University Transportation Research Center - Region 2

Final Report

Spectral-based Controllability Pedestrian Evacuation Network Synthesis Using Multilayered Estimation Models in Real-time

Performing Organization: The Cooper Union for the Advancement of Science and Art

December 2019

Sponsor:
University Transportation Research Center - Region 2

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The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

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The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

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16. Abstract

The high uncertainty associated with emergency situations such as blasts, fires, and structural failures makes it extremely difficult to develop evacuation plans that can accommodate in advance every possible systematic failure that may occur in the predetermined tenable evacuation paths. The unpredictability of human decision making under stress adds to the complexity of the problem. It is extremely important to build evacuation paths in real-time. The main objective of this study is to be able to map the environment in real time evaluating the structural health that can be then used to create feasible evacuation paths for pedestrians. In this study, we performed the following: 1. Studied pedestrian data from Bluetooth and Wi-Fi sensors to assess its potential in building pedestrian evacuation network under emergency conditions, 2. Explored SLAM-based environment mapping technology for areas that lack access to GPS which then could be used to create maps in dynamic environments.

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Executive Summary

The high uncertainty associated with emergency situations such as blasts, fires, and structural failures makes it extremely difficult to develop evacuation plans that can accommodate in advance every possible systematic failure that may occur in the predetermined tenable evacuation paths [21]. The unpredictability of human decision making under stress adds to the complexity of the problem. It is extremely important to build evacuation paths in real-time. The main objective is to be able to map the environment in real-time evaluating structural health that can be then used to create feasible evacuation paths for pedestrians. In this study, we performed the following: 1. Studied pedestrian data from Bluetooth and Wi-Fi sensors to assess its potential in building pedestrian evacuation network under emergency conditions, 2. explored state-of-the-art SLAM-based autonomous mapping technology.

We initially performed preliminary analysis using Bluetooth and Wi-Fi data obtained from a pilot study at the Port Authority Bus Terminal. Sensors that registered an encrypted MAC address for active Bluetooth and Wi-Fi devices were deployed. This enabled us to obtain information about the density, flow, and origin-destinations of the users of the terminal. This data was collected and used to build models that simulate users moving through the terminal. All the data was filtered, hypothesis testing was performed to asses usability of the model, where it was then placed in a simulated M/M/1 queue, where data about wait times and lengths was produced. Even though this data proved to be useful to determining day to day operations of the terminal, and historical data could give us some basis to build models for nonrecurring conditions, using this data to determine operations for emergency conditions proved to be inappropriate. Therefore, in this study, we explored state of the art technology and algorithms, i.e. SLAM, for real-time mapping of indoor and outdoor areas with limited access to GPS.

Simultaneous localization and mapping (SLAM) has been an emerging research topic in the fields of robotics, autonomous driving, and unmanned aerial vehicles over the past thirty years. SLAM can be extremely useful for exploring and mapping new environments without a prior map and with limited access to GPS which is ideal for use in emergency conditions. We present a cost-friendly vehicle research platform and a robust implementation of SLAM. Our SLAM algorithm fuses visual stereo image and 2D light detection and ranging (Lidar) data and uses loop closure for accurate odometry estimation. Our algorithm is benchmarked against other popular SLAM algorithms using the publicly available KITTI dataset and shown to be very accurate. For educational purposes, we publicly share the models and code presented in this work.

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1 INTRODUCTION

The high uncertainty associated with emergency situations such as blasts, fires, and structural failures makes it extremely difficult to develop evacuation plans that can accommodate in advance every possible systematic failure that may occur in the predetermined tenable evacuation paths [21]. The unpredictability of human decision making under stress added to the complexity of the problem. Therefore, it is vital to understand pedestrian networks in high occupancy buildings within highly concentrated facilities such as large malls, high-rise buildings, as well as public transit hubs particularly under emergency conditions. It is also especially important to be able to build evacuation paths in real-time.

As a general framework, certain pedestrian data, representing pedestrian flow and paths, can be used to develop data-driven on-line synthesis of pedestrian evacuation subnetworks, depicted in Figure 1, that make use of advances in sensing technologies. The data is obtained in real-time from the various sensors installed in the structure and is then used for estimation of pedestrian networks at multiple layers: topological, operational, and pattern-based. All three layers will then contribute to updating the graph model of the pedestrian network by updating the adjacency, degree, and weight matrices indicating usability of links. After updating the network graph model, developing evacuation paths can be performed. The evacuation problem is then posed as a subnetwork synthesis problem. At this stage, we are given a number of usable links for the overall network with different weights indicating the level of usability, and the problem is to synthesize evacuation paths that can be considered as subnetworks, Figure 2, and thus modeled as subgraphs of the original network. The chosen paths are then evaluated based on how they affect the overall network as a system in the sense of flow maximization as long as controllability is maintained. Flow maximization at a given moment is a local optimum; however, when given the choice, using links that sustain controllability of the system may lead to a global optimum. This leads us to the next step which is the controllability check. If the system us uncontrollable update the links choice; otherwise, implement the synthesized plans and reevaluate the system.

Unfortunately, the existing pedestrian infrastructure rarely supports the collection of such rich data to make such an intricate emergency response algorithm possible. The proposed work assesses existing commonly used cost-effective pedestrian sensors for building such models. Also, it explores new technology and algorithms for real time mapping. This study fills in the gaps in data and map creation under emergency in order to advance potential contributions to the modeling, sensing fusion, estimation, and optimal evacuation aspects of the pedestrian flow networks.

