GENERATION OF AN INDOOR NAVIGATION NETWORK FOR THE UNIVERSITY OF SASKATCHEWAN

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By

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ABSTRACT

Finding ones way in unknown and unfamiliar environments is a common task. A number of tools ranging from paper maps to location-based services have been introduced to assist human navigation. Undoubtedly, car navigation systems can be considered the most successful example of location based services that widely gained user acceptance. However the concept of car navigation is not always (perhaps rarely) suitable for pedestrian navigation. Moreover, precise localization of moving objects indoors is not possible due to the absence of an absolute positioning method such as GPS. These make accurate indoor tracking and navigation an interesting problem to explore.

Many of the methods of spatial analysis popular in outdoor applications can be used indoors. In particular, generation of the indoor navigation network can be an effective solution for a) improving the navigation experience inside complex indoor structures and b) enhancing the analysis of the indoor tracking data collected with existing positioning solutions. Such building models should be based on a graph representation and consist of the number of 'nodes' and 'edges', where 'nodes' correspond to the central position of the room and 'edge' represents the medial axis of the hallway polygons, which physically connects these rooms. Similar node-links should be applied stairs and elevators to connect building floors.

To generate this model, I selected the campus of University of Saskatchewan as the study area and presented a method that creates an indoor navigation network using ESRI ArcGIS products. First, the proposed method automatically extracts geometry and topology of campus buildings and computes the distances among all entities to calculate the shortest path between them. The system navigates through the University campus and it helps locating classrooms, offices, or facilities. The calculation of the route is based on the Dijkstra algorithm, but could employ any network navigation algorithm. To show the advantage of the generated network, I present results of a study conducted in conjunction with the department of Computer Science. An experiment that included 37 participants was designed to collect the tracking data on a university campus to demonstrate how the incorporation of the indoor navigation model can improve the analysis of the indoor movement data. Based on the results of the study it can be concluded that the generated indoor network can be applied to raw positioning data in order to improve accuracy as well as be employed as a stand-alone tool for enhancing of the route guidance on a university campus, and by extension any large indoor space consisting of individual or multiple buildings.

ACKNOWLEDGMENTS

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INTRODUCTION

1.1 Background

Humans spend over 75% of their time indoors (Klepeis et al., 2001), therefore their movements are rarely limited to streets routes and mainly take places within buildings of different dimensions (size and number of levels). With the growing complexity of such built environments, interest in providing navigation guidance for indoor spaces is growing. Unfortunately, due to a number of GPS limitations, obtaining an accurate positioning or tracking results indoors is rarely possible, making indoor mobility, navigation, and movement analysis challenging.

Indoor movements are constrained for a variety of reasons: the compact nature of the spaces, the limited number of indoor paths, and the short temporal duration of many indoor movement trajectories. Nevertheless, accurate indoor positioning and mapping can significantly improve emergency evacuation response, asset management, and route guidance. Efficient indoor navigation solutions can be also used as a research tool to better understanding of indoor pedestrian mobility. Analysis of pedestrian flow could help architects design, plan, and build indoor facilities. Building managers and urban planners could monitor indoor human behavior for the purposes of efficient public event management, that could include visitor densities, waiting times, and localization of possible congestion (Liebig, Xu, May, & Wrobel, 2012). Geographers and psychologists would find the large amount of route selection, navigation, and wayfinding information useful for examining how we make spatial decisions during our everyday lives.

One of the important problems associated with indoor navigation and routing is whether or not it can be applied in such a way to that can be profitable. Critics are skeptical about implementing these methods because they tend to focus on a very small user groups and are only useful within the confines of a single built environment. However this is arguable, as indoor routing systems can improve and add value to the quality of service as well as increase overall customer satisfaction. Indoor environments, which currently lack, and can therefore significantly benefit from, location-based applications, contain a number of elements that are difficult to locate or capture (Giaglis, 2002); examples include such spaces as large supermarkets, museums, libraries, and airports.

Enclosed environments such as shopping malls or museums could benefit from tracking human behavior and adapting their findings to improve the design of the facilities and improve the efficiency of their customers or patrons. The benefit could serve a dual purpose, in one case, the application of indoor way-finding systems in supermarkets will assist the consumer to navigate and locate stories and products. On the other hand, it will give the retailers the opportunity to record and analyze this data for future marketing campaigns as well as improve the arrangement and of products and services offered (Kourouthanassis, 2003).

In complex buildings, location-based applications can be incorporated in devices that provide personalized guided tours. Such systems can deliver excursions based on the personal interests of the visitor as well as his or her current location (Oppermann & Specht, 1998). In libraries, incorporation of the navigation and routing solution could significantly decrease the lines and waiting times, as visitors could specify requests to a personal hand-held mobile device in order to query the library database and identify the exact position of a given title and a possible route to it (Giaglis, 2002).

A number of solutions have been introduced to improve indoor navigation. One of the examples is to generate a navigable network model that represents possible routes inside buildings. Such models depend on a geodatabase, support calculation of shortest paths, assure efficient navigation between selected locations, as well as provide realistic 3D visualization of the build-up environment. Moreover such building representations can be also used for existing indoor navigation solutions. In particular these models can serve as a tool for post-processing to improve the believability of the collected indoor tracking data or even correct positioning results on the fly.

The concept of pre-planning is widely used in GPS systems and portable navigation devices. In such environments as city centers or urban canyons navigation solutions employ vector representation of road networks, which correct GPS data or compensate a for short term signal loss (Scott, 1994). Several corporations provide outdoor navigable networks primarily suited for automobile navigation (such as Navteq and TomTom). However, indoor spaces are quite different from outdoors spaces (even network spaces, like indoor hallways compared to outdoor roadways); differences that can influence navigation decisions (Gilliéron & Merminod, 2003). The topological structure of a road network is less complex and diverse than the structure of even a simple building (Lorenz, Ohlbach, & Stoffel, 2006). While roads are easily defined as structures that rarely have more than one instance in a single location, buildings should be regarded as 2.5 (Hölscher, Meilinger, Vrachliotis, Knauff, & Brösamle, 2006) or even 3-dimensional, demanding a 3D topological model or graph with an extra degree of freedom in the node labels. The creation of an indoor network model depends on the physical constraints of the building, internal design, presence of other indoor restrictions, and specific indoor properties such as stairwells, doorways, elevators, or escalators (Thill, Dao, & Zhou, 2011). Moreover, unlike outdoor navigation there are no well-established methods that support accurate routing and way-finding based on the linear road representations (Taneja, 2011), which makes a problem of finding of efficient method for capturing and generating of indoor network an interesting problem to explore.

1.2 Literature Review

1.2.1 WiFi based Positioning

The popularity of location-based services increases every year. The availability of equipment at affordable prices leads to a number of localization applications installed in many consumer goods (Izquierdo, Ciurana, Barceló, Paradells, & Zola, 2006). The Global Positioning System (GPS) is the leading location technology which is commonly used to provide real-time directions or traffic information. While GPS technology works well outdoors, positioning indoors remains a problem. Accurate positioning in indoor environments faces challenges not faced outdoors. GPS cannot be used reliably indoors since it requires 'line of sight' to the satellites (Giaglis, Pateli, Fouskas, Kourouthanassis, & Tsamakos, 2002). Moreover with a common accuracy range up to 10 meters (Giaglis, Kourouthanassis, & Tsamakos, 2003) location using the mobile phone network is not suitable inside buildings.

A number of companies and researchers have introduced additional or alternative positioning solutions that work indoors to replace or enhance GPS systems. Cellular network technology can be leveraged; however cellular signals alone produce positional results with errors up to several hundred meters (Zandbergen, 2012). Methods using Bluetooth, Cellular, Radio Frequency ID (RFID), and ultra wide band, have been introduced for indoor tracking, but their implementation is often labor intensive, targets a small spatial extent, and requires additional infrastructure (Curran et al., 2011).

WiFi technology can often leverage existing infrastructure to provide similar spatial resolutions to GPS (Jan, Hsu, & Tsai, 2010), becoming one of the most promising technologies for indoor positioning. WLAN (WiFi) technology is widely installed on devices such as laptops, smartphones, and tablet computers. Given the ubiquity of both fixed beacons (WiFi routers) and mobile receivers (WiFi enabled devices), WiFi-based indoor position solutions can be deployed quickly (Gu, Lo, & Niemegeers, 2009).

Two popular methods exist for WiFi based indoor navigation – fingerprinting and trilateration. In general fingerprinting is considered to be more accurate (Jan, et al., 2010), however, it is more expensive and less flexible compared to triangulation methods (Yim, Joo, & Park, 2011). Fingerprinting requires measuring Wi-Fi signal strengths at different calibration points; positioning systems that use fingerprinting contains two phases – offline and online. During the offline phase, a map of signal strength is created based on the values from calibration points. During the online phase, the system estimates the user location by comparing the received signal strength with recorded points (Kaemarungsi & Krishnamurthy, 2004). The fingerprinting method has been widely applied in different indoor positioning systems.

Alternatively, the trilateration method does not require the off-line stage. A trilateration algorithm is used for the Global Positioning System and can be successfully applied to localization with Wi-Fi technology. This algorithm uses the received signal strength (RSS) to calculate the distance from the aces points (AP) to the device. When three different APs are used the exact location is calculated. Trilateration requires a database with AP coordinates and Media Access Control (MAC) for every AP. After the system calculates signal strength (average or maximum) from "visible" APs, it uses the location of each AP to estimate the user's location (Izquierdo, et al., 2006).

1.2.1.1 Examples of the Existing WiFi-based Positioning Systems

Many researchers have experimented with WiFi-based positioning systems (Gu, et al., 2009). Commercial WiFi-based indoor tracking systems include Google, Apple, Skyhook Wireless, WeFi, and PlaceEngine. All work in a relatively similar manner (Zandbergen, 2012). An application installed on a WiFi-enabled device records available WiFi signals. These signals are stored on the remote server which sends an estimated location back to the device. Examples include RADAR (Bahl & Padmanabhan, 2000), which was proposed by a Microsoft research group and the COMPASS system (King, Kopf, Haenselmann, Lubberger, & Effelsberg, 2006) that relies on WiFi infrastructure and a digital compass to locate a user.

In 2010 researchers from the University of Saskatchewan proposed and produced SaskEPS (Bell, Jung, & Krishnakumar, 2010). Similar to RADAR it uses a trilateration algorithm that can calculate location on-device or on an external server. Distances for trilateration are measured according to signal strength from "visible" access points (APs). The exact location of APs is stored in a server-located database. To ensure correct positioning, the system also calibrates the signal strength and assesses whether an AP signal is experiencing interference from structures such as floors or walls. SaskEPS produces 2.5 dimensional positioning information that consists of X, Y coordinates, and floor information. Jung (Jung, Bell, Petrenko, & Sizo, 2012) has installed SaskEPS and tested its performance at the University of Saskatchewan. His results showed the system provides GPS-like indoor positioning accuracy, although it has some problems associated with the arrangement of WiFi routers and the structural characteristics of the buildings. All these "problems" are consistent with the physical nature of the trilateration process and the non-universal arrangement of routers in the built environment.

1.2.1.2 Limitations of the WiFi-Based Positioning Systems

To ensure proper functioning of an indoor navigation system certain environmental conditions are required. Zou (2006) identified the following:

1. There should be enough visible Wi-Fi Access Points (APs). The number of APs should vary between three and six, whereas three is the required minimum and six represents a threshold number to maximize accuracy.
2. The location of APs is also important. If all APs are placed within the same channel or direction the performance of the system will be low.
3. The distance between two adjacent calibrated locations should be within 1- 2 meters.

Even if all above conditions are met, the complexity of the environment leads to many challenges to the development of an accurate and reliable Wi-Fi positioning system. Signal propagation and attenuation caused by NLOS (non line of sight), signal multipath loses, and noise interference are common sources of degraded accuracy. Signal propagation and attenuation caused by non-line of sight (NLOS) routers, multipath signal attenuation, geometric environmental effects, and noise interference from other devices are common sources of degraded accuracy (Gu, et al., 2009) in WiFi positioning systems. Time of day, the number of people in a local area, and obstacles (such as walls or additional devices) can also influence the performance of the system (Chen, Yang, Yin, & Chai, 2006). There is also evidence that users are sensitive to the context of the positioning results and they are aware that some positioning results are untrustworthy (Wei & Bell, 2012). Moreover, due to signal variability and attenuation the number of APs covering a location can vary with time. Therefore the signal strength received from an AP at a fixed location changes with time and its physical surroundings. Figure 1 gives an example of the normalized histogram of the signal strength received from an AP at a fixed location.

The accuracy of the system is also highly dependent on the algorithms employed for location estimation. For example, the fingerprinting method – which uses pattern matching techniques to locate a user on a grid – is negatively affected by the non-Gaussian distribution of the WiFi signal (Rizos, Dempster, Li, & Salter, 2006). Router replacement, antennae orientation changes, changes in router array, or episodic attenuation can require recalibration of the system (Ladd, Bekris, Rudys, Kavraki, & Wallach, 2005). A fingerprinting database requires repeated time and effort to maintain an acceptable spatial resolution (Li, et al., 2006). Trilateration problems are generally associated with determining distance to each WiFi point, in particular the trilateration process is sensitive to the arrangement of indoor routers (Jung, et al., 2012).

