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Research paper

An Expanding Neighbourhood Search Technique for Avalanche Search-and-Rescue Operations using Air Ground Collaborative Wireless Networks

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Abstract

Due to avalanches, a considerable number of travellers deceases every year. The number is increasing over the past few decades. Hence, to speed up the rescue mission and thereby, to mitigate number of fatalities, collaborative rescue missions are envisioned. However, most of the existing techniques that are utilized in rescue missions are non-collaborative. In this paper, we propose a new searching technique, named Expanding Neighbourhood Search Technique (ENST) to facilitate collaborative rescue missions. We performed an extensive simulation campaign and compared our proposed technique with other prominent existing techniques to find out the effectiveness of the proposed scheme.

Keywords: *Search-And-Rescue; Collaborative Search-And-Rescue; Random Seatch Technique; Probabilistic Search Techique; Enhancing Neighbourhood Search Technique*

1. Introduction

In parallel to the increasing number of mountain visitors—which includes climbers, skiers, snowmobilers, tourists, and others—the casualties due to avalanches are also increasing [1, 2]. One of the major reasons for this is the boom in mountain industries and recreations that force to build more roads, buildings, and towns in avalanche prone areas.

To aid people in distress or in imminent danger due to avalanches, every mountain area employs one or multiple Search And Rescue (SAR) teams—they follow certain strategies to discover the victims and rescue them out from there. The SAR has many subfields, among which Avalanche Search-And-Rescue (ASAR) [3] is the point of interest in this paper; hence, others are out of the scope.

To reduce the number of fatalities, the ASAR activities have been taken into account with significant concern for the last couple of decades. With this vision, a European project has been launched, named Smart collaboration between Humans and groundaErial Robots for imProving rescuing activities in Alpine environments (SHERPA) [4]. The primary objective of this project is to deploy an Air-Ground Collaborative Wireless Network (AGCWN) [5, 6] to facilitate Collaborative Avalanche Search And Rescue (CASAR) activities through employing Unmanned Aerial Vehicle (UAVs), Human Rescuers (HRs), and Ground Rovers (GRs). This collaborative effort is envisioned as a promising solution to reduce the rescue related delays in this project, and thus, targeting in saving more human lives after avalanches.

Most of the existing search technologies are non-collaborative [7, 8, 9]; whereas, the CASAR assumes a collaborative effort. To facilitate the CASAR, a collaborative searching technique is also mandatory. In this paper, we propose a collaborative search technique, which is a variant of probabilistic search technique. The proposed technique is discussed in details in Section II.

2. Proposed Technique

Our proposed approach is a variant of existing probabilistic searching technique [8, 10]. To make our proposed technique suitable for the CASAR, we divide the considered area into multiple grid cells. It reduces overlapping in searching operation; especially, when multiple teams are involved. When a team does not discover the target in the current cell, it moves to the next cell. The performance of the CASAR activities are closely related with the next cell selection. Hence, in our proposed technique, until α-level neighbourhood is searched to select the next cell; and by that mean, the proposed technique is different from its ancestor; where $\alpha \in Z+$. The cell that has the highest probability to be the target point within α-level neighbourhood is selected as the next cell to visit. During this course of action, the proposed technique expands the searching operation from 1-level neighbourhood to α-level neighbourhood; and hence the name, Expanding Neighbourhood Search Technique (ENST). Before moving to the new cell, the probability of the current cell is revised. Again, if all the cells are already visited until α-level neighbourhood, then it employs the random search technique to select a random cell between 1- to α-level neighbourhood.

