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Developing An Agent Model of a Missing Person in the Wilderness

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***Abstract*—In this paper, we consider the problem of developing a model of the behaviour of a Missing Person (MP) who is lost in the wilderness. Traditional models have treated the movement of an MP as a type of diffusion process, without regard for the MP's internal state or goals. However, this fails to include many important factors, including the effects of fatigue or the use of reorienting strategies, which are known to be important from empirical studies of actual lost person behaviour.**

To overcome these limitations, we develop a novel agent-based model of MP behaviour. This model incorporates the effects of the environment, perception and goals on the MP's movement and uses them to model the continuous switching of short and medium term goals by missing people.

To validate the model, we compared the trajectories simulated by it with actual recordings of movements of participants in an unfamiliar wilderness environment. By comparing the predicted and actual trajectories, we show that the generated trajectories much more faithfully represent the actual movements of the participants than state-of-the-art diffusion models.

***Index Terms*—Agent modelling, empirical experimentation, missing person, wilderness search and rescue.**

I. Introduction

A fundamental step in Wilderness Search and Rescue (WiSAR) is search. Until a Missing Person (MP) has been found, they cannot be rescued or recovered. Search often involves observing large tracts of the environment to detect potential evidence of where the MP has gone. The increasing availability of low-cost high performance UAVs has begun to transform this search process. However, most UAVs are still manually operated. This can be both resource intensive and inefficient [1], [12]. Therefore, there is great interest in using autonomous UAVs which are able to plan and execute search missions entirely on their own. There are many advantages to autonomous operations, ranging from greater adaptability and flexibility to potentially more efficient and more coordinated search processes. In this paper, we are particularly concerned with how the search process can be optimised.

Search algorithms can be posed as Bayesian decision problems [5], [8]. As the UAV explores its environment and monitors it with vehicle-mounted sensors, the distribution of the MP's location is updated through the use of Bayes Rule. The decision of where to look next is determined through knowledge of the new posterior distribution. Because the problem is characterised by a large state space and sparse observations, most current literature uses occupancy grid-based representations in which the environment is decomposed into a set of cells [6], [17], [19]. The prior over this distribution is created using a diffusion model, in which the prior over the location of the MP is given by considering the transition probabilities between neighbouring cells. Although this makes it possible to model a number of environmental effects such as local slope and ground classification, it cannot incorporate a number of state-dependent effects including fatigue [16], speed variability [29] and perception [27]. It also excludes behavioural effects. For example MPs tend to walk in a straight line unless faced with obstacle [25], tend to reduce total angle turned [7] and perform re-orientation strategies [17] which only make sense when the environment is considered globally. One example is *view enhancing* [15], in which a person will walk up to a high place, such as the top of a hill, to improve their knowledge of the surroundings.

In [20], we explored the utility of modelling some of these behaviours. Using a very rudimentary model such as fatigue, we demonstrated that, in simulation, search times could be reduced by up to 40%. In this paper, we extend our earlier work by developing a comprehensive agent model which explicitly describes the behaviours of lost people. In particular, the agent does not follow a single goal. Rather, it has a set of goals. Each goal models a basic behaviour, such as route following or view enhancing. However, agents can change their goals based on a number of conditions such as encountering unexpected obstacles. These goals are also controlled by an agent's memory process which can be faulty, causing an agent to move in a direction unlikely to satisfy a goal.

The structure of this paper is as follows. The problem statement is described in Section II. Agent-based models are reviewed in Section III. The high-level processes of perception and memory — which drive the agent model — are presented in Section IV. Section V describes the probabilistic implementation of this model. Our empirically-based evaluation study is described in Section VI. We show that the prior predicted by our model is much more accurate other methods. Conclusions are drawn in Section VII.

II. Problem Statement

A. Description of the Search Mission

A WiSAR operation begins when an individual – known as a Missing Person (MP) — is reported missing by relatives or friends [13]. The first stage in the response is to construct a Missing Person Profile (MPP) P. P contains information such

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as information about the MP's physical state (e.g., physical well-being, experience), together with the time and point where the MP was last seen, the direction the MP was traveling and information about where the MP was intending to go. In addition, information about the environment (including elevation, vegetation and topography) is collected. From this, the search region $\mathscr{A}$ is constructed within which the search activities will take place [13]. The distributions are non-Gaussian and a grid-based decomposition of $\mathscr{A}$ [5], [19] is used. Specifically, $\mathscr{A}$ is decomposed into a set of $M = |\mathscr{A}|$ identically-sized cells, where a is the a^{th} cell. Suppose $\mathbf{x}$ is the cell which contains the MP. $p(\mathbf{x}_k = a)$ is the probability that the MP lies in cell a at time k. Bayes rule can be used to update this over time. To begin this process, the prior $p(\mathbf{x}_{k_0} = a)$ must be chosen. However, this is strongly dependent upon the environment itself.

