
EVALUATION OF AN ENVIRONMENT-AWARE SEQUENCE-BASED LOCALIZATION ALGORITHM FOR BUILDING FIRE EMERGENCY SCENARIOS

Nan Li, PhD Candidate, nanl@usc.edu

Burcin Becerik-Gerber, Assistant Professor, becerik@usc.edu

Lucio Soibelman, Professor, soibelman@usc.edu

Astani Department of Civil and Environmental Engineering, University of Southern California, Los Angeles, CA, U.S.A.

Bhaskar Krishnamachari, Associate Professor, bkrishna@usc.edu

Ming Hsieh Department of Electrical Engineering, University of Southern California, Los Angeles, CA, U.S.A.

ABSTRACT

Real-time access to indoor localization information is critical to the success of building emergency response operations. It enables first responders not only to locate themselves to avoid getting lost or disoriented, but also to quickly find and rescue trapped occupants. The environment-aware sequence-based localization (EASBL) is an algorithm proposed by the authors for indoor localization at emergency scenes. With an integration of metaheuristics, the algorithm instructs the establishment of an on-scene ad-hoc sensor network, by reducing the deployment effort and by improving quality of sensing space divisions. Building information is utilized to enable building-specific space divisions and to support context-based visualization of localization results. In this paper, the EASBL is evaluated by using a simulated real-life building fire emergency scenario. Spatial information of a burning building is extracted from a building information model. Results show that tabu search outperforms genetic algorithm and simulated annealing in terms of both the convergence speed and the fitness of solutions. The EASBL algorithm is resistant to partial loss of deployed sensor nodes, and simulations show that over 80% of its accuracy can be retained when almost half of the deployed sensors are lost. The results also reveal that the computational complexity in improving the space division quality increases disproportionately faster than the number of candidate locations for sensor node deployment increases. It suggests that dividing emergency scenes into sub areas and performing indoor localization independently within each sub area may be necessary at large scenes.

Keywords: indoor localization, building emergency response, sequence based localization, BIM, metaheuristic

1. BACKGROUND

Building emergencies are big threats to the safety of building occupants and first responders. Taking building fires as an example: 484,500 building fire incidents happened in the U.S. in 2011, which caused 2,460 deaths and 15,635 injuries (Karter 2012). First responders are the first line of defense when building emergencies happen. However, unfamiliar environments are difficult and dangerous for them 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 2012). Statistics show that 87% of fire-related firefighter injuries and fatalities occur in structure fires (USFA 2011). A total of 159 firefighters died from 2000 to 2011 in the U.S. when responding to structure fires, one major cause of which was firefighters getting lost (Fahy 2010; USFA 2012). One way to reduce such hazards is to provide firefighters with timely access to

accurate location information. Their increased awareness of own locations the spatial context would significantly reduce their chances of getting lost in buildings as well as the associated injuries and fatalities.

It is also of critical importance for an incident commander to know the locations of the first responders in real time, so that decision-making process is made faster and in a more informed fashion. 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 and requires a complete inspection of all indoor spaces. Such a blind search process is highly inefficient and 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 of the trapped occupants, and it can be achieved by making the locations of trapped occupants more visible to first responders at emergency scenes.

Despite its importance, access to the location information during emergency response operations is far from being automated and efficient. Currently, after a size-up of an emergency, which evaluates the severity of an incident and estimated required resources based on visual inspections from outside a building, first response teams are sent in to the building, usually in groups of four, to perform various tasks such as fire attack, ventilation, and search and rescue. The deployed first responders communicate over radios with an incident commander outside the building, who marks tasks and locations of the deployed teams in a command post and updates them based on vocal reports from the deployed teams. However, it is challenging to keep this information organized and updated, considering the ever changing situations inside the building, especially when multiple teams use multiple radio channels. Access to real-time location information, if made possible, would enable the incident commander to better monitor and guide the deployed first responders. This would lead to reduction of their chances of getting lost or trapped, and improvement of their efficiency in performing the assigned tasks. On the other hand, search for trapped occupants is usually done in two rounds. During a primary search, first responders traverse the building, determine a rough number and location of trapped occupants and rescue them. During a secondary search, first responders make sure all spaces are thoroughly searched, and rescue the occupants who are still trapped. Although radios (and in some cases thermal cameras) are used to help detect the occupants at emergency scenes, the search process is generally low-tech and blind. First responders usually have little clue of how many occupants are trapped, where they are, and how to reach them. Therefore, all spaces in a building need to be traversed, requiring significant amount of time and labor. There is a need for an indoor localization solution that enables the first responders to obtain real-time location information of both themselves and trapped occupants during emergencies when they perform the emergency response operations.

