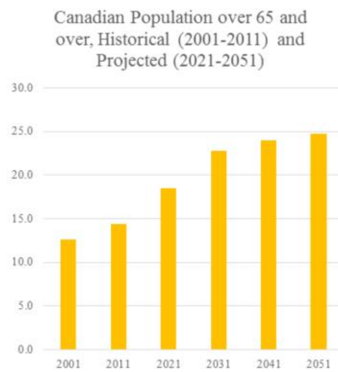
Welcome and thank you..

Motivation

- Canada's elderly demographic is rapidly growing – 25% by 2051.
- Advancements in home care and assisted living enable aging-in-place.
- Preferred by elderly demographic and reduces load on healthcare infrastructure.
- Aging in place requires ability to perform Independent Activities of Daily Living (IADLs):
    - Housework
    - Meal Preparation
    - Shopping
    - Managing money
    - Transportation



S. D. C. Government of Canada, "Canadians in Context - Population Size and Growth / Indicators of Well-being in Canada," Sep. 2006.

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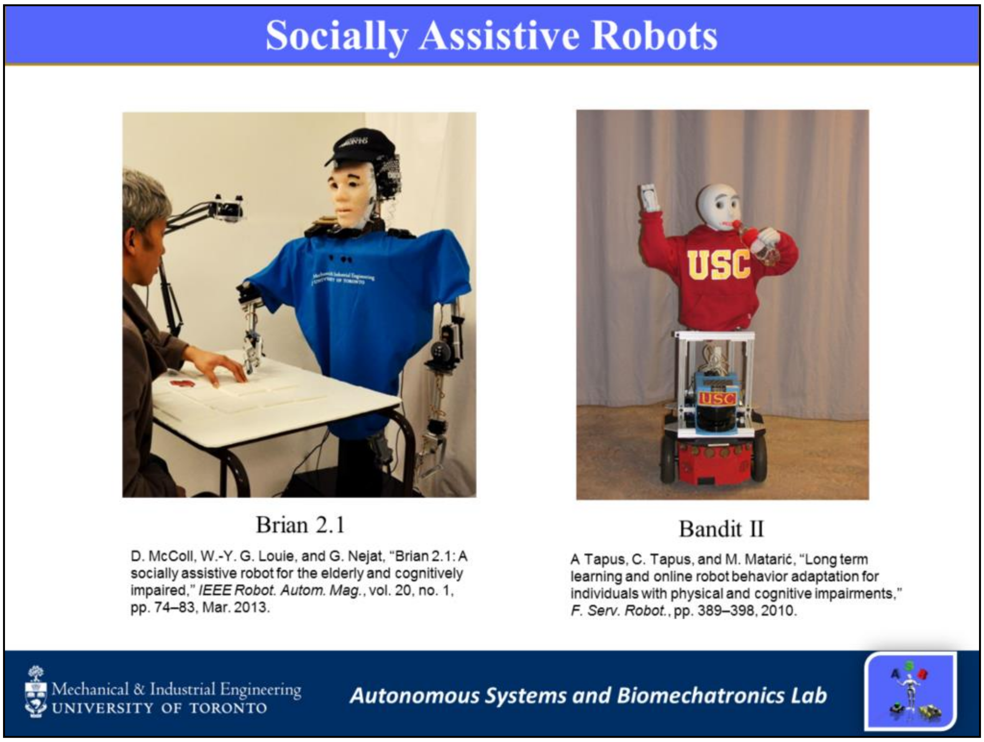
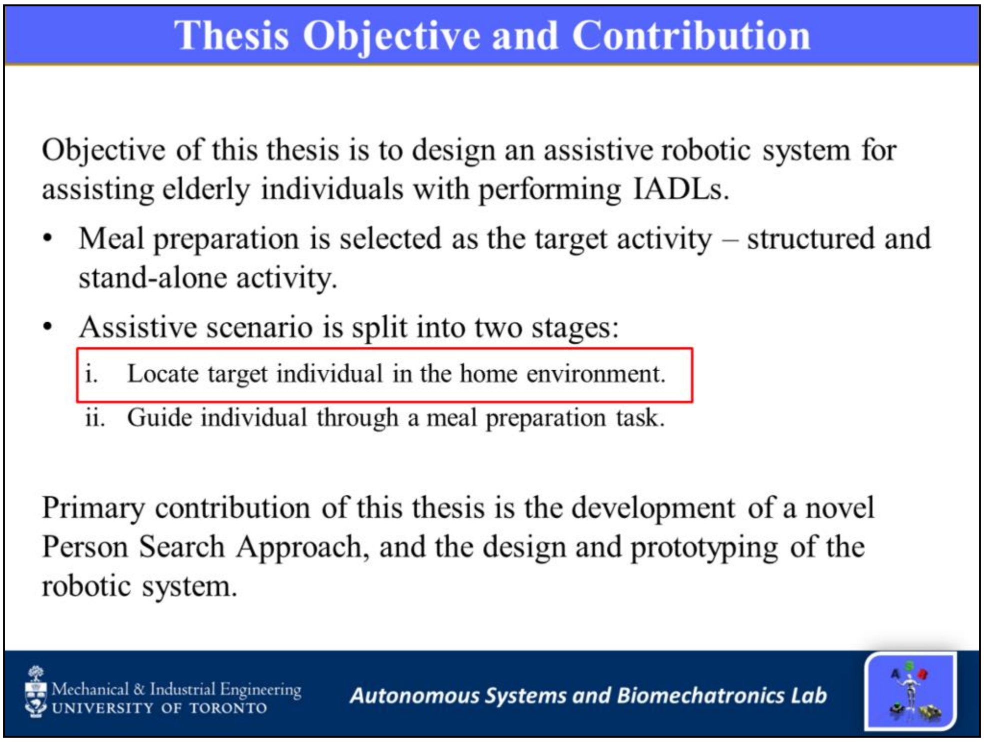
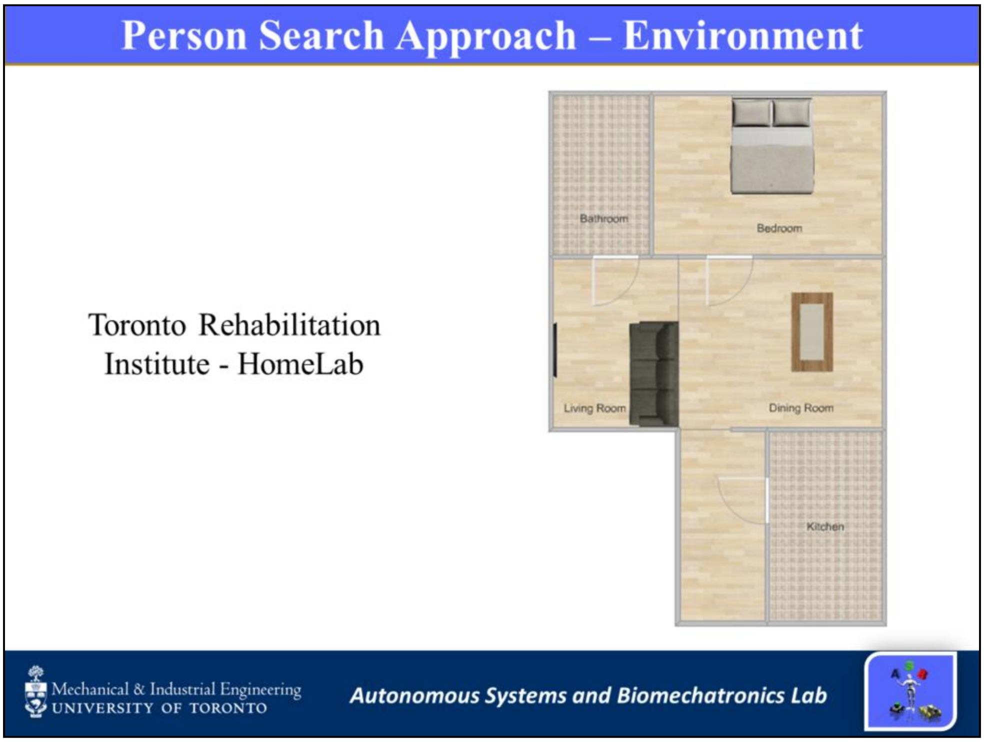
- The motivation for this work is Canada's rapidly growing elderly demographic, going to comprise 25% of Canada's population by 2051.
- A popular approach to reducing the load on healthcare infrastructure is to enable aging in place, by using new technology to help elderly individuals maintain independent function.
- This ability to function independently is often broken down into several discrete components called Independent Activities of Daily Living (IADLs)



