Behavior Tree-Based Person Search for Symbiotic Autonomous Mobile Robot Tasks

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Abstract— We consider the problem of people search by a mobile social robot in case of a situation that cannot be solved by the robot alone. Examples are physically opening a closed door or operating an elevator. Based on the Behavior Tree framework, we create a modular action sequence with the goal of finding a person to assist the robot. An online trainable and extendable model based on locally defined Poisson processes is presented, stochastically predicting the presence probability of people. By decomposing the Behavior Tree as a Discrete Time Markov Chain, we obtain an estimate of the probability and rate of success of the options for action, especially where the robot should wait or search for people. In a real-world experiment, we compared the presented method with other common approaches in a total of 588 test runs over the course of one week, starting at two different locations in a university building. We show our method to be superior to other approaches in terms of success rate and duration until finding person and returning to the start location.

Fig. 1: Different areas in a public building have a varying expected rate of people occurrence λ. The underlying model is used to find or wait for helpers in spatially situated tasks.

I. INTRODUCTION

Social service robots are entering an increasing number of areas of everyday life. Thanks to powerful interaction interfaces, often based on natural language, they are already being used commercially, for example to provide information [1], guiding or automated delivery [2]. Contrary to their strength in interacting with people, they usually do not have manipulators for reasons of cost and complexity. This prevents them from making full use of the environment and, for example, open doors or operate lifts. An approach to compensate for these weaknesses is *symbiotic autonomy*, which considers the recognition of an individually unsolvable situation and the active involvement of people in problem solving [3]. Depending on the problem, there are often no people available on site to help, so that helpers must be actively searched for. In this paper we present a Behavior Tree based approach to find people in an open space based on a model of person occurrence rate (see Fig. 1). The method thus balances between a proactive search and waiting on site to avoid unnecessary travel and waiting times.

Behavior Trees (BTs) are a procedural control approach that has become increasingly popular in the robotics community in recent years. Compared to other approaches, such as hierarchical finite state machines, they have clear advantages in terms of modularity, reusability or expandability [4]– [6]. In addition, they can be analyzed stochastically, which enables a prediction of the probability of success or failure of a particular tree while maintaining the interpretability of the tree's graphical representation [4]. In our method

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the BTs are synthesized based on an online trainable and extendable model, which indicates the occurrence of people using locally defined Poisson processes. We use the exponentially distributed inter-arrival times of these models as input for a decomposition of the BTs as Discrete Time Markov Chains (DTMCs) for the stochastic analysis. This work explicitly focuses on the search for people and excludes social aspects such as the appropriate approach to a person and verbal questions for help. However, the resulting trees can be integrated into a tree that models these aspects without further modification.

II. RELATED WORK

Overcoming the limitations of a robotic system by actively involving humans has been considered in various contexts. Malfunctions can be mitigated by forewarning the users [7] or purposefully utilizing human collaboration in autonomous plans [8]. When a situation occurs where the robot needs help, this must first be identified, for example by detecting a closed door [9] or an elevator [10].

Independent of the search for help, different approaches to *finding people* were introduced. Volkhardt *et al.* [11] present a greedy search strategy based on a person occurrence map in a home environment. For a similar application, in [12] a prioritizing predictive search strategy is established using a hidden Markov model. In [13] the probability of human presence is modeled as a function of time by a Periodic Gaussian Mixture model with an a priori known periodicity and person search is performed on a static topological map. Compared to searches in the aforementioned applications, the search for symbiotic autonomous tasks has the additional requirement that people should not only be found, but then

accompany the robot to the location demanding assistance. Since people are only willing to travel a limited distance to help [14], this imposes an additional constraint on the search locations. Most work in this context assumes that help is always available at the immediate help location, e.g. by supervisors [15] or bystanders [16], and there is only little work on proactively searching and finding people to fulfill a task that cannot be achieved alone by the robot. Rosenthal *et al.* [17] showed that navigating the environment to search for humans could decrease the time until a potential helper is found. They employ an A* based planner to decide where to seek help in an office building based on the location of offices and availability of the person. However, it is only evaluated with static locations, using occupancy sensors installed in the offices and the time saving of their algorithm is shown in simulation only.

Approaches to *model the occurrence of people* generally use a spatial and temporal partitioning to assign a probability density to each region. This is for example done by using a Poisson process [18], which is commonly used to stochastically model the number and time of occurrences of random events in a time interval. Ihler *et al.* [19] present a nonparametric Bayesian model of intensity functions representing events over time by learning the rate of a Poisson process for a spatially fixed scenario. The authors of [20] extend this approach by spatial and temporal variation of the rate parameter as a piecewise homogeneous Poisson process and then use this model to actively search for people. Although related to our approach, the evaluation is conducted with a focus on a specific office in simulation and not learned by actual people detections of a mobile robot.