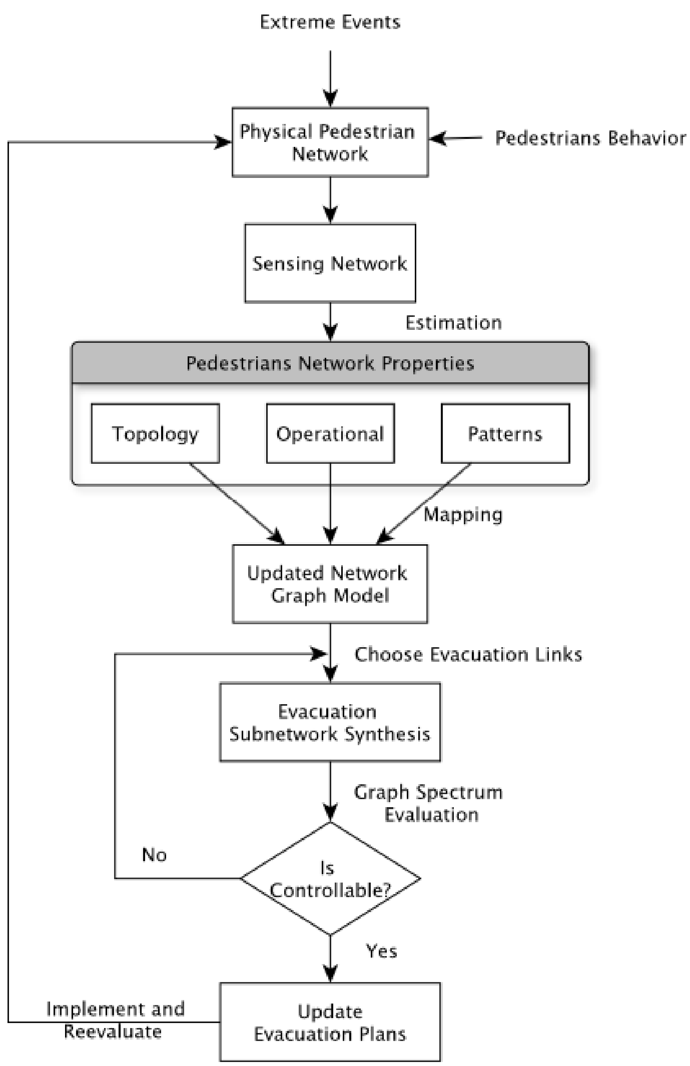

Figure 1 Proposed Framework of Subnetworks Synthesis for the Pedestrian Evacuation Problem.

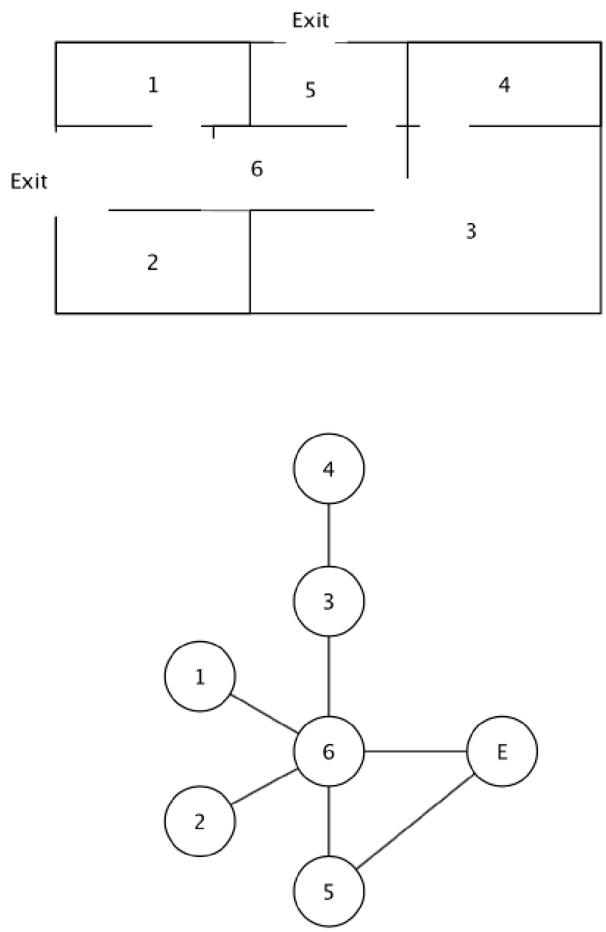

Figure 2 Example of a Building floor and its Corresponding Network Graph.

1.1 Research Objective and Approach

The main objective of this study is to be able to map the environment in real time evaluating structural health that can be then used as feasible evacuation paths for pedestrians. In this study, we performed the following: 1. Studied pedestrian data from Bluetooth and Wi-Fi sensors to assess its potential in building pedestrian an evacuation network under emergency conditions, 2. explored state-of-the-art autonomous mapping technology. The proposed research can be seen as a significant contribution to the current state-of-the art and state-of-the practice because those heavily depend on optimal evacuation paths obtained from off-line tools and plans.

We initially studied Bluetooth and Wi-Fi data from a pilot study that was performed at the Port Authority Bus Terminal which enabled us to obtain information about the density, flow, and origin-destinations of the users of the terminal. This data was collected and used to build models that simulate users moving through the terminal. All the data was filtered, hypothesis testing was performed to asses usability of the model, where it was then placed in a simulated M/M/1 queue, where data about wait times and lengths was produced. We then explored SLAM algorithms for real time mapping of indoor and outdoor areas with limited access to GPS.

2 DATA ASSESSMENT FROM WI-FI & BLUETOOTH SENSORS

Port Authority Bus Terminal is a key part of the transportation system in New York City, servicing 225,000 people on an average weekday [22]. Creating a model that predicts the movement of users within the terminal would help identify bottlenecks and would be vital to streamlining the process. Port Authority is unique when compared to other transportation hubs in the city. Unlike the vast subway system where user movement can be easily recorded by the turnstiles that every user goes through, users of Port Authority do not go through such a centralized system. As a result, this study is based on cellphone data that was collected during a ten-week period during the summer of 2016. Six tablets were placed by two entrances (North, and South) and four different gates (202, 204, 223, and 233). Each tablet collected a unique hardware address and a timestamp to each phone that is Wi-Fi enabled and put it into a text file. This method offers a good sample of the people moving through the system, Table 1 presents the available data with good dates. These text files were put into a mongo database and where they were queried and fit for hypothesis testing. Fitting was done to both arrival (lambda) and exit (mu) rates and then simulated in a M/M/1 queue. Which then can be used to build a Markov Chain model such as Xu, Liu et al [23].