B. Environment Model

The environment plays a fundamental role in the behaviour of the MP and the modelling of the search problem. The environment is characterised in three ways:

1) **Elevation Model,** Γ. The elevation model describes the *perceived slope* of the environment [26]. The slope is classified according to $dom(\Gamma) = \{|Sl| < Sl_{\min}, Sl_{\min} < |Sl| < Sl_{\text{med}}, Sl > +Sl_{\text{med}}, Sl < -Sl_{\text{med}}, |Sl| < Sl_{\max}\}$ where Sl is the local slope, $Sl_{\min}$, Sl_{med} and $Sl_{\max}$ are minimum, medium and maximum Sl thresholds.
2) **Topography Classification Model,** Ψ. This model classifies the search area according to its topography, $dom(\Psi) = \{Obstacle, Water, Ground, Path\}$ [23], [24].
3) **Vegetation Classification Model** Φ, This classifies the density of vegetation using the categories $dom(\Phi) = \{Sparse, Medium, Dense\}$ [19].

C. Diffusion-Based Prior Generation

A common way to compute the prior is to use a diffusion-based model [19]. An occupancy grid is initialised with the distribution $p^*(\mathbf{x}_0 = a)$ which is derived from the MPP. The diffusion model is run S times, where the k^{th} iteration is

$$p^*(\mathbf{x}_k = a|\Gamma,\Phi,\Psi) = \gamma_k \times \sum_{m\in\mathscr{A}} p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Gamma,\Phi,\Psi)\, p^*(\mathbf{x}_{k-1} = m|\Gamma,\Phi,\Psi),$$

where γ_k is the normalisation constant and $p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Gamma,\Phi,\Psi)$ is the probability that an MP transitions into cell a from cell m in a single timestep. After S iterations have been completed, the prior for the search process is given by $p(\mathbf{x}_{k_0} = a) = p^*(\mathbf{x}_S = a)$ where k_0 is the time the search operation starts..

The transition probability is affected by the physical constraints of the environment such the gradient of the terrain, vegetation density and the topography of the ground [19] *locally*. The impacts of the different characteristics of the environment are assumed to be independent of one another,

$$\begin{aligned} p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Gamma,\Phi,\Psi) = {} & p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Gamma) \\ & \times p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Phi) \\ & \times p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Psi). \end{aligned} \quad (1)$$

For example, with respect to vegetation density, the probability of MP transitioning into cell a from cell m is given by

$$p(\mathbf{x}_k = a|\mathbf{x}_{k-1} = m,\Phi) = \begin{bmatrix} \Phi_{(1,1)} & \Phi_{1,2)} & \Phi_{(1,3)} \\ \Phi_{(2,1)} & \Phi_{(2,2)} & \Phi_{(2,3)} \\ \Phi_{(3,1)} & \Phi_{(3,2)} & \Phi_{(3,3)} \end{bmatrix}, \quad (2)$$

where $1,2,3$ in the subscript correspond to the classes of vegetation sparse, medium and dense respectively and in $\Phi_{(i,j)}$, i and j correspond to feature types in cells m and a respectively.

D. Limitations of Diffusion-Based Prior Generation

The diffusion approach fails to model the fact that an MPP is an intelligent entity whose internal state evolves over time. For example, an MP's movement is a function of their level of fatigue, which in turn is a function of the terrain they have traversed. Their way-finding capability is highly dependent on what they can see and what they can remember about the environment [3], [32], [33]. Furthermore, they are active agents, able to engage in re-orientation strategies trying to re-orient themselves [15], [17]. Given these limitations, we propose to develop new models which capture these important behaviours.

III. Agent-Based Models

Agent-model uses an internal state which can be used to describe complex behavior and human / environmental interactions within a spatial framework [4], [9]. Most agent models have been developed to study the behaviour of people in urban environments. This includes the movement of individuals in buildings [30] and galleries [31], together with the motions of crowds in normal [2], [3] or emergency [14] situations. Some agent models have been developed which describe the motion of people in the wilderness. For example, Gloor et al. developed a hiker-based agent model which included the agent's perception of the environment and used social force models to perform obstacle avoidance [10]. The work was subsequently extended to use differential equations and restricted agent movements to paths [11]. With this model, Gloor et al. were able to generate an activity plan for each agent that includes visiting particular sites according to which route are generated using a cost function, which are then used by agents to get to their destination.

