Using Features at Multiple Temporal and Spatial Resolutions to Predict Human Behavior in Real Time

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Abstract. When performing complex tasks, humans naturally reason at multiple temporal and spatial resolutions simultaneously. We contend that for an artificially intelligent agent to effectively model human teammates, i.e., demonstrate computational theory of mind (ToM), it should do the same. In this paper, we present an approach for integrating high and low-resolution spatial and temporal information to predict human behavior in real time and evaluate it on data collected from human subjects performing simulated urban search and rescue (USAR) missions in a Minecraft-based environment. Our model composes neural networks for high and low-resolution feature extraction with a neural network for behavior prediction, with all three networks trained simultaneously. The high-resolution extractor encodes dynamically changing goals robustly by taking as input the Manhattan distance difference between the humans' Minecraft avatars and candidate goals in the environment for the latest few actions, computed from a high-resolution gridworld representation. In contrast, the low-resolution extractor encodes participants' historical behavior using a historical state matrix computed from a low-resolution graph representation. Through supervised learning, our model acquires a robust prior for human behavior prediction, and can effectively deal with long-term observations. Our experimental results demonstrate that our method significantly improves prediction accuracy compared to approaches that only use high-resolution information.

Keywords: Theory of Mind · Urban search and rescue · Neural networks.

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1 Introduction

Artificially intelligent (AI) teammates should have a number of capabilities to be effective [1], including inferring the internal states of other agents [2,4], solving problems collaboratively with them [5,7], and communicating with them in a socially-aware manner [8,9]. While these capabilities have been developed to some extent for simple domains (e.g., 2D gridworlds) and simulated agents, current state of the art approaches still face significant challenges when it comes to dealing with complex domains and modeling actual human teammates (as opposed to simulated agents). We attempt to address some of these challenges in the context of an experiment involving humans conducting a simulated urban search and rescue (USAR) mission set in a Minecraft-based environment [10].

This domain is significantly more complex than the domains previously studied in the literature on computational theory of mind (ToM) [2,3]. Enabling AI agents to understand human behavior in complex domains will be essential to achieve the goal of better human-AI teaming. The complexity of the domain and the emphasis on analyzing human subjects lead to a few unique challenges, which we describe below.

- **Limited data.** Since collecting human subjects data is expensive and time-consuming, the amount of training data available to us is very limited. This rules out using certain classes of modern machine learning approaches (e.g., transformer architectures) that require a large amount of training data.

- **Noisy data.** Human subjects data is typically noisy, especially in the short term, with participants frequently violating assumptions of rationality that are used in existing works on computational ToM [2,3,11]. This expresses the need for a two resolution approach as rationality can often be recovered when the domain is represented at a lower resolution and the noise is averaged over, yet the high resolution is required for real-time predictions.

- **Long horizon.** In contrast to earlier works on computational ToM [2,3,11] that study domains with $\approx 10^2$ primitive actions per episode, our work considers a domain with episodes containing $\approx 10^3$ primitive actions and a far larger observation space including more than 20 areas and complex connectivity. This requires us to implement a long-term memory mechanism and the ability to extract key features from large amounts of noisy data, both of which are challenging in their own right.

- **Complex dynamics.** Our domain is large and possesses a complex topological structure, coupled with a complex rescue mechanism setting (for details, please refer to the approach section), which require us to consider human behavior at different levels of spatial and temporal granularity. Our model simultaneously takes into account both the short-term goal preference in a local area and the long-term rescue strategy.

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1 We use the term *episode* to denote a sequence of actions taken by an agent to perform a given task. We also use the term *trial* elsewhere in the paper to denote the same thing.
To address the above challenges, we propose a two-level representation. The first is a low-resolution level that contains information about the topology of the environment (i.e. which areas are connected to each other) and the status of victims in each area. The second is a high-resolution level that contains more granular information about the environment, such as the Cartesian coordinates corresponding to the agent’s current location, walls, openings, and victims inside the rooms.

For the low-resolution representation, we build a matrix that encodes key historical information, which helps our model learn high-level features of human behavior, such as long-term search and rescue strategies. In contrast, for the high-resolution representation, we organize the input vector to our proposed model based on the latest short-term observations, which are more conducive to recognizing short-term goal preferences. Using the high and low level resolutions simultaneously aligns with the way humans reason about complex tasks, and also results in better performance on our prediction tasks, compared to considering only a single resolution.

2 Related Work

There exist a number of other approaches to computational ToM in the literature. In this section, we describe some of them, along with their advantages and disadvantages compared with our approach.