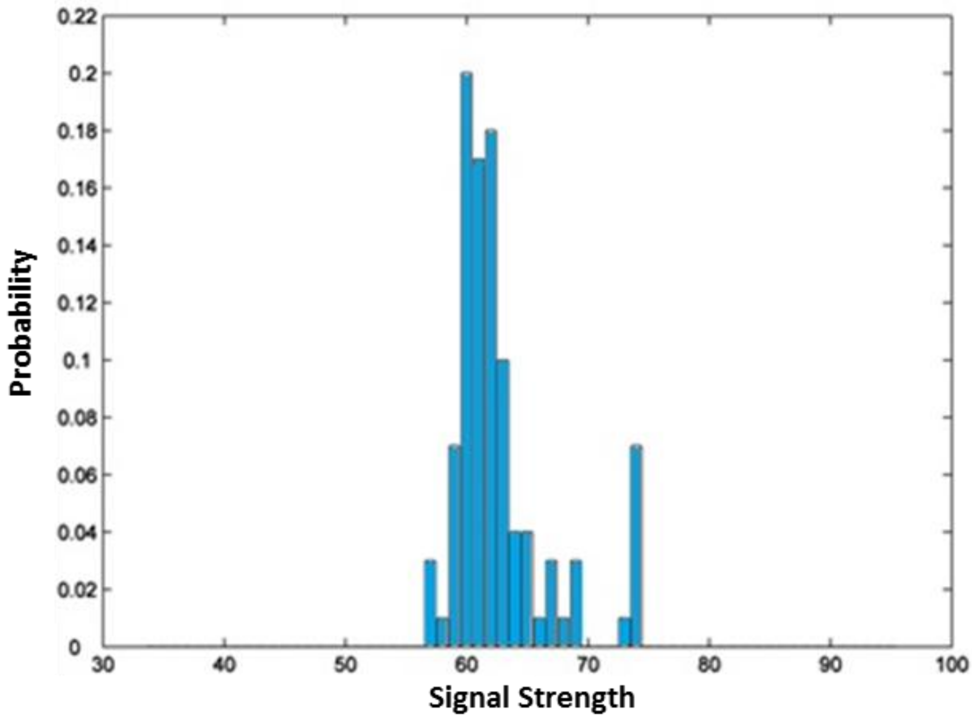


Figure 1. An example of signal strength distribution (adapted from Chen, et al., 2006)

1.2.2 Indoor Navigation Networks

It is widely known that many of the methods of spatial analysis popular in outdoor applications can be used indoors. For example, the results of longer-term indoor pedestrian tracking can be significantly improved by incorporating additional information about building where the movements take place (Harle, 2013). In particular, the generation of an indoor navigation network to correct tracking data from positioning devices can be an effective solution to be implemented as an intermediary step between raw positioning data and higher level patterns of human spatial behavior. Most GPS-based navigation systems are linked with road infrastructure, where the road is represented as linear features to which the estimated location is matched. This method, also known as map-matching (Quddus, Ochieng, Zhao, & Noland, 2003; Scott, 1994; X. Zhang, Wang, & Wan, 2003) can be successfully adopted for correcting of the WLAN positioning if indoor navigation networks exist.

Another possible application of indoor navigation networks is route-planning. In indoor environments route-planning produces a walkable path formed by number of points-of-interests with certain constraints (Werner & Kessel, 2010). Such constrains include the ability to use stairs or cross different parts of buildings. Receiving route guidance in order to avoid some of these structures can be especially important for individuals with limited mobility or when it is required to reach the destination inside the complex multi-storey buildings. Indoor navigation networks can be also employed in evacuation guidance which in the future can enhance existing emergency management applications (Pu & Zlatanova, 2005).

1.2.2.1 Generation of the Indoor Networks

Substantial work has already been done in the area of developing algorithms for the generation of network structures, the most commonly employed algorithms include the Medial Axis Transform (Lee, 1982), Generalized Voronoi Graphs (Wallgrün, 2005), and Straight Medial Axis Transform (S-MAT) (Lee, 2004). The Geometric Network Model is a GIS model that contains connectivity information and allowed for shortest path computation; it was first introduced by Lee (Lee, 2001). Later, a Combinatorial Data Model (Lee & Kwan, 2005) for representing topological relations in 3D was presented by the same researcher. These models employ Medial Axis Transformation and support hierarchical and geometrical relationships within a building. Gillieron (Gilliéron & Merminod, 2003) have developed an indoor pedestrian navigation system, where a topological model of navigation spaces for route guidance and map matching was introduced.

To perform network analysis indoors, a model of the building should be generated. However this model should not only provide 3D visualization of the building but contain topologic information, containing the geometry of the buildings on screen (Karas, Batuk, Akay, & Baz, 2006). In general, the generation of a comprehensive indoor network requires aspects of existing 2D street network models with additional specifications related to topological relationships between elements in 3D space, summarized in (Taneja, 2011) as the following:

1. The indoor network should be a dimensionally weighted topology network that represents indoor route lengths and connections in 3D space.
2. The indoor network should represent the indoor navigable routes that results from decomposition of planar polygons.
3. Space centerlines or medial-axes are an appropriate abstraction for indoor navigation networks.

This means that indoor network structures should be abstracted as a room-to-room connectivity graph (Becker, Nagel, & Kolbe, 2009). A traditional 2D node-link structure can also be employed (Figure 2); however, it should be modified in a way that rooms are represented as nodes and links connect these nodes. To combine floors, the same node-link method can be applied along level connectors.

Indoor navigation networks require the generation of a specific geodatabase that meets the following requirements; summarized by Spassov (Spassov, 2007) as the following:

1. The database model should support the correspondence between the location of the object and the geographic coordinates of this object. Therefore it should identify a geographic object by its coordinates and vice versa,
2. Computation and guidance should be allowed,
3. Network-based model should be compatible with the process of map-matching.

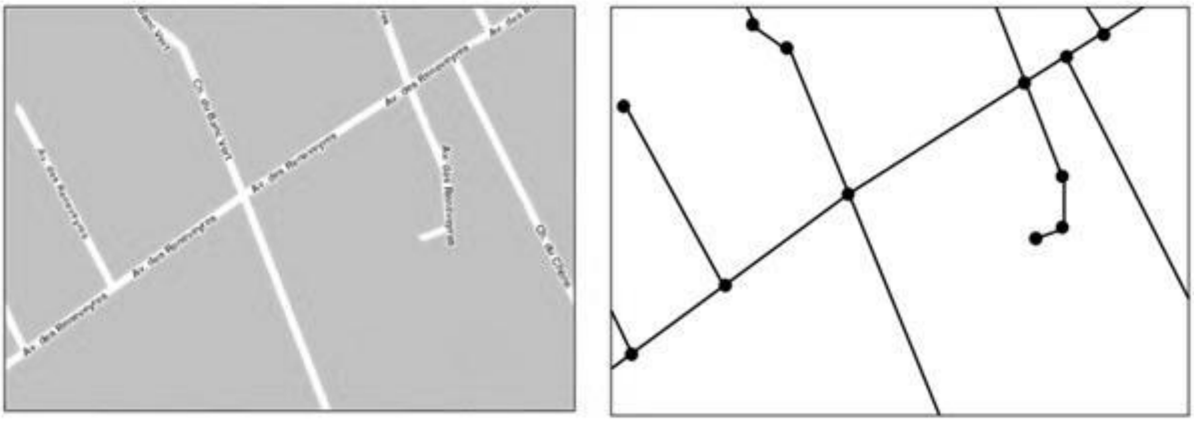


Figure 2. Graph representation of street network (adapted from Spassov, 2007)

1.2.2.2 Requirements for Indoor Navigation Networks

Various types of application domains require different approaches for the generation of attributive schema for navigation networks. In particular, certain information (such as floor elevation) can be excluded from network attributes, whereas other information (such as spatial connectivity) should be preserved for all types of analysis. Taneja (Taneja et al., 2011) analyzed possible use of navigable networks and identified information requirements for various application domains (Table 1).

Table 1. Information requirements for navigation network analysis in different application domains (Taneja, et al., 2011)

Information requirements for navigation network analysis	Spatial connectivity	Network distance	Portal dimension	Network geometry	Floor elevation
Building accessibility analysis	■		■		■
Wayfinding	■	■			
Indoor positioning	■	■		■	■
Indoor navigation guidance	■	■		■	■

1. *Building accessibility analysis (BAA)*. BAA analyzes indoor building structure and determines constraints that can impede people with limited mobility. This type of network analysis requires knowledge of spatial connectivity, width of entrance spots, portal type (door, elevator or stair), and floor elevation (Taneja, et al., 2011).
2. *Indoor wayfinding*. Wayfinding provides the information about possible routes between two selected points. This type of analysis requires knowledge of spatial connectivity and network distances (Taneja, et al., 2011).
3. *Indoor positioning*. Indoor navigation networks can be successfully used for indoor positioning systems (Spassov, 2007). In particular, if the topology and geometry of the navigation path is accurately represented, such networks can significantly enhance the analysis of the data collected with indoor positioning systems. Therefore this type of analysis requires knowledge of indoor network geometry, spatial connectivity, and network distance calculation (Taneja, et al., 2011).
4. *Indoor navigation guidance (NG)*. NG implies providing direction (turn-by-turn) for routing and finding the way in complex indoor environment. Such analysis requires detailed knowledge of the building layout in particular network geometry, portal type, and floor elevation (Taneja, et al., 2011).

1.2.2.3 Example of the Existing Network Model

Researchers have utilized graph-based models for addressing wayfinding and navigation guidance as well evacuation tasks in indoor environments. Wu (Wu & Chen, 2009) developed a method to generate the 3D geometric network model from the 2D building plans using C++ and the OpenGL environment; the data for the network is stored in an MS Access database. The network is used to perform shortest path analysis and provides a method for fire fighters to rapidly locate the site of a fire and reduces response time to emergency accidents.

Thill (Thill, et al., 2011) proposed 3DCityNet - a custom application that models personal movements indoor as well as multiple transportation modes outside the buildings. This system uses 3D network connectivity through a 2.5D approach which combines the existing 2D data structures and 3D visualization. 3DCityNet is an interactive environment that runs under ArcGIS. Computations of the optimal navigation route and accessibility analysis are the main functions of this application. The system generates a 3D topological data model; the final network dataset for activities outside buildings is represented as a two-dimensional multimodal network. The tool can be used for emergency response, although the authors argue that it is not its sole application and it is possible to employ it for other urban transportation and urban geography applications.

Kwan (Kwan & Lee, 2005) demonstrated a network data model for GIS based Intelligent Emergency Response System (GIERS) that combines the ground transportation system and multi-level structures into a navigable 3D GIS. They measured the relative accessibility of emergency response between a disaster site and an emergency station. Access was analyzed with consideration to multi-transport modes: vehicle movements in a street network (in 2D space) and pedestrian movements within a built-environment (in 3D space). Testing of the system demonstrated that using the analytical functionality available in a 2D GIS for a 3D GIS to model and analyze indoor environments of buildings can be very beneficial for the speed of emergency rescue procedures.

Nevertheless, implementing and generating the indoor network is not a trivial task. Werner (Werner & Kessel, 2010) pointed out that navigation data tailored to a specific query can be generated by hand. However such research is suitable only for small test areas, and is problematic and time-consuming for more extensive spaces such as multi-floor buildings. Pu (Pu & Zlatanova, 2005) demonstrated that automatically extracting geometry and logic models of a building is a complicated task because nodes and links often have to be created manually or half-manually.

1.3 Research Questions

Accuracy of indoor positioning systems can vary according to techniques and algorithms. Performance of the system may change in different testing environments due to signal propagation and attenuation. For positioning systems that use WiFi signal strength to determine a location, the influence of these negative effects is particularly acute. Although such negative effects cannot be completely eliminated, incorporation of indoor networks can be applied to raw positioning data in order to improve accuracy and route generation. Furthermore, applications that support turn-by-turn navigation and guidance in complex buildings become more popular. Such applications are usually based on the indoor navigation networks and do not only improve the navigation experience, but can be applied in emergency evacuation response or asset management.

This demand leads to the question of how to create an indoor navigation networks suitable to support various applications. It is clear from the literature that such spatial databases and tools should ensure efficient navigation between selected locations, support a calculation of optimal paths and be easy to generate and reconstruct. Also, based on the example of previous researcher, it is evident that a graph-based model is suited for representing of navigation networks. The efficiency of the indoor navigation network is fully dependent on the accurate geometry and semantics of network. The complex geometric information of the network can be depicted with GIS technologies that can translate 2D CAD files into complex 2.5D network models. This raises a series of questions regarding the generation of the indoor navigation networks and its performance:

1. How to generate an indoor navigation network for complex building structures? It is important to develop a method that will create an indoor navigation network in a fast and efficient way. For our study a campus of University of Saskatchewan will be used; however, the method should be applicable for buildings of various complexities and require no or minor manual adjustments.
2. How the created network can be employed for improving the analysis of the data collected with existing indoor tracking solutions? After the network is generated, it will be necessary to test the performance of the network and understand whether such models can be useful for better visualization and understanding of tracking results.
3. What type of the network analysis can be performed if a navigation network exists?

The contribution of this thesis is to create an efficiently implemented tool for generating an indoor navigation network from existing AutoCAD files. To address the need of this network, I will demonstrate the possible usage of generated result by presenting examples of two possible application domains. In particular, by taking the example of University of Saskatchewan campus, I will show the possible applicability of the network for way-finding and route guidance. Such systems, generated on the basis of the network, could direct users toward the selected destinations and lessen the chance of the individuals to get lost. Additionally, I will present the results of the experiment, which demonstrates the application of the created network for improving the analysis of movement data collected with existing positioning methods. I will show the advantages of using the network for better visualization of the collected data. This will allow for better representation and identification of various movement patterns, including the generation of the accurate moving trajectories and performing the usage analysis for indoor environment.

II

METHODS: GENERATING OF WALKABLE CentreLINE NETWORK

Presently, the generation and analysis of the complex multidimensional transformational networks is possible using the capabilities of number of commercial software packages (such as ArcGIS, see (Lim, Abdullah, Setan, & Othman, 2009) as example) or open source solutions (such as PostGIS spatial objects for the PostgreSQL database, for example in (Liu, Lyons, Subramanian, & Ribarsky, 2010)). I selected ArcGIS for modeling the campus indoor navigable network. In particular, Model Builder was used to simplify the network development process; this approach allowed for the creation of a complex indoor navigable model which is easy to edit and reorganize.

I called our network model the Walkable CentreLINE Network (WCN) and generated five ArcGIS models of different complexity to convert non-georeferenced CAD blueprints to a final network product. The resulting network covered 20 interconnected buildings, representing the primary navigable areas of the university (Figure 3). An approach similar to the one presented by Thill (Thill, et al., 2011) was applied; each of the 20 interconnected buildings were represented as a multi-level structure subdivided into separate elements representing individual floors. The WCN was built upon the CentreLINE feature dataset that combines together linear and point feature classes that model the center position of the hallways, corridors, and rooms.

