An Environment-Aware Sequence-Based Localization Algorithm for Supporting Building Emergency Response Operations

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ABSTRACT

Building emergencies are big threats to the safety of building occupants and first responders. When emergencies occur, unfamiliar environments are difficult and dangerous for first responders to search and rescue, sometimes leading to secondary casualties. One way to reduce such hazards is to provide first responders with timely access to accurate location information. Despite its importance, access to the location information at emergency scenes is far from being automated and efficient. This paper identifies a set of requirements for indoor localization during emergency response operations through a nationwide survey, and proposes an environment-aware sequence-based localization algorithm that is free of signal path loss models or collection of prior data, and mitigates signal multipath effects. The algorithm enables efficient on-scene ad-hoc sensor network deployment and optimizes sensing space division by strategically selecting sensor node locations. Building information is integrated, in order to enable building-specific space divisions and to support context-based visualization of localization results. Proposed algorithm is evaluated through a building-size simulation. Room-level accuracy of up to 87.3% was reported, and up to 15.0% of deployment effort was reduced compared with using randomly selected sensor locations. The algorithm also showed good computational speed, with negligible time required for refreshing location estimation results in simulation.

INTRODUCTION

Building emergencies, including flooding, building collapses, terrorist attacks and especially structure fires, are big threats to the safety of building occupants and first responders. For example, public fire departments across the U.S. attended 484,500 fires in buildings in 2011, which caused 2,460 deaths and 15,635 injuries (Karter 2012). When emergencies occur, unfamiliar environments are difficult and dangerous for first responders to search and rescue, sometimes leading to secondary casualties. With the increasing number of complex buildings, and less live-fire training, first responders are twice as likely to die inside structures as they were 20 years ago, and the leading cause of these line-of-duty deaths is getting lost, being trapped or disoriented (Brouwer 2007). One way to reduce such hazards is to provide firefighters with timely access to accurate location information. It is also of critical importance for an incident commander to know the locations of deployed first responders in real time, so that decision-making process is faster and more informed.

When an emergency happens, first response teams are sent to carry out search and rescue operations. In most cases, searching for occupants is a manual process, which could be prohibited by fires, smoke or structural damage. Reducing the time spent on searching for occupants has great potential to reduce chances of fatalities and injuries.

LITERATURE REVIEW

Regardless of the high value of location information for building emergency response operations, current access to location information mainly relies on manual blind search by first responders. There are a few indoor localization solutions proposed in literature, but none has been widely adopted. Chandra-Sekaran *et al.* (2009a; 2009b) proposed a system to locate doctors and patients carrying radio nodes in outdoor/indoor emergencies. Monte Carlo and unscented Kalman filter techniques were used for location estimation. Accuracies between 5 to 10 m in simulation were reported. A system proposed by Duckworth *et al.* (2007) required no existing infrastructure or pre-characterization of the area of operation. The system relied on an ad-hoc network built on transmitters carried by both first responders in a building and vehicles outside the building. Cavanaugh *et al.* (2010) reported up to sub-meter accuracy with their system. The system required a considerable investment for on-site deployment of localization system-equipped vehicles. Rantakokko *et al.* (2011) proposed a system that integrated foot-mounted inertial sensors and Ultra Wide Band (UWB) sensors to support first responders. Field tests reported accuracy of 1 to 4 m. The system suffered from heading drifts. Akcan and Evrendilek (2012) proposed a system that utilized UWB technology. Directional localization was enabled in static networks. Reported accuracy through simulations was up to 6 m, depending on the node density. Another UWB-based system was proposed by Lo *et al.* (2008). It used a time difference of arrival (TDOA)-based algorithm for 3D location estimation, and reported accuracy of 1 to 2 m in field tests. The system required a significant deployment effort for a sensing network, and could not locate building occupants that had no access to mobile units. Kaya *et al.* (2007) used a backward ray-tracing algorithm to analyze angle of arrival (AOA), time of arrival (TOA) and signal power for locating first responders wearing beacons. Using multiple receivers, they were able to cover 80% of a building and achieve an accuracy of within 10 m.

There are also a few commercial solutions. Stemming from research sponsored by the Department of Homeland Security, SPIE's (Mapar 2010) solution, named "GLANSER", combined various technologies including global positioning system (GPS), IMU, UWB, Doppler radar, as well as a magnetometer, compass, pedometer, and altimeter inside a tiny wearable electronic unit. The algorithm was not disclosed, but an accuracy of 3 m was claimed in field tests. Exit Technologies (E2010) provided another solution that used handheld devices using low-frequency radios. A distressed first responder attempting reorientation or self-rescue could send out signals with a handheld device. Signals could then guide other first responders to the transmitting device. No details of the algorithm or accuracy were disclosed.