To address such need, a number of indoor localization solutions have been proposed in literature. For example, Duckworth et al. (2007) proposed a system that could work without existing infrastructure or pre-collected data. The system relied on an ad-hoc network built on transmitters carried by both first responders in a building and vehicles outside the building, and yielded an accuracy of a few meters. Rantakokko et al. (2011) proposed a system that integrated foot-mounted inertial sensors and Ultra Wide Band (UWB) sensors for locating first responders at emergency scenes. They reported an accuracy of 1 to 4 m, and noted that the accuracy could drop due to heading drifts. A commercial system 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, and could reportedly achieve an accuracy of 3 m. Cavanaugh et al. (2010) proposed a system, which relied on extensive on-site deployment of localization system-equipped vehicles, and reported up to sub-meter accuracy. Akcan and Evrendilek (2012) proposed a system that utilized UWB technology. Reported accuracy through simulations was up to 6 m, depending on the density of deployed UWB nodes. 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.

Most of the existing solutions are characterized by meter or sub-meter level accuracy or an independence from existing sensing infrastructure in buildings. However, it is arguable whether such high accuracies are necessary. Although more fine-grained location information is desirable, it is usually associated with a more sophisticated sensing network or additional prior data input, which may significantly add to the difficulty of onsite deployment and hence limit the adaptability of the solution. Furthermore, a high meter-level accuracy does not

necessarily lead to a high room-level accuracy, and the latter is more important at building emergency scenes. 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 partial loss of deployed sensing infrastructure. These challenges are imposed by emergency scenes and require further examination. Moreover, there is lack of discussion in prior research about a complete set of requirements other than accuracy and robustness. However, other requirements, such as computational speed, may be just as important to the success of emergency response operations. To address this challenge, the authors evaluated the requirements for indoor localization at building emergency scenes, and proposed an environment-aware sequence-based localization (EASBL) algorithm (Li et al. 2013). This paper provides further evaluation of the EASBL algorithm. It examines the selection of metaheuristics, and assesses the robustness of the EASBL algorithm against partial loss of deployed sensor nodes. It also evaluates the increase of computational complexity of the algorithm as the number of candidate nodes locations increases.

2. REVIEW OF EASBL

2.1 Indoor Localization Requirements

An online survey was conducted to investigate indoor localization requirements for emergency response operations (Li et al. 2013). A list of eleven possible requirements was given to 1151 first responders across the U.S. invited by email. A total of 197 valid responses were received, which supported a $\pm 6.8\%$ 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. The top five important requirements, agreed upon by more than half of the survey respondents, include: (1) accuracy of location information; (2) ease of deploying the solution on scene; (3) resistance to heat, water and other physical damages; (4) speed of calculating and presenting location information; and (5) size and weight of devices attached to first responders and occupants.

2.2 Algorithm Design

The EASBL algorithm was proposed to address these requirements. It is based on a Sequence-Based Localization (SBL) algorithm, which is a range-free indoor localization algorithm (Yedavalli et al. 2005; Yedavalli and Krishnamachari 2008). It has a number of advantages that make it desirable 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.

On the other hand, the 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 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. To address these challenges, the EASBL algorithm was proposed. The algorithm was designed to improve the sensing space division by decreasing chances of false room-level estimation, and to reduce the effort for deploying sensor nodes at emergency scenes, by strategically selecting node locations. Metaheuristics are used to optimize a dual objective function for this algorithm. The details of the EASBL algorithm can be found in (Li et al. 2013). Building information is used in the localization process to identify candidate locations for node deployment, and lay the basis of evaluation of space division quality.

This paper presents further evaluation of the EASBL algorithm, including comparison of multiple metaheuristics in finding satisfactory solutions, examination of robustness of the algorithm, and the computational complexity of the algorithm.