In summary, the application of dynamically created person models to symbiotic autonomy and a generally applicable action description to find people for this kind of tasks are open problems. The contributions of this paper are therefore

1) a task descriptive model of a symbiotic autonomous person search, based on the Behavior Tree framework,

2) a dynamically generated and online extensible model of person occurrence probability, complying with the requirements of a Stochastic Behavior Tree,

3) real-world experiments showing the effectiveness of the approach, i.e. in reducing waiting times for spatially problematic helping tasks.

The remainder of this paper is structured as follows: The next section III gives a short overview over BTs and our robot. We then introduce the person occurrence model (Sec. IV) and how the stochastic actions are derived from it (Sec. V). Sec. VI shows the effectiveness of the approach compared to other methods in experiments and Sec. VII gives a conclusion.

III. PRELIMINARIES

A. Behavior Trees

A Behavior Tree (BT) is a directed rooted tree, consisting of internal nodes for control flow and leaf nodes for action execution or condition evaluation [6]. Pairs of adjacent nodes are denoted as *parent* (outgoing) and *child*

(incoming). The node without parents is called the root node, which periodically sends an enabling signal (*tick*) through the tree that is propagated according to the policies of different control flow nodes. When a node receives a tick, it returns one of three status: *running* (*R*, execution ongoing), *success* (*S*, goal achieved) or *failure* (*F*). There are four types of control flow nodes (selector, sequence, parallel, decorator) and two types of leaf nodes (action, condition). Their graphical representation is depicted in Fig. 2.

Selector node: Routes the tick from left to right, until a child returns either *S* or *R* as status, which is then again returned to the parent of the selector node. Only if all children return *F*, the node returns *F*.

Sequence node: Routes the tick from left to right, until a child returns *F* as status, which is then again returned to the parent of the sequence node. Only if all children return *S*, the node returns *S*.

Action node: Returns *S* if the action is completed, *R* if the action is ongoing and *F* if the action cannot be completed.

Condition node: Returns *S* if a specific condition is satisfied and *F* if not.

Decorator nodes and *parallel nodes* are not used in this paper and therefore omitted for the sake of brevity.
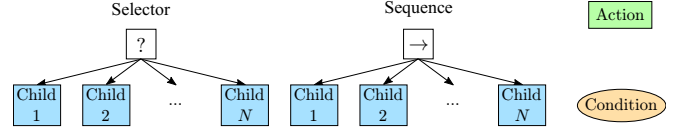

Fig. 2: Graphical representation of the node types.

In the primary model of BTs the execution order of selector and sequence node children is inherently fixed. Therefore, the execution order of actions and conditions must be decided beforehand by the designer, which often is non-trivial. To overcome this problem, Stochastic Behavior Trees (SBTs) were introduced by Colledanchise *et al.* [4]. In an SBT each action $\mathcal{A}$ is extended by a tuple $\mathcal{A}_{\text{St}} : (p_{\text{s}}(t), p_{\text{f}}(t), \mu, \nu)$ and condition $\mathcal{C}$ by a tuple $\mathcal{C}_{\text{St}} : (p_{\text{s}}(t), p_{\text{f}}(t))$, where $p_{\text{s}}(t)$ $(p_{\text{f}}(t))$ is the probability to succeed (fail) at any given time. The time to succeed (fail) is a random variable with exponential distribution and rate μ (ν). By describing the inner flow of an SBT as a Discrete Time Markov Chain (DTMC), an indication of the success probability $p_{\text{s,T}}(t)$ of the whole tree can be made by summing up the probabilities of being in one of the DTMC success states $\mathcal{S}_{\text{S}}$:

$$p_{\text{s,T}}(t) = \sum_{i:s_i \in \mathcal{S}_{\text{S}}} \pi_i(t). \tag{1}$$

The probability vector $\pi(t)$ is obtained by solving the Cauchy problem

$$\dot{\pi}(t) = Q(t)\pi(t), \quad \pi(0) = \pi_0, \tag{2}$$

with Q as the infinitesimal generator matrix of the DTMC. The success rate μ_{T} of the tree is calculated as

$$\mu_{\text{T}} = \text{avg}\left(\frac{\sum_{i=1}^{|\mathcal{S}_{\text{S}}|} u_{i1}^{\text{S}}(k) \log\left(h_{i1}^{\text{S}}(k)\right)}{\sum_{i=1}^{|\mathcal{S}_{\text{S}}|} u_{i1}^{\text{S}}(k)} \right)^{-1} \tag{3}$$

with $\mathrm{avg}(.)$ as the average function over time and k as a time step. The matrices $H^{\mathrm{S}}(k, \boldsymbol{\mathcal{A}}_{\mathrm{St}}, \boldsymbol{\mathcal{C}}_{\mathrm{St}})$ and $U^{\mathrm{S}}(k, \boldsymbol{\mathcal{A}}_{\mathrm{St}}, \boldsymbol{\mathcal{C}}_{\mathrm{St}})$ are depending on the transit times, number of steps between transient states and success states and the success and failure probabilities and rates of all actions $\boldsymbol{\mathcal{A}}_{\mathrm{St}}$ and conditions $\boldsymbol{\mathcal{C}}_{\mathrm{St}}$.