Although these models can account for various factors including occlusion and lack of prior knowledge about the environment, none of them can account for an agent being lost. In particular, they assume that the agent knows where it is, and knows where its intended destination lies. However, when people become lost, they can be unsure of where they are and where to go. The only agent model we are aware of that attempts to capture this behaviour is Goodrich's diffusion model [19] which, as explained above, fails to account many

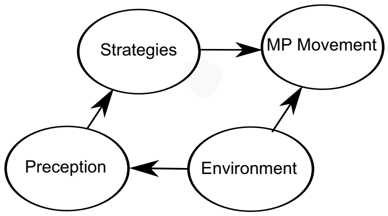
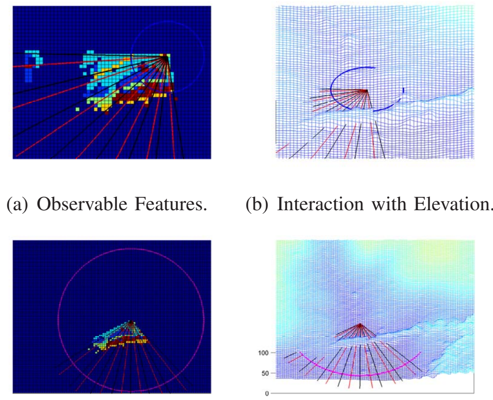


Fig. 1: The agent model framework.



(a) Observable Features. (b) Interaction with Elevation.

(c) Observable Features. (d) Interaction with Elevation.

Fig. 2: The agent view cone. Plots (a) and (b) show the narrow close condition ($\{N_{FOV}, C_V\}$) and plots (c) and (d) show ($\{N_{FOV}, F_V\}$) narrow far condition. The occluding effects of obstacles such as elevation are illustrated in plots (b) and (d).

important properties of MP behaviour. As a result, we develop a new agent model which captures these lost behaviours.

IV. Agent Models of Perception and Strategies

Because the agents do not know where they are in the environment and do not have a fixed goal, we let the agents have a number of different goals that the agent can switch between. These different goals reflect various kinds of re-orientation strategies. To accommodate this goal-switching behaviour element, we extended Lin's model [19] using a modified version of the framework proposed in [28]. Our framework is illustrated in Fig. 1. The agent's overall behaviour is controlled by a set of *Strategies*, which affect the agents *Movement*. These strategies include moving towards a defined feature or point, exploring the environment to acquire further information, moving randomly or simply stopping. These are driven by user's *Perception* (vision, memory) of the *Environment*.

A. Perception

Perception is the processes by which the agent monitors the environment and interprets its meaning. Limitations in perception are the root cause of why people become lost in the first place. There are two key elements: *vision* and *memory*.

1) Vision: The goals used by an agent are strongly determined by what they can see [3], [32]. We model this dependency as the ability to detect objects and features which lie within a View Cone (VC) centered on the agent's current location and oriented in its current direction. The VC is illustrated in Fig. 2. Because the terrain is not flat, features can be occluded. Therefore, a visibility graph is used to perform occlusion calculations on the features which lie within the view cone [21]. The (unoccluded) view cone is parameterised by two variables:

1) **Field of View (FOV).** This is the angle over which features can be perceived and has two possible values: *narrow* (N_{FOV}) and *wide* (W_{FOV}). N_{FOV} is used when an agent moves forwards in a purposeful manner. W_{FOV} is used when the agent looks around. For example, an agent will search for an alternative directions of travel when at a junction or when the path forwards is blocked.
2) **Vision Critical Length (VCL).** This models the maximum distance at which a feature can be seen. An agent has two modes of operation: *close* (C_V) and *far* (F_V). Close vision is used when an agent checks locally for obstacles. In this mode, features are seen only if the distance to the agent is less than S_{VCL}. Far vision is used when the agent is looking around to, for example, reorient or select a new point to head towards. With this mode, some features (such as path and water features) can be seen at the medium distance M_{VCL}. Other features — such as houses — can be seen from the greater distance L_{VCL}.

2) Memory: Each agent possess a rudimentary memory system. This memory system stores the agent's understanding of the environment. It is used to formulate strategies and execute agent motion, particularly when performing various re-orientation strategies [16]. We support both short-term and long-term memory.

1) **Short-term memory**, M_S. This has two types. The first consists of recent history of the cells visited by the agent, $M_{S1} = \{a_{i+n}, a_{i+n-1}, \cdots, a_i\}$. This is used to help the agent retrace its steps (back tracking) or, conversely, avoid unintentional doubling back. The second, consists of the recent history of the heading of the agent $M_{S2} = \{\lambda_{k-n}, \lambda_{k-n+1}, \cdots, \lambda_{k-1}\}$. These are used to smooth the heading.
2) **Long-term memory,** M_L. This stores the recalled location of significant landmark features such as a house that an agent has recently noticed. However, the memory must account for the fact that the agent will become more and more uncertain of each landmark's location over time and can eventually be forgotten if not re-observed.

