Combining imitation and deep reinforcement learning to human-level performance on a virtual foraging task

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Abstract

We develop a framework to learn bio-inspired foraging policies using human data. We conduct an experiment where humans are virtually immersed in an open field foraging environment and are trained to collect the highest amount of rewards. A Markov Decision Process (MDP) framework is introduced to model the human decision dynamics. Then, Imitation Learning (IL) based on maximum likelihood estimation is used to train Neural Networks (NN) that map human decisions to observed states. The results show that passive imitation substantially underperforms humans. We further refine the human-inspired policies via Reinforcement Learning (RL) using the on-policy Proximal Policy Optimization (PPO) algorithm which shows better stability than other algorithms and can steadily improve the policies pre-trained with IL. We show that the combination of IL and RL match human performance and that the artificial agents trained with our approach can quickly adapt to reward distribution shift. We finally show that good performance and robustness to reward distribution shift strongly depend on combining allocentric information with an egocentric representation of the environment.

Keywords

Decision-making, foraging, reinforcement learning, imitation learning, autonomous navigation, deep learning, bio-inspired control

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1. Introduction

Human beings are exceptional learners: capable of conceiving solutions for individual problems, generalizing acquired skills to new tasks, exploring new strategies, and inferring causal relationships (Goddu et al., 2020; Gopnik et al., 2015; Ruggeri et al., 2021; Walker et al., 2012). Since the earliest stage of Machine Learning (ML), the research community has sought to emulate humans’ learning capacities; and only recently, works which combine Deep Learning (DL) with Reinforcement Learning (RL), have accomplished outstanding results in this regard (Silver et al., 2017). DL and RL have shown to be indispensable ingredients to accomplish human-like intelligence in artificial systems; however, they still require a massive amount of computational resources and do not show the same level of efficiency compared to human beings (Botvinick et al., 2019). A viable option to tackle the efficiency issue, again inspired by human learning (Jones, 2009; Offerman & Sonnemans, 1998) is to leverage human demonstrations by combining DL and RL with imitation in a procedure known as imitation learning (IL) (Pomerleau, 1991). It is worth noting that a great number of tasks, such as navigating or exploring unknown environments, are relatively straight-forward for humans and can be successfully learned in a limited number of trials. On the other hand, this is often not
the case for artificial agents, where the amount and the quality of the information retrieved, in addition to a sound design of the reward function and/or a good exploration strategy of the environment, are crucial for successfully learning from scratch. Hence, artificial agents might benefit from directly imitating human behavior or, alternatively, from reconstructing human-inspired reward functions (Abbeel et al., 2010).

In this study, we investigate the potential of learning from humans taking into account not only performance but also data-efficiency, that is, the amount of interactions with the environment an agent needs in order to master the task. We start by collecting movement data from a series of human participants while they are performing a virtual foraging task in which the rewards, in the form of coins, are condensed in clusters throughout the environment. The participants, subject to time constraints, have to collect the highest number of coins, effectively trading-off between foraging within a single cluster (exploitation) and exploration. Humans are initially unaware of the number of clusters and of their locations but are able to learn the reward distribution throughout the course of the experiment.

Note that, time-constrained foraging problems occur in several realistic scenarios, including scientific exploration; where a rover might want to sample chemical or geological features as fast as possible; search and rescue operations, where a vessel needs to rescue as many people as possible (Otte et al., 2013; Scone & Phillips, 2010), wildlife tracking, agriculture pollination, agriculture harvesting and so on. Moreover, these missions can be dangerous and time demanding, and the use of aerial, marine, or ground unmanned vehicles would significantly mitigate risks and save time. However, without assumptions about the distribution of targets, classical control techniques are not applicable. Tele-operation is also a feasible option, but it may be hindered due to unreliable communications, and this approach does not scale as well as completely autonomous options. For these reasons, ML techniques supporting full autonomy represent an interesting alternative solution. Therefore, our main objective is to develop a method which effectively combines IL with DL and RL and allows for efficient human-level learning in a foraging task with sparse rewards.