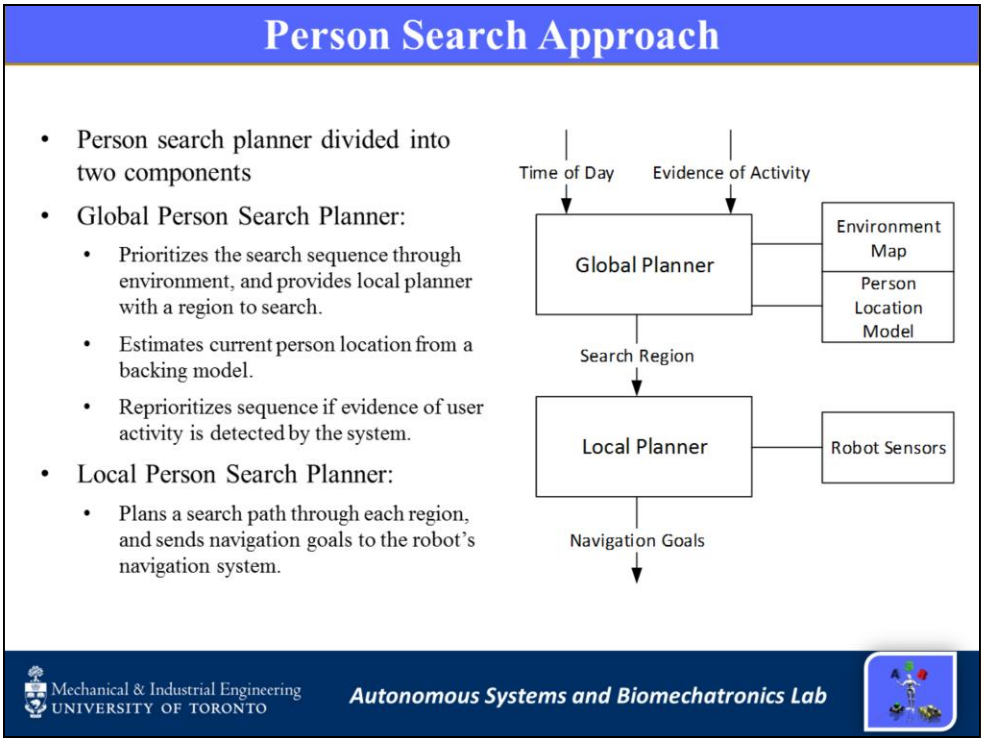
- One approach to enabling IADLs is with the help of socially assistive robots.
- Socially assistive robots use natural communication methods to engage in interaction.
- The Brian and Bandit robots are both designed to assist cognitively impaired individuals with rehabilitative and therapeutic activities.



- The objective of this work is to design an assistive robot to enable elderly individuals to perform independent activities of daily living.
- Specifically, meal preparation was chosen since it's a free-standing activity that is sequentially structured, repeatable, and occurs entirely at home.
- The actual assistive scenario is broken down in to two parts – finding the person in the target environment (their home), and then guiding the individual through the meal preparation activity.
- Primary contribution of this work is the development of a novel person search approach, and also the design and prototyping of the actual robotic system.
- I will begin by discussing the person search approach used for the first part of the scenario.

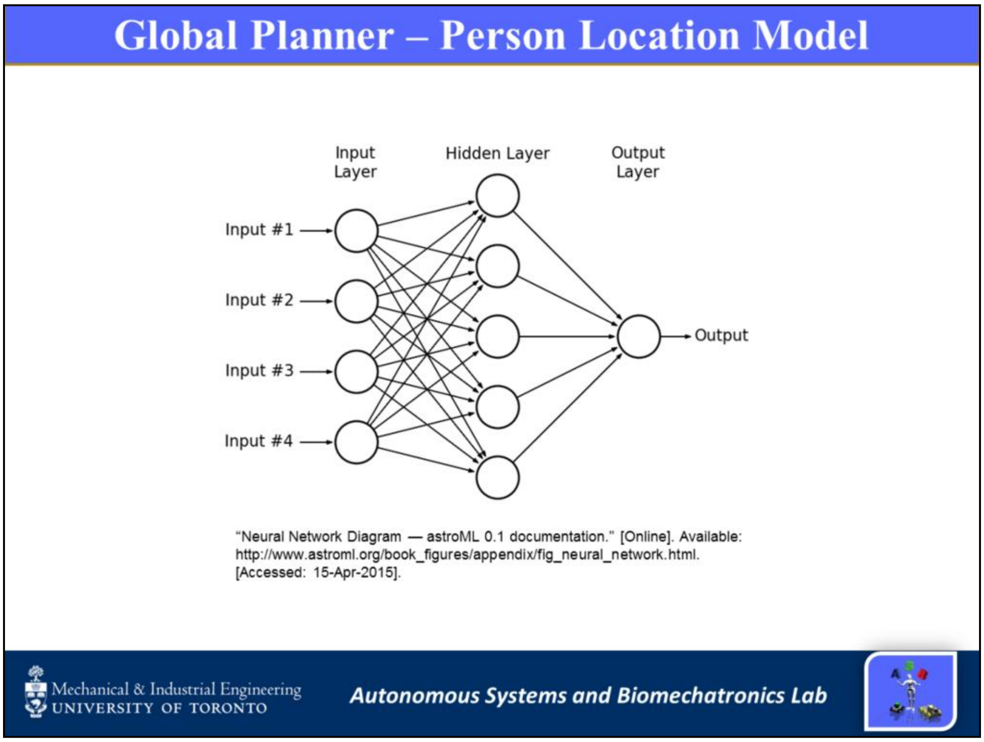


- While the person search approach has to be general and applicable to any home environment, the target environment, was the Toronto Rehabilitation Institute's Homelab.
- For the scenario, the target person would be located somewhere in this apartment. At a specific time of day, say 5 PM, the robot would be required to find the person before starting the meal preparation activity.
- One way to do this would be to search the environment randomly, however our goal was to develop an approach to search intelligently based on patterns in person location and behaviour.
- An important restriction here is that the robot's sensors had to be self-contained, unlike other approaches to this problem that embedded sensors throughout the environment.

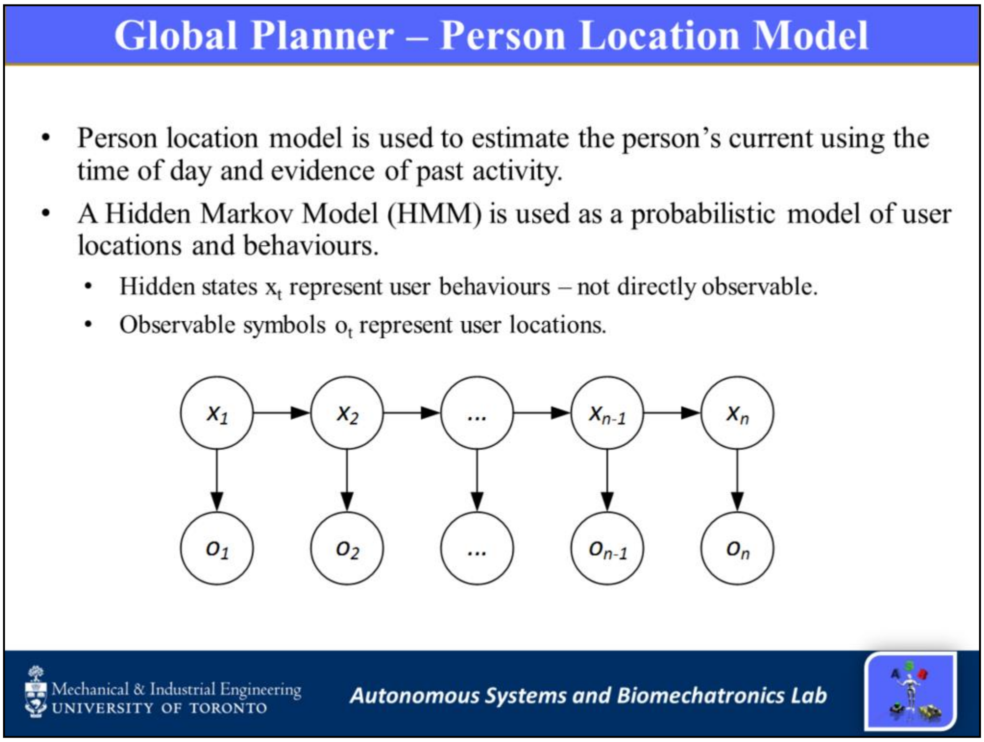


The person search planner is split into two components.