2.1 Recursive Bayesian Estimator (RBE)

The observation model parameters for the RBE are the probability of false positive and the probability of false negative, and let us denote them as φC and βC, respectively for a certain cell C. If dC be the detection measurement of cell C—when dC = 1, a positive target detection event occurs and when dC = 0, a negative target detection event occurs—and A is the target cell. Then, using Chung's [7] error model, following four conditions may be observed:

Pr(dC = 1; C = A) = 1 - βC
Pr(dC = 0; C = A) = βC
Pr(dC = 0; C ≠ A) = 1 - φC
Pr(dC = 1; C ≠ A) = φ

During the CASAR operations, if the object is positively detected; then, it is the end of the searching operation and rescue operation starts afterwards. Otherwise, the RBE updates the probabilities based on positive or negative detection events are encountered. Equation 1 and 2 show the update equations for both the conditions (Symington, 2010):

if dC = 1;

$$P_C = \frac{(1-\beta_C)P_{C_P}}{(1-\beta_C)P_{C_P} + \alpha_C(1-P_{C_P})}; \quad (1)$$

if dC = 0;

$$P_C = \frac{\beta_C P_{C_P}}{\beta_C P_{C_P} + (1-\alpha_C)(1-P_{C_P})}; \quad (2)$$

where, PCp is the previous probability value of cell C. Afterwards, the normalized posterior distribution operation is performed, and the posterior probability of a cell, C be P′C and could be calculated using Equation 3.

$$P'_C = \frac{P_C}{\sum_{i=1}^{N} Pi}; \quad (3)$$

where, PC is the current probability of the cell C, N is the number of cells in the avalanche area, and $\sum_{i=1}^{N} Pi \le 1.$

3. Evaluation

In this section, we evaluate the performance of the proposed searching technique for the CASAR operations.

3.1 System Model

In our simulation, we consider a Euclidean 2D-area of 10000m × 10000m, which is equally divided into a fixed number of cells—100 × 100 in our simulation—to avoid overlapping during CASAR activities. Note that at a certain time, only one team can visit a single cell. Most of the simulation tasks were carried out through implementing programs in C++, except the probability generation task for the cells. In the latter case, we utilize MATLAB.

A) Generating Probabilities for Cells:

We generate probabilities of various cells employing Algorithm 1 using MATLAB and save them in w. At the end, w is written on a text file for future utilization.

Algorithm 1 Finding probabilities of the considered area

```
w ← peaks(100)
total ← 0
Comment: Eliminate negative values from w and find out total.
for i ← 0 to 100 do
    for j ← 0 to 100 do
        w(i, j) ← |w(i, j)|
        total+ = w(i, j)
    end for
end for
Comment: Calculate probability for every cell and stores it.
for i ← 0 to 100 do
    for j ← 0 to 100 do
        w(i, j) ← w(i, j)/total
        Store w(i, j) in a text file
    end for
end for
```

B) Finding Avalanche Point:

Although, avalanche could spread to multiple consecutive cells, but to stretch our simulation, we consider a single cell as an Avalanche Point (AP). Again, likelihood of occurring avalanche is higher in higher probability cells than others. Hence, we need such a random number generator which generates a random number, ρ accordingly. For this, we utilize a Sigmoid Function and modifies it to generate our desired random number, ρ using Equation 5.

$$y = \frac{1}{1+e^{-1\times(10\times(\nu\times 0.55))}}; \quad (4)$$

where, υ is a uniform random number, which ranges between 0 to 1. If μ is the highest value in w; then, using Equation 4, ρ can be generated as follows:

$$\rho = \frac{(y-0.5)\times\mu}{0.4959}; \quad (5)$$

Figure 1 displays some ρ values that are generated using Equation 5. Now, based on ρ, we have to select an avalanche point. For this, we employ a randomization based technique. Again, it may happen that the selected probability does not exist in w. In this case, we use approximately equal values with an allowable difference of 106.

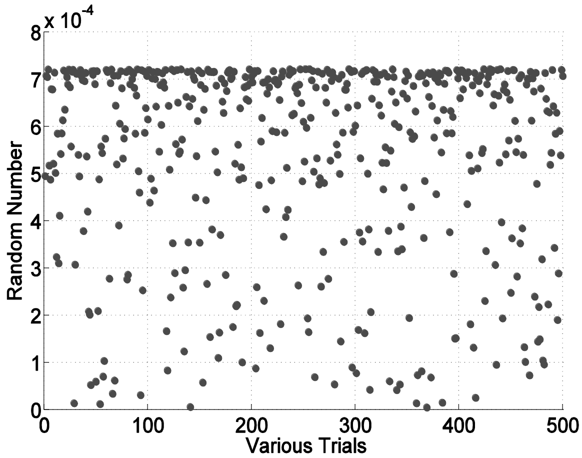


Figure 1: Various ρ values are generated using Equation 5.