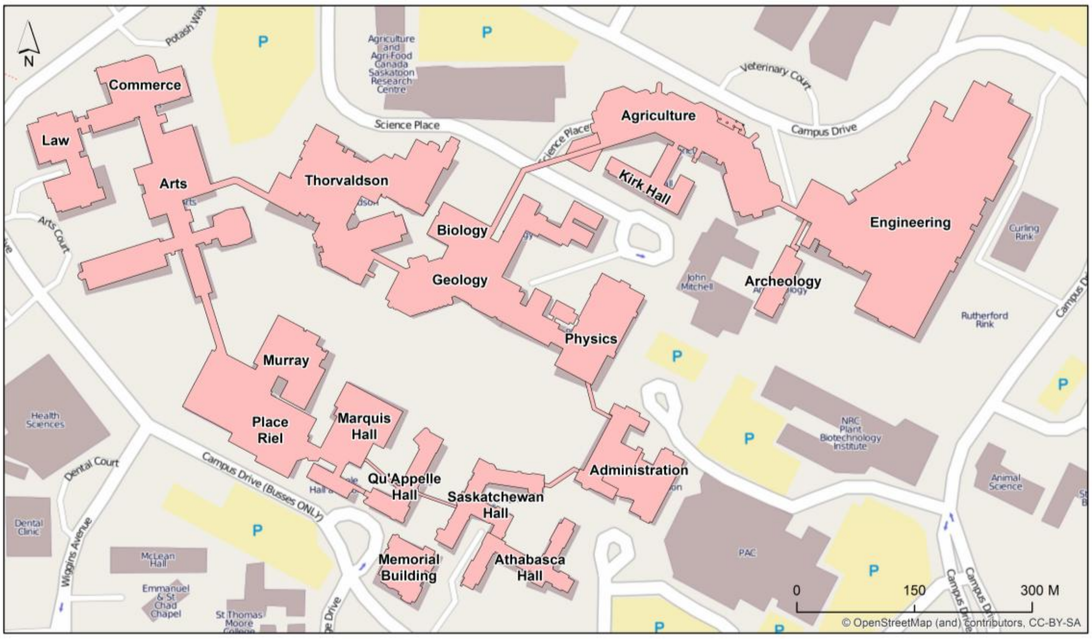


Figure 3. Campus buildings covered by WCN

Detailed floor and building corridor plans for U of S campus were requested from FMD and employed as the initial data source for the model. The process to automatically convert building data to 2.5D indoor network representation contained several steps (Figure 4).

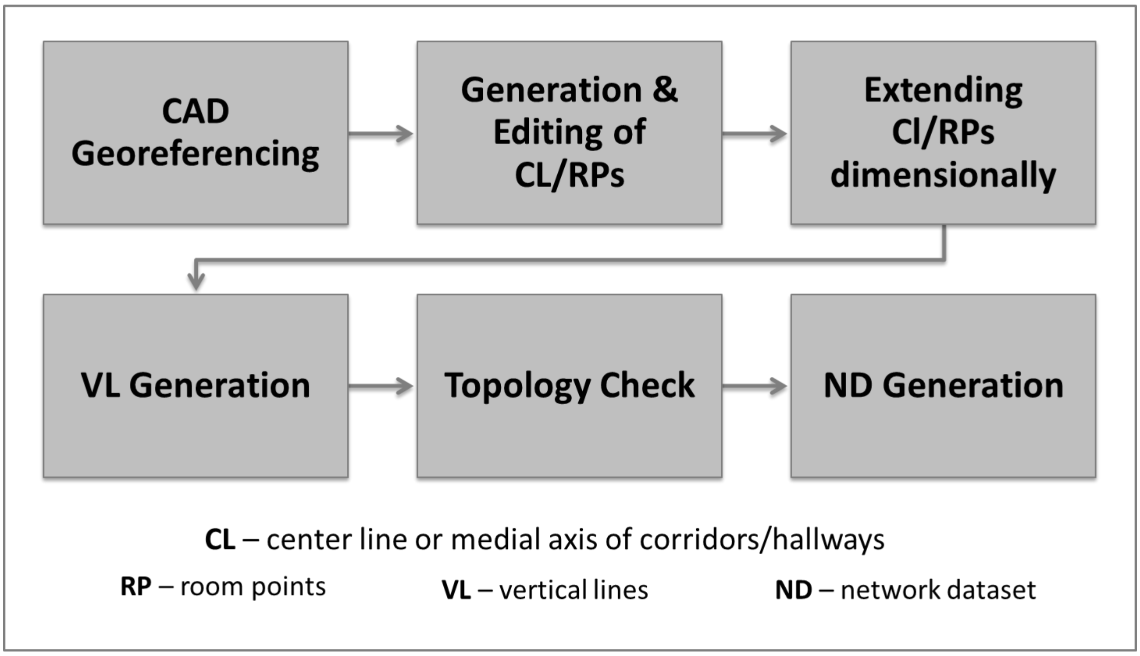


Figure 4. Methodology Flowchart for Network Dataset Generation

1. *Data processing*. The first step involved georeferencing and consistency check of the CAD files that were received from FMD.

2. *Generation of the CenterLINE (CL)*. Afterwards, georeferenced CAD files were used as the source from which to extract the medial axis of the campus hallways and corridors. This step was implemented using ArcGIS Model Builder. The information contained in the AutoCAD files were sorted into 5 feature classes: point, polyline, polygon, annotations, and multipatch. For CLs creation only polylines and polygons were selected. An algorithm similar to the one presented in (Wallgrün, 2005) was employed, where Voronoi diagram were used to extract a center line position of the polygon (Figure 5). Voronoi polygons were created from the points that represented the position of the corridor edges. These polygons represent the regions of locations nearest these generated points. Prior to polygon generation only polylines that correspond to the position of walls and windows were selected.

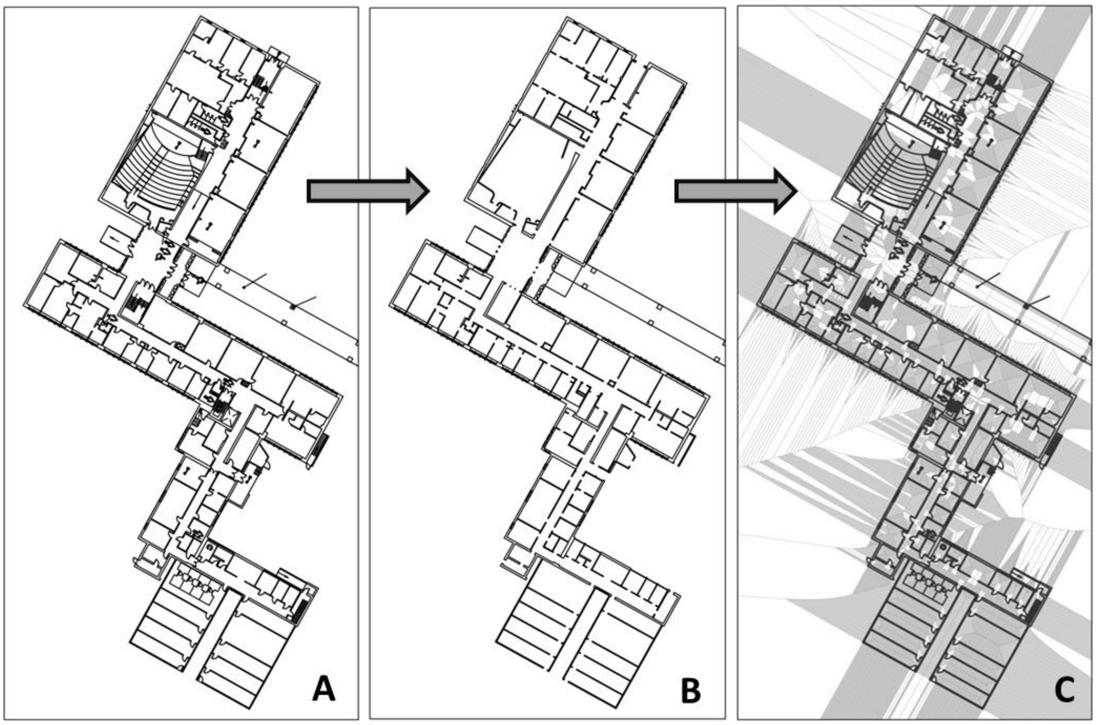


Figure 5. Intermediate model outputs. A: initial CAD file; B: only glass and window structures; C: position of the Voronoi polygons created based on the room points of the corridor edges

Redundant lines were eliminated by applying additional ArcGIS tools such *trim line* and *simplify line*, which resulted in a single line representation for each unique corridor/hallway (Figure 6A). Although the algorithm allowed for a relatively accurate representation of the position of the CentreLINEs, certain manual editing (such as changing of the position of a several lines and deleting any that are redundant) was performed to ensure the correct position of the lines (Figure 6B). Additionally, eliminating data errors and a consistency check were performed to avoid topological conflicts.

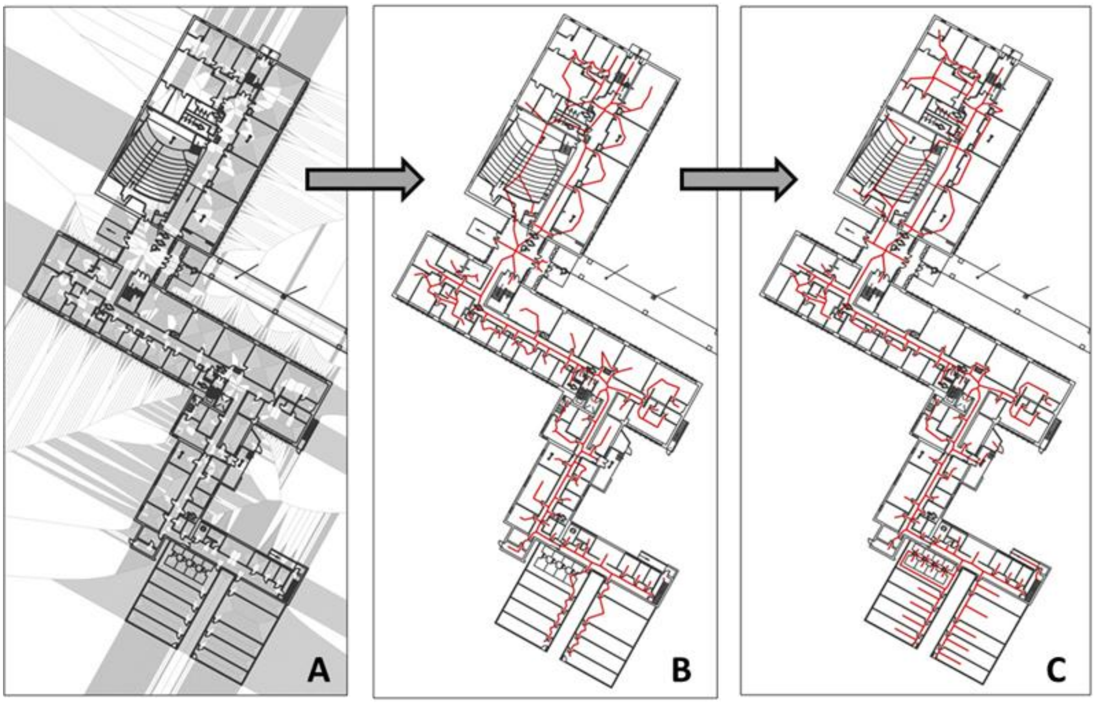


Figure 6. Generation of the medial axis of campus corridors/hallways. A: all Voronoi polygons; B: generated CL after application of the trim and simplify line tools; C: Final CL representation

3. *Generation and Classification of room points*. Using ArcGIS Model Builder, a point feature class that corresponded to rooms was generated from CAD annotations (Figure 7). To ensure the accuracy of the eventual network, redundant points (such as corridor names) were deleted; remaining room

points were classified into four different groups. The following groups were identified: elevators, stairs ramps, rooms, and doorways.

4. *Generation of the vertical lines (VL).* This step involved connecting corresponding vertical portals via *feature to line* tool of ArcGIS.

Figure 7. Generation of the room points. A: Initial CAD files; B: automatically generated room points

5. *Extending Centre Lines and Room Points to 2.5D.* To represent height information and demonstrate the elevation difference between various floors, a Z-coordinate was introduced (Figure 8). Adding Z-value to existing 2D lines and points resulted in three major improvements:

   – Variability of floor numbers among buildings meant that a change in elevation or level might result between two different levels of the same “floor.” So, Floor 2 in one building might be connected to Floor 3 in another building, but be the same elevation, or two floors in different buildings might both be Floor 2, but be at different elevations and became distinguishable by adding the z-value.

- Connectivity for the network dataset will now be possible only for locations where source features share all three coordinate values.
- Displaying the connections between the portal systems (such as stairs and elevators) better corresponds to their real-world representation.

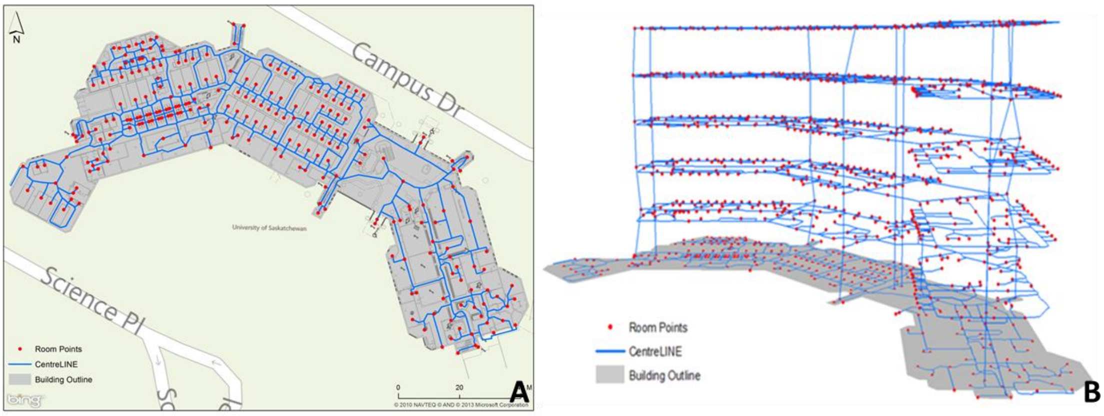


Figure 8. Generated CLs and RPs for Agriculture Building. A: 2D view, 1st floor; B: 2.5D view, entire building

6. *Topology check*. Since improperly connected edges might have a significant negative effect on the development of the whole dataset, it was important to ensure the topological completeness of the model. Incorrect connections between elevators and corridors were corrected with the *Snap to* feature in Arc editor. All the connections were checked through the number of Topology rules available in ArcGIS.
7. *Generation of the Network Dataset (ND)*. Using ArcGIS Network Analysis extension, all created line and point features were linked and integrated in a single 2.5D network that represents a topologic structure of the university campus. A Dijkstra's graph search algorithm (Dijkstra, 1959) was employed to determine the shortest path between a given node and any other node in a graph. The algorithm starts with the source node and maintains tentative

distance *d(v)* for each node v during the execution. It visits the nodes in order of increasing distance, and maintains a set of visited nodes whose distance from the source node has been computed (Spassov, 2007). Network attributes associated with edges visited along a route allowed for the estimation of several parameters and introduce a basic cost function to calculate the travelling time and distance between an origin and destination.