Bayesian Theory of Mind (BToM) models [3,12,13] calculate the probabilities of potential goals of an agent and other’s beliefs. These models are primarily based on Markov Decision Process (MDP) formalisms and thus suffer from high computational costs for complex domains.

Zhi-Xuan et al. [11] proposed an online Bayesian goal inference algorithm based on sequential inverse plan search (SIPS). This approach allows for real-time predictions on a number of different domains. Notably, their approach models agents as boundedly rational planners, thus making them capable of executing sub-optimal plans, similar to humans. However, this approach cannot be directly applied to our domain due to the fact that our agents (i.e., humans) have incomplete knowledge of their domain and thus the short term planning would suffer without added hierarchical complexity or longer term planning. In our proposed approach, we use a similar idea of calculating the probabilities of potential goals, but we use neural networks which allow for the automatic extraction of features and correlations from the data without having to hand-craft conditional probability distributions.

Our supervised learning approach considers both long-term historical and real-time high-resolution features in a robust fashion, dramatically reducing the computational costs of training and deployment in online settings even for complex domains.

Inverse reinforcement learning (IRL) methods [14,17] make real-time predictions about an agent from learning the agent’s reward function by observing its
behavior. However, IRL methods suffer in online settings for complex domains because they are based on MDP formalisms, similar to BToM approaches [18,19].

Approaches based on plan recognition as planning (PRP), which use classical planners to predict plan likelihoods given potential goals, can also give real-time predictions for complex domains [20–25]. However, these methods require labor-intensive manual knowledge engineering, which can be prohibitive for environments that have complex dynamics. Additionally, these methods struggle with the noisy and sub-optimal nature of human behavior. In contrast, our neural network based approach requires minimal manual knowledge engineering and our two levels of resolutions allow for an effective treatment of noisy/sub-optimal behavior.

Guo et al. [26] study the same domain as the one in this paper, and use a graph-based representation for their model as well. However, they focus on transfer learning as a way to improve training when dealing with a limited amount of training data. Additionally, their agent predictions are focused on navigation. The techniques developed in their work are applicable to us and could be useful to further expand our model in the near future.

Lastly, Rabinowitz et al. [2] used meta-learning to build models of the agents from observations of their behavior alone. This resulted in a prior model for the agents’ behavior and allowed for real-time predictions. However, this approach only studied situations where the agents followed simple policies, and the dynamics of their domain are much simpler than ours.

3 Approach

3.1 Domain and task

The domain we consider is that of a USAR mission simulated in a Minecraft-based environment [10]. In this scenario, the participants must navigate an office building that has suffered structural damage and collapse due to a disaster. The original building layout is altered by the collapse, with some passages being closed off due to rubble, and new openings being created by walls collapsing.

The goal of the mission is to obtain as many points as possible by triaging victims of the building collapse within a 10-minute time limit. There are 34 victims in the building, among whom 10 are seriously injured and will expire 5 minutes into the mission. These critically injured victims take 15 seconds to triage and are worth 30 points each. These victims are represented by yellow blocks. The other victims are considered non-critically injured, take 7.5 seconds to triage, and are worth 10 points each. These victims are represented by green blocks.

Each participant conducts three versions of the mission, with different levels of difficulty (easy, medium, and hard). On higher difficulty levels, the victims are less clustered, further away from the starting point, and are more difficult to find. Higher difficulty levels also have more alterations from the original static map that the participants are provided at the beginning of the mission (i.e., more blockages and openings).
Fig. 1. A visualization of the high-resolution representation for our domain. The red dot represents the agent (i.e., the human’s Minecraft avatar), and the grey dots represent grid cells that the agent has traversed in the past. Green and yellow squares represent untriaged victims, blue squares represent triaged victims, brown squares represent walls, and grey squares represent obstacles. Walls and obstacles are not traversable, and the blank (white) squares are walkable areas.

3.2 Representation

High-Resolution Representation We use a highly simplified 2D gridworld environment representation for the high resolution representation. In this representation, we encode different objects and store them in a $51 \times 91$ integer matrix. The specific encodings are shown in Table 1.

| Object                         | Value |
|--------------------------------|-------|
| Empty                         | 0     |
| Wall                          | 4     |
| Critical victim               | 81    |
| Non-critical victim           | 82    |
| Unavailable victim (triaged or expired) | 83 |
| Obstacle                      | 255   |
| Agent                         | 0     |

In Fig. 1, we show a visualization of the high-resolution representation. Our primitive action space consists of two types of actions: move and triage. The high-resolution visualization code implementation is based on this repository: [https://gitlab.com/cmu_asist/gym_minigrid](https://gitlab.com/cmu_asist/gym_minigrid)
‘move’ action can be carried out in four directions: up, down, left, and right, moving one cell at a time when the direction of moving is not obstructed. The ‘triage’ action can only be performed when the agent reaches locations cells where victims are located.