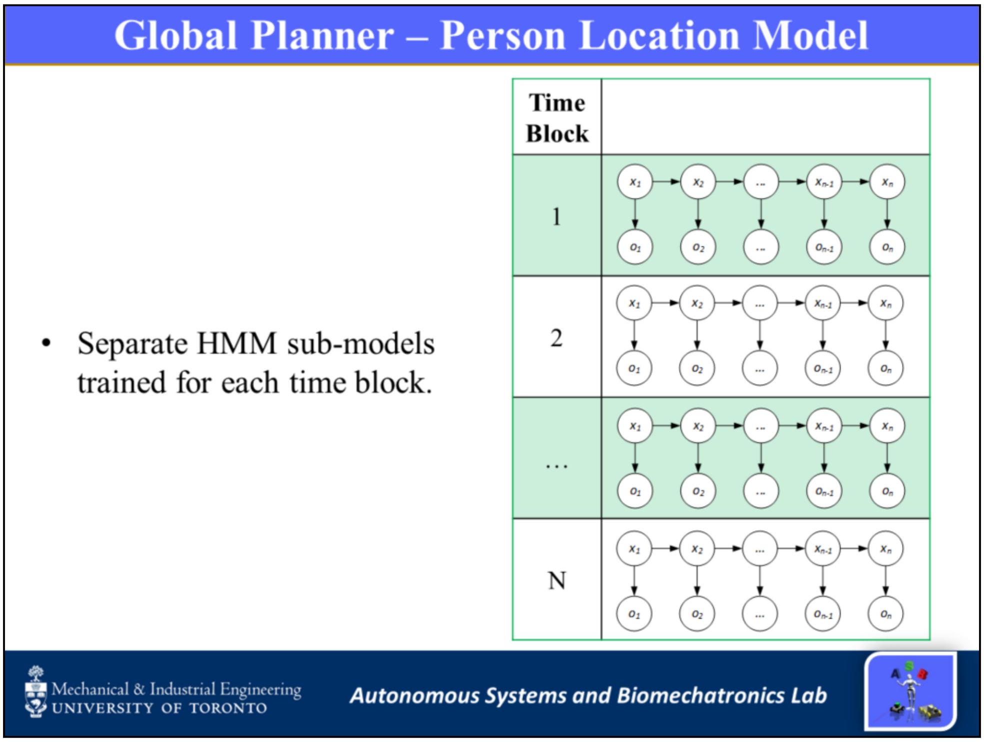
- The global search planner has access to a person location model, and a map of the environment separated into sub-regions.
- It queries the model to estimate the person's current location, and then prioritizes the order in which sub-regions are searched.
- The local search planner receives the current search sub-region from the global planner,
- and is responsible for actually planning the robot's search path.
- An important feature of this model structure is the addition of 'evidence of activity' as an input to the global planner.
- Essentially, if during the search process the robot finds information in the environment about a person's recent activity, such as 'dirty dishes in the sink',
- This can be fed back into the global planner and used to update the search priority.



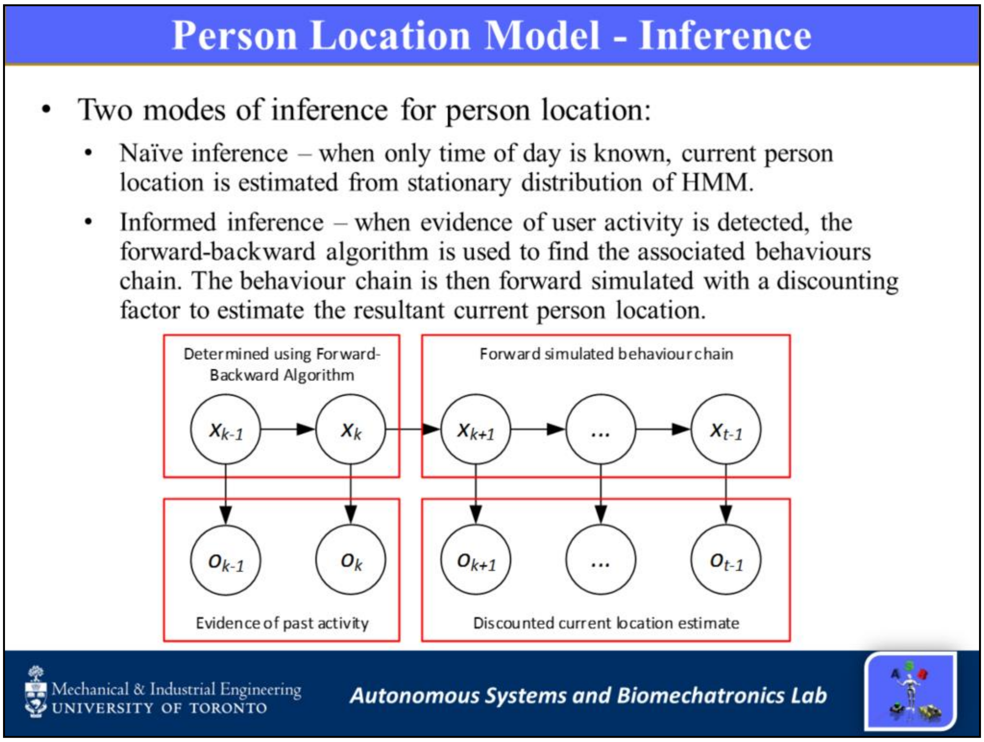
- The key differentiating component of many high level person search planners is the backing person location model.
- Some approaches use non-parametric models, such as neural networks,
- and train exclusively on sequences of location to predict the 'next' location in a new sequence.
- Since person location patterns are not static throughout the day, some models include an additional input dimension for time –
- these models can be classified as time-aware.
- Yet another group of models incorporates person behaviour into their structure – for example using Bayesian networks to determine associations between location and behaviour – these models are classified as behavior aware.
- The goal of our approach is to make the model structure explicitly both time- and behaviour-aware.



- To this end, A Hidden Markov Model (HMM) is used to model sequences in person behaviour and location, which is in essence a very simple Dynamic Bayesian Netowrk
- The hidden states x represent behaviour sequences, which cannot be directly observed by a robotic system.
- The observable symbols o represent person locations.
- It's important to note that in this model, neighbouring locations are conditionally independent given the backing behaviour sequence.
- An alternative model structure could be fully connected, however this drastically increases the training and inference complexity, as well as the amount of training data required.

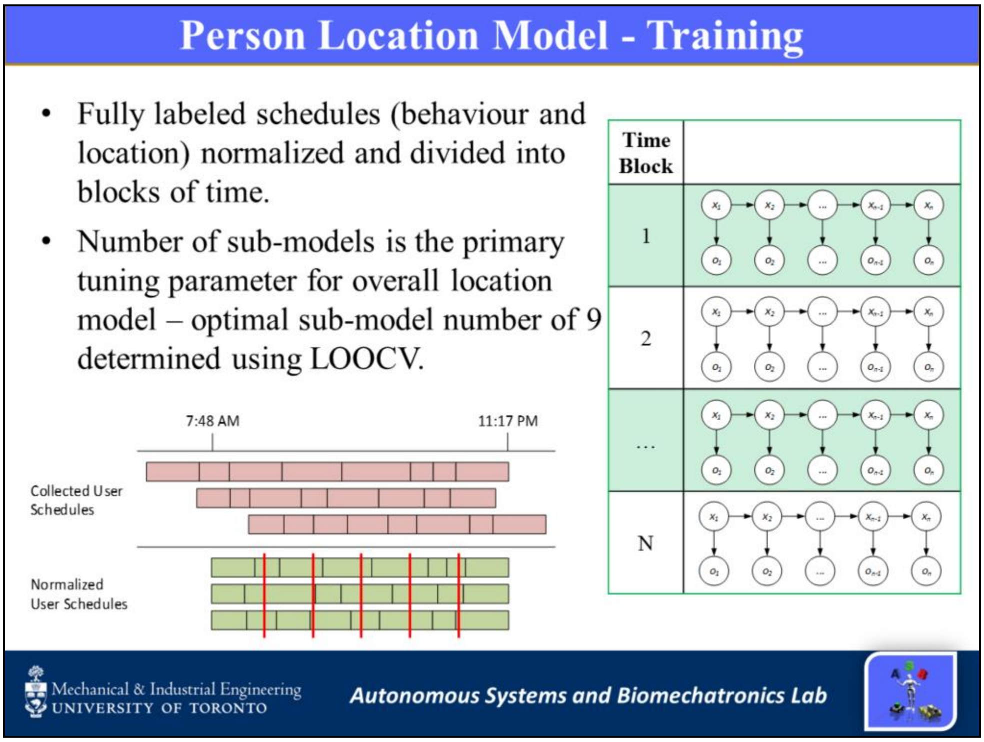


The time-aware component is achieved by having several discrete HMM sub-models, each one active at a certain time of day.

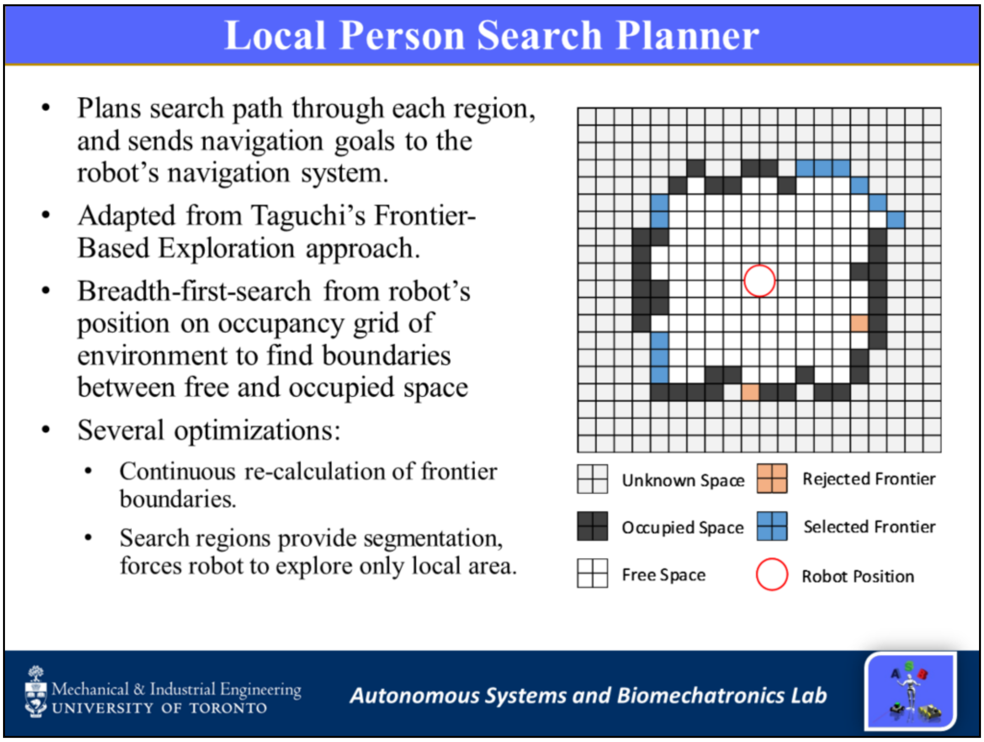


This model structure allows two modes of inference:

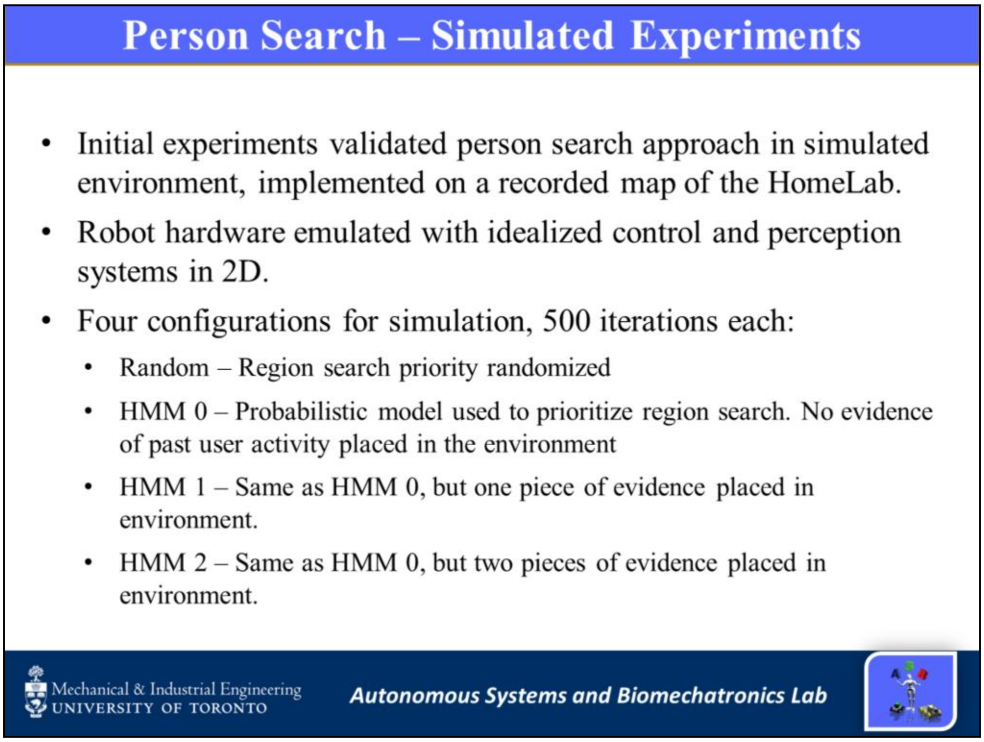
- The naïve inference method is used when time of day is the only input into the global planner, and estimates the person location directly from the stationary distribution of the markov chain representing behaviour.
- When evidence of past activity is available, such as dirty dishes in the sink indicating to the robot that the person was recently in the kitchen, the informed inference method uses the forward backward algorithm to determine the likely backing behaviour chain, which is then forward simulated with discounting, to obtain an aggregate location estimate.



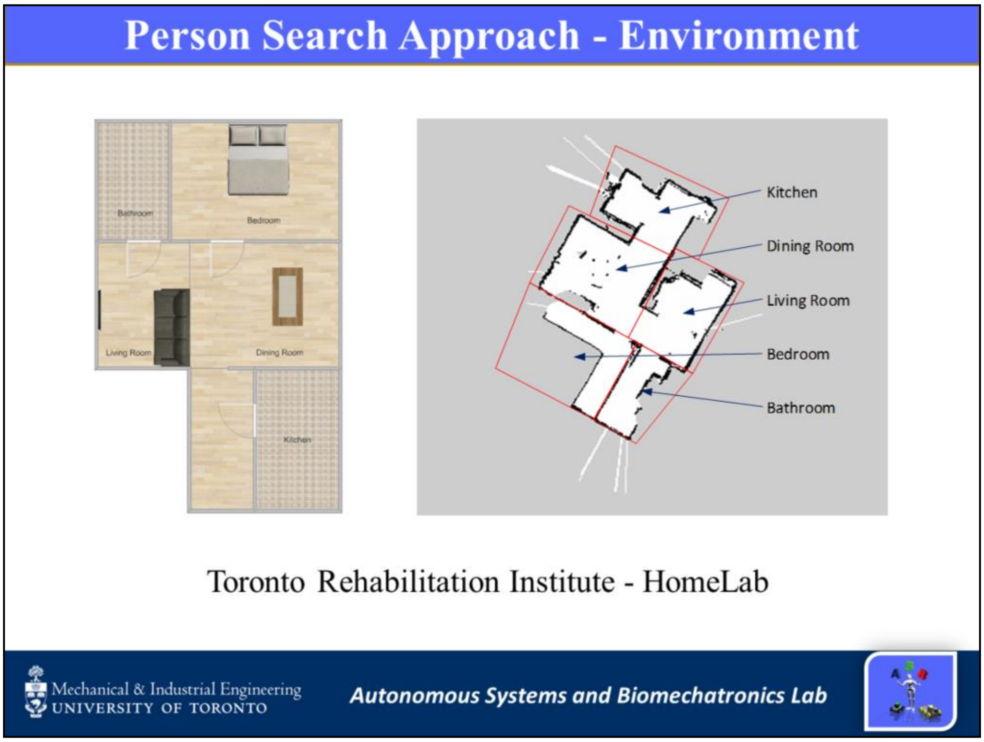
- To train the model, we collected sample user schedules, normalized them, and separated into time blocks to train each HMM sub-model.
- The sampled schedules were fully labeled with both behaviour and location information, such as ‘cooking in the kitchen’, which allowed us to train the model in a supervised fashion using MLE, which in this case is essentially frequency counting.
- The number of sub-models was empirically determined during model training using leave one out cross validation (LOOCV).
- The model is trained on all-but-one user schedule, and it’s generalization ability is checked against the holdout schedule. The highest generalization measure was found when the using nine sub-models.



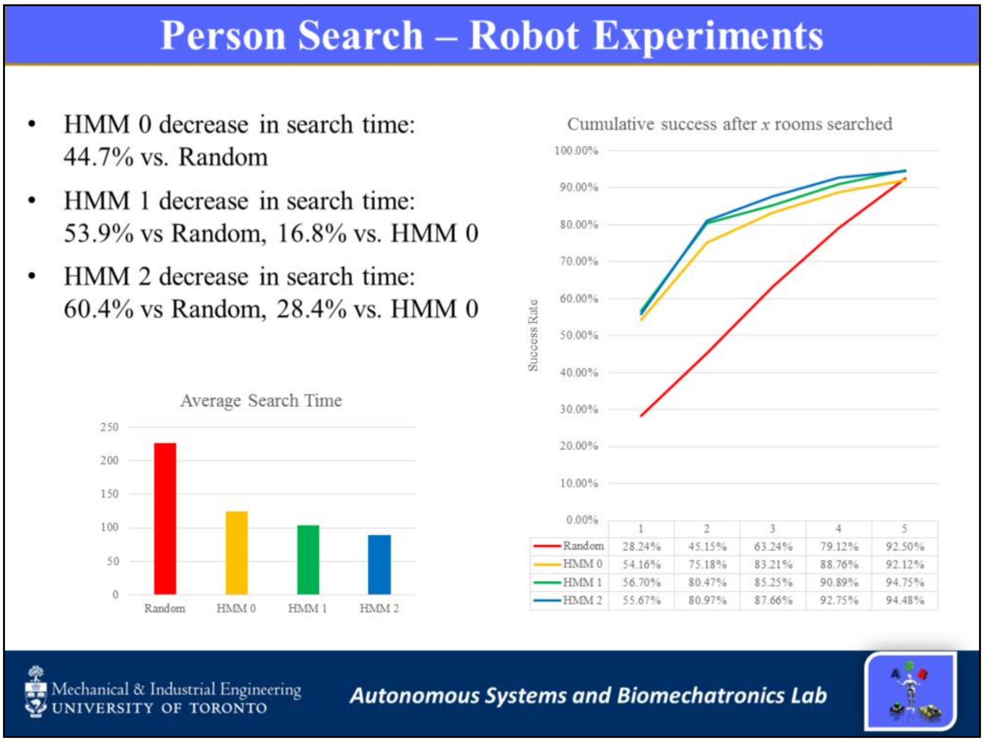
- The local person search planner is responsible for actually planning the search path through each sub-region.
- This is done using a Frontier-Based Exploration approach on an occupancy grid of the region.
- In essence it's a breadth first search from the robot's position, to find the closest frontier, which is a boundary between free and occupied space.