III

RESULTS: WALKABLE CentreLINE NETWORK

The purpose of the WCN was to capture and simplify the geometry of the building layout to improve positioning and support indoor navigation. The network consists of nodes and links, where nodes correspond to the central position of the room or decision-points and links represent the medial axis of the hallway polygons that physically connect these rooms and decision points. A similar node-link method is applied along the stairs and elevators to connect building floors. Node and link elements are stored as 2.5D features that allow for the display of differences between various building floors. The 2.5D network model is fully routable. Connections between the floors are allowed only at defined nodes that correspond to the position of stairs, ramps, or elevators. Automatically generated from architectural plans, the building and network model performs the shortest path computation between two selected locations and provides either 2D or 3D visualization and analysis of the paths. Table 2 provides the summary information on the network elements that were generated for the project; by using this method, it became possible to create a 2.5D indoor navigation models for group of buildings of different structures and complexities.

Table 2. Summary of the network elements

Number of campus buildings	20
Building floor range	3 -13 (total 98)
Number of pedestrian links	29
Number of elevators	43
Number of stairs	129 (including 1 ramp in Arts)
Number of nodes	6751
Number of interconnected lines	38592

To generate WCN three line feature classes were used (*CenterLine* to represent connections between nodes for each building, *VerticalLine* to demonstrate the vertical connections between respected nodes, and *Connection* for combine interconnected buildings). *RoomPoint* is a room feature classes that store information of the geometry and function of every room.

A

Object ID	Object ID	unique object identifier
Shape	Geometry	object geometry
height	Double	arbitrary height of the building
name	Text	function of the line
build_id	Short Integer	unique building ID from PDF document
bname	Text	building name (short name)
fname	Text	floor name
Shape_Length	Double	length of the object

B

Object ID	Object ID	unique object identifier
Shape	Geometry	object geometry
height	Double	arbitrary height of the building
build_id	Short Integer	unique building ID from PDF document
rname	Text	room number from CAD files
bname	Text	building name (short name)
fname	Text	floor name

C

Object ID	Object ID	unique object identifier
Shape	Geometry	object geometry
Length	Double	3D length of the object
bname	Text	building name (short name)
build_id	Short Integer	unique building ID from PDF document
vname	Text	vertical portal name from CAD files
tname	Text	vertical portal type
direct	Text	dummy field for instructions
Shape_Length	Double	length of the object

D

Object ID	Object ID	unique object identifier
Shape	Geometry	object geometry
frombname	Text	building name start
tobname	Text	building name finish
fromfname	Text	floor name start
tofname	Text	floor name finish
cname	Text	pedestrain link type
plname	Text	dummy field for instructions
SHAPE_Length	Double	shape length of the object
frombuild_id	Short Integer	building id start
tobuild_id	Short Integer	building id finish

Figure 9. Attribute schema for feature classes. A: CenterLine Feature Class, B: RoomPoint Feature Class, C: VerticalLine Feature Class, D: Connection Feature Class.

The final indoor network is stored in a geodatabase that consists of the four feature classes, a table of the buildings identification numbers, and official building names. Also, five relationship classes are created in order to manage the associations between the objects (Figure 10).

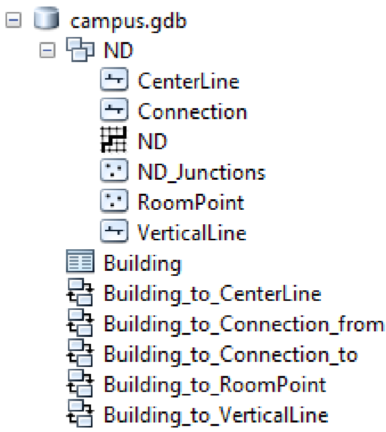


Figure 10. Content of the final geodatabase

By using ArcMap or ArcScene, it became possible to view the 2D or 2.5D dimensional building model and complete network on the screen. When a user selects two locations, a shortest path between them is calculated and displayed (Figure 11). Generated WCN allowed for path computations at different levels of detail. At the coarsest level, it is possible to calculate the path between two distant campus locations (Figure 11 A, C). If a particular building is selected, it is possible to represent a path for a larger scale (Figure 11 B, D). Further zooming is allowed for computation of the path within a single floor of a building.

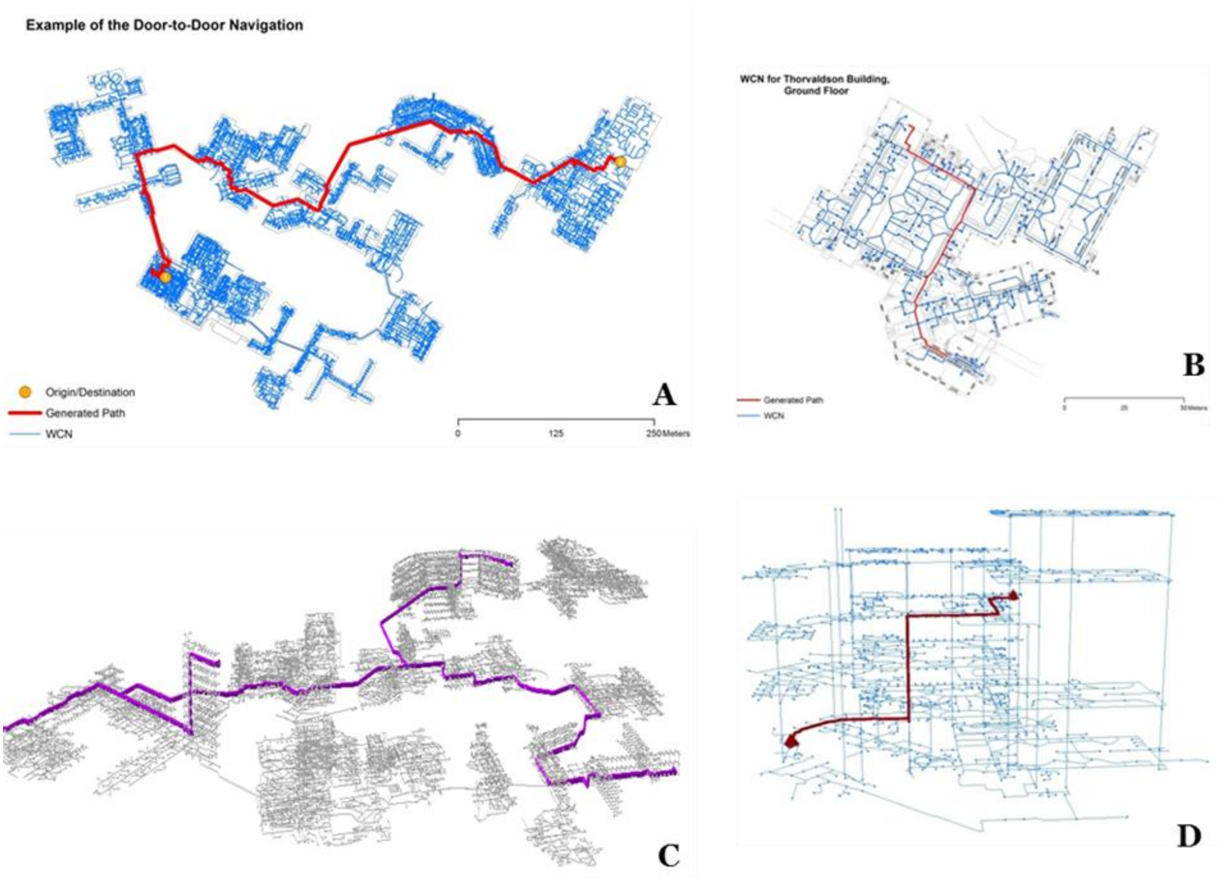


Figure 11. WCN network with examples of shortest path calculations. A: 2D view entire campus; B: 2D view, ground floor of the Thorvaldson Building; C: 3D view entire campus, path calculation between multiple locations; D: 3D view, Thorvaldson Building

Apart from displaying a map of the requested buildings with the line symbol representing the shortest path, an ASCII or HTML file with detailed turn-by turn instructions can be delivered to the user on request (Figure 12). By clicking on the '+'

sign in the instruction menu the user can expand the text and get more detailed information on the suggested route.

62:	[-]	Bear left on corridor main floor	31.9 m	Map
62.1:		Enter Place Riel		Map
63:	[+]	Bear right on pedestrain link	3.3 m	Map
64:	[+]	Continue at 86 on corridor ground floor	13.5 m	Map
65:		Continue to stay on corridor ground floor	14.1 m	Map
66:	[+]	Continue on pedestrain link	39.7 m	Map
67:	[+]	Continue on corridor basement floor	4 m	Map
68:		Bear left at 2 on ramp basement floor	7.9 m	Map
69:		Turn left on corridor basement floor	0.8 m	Map
70:	[+]	Turn right on pedestrain link	36.6 m	Map
71:	[+]	Continue on stair basement floor	2.3 m	Map
72:		Continue on corridor basement floor	2.6 m	Map
73:		Turn left to stay on corridor basement floor	32.8 m	Map
74:		Bear right to stay on corridor basement floor	5 m	Map
75:		Turn right at 83 to stay on corridor basement floor	41 m	Map
76:	[+]	Continue at 7 on pedestrain link	46.7 m	Map
77:	[+]	Turn left on corridor ground floor	2.5 m	Map
78:		Turn right to stay on corridor ground floor	4.8 m	Map
79:	[+]	Make sharp left on stair	3.8 m	Map

Options... Print Preview... Save As... Print Close

Figure 12. Example of the instructions delivered to the user

The created application was employed and tested in several university projects and shows positive results for improving the accuracy of SaskEPS system (Jung, et al., 2012) and indoor routing on University campus. In particular, the network became accessible from any client's PCs or mobile device since it was published on the University server (http://quimby.usask.ca/campus/). To use the application, the user specifies the source and destination on the screen and an optimum path is calculated and visualized in 2D (Figure 13).

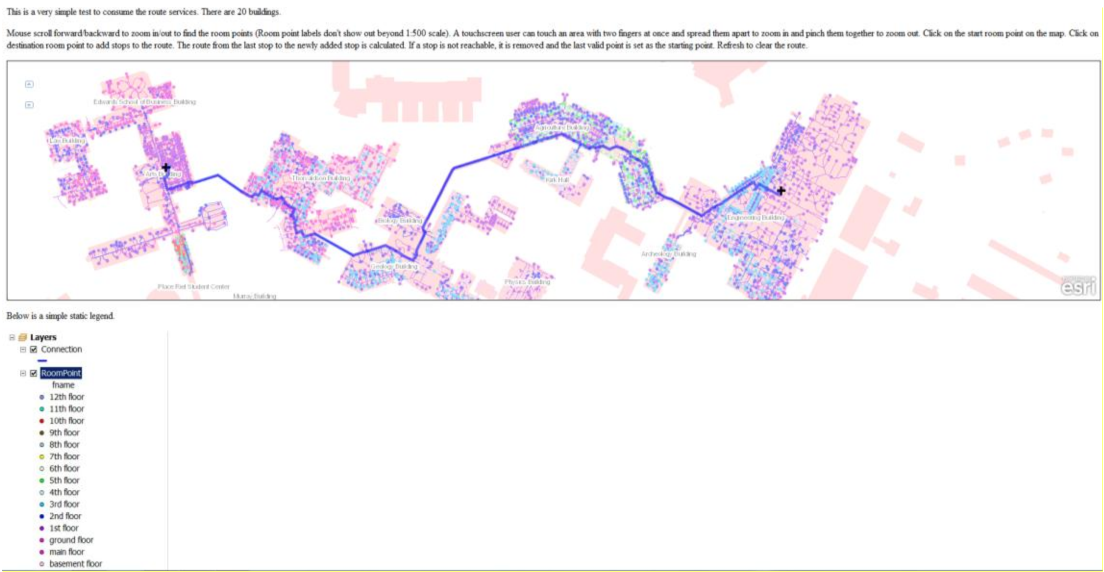


Figure 13. WCN network with examples of shortest path calculations (uploaded at http://quimby.usask.ca/campus/)

IV

APPLICATION OF WCN FOR INDOOR TRACKING: POSITIONING AND TRAJECTORY EXPERIMENT

Recently, significant effort has been invested in the development of tracking solutions for indoor human mobility (Seifeldin & Youssef, 2010; Stange, Liebig, Hecker, Andrienko, & Andrienko, 2011; Zhang, Liu, & Ni, 2011; Zhou et al., 2008). In particular, the deployment of an indoor positioning system in conjunction with a multi-sensor smartphone provides a promising solution for tracking movement indoors and uncovering human spatial behavior. However, the limited accuracy of current indoor positioning solutions requires the incorporation of additional tools to correct erroneous positioning and to provide reasonable interpolation and extrapolation when signals disappear or degrade beyond functional utility. The generation and use of an indoor navigation network to correct tracking data from positioning results is one solution for this problem. Such correction can take even relatively accurate positioning results and "snap" them to the logical room or hallway centerline; this action can improve the "believability" of positioning results represented on a map of the indoor environment.

An experiment using the previously described CentreLINE database was conducted in the indoor positioning and tracking application area. One of the experimental goals was to identify whether the usage of WCN improves the utility of indoor positioning data for interpreting indoor mobility through space and time. In particular, the experiment explored whether correcting, or "snapping," WiFi-based positioning results to an indoor navigation network (WCN) can a) be applied to raw positioning data in order to improve accuracy and route generation and presentation, and b) be used as a tool to generate movement trajectories that provide a better representation of human spatio-temporal mobility. The iEpi system (Hashemian, Stanley, Knowles, Calver, & Osgood, 2012) was employed for data collection, while SaskEPS (Bell, et al., 2010) was used for positioning. The flowchart depicts a general overview of our methodology in Figure 14. This conceptual model is an abstract that describes the primary steps required to produce the reliable indoor tracking data.