From our experiment, we collect 50 human trajectories and further process them to include both allocentric and egocentric information in our model. Where allocentric means the coordinates with respect to the environment frame and egocentric means the perception of the surrounding. We then run IL on each of the trajectories, yielding 50 policies with different performance. None of these policies succeed in matching human results. Finally, we use the imitated policies as initial solutions and further refine them with RL. By combining the two methods, we outperform the average human performance and the respective participant from which the agent imitates with a success rate of 78% and 62%, respectively, while using a reasonable amount of training steps ($\leq 10^7$). We also compare our method with a pure RL alternative, and show that such an approach remarkably underperforms humans.

In the final part of the work, we test the learned policies for generalization and robustness in a new scenario with an unknown reward distribution. We are able to show that the artificial agents quickly adapt to this new scenario and conjecture that, when combined with allocentric information, the egocentric representation of the environment plays a key role in enabling learning as also observed in neurological recordings from rodents (Alexander et al., 2020). To empirically test this hypothesis, we rerun the entire set of experiments only considering allocentric coordinates. We show that in the absence of an egocentric representation of the environment, RL is unable to further improve IL and the final performance does not reach the level of human subjects. For the sake of completeness, we rerun the experiments also considering only the egocentric representation of the environment. This setup, however, violates the MDP assumption and, since our agents are not equipped with explicit memory, the learned policies underperform those of the other experiments. A figure illustrating all these experiments for the full set of 50 human trajectories is included in the Supplementary Materials. We conclude that proper modeling is as crucial as the right algorithmic choices in order to enhance general and robust learning in artificial agents.

1.1. Related work and contribution

We focus on combining IL with RL in order to address the shortcomings of these two approaches when used individually. IL was initially proposed as a supervised learning method for faster policy learning (Pomerleau, 1991; Schaal, 1999). Recent works have studied the limitation of IL including the covariate shift problem and its dependency on the quality of the demonstrations (Ross & Bagnell, 2010; Syed & Schapire, 2010). RL instead was proposed to enable learning through direct interaction with the environment (Sutton & Barto, 2018). RL combined with IL has achieved outstanding results in policy learning (Silver et al., 2017); however, sample inefficiency and safety remains an obstacle for its deployment in real world scenarios (Dulac-Arnold et al., 2019; Serrano-Cuevas et al., 2020). Recent works have endeavored to combine IL with RL either to address the limitations of IL (Cheng et al., 2019; Ross & Bagnell, 2014; Ross et al., 2011; Sun et al., 2018) or to improve efficiency in RL (Kober et al., 2010; Libardi et al., 2021; Nair et al., 2018; Subramanian et al., 2016; Uchendu et al., 2021; Vecerik et al., 2017).

Another line of research, known as Inverse Reinforcement Learning (IRL), leverages demonstrations in order to infer a reward function which is then used for RL in order to
recover the demonstrator policy (Abbeel & Ng, 2004; Finn et al., 2016; Ratliff et al., 2006; Ziebart et al., 2008). IRL has the pros of being immune to the covariate shift problem but the cons of being as sample inefficient as the used RL algorithm. A unified view of IRL and IL as an f-divergence minimization problem has been recently proposed (Ghasemipour et al., 2020; Ho & Ermon, 2016) and addressed using Generative Adversarial Networks (Goodfellow et al., 2020) (GAN) for either IL (Ho & Ermon, 2016) or reward shaping (Kang et al., 2018).

We place our work in the Reinforcement Learning with Expert Demonstrations (RLED) framework, where the RL agent learns in the same environment of the demonstrator and using the same reward function (Hester et al., 2018). Our main contribution is leveraging a non-trivial case study to show how modeling, imitation and reinforcement, when effectively combined, can lead to human-like performance in navigation tasks with sparse rewards without requiring a massive amount of training steps. Note that, this does not mean that RL-only algorithms cannot achieve human-level performance in this type of tasks, rather that they need a significantly larger number of steps to do so. Furthermore, dense reward signals would have most likely improved RL-only performance but also assumed prior knowledge of the environment invalidating therefore the comparison with the human agents. Finally, we analyze our results for robustness and empirically show a strong correlation between egocentric representation of the environment and performance. We reemphasize the importance of the right algorithmic choices as well as the right model in order to enhance effective learning in artificial agents.