REQUIREMENT ANALYSIS FOR INDOOR LOCALIZATION

Most of the above solutions are highlighted by either their high accuracy or their independence from existing infrastructure. However, it remains unclear what level of accuracy is sufficient to support emergency responses. Although a higher accuracy is desired, it may require a more sophisticated sensing network or additional prior data input. Independence from existing infrastructure is desired as it increases the robustness of a solution. However, robustness is also impacted by other factors, such as resistance to heat. These challenges are imposed by emergency scenes and require further examination. Prior research rarely discussed requirements other than accuracy and robustness. However, other requirements, such as computational speed, may be important to the success of emergency response operations.

To investigate indoor localization requirements for emergency response operations, an online survey was carried out. A list of eleven possible requirements was used in the survey (Table 1). The list was generated based on extensive discussions with first responders from the Los Angeles Fire Department (LAFD). A total of 1151 survey invitation emails were sent to first responders across the U.S. A total of 197 valid responses were received, which supported a ±6.8% confidence interval at a 95% confidence level. Participants had on average 25.7 years of experience, with all ranking levels from firefighters to fire chiefs.

Survey Results

Based on survey results, the requirements were organized in a descending order according to their importance in participants' point of view (Table 1).

Table 1: Importance of Indoor Localization Requirements

Rank	Requirement	% of Total Responses
1	Accuracy of location information	90.4%
2	Ease of deploying the solution on scene	83.8%
3	Resistance to heat, water and other physical damages	67.0%
4	Speed of calculating and presenting location information	66.0%
5	Size and weight of devices attached to first responders and occupants	58.9%
6	Purchase and maintenance costs	38.7%
7	Independence from building infrastructure (e.g. installed equipment) and building power supplies	22.8%
8	Independence from prior data collection (e.g. building layouts, and survey of radio features)	14.2%
9	Scalability of the solution to cover large numbers of people	14.2%
10	Ease of assembling the solution before dispatch	14.2%
11	Independence from on-scene data input (e.g. a few known locations inputted by first responders)	13.7%

Survey results showed that the most important requirements were: accuracy, ease of on-scene deployment, robustness (resistance to heat, water and other physical damages), computational speed (speed of calculating and presenting location information), and size and weight of devices. All of these five requirements were considered important by more than half of the total responders, which was remarkably higher than the percentage of all other requirements (13.7% to 38.7%). Accuracy was the foremost important, and participants indicated that room-level accuracy was more desired than meter-level, floor-level or building-level accuracies. As measure of ease of on-scene deployment, participants reported that a maximum of 135 seconds was allowed to be spent on on-scene deployment. In terms of computational speed, an appropriate time reported by participants for data processing/location computation varied from 5 to 180 seconds, with an average of 40.34 seconds. Resistance to physical damages, and size and weight of devices are related to hardware, and therefore they are not in the scope of this paper.

EASBL ALGORITHM

Review of Sequence-Based Localization Algorithm

Sequence-Based Localization (SBL) is a range-free indoor localization algorithm (Yedavalli *et al.* 2005; Yedavalli and Krishnamachari 2008). It has a number of advantages that make it a desirable algorithm for satisfying the aforementioned indoor localization requirements. These advantages include capability of providing high accuracy, requiring low number of reference nodes, free of pre-data collection, and capability of mitigating multipath and fading effects.

At the heart of the SBL algorithm is the division of a 2D space into distinct regions. Consider a 2D space that consists of n reference nodes. For any two reference nodes, draw a perpendicular bisector to the line joining them. For n reference nodes, there are a total of $n(n-1)/2$ pairs and hence $n(n-1)/2$ perpendicular bisectors, dividing the space into a number of regions. For each region, an ordered sequence of reference nodes' ranks based on their distances to the region is defined as a location sequence of that region. Then, RSSI values of all reference nodes received by a target node are used to form the target node's location sequence. The centroid of a region whose location sequence is "nearest to" the target node location sequence is used as an estimated location of the target node. The nearness can be determined by e.g. Euclidean distance. The reference nodes and target nodes can be any type of radio frequency sensors that can communicate with each other.

Design of Environment-Aware Sequence-Based Localization Algorithm

Success of the SBL algorithm relies on the success of space division, which is essentially determined by the deployment of reference nodes. At emergency response scenes an ad-hoc sensor network must be quickly set up. There are a few challenges that must be addressed. Use of fewer reference nodes is crucial, as fast deployment is desired. In addition, SBL provides coordinate-level estimation. However, locations within the same region are not necessarily within the same room. This leads to a false room-level estimation. In other words, even when a coordinate-level accuracy is high, room-level accuracy may be low. Lastly, building elements such as walls impact accuracy and should be taken into consideration.