Table 1 Dates with good data.

Gate	Dates with Data
202	5/03-5/10, 5/18-5/22, 5/24-6/04, 6/16-7/11
204	5/03-7/11
223	5/24-7/04
233	5/03-5/09, 5/20-5/27, 6/01-6/04
North	5/13-5/17
South	5/03-7/11

2.1 DATA FILTERING AND FITTING

After running preliminary tests on the data, it was quickly realized that there are many users who are only seen once and never seen again. Therefore, the first task of filtering was to remove these users. Users who were seen only once were regarded as unusable data. Another conclusion from the preliminary tests was that the data from all ten weeks would not fit a Poission distribution with a constant lambda (arrival rate). Therefore, it was decided to select a several different time windows in a day and restrict the fitting to a few weeks period disregarding certain days of the week. Following this it was necessary to define what constitutes an arrival and an exit. If the system is to be regarded as a bus terminal where people are exiting on busses and arriving from outside, it would make sense to define an exit when the user leaves the whole system of gates for an extended period of time (in this work that period of time was two hours) and an arrival when a user arrives after not being in the system for two hours. There were a few issues with this fit. The main issue was that for all the different time intervals that were selected for the fit to the Poission distribution, there were some gates where their arrivals from outside were greater than their service rate (resulting a rho greater than one). On top of that, with the probability matrix, even some of the other gates that had their service rate greater than their arrival rate from outside still had a rho greater than one. This issue could have stemmed from a greater issue with the incompleteness of the data. The data is incomplete in two ways. First the tablets for the North entrance and gate 233 shut off for a great majority of the sampling period, leaving very few days of good data for them. Subsequently, their arrival rates that were calculated from the days they were on could be inaccurate because it is not a big enough sample time. Yet, even when putting those gates to the side, there were still some gates with a rho greater than one. Another possible source of this issue could be the fact that because there were only sensors at select gates, certain users were considered exits at places that they did not exit. Fitting results are shown in Table 2.

Table 2 Lambda and Chi Squared, from 2-6pm excluding weekends with 40 bins.

Gate	Lambda	Chi-Squared
202	82.83	28
223		
233		
204	75.68	69
North		
South	66.62	180

Alternatively, if the system is regarded to be a set of points where people walk through an arrival would be the first time a person comes into that point and an exit would be the first time the person leaves that point. This method is easier to implement for many different reasons. First it allows for bad gates where rho is greater than one to be thrown out completely. In addition, it does not have the complexity of a probability matrix where there is a back and forth movement of users from one gate to another. However, this gate does not provide a true queuing model of the users in the terminal.

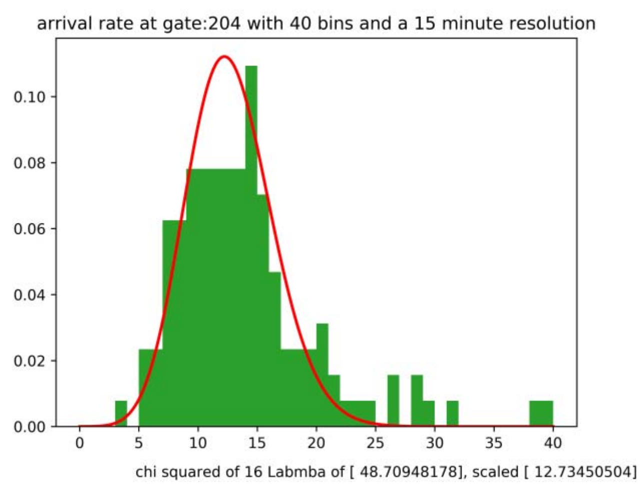

Figure 3 Poission Distribution Fitted to gate 204 arrival data.

The final results for gates 204 (Depicted in Figure 3), and 223 were fit from 06/20-7/04 excluding Saturdays, Sundays from 7pm to midnight. The result for gate 233 was fit from 05/04- 05/07 from 10pm to midnight.

The results, Table 3, show that at gates 204 and 233 users move quickly, less than two minutes. Gate 223 on the other hand, has a little bit longer of a wait ~5 minutes.

Table 3 Computed Data for each Gate.

GATE	ARRIVAL RATE (15-MIN INTERVALS)	SERVICE RATE (15-MIN INTERVALS)	EXPECTED # OF USERS IN QUEUE	EXPECTED TIME IN QUEUING SYSTEM (MINUTES)	EXPECTED TIME IN QUEUE (MINUTES)
204	48.70	69.80	1.61	0.71	0.49
223	61.57	72.48	4.79	1.37	1.17
233	33.54	65.97	0.52	0.46	0.24

2.2 Proposed Model and Estimation

A Queuing Network-based Network Model is presented, as depicted in Figure 4. The proposed model requires the computation of the transition matrix. We then define A_{ij}, the percentage from gate i to gate j using maximum likelihood.

