An Automated Framework for Assistance in the Search for Missing Child

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***Abstract*—More than 460,000 entries for missing children were reported to National Crime Information Center each in years 2014 and 2015. This large figure indicates an urgent need for developing efficient strategies, to guide the search action. In the presence of uncertainties in the circumstances surrounding the missing person, scientific methods can be used to systematically evaluate potential scenarios, and design a solution to maximize the overall probability of detection. In this pilot study, we introduce an automated framework for optimal search plan construction, to assist the decision making by prioritizing search directions, and allocating time resources. Given necessary information about a missing person, a potential search area is first identified, and then divided into equal-sized search units, based on a user specified granularity. A prior probability of finding the missing person is computed over all search units. Then, a detection model is designed in line with optimal search theory. Based on progress of search action, the posterior probability of finding the missing person is estimated according to Bayesian method, to construct a maximum probability search plan that assigns search effort to the unit with highest posterior probability. This search plan is proved to be optimal within a cumulative search effort constraint under our framework. For the purpose of validation and visualization, we have developed a web-based application to render the proposed framework on an interactive GIS map.**

I. Introduction

According to the FBI, there were 460,000 entries for missing children reported to National Crime Information Center each in years 2014 and 2015 [1]. This huge number reveals an urgent demand for effective search strategies that can lead to successful detection, in the presence of uncertainties in the circumstances surrounding the missing person, and the constraint of search resources.

Search for a missing child is a highly time-sensitive task. Due to the limited search efforts in a real scenario, it is impractical to conduct an exhaustive screening over all possible places. Therefore, an optimal allocation of resources, in terms of available staff and time investment, is crucial for the success of a missing child detection.

However, because the decision making in search action is commonly based on empirical analysis of obtained information, the result of such analysis can be subjective, and thus varies from one person to another. To control the bias in personal perspective, it necessitates the use of scientific approaches for information analysis and probability estimation.

Several studies [2], [3] have explored the potential of Bayesian method in the search for missing aircraft and ships.

TABLE I: NISMART-2 Reported Missing Children Percentage by Episode Type [4]

ID	Episode Type	Percent(%)
1	Nonfamily abduction	2
2	Family abduction	7
3	Runaway / thrownaway	45
4	Missing involuntary, lost or injured	8
5	Missing benign explanation	43

Their results demonstrate that Bayesian search is an effective approach for planning the search for missing objects.

In this pilot study, we introduce an automated framework for optimal search plan construction, by leveraging statistical analysis with Bayesian search theory to provide assistance in search planning and resources allocation.

As discussed in NISMART-2 (National Incidence Studies of Missing, Abducted, Runaway, and Thrownaway Children) [4], missing child incidents are commonly categorized into five types, as listed in Table I. One thing to note is, the summation of percentage in this table is more than 100, because a few cases have been counted for more than one episode type.

It is evident from Table I that the majority of reported missing incidents belong to the type of *Runaway / thrownaway* and *Missing benign explanation*. The former one occurs when a child leaves home, or is asked to leave home, and stays away overnight; the latter occurs when the child's caretaker is aware of the child being missing, but none of the other four episodes applies [4]. Because these two types happened much more frequently than others, in this study, we focus on missing incidents of these two types. To the best of our knowledge, this is the first systematic effort to design and develop an automated framework to assist the decision making in the search for missing child.

The main contributions of this paper are: 1) a programmable segmentation approach designed to generate equal-sized search units for prioritization; 2) an algorithm designed to construct a maximum probability search plan, that is proved to be optimal for a given cumulative time investment; 3) a web-based application developed to render the proposed framework on an interactive GIS map; 4) qualitative validation under several scenarios to demonstrate the correctness of this framework.