M_{S1} and M_{S2} are implemented using circular buffers. M_L consists of a weighted set of m landmark features,

$$M_L = \{\mathbf{f}_i, \omega^i(v_t^i, \xi) : i = 1, 2, \cdots, n\}, \quad (3)$$

where $\mathbf{f}_i$ is the i^{th} feature. It is the tuple $\mathbf{f}_i = [q_f, \mathbf{k}^\top, \lambda_f, \rho_f, t_f]$, where q_f is the id, $\mathbf{k}^\top$ is the agent position and bearing the

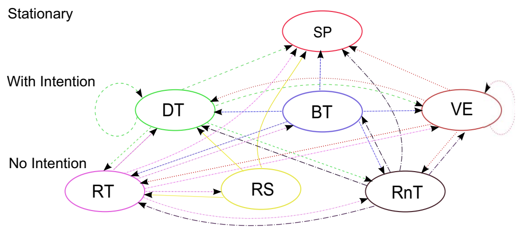


Fig. 3: Agent strategy transition diagram.

feature was observed from, λ_f is the bearing to the feature, t_f is time since last observed and ρ_f is the feature type. The weight of a feature is used to represent its importance when selecting a goal target for the agent. Its value is updated by $\omega^i = v_t^i\,\xi(\rho^i)$, where v_t^i is used to weight observed features more than un-observed features, and ξ is the importance of a feature type.

At each timestep, all the visible features are detected. If a new feature is observed, it is created and inserted into M_L. For existing features, both t_f and λ_f are updated. This causes the value of ω to change. When a feature is not observed, two effects are modelled. First, the agent gradually loses knowledge of where the feature is. This is achieved by adding a small random value to λ_f^i. The second is that the agent can forget the feature if $|t_{max} - t_f^i| = 0$ (modelled by removing the feature from the memory) where t_{max} is the maximum number time-steps not observing a feature in memory can be tolerated.

B. Agent Strategies

Missing people rarely move in a completely random fashion. Rather, they are typically driven by a strategy which they believe will guide them to a known place or to safety [15]. For example, Koester notes that lost hikers typically follow the path of least resistance and, when near linear features such as paths and roads, may continue walking along them believing they would get them to safety [17].

Koester identifies eight different strategies that lost people can execute [17], seven of which are relevant for our problem domain. These can be organised into three groups:

1) **Stationary:** The agent has no goal and does not move. This consists of just the *Stay Put* (SP) strategy.
2) **Clear intention to move to a particular point:** The agent has identified a particular point in the environment and is heading to it. This includes *Back Tracking* (BT), *View Enhancing* (VE) and *Direction Travelling* (DT).
3) **No clear intention to move to a particular point:** The agent does not have a specific point to go to. Strategies include *Random Travelling* (RnT), *Route Travelling* (RT) and *Route Sampling* (RS).

C. Choosing a Strategy

The agent will switch strategies over time depending upon the agent's internal state and perception of the environment. The transition diagram between the different strategies is shown in Fig. 3. When an agent moves towards a definite direction, they will keep going until either (a) they satisfy the current objective or (b) are blocked in some way. If they reach their destination they can then either select another goal and use a one of the corresponding strategies with definite goal to get to it or continue traversing the environment using strategies with no definite goal. If they are blocked, they *Back Track*, assess the environment using $(\{W_{FOV}, F_V\})$ and continue either with a new selected end goal or without. For the strategies in which there is no definite end goal, the agent will reassess changing between the strategy with both positive and negative observation of paths and junctions. When a goal is selected, the agent changes back to strategies with definite end goal. At any time during this process, the *Stay Put* strategy can used by the agent to make it stationary. This could be due to fatigue, injury or simply not wanting to move.

V. Probabilistic Agent Model

A. Model Structure

Let $\mathbf{t}_k$ be the state of the agent at time k with the structure

$$\mathbf{t}_k = \left\{ \mathbf{k}^\top \; G \; M_{S1} \; M_{S2} \; M_L \; e \; d \right\}_k, \tag{4}$$

where $\mathbf{k}_k^\top$ are the kinematic states (position, heading), G_k is the current strategy, $M_{S1,k}$, $M_{S2,k}$ and $M_{L,k}$ are the short and long term memories, e_k is the energy level and d_k is the total distance travelled. Creating a prior is equivalent to computing the distribution

$$p(\mathbf{x}_{k_0} = a) = p\left(\mathbf{t}_{k_0} \in a | P, \Gamma, \Phi, \Psi\right). \tag{5}$$

This requires the computation of $p\left(\mathbf{t}_{k_0} | P, \Gamma, \Phi, \Psi\right)$. Using the Markov assumption,

$$p\left(\mathbf{t}_{k_0} | P, \Gamma, \Phi, \Psi\right) = p\left(\mathbf{t}_{k_\alpha} | P\right) \prod_{k=\alpha+1}^{k_\beta} p\left(\mathbf{t}_k | \mathbf{t}_{k-1}, P, \Gamma, \Phi, \Psi\right), \tag{6}$$

where k_α is the time MP was last seen and k_β is the time the MP is assumed to have become stationary. Because of the complexity of the our agent model, closed form solutions do not exist. Therefore, we use the particle filter approximation

$$p\left(\mathbf{t}_k | P, \Gamma, \Phi, \Psi\right) \approx \sum_{i=1}^{N} w_k^{(i)} \delta\left(\mathbf{t}_k - \mathbf{t}_k^{(i)}\right), \tag{7}$$

where $w_k^{(i)}$ is the weight on the i^{th} particle and $\delta(\cdot)$ is a suitably defined delta function. Given this approximation, we must define the proposal distribution which specifies how each agent particle evolves over time,

$$\mathbf{t}_k^{(i)} \sim q\left(\mathbf{t}_k | \mathbf{t}_{k-1}^{(i)}, P, \Gamma, \Phi, \Psi\right). \tag{8}$$

