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Estimation and Control for Cooperative Autonomous Searching in Crowded Urban Emergencies

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Abstract— **This paper presents the Updateable Probabilistic Evacuation Modeling (UPEM) technique, which allows sensor observation data to be included in the problem of estimating the state of an evacuating crowd, as the data are obtained. Each individual is modeled as a Newtonian particle which interacts with obstacles, such as walls and other individuals. The UPEM technique estimates not only the general trend of the crowd as a whole, but also the specific states of each of the evacuees in the crowd. Furthermore, an approach to cooperative autonomous searching in crowded urban emergencies is developed using UPEM. A number of simulated searches in emergency evacuations highlight the efficacy of the technique in reducing the time required to detect targets and in increasing the level of safety for human evacuees.**

I. INTRODUCTION

A team of robots with the ability to operate in crowded urban emergencies may be useful in minimizing the risk to humans in tasks such as urban search and rescue, detecting hazardous materials, or evacuation guidance and assistance. If the robots in the team have the ability to not only avoid observable obstacles in their vicinity, but also to avoid moving into heavy traffic areas or congestion points, then the objectives of both safe and efficient evacuation and the robot mission may be better achieved.

Recursive Bayesian Estimation (RBE) has been successfully applied in the area of mobile robotics, for collision avoidance, involving moving pedestrians, in both indoor office environments [1] and outdoor urban environments [2]. However, these approaches reduced the computational complexity by considering only observable, or recently observable, obstacles. Whilst this may be sufficient in low traffic density scenarios, where pedestrians move independently, during evacuations large volumes of pedestrian traffic move with common purpose, and therefore consideration should be given to unobservable evacuees, so that the robots can avoid moving into areas with high volumes of traffic flow or congestion.

Within the field of pedestrian dynamics, a large body of work exists concerning evacuation modeling. A comprehensive survey [3] divides the field into macroscopic techniques, which attempt to model the aggregate behavior of crowds, and microscopic techniques, which focus on individual actions and interpersonal behavior. Macroscopic techniques, such as the *space syntax* technique used in [4], make no attempt to model or track individual evacuees. As a result, the robots in [4] did not include sensor observation data in their estimates and made no attempt to avoid moving into congested areas. The *virtual forces* model presented in [5] is a widely known microscopic technique. However, the virtual forces model is deterministic, and microscopic techniques are in general highly dependent on initial conditions. Furthermore, a means of determining the true evacuation scenario requires the inclusion of sensor observation data, which is not considered by the microscopic techniques.

RBE techniques such as the Kalman Filter and its variants [6], and Sequential Monte-Carlo (SMC) methods, or particle filters [7], [8], have been applied to the problem of tracking multiple targets based on sensor observation data. Estimation of the state of targets undergoing constrained motion using the grid-based method was presented in [9]. The unified searching-and-tracking (SAT) framework presented in [10] extended that work to provide a means for continuously updating the estimated state of multiple targets, using sensor observation data corresponding to both detection and non-detection events. However, to be effective these approaches depend upon the availability of accurate, probabilistic models of the targets' motions, which are not provided by existing evacuation modeling techniques.

This paper presents the Updateable Probabilistic Evacuation Modeling (UPEM) technique. The proposed UPEM technique allows sensor observation data to be included in the state estimation problem as they are obtained, by estimating the state of each individual evacuee with its own probabilistic filter, maintained under the SAT framework. Each individual is modeled as a Newtonian particle which interacts with obstacles such as walls and other individuals to give its probabilistic motion model. The advantage of the technique is that it estimates not only the general trend of the crowd state, including unobservable evacuees, but also the specific states of each of the evacuees in the crowd. Additionally, an approach to cooperative autonomous searching in crowded urban emergencies is developed, in order to demonstrate a robotics application of the UPEM technique.

This paper is organized as follows. Section II describes the foundations of pedestrian dynamics and RBE. The UPEM technique is formulated in Section III, along with the approach developed for cooperative autonomous searching in crowded urban emergecies. Numerical examples are shown in Section IV and conclusions and future work are discussed in Section V.