Other works which likewise combine IL with RL are Hester et al. (2018); Rajeswaran et al. (2017); Uchendu et al. (2022) and Silver et al. (2017). However, AlphaGo in Silver et al. (2017) lies in the model-based spectrum, whereas, our work considers a pure model-free RL setting. Deep Q-Learning from Demonstrations (DQfD) in Hester et al. (2018), on the other hand, explores pre-training a deep Q network (Mnih et al., 2013) using demonstrations before performing RL. In order to do so, the agent needs access not only to the demonstrator state-action pairs but also to the rewards collected along the trajectories. In other words, DQfD assumes access to the full MDP transition (states, actions, and rewards) and as a result, its pretrain step can be seen as a first form of offline RL (Levine et al., 2020). In our study, we assume access only to demonstrator state-action pairs (without rewards) and therefore DQfD is not directly applicable. Furthermore, none of the aforementioned works investigate the effects of modeling on algorithmic performance. Closer to our approach are the algorithms presented in Rajeswaran et al. (2017) and Uchendu et al. (2022). However, our study is focused on a unique foraging domain that poses particular challenges. In addition, we explore the resilience and adaptability of our artificial agents and draw comparisons with human performance.

1.2. Outline and notation

The remainder of the paper is organized as follows. The Materials and Methods section presents the experimental setup used to collect the human foraging data, introduces the MDP model used for representing human behavior, discusses the IL for learning policies from data, and outlines the RL algorithms used to refine the imitated policies. In the Results section, we compare our method with human and RL-only performance on the original setup; then, we test all the artificial agents for robustness to reward distribution shift and demonstrate the importance of egocentric information. We discuss the results in the Discussion section.

Unless otherwise indicated, we use uppercase letters (e.g., $S_t$) for random variables, lowercase letters (e.g., $s_t$) for values of random variables, script letters (e.g., $S$) for sets, and bold lowercase letters (e.g., $\mathbf{0}$) for vectors. Let $[t_1 : t_2]$ be the set of integers $t$ such that $t_1 \leq t \leq t_2$; we write $S_{t_1 : t_2}$ such that $t_1 \leq t \leq t_2$ as $S_{t_1 : t_2}$. We denote by $\mathcal{N}(\mu, \sigma^2)$ the normal distribution, where $\mu$ is the mean and $\sigma$ the standard deviation. $I$ denotes the identity matrix. We denote the multivariate normal distribution with $\mathcal{N}(\mu, \sigma^2 I)$ where $\mu$ is the mean vector and the covariance matrix is diagonal with only $\sigma^2$ as elements on the diagonal. Finally, $E[\cdot]$ represents expectation and $P(\cdot)$ probability.

2. Materials and methods

2.2. Experimental setup

In the following section, we provide a description of how the human foraging datasets were collected. In the Supplementary Materials we include the full dataset of 50 search trajectories. We focus on five participants in the context of a larger study investigating human foraging (Moore et al., 2021). An example of two foraging search trajectories is given in Figure 2. All the experiments have been carried out in accordance with the relevant guidelines and regulations and approved by the Boston University’s Institutional Review Board.

Participants consisted of male and female, neurologically healthy, English-speaking volunteers between the ages of 18–35 with normal or corrected-to-normal vision. Participants were recruited from Boston University and the surrounding community. Individuals with a history of drug abuse, use of psychoactive medication, neurological or psychiatric disorders, or learning disabilities were excluded. Additionally, participants with a history of motion sickness when watching or playing video games were also excluded. All participants were compensated and gave written
informed consent in accordance with Boston University’s Institutional Review Board.

The task consisted of a 160m × 160m virtual “open-field,” that is, obstacle free, paradigm surrounded by four differently colored and textured walls created using Vizard 6.0, a Python-based virtual reality development platform (Figure 1(a)). 325 coins were distributed throughout the environment, of which 100 were uniformly randomly distributed and 225 were distributed according to four different multivariate Gaussian distributions of varying sizes: 75 according to \( N((60, 75), 5^2 I) \), 40 according to \( N((-15, -50), 11^2 I) \), 60 according to \( N((-50, 30), 18^2 I) \) and 50 according to \( N((49, -40), 13^2 I) \) (Figure 1(c)). Each participant’s starting location was randomized at the beginning of each run. Participants could move forward and turn left or right. They could not move backwards. They were instructed to freely explore the environment and collect as many coins as possible but were not told anything about the distribution or total number of coins. They were also able to see a running count of the coins they had collected for each run. After being collected each coin disappears for the remaining duration of the run. Participants performed the foraging task over two consecutive days. On the first day, naive participants were presented with the task on a desktop computer in a behavioral testing room. On the second day, they performed the same task in an MRI scanner. Subjects performed 10 eight-minute runs on Day 1 and 10 eight-minute runs on Day 2. In the desktop condition (Day 1), participants moved using keyboard arrow keys, and in the scanner (Day 2), they moved using a diamond-shaped button box. For our purposes here, we utilize the 80 minutes of behavioral data from Day 2 of the experiment for 5 participants which collected an average of 243.98 coins each. Selecting behavioral data from Day 2 rather than Day 1 is motivated by the fact that, during Day 2, the participants were already familiar with the task and achieved improved performance compared to Day 1.