In this high-resolution representation, we can analyze human behavior based on discrete primitive actions combined with the layout of the building, which enables modeling real-time changes in short-term goal preferences. However, these actions also introduce noise, and inference based on them alone is not conducive to extracting high-level features and organizing long-term memory due to the large number of primitive actions per trial ($\approx 10^3$).

**Low-Resolution Representation** To facilitate the extraction of high-level features from human behavior and the organization of long-term historical information, we construct a graph-based representation to simplify our domain further. The nodes of the represent areas (e.g., rooms, hallways, etc.) of the building, the edges represent connections between areas, and each node has three integer-valued attributes:

- Number of green victims in the area.
- Number of yellow victims in the area.
- Visited status. This attribute can take one of four possible values:
  - 0: The node has not been previously visited by the agent.
  - 1: The node has been previously visited by the agent.
  - 2: The agent is currently located at the node.
  - 3: The node was the previous node the agent was at.

For ‘visited status’ attribute, if two conditions are met at the same time, the higher encoding value has a higher priority. For example, if the agent returns to a previously visited room, the visited status of the current room defaults to 2 instead of 1 even though both are applicable. The visited status in the memory matrix is updated according to the above rules when the agent moves from one area to the next. In addition, when the agent successfully triages a specific type of victim, the number of victims of that type in the current area is reduced by one. Therefore, the updates to this matrix record the historical behavior of the current agent.

This is a dramatic simplification of our domain, since we ignores many details from the environment, such as the specific locations of agents and victims, the detailed layout of the building, etc. Therefore, the low-resolution representation provides a more concise encoding of crucial historical information, making it easier for the model to extract high-level features in human behavior. We organize this information into a matrix. However, the time interval for state updates is longer than that in the high-resolution representation, since we are not encoding primitive actions for this representation, and it cannot grasp real-time changes in human intentions. Figure 3 shows an example sketch of the time intervals for updates to the state in the two resolutions. In order to leverage the complementary strengths of these two resolutions, we propose a model that uses both as inputs simultaneously.
Fig. 2. Visualization of an example low resolution graph representation and the corresponding memory matrix. The nodes represent the areas in the building, and the edges the connections between them. The number and type of victims in each area are recorded as attributes on each node, and are shown using a color and number indicating the type and quantity of victims. The red node represents the node the agent is in. The matrix below the graph is the corresponding low resolution memory matrix.

| Area ID         | Yellow victims | Green victims | Visited status |
|-----------------|----------------|---------------|----------------|
| Room 101        | 1              | 0             | 0              |
| Room 102        | 0              | 2             | 1              |
| Front Yard      | 0              | 0             | 2              |
| Entryway        | 0              | 0             | 3              |
| Hallway         | 0              | 0             | 1              |
| Computer Farm   | 1              | 2             | 0              |

Fig. 3. An example sketch showing the different time intervals of state updating for the two resolutions. Each tick line indicates an update to the state, and the red dotted lines connect ticks with the same timestamp. The high resolution input is updated for every primitive action, while the low resolution input is only updated when the agent leaves a node or changes the attributes of a node (triaging a victim), hence the lesser number of ticks.
3.3 Model

Our model produces two types of outputs: (i) goals, i.e., objects/locations that the agent is trying to get to, and (ii) the next type of victim (green or yellow) that the agent will attempt to triage.

| Goal | $\Delta_{MD}$ | Likelihood |
|------|---------------|-------------|
| G1   | -5            | 0.4298      |
| G2   | 3             | 0.2075      |
| G3   | 3             | 0.1813      |
| G4   | 3             | 0.1814      |

Probability that the next victim to be triaged is yellow

$0.8994$

**Goals** The primary outputs of our model are similar to methods based on Bayesian ToM approaches [3,12,13]. We consider victims and portals connecting adjacent areas as potential goals, and aim to predict which goal the agent is currently pursuing. See Figure 4 for an example set of goals available to an agent when entering a particular room.

**Next Triaged Victim Type** In addition to predicting the probability of the agent pursuing a potential goal, we also predict the type of victim to be triaged next, which helps us identify the agent’s strategy or long term behavior. For example, we observed that some players prioritize triaging yellow victims because they are worth more points and expire sooner, while some players are more opportunistic, triaging victims in the order they appear in their field of view.
Note that the next victim to be triaged may not be in the current area that the player is in. Thus, we need to leverage information from both the high and low resolution representations to make this prediction, making it an important output that takes advantage of our multi-resolution architecture.