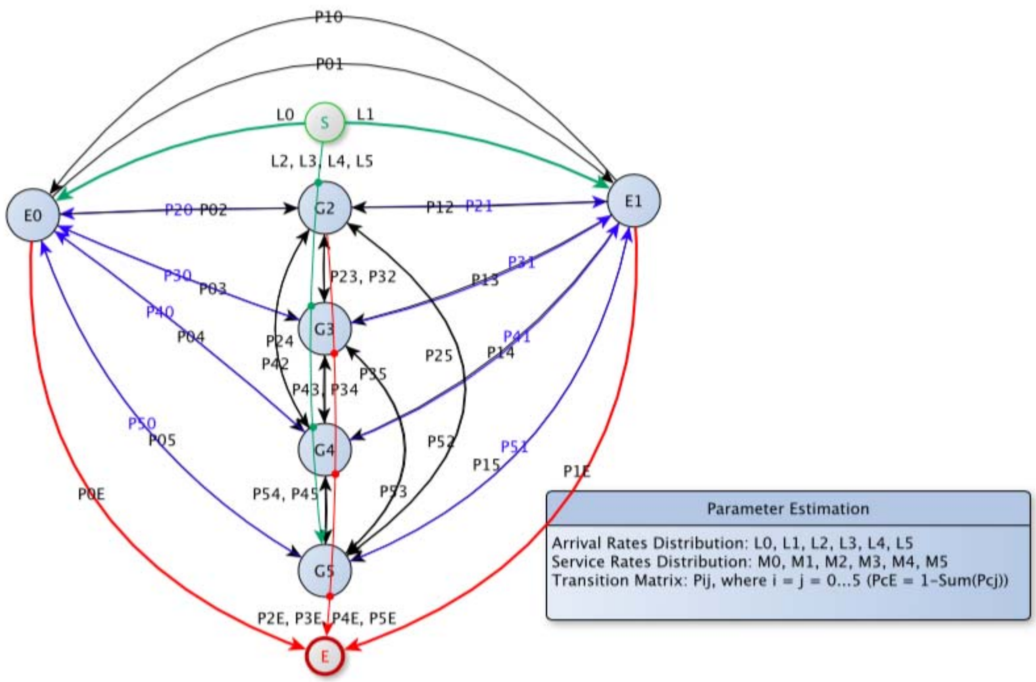

Figure 4 Queuing Network-based Network Model

Herein, the parameter estimation techniques for the proposed model are presented. First In order to compute the transition matrix, a transition for a user would be counted in the three following situations**:**

1. If the user has been seen within two hours of her last appearance and is at a different gate. This would constitute a transition from last gate to current gate.
2. If it has been more two hours. This would constitute a transition from last gate to sink and from source to current gate.
3. The absolute first and absolute last occurrence. The absolute first counts as source to first gate where the absolute last counts as last gate to sink.

As is apparent in Table 4, all the values for the northern gate are zero. This is due to the fact that there was no intersection where all the sensors were working, refer to Table 2; therefore, the best selection was chosen. This implies that the model will be modified to not include the North gate.

Table 4 Transition Matrix.

	North	South	Source	202	204	223	233
North	—	0.00	0.00	0.00	0.00	0.00	0.00
South	0.00	—	0.31	0.03	0.04	0.05	0.01
Sink	0.00	0.69	—	0.14	0.25	0.47	0.50
202	0.00	0.12	0.37	—	0.59	0.13	0.15
204	0.00	0.08	0.16	0.75	—	0.06	0.14
223	0.00	0.07	0.09	0.03	0.03	—	0.20
233	0.00	0.04	0.07	0.05	0.09	0.29	—

The other parameters to be estimated are the external arrival and the service rate distributions. The external arrival distribution (time dependent) must be found for each gate and entrance. This includes persons seen for the first time outside of a 2-hour time interval. This should not include arrivals of people that are already in the system and transitioning from one node to another since this is included in the transition matrix. The Service rate distribution (time dependent) must also be found for each gate and entrance.

The origin-destination matrix, Table 5 (Read it Horizontal to vertical as in SOUTH→ 204 would be 2rd column 5th Row), was calculated by first taking each address' known timestamps and gate locations. The spotting data was then sorted by time. *An origin:* is the first spotting of an address and the first spotting after a two-hour gap. *A destination:* is the last spotting of an address and the last spotting of an address before a two-hour gap.

Table 5 Origin Destination matrix (Top is counts bottom is percentages.)

	North	South	202	223	204	233
North	0	20,351	1,986	1,648	8,572	1,513
South	17,290	0	54,229	49,599	67,039	16,670
202	2,829	62,457	0	16,687	115,459	6,663
223	1,854	71,677	20,535	0	20,978	10,055
204	12,312	104,644	219,792	23,052	0	9,939

233	1,242	23,596	24,830	15,388	20,799	0
TOTAL	35,527	282,725	321,372	106,374	232,847	44,840
	North	**South**	**202**	**223**	**204**	**233**
North	0.00%	7.20%	0.62%	1.55%	3.68%	3.37%
South	48.67%	0.00%	16.87%	46.63%	28.79%	37.18%
202	7.96%	22.09%	0.00%	15.69%	49.59%	14.86%
223	5.22%	25.35%	6.39%	0.00%	9.01%	22.42%
204	34.66%	37.01%	68.39%	21.67%	0.00%	22.17%
233	3.50%	8.35%	7.73%	14.47%	8.93%	0.00%
TOTAL	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

2.3 Conclusion

The results are the first step into continuing the analysis on Port Authority. To get a fuller picture, it would be useful to get a more complete dataset. More complete in both the weeks of data and the number of gates where the data is recorded. Additionally, using the strength of the Wi-Fi signal may be an additional method to filter the data.

The results also demonstrated that the data could not be fit into a Poission process. This could be due to missing information and lack of consistency. Other options for continuing analysis include fitting the data with an arrival rate that depends on time, or fitting the data to a time series instead of a Poission distribution. Methods such as those that were used by Hanseler, Bierlaire et al [24]. could prove to be useful. Therefore, moving forward, this research looked at the possibility of using SLAM technology to be able to create online maps of the environment which proves to be an essential feature for emergency response.

3 EMERGENCY MAPPER WITH SLAM

Simultaneous localization and mapping (SLAM) is the process by which a mobile robot can build a map of an environment and at the same time use this map to compute its own location [7]. In other words, it comprises the simultaneous estimation of the state of a robot equipped with on-board sensors, and the construction of a model (the map) of the environment that the sensors are perceiving. In simple instances, the robot state is described by its pose (position and orientation), although other quantities may be included in the state, such as the robot's velocity, sensor biases, and calibration parameters. The map, on the other hand, is a representation of aspects of interest (e.g., the position of landmarks, obstacles, etc.) describing the environment in which the robot operates [4].