The rest of this paper is organized as follows. Section II

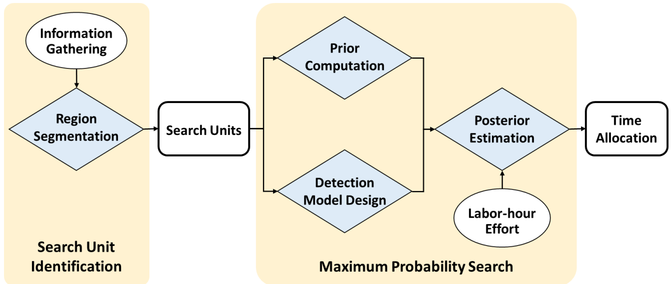


Fig. 1: Architecture of the framework for optimal search plan construction

gives an overview of the proposed framework, as well as the definition of notations and symbols adopted in this paper. Section III introduces the search unit identification. Section IV elaborates the four steps to construct a maximum probability search plan. Section V presents the implementation of a web-based application. Section VI shows the framework validation, and also discusses the corresponding results. In Section VII, we conclude the current study, and briefly talk about our future work.

II. Framework Overview

Fig. 1 shows the architecture of the proposed framework for optimal search plan construction. It consists of two major computational phases, namely *search unit identification* and *maximum probability search*. In the first phase, necessary information relevant to the missing person is first collected in person; it is then input into the framework, to produce equal-sized search units for prioritization simplicity in the second stage. In the second computational phase, a prior probability of the target distribution is first calculated over all the search units. Then, a detection model is designed to compute the probability of detection, following optimal search theory [5]. Then, Bayes' theorem is used to update the posterior probability of the target distribution, as the search progresses. The final output of this phase is a time allocation over all the search units, with respect to a given cumulative time investment.

This framework aims to assist the decision making and resources allocation in the search for a missing child, with an objective of maximizing the overall probability of detection, given a cumulative time constraint.

A. Notations and Symbols

Before elaborating the two computational phases, we first give the definition of notations and symbols used in the rest of this paper.

- $L_0 = (lng_0, lat_0), lng_0, lat_0 \in \Re$: last known location represented by its longitude and latitude.
- $L = \{L_1, L_2, ..., L_n\}, n \in \Re^+$: n possible destinations that the missing child is familiar with, or is likely to be at, and n is a positive integer.
- $g(L_i) \in [1, 10], i \in [1, n]$: an integer score corresponding to each $L_i \in L$, that indicates how likely the missing child may go to L_i.
- $R = \{R_1, R_2, ..., R_n\}$: n rectangular regions corresponding to each $L_i \in L$.
- $N = (a, b), a, b \in \Re^+$: a programmable tuple indicating the granularity of search region segmentation, such that a and b is the number of divisions along the North-South and East-West direction, respectively.
- $t \in [0, \infty)$: relative time (labor-hour) spent on searching.
- $U = \{U_1, U_2, ..., U_m\}, m \geq 2$: m search units defined by the longitude and latitude of two diagonal points, and m depends on the given granularity, such that $m \leq a \times b$.
- $a(D)$: geometric area of a region D.
- $p(D)$: probability of the missing child is in a region D.
- $W \in \Re^+$: a programmable parameter representing average sweep width in the search.
- $V \in \Re^+$: a programmable parameter representing average screening speed.
- $b(U_i, t) \in [0, 1), U_i \in U, t \geq 0$: a detection function that returns the conditional probability of detection with an amount of time t spent in U_i, given that the missing person is in U_i. Section IV-B details the design and properties of this function.
- $\varphi(U_i), U_i \in U$: a search plan that gives the expected amount of time assigned to U_i.

III. Search Unit Identification

In spite of the large uncertainty in the circumstances surrounding the missing person, for the two types of missing incidents we are tackling in this study, the missing person's movement has some degree of voluntariness. Therefore, in addition to the last known location L_0, it is also important to obtain detailed information about the possible destinations where the missing person is likely to be at.

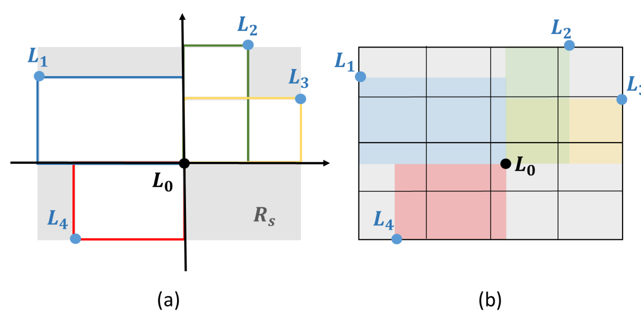


Fig. 2: An example of search region filling and segmentation

The information provided by people familiar with the missing child could be inaccurate, conflict, or even be misleading, especially with the emotional nature of missing child case. However, we do not question the trustworthiness of obtained information at this stage, to control the overall uncertainty in the framework design.