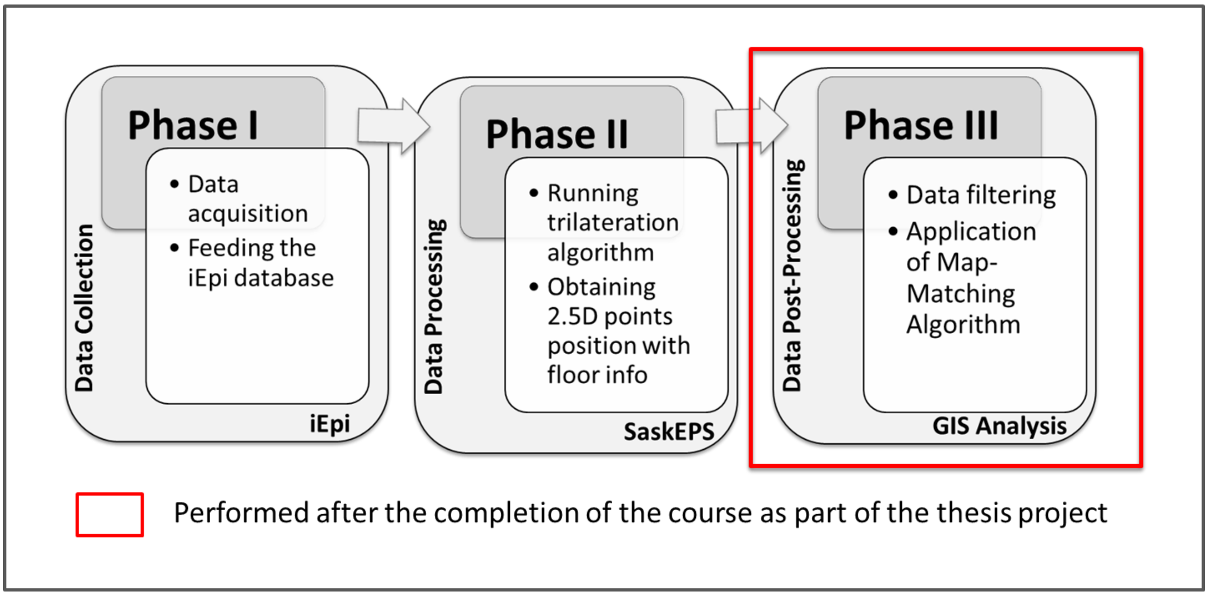


Figure 14. Experiment Methodology Flowchart

It is necessary to emphasize that the experiment was collaborative and was carried out by a collection of seven students from the departments of Computer Science and Geography and Planning. All data acquisition and coordinate calculations were performed by graduate students of the department of Computer Science. In particular, students from the department of Computer Science were responsible for configuration of the iEpi system, uploading the data from iEpi to SQL server and translating this data to geographic coordinates using the SaskEPS algorithm. Initial GIS analysis, which included preliminary data filtering, was also performed during the course by the students from the department of Geography and Planning. However the major GIS post-processing, analysis, and trajectory generation were performed in February and March 2013 after the end of the Ubiquitous Sensor Systems course. During this period, I enhanced the script that performed map-matching algorithm by incorporating additional tools that control the selection of the correct edge on the network. I wrote a script that calculated individual daily trajectories for every participant over the course of four weeks using the capabilities of ArcGIS network analysis. I also performed the usage analysis of the campus based on the individual daily trajectories and validated the result by incorporating additional functionalities and variables to determine if any part of the created path segment belonged to the outdoor environment. This work was done using the geoprocessing capabilities of ArcGIS, all the created scripts and models were translated into ArcGIS tools. These tools are now available via shared drives at the laboratory of Spatial Analysis and can be rerun by other researchers. The following chapter will introduce the experimental settings and data acquisition process as well as demonstrate post-processing results that were obtained with the help of WCN.

4.1 Design and Data Collection

Android Phones programmed the with the iEpi application (Hashemian, et al., 2012) were used to collect indoor mobility data (Figure 15). Thirty seven participants were recruited from a single undergraduate class to ensure that common trajectories between participants would be observed at least twice per week. After receiving study approval from the research ethics board, phones were distributed to participants during orientation sessions; in these sessions participants were shown how to use the phone and completed a pre-survey questionnaire. Participants were asked to carry the phones with them at all times during the day for the entire duration of the experiment, to charge their phone nightly, and to participate in daily on-line phone surveys. At the end of the four-week trial all phones were returned. Because of technical problems with several phones and some participants' absence from campus for long periods of time, it was possible to record reliable and valid data from 32 of the 37 participants.

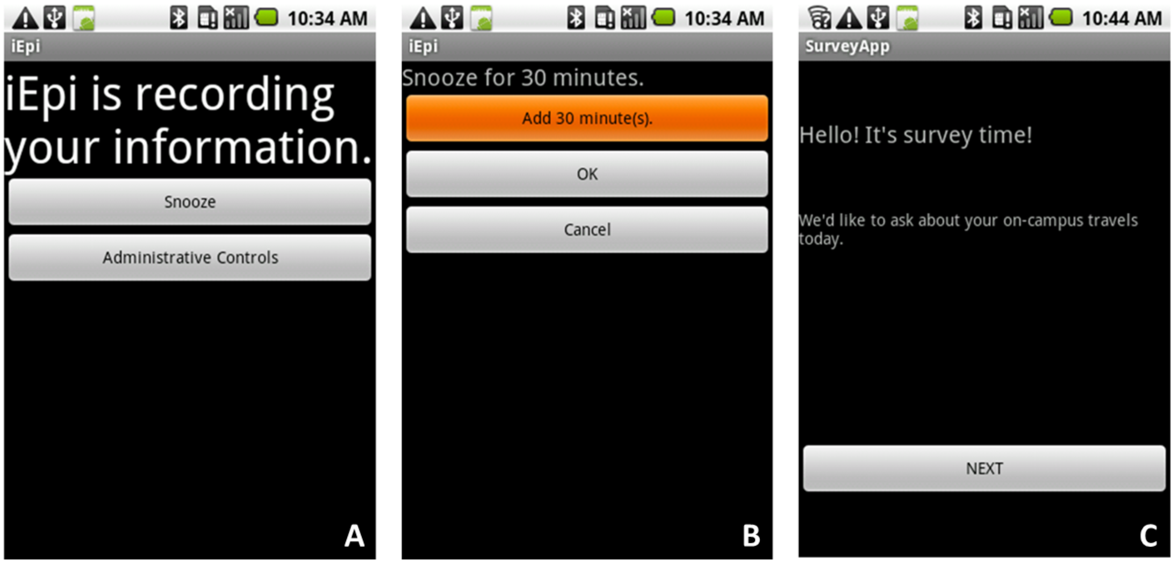


Figure 15. Interface of the iEpi application. A: Main menu B: Snoozing options C: Survey interface

As part of the questionnaire, participants were asked to draw a number of sketch maps that indicated their familiarity with the University campus, including the top three on-campus routes they took each day of the week. 2D representations of the campus as a map background were used and did not restrict paths to indoor environments. Example and aggregate trajectories are presented in Figure 16.

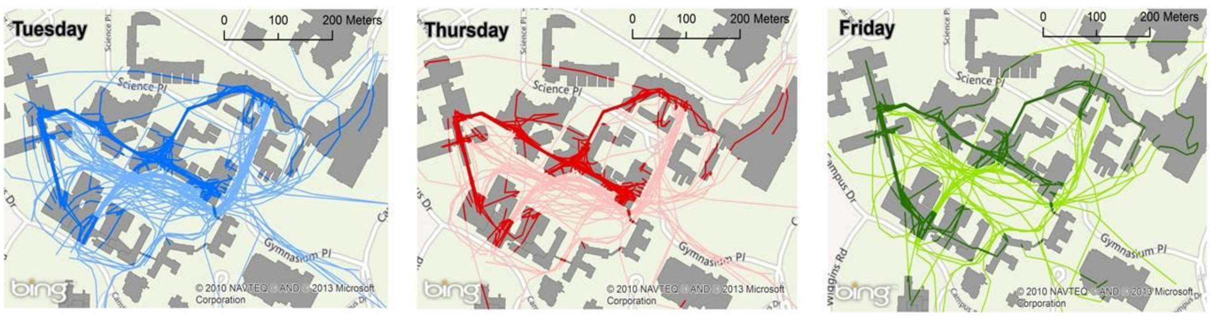


Figure 16. Aggregate trajectories drawn by participants; darker areas correspond to indoor campus paths

4.2 Generating of the Positioning Results

4.2.1 Position estimation

Data collection was consistent with earlier applications of iEpi (Hashemian, et al., 2012). To ensure sufficient battery life for a full day of monitoring, continuous tracking was not possible. Instead, the phones performed measurements for thirty seconds (referred to as the On Cycle) every two minutes (referred to as the Duty Cycle). Every On Cycle was further divided into 5-second epochs during post-processing. Every Duty Cycle the phones collected 30 seconds of accelerometer records, Bluetooth contacts, WiFi contacts, and 10 records of battery state. During the 30 day study over 100 million records were made from 6 sensors; magnetometer, accelerometer, Wi-Fi, and compass sensors were the most common. Using the University of Saskatchewan secure WiFi network, the phones uploaded data opportunistically. The data was stored initially in flat files and parsed at regular intervals and inserted into a central database. A moving window computation was employed to determine participant location. Within each On Cycle a position of a participant for every second was calculated, based on the preceding 5 seconds of WiFi router identifiers and received signal strength indicators (RSSI) values (for a total of 25 records per On Cycle). To establish location, this group of unique three-tuples was trilaterated using SaskEPS for all combinations of routers during the 5 second window. The use of duty cycles, while necessary for maintaining measurement longevity, resulted in patchy position updates with up to 25 points available over a 30 second period followed by 90 seconds where no data was available.

4.2.2 Data Post-Processing in GIS

To visualize and spatially analyze the output of SaskEPS, the calculated locations were further processed in ArcGIS 10.1. Positioning outliers were removed by identifying the geographic center for a set of recorded points unique for every participant in each one-second interval. Such data filtering significantly reduced the number of the points used in the later stage of data post-processing. Figure 17 shows SaskEPS data before and after the removal of the outliers for the ground floor of Murray building.

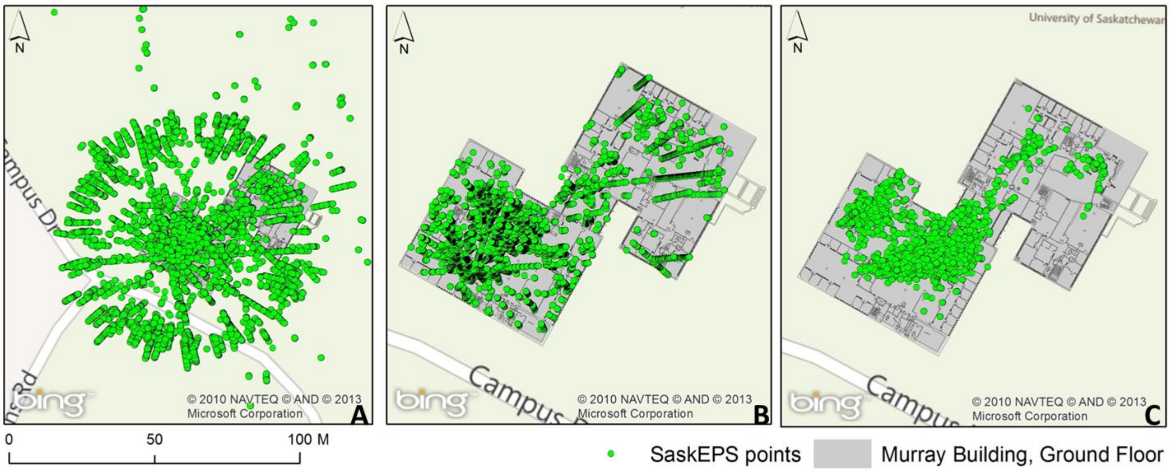


Figure 17. Filtering the SaskEPS points. A: non-filtered SaskEPS points; B: SaskEPS points after clipping with corresponding building floor; C: filtered SaskEPS points, corresponding to position of the participant within one second interval

Because the data was collected for the first thirty seconds within each two-minute interval, gaps in participant mobility records were evident. To address this problem a map-matching algorithm described above was applied. In general such algorithms can be categorized into four different groups(Quddus, et al., 2003): probabilistic algorithms, advanced algorithms, topological analysis based, and geometric analysis based. The last is employed in this study. This type of map-matching employs the geometric information of the spatial road network data and considers only the shape of the links (Greenfeld, 2002); in other words, the map matching employs a technique that snaps a position to the closest *node* or *edge* of a road segment. Three different types of map-matching algorithms can be identified (Quddus, et al., 2003): *point-to-point matching* that snaps raw position point to the nearest node in the network; *point-to-curve matching* that snaps raw position point to the nearest edge in the network; *curve-to-curve matching* that resembles the shape of the curve of the raw data to the shape of road network segment. Geometric map-matching algorithms are easily and efficiently implemented, they can be executed using the capabilities of the existing ArcGIS tools and provide accurate results (Bernstein & Kornhauser, 1996). However they are highly dependent on the spatial road representation and may perform poorly when errors exist on the network. Nevertheless, several solutions exist to improve the accuracy of the method (Bernstein & Kornhauser, 1996; White, Bernstein, & Kornhauser, 2000). In particular, this problem could be overcome by including more vertexes for every arc used for snapping. The drawback of this solution is increased computational time; however this can be neglected due to the relatively small size of the created network.

I employed a geometric map-matching algorithm (Quddus, et al., 2003) to link filtered SaskEPS points to a corresponding position on the WCN. Prior to snapping, vertexes were inserted along the WCN (with one meter distance between neighboring vertexes) to simplify the snapping process to WCN vertexes rather than segments (Figure 18). This allowed for calculation of snapped SaskEPS points based on CentreLINE vertexes and produced more consistent representation of the participants' movements.

GIS network analysis capabilities allowed for the calculation and generation of a number of shortest/least cost paths that give an appropriate representation of indoor movement trajectories. These algorithms were used to link the strings of known locations calculated by SaskEPS from the 30 second duty cycles. Using ArcGIS 10.1 Network Analyst, a tool was created that generated a shortest path by connecting all daily tracked SaskEPS points recorded for a unique person. This yielded 306 daily individual paths, which corresponded to an individual's trajectories followed for a single day; these trajectories were later aggregated based on day of the week.