3. EVALUATION SETUP

Autodesk Revit (version 2013) was used as a BIM authoring tool. A C# code was written to implement the EASBL algorithm. The code was compiled as a dynamic link library (DLL) file, and integrated into Autodesk Revit as an add-on function. Once started, the add-on informs users that a localization algorithm is initialized, and asks users to choose a sensing area and specify spaces that could be accessed for sensor deployment through the GUI. Upon receiving the user input, the add-on interacted with Revit API (version 2013), and extracts building geometries from the BIM model. The add-on then processes the geometries, search for a satisfactory space division based on the building geometries and user input, and carries out location computation if a target is specified. It then displays localization results through the GUI by a dialog box that lists space division results as well as the estimated room numbers for targets. The add-on also demonstrates the estimated location of targets on floor plans. In this way, the results can be presented to users in both textual and visual formats.

The following test bed and scenario was simulated. The test bed was the fourth floor of the Ronald Tutor Hall (RTH) on the USC campus (Figure 1). In the simulated building fire scenario, two single offices (shown red in Figure 1), are on fire. People in both offices, all neighboring single offices, and the offices and conference room that are across the hallway and have doors open to the hallway (shown orange in Figure 1) need to be evacuated. Due to spreading smokes, the visibility in hallway outside the offices (shown cyan in Figure 1) is low, resulting in increased risks to first responders. The sensing area is the color-coded area in Figure 8 with a size of 221 m², including 11 offices, 1 conference room, and 1 segment of a hallway.



Figure 1: Simulation scenario

When evaluating the localization accuracy of a given space division, a total of 50 targets were randomly generated within the sensing area. Their room level and coordinate level locations were computed, and the accuracies were evaluated. It needs to be noted that the targets can be either first responders who carry mobile sensor nodes, or trapped occupants who have access to mobile devices, such as smartphones, that can emit signals detectable by the deployed sensor network. In the simulation, the following signal propagation model was used:

$$L(d) = L_0 + 10\gamma \log(d) + \sum_{p=1}^P WAF(p) + \varepsilon$$

where $L(d)$ is path loss of signal strength [dB] in distance d [m], L_0 is reference signal strength loss value [dB] for 1 m, γ is path loss exponent, WAF is wall attenuation factor, 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 (Li et al. 2013).

4. FINDINGS

4.1 Evaluation of Metaheuristics

The EASBL algorithm depends on a metaheuristic for finding satisfactory solutions. The classic and most widely used metaheuristics for optimization problems include genetic algorithm (GA), simulated annealing (SA), and Tabu search (TS) (Pham and Karaboga 2000). The genetic algorithm locates optima using processes similar to those in natural selection and genetics. The simulated annealing finds optima in a way analogous to the reaching of minimum energy configurations in metal annealing. The tabu search is a heuristic procedure that employs dynamically generated constraints or tabus to guide the search for optimum solutions. It needs to be emphasized that none of these metaheuristics are guaranteed to find the global optima. However, after a sufficiently large number of evaluations, they usually yield satisfactory, but not necessarily global optimal, solutions to a given problem, which are referred to as their reported optima or satisfactory solutions in this paper.

Efficiency, which is measured by the speed that a metaheuristic converges to a reported optimum is critical to indoor localization at emergency scenes. Because the efficiency of metaheuristics is highly dependent on the particular problem they are applied to, this paper assesses the efficiency of the three metaheuristics by examining their convergence speed in the given simulated scenario. Each metaheuristic is run for 10,000 evaluations, and the best solution found after each evaluation is recorded. Each metaheuristic is given the most commonly used parameter values seen in various optimization problems. The parameter values are summarized in Table 1.

Table 1: Summary of metaheuristics parameter values

Genetic algorithm	Simulated annealing	Tabu search
Population size: 100	Initial temperature: 400	Tabu list size: 25
Number of generations: 100	Reduction ratio: 0.999	
Crossover rate: 0.6		
Mutation rate: 0.01		

The results are plotted in Figure 2. As can be seen from the results, TS converges to a reported optimum after 570 evaluations, while it takes GA and SA 2,059 and 2,150 evaluations, respectively, to converge to their reported optima. The TS convergence curve has more zigzags than the other two curves, showing that TS keeps improving the solution at the beginning of the search process. The time each metaheuristic takes to complete the 10,000 evaluations is plotted in Figure 3. Although TS has a longer computational time than GA and SA per evaluation, the overall time it takes to converge to its optimum is 53% and 65% less than GA and SA, respectively.