Fig. 2 gives an example of search unit identification, where the last known location L_0 is marked with black dot, and four possible destinations are marked with blue dots. The granularity of search region segmentation is set to (4×4) in this example.

The first step of search unit identification is to draw a rectangular region $R_i \in R$ for each $L_i \in L$, by identifying the diagonal points as L_i and L_0, as shown in Fig. 2 (a). The motivation is to make R_i cover possible paths from L_0 to L_i, among which is the trajectory of the missing child, if L_i is the actual destination after leaving from L_0.

The second step is to recognize a search region R_s that contains all $R_i \in R$, using the maximal and minimal longitude and latitude of all $L_i \in L$ and L_0. Then, with a programmable tuple $N = (a, b)$, R_s is divided into $a \times b$ equal-sized search units along the North-South and the East-West directions.

The reason to design a programmable granularity of region segmentation is to provide flexibility in actual search action. Although the produced search units have equal size originally, in practice, the search effort can be deployed over unequal regions by merging or dividing the original search units. Section VI-C discusses this feature in detail.

If an acquired unit has no overlap with any $R_i \in R$, it is discarded. As a result, a unit having overlap with one or more rectangular regions is identified as a *search unit*. The output of this phase is geographical information of m search units, in terms of their longitude and latitude of two diagonal points.

IV. Maximum Probability Search

A *maximum probability search* always assigns available search effort to one or more search units with highest posterior probability [5]. To construct a search plan that can lead to a maximum probability search with cumulative time effort, we first compute the prior probability of the distribution, and define a detection model to compute the conditional probability of detection on each search unit. These two components, along with the feedback as the search progresses, are used to update the posterior probability of the distribution.

A. Prior Probability Computation

As mentioned in Section II-A, n possible destinations $L = \{L_1, L_2, ..., L_n\}$ is obtained in the information gathering phase, together with an integer score $g(L_i) \in [1, 10]$ for each L_i that indicates how likely the missing child may go there. The prior probability $p(R_i)$ that the missing child is in R_i depends on the likelihood of L_i being the actual destination, as shown in the equation below.

$$p(R_i) = \frac{g(L_i)}{\sum_{j=1}^{n} g(L_j)}, R_i \in R.$$

Due to the random nature of missing incidents discussed in this study, and for simplicity, the missing child's location inside one search unit $U_i \in U$ is assumed to be uniformly distributed. Therefore, the prior probability $p(U_i)$ is computed as follows:

$$p(U_i) = \sum_{j=1}^{n} p(R_j) \times \frac{a(U_i \cap R_j)}{a(R_j)}, \tag{1}$$

where $a(U_i \cap R_j)$ is the geometric area of the overlap between U_i and R_j, and $p(R_j)$ works as a weight parameter between $[0, 1]$ corresponding to a destination L_j.

In short, the prior probability of the missing child distribution across the search units is computed by a weighted average over all the possible destinations.

B. Detection Model Design

Because missing child search is a highly time-sensitive task, the amount of time spent on searching is chosen as the argument in our detection model. Therefore, a function $b(U_i, t)$ is defined as the conditional probability of detection in an amount of time t spent on U_i, given that the missing child is in U_i.

Due to lack of detailed information about human resources available or involved in the search action, variable t in this framework refers to the amount of labor- or man-hours, instead of absolute clock-time. As a result, the case that multiple people search in different units simultaneously will not affect the estimation of time allocation using our detection model.