The failure probability of the tree $p_{\mathrm{f,T}}(t)$ follows likewise based on the failure states $\mathcal{S}_{\mathrm{F}}$. For more in-depth explanations we refer to [4] and [6].

B. Mobile Robot and People Perception Pipeline

The mobile robot Sobi, which is used for evaluation, is designed as an information providing and guiding service system for a university campus. For localization and perception purposes it is equipped with two RGBD cameras (Intel D435), one 3D Lidar (Velodyne VLP-16) and one 2D Lidar (SICK S300). Like most social robots, Sobi does not have manipulators and is therefore incapable of autonomous door opening or elevator operation. The system was developed with a focus on social interaction, especially via speech, and is therefore well suited to compensate for its inability for manipulation. Fig. 3 shows the ROS-based robot with its core elements.

People perception and tracking is conducted through the 3D Lidar and RGBD cameras. We use an individually trained version of [21] for 3D pointcloud segmentation, extended by the approach proposed in [22] for 2D clustering to decrease the false negative rate. In addition, YOLO v2 [23] is used for detection in the RGB images, which is then registered via a median filter based on the distance either with the 3D Lidar data or the depth data of the cameras. The aggregation and tracking is performed with the SPENCER framework [24], which outputs people tracks $\mathcal{X}$ in Cartesian space with uncertainty information. Fig. 4 shows an overview of the perception and tracking pipeline.
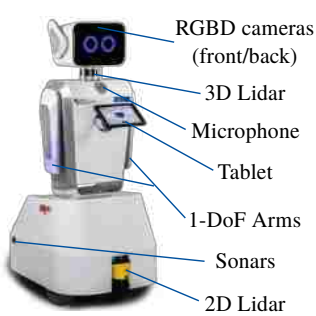

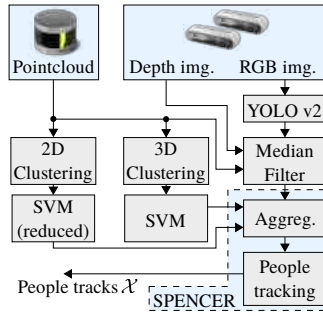Fig. 3: The mobile social robot Sobi.

Fig. 4: Person perception and tracking pipeline based on the SPENCER framework [24].

IV. PROBABILISTIC PERSON OCCURRENCE MODEL

The common approach for probabilistic temporal and spatial description of the occurrence of events, e.g. the appearance of people within an area, is the Poisson process. In general, a Poisson process is a renewal process with Poisson-distributed random variable $(N(t), t \geq 0)$. The probability of

$N(t)$ being equal to a count k is given by

$$P\left(N(t) = k\right) = \frac{(\lambda t)^k}{k!} e^{-\lambda t} \quad k = 0, 1, 2, ..., \tag{4}$$

where λ is the rate parameter of the process. When $\lambda(t)$ is variable, the process is called *inhomogeneous*. An inhomogeneous *spatial* Poisson process introduces an additional spatial dependency $\boldsymbol{x} \in \mathbb{R}^d$ in an Euclidean space $\mathbb{R}^d$ for the rate $\lambda(\boldsymbol{x}, t)$. As proposed in [25], for $\boldsymbol{x} \in \mathbb{R}^2$ the inhomogeneous spatial Poisson process can be approximated by a 2D grid representation

$$G: \quad \lambda(\boldsymbol{x}, t) \simeq \sum_{i=1}^{m} \sum_{j=1}^{n} \lambda_{ij\tau} \mathbf{1}_{ij\tau}(\boldsymbol{x}, t) \tag{5}$$

with $G: \mathbb{R}^2 \rightarrow \mathbb{R}$ and $\mathbf{1}_{ij\tau}(\boldsymbol{x}, t)$ as the indicator function. $\lambda_{ij\tau}$ is the constant rate of a piecewise homogeneous Poisson process

$$P_{ij\tau}\left(N(t) = k\right) = \frac{(\lambda_{ij\tau}(t - t_\tau))^k}{k!} e^{-\lambda_{ij\tau}(t - t_\tau)} \tag{6}$$

which is valid for a time interval $[t_\tau, t_{\tau+1}]$. Learning the probabilistic representation of person occurrences can then be achieved by learning the constant rates $\lambda_{ij\tau}$. For a confidence-sensitive estimation of the rate parameter, we use *Bayesian inference*, with $\lambda_{ij\tau}$ as the *prior* distributed according to the Gamma distribution

$$\lambda_{ij\tau} \sim \Gamma\left(\lambda_{ij\tau}; \alpha_{ij\tau}, \beta_{ij\tau}\right), \tag{7}$$

which is the conjugate prior for a Poisson distributed *likelihood*. Given a set of person tracks $\mathcal{X}_{1...n}$ the posterior distribution is calculated as

$$P_{ij\tau}(\lambda_{ij\tau} \mid \mathcal{X}_{1...n}) = \Gamma(\lambda_{ij\tau}; \alpha_{ij\tau} + \sum_{i=1}^{n} x_i, \beta_{ij\tau} + n). \tag{8}$$