To specify the proposal distribution, we make a further decomposition. Suppose θ_k is the direction that the agent could take in the next time step. This can take on one of a finite number of values $\theta_i^{[m]}$. Assuming that the proposal distribution is given by marginalising out this heading angle,

$$q\left(\mathbf{t}_k | \mathbf{t}_{k-1}^{(i)}, P, \Gamma, \Phi, \Psi\right) = \sum_{m=1}^{M} q\left(\mathbf{t}_k | \mathbf{t}_{k-1}^{(i)}, \theta, P, \Gamma, \Phi, \Psi\right) p\left(\theta = \theta_i^{[m]}\right). \tag{9}$$

To compute $q\left(\mathbf{t}_k|\mathbf{t}_{k-1}^{(i)},\theta,P,\Gamma,\Phi,\Psi\right)$, we use a sample—accept approach. The next position of the agent, $\tilde{\mathbf{t}}_k$, is predicted using a dead reckoning model. The event that this move is accepted is A_k. The probability of its acceptance is governed by the move being both consistent with both the agent's strategy and the constraints placed by the environment. Specifically,

$$\begin{aligned}q\left(\mathbf{t}_k|\mathbf{t}_{k-1}^{(i)},\theta,P,\Gamma,\Phi,\Psi\right) &= p\left(\tilde{\mathbf{t}}_k,A_k|\mathbf{t}_{k-1}^{(i)},\theta,P,\Gamma,\Phi,\Psi\right)\\ &= p\left(\tilde{\mathbf{t}}_k|\mathbf{t}_{k-1}^{(i)},P,\Gamma,\Phi,\Psi\right)\\ &\quad\times p\left(A_k|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},\theta,P,\Gamma,\Phi,\Psi\right).\end{aligned} \tag{10}$$

The first term describes the probability that a predicted state would be sampled. The second term is the probability that this prediction would be accepted.

B. Kinematic Prediction Equation

MPs tend to walk in a straight line with constant motion [17]. Because most person-based decisions for navigation are carried out in a person-centric frame, the motion model uses piecewise constant speed and heading. Therefore, the following model is used

$$\begin{aligned}u_k &= G\left(\frac{\sum\lambda_{k-n:k-1}}{n},\sigma_\lambda^2\right)\\ x_k &= x_{k-1}+\Delta t s_k(s_{max},\Gamma,\Phi,\Psi)\cos[u_k+\theta]\\ y_k &= y_{k-1}+\Delta t s_k(s_{max},\Gamma,\Phi,\Psi)\sin[u_k+\theta]\\ \lambda_k &= u_k+\theta\\ d_k &= d_{k-1}+\Delta t s_k(s_{max},\Gamma,\Phi,\Psi)\\ e_k &= e_{k-1}-\Delta e_k(s_{max},\Gamma,\Phi,\Psi),\end{aligned} \tag{11}$$

where u_k is the control input calculated using agent bearing history in M_{S2}, s_k is the speed of the MP, Δt is the time increment for one step, σ_λ is noise perturbing the bearing of the agent, Δe is the energy spent and θ is the visual ray bearing. Each agent starts with a maximum energy level $e_{max}(P)$, which is decremented as the agent traverses the environment, and when $e < 25\%$, the agent stops and pauses for awhile. This results in increase in its energy level $e_k = e_k + e(\Delta t)$ allowing it to start moving again.

C. Acceptance Probability

We can view A_k as the outcome of a voting process where the the current strategy and the three types of classification of the environment determine if the proposed move is valid. We model these by $A_k = A^{G_k}\cap A_k^{\Gamma}\cap A_k^{\Phi}\cap A_k^{\Psi}$ respectively. Using the chain rule and assuming independence, the acceptance probability can be decomposed into

$$\begin{aligned}p\left(A_k|\tilde{\mathbf{t}}_k,P,\Gamma,\Phi,\Psi\right) &= p\left(A^{G_k}|\tilde{\mathbf{t}}_k,P\right)p\left(A_k^{\Gamma}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Gamma\right)\\ &\quad\times p\left(A_k^{\Phi}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Phi\right)p\left(A_k^{\Psi}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Psi\right).\end{aligned} \tag{12}$$

1) Compatibility with the Current Agent Strategy: When a move is proposed, the term $p\left(A_k^{G_k}|\tilde{\mathbf{t}}_k,P\right)$ determines the probability that $\tilde{\mathbf{t}}_k$ is compatible with agent's current strategy. We model this as $p\left(A_k^{G_k}|\tilde{\mathbf{t}}_k,P\right) = \mathscr{G}\left(\lambda_k-\lambda^{\mu};0,\sigma_\lambda^2\right)$.