As mentioned earlier, we assume the missing child location is uniformly distributed inside one search unit. Let D represent a small region inside U_i, which is screened during a small amount of time Δt, so that $a(D) = WV\Delta t$; W and V are defined as the average sweep width and screening speed in Section II-A. Therefore, given that the missing child is in U_i,

$$p(D) = p(U_i) \times \frac{WV\Delta t}{a(U_i)}.$$

We further assume the search effort is applied independently and randomly inside one search unit; this means that the probability of detection in an amount of time t, and the probability of detection in an additional Δt, are independent. Thus, the conditional probability of detection in U_i in a total amount of time $(t + \Delta t)$ is

$$b(U_i, t + \Delta t) = b(U_i, t) + [1 - b(U_i, t)]\frac{WV\Delta t}{a(U_i)}.$$

Thus,

$$\begin{aligned} b'(U_i, t) &= \lim_{\Delta t \to 0} \frac{b(U_i, t + \Delta t) - b(U_i, t)}{\Delta t} \\ &= [1 - b(U_i, t)]\frac{WV}{a(U_i)}, \end{aligned}$$

with initial condition

$$b(U_i, 0) = 0, \forall\ U_i \in U.$$

Therefore, the detection function b on a search unit U_i is then given by:

$$b(U_i, t) = 1 - \exp[-\frac{WV}{a(U_i)}t], \text{ for } t \geq 0. \tag{2}$$

Since search for a missing child is usually carried out by human beings, W is limited by the range of observation in specific environment. For example, if one is searching in a residential area by car, the vision is blocked by the buildings on both sides of the road, and hence, the sweep width is roughly equal to the width of the road.

In real-world scenario, W and V also depends on actual searching approach (i.e., on foot or by car). Moreover, it can vary from one search unit to another, even when the search action is conducted in a similar manner by the two units. For simplicity, we assume that V and W do not change over different search units in a given case.

As described in Section III, since search units are equal-sized, the factor $\frac{WV}{a(U_i)}$ in (2) is same for all $U_i \in U$. Defining $\alpha = \frac{WV}{a(U_i)}$, the detection function becomes

$$b(U_i, t) = 1 - e^{-\alpha t}, t \geq 0. \tag{3}$$

In summary, (3) shows that with the increase of applied time effort in a search unit, the probability of detection approaches one. It can be proved that for $U_i \in U$:

1) $b'(U_i, \cdot)$ is continuous, positive and strictly decreasing.
2) $b(U_i, 0) = 0$.
3) b is a homogeneous exponential detection function for any search unit.

C. Posterior Estimation

As the search action progresses, if the missing person is not found in an amount of time T, the posterior probability of the missing child's location can be estimated using Bayesian method. To illustrate this process, we first define an event F_T of failing to detect the missing person in an amount of time T, which is the cumulative time effort across all the search units. Therefore, the posterior probability that the missing person is in U_i, given the previous failure is:

$$\begin{aligned} p(U_i \mid F_T) &= \frac{p(U_i) \times [1 - b(U_i, t_i)]}{p(F_T)} \\ &= \frac{p(U_i) e^{-\alpha t_i}}{1 - \sum_{j=1}^{m} b(U_j, t_j)} \end{aligned} \tag{4}$$

where $T = \sum_{i=1}^{m} t_i$ for a total number of m search units.

Let φ^* be a maximum probability search plan, which always assigns the next time effort to one or more search units having the highest posterior probability. The result of φ^* is that, for any two search units U_i and U_j, as long as $\varphi^*(U_i) > 0$ and $\varphi^*(U_j) > 0$, it must be the case that $p(U_i \mid F_T) = p(U_j \mid F_T)$; otherwise, only the search unit with higher posterior probability should be assigned additional time effort [5].

Because the denominator in (4) is same for all the search units, the above observation can be expressed as follows:

$$\begin{aligned} & p(U_i) e^{-\alpha \varphi^*(U_i)} = p(U_j) e^{-\alpha \varphi^*(U_j)} \\ & \qquad \text{if } \varphi^*(U_i) > 0 \text{ and } \varphi^*(U_j) > 0; \\ & p(U_i) e^{-\alpha \varphi^*(U_i)} \leq p(U_j) e^{-\alpha \varphi^*(U_j)} \\ & \qquad \text{if } \varphi^*(U_i) > 0 \text{ and } \varphi^*(U_j) = 0. \end{aligned} \tag{5}$$

D. Search Plan Construction

Given a finite positive time constraint as an initial search effort, a maximum probability search plan is automatically constructed in the form of time allocation over all the search units. Algorithm 1 shows the pseudo-code of this process that satisfies equation (5).