The shape parameter $\alpha_{ij\tau}$ and inverse scale parameter $\beta_{ij\tau}$ are determined incrementally for a discrete time step σ for all $t_\sigma < t$ via the update rules

$$\alpha_\sigma = \alpha_{\sigma-1} + x_\sigma \mathbf{1}_\mathcal{D}(\boldsymbol{x}_\mathrm{R}, t_\sigma), \quad \beta_\sigma = \beta_{\sigma-1} + \mathbf{1}_\mathcal{D}(\boldsymbol{x}_\mathrm{R}, t_\sigma) \tag{9}$$

with initial values $\alpha_0 = \beta_0 = 1$. Here, the indicator function $\mathbf{1}_\mathcal{D}(\boldsymbol{x}_\mathrm{R}, t_\sigma)$ results from the detection area $\mathcal{D}$ of the robot at pose $\boldsymbol{x}_\mathrm{R}$. Since the employed 3D Lidar provides a full 360-degree environmental view, we approximate $\mathcal{D}$ by a circle with radius r. Therefore, only the grid cells which lie within the detection range of the robot will be updated.

Based on the Gamma-shaped prior, the posterior expected value and variance of the rate result to:

$$\hat{\lambda}_{ij\tau} = \mathrm{E}\left[\lambda_{ij\tau}\right] = \frac{\alpha_{ij\tau}}{\beta_{ij\tau}}, \quad \mathrm{Var}\left[\lambda_{ij\tau}\right] = \frac{\alpha_{ij\tau}}{\beta_{ij\tau}^2}. \tag{10}$$

By providing an estimation of person encounter probability at a specified location, the person occurrence model therefore forms the basis for the decision whether the robot should wait at the place where help is needed or actively search for help.

V. BEHAVIOR TREE BASED PERSON SEARCH

The goal of the BT description is to set up a sequence of actions that maximizes the probability of meeting a person, or in other words, to determine if and where the robot should search for or wait for people. Therefore, to create the tree, the atomic actions $\mathcal{W}_{A,i}$: *Wait at place $\mathcal{P}_i$* and $\mathcal{S}_{A,i \to j}$: *Search from place $\mathcal{P}_i$ to place $\mathcal{P}_j$* are defined, where a *place $\mathcal{P}_i \in G$* refers to a specific cell in the person occurrence grid G from eq. 5.

A. Definition of Atomic Actions

At this point we assume that there is a number of n known places the robot could move to and/or wait at, including the robot's position $\mathcal{P}_0$, which is the location where help is needed. To decide between different behaviors (i.e. Behavior Trees), the tuple $\mathcal{A}_{St}$ must first be defined for the different actions. The wait action as an action node $\mathcal{W}_{A,i}$ in the BT will return S when a person is found and F when a maximum time has been reached. The success rate μ_w then results directly from the property that the time differences between events of the Poisson process (i.e. interarrival times of people) are exponentially distributed. When the robot starts waiting at a time t_0, the probability density function of the exponential distribution

$$f(t; \mu_w) = \begin{cases} \mu_w e^{-\mu_w t} & t \geq t_0 \\ 0 & t < t_0 \end{cases}, \quad \mu_w = \sum_{\mathcal{D}} \lambda_{ij\tau} \quad (11)$$

describes the waiting time. This requires the assumption that $(t - t_0) < (t_{\tau+1} - t_\tau)$ i.e., the rates $\lambda_{ij\tau}$ can be regarded as constant while waiting. The success rate μ_w results from the accumulated rates of all visible cells at the waiting position. The probability to meet a person while waiting is given by the corresponding cumulative distribution function

$$p_{s,w}(t; \mu_w) = \begin{cases} 1 - e^{-\mu_w t} & t \geq t_0 \\ 0 & t < t_0 \end{cases}. \quad (12)$$

By manually specifying a desired confidence p'_s (e.g. $p'_s = 0.9$), this equation can be rearranged to determine the expected waiting time T' until the next event occurs. If no person appears after T', the wait action is considered as failed:

$$\nu_w^{-1} = T' = -\log(1 - p'_s)\mu_w^{-1}, \quad p'_s > p_{s,w}(\mu_w^{-1}; \mu_w). \quad (13)$$

Because the wait action will never fail before T' has passed, the fail probability is defined as

$$p_{f,w}(t; \mu_w) = \begin{cases} 1 - p'_s & t \geq t_0 + T' \\ 0 & t < t_0 + T' \end{cases}. \quad (14)$$

For proactive search, we define a search path as

$$\mathcal{S}_{i \to j} : (\mathcal{P}_i, \mathcal{P}_j, \mathcal{G}, l, \bar{v}), \quad i, j \in \{0, 1, ..., n\}, \, i \neq j \quad (15)$$

where $\mathcal{P}_i$ and $\mathcal{P}_j$ are the start and end places, $\mathcal{G} \subset \mathbb{R}^2 \times \mathbb{N}$ is the geometric description, l is the length of the path and $\bar{v}$ the average velocity of the robot while driving on the path. $\mathcal{G}$ and l directly follow from a geometric path planner (e.g. the A* algorithm on an occupancy grid map).