### 3.4 Architecture

The architecture of the model is shown in Figure 5. First, the information from the high and low resolution representations are used as inputs. The high-resolution input \( I_{hr} \) is a vector of \( \Delta_{MD} \) values, one for each goal. The low-resolution input \( I_{lr} \) is the memory matrix described earlier. The corresponding features \( e_{hr} = f_{hr}(I_{hr}) \) and \( e_{lr} = f_{lr}(I_{lr}) \) are extracted by the feature extractor networks \( f_{hr} \) and \( f_{lr} \), respectively. Then, these two features from the two different resolutions are concatenated and fed into the prediction net \( g \). The next goal and victim type to be triaged predictions \( O_{gp} \) and \( O_{vp} \) take the form of estimating the two probabilistic outputs with \( g(e_{hr}, e_{lr}) \). Since the inputs consider state differences rather than the entire state, the size of the input observation space is significantly reduced, thereby reducing the training difficulty of our deep learning model. We use a fully connected (FC) layer combined with a batch normalization layer as a basic building block for our three neural networks. The output FC layers in the prediction network \( (g(e_{lr}, e_{hr})) \) are passed through softmax and sigmoid functions to obtain the probabilities of the agent’s goal \( (O_{gp}) \) and the likelihood that the next victim is triaged \( (O_{vp}) \), respectively.
High-Resolution Input  Similar to the setting of the BToM [3], we infer the probability of pursuing a goal. As shown in Figure 4, we compute the quantity $\Delta_{\text{MD}}$, defined as follows:

$$\Delta_{\text{MD}}(g, m) = D(x^m_i, x_g) - D(x^m_f, x_g) \quad (1)$$

where $x^m_i$ and $x^m_f$ are the initial and final positions of the agent computed with respect to a window of the past $m$ ‘move’ primitive actions, $x_g$ is the location of the goal $g$ for which $\Delta_{\text{MD}}$ is being calculated, and $D(a, b)$ is the Manhattan distance between locations $a$ and $b$. We found that setting $m = 6$ to be the best fit choice, which still gives real-time predictions, while also handling some noise in the agent’s actions. See Table 4 for a comparison of results with different values of $m$.

Low-Resolution Input  As shown in Figure 2, we record the victim status and area visitation status of each area in a matrix and use it as an input to the proposed model. This input helps us extract long-term historical information to form memory and facilitate the extraction of high-level features (long term strategies) as a prior to human behavior predictions.

4 Evaluation

Our model is trained in an end-to-end manner via supervised learning using an Nvidia V100S GPU and the Adam optimization algorithm [27]. We calculate the softmax cross entropy loss for goal prediction and the binary cross entropy loss for victim type prediction. The training loss $L_{\text{total}}$ is the sum of the goal prediction loss $L_{\text{gp}}$ and the victim type loss $L_{\text{vp}}$ as seen in eq. 2, where the victim type loss weight, $W$, is given in Table 2 along with the rest of the training hyperparameters after tuning.

$$L_{\text{total}} = L_{\text{gp}} + W * L_{\text{vp}} \quad (2)$$

Figure 4 illustrates how our proposed model works. As shown in Fig. 1 in the room that the agent searched just prior to the room that it is currently in, the agent only triaged the yellow victim and left the two green victims, which hints that that the agent is likely following a strategy that prioritizes rescuing all the yellow victims first. Our model encodes this behavior as prior knowledge and predicts that the probability that the next victim to be triaged will be yellow is $\approx 0.9$.

Without a prior about the rescue strategy we may naively expect that the agent will move from G2 to G3 or G4 (i.e., to the next closest victim) with a high probability. In contrast, our model predicts that the most likely next short-term goal is the room’s exit, with a probability of $\approx 0.43$. In Figure 6 (similar to Fig. 4), the same player finally chose to leave after finding there is no yellow victims in this room. The probability of the agent returning to G1 to try and find a yellow victim to triage next can be seen to increase from about 0.90 to 0.95.
Table 2. Hyperparameters for our model training.

| Hyperparameter                        | Value |
|--------------------------------------|-------|
| Learning rate                        | 0.001 |
| Low resolution feature size          | 64    |
| High resolution feature size         | 4     |
| Hidden size for prediction net       | 64    |
| Batch size                           | 16    |
| Random seed                          | 0     |
| Victim type loss weight ($W$)        | 0.3   |

This demonstrates that our model can learn about high-level strategies that a player is following, and can also detect instantaneous changes in the short-term goals of human players.