Algorithm 1 Maximum probability search plan construction

```
Input: T ∈ [0,∞), α ∈ ℜ and U = {U_1, U_2, ..., U_m}
A[1 : m] ← 0, a non-negative vector of length m
t_sum ← 0, cumulative time spent in total
n ← 1, number of search units been assigned positive time effort
Let p(U_1) ≥ p(U_2) ≥ ... ≥ p(U_m)
while t_sum < T do
  if n < m then
    t ← (1/α) ln[p(U_n)/p(U_{n+1})]
    if t_sum > T − t · n then
      t ← (T − t_sum)/n
    end if
    A[1 : n] ← A[1 : n] + t
    t_sum ← t_sum + n · t
    n ← n + 1
  else
    t ← (T − t_sum)/m
    A[1 : m] ← A[1 : m] + t
    break
  end if
end while
Output: Time allocation A
```

As discussed in Section IV-B, the detection function b in this framework is homogeneous and exponential. According to Theorem IV.1 from optimal search theory [5], the output of algorithm 1 is an uniformly optimal search plan in a cumulative time effort T, given the search units and the prior probability distribution. The proof can be found in [5].

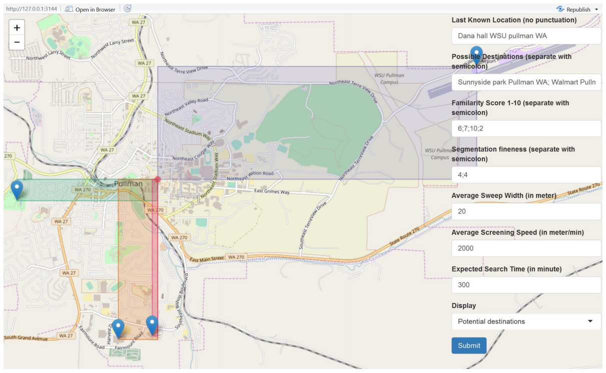
Theorem IV.1. *Suppose that U has at least two search units, and b is the detection function such that $b(U_i, 0) = 0$ and $b'(U_i, \cdot)$ is continuous and decreasing for $U_i \in U$. Let time effort be a non-negative value for all $U_i \in U$, and let T be the summation of cumulative time effort over all search units. Each maximum probability search plan for each target distribution over U is uniformly optimal within T, if and only if b is homogeneous exponential detection function.*

In conclusion, given a finite positive time constraint, the proposed framework automatically computes an optimal search plan over the identified search units, that can maximize the overall probability of the missing child detection.

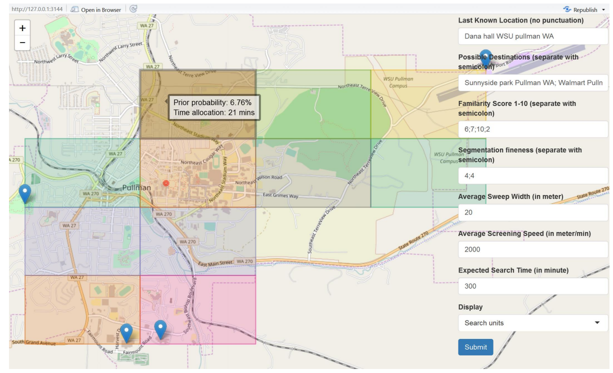
V. Framework Implementation

For the purpose of visualization and qualitative validation, we implement a web-based application using R package Shiny [6], Leaflet [7] and Gmapsdistance [8], to render the proposed framework on an interactive map. Fig. 3 shows two screenshots of the application in a test case for optimal search plan construction.

Two types of input is required for search plan construction.



(a) Identified last known location and possible destinations



(b) Segmented search units and resulting time allocation

Fig. 3: An example of optimal search plan application

1) Information gathered from people familiar with the missing child, including the last known location, a list of possible destinations and their likely scores, separated by semicolon. Each location needs to be described in plain English, to facilitate locating it through Google Map API.
2) Parameters in computational models, including desired segmentation granularity (default is 4×4), average sweep width (default is 10 meters), average screening speed (default is 1800 m/min), and total time constraint in unit of minute.