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II. PEDESTRIAN DYNAMICS AND RECURSIVE BAYESIAN ESTIMATION

A. Evacuation Modeling using Virtual Forces

The virtual forces model represents a human crowd as a set of Newtonian particles which simultaneously attempt to reach a desired destination and avoid collisions with other individuals and the environment. Each individual i in a crowd of n_e evacuees is represented by a single particle with radius r_i and mass m_i and desires to move with velocity $\mathbf{v}_i^d(t)$. It therefore tends to adapt its actual velocity $\mathbf{v}_i(t)$ to meet this desire, with a characteristic time τ_i, whilst trying to avoid the other evacuees, j, and walls, w, in the vicinity. These influences are modeled by the 'interaction forces' $\mathbf{f}_{ij}$ and $\mathbf{f}_{iw}$, respectively. The virtual force applied to the ith particle at each iteration is therefore given by the equation

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{\mathbf{v}_i^d - \mathbf{v}_i}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_{w} \mathbf{f}_{iw}. \quad (1)$$

The interaction force between individuals is given by

$$\mathbf{f}_{ij} = \{A \exp[(r_{ij} - d_{ij})/B] + \kappa_n g(r_{ij} - d_{ij})\}\, \mathbf{n}_{ij} + \kappa_t g(r_{ij} - d_{ij}) \Delta \mathbf{v}_{ij}^t \mathbf{t}_{ij}. \quad (2)$$

Here $A \exp[(r_{ij} - d_{ij})/B] \mathbf{n}_{ij}$ represents the socio-psychological urge to distance oneself from other pedestrians and $\kappa_n g(r_{ij} - d_{ij}) \mathbf{n}_{ij}$ and $\kappa_t g(r_{ij} - d_{ij}) \Delta \mathbf{v}_{ij}^t \mathbf{t}_{ij}$ are the physical forces which occur when two individuals come into contact. They represent the resistance to body compression and resistance to relative tangential motion respectively. A, B, κ_n and κ_t are constants, $r_{ij} = (r_i + r_j)$, d_{ij} is the distance between the evacuees' centers of mass, $\mathbf{n}_{ij}$ is the normalized vector from j to i (i.e. the unit normal), $\mathbf{t}_{ij}$ is its corresponding tangent and $\Delta \mathbf{v}_{ij}^t$ is the tangential velocity difference. The function $g(x)$ serves to indicate contact between evacuees:

$$g(x) = \langle x \rangle \quad (3)$$

where $\langle . \rangle$ is the Macaulay bracket. Similarly, the interaction force between individuals and walls is given by

$$\mathbf{f}_{iw} = \{A \exp[(r_i - d_{iw})/B] + \kappa_n g(r_i - d_{iw})\}\, \mathbf{n}_{iw} - \kappa_t g(r_i - d_{iw})(\mathbf{v}_i \cdot \mathbf{t}_{iw}) \mathbf{t}_{iw}. \quad (4)$$

The dynamic system equation (1) may be easily integrated, for example using Euler or Vertlet integration techniques [11], to determine the velocity and position vectors of each of the evacuees at each time step.

B. Recursive Bayesian Estimation

In general, RBE for SAT estimates $p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k}, \tilde{\mathbf{x}}_{1:k}^s)$, the posterior probability distribution over $\mathbf{x}_k^t$. Here $\mathbf{x}_k^t \in \mathcal{X}^t$ is the state of a target, t, at time step k, $\tilde{\mathbf{x}}_{1:k}^s = \{\tilde{\mathbf{x}}_1^s, \ldots, \tilde{\mathbf{x}}_k^s\}$ is the sequence of search vehicle states and ${}^s\tilde{\mathbf{z}}_{1:k} = \{{}^s\tilde{\mathbf{z}}_1, \ldots, {}^s\tilde{\mathbf{z}}_k\}$ is the sequence of observations. Note that the tilde is used here to represent an instance $\tilde{(\cdot)}$ of a variable $(\cdot)$. Furthermore, it will be assumed in this paper that the search vehicles have the ability to accurately localize themselves, since a variety of sophisticated localization techniques already exist and the discussion of such is beyond the scope of this paper.

The posterior distribution at any time step may be calculated recursively, given an initial density function $p(\mathbf{x}_0^t)$ and the sequences, $\tilde{\mathbf{x}}_{1:k}^s$ and ${}^s\tilde{\mathbf{z}}_{1:k}$. The posterior distribution is given by the Bayesian update equation

$$p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k}, \tilde{\mathbf{x}}_{1:k}^s) = \frac{p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^t, \tilde{\mathbf{x}}_k^s) p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k-1}, \tilde{\mathbf{x}}_{1:k-1}^s)}{\int_{\mathcal{X}^t} p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^t, \tilde{\mathbf{x}}_k^s) p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k-1}, \tilde{\mathbf{x}}_{1:k-1}^s) d\mathbf{x}_k^t}. \quad (5)$$