- To perform an initial evaluation of the person search approach, we used a simulator which modeled the HomeLab as a 2D environment.
- We performed 500 iterations of 4 different planner configurations:
    - The baseline planner uses a random search prioritization
    - The HMM 0 planner configuration had no evidence of user activity available in the environment, which means it's using only the naïve inference method.
    - The HMM 1 configuration enables the informed inference approach with 1 piece of evidence in the environment, of the person's last location.
    - And HMM 2 configuration has 2 pieces of evidence, of the person's last 2 locations.

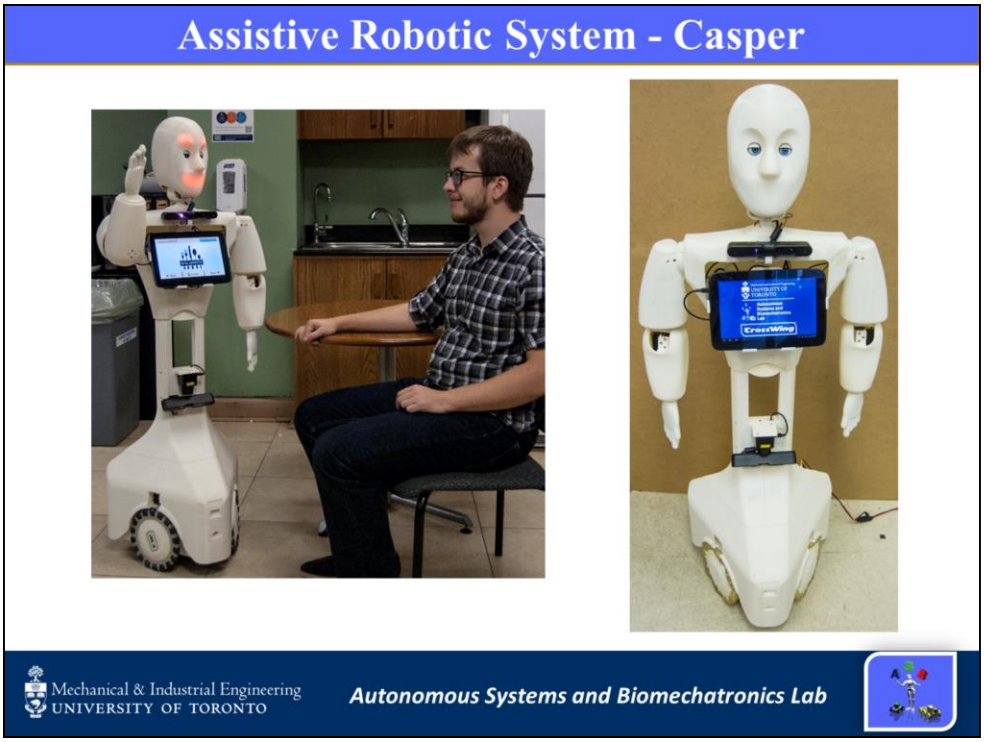


- Here you see a real navigable map of the Homelab created by the robot using a SLAM approach. The map is manually divided into segments based on the semantic room definitions.
- This same map is used to create the simulation environment.
- Prior to each simulation trial, a simulated person would be placed in the 2D environment, and the robot simulator would be given a goal to find the person.

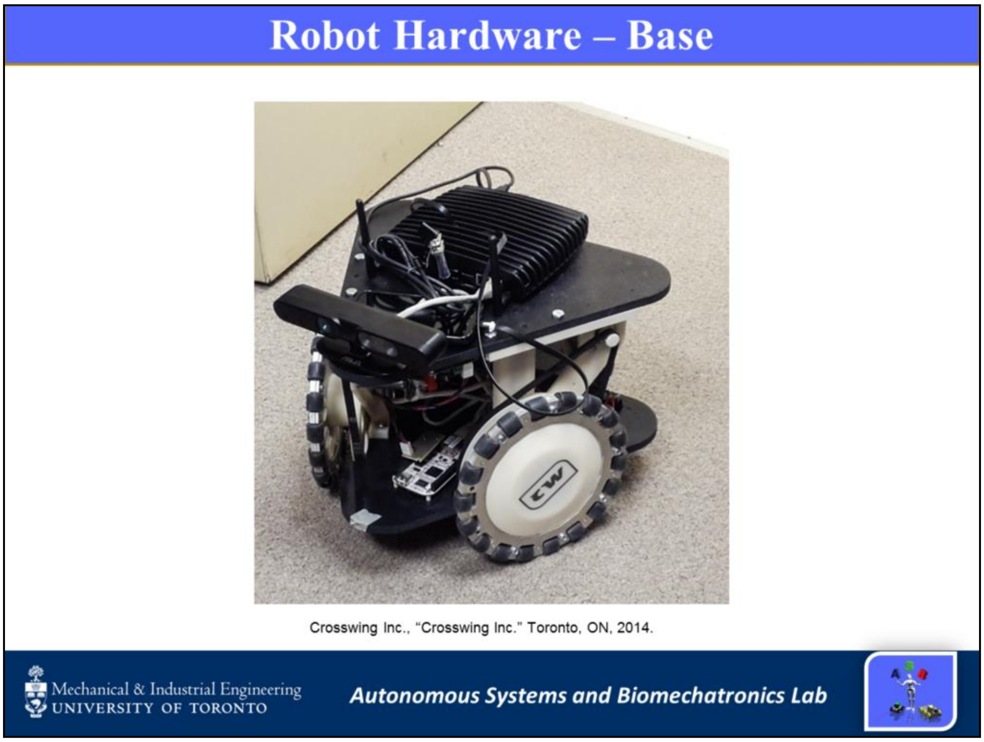


	1	2	3	4	5
Random	28.24%	45.15%	63.24%	79.12%	92.50%
HMM 0	54.16%	75.18%	83.21%	88.76%	92.12%
HMM 1	56.70%	80.47%	85.25%	90.89%	94.75%
HMM 2	55.67%	80.97%	87.66%	92.75%	94.48%

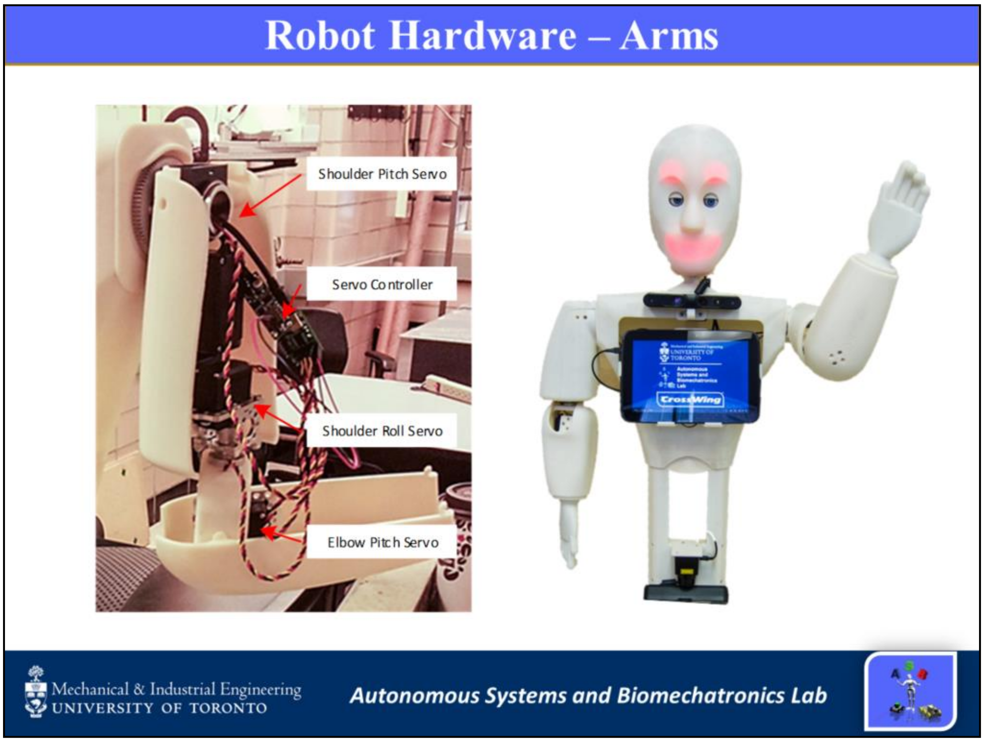
- Here you can see the results of each scenario
- A large improvement is immediately achieved when using the naïve inference method, and additional benefits are captured when incorporating evidence of user activity using the informed inference approach.
- To test this approach with a real robot, as well as implement the second part of the scenario, which is the assistive activity, we had to actually design and prototype the assistive robotic platform.