An Environment-Aware Sequence-Based Localization (EASBL) algorithm is proposed to address these challenges. EASBL measures the quality of space division with "breakaway area" p_{ba}. In SBL, the centroid of a region is used as an estimated location of a target node anywhere within that region. However, part of the region may be in a room different than the centroid, causing false room-level estimations. This part of the region is defined as a "breakaway area". A smaller p_{ba} within the sensing area indicates better space division and hence a higher room-level accuracy.

On-scene deployment effort is represented by the total number of reference nodes n, and by the difficulty in deploying each reference node. The difficulty in deploying reference node *i* is measured by penalty $c_i, 1 \le i \le n$. There are two kinds of reference nodes: (1) hallway nodes (placed at hallway close to doors) are easy to deploy, and c_i is set to be 1; (2) room-center nodes (placed at centers of rooms) require more effort to deploy, and c_i is set to be 2. By using these candidate locations that do not need exact coordinates to be recorded or communicated, an incident commander can easily provide deployment commands to the first responses, and first responders can easily place the nodes and execute the commands.

Optimal ad-hoc sensing network deployment solution is one that minimizes the breakaway area and the penalty of all deployed nodes. From the computational point of view, this problem can be mathematically abstracted and expressed as: There are *m* candidate locations chosen based on building layout, and *m* reference nodes. Each candidate location $i(1 \le i \le m)$ can hold up to one node for deployment penalty c_i. Each node can be deployed at either one of the candidate locations or none of them (unused). For a given sensing area and given deployment of all nodes, a coverage penalty p_{ba} can be calculated based on the sensor locations and building layout. The objective is to minimize the total penalty (TP):

$$\begin{aligned}
&\min_{p_{ba},\{c_i\},\{k_{ij}\}} TP = e\,p_{ba} + \sum_{i=1}^{m}\sum_{j=1}^{m} c_i k_{ij} \\
&s.t.\ c_i = \{\frac{1,\ if\ \ location\ i\ is\ at\ hallway}{2,\ if\ \ location\ i\ is\ at\ room\ center} \\
&\quad k_{ij} \in \{\frac{1,\ if\ \ node\ \ j\ is\ deployed\ at\ location\ i}{0,\ othersize} \\
&\quad 0 \le p_{ba} \le 1 \\
&\quad e > 0
\end{aligned} \tag{8}$$

where e is a coefficient balancing importance between the space division quality and the on-scene deployment effort, and k_{ij} is a binary variable that denotes whether a node j is deployed at candidate location *i* or not. Heuristics can be used for finding the optimal solution. As a widely used heuristic, a genetic algorithm is used in this paper. Other heuristics, such as simulated annealing and Tabu search, will be evaluated in future research.

Building information is used in three essential and critical ways in EASBL: (1) it is used to identify candidate locations for node deployment; (2) it lays the basis of calculating p_{ba} for a particular space division; (3) annotations such as room numbers can be used to facilitate quick recognition of a specific location for node deployment.

Simulation Setup and Scenarios

A C# script was written to implement EASBL. The script was compiled as a dynamic link library (DLL) file, and integrated into Autodesk Revit as an add-on. The add-on takes user input, extracts building geometries, performs space division optimization, and computes target locations. It then visualizes the estimated locations on floor plans. A simulation tool was programmed to simulate different localization scenarios. It generates a number of targets in a sensing area and implements both a Random Placement SBL (RPSBL) and EASBL algorithms. It simulates the following signal propagation model (Rappaport 1996): $L(d) = L_0 + 10\gamma \log(d) + \sum_{p=1}^{P} WAF(p) + \varepsilon$, where $L(d)$ is path loss of signal strength (dB) in distance d (m), L_0 is reference signal strength loss in 1 m, γ is path loss exponent, WAF is wall attenuation factor, p is number of walls, and ε is a Gaussian term in log-normal fading. The values of L_0, γ and WAF used in simulation were 55.0 dB, 4.7 and 2.0 dB, respectively.

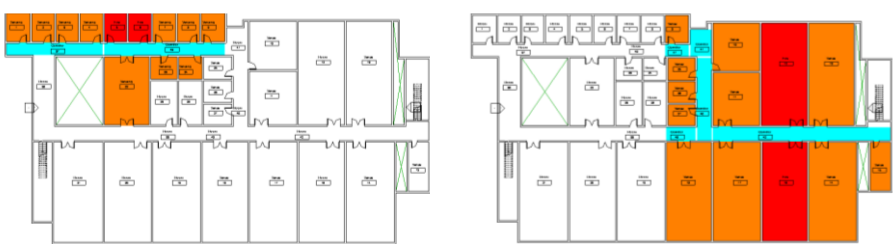
The fourth floor of the Ronald Tutor Hall (RTH) building on the University of Southern California campus was used as a simulation test bed. Two building fire scenarios with different scales were simulated. Both scenarios were designed based on suggestions from a number of first responders, and were verified by two battalion chiefs from the LAFD. In scenario 1 ((a) **(b)**