The SAT approach hinges on the observation likelihood $p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^t, \tilde{\mathbf{x}}_k^s)$, which will be discussed in greater detail in Section II-C. Note that if $k = 1$ then $p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k-1}, \tilde{\mathbf{x}}_{1:k-1}^s) = p(\mathbf{x}_0^t)$, otherwise it is determined using the target's Markov motion model, $p(\mathbf{x}_k^t | \mathbf{x}_{k-1}^t)$ and the Chapman-Kolmogorov prediction equation

$$p(\mathbf{x}_k^t | {}^s\tilde{\mathbf{z}}_{1:k-1}, \tilde{\mathbf{x}}_{1:k-1}^s) = \int_{\mathcal{X}^t} p(\mathbf{x}_k^t | \mathbf{x}_{k-1}^t) p(\mathbf{x}_{k-1}^t | {}^s\tilde{\mathbf{z}}_{1:k-1}, \tilde{\mathbf{x}}_{1:k-1}^s) d\mathbf{x}_{k-1}^t. \quad (6)$$

C. Searching and Tracking

1) Observation Model for Searching and Tracking: Successful SAT requires the search vehicle to distinguish between detection events, where a target is observed, and non-detection events. This may be determined based on the probability of detection, $0 \leq P_d(\mathbf{x}_k^t | \mathbf{x}_k^s) \leq 1$. The vehicle's 'detection space', ${}^s\mathcal{X}_k^t$ may be defined as,

$${}^s\mathcal{X}_k^t = \{\mathbf{x}_k^t | \epsilon < P_d(\mathbf{x}_k^t | \tilde{\mathbf{x}}_k^s) \leq 1\} \quad (7)$$

where ϵ is a positive threshold value which determines a detection event. If the target falls within the search vehicle's detection space the vehicle uses the detection likelihood, $l_d({}^s\tilde{\mathbf{z}}_k | \tilde{\mathbf{x}}_k^t, \tilde{\mathbf{x}}_k^s)$, otherwise the vehicle assumes the non-detection likelihood, $l_{nd}(\mathbf{x}_k^t | \tilde{\mathbf{x}}_k^s)$. The unified SAT observation likelihood is therefore given by

$$p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^t, \tilde{\mathbf{x}}_k^s) = \begin{cases} l_d({}^s\tilde{\mathbf{z}}_k | \tilde{\mathbf{x}}_k^t, \tilde{\mathbf{x}}_k^s) & \exists \tilde{\mathbf{x}}_k^t \in {}^s\mathcal{X}_k^t \\ l_{nd}(\mathbf{x}_k^t | \tilde{\mathbf{x}}_k^s) & \nexists \tilde{\mathbf{x}}_k^t \in {}^s\mathcal{X}_k^t. \end{cases} \quad (8)$$

2) Cooperative SAT: Multiple search vehicles may cooperatively perform SAT using sensor data fusion. For n_s search vehicles the multiple-vehicle observation likelihood is

$$p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^{t_j}, \tilde{\mathbf{x}}_k^s) = \prod_{i=1}^{n_s} p({}^{s_i}\tilde{\mathbf{z}}_k^{t_j} | \mathbf{x}_k^{t_j}, \tilde{\mathbf{x}}_k^{s_i}) \quad (9)$$

where $\tilde{\mathbf{x}}_k^s = \{\tilde{\mathbf{x}}_k^{s_i} | \forall i \in \{1, \ldots, n_s\}\}$ and ${}^s\tilde{\mathbf{z}}_k^{t_j} = \{{}^{s_i}\tilde{\mathbf{z}}_k^{t_j} | \forall i \in \{1, \ldots, n_s\}\}$ represent the states of the n_s platforms at time k and their corresponding observations of target t_j respectively, and $p({}^{s_i}\tilde{\mathbf{z}}_k^{t_j} | \mathbf{x}_k^{t_j}, \tilde{\mathbf{x}}_k^{s_i})$ is the observation likelihood for search vehicle s_i. For fully connected, lossless and delay free communication, each search vehicle i can receive $p({}^{s_q}\tilde{\mathbf{z}}_k | \mathbf{x}_k^{t_j}, \tilde{\mathbf{x}}_k^{s_q}), \forall q \neq i$ and decentrally construct (9). Substitution of (9) in the place of $p({}^s\tilde{\mathbf{z}}_k | \mathbf{x}_k^t, \tilde{\mathbf{x}}_k^s)$ in (5) gives the update equation for multiple vehicles.