When the agent is moves towards a definite goal, λ^{μ} is set to the bearing of the landmark feature the agent wants to get to. For the strategies in which there is no definite goal, $\lambda^{\mu} = \lambda_{k-1}$ ensuring smooth running of the trajectory.

2) Traversability with Respect to the Elevation: The term $p\left(A_k^{\Gamma}|\tilde{\mathbf{t}}_k,P,\Gamma\right)$ models how the slope affects the agent's movements. For example, people follow paths of least resistance and tend to veer away from low traversable areas such as a steep slope [17]. We consider the effects of slope with respect to both the agent's *local movement* and *orientation*. Because the agent movement steps can be smaller than the quantised representation of the search area, we model *local movement* and *orientation* as follows. Considering $\mathbf{t}_{k-1}^{(i)}\in m$ the cell the agent particle is in, we use the elevation value of cells that intersect the visual ray along which $\tilde{\mathbf{t}}_k$ the proposed agent next position exists at two distinct locations. First, a neighbouring cell $\tilde{\mathbf{t}}_k^n\in N(m)$, where $N(.)$ is the set of cells immediately adjacent to m. Second, a cell at the end of the agent's VC. We name this $\tilde{\mathbf{t}}_k^e\in b$. We use slope with respect to the elevation in the prior to model agent's *local movement*, and the same with respect to the later to model agent's *orientation* (going uphill, downhill).

$$\begin{aligned}p\left(A_k^{\Gamma}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Gamma\right) &= p\left(A_k^{\Gamma}|\tilde{\mathbf{t}}_k^n\in a,\mathbf{t}_{k-1}^{(i)}\in m,\Gamma\right)\\ &\quad\times p\left(A_k^{\Gamma}|\tilde{\mathbf{t}}_k^e\in b,\mathbf{t}_{k-1}^{(i)}\in m,\Gamma\right).\end{aligned} \tag{13}$$

With elevation in cells a and b given, each term in (13) is computed similar to (2).

3) Traversability with Respect to Vegetation Density: This is modelled in a similar fashion to topography. There is a natural preference for people to walk on sparse vegetation types [17], [19]. This term, only considers *local movement* effects, giving us $p\left(A_k^{\Phi}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Phi\right) = p\left(A_k^{\Phi}|\tilde{\mathbf{t}}_k^n\in a,\mathbf{t}_{k-1}^{(i)}\in m,\Phi\right)$.

4) Traversibility with Respect to Topography: The final term accounts for the fact that the ground classification determines the ground traversability. For example, MPs cannot traverse some environmental features such as deep water. Furthermore, they tend to stay on paths. As with the elevation, we consider effects of ground classification on both the agent's *local movement* and *orientation*. While all categories of topography affect the agent's *local movement*, only obstacles and paths impact its *orientation*. This because a lost person normally tends to keep a lookout for features that can either attract or prevent them from continuing along a particular direction, which could have significant influence on the agent's movement.

While the *local movement* is computed in a similar fashion to previous terms, the *orientation* is modelled using two sub models: The *repulsive force* of obstacles like places with water

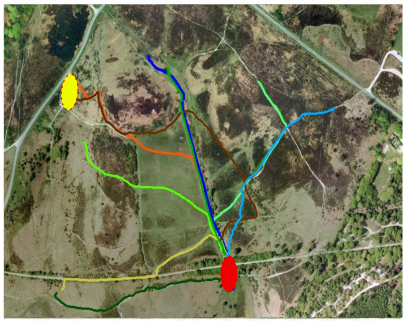


Fig. 4: The search area overlaid with logged GPS trails. Participants started at the red circle and had the goal of reaching the yellow circle.

and the *attractive force* of features like paths with only one force being active at any time. The repulsive force is modelled using a decay function with respect to the distance between agent's current position and the obstacle perturbed with some additive noise. The attractive force is modelled using the topography transition table. The difference between this and previous models is that in this model, $\tilde{\mathbf{t}}_k^e$ is intersected by cell b where b is a cell with first instance of a path, obstacle or water within VC from agent's vantage point.

$$p\left(A_k^{\Psi}|\tilde{\mathbf{t}}_k,\mathbf{t}_{k-1}^{(i)},P,\Psi\right) = p\left(A_k^{\Psi}|\tilde{\mathbf{t}}_k^n \in a,\mathbf{t}_{k-1}^{(i)} \in m,\Gamma\right) \times p\left(A_k^{\Psi}|\tilde{\mathbf{t}}_k^e \in b,\mathbf{t}_{k-1}^{(i)} \in m\right) p\left(A_k^{\Psi}|\tilde{\mathbf{t}}_k^e \in b,\mathbf{t}_{k-1}^{(i)} \in m,\Gamma\right), \quad (14)$$

where the terms in (14) models local movement, repulsive force and attractive force respectively. If cell b contained an *obstacle* or *water*, term two is calculated and term three is set to 1. In all other cases vice-versa is performed.