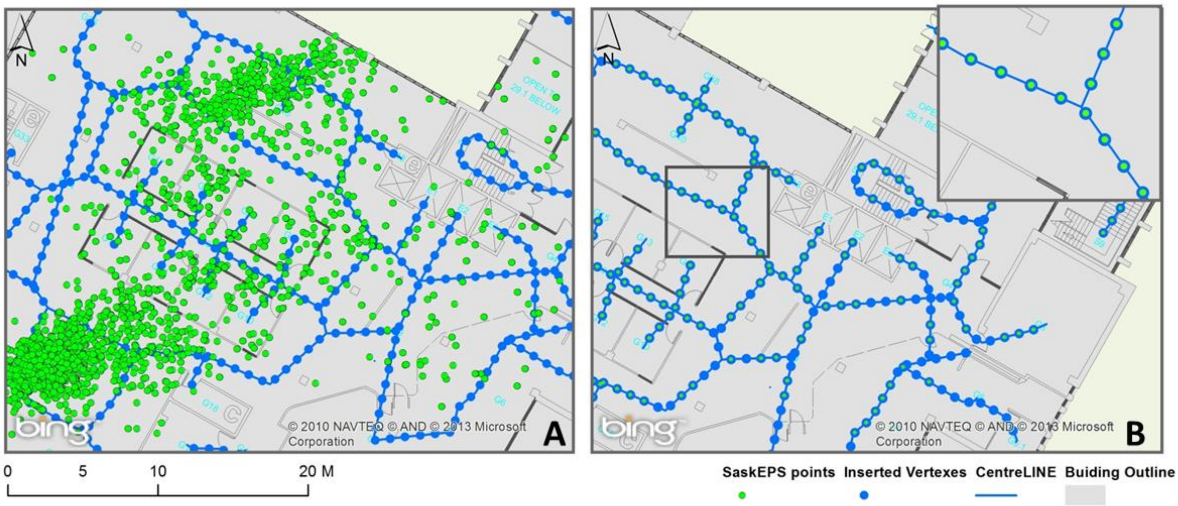


Figure 18. Applying geometric map-matching to SaskEPS points. A: raw SaskEPS data; B: after implementing map-matching

4.3 Position Tracking Results

The kind of dataset described in this paper can be used to understand human spatial behavior. It represents a compilation of millions of data points for a discrete group of individuals. This represents a unique type of Big Data, one that is disaggregating in form and deep in relevant context. Specifically, route selection, navigation behavior and collective/shared path choice could be examined. After post processing, 180,000 2.5 D location records were available to represent the spatio-temporal trajectories of individuals while on campus.

During the four weeks of the experiment, participants were tracked in 14 campus buildings (Figure 19). Figure 19A shows the number of unique times a participant entered a given building, corresponding to visits. Figure 19B shows the number of epochs any participant was found in a particular building and corresponds to an aggregate measure of time spent in the building (in participant-epochs). In general, the location of the participants was consistent with their academic schedule. Most of the identified locations were found in the classrooms and labs of the Arts building and study halls of Murray Library (the main campus library), whereas the Law building and Memorial Hall (unlikely destinations for undergraduates) were the buildings with the fewest, non-zero individual participant visits. Although the Arts and Murray buildings remained in the top two based on the number of counted epochs (meaning that participants were spending considerable time there), results for the Physics building demonstrated that despite the relatively low number of unique participant visits, participants stayed in this building for extended periods of time.

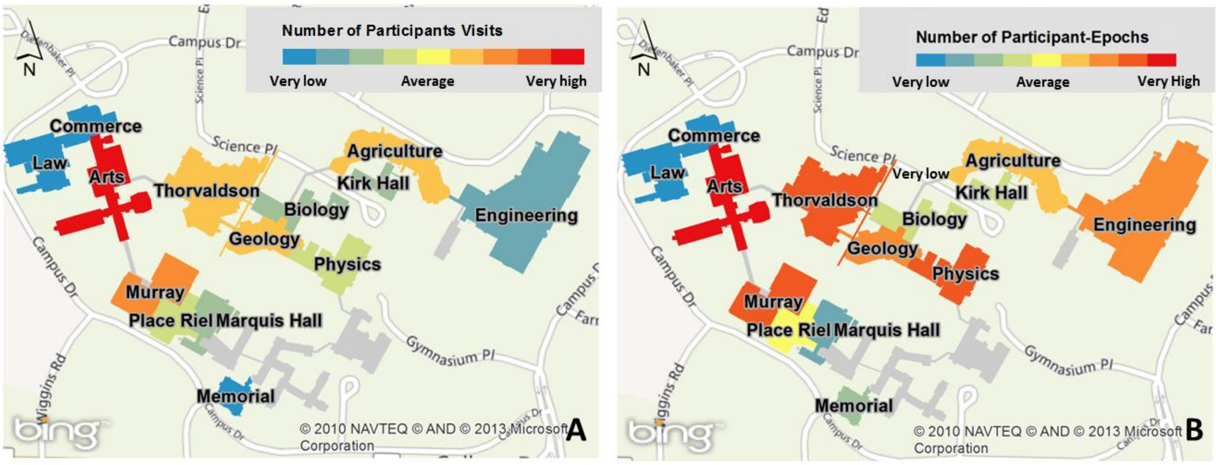


Figure 19. Results of participants tracking on campus. A: Buildings mostly visited by participants B: Buildings where participants mainly spending time

Analysis of the most visited locations separated by floor was performed. In particular, the 1st level of Physics and the 1st floor of the Arts building were the most popular locations among the participants. The graph below displays the ten most visited building floors on campus (Figure 20). This result allowed us to identify frequently visited locations that were used primarily as transit areas to reach other locations on campus and separate them from destinations at which participants were more likely to linger. The red line on Figure 20 indicates such locations. For instance, despite a high number of participants visiting the ground floor of the Arts building, the overall number of epochs is relatively low, implying that participants were crossing this floor to reach their final destination. A similar pattern was evident in the first floor of the Thorvaldson building and the second floor of Geology, which both attach directly to inter-building enclosed skywalks.

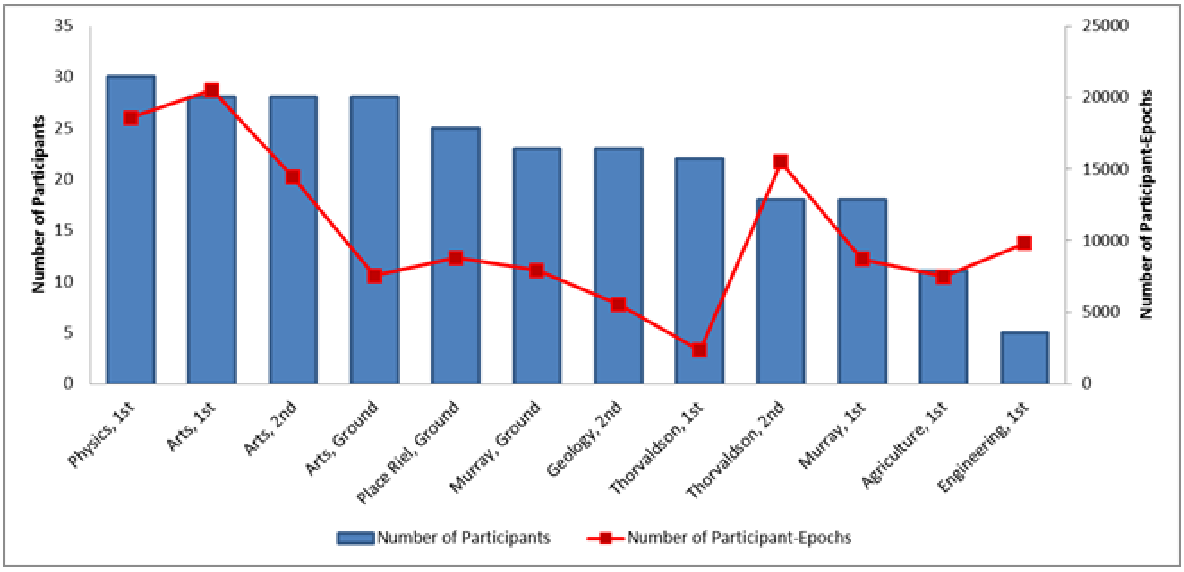


Figure 20. Most visited building floors on campus

To further explore the data, spatio-temporal analysis of the campus locations that were mainly visited by participants was conducted (first floors of Arts and Physics buildings). Figure 21 shows counts of SaskEPS points snapped to WCN for the entire duration of the experiment for first floor of Physics. Colors close to red indicate a higher number of tracked points, whereas colors closer to green are related to lower numbers. By visualizing this data in ArcGIS environment and overlaying it with campus blueprints, it is possible to detect that room 107 was the building primary visited location. Moreover, temporal analysis of the data demonstrated that this location was visited mainly between 8h00 and 10h00 am on Tuesday and Thursday. These results were consistent with the academic schedule of participants because 8h00 and 10h00 am was the lecture schedule for Introduction to Geomatics.

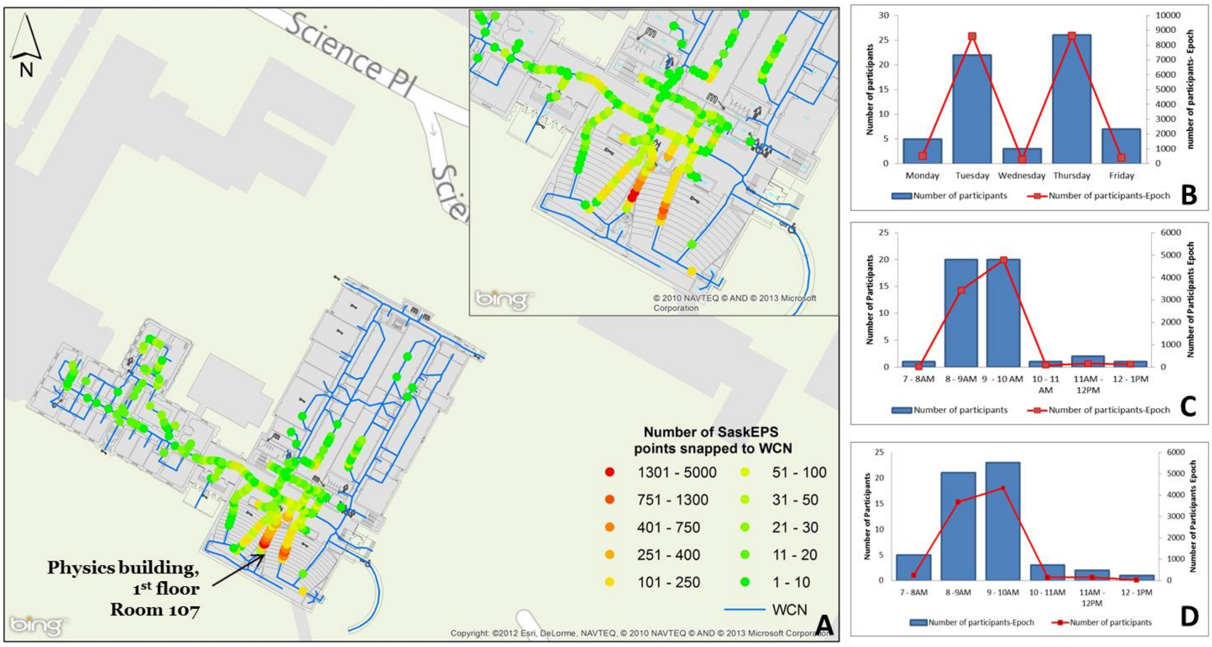


Figure 21. Distribution of SaskEPS recordings for Physics, 1st floor. A: spatial distribution; B: Temporal distribution by weekday; C-D: Temporal distribution by hour on Tuesday & Thursday

Further to this example spatio-temporal analysis of participant mobility was performed in the first floor of Arts building (Figure 22). In distinction to the first floor of Physics, no discrete daily patterns were observed.

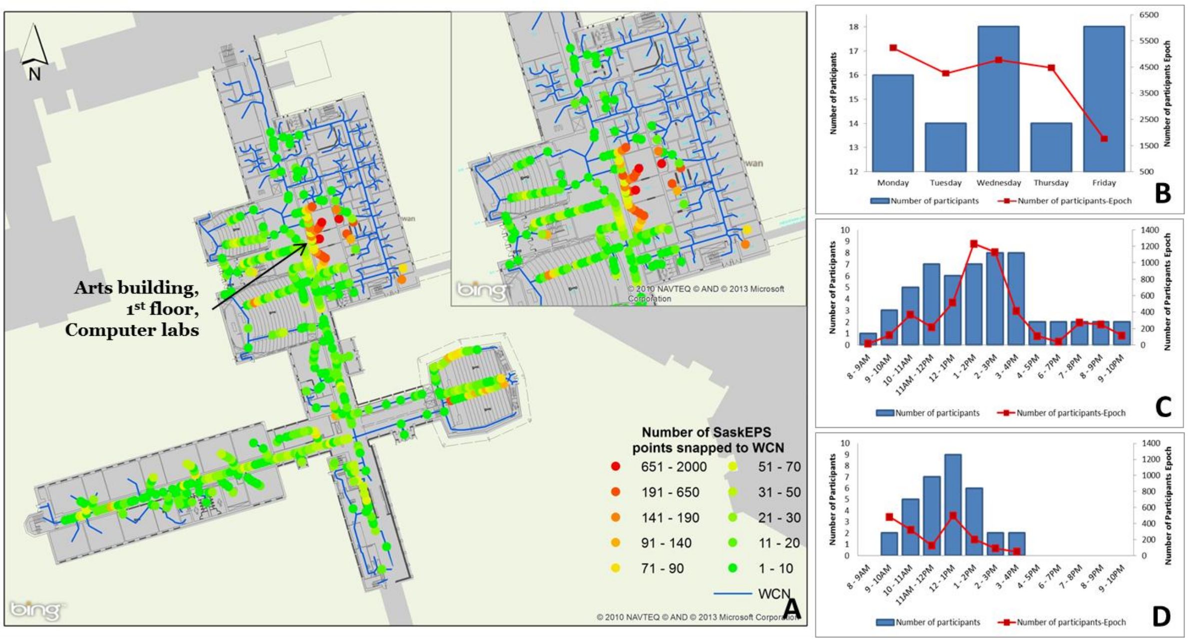
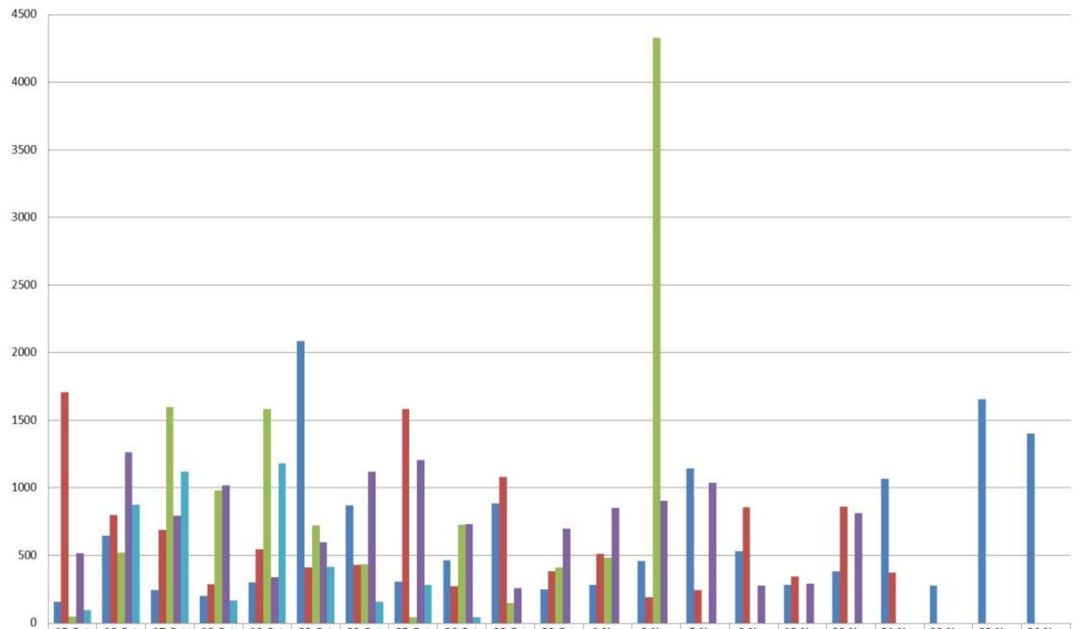


Figure 22. Distribution of SaskEPS recordings for Arts, 1st floor. A: spatial distribution; B: Temporal distribution by weekday; C-D: Temporal distribution by hour on Wednesday & Friday

In general, a relatively high number of participants' visits with the highest concentration of recordings were found in and around computer laboratories. Apart from Fridays, the duration of visits is evenly distributed, meaning that participants spend considerable, but consistent time in the different rooms of the Arts building. However, despite of a high number of students' visits for the first floor of Arts building for every selected weekday, we can see the daily differences between the overall numbers of Epoch recordings. In particular, Friday is characterized by the big number of short visits, meaning that participants were mainly crossing this floor to get to their final destination.