There are many situations where a map is needed. For example, a map may be in need to support other tasks like informed path planning. However, most importantly, the map allows limiting the errors committed in estimating the state of the robot [4]. In the absence of a map, dead-reckoning would quickly drift over time; on the other hand, using a map, e.g., a set of distinguishable landmarks, the robot can reset its localization error by revisiting known areas, also referred to as loop closure. Therefore, SLAM finds applications in many scenarios in which a prior map is not available and needs to be built [4].

SLAM has been formulated and solved as a theoretical problem in a number of different forms [7]. It has also been implemented in a number of different domains including indoor robots, outdoor robots, and underwater and airborne systems. At a theoretical and conceptual level, SLAM can now be considered to be a solved problem pertaining to the estimation of the trajectory of a moving robot and building a map of its environment simultaneously [17]. However, in practice, substantial issues remain in realizing more general SLAM solutions and notably in building and using perceptually rich maps as part of a SLAM algorithm [7]. Even though the formulation of the SLAM problem has been well established and the robotics research community has seen tremendous progress over the past few decades, there are still a many open problems left unsolved including failsafe SLAM algorithms, efficient map representations, and resource-aware SLAM systems [4]. Furthermore, a general SLAM solution that can run in real time and adapt to the available computing platforms has not yet been proposed. Also, many of the existing SLAM algorithms fail to identify previously visited locations and correct the corresponding odometry estimations, thus performing loop closure [6].

We introduce a robust and flexible multi-sensor data fusion architecture that leverages state-of-the-art Lidar algorithms. Our system provides custom configurations to allow further research, for example, in innovative image registration algorithms, frame matching algorithms, and backend nonlinear least-squares pose-graph solvers. We have also supplemented the multi-sensor data fusion model with the necessary hardware, control, and planning module to provide a cost- friendly autonomous driving platform. This platform, with the physical form of a differential drive robot, is capable of driving around in an unknown environment, creating a map of its surroundings and performing autonomous navigation to any targeted location in the self-created map.

In this section, we first provide a high-level overview of multi-sensor data fusion. Then, we present our multi-sensor data fusion pipeline. The system implementation, along with hardware and software dependencies, is then described. Then we present our experimental results. Finally, we present our conclusions and explore possible future work.

3.1 Background

An autonomous mobile robot operates by processing information from its surroundings and then making intelligent and accurate driving decisions. This means that the perception system, the very first module to acquire peripheral information on which other parts of the platform depend, needs to be as robust and accurate as possible to safeguard the performance of the whole system. A system operating with a single sensor often fails to capture the rich physical attributes of the environment. The camera, a typical visual perception sensor, is likely to fail in environments where the lighting intensity is dramatically changed or the lighting intensity is particularly low. On the other hand, a radar sensor has a longer sensing distance and lower computational demands but is less accurate than the light imaging detection and ranging (Lidar) in terms of angular accuracy. Due to the inherent vulnerability of the single-sensor system, multi-sensor data fusion has become an overarching paradigm for avoiding single-point failure and enhancing the system with reduction in ambiguity and uncertainty, increase in accuracy, robustness against interference, etc. [15]. For instance, Tesla's Autopilot leverages a hardware suit of eight cameras, a forward-looking radar, and twelve ultrasonic sensors to ensure 360 degrees of visibility for its perception system.

In the last decade, significant progress has been made in the field of multi-sensor data fusion to solve problems related to combining multi-model data efficiently and support intelligent robots in decision making [2], [3], [12]. The diversity offered by multiple sensors can positively contribute to the perception task of the intelligent robot. Overcoming heterogeneity of different sensors through robust fusion algorithms lead to effective utilization of the redundancy across the sensors [5]. However, data coming from different sources are typically in different formats and also propagate different sensing uncertainties. Multi-sensor data fusion research is typically focused on the effective alignment of different sensor streams which could be either partially, geometrically, or temporally aligned [13]. The introduction of the multi-sensor data fusion model, though effective in theory, does lead to some practical challenges including how to handle noise in the operation, data imputation, the determination of where in the processing pipeline to perform the fusion algorithm, and how and when to keep or drop the previously acquired information. Moreover, due to inevitable sensor manufacturing variations, extreme external calibration efforts across the sensors is often needed to ensure the performance of the fusion architecture.

3.2 Approach

To address the problems mentioned in the previous Section and to maximize the cost efficiency along with the mapping accuracy, we introduced a loosely coupled time-stamp-based multi-sensor data fusion architecture which leverages camera and Lidar data as default. On top of the default fusion setup, the system provides custom configuration freedom for researchers to add additional sensor modality and experiment with various fusion algorithms. The default fusion architecture, which leverages the state-of-the-art Lidar SLAM pipeline multiple visual place recognition algorithms, ensures the basic functionality for accurate mapping with global closure and reduces the unnecessary exterior calibration effort [19].

In Table 6, the features of a few typical implementations of the SLAM algorithm are summarized. As can be seen, most existing solutions do not incorporate 2D Lidar, a camera module, and global loop closure. For example, V-LOAM typically does not implement loop closure even though it uses both a 3D Lidar and a camera; however, some form of loop closure is introduced in some relevant work [16]. Another issue is that all of them except Cartographer require a 3D Lidar component, which is costly. The proposed solution herein can be used with either 2D or 3D Lidar sensors in tandem with a camera, and at the same time offers both global loop closure and online operation.

Table 6 Typical Implementations of SLAM.

	2D Lidar	3D Lidar	Camera	Global Loop Closure	Online Operation
BLAM		●			●
Laser SLAM		●		●	●
Cartographer	●	●		●	●
LOAM		●			●
V-LOAM		●	●		●
Our Solution	●	●	●	●	●

While state-of-the-art visual and Lidar SLAM algorithms are equivalent in terms of accuracy, visual pipelines are more robust for dynamic scenes and less expensive computationally. Lidar SLAM systems, on the other hand, are more consistent and less sensitive to changes in illumination and appearance due to their heavy dependence on the geometric structure of the surrounding. Even though most of modern Lidar SLAM algorithms have shown impressive results [8], they failed to address the drift problem over time with the assumption that the world is an "infinite corridor" [4]. Therefore, we propose a fusion mechanism that supplements the Lidar SLAM algorithm with visual stereo image data for place recognition and drift correction. In order to implement Lidar SLAM, we tested our vehicle with various open-source libraries including Hector SLAM, Fast SLAM, and Gmapping. In this section, we discuss the various Lidar-SLAM libraries tested. Then, we introduce our perception system by explaining the selection of the sensors, the base SLAM module, and the data fusion model proposed for the heterogeneous sensors involved.