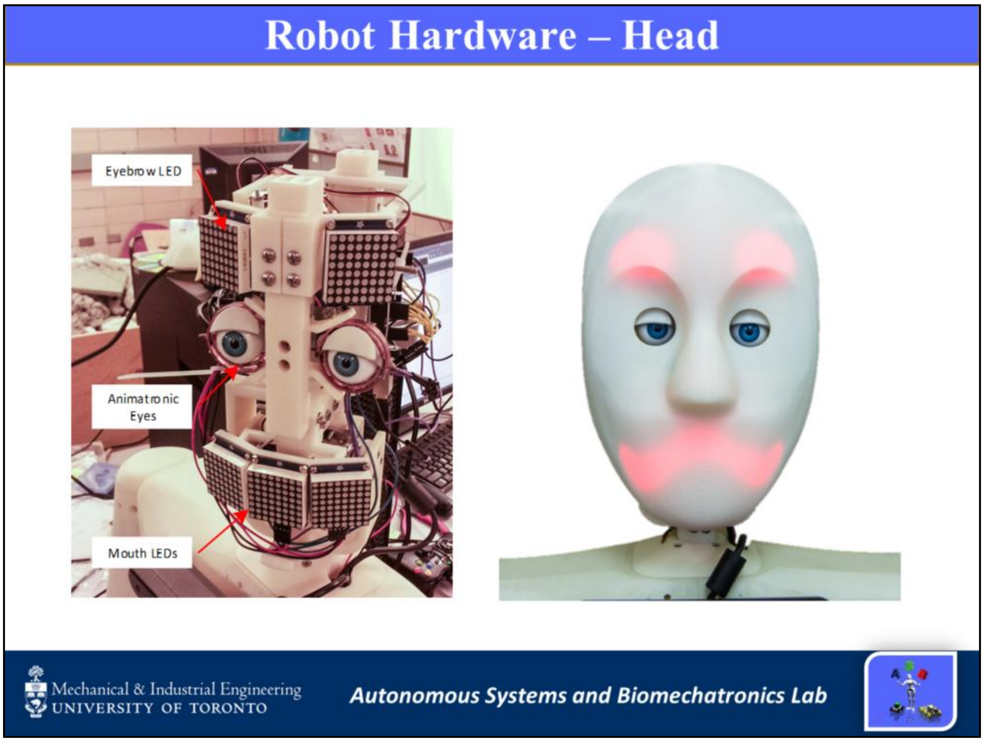
- Here you can see the final result, the Casper robot
- Constructed primarily from 3D printed materials and off the shelf electronic components
- Software created using ROS framework, which manages complexity by composing the robot software from an interconnected set of individual nodes
- ROS also allowed for easy integration with existing software for mobile robot control and navigation.



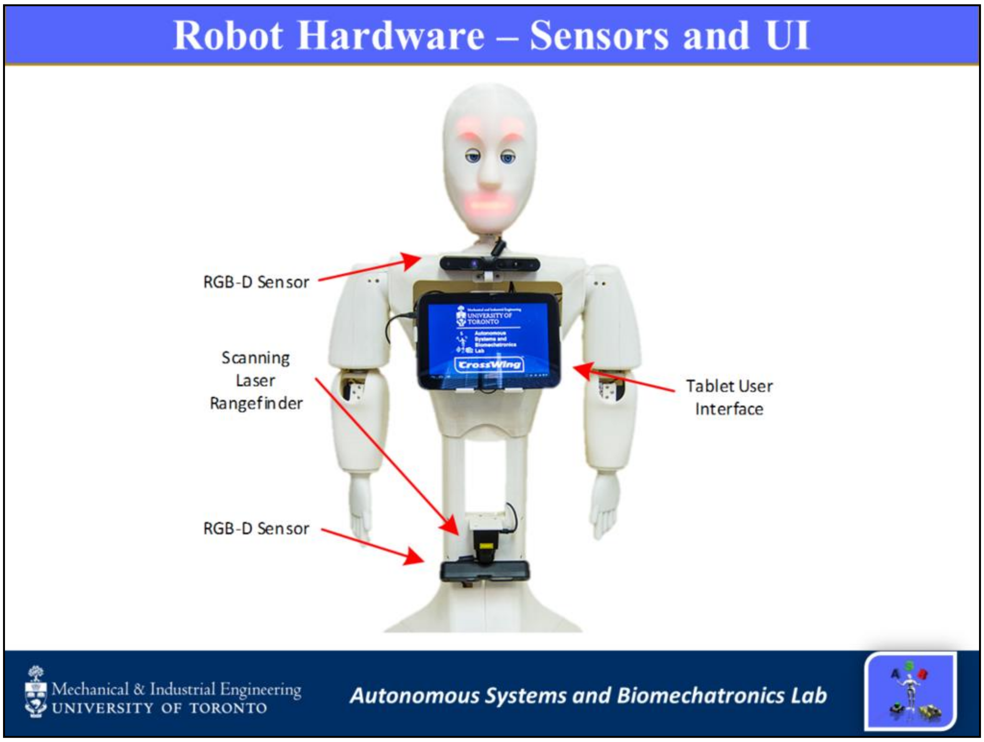
- This is an image of the robot's base, with an experimental sensor configuration used for navigation testing
- Provided by our industrial sponsor Crosswing Inc
- Fully holonomic thanks to the omniwheel configuration, which makes more agile:
    - Follow complex curved paths
    - Exit unexpected dead ends



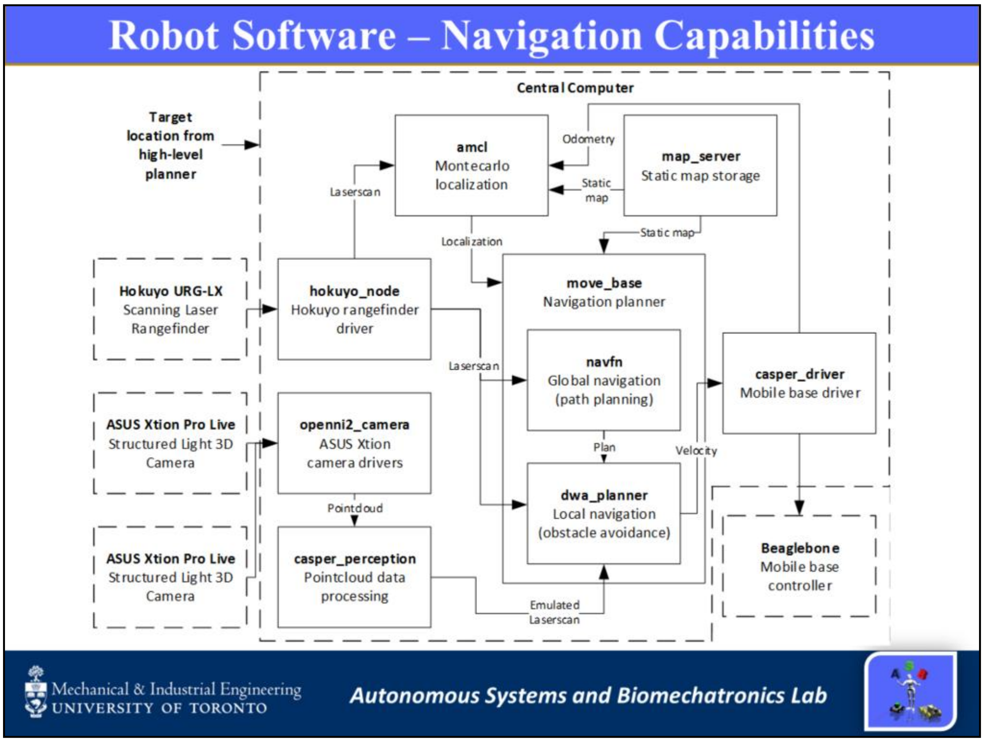
- The robot's arms were designed in collaboration with several students in the lab, I worked on generating the overall form-factor, as well as the control integration and motion planning.
- The arms are 3 DOF and non-contact, designed specifically to perform a set of gestures:
    - waving, pointing at objects in the environment, hand-talking during conversation



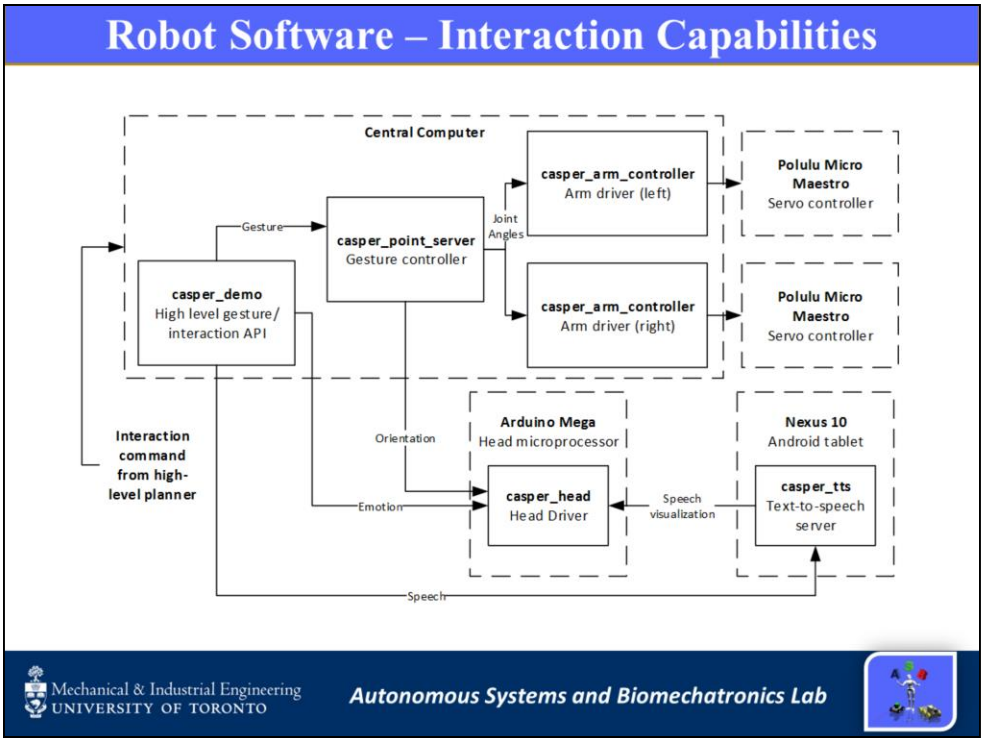
- The head was also designed in collaboration with another student in the lab. I worked on the initial mechanical design and the software integration.
- A set of LED matrices are used to output an emotional state for the robot, and the animatronic eyes are used to supplement the robot's gestures and emotions.