III. CROWD ESTIMATION AND COOPERATIVE CONTROL FOR URBAN SEARCHING MISSIONS

A. The Updateable Probabilistic Evacuation Modeling Technique

The UPEM technique estimates the state of each evacuee using a unique probabilistic filter, which is maintained under the SAT framework described in Section II-C. The complete state of a crowd is given by

$$\mathbf{x}_k^e = \{\mathbf{x}_k^{e_1}, \mathbf{x}_k^{e_2}, \ldots, \mathbf{x}_k^{e_{n_e}}\} \tag{10}$$

where an evacuee $n \in \{1, \ldots, n_e\}$ is represented by its two-dimensional position and velocity

$$\mathbf{x}_k^{e_n} = [x_k^{e_n}, \dot{x}_k^{e_n}, y_k^{e_n}, \dot{y}_k^{e_n}]^T. \tag{11}$$

Therefore it is assumed that the actual change in the crowd state is given by

$$\tilde{\mathbf{x}}_k^e = \mathbf{f}^e(\tilde{\mathbf{x}}_{k-1}^e, M, \tilde{\mathbf{w}}_{k-1}^e) \tag{12}$$

where $\mathbf{f}^e$ calculates the the positions and velocities of the evacuees using the virtual forces model (1) and $\tilde{\mathbf{w}}_{k-1}^e$, a noise vector representing the inherent uncertainty in human movement. Note that an individual's desired velocity, $\mathbf{v}_i^d$ may be determined on the basis of a map, M.

Attempting to stochastically model this complete system is generally intractable for large crowds since the computational complexity of such a system grows exponentially with increasing numbers of modeled individuals. However, the assumption of conditional independence allows the posterior to be written in the following factored form,

$$p(\mathbf{x}_k^{e_1}, \mathbf{x}_k^{e_2}, \ldots, \mathbf{x}_k^{e_{n_e}} | {}^{s_i}\tilde{\mathbf{z}}_{1:k}^e, \tilde{\mathbf{x}}_{1:k}^{s_i}) = \prod_{n=1}^{n_e} p(\mathbf{x}_k^{e_n} | {}^{s_i}\tilde{\mathbf{z}}_{1:k}^{e_n}, \tilde{\mathbf{x}}_{1:k}^{s_i}). \tag{13}$$

The computational complexity then only increases linearly as n_e increases. However, in the case of emergency evacuations, this assumption disregards the significant socio-psychological and physical interactions between evacuees. Therefore the UPEM technique models each evacuee independently, but with a motion model based on the virtual forces model (1), evaluated on the mean crowd state. That is,

$$\mathbf{x}_k^{e_n} = \mathbf{f}^{e_n}(\bar{\mathbf{x}}_{k-1}^e, M, \mathbf{w}_{k-1}^{e_n+\lambda}) \tag{14}$$

where $\mathbf{f}^{e_n}$ is the individual evacuee equivalent of the crowd motion function $\mathbf{f}^e$, the mean crowd state is

$$\bar{\mathbf{x}}_{k-1}^e = \{[\bar{x}_k^{e_n}, \bar{\dot{x}}_k^{e_n}, \bar{y}_k^{e_n}, \bar{\dot{y}}_k^{e_n}]^T, \forall n \in \{1, \ldots, n_e\}\} \tag{15}$$

and

$$\mathbf{w}_{k-1}^{e_n+\lambda} = \mathbf{w}_{k-1}^{e_n} + \lambda \tag{16}$$

is a noise vector which takes into account the uncertainty of the individual's motion, $\mathbf{w}_{k-1}^{e_n}$, and compensates for the flawed assumption of independence and the approximation of the crowd state vector with the additive noise component λ.

Initially, the UPEM technique requires an estimate of the number of evacuees and their initial positions in the map. Information such as the time of day and the expected number of employees at work, students in a lecture theater or fans at a sporting event can serve to form the basis of both the estimate of n_e and the initial distribution of the evacuees. Note that since the estimate is to be updated with sensor observation data, these initial estimates need not be particularly accurate. HOne approach to estimating n_e consists of reducing the value of n_e and removing the appropriate filters if, following the Bayesian update,

$$\Pr(\mathbf{x}_k^{e_n}) \in M = 0, n \in \{1, \ldots, n_e\}. \tag{17}$$

This occurs whenever an evacuee is estimated to have successfully evacuated the building, or if all an evacuee's nonzero probability density falls within a sensor's detection space, without a detection event occurring. Furthermore, increasing the value of n_e, and creating new filters, only when an individual enters a sensor's detection space and all existing filters have been associated with previously observed individuals, avoids increasing n_e when unassigned filters are available. Note that there are other approaches to the problem of estimating n_e based on sensor observation data, such as Minimum Description Length (MDL) approaches [12]. However, because MDL approaches require large amounts of computation time to be spent maintaining multiple instances of the model for different possible n_e values, they will not be discussed further in this paper.