Furthermore, since metaheuristics are not guaranteed to find the global optima, and the fitness of reported solutions by different metaheuristics may differ. Comparing these reported optima, the one reported by TS has the highest fitness, followed by solutions reported by GA and then SA. Because TS outperforms GA and SA in terms of both convergence speed and fitness of the reported solution, TS is used in assessment in the rest of this paper.

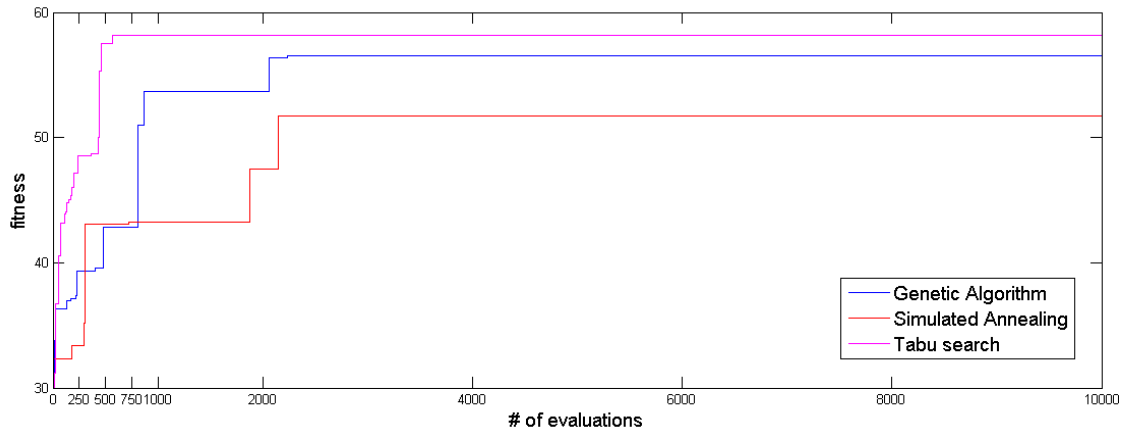


Figure 2: Convergence speed of three metaheuristics

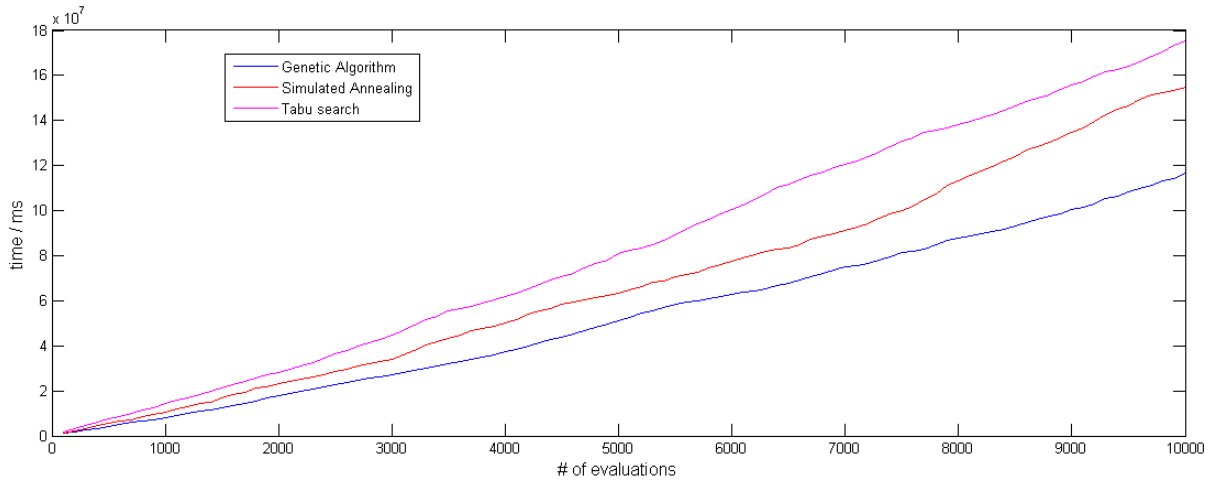


Figure 3: Computational time of metaheuristics

4.2 Evaluation of Robustness

One of the aforementioned requirements for indoor localizations is the resistance to heat, water and other physical damages, namely the solutions' robustness to possible damages at emergency scenes. The robustness is assessed in this paper by simulating partial losses of deployed sensor nodes, and examining the impact on the accuracy of localization results. The assessment includes three steps: (1) find the optimal sensor deployment solution with the EASBL algorithm; (2) incrementally reduce the number of deployed sensor nodes starting from the optimal solution. The selection of the set of removed or "lost" sensor nodes is randomized, and is repeated 50 times; (3) for every set of remaining sensor nodes resulting from step 2, perform the localization process, and evaluate the localization accuracies.