Similar to the waiting action, we define the searching action $\mathcal{S}_{A,i \to j} = \mathcal{A}_{St} \cup \mathcal{S}_{i \to j}$ to return S when a person is found and F when the whole path was driven without finding anyone. Additionally, this action can also return F if the navigation execution fails, e.g. due to an obstructed goal. While the robot moves on the path, it observes different cells of the person occurrence grid G, each for an individual time span. This imposes a time dependency on the occurrence rate $\mu_{sp}(t) = \sum_{\mathcal{D}(t)} \lambda_{ij\tau}$ ($\#_{sp}$ denotes *search path*). The rate is calculated by discretizing the path with $t_k = k \Delta t$ and calculating the corresponding rate $\mu_{sp,k}$ for each point in time. Fig. 5 illustrates this as an example of different paths in an environment.
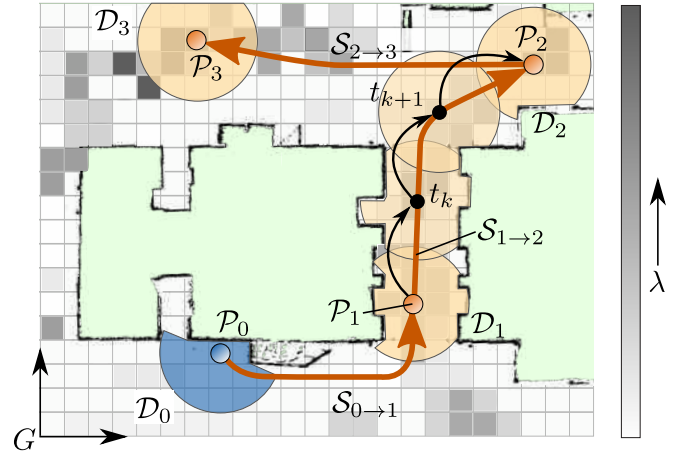

Fig. 5: Exemplary arrangement of different search locations and paths. $\mathcal{P}_i$ denotes a cell of the person occurrence grid, $\mathcal{D}_i$ a detection zone and $\mathcal{S}_{i \to j}$ a search path. For search planning, the detection zone is slid along the search paths with discretization k. (The discretization shown is only for comprehensibility.)

The minimal time until a person is found on the path, including the time to move to the corresponding location is defined as

$$\mu_{sp,tot}^{-1} = \underset{t_k \in [t_0, t_0 + \bar{v}l]}{\arg \min} \left(t_k - \log(1 - p'_s)\mu_{sp,k}^{-1} \right), \quad (16)$$

where p'_s again is a confidence value and t_0 the time when the search is started. The total success rate $\mu_{sp,tot}$ of the whole search path is the inverse of this time. The success probability $p_{s,sp}(t)$ of finding a person on the path follows as the counter probability of not having found anyone until time t to

$$p_{s,sp}(t; \mu_{sp}) = 1 - \exp \int_{t_0}^{t} \mu_{sp}(\tilde{t})d\tilde{t}. \quad (17)$$

When nobody has been found until the goal is reached or the navigation fails, the action *search person* is considered as failed. The fail rate ν_{sp} is approximated by

$$\nu_{sp} = \frac{\bar{v}}{l} + \frac{\bar{v}}{l_{fail}}, \quad (18)$$

where l_{fail} is an expected distance the robot can move until a navigation failure occurs, which we also assume

as exponentially distributed. This value can for instance be estimated by observation. Before the proactive search action is finished, the action can only fail due to the navigation and only after it has been finished, due to it not finding a person. The probability $p_{\mathrm{f,sp}}(t; \nu_{\mathrm{sp}})$ to fail is therefore defined as a piecewise function:

$$p_{\mathrm{f,sp}}(t; \nu_{\mathrm{sp}}) = \begin{cases} 1 - p_{\mathrm{s,sp}}(\nu_{\mathrm{sp}}^{-1}), & t \geq \nu_{\mathrm{sp}}^{-1} \\ 1 - \exp(-\frac{\bar{v}}{l_{\mathrm{fail}}} t), & t < \nu_{\mathrm{sp}}^{-1} \end{cases}. \quad (19)$$

For this equation to be applicable, the condition

$$p_{\mathrm{s,sp}}(\nu_{\mathrm{sp}}^{-1}) \leq \exp(-\frac{l}{l_{\mathrm{fail}} + l}) \quad (20)$$

must hold. This is fulfilled for $l \ll l_{\mathrm{fail}}$, which is the case for the present application, since all longer paths can be discarded to avoid searching far away from the help location.