With above information, the application first identifies input locations, and highlights the corresponding rectangular regions, as shown in left image of Fig. 3. Then, the equal-sized search units are segmented and displayed on the map. An maximum probability search plan is generated in the background. As a result, both prior probability and time allocation for each search unit is shown by moving the cursor to that unit; this is shown in right image of Fig. 3.

VI. Validation and Discussion

With no access to real data of missing child case, it is hard to validate the accuracy of the proposed framework quantitatively in an unbiased manner. Therefore, we provide qualitative validation in several scenarios to test the correctness of the constructed search plan. A test case with three possible destinations is used as the basic test case, as shown in Fig. 4

A. Unbalanced Likely Scores

In this scenario, one or more possible destinations are much more likely to be the actual destination than others. If there is little overlap among the rectangular regions determined by these possible destinations, the prior distribution of the missing child should be unbalanced over the segmented search units. Moreover, the resulting time allocation over the search units should also have remarkable difference.

To validate this hypothesis, we test five trials with different likely scores in the basic case. In Fig. 4, the three possible destinations are located in different directions to the last known location, so that their corresponding rectangular regions have as little overlap as possible.

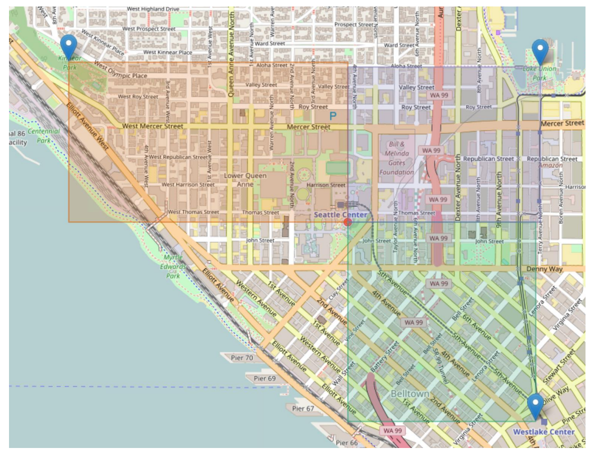


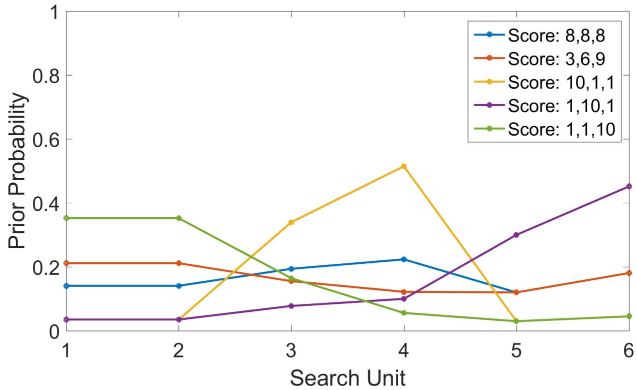
Fig. 4: A test case with the last known location of Space Needle (marked with red circle) and three possible destinations (marked with blue balloon) in Seattle, WA

Fig. 5 shows the results computed on six search units in five trials. It can be observed that: 1) the amount of time allocation on individual search unit is in accordance with its estimated prior probability; 2) in the first two trials with non-extreme scores, the results over six search units have no remarkable difference. However, for the trials with one possible destination having an extremely high score, the two search units closer to that destination have much higher prior probability and more time allocated than the other search units.

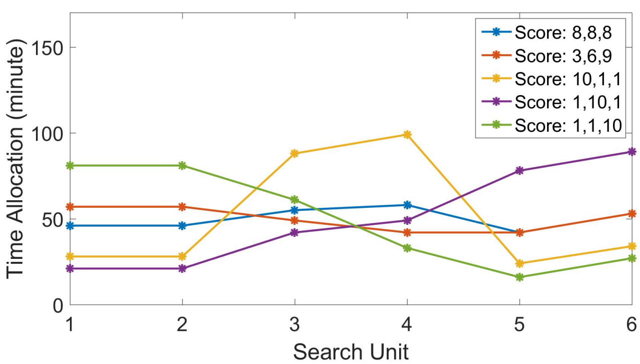
This test shows that, the optimal search plan constructed in our framework correlates well with the obtained likelihood of possible destinations.