Furthermore, the data association problem must be solved before the SAT update for multiple evacuees may be applied. The *nearest neighbor* approach to data association is a straightforward method which has the advantage of maintaining individual beliefs even when the observed evacuees are in close proximity to each other, which often occurs in crowded evacuation scenarios.

B. Cooperative Search in Crowded Emergencies

One possible application of the UPEM technique is in cooperative autonomous searching missions during mass evacuations. An emergency situation may call on a team of autonomous robots to search for targets such as immobile or trapped victims, or explosive, toxic or otherwise hazardous materials, during a large scale evacuation. For n_t number of targets, the state of a single target object t_j may be represented by the vector $\mathbf{x}_k^{t_j}$, which in general consists of the target's position, but may also include terms representing the accessability or physical condition of the target. The target's state may then be estimated using RBE. It is reasonable to assume that targets such as immobile or trapped victims or explosive devices are stationary, in which case the two-dimensional state vector becomes $\mathbf{x}^{t_j} = [x^{t_j}, y^{t_j}]^T$. This assumption also eliminates the need to perform the prediction step (6) in the RBE, since in the static target case $p(\mathbf{x}_k^{t_j} | {}^{s_i}\tilde{\mathbf{z}}_{1:k-1}^{t_j}, \tilde{\mathbf{x}}_{1:k-1}^{s_i}) = p(\mathbf{x}_{k-1}^{t_j} | {}^{s_i}\tilde{\mathbf{z}}_{1:k-1}^{t_j}, \tilde{\mathbf{x}}_{1:k-1}^{s_i})$.

For urban search spaces such as office buildings which feature distinct, searchable, subspaces, the optimal search problem becomes that of selecting the subspace to search which maximizes the utility, that is the probability of detecting a target, considering the time cost required to reach the area and thoroughly search it. For a lone search vehicle it is sufficient to consider this utility-cost analysis only. For multiple search vehicles the team must bargain in order to achieve the team's optimal allocation of search areas to each vehicle.

1) Individual Utility and Cost: The utility for vehicle s_i in searching subspace a is based on the probability of the vehicle detecting a target in the subspace and is given by

$$u_a^i = \sum_{j=1}^{n_t} w_j^i \Pr(\mathbf{x}_k^{t_j} \in a | {}^{s_i}\tilde{\mathbf{z}}_{1:k}^{t_j}, \tilde{\mathbf{x}}_{1:k}^{s_i}) \quad (18)$$

where w_j^i is an importance weighting giving to target j.

The total cost for vehicle s_i to search subspace a is the weighted sum of the time cost associated with the search vehicle traveling from its current position to the subspace and the time cost associated with searching the subspace itself. The cost of traveling increases with the distance the vehicle has to move in order to reach the room, and with the probable crowd congestion along the path. It is given by

$${}^{t}c_a^i = f^{{}^{t}c}(\mathbf{x}_k^{s_i}, P_k^e, a, M) \quad (19)$$

where

$$P_k^e = \{p(\mathbf{x}_k^{e_1} | {}^{s_i}\tilde{\mathbf{z}}_{1:k}^{e_n}, \tilde{\mathbf{x}}_{1:k}^{s_i}), \ldots, p(\mathbf{x}_k^{e_{n_e}} | {}^{s_i}\tilde{\mathbf{z}}_{1:k}^{e_n}, \tilde{\mathbf{x}}_{1:k}^{s_i})\}. \quad (20)$$

The cost of searching a subspace increases with the size of the subspace and the probable crowd congestion. If additional information, such as the setup of the room or the presence of steps or other obstacles is available, then these data may also be included in determining the search cost. The search cost is given by

$${}^{s}c_a^i = f^{{}^{s}c}(P_k^e, a, M). \quad (21)$$

Therefore the individual optimal search problem reduces to determining the best subspace to search next, traveling to the subspace and performing the search. Once a full search coverage of the subspace has been achieved, the next best area is chosen, and so on until the probability of targets remaining undetected vanishes. The best subspace to search may be found by solving

$$\arg\max_a [w_u u_a^i - (w_{{}^{t}c} {}^{t}c_a^i + w_{{}^{s}c} {}^{s}c_a^i)] \quad (22)$$

where w_u, $w_{{}^{t}c}$ and $w_{{}^{s}c}$ are weights on the utility, travel cost and search cost respectively.