VI. Evaluation

In this section, we evaluate the ability of our model to reproduce the trajectories of people who are lost in an unfamiliar wilderness environment.

A. Data Collected

We collected GPS logs of participants moving through a part of the New Forest, UK. Fig. 4 shows the search area and a participant walking through the environment with a high-accuracy GPS logging system.

All participants began at a common starting location (which was treated as the Point Last Seen) and traversed the terrain to locate a car park. The environment required the participants to move up hill. Their view of the environment was blocked by both vegetation and the uphill slope. There were a number of trails, both over open grassy areas and in pathways that run between dense foliage. Data was collected from 10 participants. Two GPS units (one stationary at the start location, the other carried with participants) were used. The static GPS logged data was used to perform differential correction, improving the GPS position accuracy to approximately 1.5m.

B. MP Models

We compared Goodrich's state-of-the-art diffusion model [19] with our proposed agent model. To model the uncertainty of MP decision making and its change of behaviour and preference from time k to time $k+n$, the prior distributions over the transition tables Γ, Φ and Ψ were sampled and normalised at every n^{th} time step.

The agent based prior was generated using 1000 agent samples each initialised with a sampled speed $s_{max} \sim \mathscr{G}(1.2\text{m}\,\text{s}^{-1}, 0.2\text{m}\,\text{s}^{-1})$ [3] and direction $\lambda_{k=1} \sim \mathscr{G}(\lambda_{k_\alpha}, 30^\circ)$ where λ_{k_α} is the initial reported bearing of the MP. The $\sigma = 30^\circ$ is simply used to model for uncertainty in the reported direction of travel for the MP. The agent vision parameters were set with $N_{FOV} = 100^\circ$ and $W_{FOV} = 170^\circ$, $S_{VCL} = 50m$, $M_{VCL} = 200m$ and $L_{VCL} = 300m$. N_{FOV} and W_{FOV} VCs were modelled using 9 and 11 bins respectively, with bins on the side being 5 degrees wider the bins in front. The slope thresholds were set to $Sl_{min} = 10^\circ$,$Sl_{mid} = 20^\circ$ and $Sl_{max} = 50^\circ$. The terms $\sigma_\lambda = 40^\circ$ and $n = 4$ in (11) were selected heuristically to enable the model produce smooth trajectories.

Considering an average walking speed of $1.5\text{m}\,\text{s}^{-1}$ [22] and assuming that on average two steps are taken per second, the agent model was run for 1560 time steps with each time representing a step taken by the agent. For the diffusion model, the length of each timestep was $t = 3.3$s. This is the average amount of time required for a person to move from the centre of one cell to the centre of an adjacent cell of $5m$ resolution.

C. Evaluation Metrics

To evaluate the similarity of priors generated using both agent and diffusion models over the trajectory of MP with the distribution of trajectories taken by experiment participants given as GPS measurements, we use the Earth Mover's Distance (EMD) [18], a dissimilarity distance measure between two multi-dimensional distributions. The reason for using this metric unlike, say, the Kullback-Leibler Divergence, is that it is both symmetric and can be applied even when the support of the two distributions are not the same. To show the convergence of the two models, we run both models for a set time (13 minutes), assessing the EMD distance measure for each of the generated distributions with respect to the GPS measurement distribution. The distribution with lower EMD measure represents higher similarity than distribution with higher EMD measure. Therefore assessing the difference between the EMD measures of the two models, we run the model with the higher EMD over a longer period of time and compute its EMD at regular intervals to check for improved similarity.

D. Results

Fig. 4 shows the first 13 minutes of the GPS logs of each experiment. Qualitatively, these logs support the behaviour predicted in [17]: when missing people encounter linear features they will follow them until their goal is achieved or they are forced to abandon that feature. The traces also show that when an agent spots a destination globally, they will

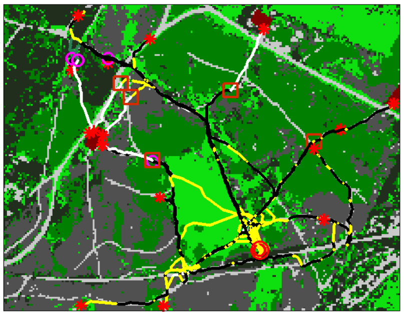


Fig. 5: Several simulated runs of the agents. The colours of the background image denote pixelwise classification. The strategies used in each trajectory are colour coded. RT, RnT, DT and SP are represented by black, yellow, white and red stars respectively. The red circle and square represents PLS and the location from which a candidate target was observed.