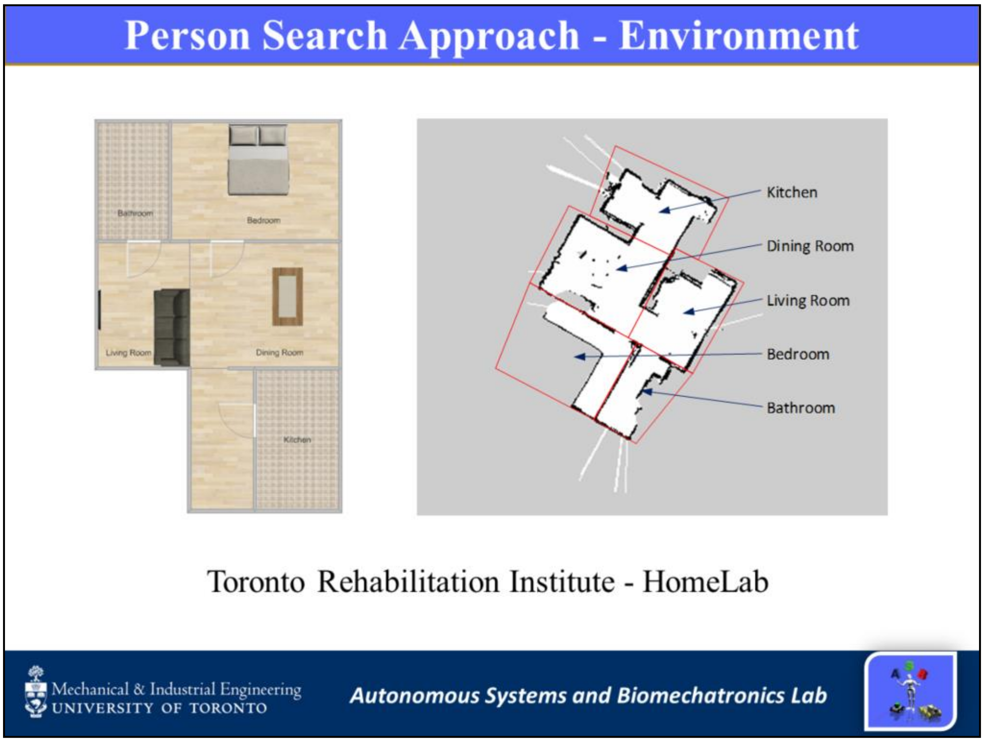
- Here you can see the tablet used for the user interface and text to speech, as well as the final sensor configuration.
- The sensors consist of two ASUS Xtion RGB-D cameras, and one Hokuyo URG scanning laser rangefinder. The rangefinder is primarily used for mapping, localization, and navigation, while the RGB-D cameras are used for local obstacle avoidance and person detection.



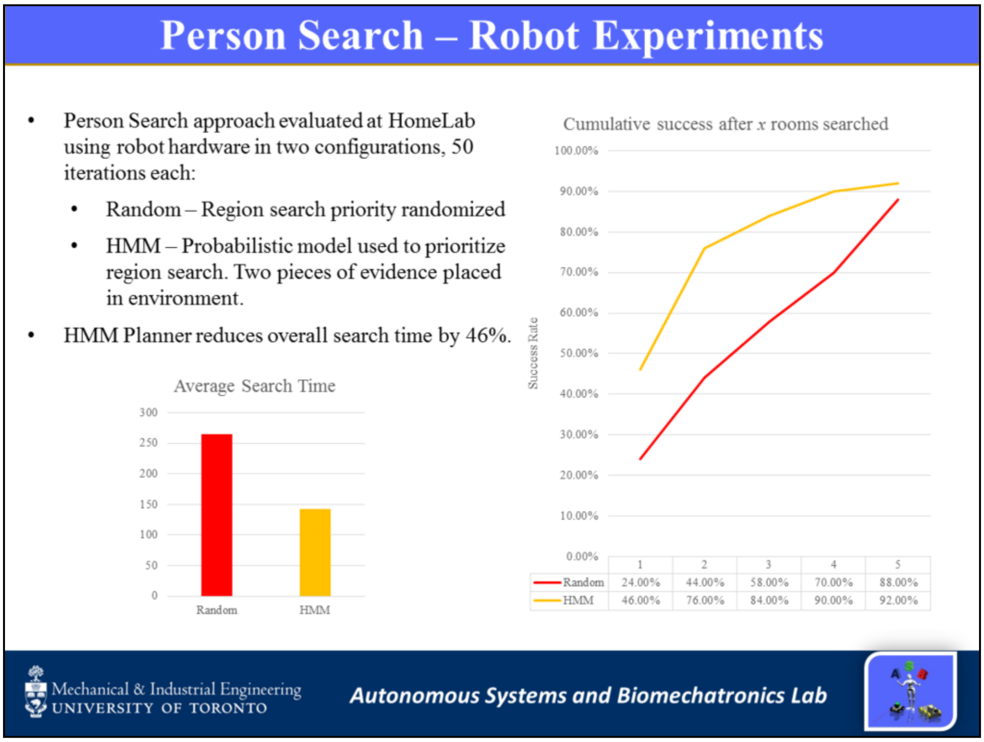
- The robot is capable of navigating autonomously when given a navigation goal.
- Here you can see a flowchart of the software modules used.



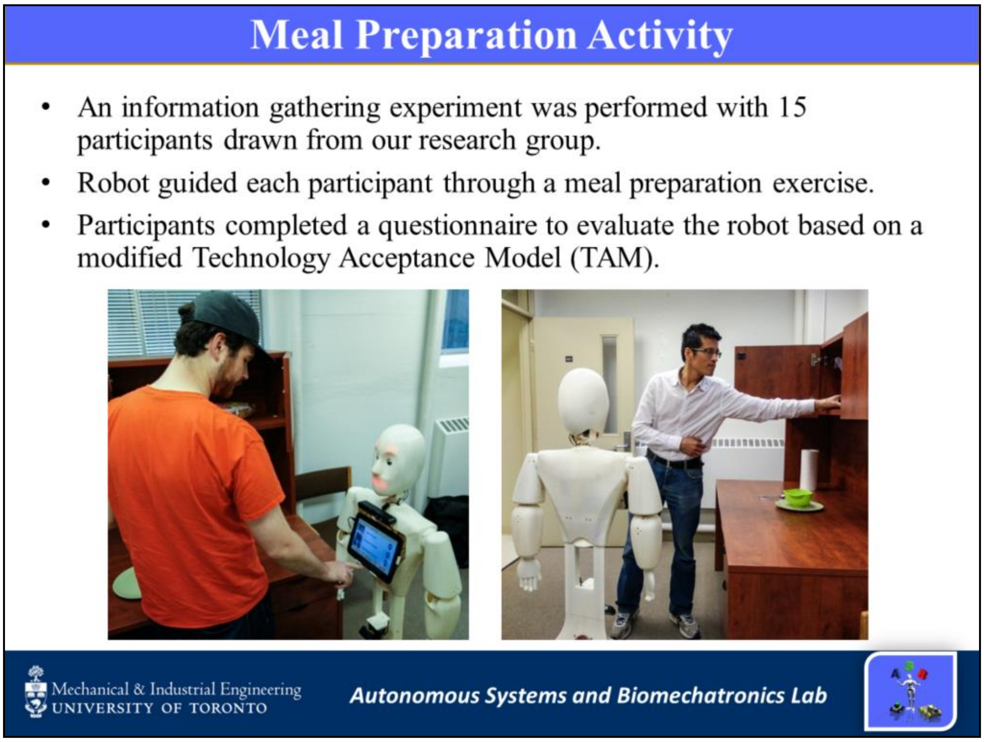
- This is a flowchart of the robot's interaction library, which is used to trigger speech, gestures, and emotional display.