Figure 1a), two single offices (red) were on fire. Occupants in both offices, all neighboring single offices, and offices and conference room that were across the hallway and had doors open to the hallway (orange) need to be evacuated. Due to the spreading smoke, visibility in the hallway outside the offices (cyan) was low, resulting in an increased risk to first responders. The sensing area is color-coded in (a) **(b)**

Figure 1a with a size of 221 m^2. In scenario 2 ((a)

(b)

Figure 1b), a fire started in one lab and soon spread to a lab across the hallway (red). All labs on the east side of the floor were shut down for fire attack and search & rescue (orange 错误!未找到引用源。). Visibility in the hallway was low due to smoke (cyan). The sensing area is color-coded in 错误!未找到引用源。 with a size of 729 m^2.



(a) **(b)**

Figure 1: Simulation Scenarios

Simulation Results

In the simulation, a total of 50 targets (first responders and occupants) were randomly generated in the sensing area. Each scenario was simulated five times to offset the impact of randomness of target generation, and the simulation results were averaged. In addition, when running the genetic algorithm, every individual in the first generation was considered a random sample resulting from RPSBL, as their attributes were not impacted by crossover or mutation processes. All these first-generation individuals were averaged to get the results for RPSBL. Simulation results for both algorithms are presented in Table 2 for comparison.

The following four conclusions could be drawn based on these results. First, breakaway areas with EASBL were significantly lower than that with RPSBL in both scenarios, indicating a larger possibility of correct room-level estimation using the EASBL. Second, the total number of reference nodes to be deployed was generally comparable between two algorithms; however, a larger portion of reference nodes had to be deployed at room centers with RPSBL, which pointed to a larger deployment effort. When the reference nodes were weighted with deployment penalty c_i, the total deployment effort with EASBL was 15.0% and 11.4% less than RPSBL in scenario 1 and scenario 2, respectively. Third, EASBL yielded both higher coordinate level accuracy and room level accuracy than RPSBL, with an overall improvement by 35.98% and 18.27%, respectively. Lastly, it was noticed that, after space division optimization was done, refreshing localization results took negligible amount of computational time with both algorithms, which was significantly less than 40.34 seconds, the maximum time allowed by survey participants.

Table 2: Indoor Localization Simulation Results

<table>
<tr><th></th><th colspan="2"></th><th>RPSBL</th><th>EASBL</th></tr>
<tr><td rowspan="6">Scenario 1</td><td colspan="2">Breakaway area (%)</td><td>24.8</td><td>7.7</td></tr>
<tr><td rowspan="2">Sensor node deployment penalty</td><td>Room-center</td><td>9.2</td><td>7.3</td></tr>
<tr><td>Hallway</td><td>2.3</td><td>3.0</td></tr>
<tr><td colspan="2">Average meter level accuracy (m)</td><td>2.43</td><td>1.52</td></tr>
<tr><td colspan="2">Average room level accuracy (%)</td><td>71.5</td><td>82.1</td></tr>
<tr style="display:none"></tr>
<tr><td rowspan="5">Scenario 2</td><td colspan="2">Breakaway area (%)</td><td>19.3</td><td>9.2</td></tr>
<tr><td rowspan="2">Sensor node deployment penalty</td><td>Room-center</td><td>10.3</td><td>8.4</td></tr>
<tr><td>Hallway</td><td>3.1</td><td>4.2</td></tr>
<tr><td colspan="2">Average meter level accuracy (m)</td><td>2.46</td><td>1.81</td></tr>
<tr><td colspan="2">Average room level accuracy (%)</td><td>76.3</td><td>87.3</td></tr>
</table>

CONCLUSIONS

This paper identified a set of requirements for indoor localization at building emergency scenes. An EASBL algorithm was proposed to satisfy algorithm-related requirements. Results from a building-size simulation indicated that EASBL, while maintaining the advantages of SBL, was capable of addressing the challenges SBL had under emergency situations. The EASBL could serve to reduce on-scene deployment efforts and increase room-level accuracy, as desired by first responders when they carried out emergency response operations. In addition, since refreshing localization results could be done instantly in simulation, it suggested that the EASBL algorithm had a satisfying computational speed.

To further improve and evaluate the performance of EASBL, future research will be carried out to assess the impact of two parameters, including coefficient e and penalty c_i, on the optimization results and consequently on the localization accuracy and on-scene deployment effort. Parameter values of signal path loss models used in simulation also have impact on the evaluation results, hence deserving further examination. More importantly, the authors plan to perform real-world experiments, so that more comprehensive evaluation of the EASBL algorithm against all requirements including hardware-related ones can be carried out.

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