The results, in terms of room-level and coordinate-level accuracies, are plotted in Figure 4. Given a total of 22 candidate locations for sensor deployment, the satisfactory solution found the algorithm includes 11 sensor nodes, and yields a coordinate-level accuracy of 1.74 m and room-level accuracy of 85.8%. As can be seen from Figure 4, neither the coordinate-level accuracy nor the room-level accuracy is noticeably impacted when up to 3 sensor nodes, or 18.2% of the total deployed sensor nodes, are lost, which indicates that the EASBL algorithm bears a certain extent of robustness against partial loss of the deployed sensor nodes. The coordinate-level and room-level accuracies decrease gradually, with an extent up to 17.8% and 12.2%, respectively, when 5 out of the 11 sensor nodes are lost. Both accuracies decrease significantly with further loss of sensor nodes. It needs to be noted that, since the removed nodes were randomly selected and the process was repeated 50 times in the simulation, the impact of the location of removed sensor nodes and the order in which they were removed was offset.

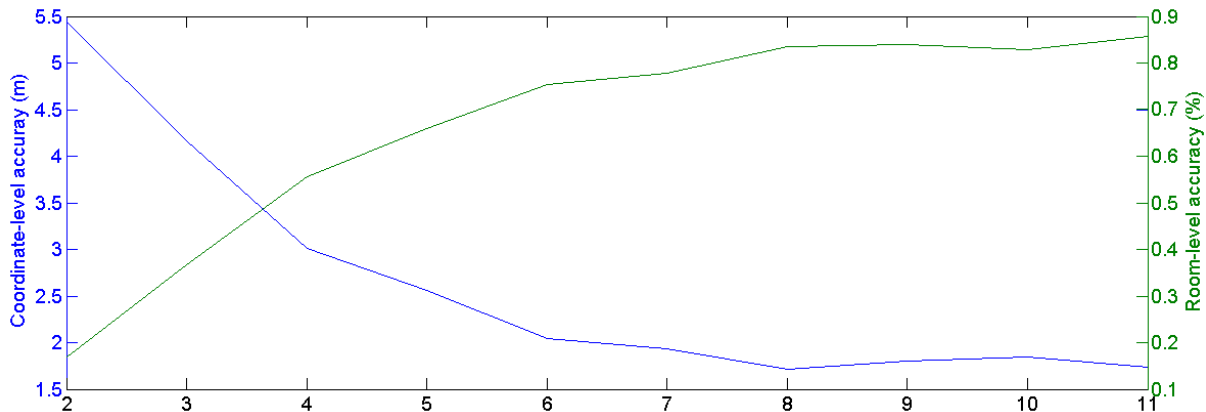


Figure 4: Assessment of robustness against partial loss of deployed sensor nodes

4.3 Evaluation of Computational Complexity

In order to assess the computational complexity of the EASBL algorithm as the number of candidate node locations increases, this paper examines the number of evaluations that TS takes to find a satisfactory solution, given different numbers of candidate locations. The candidate location number is increased incrementally from 2 to 17 in simulation. After each increment, the TS metaheuristic is used to search for the optimum, and a solution is considered a satisfactory solution if no better solution is found in the following 2,500 evaluations. The number of evaluations to find satisfactory solution for each given number of candidate locations (in logarithmic scale) is plotted in Figure 5.