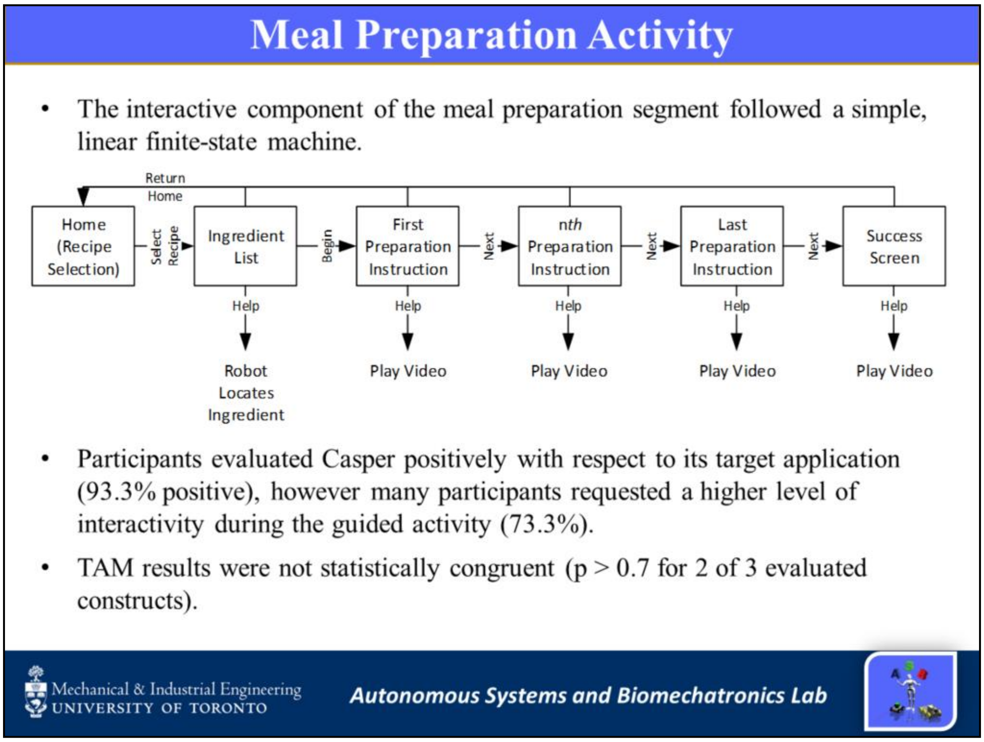
- The person search approach was tested at the HomeLab with the Casper robot.
- Similar to simulation, prior to each trial, a person is placed somewhere in the environment, and the robot is asked to find them given the appropr



- The experiments were run in two configurations
- One configuration with the random priority search planner as before, and one with the full HMM planner, including two pieces of evidence in the environment.
- For these trials, a QR code recognition module was used to enable the robot to detect people and evidence.



- To evaluate the interactive components of the robot’s design, we ran an information gathering experiment with fifteen participants for our research group
- Using an office as a substitute kitchen, the robot would lead a person into the room, and guide them through a meal preparation exercise.
- Participants then completed a questionnaire, which consisted of general purpose questions, as well as questions designed to evaluate constructs from the Technology Acceptance Model
- Here, we specifically wanted to determine how Perceived Ease of Use, Perceived Enjoyment, and Perceived Usefulness metrics of the model related to the Behavioural Intent to Use of the participants.



- The meal preparation activity itself followed a very simple linear finite state machine, where each state of the activity had an associated ‘help’ action.
- Depending on the context, when asked for help, the robot would either point out an ingredient’s location, or play a video of the preparation step,
- Overall the participants evaluated Casper very positively, however many responded that the activity was too static and non-interactive
- The TAM portion of the experiment failed to yield any statistically relevant results.

Conclusions

Objective of this thesis is to design an assistive robotic system for assisting elderly individuals with performing IADLs.

Summary of contributions:

- Developed a novel person search approach, using a time- and behaviour aware HMM with two inference modes.
- Prototyped an assistive robotic system (Casper) to integrate the person search approach, and perform a guided meal preparation activity.
- Performance evaluation of person search approach in simulation and on the real robot
- Experimental evaluation of Casper's interactive capability.

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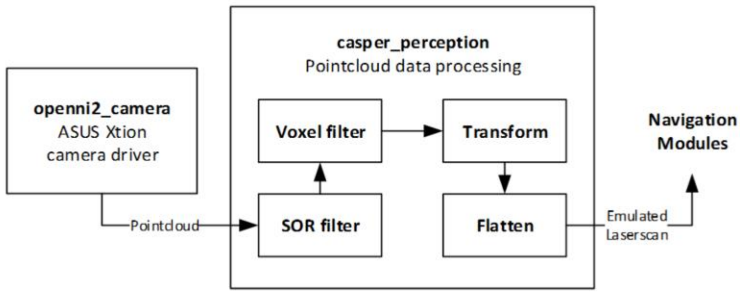
To reiterate…

Thank you

Robot Software – Point Cloud Processing



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Person Location Model - Equations

Model

$$P(x_t = j | x_{t-1} = i) = T_{ij} \qquad x_t = T x_{t-1}$$

$$P(o_t = j | x_t = i) = E_{ij} \qquad o_t = E x_t$$

Training

$$T_{ij} = \frac{\sum_{n=1}^{t-1} \left(\delta(\pi_n, X_i) \delta(\pi_{n+1}, X_j) \right) + 1}{\sum_{n=1}^{t-1} \delta(\pi_n, X_i) + |X|}$$

$$E_{ij} = \frac{\sum_{n=1}^{t} \left(\delta(\pi_n, X_i) \delta(\varphi_n, O_j) \right) + 1}{\sum_{n=1}^{t} \delta(\pi_n, X_i) + |O|}$$

Person Location Model - Equations

Naïve Inference

$$\alpha T = \alpha \qquad \lim_{n\to\infty} UT^n = \alpha$$

$$o^* = E\alpha$$

Informed Inference

$$P(x_k|o_{1:t-1}) = \frac{P(x_k, o_{1:k})P(o_{k+1:t-1}|x_k)}{P(\ o_{1:t-1})} \quad = c^{-1}\alpha_k\beta_k$$

$$o^* = \lim_{n\to\infty}\sum_{i=0}^{n} E(1-\gamma)^i T^i x_t$$

Frontier Search - Algorithm

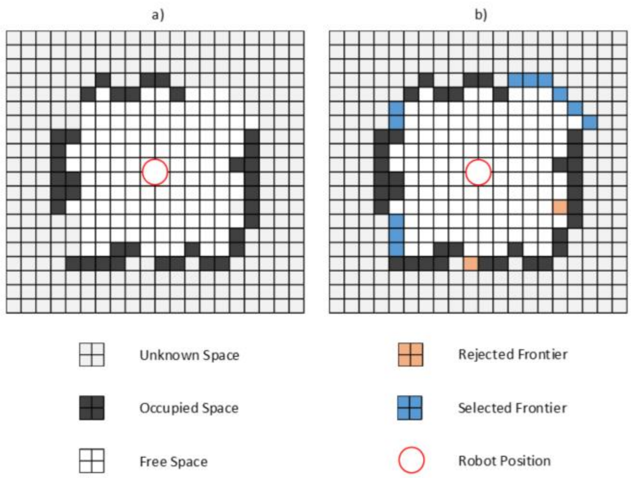

Figure 1: a) Initial gridmap, b) Clustered and filtered frontiers

Frontier Search - Algorithm

function breadth-first-search
(position P, grid G, free F, unknown U)

$Let\ Q = \{P\}$
$Let\ U = \{\}$
$while\ (Q \neq \{\})$
  $Let\ C = Q_1$
  $Q = Q - \{C\}$
  $foreach\ X \in (C_{n4} \cap \mathrm{G})$
    $if\ X \in F \rightarrow Q = Q + \{C\}$
    $if\ X \in U \rightarrow U_R = U_R + \{C\}$
$return\ U_R$

function cluster-frontiers(cells U_R, grid G)

$Let\ F = \{\}$
$while (U \neq \{\})$
  $Let\ X = \{\}$
  $Let\ Q = U_1$
  $while\ (Q \neq \{\})$
    $Let\ C = Q_1$
    $Q = Q - \{C\}$
    $X = X + C_{n8} \cap \mathrm{U}$
    $U = U - C_{n8} \cap \mathrm{U}$
  $if\ |X| > 1 \rightarrow F = F + \{X\}$
$return\ F$

function get-goal(position P, frontiers F)

$Let\ D_{min} = \infty$
$foreach\ X \in \mathrm{F}$
  $Let\ D = distance(X_{mid}, P)$
  $if\ D < D_{min} \rightarrow$
    $min = D$
    $Let\ G = X_{mid}$
$return\ G$

a) b)

Figure 1: a) 4-connected neighbourhood b) 8-connected neighbourhood

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Person Search – Result Tables

Simulated – Evidence Detection Rate 100%

Scenario	Success after x rooms searched					Total Trials	Average Time (s)	Evidence per Trial
	1	2	3	4	5			
Random	28.24%	45.15%	63.24%	79.12%	92.50%	500	225.98	-
HMM 0	54.16%	75.18%	83.21%	88.76%	92.12%	500	124.93	-
HMM 1	56.70%	80.47%	85.25%	90.89%	94.75%	500	103.97	0.63
HMM 2	55.67%	80.97%	87.66%	92.75%	94.48%	500	89.49	0.88

Simulated – Evidence Detection Rate 80%

Scenario	Success after x rooms searched					Total Trials	Average Time (s)	Evidence per Trial
	1	2	3	4	5			
HMM 1	57.56%	79.04%	83.63%	90.94%	93.46%	500	109.69	0.51
HMM 2	55.35%	80.22%	86.81%	91.60%	94.65%	500	95.20	0.69

Robot – Estimated Evidence Detection Rate 84.2%

Scenario	Success after x rooms searched					Total Trials	Average Time (s)	Evidence per Trial
	1	2	3	4	5			
Random	24.0%	44.0%	58.0%	70.0%	88.0%	50	264.03	-
HMM	46.0%	76.0%	84.0%	90.0%	92.0%	50	141.72	0.73