3.2.1 Lidar-SLAM Libraries

Hector SLAM was developed for a system capable of autonomous exploration in Urban Research and Rescue environments [11]. It serves as a general open-source algorithm, which only needs minor modifications to operate on a given platform. A remarkable feature of this algorithm is that it does not necessarily need the odometry data to support its operation. Another feature of Hector SLAM is its elevation and cost mapping. The Hector-elevation-mapping module allows us to fuse the point cloud measurements produced by a stereo camera into an elevation map, resulting in a 2D

grid with another variable height stored in a corresponding variance for each cell. Odometry, however, is notoriously known to be unreliable in an environment where there are many altitude changes (such as an uneven floor). Therefore, we decided to test Hector SLAM on our data. Even though it was able to create a map, the drift was large. This meant that the odometry data had to be fed to the system so that the algorithm can make more informed estimations of its pose and create a more accurate map.

Instead of entirely relying on fast Lidar data feature selection and scan-matching, Fast SLAM uses a particle filter method which uses numerous small particles to perceive a submap and then creates a complete map by stitching those submaps together. The particles are generated randomly, and submaps are then compared with each other to test for agreement about the perceived environment given their poses. In other words, a particle's correctness is evaluated by consensus and inference based on the other submaps. Faulty particles are immediately discarded. Eventually, only the particles that can make sense of each other's submaps are kept and used to stitch together the whole map. However, the particle-filter-based method is relatively memory intensive since each particle needs to be kept in a joint state matrix and updated every frame. Also, the comparison process consumes a tremendous computing power. The problem could be largely simplified by providing a prior map. The particles' submaps could then be compared with the prior map and discarded if the difference is too large. Thus, the particle number would quickly decrease and converge to allow the construction of a complete map. This is especially useful in the re-localization problem for self-driving automobiles where a prior high definition (HD) map is available.

Gmapping has been implemented as described in Grisetti et al. [9] and is then improved using the Rao-Blackwellized particle filters (RBPF) method, which shares a similar idea with the particle filter method introduced above. The key idea behind RBPF is to estimate a posterior of potential trajectories of the robot given its observation and its odometry measurements. The posterior is then used to compute a posterior over maps and trajectories and thus gives a relative pose estimation. To do so, RBPF uses a particle filter in which an individual map is associated with every sample. The robot's trajectory changes over the robot's motion, therefore the proposal distribution is chosen to be the same as the probabilistic odometry motion model. One of the most common particle filtering algorithms is the sampling importance resampling (SIR) filter. An SIR filter incrementally processes the observations and the odometry readings as they become available. This is done by updating a set of samples representing the posterior about the map and the trajectory of the vehicle. The algorithm for RBPF is then applied by computing an improved proposal distribution on every particle so that information obtained from the sensors can be used while generating the particles. This algorithm has two main advantages: First, the algorithm draws the particles more effectively; computing accurate proposal distribution handles not only the movement of the robot but also the most recent

observation, which causes the uncertainty in the prediction of the robot's pose to decrease. Second, the highly accurate proposal distribution allows the system to utilize the number of effective particles as a robust indicator to decide whether or not a resampling has to be carried out. This effect further reduces the particle depletion problem, which refers to the scenario where no particle is valid at all. Therefore, we decided to use the Gmapping algorithm to implement an improved version of the visual Lidar [9].

3.2.2 Sensors

By using the multi-sensor data fusion pipeline, our algorithm can perform SLAM using a stereo camera with a 2D or 3D Lidar as shown in Figure 5. With this specific combination, we can avoid disadvantages of each sensor and make the system more robust. For example, the camera will not perform as well as the Lidar in dark environments. However, each kind of Lidar has its own problems: 3D Lidars are costly and 2D Lidars alone do not offer enough resolution. To solve this issue, we supplement the 2D Lidar with a stereo camera so that we can extract more information from the images. This way, researchers can perform accurate SLAM algorithms with a cheaper 2D Lidar

RPLiDAR A2: Whereas Hokuyo UST-20LX scanners are now the standard 2D Laser scanners for SLAM research, we found the RPLIDAR A2 scanners to be a cheaper option. Though 3D Laser scanners have the advantages of high resolution and a 360-degree range for 3D SLAM algorithm research, their high cost made the actuated 2D Lidar more suitable for our purpose. With a reasonable cost, the RPLIDAR A2 can perform 360-degree scans within a range of 12 meters or 18 meters and generate 8000 points per second with a 15 Hz sampling rate. Also, DJI has released Livox Mid-40, a 3D Lidar with a reasonable price, which future researchers with a generous budget could consider for dense mapping purposes.

ZED stereo camera: ZED is the best-suited camera for our platform due to its detailed API documentation and its smooth integration with the Robotics Operating System (ROS) which most of robotics research uses. With its high resolution and frame rate, ZED can serve multiple applications such as depth perception, positional tracking and 3D mapping.

Figure 5 Used Sensors.

3.2.3 Base SLAM Module

We present a SLAM module which extends the state-of- the-art Lidar odometry estimator, LOAM [20], with back-end pose-graph optimization to correct drift and a place recognition system to allow global loop closure [10]. LOAM, with its high accuracy, robustness and real-time operation, takes in raw 3D point clouds, calculates the rigid transformation due to the corresponding sensor motion and outputs the global pose estimation, a local representation of the map, and the registered point clouds. The original work has been refactored, optimized, and made modular in this work to support custom configuration and allow smooth adaption to other SLAM backend solutions.