2) Multi-Vehicle Task Allocation: For multiple search vehicles, the task allocation problem arises. Each vehicle must select a subspace to search from the total n_a distinct subspaces, in order to achieve the best overall team allocation of tasks. The optimal allocation may be found by finding the Nash bargaining solution [13],

$$\arg\max_{a,i} \sum_{a,i=1}^{n_a,n_s} [w_u u_a^i - (w_{{}^{t}c} {}^{t}c_a^i + w_{{}^{s}c} {}^{s}c_a^i)] \quad (23)$$

subject to the constraints that each vehicle can only be assigned to search one subspace at a time and that each subspace can only be assigned a single search vehicle at a time.

TABLE I
EVACUATION PARAMETERS

Parameter	Units	For Simulation	For Estimation
$\mathbf{v}_i^d$	m s^{-1}	[0.5,1.5]	1.0
r_i	m	[0.25,0.35]	0.30
m_i	kg	80	80
τ_i	s	0.5	0.5
A	N	2×10^3	2×10^3
B	m	0.08	0.08
κ_n	kg s^{-2}	1.2×10^5	1.2×10^5
κ_t	kg m^{-1}s^{-1}	2.4×10^5	2.4×10^5

IV. NUMERICAL EXAMPLES

A number of scenarios involving large scale evacuations were simulated in order to validate the proposed UPEM technique and to highlight its efficacy in robotics systems for emergency response. The deterministic virtual forces model was used to simulate the true state of the crowds, whilst the UPEM technique was used for estimation. Table I lists the parameters used in the models.

Two cooperative autonomous search vehicles were also simulated. Each search vehicle was simulated to carry two range-and-bearing sensors, one for detecting search targets, the other for detecting obstacles such as evacuees and walls. Each sensor had a sweep angle of 180° and the effective ranges of the target and obstacle sensors were 3m and 8m respectively. Each search vehicle had a maximum speed of 1.5 m.s^{-1}. The floor plan shown in Fig. 1 was used as the map in each simulation and particle filters were used both in the UPEM technique and for estimating the state of the search targets. One hundred particles were used for each evacuee modeled. Five thousand particles were used in the estimation of search targets and were distributed with the probability density shown in Fig. 1. Evacuees were allocated initial rooms to occupy according to the limits displayed in Table II. The initial positions of the occupants within each room were uniformly distributed.

A. Evacuation Simulation

One hundred different scenarios were run for each of the cases where 200, 250, 300, 350 and 400 evacuees were simulated. The total evacuation times required for each case are shown in Fig. 2. It can be seen that the

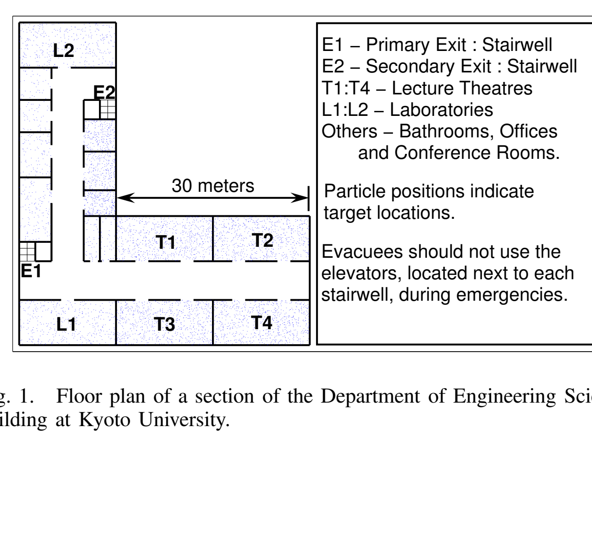


Fig. 1. Floor plan of a section of the Department of Engineering Science building at Kyoto University.