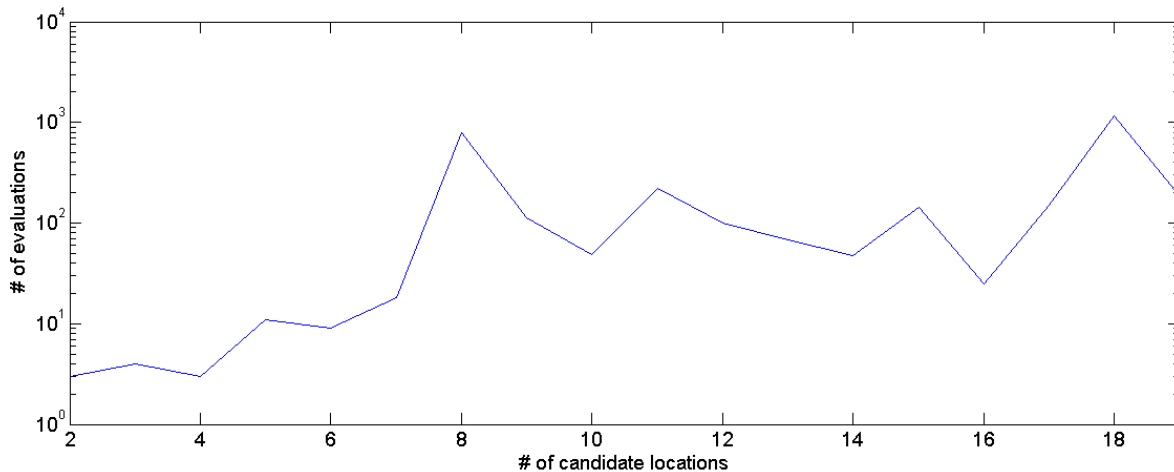


Figure 5: Assessment of computational complexity

The results show that the computational complexity increases disproportionately faster than the number of candidate locations, although it is difficult to conclude with any mathematical expression of the computational complexity. The results suggest that, when used to cover a large building emergency scene that involves tens or hundreds of rooms, the EASBL algorithm would perform more efficiently if the scene is covered by a number of sub ad-hoc sensing networks, within each of which localization is carried out independently, than using a single ad-hoc sensing network that covers the entire scene. It needs to be noted that the computational complexity evaluated hereby is associated with the process of finding the satisfactory space division. Once the space division is determined and an ad-hoc sensing network is established, the computation of targets' locations can always be done instantaneously, regardless of the size of emergency scenes or the number of targets.

5. DISCUSSIONS AND CONCLUSIONS

An EASBL algorithm has been proposed by the authors in previous research to provide first responders with access to real-time indoor location information at a building emergency scene, by meeting a set of requirements. This paper provides an assessment of the EASBL algorithm, in particular about the efficiency of its integrated metaheuristics, its robustness, and its computational complexity. The results reveal that TS outperforms GA and SA in terms of both the convergence speed and the fitness of the reported optimum. The EASBL algorithm is hardly impacted by the loss of a small portion of deployed sensor nodes, and can retain over 80% of its accuracy when almost half of the deployed sensors were lost, which could happen at emergency scenes due to various hazards such as heat and water. The results also reveal that the computational speed in finding a satisfactory space division increases exponentially with respect to the number of candidate locations for sensor node deployment, which suggests that dividing the emergency scenes into sub areas and performing indoor localization independently within each sub area may be necessary at large scenes.

The evaluation of the EASBL algorithm presented in this paper is yet to be extended and improved, and there are two limitations that need to be addressed in future research. First of all, the optimal parameter values of each metaheuristic may be problem-dependent, and need to be tuned based on this particular problem. Commonly used

parameter values are used in the current assessment. However, these values may be undesirable and prevent the metaheuristics from being fully functional. Parameter tuning is therefore necessary. Secondly, the assessment of metaheuristics' convergence speed and the algorithm's computational complexity should be repeated multiple times in simulation in order to ensure statistical soundness. The current results are not based on multiple simulations, and are therefore subject to the impact of randomness.