Due to the inherent drifting error in incremental odometry estimators like LOAM, an online pose estimation back-end is needed in the system to build the pose graph based on the LOAM odometry estimation and correct LOAM odometry estimation from drifting error by performing re-localization based on the visual data. Re-localization takes place if the system identifies previously visited places. To identify previously visited places in the existing internal map, the system has to periodically query the place recognition module, which relies on the visual stereo data.

3.2.4 Data Fusion Mechanism

We propose a modular multi-sensor data fusion pipeline, as summarized in Figure 3, where Lidar is set as the default sensor for odometry estimation and visual stereo data is leveraged to perform place recognition. The Lidar-based SLAM backend keeps a set of keyframes to represent the sensor trajectory, each having an associated time stamp. With the stereo camera running constantly, the system registers stereo image data to the latest keyframe and performs cloud matching with all previously registered keyframes to find potentially matched frames. A pose graph optimization backend is running constantly to manage the environment mapping and correct odometry estimation by querying the visual place recognition system. We provide multiple state- of-the-art visual frame matching algorithms such as visual bag of words and SegMatch. Additionally, the system is able to incorporate other real-time matching algorithms and fuse with the result of existing matching algorithms [1].

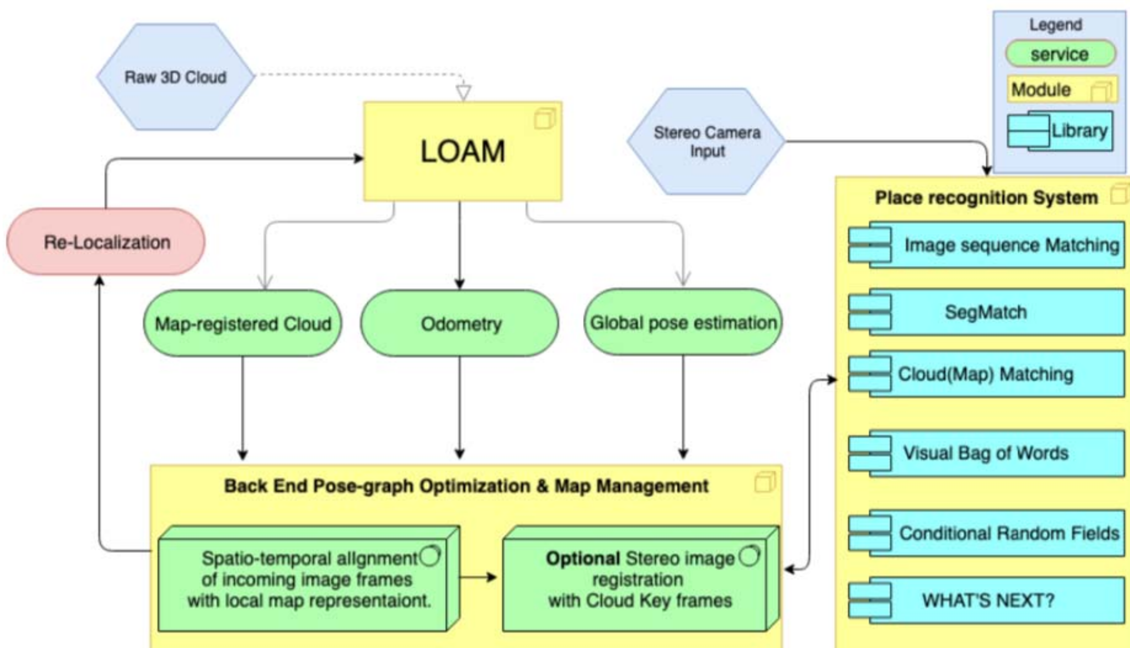

Figure 6 Sensor Fusion Architecture

When the system detects a matched frame, it calculates the transformation between the clouds of the associated keyframes using the iterative closest point (ICP) algorithm and adds a new edge to the pose graph representation of the existing map. Then, the estimated pose is fed back to the incremental odometry estimator to correct its internal motion estimation and perform the re-localization functionality.

3.3 SYSTEM IMPLEMENTATION

To make our vehicle reasonably affordable and easier to assemble, we designed our vehicle to be an educational and cost-friendly research platform with minimal software setup on which versatile applications could be run. The hardware and computing platform are introduced in this section with key design features including affordability and versatility. It is worth noting that the components used for the vehicle are resources that are inexpensive, with a total cost of approximately $1200.

3.3.1 Hardware

We designed a custom differential drive chassis on which any electronics and hardware can be installed. We relied on easily accessible computer aided design (CAD) software and prototyping tools including SolidWorks and AutoCAD. Two Pololu 12V gear motors are used to drive the rear wheels with a 2000-count-per-rev encoder mounted on each motor. Having two independently-driven rear wheels gives the platform two degrees of freedom for intuitive manipulation and control. In addition, the built-in encoders enable wheel speed control and could provide inaccurate odometry information to the system for reference. Also, a custom PCB board is used to connect electronic components and divide an electrical power feed from the batteries into subsidiary systems. Two 12V Lithium-ion batteries are used to supply power to the computing hardware and motors separately, which prevents the motor’s transient voltage from interfering with the computing hardware.

3.3.2 Computing Platform

The Nvidia Jetson TX2 is a fast, power-efficient embedded computing device which is used as the on-board computing processor. Jetson supports Ubuntu naively for ROS integration and provides the necessary processing power for online 3D mapping algorithms. The Arduino Uno is used along with the Jetson computer as an expansion to the GPIO and interrupt pins of the Jetson. Acting as a middleman, it exchanges messages between the hardware and the Jetson board. A photograph of our device with components labeled can be seen in Figure 6.