B. Choosing a Behavior Tree

Based on the wait and search actions, an action rule must now be found that maximizes the probability of finding a person, taking into account the return time to the help location. We therefore define the *Person Search Behavior Tree* (PSBT), which describes a sequence of actions that should be executed when the robot is facing a task that cannot be solved by itself. For this, a selector behavior is defined, with a general form as shown in Fig. 6. The tree contains a Move to $\mathcal{P}_0$ action, which describes the movement back to the start location and is interpreted as a search action that can only fail due to the navigation.
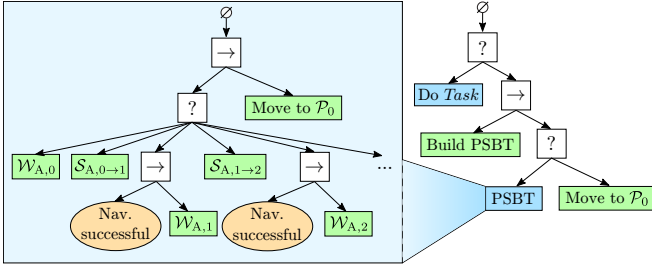

Fig. 6: General form of the PSBT. This tree is executed as a fallback of a $Task$ where the robot needs help, e.g. opening a door or operating an elevator.

To create the PSBT, we first sample a number of n places from the person occurrence grid G via roulette wheel selection, where the probability of a cell to be selected is $p \propto \lambda_{ij}$. If sampled cells are close to each other (the Euclidean distance is smaller than the detection radius r), only the cell with the larger rate λ_{ij} is kept. Also, only cells with a variance and distance to the robot below specified thresholds can be sampled. Subsequently, all wait actions $\mathcal{W}_{\mathrm{A},i}$ and search paths $\mathcal{S}_{\mathrm{A},i \to j}$ ($\forall i, j \in \{0, 1, ..., n\}, i \neq j$) are calculated. To reduce the complexity $\mathcal{O}(n!)$ of investigating all possible sequences to search all places $\mathcal{P}_{1...n}$, we determine the search order by means of an open traveling salesman problem (OTSP) with places $\mathcal{P}_{0...n}$ as nodes and the inverse of the failure rates $\nu_{\mathrm{s},i \to j}^{-1}$ as costs for corresponding graph. Although it is NP-hard to solve, there

exist various approaches to find a near optimal solution for the OTSP in acceptable time, e.g. by genetic algorithm [26], which we used for the implementation. The next step is the stochastic analysis of all possible BTs, with the goal to obtain an estimate of the success probability $p_{\mathrm{s,T}}(t)$ and success rate μ_{T} of the tree (according to eq. 1 and eq. 3) as the basis for decision-making. Therefore we apply the decomposition of each tree's flow as a DTMC by solving the Cauchy problem (eq. 2) with the infinitesimal generator matrix $Q(\mathcal{A}_{\mathrm{St,sp}}, \mathcal{A}_{\mathrm{St,w}})$ until a pre-defined maximum time $t_{\max}$. We conduct this analysis for every possible case, namely driving to specific places (or not), waiting there (or not) and finally returning to the help location, leading to a total number of $3^n + 1$ executions. The preferred tree is then chosen as the tree with maximum $p_{\mathrm{s,T}}(t_{\max})$.

VI. Experiments

The experimental evaluation is divided into two parts: The evaluation of the performance of the stochastic PSBT based on the person occurrence model and a comparison of the time to find people under real life conditions with the predicted time from the model. The environment for evaluation is the ground floor of a multi-storey $50\,\mathrm{m}$ by $25\,\mathrm{m}$ university building. The area includes lecture halls, a cafeteria, several entrances and sitting areas (see Fig. 1). We train the person model with data from two working days by moving the robot throughout the day to different places on the entire floor, so that the same locations are observed at different times of day. Only people tracks with a minimum observed time of $3\,\mathrm{s}$ in a range of $5\,\mathrm{m}$ are used, resulting in a total number of $18,362$ tracks $\mathcal{X}$. This rather high number resides in the fact that the robot partly loses the same person for a short time and then re-detects them as a new track. If a person moves more than one meter or is detected for more than $20\,\mathrm{s}$, this is also considered as a new track.

A. PSBT: Model-based Evaluation

We compare the PSBT with five other strategies: the two common heuristic methods of *greedy planning to the global maximum* (GM) and *greedy planning to a close maximum* (GC), also a *uniform random sampling of goals* (RND), the trivial approach to *wait at the help location* (W) and the strategy to sample the goals in the same manner as the PSBT, but *never wait* at sampled locations and only search proactively (NW).