4.4 Trajectory Analysis

A single representative day was selected and the top five participants by logged time on campus (Participant #s = 10, 15, 30, 31, 32) (Figure 23).



	15-Oct	16-Oct	17-Oct	18-Oct	19-Oct	22-Oct	23-Oct	25-Oct	26-Oct	29-Oct	30-Oct	1-Nov	2-Nov	5-Nov	9-Nov	13-Nov	20-Nov	21-Nov	22-Nov	23-Nov	24-Nov
Participant 10	156	644	244	199	302	2083	871	306	462	883	249	284	461	1144	533	280	382	1068	277	1656	1403
Participant 15	1706	800	691	287	545	413	429	1581	272	1081	385	510	191	242	856	343	859	374			
Participant 30	50	522	1596	982	1585	724	433	44	729	146	410	485	4328	1							
Participant 31	516	1262	796	1019	340	599	1121	1207	731	256	696	852	902	1040	278	293	813				
Participant 32	98	875	1117	168	1182	418	159	284	45												

Figure 23: Daily distribution of the number of participant-epochs for five selected participants

These participants were chosen because they had the greatest amount of data collected from their phones from the full population of participants. Their user data was then selected (which is not necessarily the same for each participant) where a) the participant had a high number of records and b) she/he visited at least 4 different buildings.

4.4.1 Trajectory Generation

To better understand an individual participant's mobility a trajectory-based approach was employed and connected corresponding individual locations according to the time stamp of the recording (a time integrated spatial representation) (Figure 24).

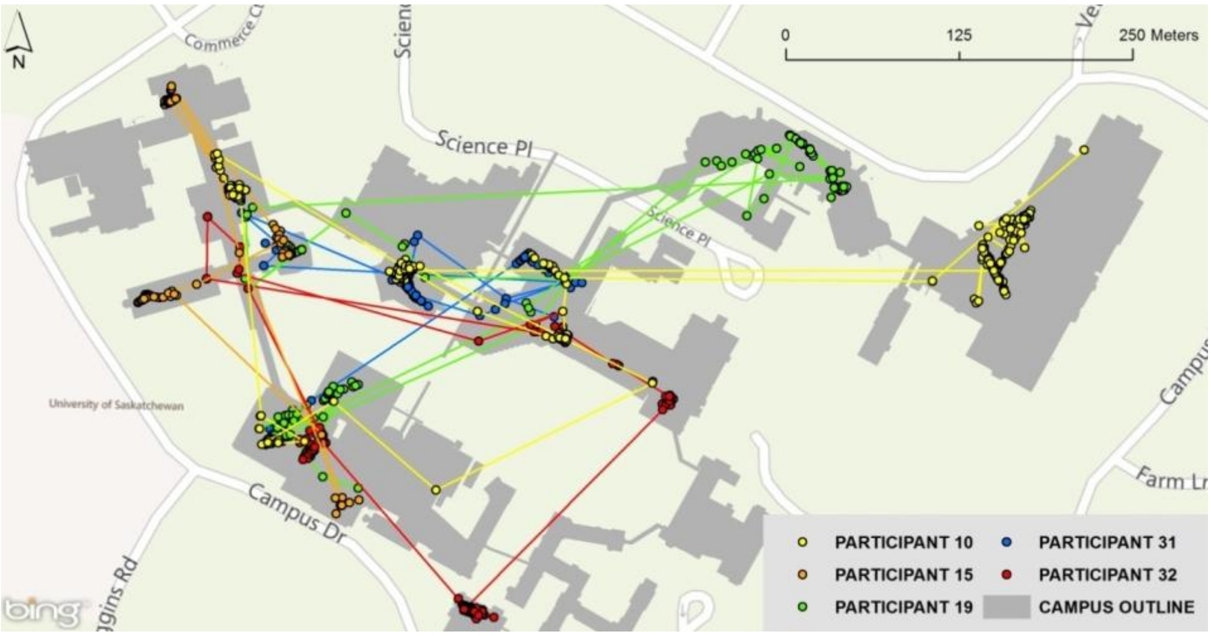


Figure 24. Raw trajectories before application of map-matching

Unfortunately, the results that were initially obtained were not precise enough to perform further analysis. Generated paths were not consistent with building layouts (halls, rooms, entrances, exits, stairs, etc.) in large part because of the sparseness of the data. Higher temporal fidelity of the positioning data would have meant that simple linear interpolation between points was sufficient. However, collecting data at a higher temporal fidelity would have exhausted of the battery in less than 6 hours. Moreover, most of the generated routes were outside the footprint of campus buildings; such locations are impossible as WiFi connectivity was recorded, indicating that the participants were indoors or very near to an indoor location. Application of map-matching and the WCN significantly improved our results. By linking the tracking position to the corresponded elements on the WCN network, it was possible to reconstruct trajectories (Figure 25). This also enabled the identification of the most visited locations as well as the temporal duration of these visits.

Figure 25. Adjusted individual trajectories after linking them to WCN

In particular, visualizing the trajectory generated using WCN allowed for the identification of spatio-temporal patterns. Likewise, for participant #15 detection the location of the participant during a single day is possible (Figure 26).

In Figure 26 colors close to blue indicate time stamps that correspond to early morning, whereas colors closer to red are related to points tracked after 3 pm. By visualizing this data over a base map of campus, it is possible to detect the primarily visited locations, the paths that connect them, and as a result how an individual moves through both time and space. In this case, the trajectory starts at the bus terminal. The participant then moves along the ground floor corridor of the Arts building to reach a classroom located in Commerce. She/he then took the stairs to continue her/his classes on the first floor of Arts. Later, different stairs were used to return to the ground floor of Place Riel and leave campus. It possible to infer that the first floor of Arts building and ground floor of Commerce were the primary visited locations, whereas the ground floor of Place Riel and Arts building were used as transit corridors to reach the locations of interest.

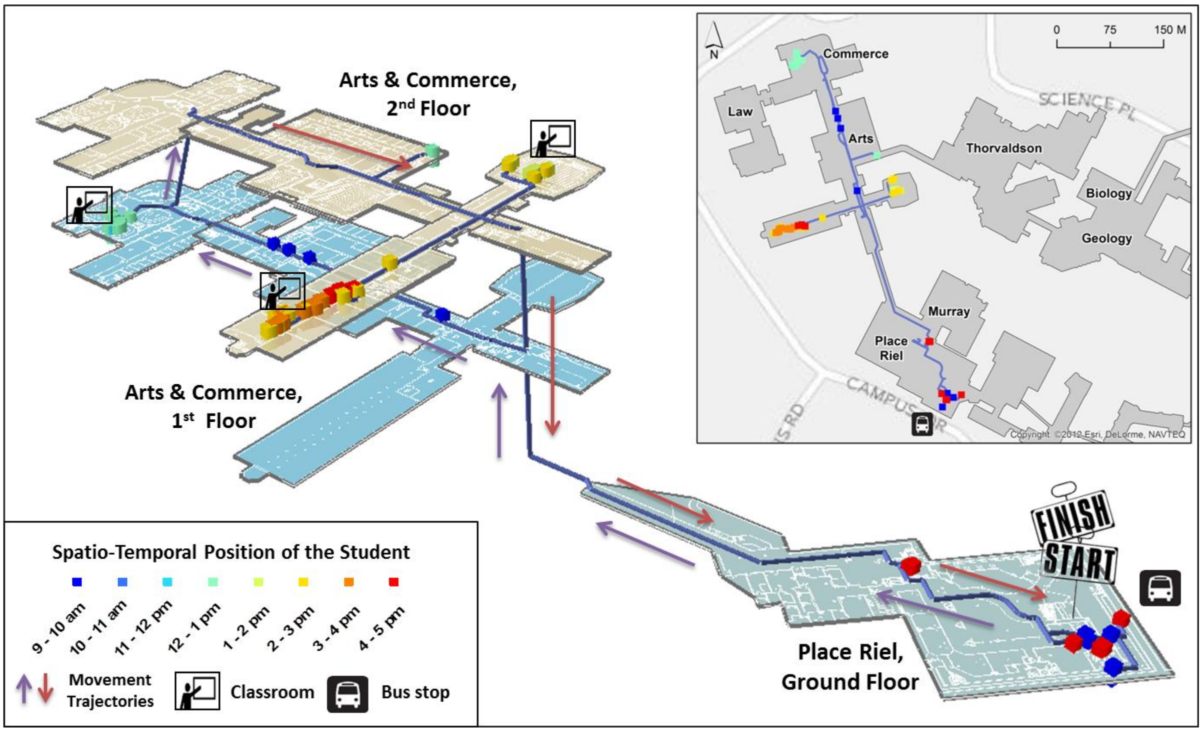


Figure 26. Trajectory of participant #15 (October 22, 2012). 2D and 3D view of the trajectories, with the arrows corresponding to the direction of the travel

4.4.2 Validation of the Results

Although the results were good enough to depict the spatio-temporal trajectories on the individual level, path estimation was still necessary. In particular, it was important to understand how reliable our indoor trajectories were. Since the current version of WCN does not support outdoor environment, it was assumed that some of the participants were taking outdoor paths to reach various locations on campus. An interesting challenge was whether we could identify false positive paths, or paths that indicated indoor movement (due to map matching to the CenterLINE network) when outdoor movement was more likely.

To check our findings, an ArcGIS model that calculates the duration of all movement trajectories fragments was created. The idea behind this model was to identify the length of every path that connects successive locations recorded with iEpi and calculates the time that was taken to travel this distance (assuming the average walking speed around 5 km/h). In other words, I split generated daily trajectories into the number of various length fragments and identify those segments that took place outside the campus buildings according to the time stamp.

Overall, this analysis revealed that only 3 segments of the five daily selected trajectories were likely taking place outdoors. The figure below (Figure 27) represents the example of three wrongly classified trajectories for participants #10, 30, and 32 (Figure 25); all paths for the participants #15, 19 (Figure 25) likely belonged to the indoor environment. According to the initially obtained results, it took 2 to 3 minutes for participants to travel between areas located relatively far apart. However, this is hardly possible, even with a high walking speed. It is more probable that participants left the building through one of the doorways (indicated in green in Figure 27) and took shorter outdoor paths.

Although this accuracy check is preliminary, it gives an opportunity to identify the trajectories that did not take place indoors. More precise accuracy estimation can be performed only if the chosen tracking method allows for the collection and estimation of position in an outdoor environment.