B. Changes in Time Constraint

With the changes in total time constraint, the output time allocation should also change consequently. However, since the missing child location is independent of the search action, the estimated prior probability for each search unit should remain the same. Therefore, the overall priority for time



(a) Prior probability of the missing child location



(b) Time allocation on each of the six search units

Fig. 5: Estimation results in five trials with distinct destination scores

allocation should be consistent, in spite of time constraint variation.

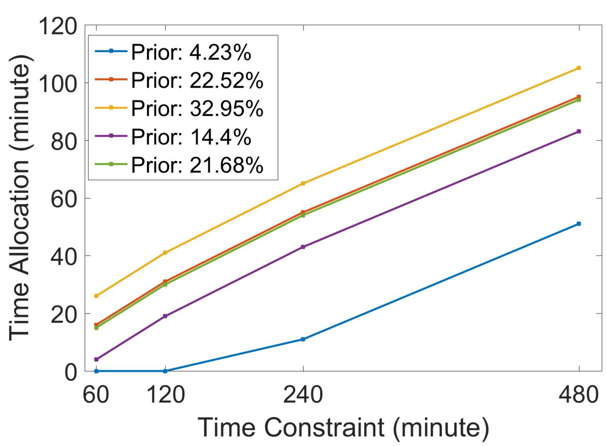


Fig. 6: Time allocation in four trials with different time constraints

To validate this hypothesis, we use the same basic test case, but change the value of time constraint in each trial. Fig. 6 shows the results of time allocation for different cumulative time constraint. Because two search units in this test case have the same results due to their identical prior probability, Fig. 6

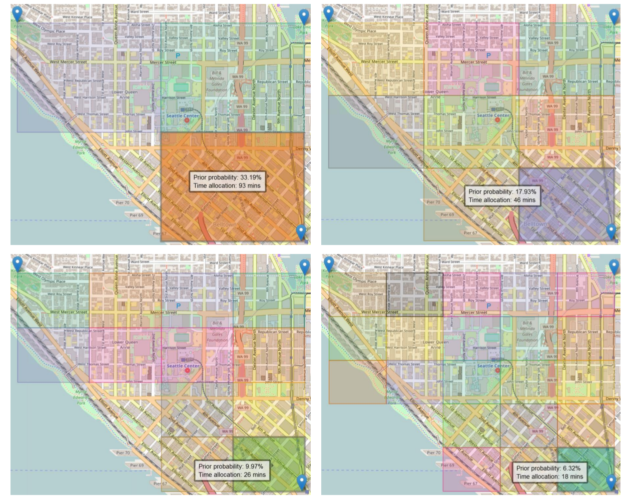


Fig. 7: Identified search units in four trials with different granularities of region segmentation

only contains five distinguishable lines, for five search units with different prior probabilities respectively.

The results indicate the consistency in the distribution of search effort for the same missing child case, regardless of the resource constraint defined by specific search action.

C. Changes in Granularity of Region Segmentation

The programmable granularity for search region segmentation offers flexibility in a search action. A rough segmentation results in fewer search units with wider coverage, whereas a fine segmentation leads to many small-sized search units. These search units can be merged by simply adding up their individual prior probabilities and the amount of time allocation. In this sense, although the default search units have equal size, search effort can be deployed on several unequal regions through the merging or division of search units.

Along with the changes in the granularity, the prior probability and time allocation on each search unit should also change, according to the coverage of an individual search unit. However, regardless of whether the coverage is wide or narrow, the prior probability over all the search units should stay in line with the given likely scores of possible destinations.