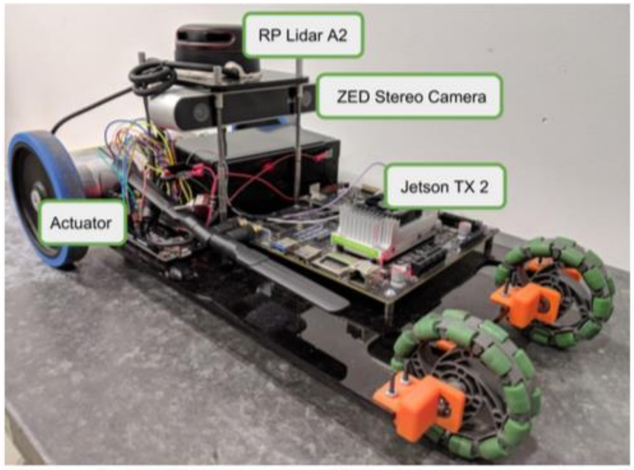

Figure 7 Platform Overview

3.4 EXPERIMENTAL EVALUATION

To evaluate the accuracy of the odometry estimation of our proposed multi-sensor data fusion architecture, we fully tested our algorithm against the publicly available KITTI odometry benchmark dataset [8]. The result was evaluated by the metrics employed by KITTI and compared with the LOAM module's result. Our architecture, with the default setup, has shown equivalent results with LOAM for KITTI sequence 00 and better performance than LOAM for KITTI sequence 05 by generating a trajectory map closer to the ground truth value in places where loop closure takes place. Figure 8 shows the results of our algorithm running on KITTI odometry dataset sequence 07. As depicted, our estimated trajectory is closer to the ground truth value than the popular SLAM module, ORB SLAM, a versatile and accurate monocular SLAM system where the loop closure happens [14].

We also ran our algorithm in a real-world indoor environment, the 6th floor of our academic building, by adapting the state-of-the-art 2D mapping algorithm, Cartographer [10], to our pipeline. Figure 9 shows the generated 2D occupancy grid map (bottom), and for comparison, the ground truth floor plan (top). As can be seen, the results are reasonable.

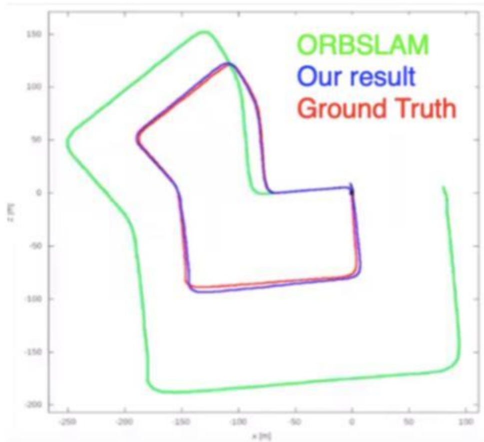

Figure 8 Experimental Results on KITTI Sequence 07

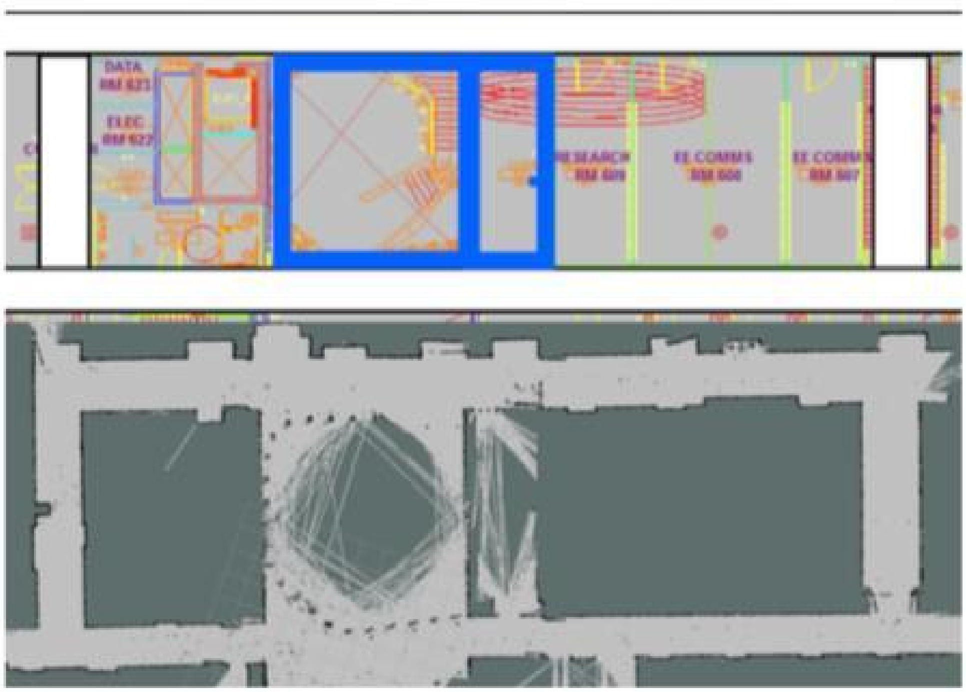

Figure 9 Top: Flor Plan, Bottom: Mapping Result

4 CONCLUSIONS

In this study, we looked at existing Bluetooth and Wi-Fi data for the potential use for creating models for emergency response. However, data analysis from a case study conducted at Port Authority showed that this data is insufficient for use for dynamic environments, i.e. in case of an emergency. A queuing network model of the system was proposed. However, the preliminary analysis showed that a more consistent data collection effort is needed in order to be able to build reliable models even for recurring, day-to-day operations. This study then looked at state-of the art technology that can be used in for mapping of environments in emergency conditions. For this purpose, a new, integrated, and modular sensor fusion architecture has been developed and fully tested against a publicly available data set. Experiments have validated the hypothesis that by leveraging the redundancy across heterogeneous sensors, multi-sensor data fusion improves accuracy and robustness for applications such as mapping and motion estimation. In addition, the modular pipeline provides robotics researchers the freedom to adapt and experiment with related algorithms. There are many directions in which this work can be expanded. For the multi-sensor data fusion model, pre-built models for sensors of different modalities can be developed. For example, a model can be built for the inertial measurement unit (IMU), which is often used in modern SLAM algorithms to improve the accuracy and robustness of mapping [18]. While we primarily focused on the perception system of the autonomous driving platform, the control and planning modules of the platform can be further developed to provide more research possibilities for the future users of our platform.

DISCLAIMER

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