First, the different methods are compared offline based on the trained person occurrence model. For this, we randomly sample 500 accessible poses on the occupancy grid map of the building as starting poses for the search for helpers. Then the probability of success $p_{\mathrm{s,T}}(t_k)$ is calculated using the methods presented in section V-A. The comparison is shown in Fig. 7 for seven points in time (every $20\,\mathrm{s}$). Although the observable variance shows a dependency on the starting pose, PSBT outperforms the other methods, leading to an on average $5.7\,\%$ higher probability of success after $140\,\mathrm{s}$ than the next best method (GM). The PSBT is always at least as good as waiting at the help location (W), because
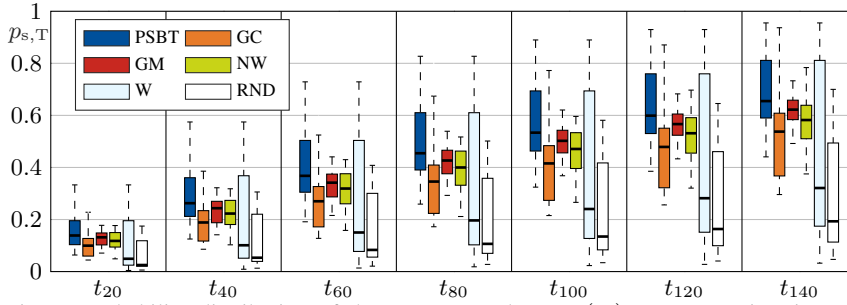
Fig. 7: Probability distribution of the BT root nodes $p_{s,T}(t_k)$ at seven points in time for 500 randomly sampled starting poses on the map.
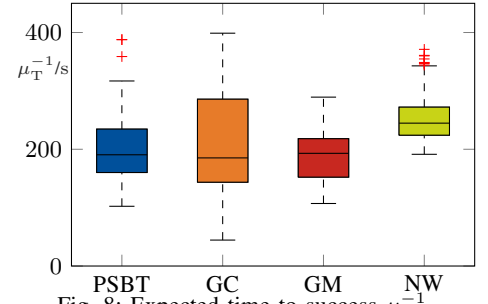

Fig. 8: Expected time to success μ_T^{-1}.

the stochastic analysis also explicitly considers this case and can execute it accordingly. Fig. 8 shows the expected time to success μ_T^{-1} for the four best methods. The time μ_T^{-1} refers to the expected time to find a person and then return to the help location. Here, the expected time for the PSBT is averagely $11.05\,\mathrm{s}$ higher than for GM, which is due to the property that the DTMC decomposition yields more conservative estimates of the success rate for an increasing number of selector child nodes. Fig. 9 shows two exemplary help locations in front of doors and the corresponding BTs. The location $\mathcal{P}_{\mathrm{stor}}$ (Figs. 9a, 9b) is in front of a door to a storage room without a large number of people coming and going. While the greedy strategies aim for the closest (or global) maxima, the PSBT strategy moves to the nearby building entrance $\mathcal{P}_1$, waits there and then proceeds to move along the lifts to the global maximum (a sitting area). The second location is one of the entrances to the cafeteria $\mathcal{P}_{\mathrm{cafe}}$ (Figs. 9c, 9d), which is located in an area with a higher volume of people. Here the PSBT strategy first waits on site before proactively searching for people, while the greedy strategies again aim for the maxima.

B. PSBT: Real-World Experiments

To demonstrate the efficiency of the presented approach, we also conducted real-world experiments. For the two different start locations from Fig. 9, we tested the different methods over a period of five working days. The same constant person occurrence model was used for all methods, which were tested in an alternating fashion in order to compensate for biasing effects (e.g. events in the lecture halls). A single run includes the planning according to the corresponding method and the subsequent search for people. The sampled goals are not approached directly. Instead, poses are uniformly sampled in a radius of $2\,\mathrm{m}$ around them with the line of sight to the goal and then the closest reachable pose is selected. This has the advantage that the field of view of the sensors is towards the goal. Furthermore, maxima are sometimes located on blocked areas (e.g. people sitting on chairs) which otherwise could not be approached by the navigation planner. We consider a person as found if a detected track $\mathcal{X}_i$ of a person is within a radius of $2\,\mathrm{m}$ in front of the robot for a period of at least $3\,\mathrm{s}$. After a successful search, the robot returns to the starting position and the time for the whole run t_r is saved. A run is considered as failed, when the search tree returns F, i.e. when all search

and wait actions were executed without finding anyone. The waiting time for all methods is determined according to eq. 13 with a confidence value of $p'_s = 0.9$. Fig. 10 shows the results for $\mathcal{P}_{\mathrm{stor}}$ as the starting location. All proactive methods perform significantly better than waiting at the help location. The shortest average time $\bar{t}_r$ was achieved by the methods GC and GM. Although the greedy methods can be faster, PSBT delivers substantially better results in terms of the success rate (see table I). Since the greedy methods only approach one maximum and remain there, the success depends strongly on whether people can be recognized at this specific location. For example, the global maximum in this environment was a bench, often occupied by people, but sometimes in slightly different spots. This is also reflected in the high success rate of the NW method, as it is more likely to detect a person directly in front of the robot during the proactive search. An essential advantage of the PSBT method can be seen for highly frequented areas like $\mathcal{P}_{\mathrm{cafe}}$ (see Fig. 11). The exclusively proactive *never wait* (NW) method takes longer on average to find a person and return to the start location, since PSBT correctly decides that it is more worthwhile to wait on site. Based on the estimated expected time to success μ_r^{-1} the model correctly predicts the ranking order of the different methods and thus provides a good estimation for decision making. It provides more conservative estimates for the duration (see table I), which is due to the fact that cells with high variance are ignored in the calculation. Furthermore, we assume a constant velocity of the robot $\bar{v} = 0.5\,\mathrm{m\,s^{-1}}$ during the movement, which was often exceeded in the test runs.