C) Other Searching Techniques:

The performance of the proposed technique is compared with two prominent existing techniques, they are: Random Search Technique (RST) and Probabilistic Search Technique (PST). The RST is the simplest technique in terms of implementation and understanding among all the techniques discussed in this paper. As the name suggests, it selects the next cell randomly between 1-level neighbourhood. On the other hand, the PST is the ancestor of the proposed technique. Consequently, most of the steps are similar. The main difference between these two techniques is that unlike ENST, the PST does not expand the neighbourhood-level to α-level. We generate probabilities of various cells employing Algorithm 1 using MATLAB and save them in w. At the end, w is written on a text file for future utilization. It selects the next visiting cell within the 1-level neighbourhood. If all the 1-level neighbourhood is already visited—which may occur due to utilizing the local visiting knowledge or global visiting knowledge in selecting next cell—then, it selects the next cell randomly from the 1-level neighbourhood alike RST.

D) Searching Approaches:

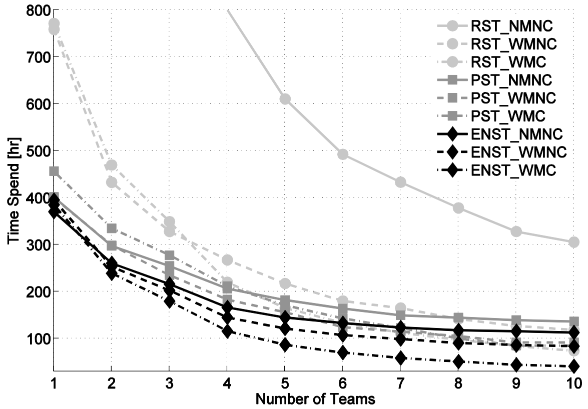
To demonstrate the impact of collaboration and memory on all the techniques considered in this paper, three variants are proposed, such that i) No Memory and Non-Collaborative (NMNC), ii) With Memory but Non-Collaborative (WMNC), and iii) With Memory and Collaborative (WMC). In NMNC, next cell is selected without considering whether the cell has been visited previously or not. Since there is no information sharing occurs among the various teams, the AGCWN is not required for this approach. On the other hand, in WMNC, local cell visiting knowledge is mandatory to select the next cell. Every team will keep information about the previously visited cells and this knowledge will be utilized during the next cell selection. Alike NMNC, the AGCWN is not also required for this approach. In WMC, global knowledge of cell visiting is necessary to select the next cell, which is acquired by sharing cell visiting information among each other. Since the area of coverage is higher, a network infrastructure is necessary to maintain the communication among different teams. Hence, the AGCWN is necessary to enable this communication or in other words, to enable this collaboration.

E) Results and Discussions

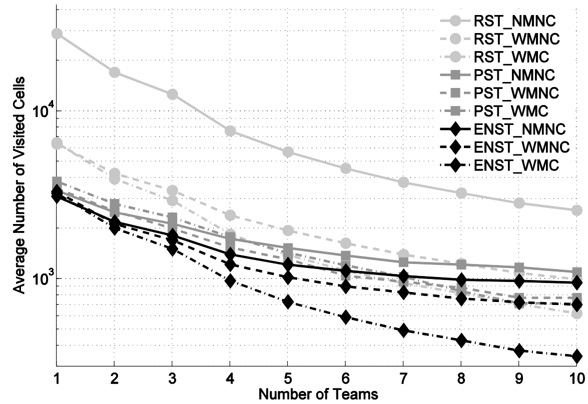
To compare the performance of the three considered searching techniques and their variants, we utilize two metrics, namely Time Spend [hr] and Average Number of Visited Cells, which are depicted in Figure 2a and 2b, respectively. The time spend in Figure 3a is calculated as follows:

$$\tau = \tau_{gst} + \tau_{pt} + \tau_{tt}; \tag{6}$$

In Equation 6, τgst is the grid search time by UAVs, which is calculates as, τgst = Ag / SUAV, where Ag is the area of the grid cell and SUAV is the average speed of the UAV. On the other hand, τpt is the preparation time, which we consider a constant time. Again, τtt is the traveling time, which depends on the distance and in the simulation, we take Euclidean distance, δ into consideration. The τtt is calculated as, τtt = δ/SGR, where SGR is the speed of the GR, which is considered equivalent to the hiking speed between 30km to 80km per day. For other parameters, we consider following values: SUAV = 10mps, τpt = 180s, SGR = 1.5mps, and α = 2.



(a) Number of Teams vs Time Spend [hr].



(b) Number of Teams vs Average Number of Visited Cells.

Figure 2: Comparing various searching techniques and their variants.

From both the figures it is conspicuous that—irrespective of any searching technique—collaborative efforts outperform other variants. It utilizes the global cell visiting knowledge to select the next cell as well as globally updated probability distribution map. The results evidently show the essentiality of collaborative rescue operations over non-collaborative operations.

Among the three technologies, the RST shows the lowest performance with respect to all the metrics considered in this paper due to its randomize nature. However, the performance of the RST could be improved if it is incorporated with the WMC approach. Again, the PST performs better than the RST since it selects the next cell based on probabilistic values. However, among three techniques, the ENST outperforms all other techniques with respect to both the metrics since it not only utilizes the probabilistic values but it also discovers the probable avalanche point through searching until α-level neighbourhood. The results in both the figures support the effectiveness of the proposed scheme.

4. Conclusion

To mitigate the number of fatalities by lowering the rescue time, we propose the ENST—a probabilistic search technique—to facilitate collaborative rescue missions. Three variants of the proposed scheme have also been introduced—namely, NMNC, WMNC, and WMC—to demonstrate the impact of memory and collaboration in the rescue mission. We perform an extensive simulation campaign to find out the effectiveness of the proposed scheme. The acquired results are compared with other two prominent techniques, namely RST and PST. Our proposed technique outperforms these two techniques for every approach considered in this paper. Again, the results of the three variants evidently demonstrate the essentiality of the collaborative approach.

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References

[1] National Snow & Ice Data Center (NSIDC), 2017. Avalanche Awarness, from http://people.uwec.edu/jolhm/EH3/Group4/
[2] references/nsidc.htm.
[3] Club Alpino Italiano, 2017 from http://www.cai.it/
[4] Floyer, J., 2013. Smartphone Avalanche Search AppsA Review, Discussion Paper, Canadian Avalanche Centre.
[5] Marconi, L., et. al., 2012. The SHERPA project: Smart collaboration between humans and ground-aerial robots for improving rescuing activities in alpine environments, in Proc. of IEEE SSRR, 5 – 8.
[6] Rahman, M. A., 2014. SHERPA: an air-ground wireless network for communicating human and robots to improve the rescuing activities in alpine environments. in Proc of 8th WiSARN, 1 – 13.
[7] Rahman, M. A., 2014. Enabling Drone Communications with WiMAX Technology, in Proc. of IISA' 2014, Greece.
[8] Chung, T., and Burdick, J., 2007, A Decision-Making framework for control strategies in probabilistic search, in Proc. of IEEE ICRA, 4386 – 4393.
[9] Groot, D., and Morris, H., 2004. Optimal Statistical Decisions, Wiley Classics Library.
[10] Symington, A., et. al., 2010. Probabilistic Target Detection by Camera-Equipped UAVs," in Proc. of IEEE ICRA, 4076 – 4081.
[11] Whitley, A., 2016. MH370 Hunters Narrow Down Most Likely Site of Wreckage, from https://www.bloomberg.com/news/articles/2015-12-02/