The same basic test case is used to validate the above hypothesis, while the granularity of region segmentation changes

TABLE II: Prior probability and time allocation over changes in granularity

Setting	N_{unit}	T_{u_1}	T_{u_2}	T_{u_3}	P_{max}	P_{min}
2×2	3	24	123	93	57.83%	8.87%
3×3	8	13	60	46	31.78%	4.42%
4×4	12	8	33	26	17.58%	1.95%
5×5	21	6	22	18	11.96%	0.28%

in varied for each of the four trials. The resulting search units after removing the segment with zero prior probability are shown in Fig. 7. The tested settings are listed in the first column in Table II, together with part of the results generated from our framework, including the time allocation (in minute) on the three search units (u_1, u_2, u_3) that are closest to the three possible destinations respectively, the maximum (P_{max}) and the minimum (P_{min}) prior probability over all the search units identified in each trial.

Table II shows that, for each individual search unit, both the prior probability and the amount of time allocation changes, in accordance with the number of search units that depends on user-specified granularity. However, although the exact value of time allocation on one search unit varies from one trial to another, the weight of the distribution is always consistent with the likelihood of possible destinations, so that it remains the same across all the four trials.

D. *Changes in Sweep Width and Screening Speed*

As mentioned in Section IV-B, the detection model tends to one with the increase in the amount of time input. One interpretation is that, longer the time been spent on searching inside one unit, more likely it is to have overlap among the areas being screened [5].

In a search action, the sweep width and screening speed determines the general efficiency of detection on individual search unit. With higher sweep width and screening speed, the unexplored area in one search unit is reduced faster; thus the probability of detection reaches a high level in a shorter time. When a scanned search unit tends to have very small increase of probability of detection, the time resource should be allocated to other unexplored search units, for their higher rate of return in the first effort. As a result, a higher sweep width and screening speed leads to a quicker turn, from a search unit under investigation to an unexplored one. Consequently, there is less difference in the cumulative time spent on individual search unit.

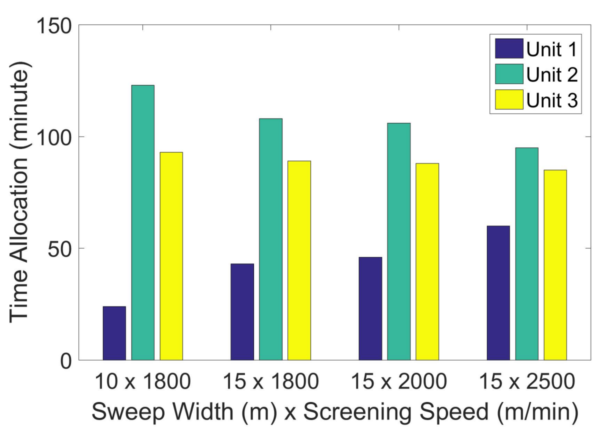


Fig. 8: Time allocation in four trials with the increase of sweep width and screening speed

To validate this hypothesis, we change the sweep width and screening speed in four trials, using the same basic test case. The results of time allocation over the three search units are shown in Fig. 8. It clearly indicates a reduced difference in the amount of time allocated to individual search unit, due to an increase in the sweep width and screening speed.

VII. Conclusions and Future Work

In this paper, we introduce an automated framework for optimal search plan construction, to assist the decision making and resources allocation in the search for a missing child. Our framework leverages statistical analysis with optimal search theory, to prioritize search directions by estimating a prior probability of the missing child's location, and then updating the posterior probability based on the result of the search action.

Given a constraint of cumulative labor-hour investment, the constructed search plan is an optimal time allocation over the identified search units. We validate the correctness of our proposed framework qualitatively under several scenarios. The results demonstrate the consistency of obtained information and produced search plan.

One major limitation of this pilot study is the underlying assumption that the target is stationary during the search action. We are currently working on modifying our framework to handle the moving target scenario. Moreover, this study aims to construct an optimal search plan for missing incidents of type *Runaway / thrownaway* and *Missing benign explanation*. Although the missing incident of abduction does not occur as frequently as the above two, it has much higher risk for the child's wellness, and hence, it is worth researching effective search strategies for abduction cases. In contrast to the above two types of missing incidents, the missing child's movement in an incident of abduction depends on the unknown suspect, and it is often purposive and not random. Therefore, it is hard to estimate the probability distribution based on a general statistical model. We will deal with this challenge in our future work.

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