TABLE II

INITIAL DISTRIBUTION OF ROOM OCCUPANTS

Room Groups		Occupants	
Group Type	No. of Rooms	Min.	Max.
Lecture Theaters	4	40	80
Laboratories	2	15	30
All Others Combined	9	10	20
Total	15	200	400

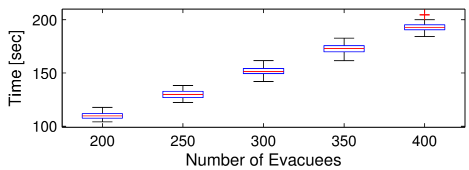


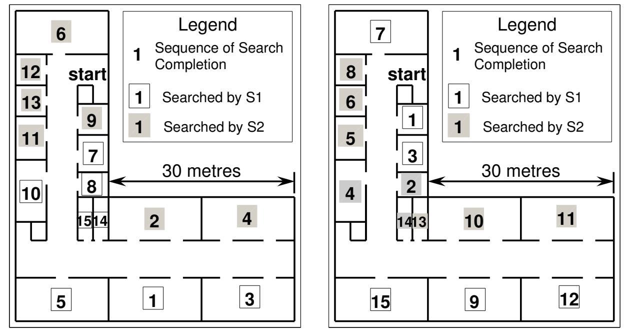
Fig. 2. Total Evacuation Time Required (sec) vs. Total Number of Evacuees.

total evacuation time required increased as the number of evacuees increased. This was caused by evacuees having to queue for longer as crowd congestion increased. The case involving four hundred evacuees was therefore chosen for further investigation using the UPEM technique, as that case exhibited both high volumes of pedestrian traffic and the greatest levels of congestion.

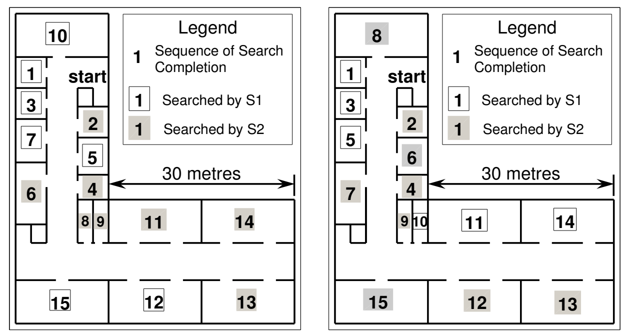
B. *Cooperative Autonomous Searching Missions*

One evacuation scenario involving four hundred evacuees was selected at random from the one hundred scenarios described above. The scenario was used to compare the conventional approach, where evacuations are completed before searching begins, with the approach based on UPEM, developed in this paper. The total evacuation time required in the chosen scenario was 195.9 seconds. Each of the initial positions of the five thousand target particles shown in Fig. 1 were used as the true position of a target, which was to be searched for by two cooperative autonomous search vehicles, denoted S1 $(\equiv s_1)$ and S2 $(\equiv s_2)$. In order to examine the efficacy of the UPEM technique, the cooperative search approach developed in this paper, used after the complete evacuation and without the UPEM technique, was applied for the conventional search approach. The approach developed in this paper, including the UPEM technique, was then used to control the search vehicles during the evacuation for comparison. Searches for the five thousand targets were carried out under both approaches, using three weighting strategies for the utility and costs. The equal weighting strategy (EWS) assigned both search vehicles to use equal weights for the utility and both costs. The time weighting strategy (TWS) assigned both search vehicles to use cost weights that were nine times the weight given to the utility. The combined weighting strategy (CWS) assigned search vehicle S1 with the weights used in the EWS and vehicle S2 with the weights used in the TWS.

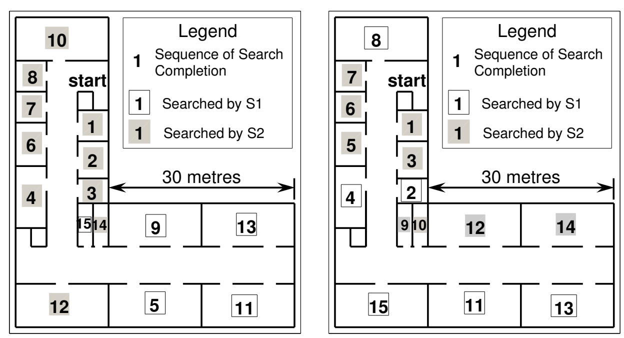
The different sequences of rooms searched, resulting from each of the different approaches and strategies, are shown in Fig. 3. The left column of the figure shows the sequences



(a) Conventional Search: Equal Weighting Strategy (b) Search with UPEM: Equal Weighting Strategy



(c) Conventional Search: Time Weighting Strategy (d) Search with UPEM: Time Weighting Strategy