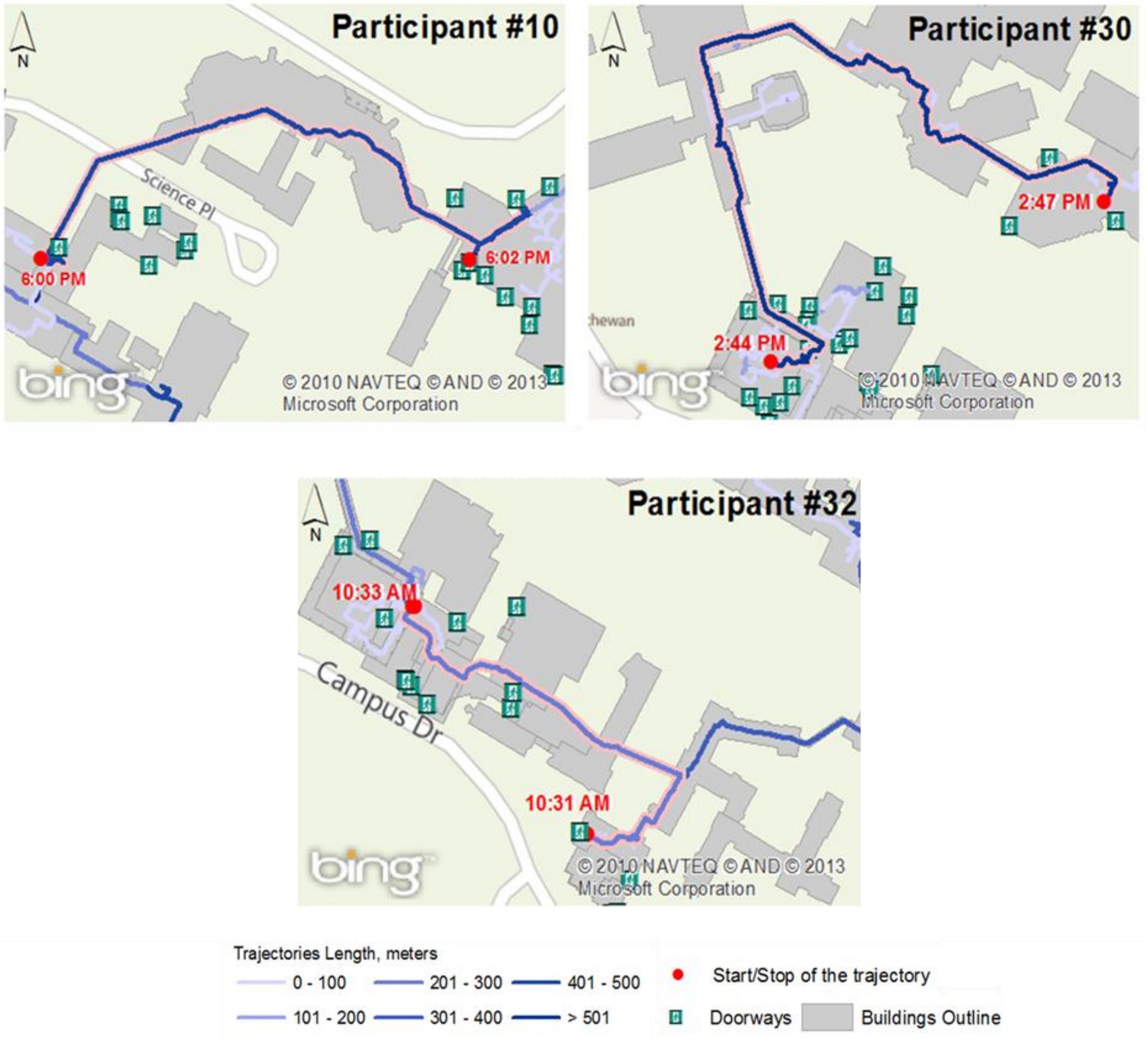


Figure 27. Outdoor trajectories that were identified as indoors paths

4.5 Usage Analysis

Generation of individual trajectories allows for an investigation of traffic flow between various locations on campus. To map the flow, a count was made of how many times each node of the WCN was visited by participants; this was represented using heat maps. The map in Figure 28 shows the aggregated path that participants took on Tuesdays, Thursdays (days when they shared a common class), and Fridays (as a counter example). Colors close to blue represent those campus areas that had fewer visits, whereas colors close to red identify the most popular campus locations.

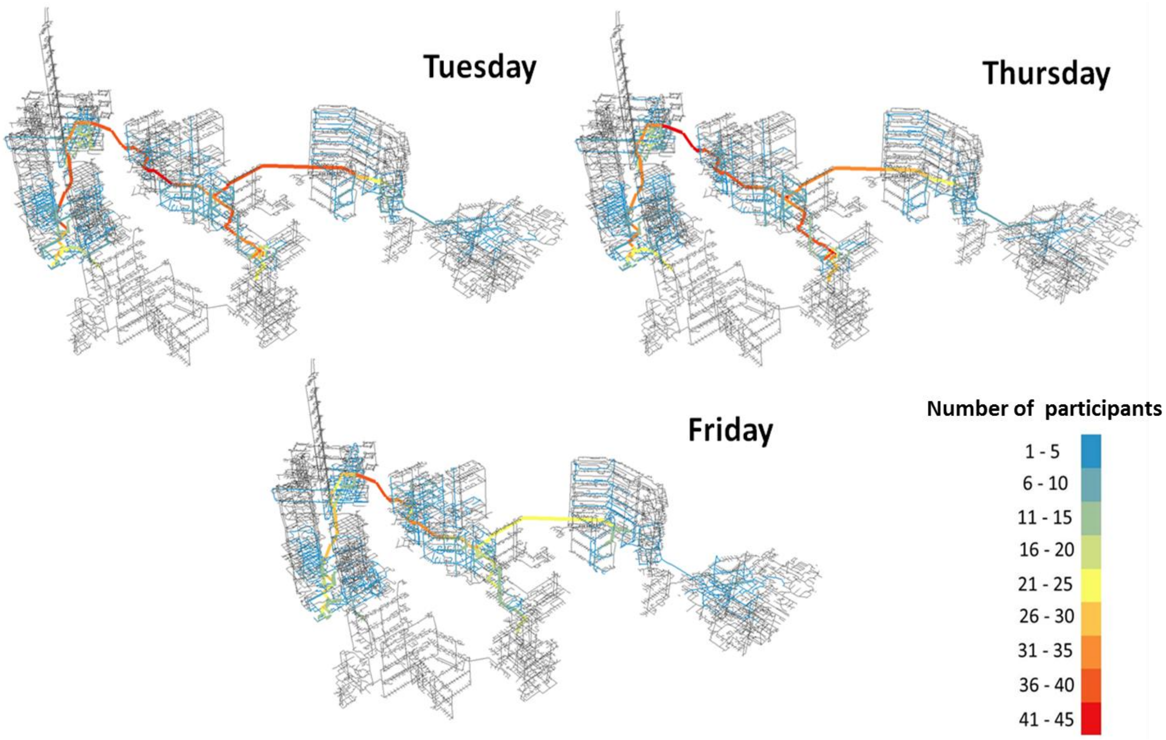


Figure 28. Usage of campus buildings by participants for different weekdays

The visual analysis of these three maps demonstrates that the highest number of visits correspond to the location of the hallways that connect various buildings on campus. The skywalks between the Arts and Thorvaldson building and between Biology and Agriculture had the highest number of tracked locations. This trend is consistent for three selected weekdays although the number of visits is lower on Fridays.

4.6 Comparison with the Sketch Maps

Trajectories generated by the WCN with the sketch maps that were drawn by participants at the beginning of the experiment were compared. After digitization of the hand drawings it was possible to perform an analysis of these maps for various days of the week. From the sketch maps only indoor paths were selected and aggregated by building. This data can be used to visualize buildings with the highest number of indoor trajectories. The maps in Figure 29 shows commonly used paths that were identified on sketch maps for Tuesday, Thursday, and Friday with the iEpi/SaskEPS trajectories created from data with the WCN for the same days. Colors in blue correspond to a low number of identified trajectories whereas colors close to red identified the locations visited frequently.

Sketch maps are considered a powerful tool for obtaining information about spatial environments (Bell & Archibald, 2011; Golledge, 1997; Golledge & Stimson, 1996; Li & Bell, 2011); it is evident, however, that they have limitations when one is interested in frequency vs. importance. There are additional drawbacks that can be overcome with tracking tools such as ours. When analyzing sketches for many people it is difficult to establish their individual intended accuracy. By constraining the sketch (as was done here) it became possible to establish common orientation and scale, but was not possible to conclude if a drawn path is a simplification of an actual path or the participant's actual or intended path. Many paths appear to be origins and destinations linked by an approximately straight line, others include multiple turns, suggesting greater accuracy or similarity to an actual path. Finally, in the case of our experiment, conducted in a multi-level environment, the sketch maps do not include information regarding floor-to-floor transitions, or floor information of any kind. Likewise, although our sketch maps demonstrate a relatively high number of indoor trajectories in several buildings, it is difficult to identify their trajectories more precisely or detect the vertical transitions of these movements.

In particular, participants did not indicate on their drawn maps, indoor paths that transited intermediary locations such as Thorvaldson and Biology; Place Riel was also rarely identified on the participants' sketch maps; however it corresponded to the location of the Bus Terminal where a significant number of visits were tracked (Figure 29).

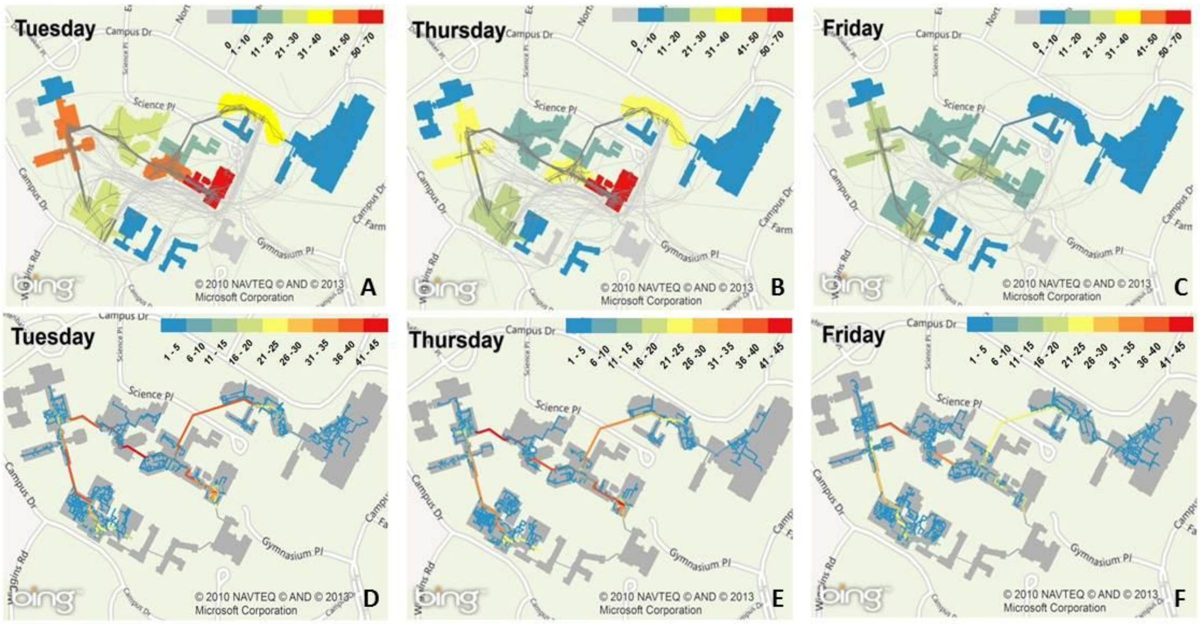


Figure 29. Usage of the campus for different weekdays. Top three maps: data obtained from sketch maps created by participants; bottom three: paths generated with WCN, 2D view

These results demonstrate a certain spatial variation in the configurations of the generated indoor paths for these locations (Figure 29 D-F), but when participants drew their indoor routes they failed to include these areas (Figure 29 A-C). In contrast, the Physics building was marked as one of the most popular locations (Figure 29 A, B) and corresponded to the location of the class taken by all participants on Tuesday and Thursday. However, this did not completely reflect the actual movement behavior of the participants, despite having to visit this location twice a week, they in fact visited other locations more often; some of these locations were not included on the maps.

Although, analysis of the generated trajectories indicated a high number of participants in the Physics building, other areas such as Murray library, Arts building, Agriculture, and the skywalks had similar visit rates, but were not included on sketch maps. Conversely, many participants indicated spending time at the Physical Activities Complex (fitness centre) but were rarely tracked there using the iEpi/SaskEPS tools. It is possible, and likely, that these locations were areas of transition, such as places that were passed through often during the day, or had to be passed through to get to a more important destination (like a class or other meeting location). Unlike the trajectory and tracking data from iEpi, such subtly in spatial behavior is more difficult to extract from a sketch map, interview, or environmental observation.

V

CONCLUSION

Development of an efficient indoor navigation model can significantly improve various applications for indoor wayfinding and tracking. With a growing demand for providing automated navigation guidance, a necessity to generate navigation networks that supports turn-by-turn instructions for complex buildings is growing. The results of this study demonstrate an efficient and easily repeatable method for generating an indoor network for buildings of various size, complexity, and connectedness. A graph representation was applied and delivered a fully routable network that covered 20 complex buildings of the campus of University of Saskatchewan. The network is stored into a geodatabase together with the elements associated with the network. The method for network generation was created in ArcGIS using of different geoprocessing tools. After developing a solid set of ArcGIS models, this approach could be successfully applied to a large range of AutoCAD architectural drawings and applied for various buildings such shopping mall and airports.

The performance of the WCN was tested; the network should be suitable for different types of indoor network analysis. The network, on the one hand, can be employed as stand-alone tool for providing the indoor guidance on this University campus. The current desktop application navigates through the University campus, it helps locate classrooms, offices, or facilities, and using the Dijkstra's algorithm can calculate routes. The application displays a map of the requested buildings with a line symbol representing the shortest path. In addition, a text/HTML file with detailed turn-by turn instructions is delivered to the user on request. Moreover once the network and software application was published the network on University server, it became accessible from any client's PCs or mobile device via internet. To use the application, the user just needs to specify the source and destination on the screen, afterwards an optimum path is calculated and visualized in 2D on the screen.

Additionally, the network can significantly improve analysis of movement data collected with existing positioning methods. In particular, application of the WCN allows for the generation of accurate indoor movement trajectories and can be employed as in a promising solution for post-processing of raw positioning data. By applying a map-matching algorithm the WCN allowed for better visualization of the collected data as well as better representation and identification of various movement patterns. In particular, it enables to visualize that collected tracking data and derived movement patterns are consistent with the layout of the building environment and depicted at a fine-grained spatio-temporal scale. Overall, employing WCN for analysis of indoor movement data offers several advantages:

1. Application of the network allowed for generating the trajectories automated data collection are not biased by participant recall.
2. Derived indoor trajectories can support indoor mobility analysis for various scale-related issues. In particular, our results are accurate enough to depict spatial dynamics either for the entire University campus or within a single building floor.
3. The presented method provides high-level of spatial details.
4. Introducing of the network allows for performing of different types of network analysis. In this thesis, I run the indoor usage space analysis by displaying/extracting traffic volume that corresponds to the most heavily utilized locations inside a building. However, other types of the analysis can be performed with the created network.

Although this study demonstrated promising results, several shortcomings could be addressed. First of all, the created network could be extended in the outdoor environment that could significantly improve the route guidance on campus. Secondly, the generation of indoor optimal route in ArcGIS 10.1 can be improved with the modification of the algorithm that calculates the shortest path. In this study only Dijkstra's method was applied and with no weighting. However depending on the application of the WCN, it would be possible to introduce additional 'costs' that more accurately represent the route. In particular, more detailed knowledge of the indoor context and participant preferences can alter the process of path calculation and interpolation between measured positions that can significantly change the representation of the participants' trajectories. Also, Djikstra's algorithm can be replaced by more advanced optimal path calculation. Since ArcGIS was used for network generation, it was only possible to apply the default search for shortest path algorithm. However by using of ArcObjects or by migrating from ArcGIS to PostGIS, it could be possible to introduce more advanced shortest path algorithms. Finally, the campus of University of Saskatchewan has dense WiFi coverage; obtaining similar accurate tracking results and high fidelity trajectories in the area with lower density might be not possible. These limitations should be included as components for improvement in future work.

VI

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