VII. CONCLUSION

In this paper, we presented a method for finding people in situations where a mobile robot needs human help to solve problems. Based on locally defined Poisson processes to model the occurrence rate of people in an environment, a Behavior Tree is created linking consecutive search and wait actions to find a person in the shortest possible time. In 198 trial runs, our method was able to produce suitable predictions of the time until success and found people in at least $91.07\,\%$ of the cases, which is a higher rate than all other compared methods. Compared to a purely proactive search, the search time can be significantly reduced by actively deciding for or against waiting at the help location while maintaining the success rate.
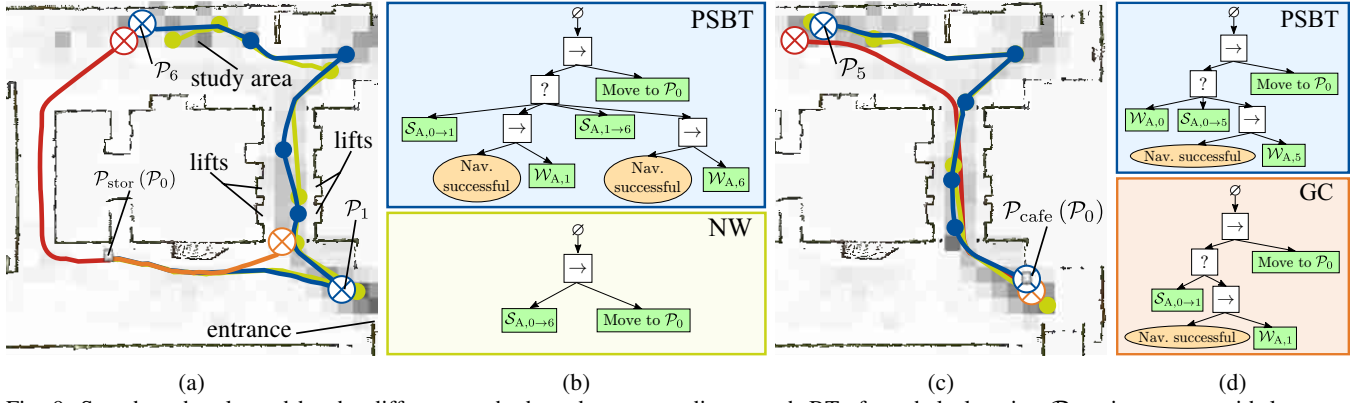
Fig. 9: Search paths planned by the different methods and corresponding search BTs for a help location $\mathcal{P}_{stor}$ in an area with low rate λ, and a location $\mathcal{P}_{cafe}$ with high rate. Colored dots indicate sampled places and crossed circles indicate a waiting location. Consecutive search paths are merged if there are no wait actions inbetween. Colors correspond to the legend in Fig. 7.
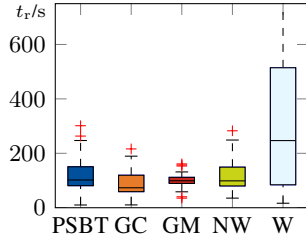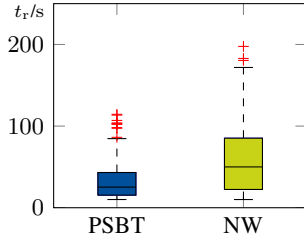

Fig. 10: t_r for all searches starting at location $\mathcal{P}_{stor}$

Fig. 11: t_r for all searches starting at location $\mathcal{P}_{cafe}$

TABLE I: Key figures of the experimental runs in the university building. Average time $\bar{t}_r$ and standard deviation $\sigma_{t,r}$ were calculated for the successful runs only. $\bar{\mu}_r^{-1}$ denotes the averagely estimated expected time to success.

Location	Method	n_{trials}	Success rate	$\bar{t}_r$	$\sigma_{t,r}$	$\bar{\mu}_r^{-1}$	$\sigma_{\mu,r}$
$\mathcal{P}_{stor}$	PSBT	86	**98.84 %**	120.49	61.20	139.53	8.65
	NW	93	88.17 %	115.40	52.25	150.82	6.95
	GM	86	62.79 %	101.13	22.43	121.50	0.0
	GC	90	65.56 %	**89.13**	49.74	108.12	0.0
$\mathcal{P}_{cafe}$	PSBT	112	**91.07 %**	**35.51**	28.15	49.99	0.0
	NW	121	90.08 %	62.97	48.91	126.78	6.00

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