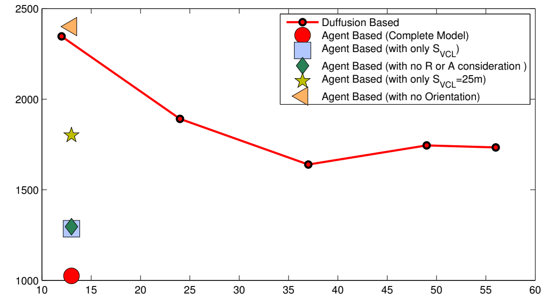


Fig. 7: EMD measure for both agent and diffusion based priors. The EMD measure is given with respect to time (in minutes) the person is considered lost. The agent model is correct to ”real time”, whereas the diffusion model is allowed to evolve to see if it converges.

plan accordingly. For example, when the car park (the target location) indicated by yellow circle is observed, the brown, red and green trajectories suddenly veer towards it changing their orientation strategy to direction travelling.

A number of simulated agent trajectories are shown in Fig.5. These illustrate the effect of goal switching. Goal switching occurs as a result of the agent observing different features in the environment. For example, when an agent sees a car park, it might decided to switch to the Direction Travelling goal (shown in white) and will tend to head directly towards it considering it to be the target destination. This is similar to the behaviour seen from the actual logs.

Fig. 6 shows the prior generated both using agent model and the diffusion model with the later for different time durations. Considering the average speed of participants, and running both models for simulation time equivalent to the duration of experiment (13 minutes), the prior generated using agent model was able to fatefully reflect the distribution of GPS logs in contrast to diffusion model generated prior. This conclusion was supported by the EMD measures of both priors with respect to the distribution of observed trajectories. The diffusion model performance was only improved by running the simulation for simulation time equivalent to 58 minutes illustrated in Fig. 6, and confirmed by improved EMD measures, as shown in Fig. 7. The results suggest that the agent model tends to take more directed, focused routes which accurately model the directed behaviour of missing people. The diffusion model, however, is less focused and its uncertainty gradually fills the map. This suggests that the diffusion models both take longer to develop, and are likely to generate less efficient priors in search algorithms. Furthermore, the diffusion algorithms can only take account of local features. They cannot model distant features, nor can they model the impact of an agent switching its goals and consider orientations.

To test the impact of observing far topographical features (both *Repulsive* (R) and *Attractive* (A)), we run the agent model with this behaviour switched off. This resulted in higher EMD measure shown in Fig. 7.

We also examined the effect of the spatial dependency of features. We performed two tests: first, where the agent vision length is only set to S_{VCL} and second, where the length of S_{VCL} is reduced $25m$. We can see from the EMD measures that this has a significant effects on the generated priors. As the VCL is reduced, the EMD increases, showing that the computed trajectory becomes less and less accurate. The final experiment we undertook was to switch the orientation strategies off, and make the agent model perform like diffusion model, by considering only the neighbourhood cells. This resulted in a high EMD measures similar to diffusion model for the same duration of time.

These results show that there is a greater advantage in using an agent based models over state-of-art diffusion models.

VII. Conclusions

In this paper, we have presented a novel model of missing person behaviour. The crucial novelty of our model is that we explicitly model lost behaviour: rather progressing with a fixed goal to a fixed destination, the agent can switch between goals.

We have describe the implementation of the model and demonstrated that, in a sample scenario, it yields greater improvements. These improvements mean that the prior generated using our model is a more accurate description of where the missing person is located. Given this, we expect that these will reduce the time required to find the MP.

There are several avenues for further research. The first is to develop more systematic ways to calibrate the models to identify the parameters in the model. The second is to study, in more detail, the goal switching and memory strategies.

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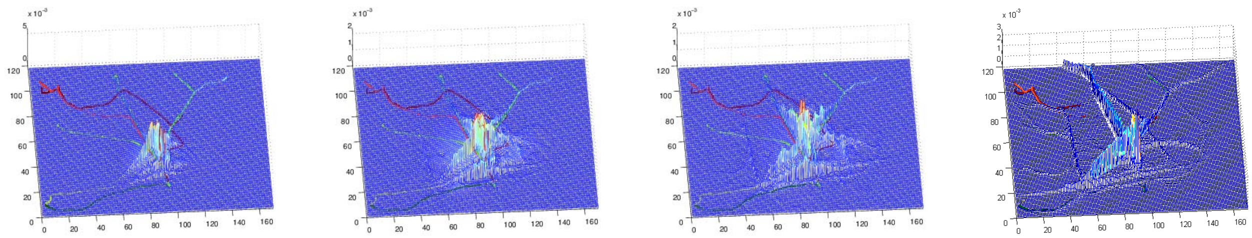

(a) Diffusion model at 13 mins. (b) Diffusion based at 37 mins (c) Diffusion model 58 mins (d) Agent model 13 minutes

Fig. 6: The computed prior distributions for the different simulation times of the diffusion model and the agent model. The higher peaks represents higher probability of MP being in that area. The measured trajectories are also drawn, each with a unique colours.

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