms often return paths with a similar path choice. For short path lengths, this is to be expected as the path choice is limited by the limited density of the indoor network. Also, given the typical network structure with a main corridor connecting various rooms and the importance of staircases in connecting various floor graphs; often not many options exist on a short distance to deviate from the shortest path. However, for paths with a more extensive total path length, we have seen varying results with sometimes large differences in path choice and sometimes barely any difference. Also, when there were differences, the least risk path algorithm selected theoretically less risky paths (when compared to our benchmark parameter set), but evenly as many times the shortest path would still be preferred to guide unfamiliar users during their wayfinding endeavours.

As shown, the least risk path algorithm does not return stable results in terms of selecting the least risky edges in indoor environments. Therefore, we are inclined to say that at this point the least risk path algorithm indoor calculates alternative routes between two points, without necessarily reducing navigational complexity. This leads us to believe the least risk path algorithm and its definition of risk should be investigated in more detail and altered to be more aligned to the specificities of indoor wayfinding.

5.1 Possible Improvements to the Algorithm

In this final section, we will suggest some other improvements to the original algorithm which will be tested and compared in our future research.

First, the way in which the risk value is defined by only taking into account the average wrong path length and the intersection complexity (i.e. number of edges converging) could be one of the reasons for the currently inaccurate results. Because of its current definition, the algorithm will always try to select the longest edge (larger risk value cost if not chosen), which is not necessarily always the least risky edge (e.g. bumping into complex intersections, less integration and visibility…). Also, the risk value weights the intersection complexity (i.e. number of edges) according to an exponential relationship: i.e. the more edges converging, the less importance to the total number of edges. It should also be noted that up to this point no aspects denoting the overall individual importance of each edge, apart from the edge length (e.g. width, number of curves, integration value), are yet incorporated in the assessment of risk. On intersection level, other aspects like the directional orientation of each edge, local visibility, etc. that can also influence the edge choice for continuation of the path, are also not considered. For example, the sight of several small corridors and a single large corridor at an intersection will highly influence path choice and comfort when selecting the widest corridor and not the smallest variant. Experiments with defining various risk value definition with more parameters, individually weighted, should be considered in future work.

Related to this topic is the fact that the risk value of a decision point is currently calculated based on the assumption that the wayfinder recognizes his mistake at the first adjacent node and returns from there to the previous node. A question could be raised whether it is actually realistic that people already notice at the first intersection that they have been going wrong. An increasing compounding function could be suggested taking into account the possibility of going further in the wrong direction.

Second, in the current implementation of the least risk path algorithm, both the length of the path as well as the sum of the risk values at intermediate decision points have an equal weight in the calculation of the total risk value. Varying the individual weight of both parameters might results in a more cognitively correct calculation of the indoor least risk paths. Three different weighing adjustments can be proposed: (1) geometric weighing by changing the length versus risk value ratio; (2) semantic weighing by classifying corridor and outdoor areas differently than rooms (resemblance with hierarchical network structure); (3) topological weighing by taking the number and complexity of intersections into the definition. The further elaboration on all three adjustments is subject for further research.

Third, the least risk path algorithm indoor was tested using a Geometric Network structure as defined by Lee (2004), which each corridor being subdivided in many hallway intersections in front of each doorway connected by short edges. We have shown that this particular network structure can lead to increased risk value calculations, deviations from the main corridor and misperceptions for the wayfinder. Therefore, in the second stage of this research, various other network structures (e.g. visibility based networks, networks without centreline transformations, cell decomposition, dynamic hierarchical networks …) will be examined in order to quantify the dependency of the performance of cognitive algorithms on various network topologies. Also, the dataset could be improved by classifying edges in a hierarchical way to be in line with user's hierarchical spatial reasoning. The main question here is which hierarchical structure should be used and how should it be defined. In this case, a natural hierarchy similar to the road classification hierarchy employed in outdoor navigational research has to be defined.

Fourth, staircases have been demonstrated in our analyses to be key elements in the path choice and are typically one of the main reasons for getting-lost episodes in a three-dimensional indoor environment (Hölscher et al. 2012). The fact that you have to walk up and down staircases could be naturally having a greater weight because taking a wrong decision might result in walking up and down the stairs twice. On the other hand, chances of taking a wrong decision by changing floors are likely to be slimmer given the effort for vertical movement and a changed cognitive thinking.

In line with this last point, wayfinding research (Hölscher et al. 2009) showed the strategy choices people make when navigating in (un)familiar buildings, which has proven to vary depending on the navigation tasks. The main strategies for indoor wayfinding are recognized as central point strategy, direction strategy and floor strategy. Tasks with either a floor change or a building part change result in no problems, with the participants first changing to the correct floor or building part. However, for tasks with changes in both vertical and horizontal direction, additional information is required to disambiguate the path choice. An algorithm that wants to minimize the risk of getting lost in a building necessarily needs to account for these general indoor wayfinding strategies as they correspond to the natural way of multilevel building navigation for all types of participants.

6 Conclusions

In this chapter, the least risk path algorithm as developed by Grum (2005) in outdoor space was implemented and tested in an indoor environment. The results of the tests on an indoor dataset show an average increase in path length of only 4 % compared to the shortest paths for theoretically less risky paths. However, it appears to be difficult to visually see and understand using a benchmark parameter set what the actual improvement in risk is when calculating the total risk. The least risk path often passes by a great amount of complex intersections with many short edges. These paths will likely not be perceived by the wayfinder as less risky compared to the shortest path. As such, at this point, the least risk path calculations return non-stable results in terms of selecting least risky edges.

Our main conclusions from the analysis suggest that improvements to the indoor variant of the least risk algorithm are required. Changes in the calculation of the risk value, together with a weighing of the parameters will be tested. Also, the influence of the network structure will be investigated in future research in a search for optimizing the algorithm to be more compliant to the cognitive notion of indoor wayfinding. This research will help with the development of appropriate tools to improve navigation experiences in indoor spaces. Instead of using the shortest path, a small increase in path length might open up a much simpler and easier route to explore and will help unfamiliar users in their wayfinding undertakings.

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