![Diagram](image)

Fig. 6. The high resolution representation at a later time than the example shown in Fig. 4. Here we see the probabilities of the agent heading to goal G1, and that the next victim triaged will be yellow are increasing, showing that our model is correctly predicting the agent’s goals in real-time, in addition to showing our prediction at an earlier timestep was correct.
Table 3. Results for 6-fold cross-validation for our approach and two baselines based on high-resolution inputs. In the first method, we encode the high resolution input as the destination locations of the agent’s most recent six ‘move’ actions. For the second method, we concatenate the high resolution input vector $I_{hr}$ with an integer representing which area the agent is in. We find that our multi-resolution approach significantly outperforms the baselines that only use high resolution inputs.

| Model - Cross Val. | Easy Goal Acc | Easy Vic. Acc | Medium Goal Acc | Medium Vic. Acc | Hard Goal Acc | Hard Vic. Acc |
|--------------------|--------------|---------------|-----------------|-----------------|---------------|---------------|
| High Res. (Locations) | 0.6313 | 0.7060 | 0.6232 | 0.6874 | 0.6031 | 0.6838 |
| High Res. ($\Delta_{MD}$) | 0.6526 | 0.7315 | 0.6412 | 0.7037 | 0.6251 | 0.6881 |
| High + Low Res. | **0.7208** | **0.9008** | **0.7146** | **0.8803** | **0.6780** | **0.8881** |

In Table 3, we compare our multi-resolution method to two baseline approaches based solely on high-resolution information. The first baseline uses the 2D coordinates of the destination cells of the six most recent ‘move’ actions as the input. The second baseline considers the high-resolution input based on $\Delta_{MD}$ and includes only a small portion of the information from the low-resolution representation. Specifically, since the current area cannot be encoded if only $\Delta_{MD}$ is considered, we encode each area with a unique integer and append this integer to the input vector $I_{hr}$.

We have 66 trials for each difficulty level, and use a 6-fold cross-validation procedure to evaluate our model. As shown in Table 3, we see that the baseline using $\Delta_{MD}$ performs better than the baseline that uses only the past six destination cells of the agent’s ‘move’ actions, and our approach that uses both high and low resolution information outperforms both the baselines. Compared to using location information alone, using $\Delta_{MD}$ (or more specifically, a vector of $\Delta_{MD}$ values, one for each goal, i.e., $I_{hr}$) as an input can lead to better features being extracted, thus improving prediction accuracy. Our proposed method based on the combination of high and low-resolution information allows our model to effectively learn the relationship between features at multiple resolutions in the data, further improving the accuracy of behavior prediction.

We also investigated the sensitivity of our approach to the choice of the parameter $m$ (the number of moves in our window when we compute $\Delta_{MD}(m,g)$). The results are shown in Table 4. The performance of our proposed method is not overly sensitive to the number of moves, and thus we choose $m = 6$ after comprehensively considering the results for the three tasks.

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3 We do not compare with an approach based solely on low-resolution information, as it would not be sufficient to differentiate between multiple short-term goals within a single area/node

4 We evaluate the accuracy of the victim type prediction only in the first five minutes of each trial because yellow victims expire after five minutes, leaving only green victims to triage
Table 4. Results for 6-fold cross-validation for our approach in which the high resolution inputs are based on different numbers of ‘move’ actions.

| $m$ moves | Easy | Medium | Hard |
|-----------|------|--------|------|
| 3         | 0.7181 | 0.9037 | 0.7071 | 0.8816 | 0.6712 | 0.8857 |
| 6         | 0.7208 | 0.9008 | 0.7146 | 0.8803 | 0.6780 | 0.8881 |
| 12        | 0.7151 | 0.9001 | 0.7118 | 0.8835 | 0.6801 | 0.8845 |

5 Conclusion

In this paper, we proposed a real-time human behavior prediction model that uses multi-resolution features. In the high-resolution input, the model observes the Manhattan distance difference between the agent and each potential goal during recent behavior, which is robust to obtain the agent’s short-term intention. The low-resolution historical state matrix effectively organizes the long-term memory and helps the model extract the high-level feature. In addition, the supervised learning-based training provides a straightforward and automatic way to organize and learn the internal correlations from the human subjects data. After training, the experimental results demonstrated that our method is robust and accurate at effectively utilizes prior knowledge to predict human behavior.

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