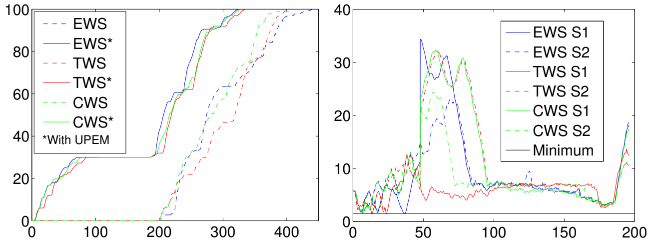


(e) Conventional Search: Combined Weighting Strategy (f) Search with UPEM: Combined Weighting Strategy

Fig. 3. Cooperative Search Sequences. L: The conventional, evacuate-then-search approach. R: The developed search approach, using UPEM

when the conventional approach was used. The search sequences, when the developed approach was used, are shown in the right column.

The time required for the search vehicles to detect the target in each of the five thousand cases examined was recorded, and the cumulative percentage of targets located is shown against the required mission times in Fig. 4(a). The large horizontal segment which occurred under each strategy using the developed approach is due to significant congestion which occurred at the intersection of the two hallways. Under the developed approach the search vehicles completely searched all of the accessible rooms, then waited for the congestion to clear before successfully continuing with their search mission. It can be seen from Fig. 4(a) that at the time searching commenced under the conventional



(a) Cumulative Percentage of Targets Detected vs. Mission Time (sec)

(b) Distance From Search Vehicle to Nearest Evacuee (m) vs. Mission Time (sec)

Fig. 4. Performance Measures for Cooperative Searching in Crowded Urban Emergencies

approach, 35.9%, 31.6% and 31.7% of the targets had already been detected under the developed approach, using the EWS, TWS and CWS, respectively. The first strategy to detect 50% of the targets under the conventional approach did so in 274.5 seconds. By that time, 90.6%, 87.4% and 88.9% of the targets had been detected under the developed approach, using the EWS, TWS and CWS, respectively. Furthermore, Fig. 4(b) shows that even though the two vehicles were searching in the presence of four hundred evacuees, the use of UPEM meant that both search vehicles remained more than 1.4 meters from each evacuee at all times in each simulation.

Whilst Fig. 4(a) clearly shows that the UPEM is beneficial in reducing the target detection time in evacuation scenarios, it is difficult, using the time to detection results only, to quantify the benefits to the human evacuees stemming from the search vehicles' ability to detect potential hazards while the evacuees are still attempting to egress. Therefore a safety rating was given to each of the five thousand detections made under each approach and strategy. The safety rating consisted of two components: an evacuee component and a time component. The evacuee component was such that detections made while evacuees were still inside the building were given fifty times the rating of the last detection made using the slowest approach and strategy. The evacuee component, for detections made after the evacuation was complete, was zero. In this way significant consideration was given to the safety of evacuees still in the building. The time component was such that detections made towards the beginning of the mission were given close to ten times the rating of the last detection made using the slowest strategy. Table III shows the average safety rating per target detection for each of the approaches and strategies. It can be seen that the average safety rating when the UPEM technique was used was approximately one order of magnitude higher than each of the strategies under the conventional approach.

TABLE III

AVERAGE SAFETY RATING

	EWS	TWS	CWS
Conventional Approaches	2.16	2.3	2.24
Approaches using UPEM	22.68	20.30	20.47
UPEM/Conventional	10.48	9.98	9.15

V. CONCLUSIONS AND FUTURE WORK

This paper presented the Updateable Probabilistic Evacuation Modeling (UPEM) technique. The UPEM technique allows sensor observation data to be included in the problem of estimating the state of an evacuating crowd, as the data are collected. Each individual is modeled as a Newtonian particle which interacts with obstacles, such as walls and other individuals, to give its probabilistic motion model. The advantage of the UPEM technique is that it estimates not only the general trend of the crowd as a whole, but also the specific states of each of the evacuees in the crowd.Furthermore, an approach to cooperative autonomous searching in crowded urban emergencies was developed. A number of simulated searches in emergency evacuations highlighted the efficacy of the technique in reducing the time required to detect targets and in increasing the average safety rating by approximately one order of magnitude.

Further work remains to be done in applying the UPEM technique, incorporating actual sensor observation data and assessing the estimates against real evacuation data. Other applications of the technique will also be investigated, such as autonomous crowd guidance or evacuation assistance, or for assisting humans teleoperating robots in crowded urban emergencies.

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