In addition to addressing the above limitations, the authors plan to carry out future research to evaluate the algorithm in a real-world environment, where a smartphone-centric sensing network will be developed and deployed, and the performance of the indoor localization solution will be evaluated under an assumed realistic building emergency scenario. The proposed EASBL algorithm, when further improved and fully examined, is expected to provide first response teams with a quick and efficient approach for locating deployed first responders and trapped occupants at building fire emergency scenes. With timely access to indoor location information, emergency response operations would be carried out in a more informed and coordinated manner. Consequently, chances for first responders and trapped occupants to avoid casualties and injuries would increase during building fire emergencies.

ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Grant No. 1201198. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

- Akcan, H., and Evrendilek, C. (2012). "GPS-Free Directional Localization Via Dual Wireless Radios." *Comput. Commun.*, 35(9), 1151-1163.
- Brouwer, E. (2012). "Trainer's corner: What are your rules for calling mayday? " <http://www.firefightingincanada.com/content/view/1274/213/> (June 1, 2012).
- Cavanaugh, A., Lowe, M., Cyganski, D., Duckworth, R. J. (2010). "WPI precision personnel location system: Rapid deployment antenna system and sensor fusion for 3D precision location." *Proc., Institute of Navigation - International Technical Meeting 2010, ITM 2010, January 25, 2010 - January 27, Institute of Navigation*, , 384-389.
- Duckworth, J., Cyganski, D., Makarov, S., Michalson, W., Orr, J., Amendolare, V., Coyne, J., Daempfling, H., Hubelbank, D., Parikh, H., Woodacre, B. (2007). "WPI precision personnel locator system - evaluation by first responders." *Proc., 20th International Technical Meeting of the Satellite Division of the Institute of Navigation 2007 ION GNSS 2007, September 25, 2007 - September 28, Curran Associates Inc.*, , 1427-1435.
- Fahy, R. F. (2010). *U.S. Fire Service Fatalities in Structure Fires, 1977-2009*, National Fire Protection Association, Quincy, MA.
- Karter, M. J. (2012). *Fire Loss in the United States 2011*, National Fire Protection Association, Fire Analysis and Research Division, Quincy, MA.
- Li, N., Becerik-Gerber, B., Krishnamachari, B., Soibelman, L. (2013). "An environment-aware sequence-based localization algorithm for supporting building emergency response operations." *Proc., Proc. 2013 ASCE International Workshop on Computing in Civil Engineering (IWCCE 2013)*, American Society of Civil Engineers (ASCE), Los Angeles, CA.
- Lo, A., Xia, L., Niemegeers, I., Bauge, T., Russell, M., Harmer, D. (2008). "EUROPCOM - an ultra-wideband (UWB)-based ad hoc network for emergency applications." *Proc., Proc. of VTC/Spring - 2008 IEEE 67th Vehicular Technology Conference*, IEEE, Singapore, 6-10.
- Pham, D. T., and Karaboga, D. (2000). *Intelligent Optimisation Techniques : Genetic Algorithms, Tabu Search, Simulated Annealing and Neural Networks*, 1st Ed., Springer.
- Rantakokko, J., Rydell, J., Stromback, P., Handel, P., Callmer, J., Tornqvist, D., Gustafsson, F., Jobs, M., Gruden, M. (2011). "Accurate and Reliable Soldier and First Responder Indoor Positioning: Multisensor Systems and Cooperative Localization." *IEEE Wireless Communications*, 18(2), 10-18.

- USFA. (2012). *Firefighter Fatalities in the United States in 2011*, U.S. Fire Administration, Emmitsburg, Maryland.
- USFA. (2011). *Fire-Related Firefighter Injuries Reported to NFIRS*, http://www.usfa.fema.gov/downloads/pdf/publications/ff_fat11.pdf, U.S. Fire Administration, Emmitsburg, Maryland.
- Yedavalli, K., Krishnamachari, B., Ravula, S., Srinivasan, B. (2005). "Ecolocation: A sequence based technique for RF-only localization in wireless sensor networks." Los Angeles, CA.
- Yedavalli, K., and Krishnamachari, B. (2008). "Sequence-Based Localization in Wireless Sensor Networks." *IEEE Transactions on Mobile Computing*, 7(1), 81-94.