2.3. Modeling the human decision process

In this section we describe the human modeling step and how the data are processed to make them suitable for IL and RL.

We consider an infinite-horizon discounted Markov Decision Process (MDP) defined by the tuple \( (S, A, P, r, D, \gamma) \) where \( S \) is the finite set of states and \( A \) is the finite set of actions. \( P: S \times A \rightarrow \Delta_S \) is the transition probability function and \( \Delta_S \) denotes the space of probability distributions over \( S \). The function \( r: S \times A \rightarrow \mathbb{R} \) maps rewards to state-action pairs. \( D \in \Delta_S \) is the initial state distribution and \( \gamma \in [0, 1) \) the discount factor. The decision agent is modeled as a stationary policy \( \pi: S \rightarrow \Delta_A \) where \( \pi(a|s) \) is the probability of taking action \( a \) in state \( s \). When a deterministic policy is required we simply take \( a = \arg \max_a \pi(a|s) \). For simplicity, we will always write \( a \sim \pi(\cdot|s) \) and according to which algorithm we are referring to it will be clear whether \( \pi \) is stochastic or deterministic. We parameterize \( \pi \) using a neural network with parameters \( \theta \in \Theta \subset \mathbb{R}^k \) and we write \( \pi_\theta \).

Given an MDP, we consider the human participants taking into account both egocentric and allocentric strategies when navigating (Alexander et al., 2020; Feigenbaum & Morris, 2004). We define the state vector as \( s = \{x, y, \psi, \chi\} \), where \( x, y \) are coordinates with respect to a frame fixed to the environment and represent the allocentric capacities of the agent. Instead, \( \psi \) and \( \chi \) are two categorical variables that describe the human egocentric behavior: the first tells the agent whether it can see a coin or not in its vicinity, \( \psi \in \{ \text{see coin, no coins} \} \), the second describes the “greedy” direction, that is, the direction of the closest coin the agent has in its view, \( \chi \in \{ \text{east, northeast, north, northwest, west, southwest, south, southeast, no coins} \} \).
The artificial agent perceives the state and takes an action to interact with the environment. For computational reasons we discretize the x, y coordinates on a fine grid of $1m \times 1m$ and define the action space as $a \in \{\text{east, northeast, north, northwest, west, southwest, south, southeast}\}$. The transition to the next state always occurs deterministically in the direction of the action $a$ taken by the agent. As convention in Figure 2, north means going from bottom to top, south from top to bottom, east is left to right and west vice versa. The categorical state $\psi$ stays 0 all the time unless there is a coin in a radius of $8m$ distance, when $\psi$ turns 1 then also $\chi$ turns from “no coins” to one of the other directions. This is aligned with the original experiment where each coin pops-up when the human is at $8m$ from it. Finally, the rewards are simply represented by the coins in the environment where $r(s, a) = 1$ for each coin collected. As in the original experiment, the agents automatically collect the reward once at $3m$ and $D$ is a uniform distribution over $S$.

2.4. Imitation learning

Given a task and an agent performing the task, IL infers the underlying agent distribution via a set of an agent’s demonstrations (state-action samples). Assuming the agent’s behavior is parameterized by a NN with optimal parameters $\theta^*$, we refer to the process of estimating $\theta^*$ through a finite sequence of agent’s demonstrations $\tau = (s_0, a_0, s_1, a_1, \ldots, s_T, a_T)$ with $2 \leq T < \infty$ as IL. One way to formulate this problem is through maximum likelihood estimation:

$$\max_{\theta} \mathcal{L}(\theta),$$

where $\mathcal{L}(\theta)$ denotes the log-likelihood and is equivalent to the logarithm of the joint probability of generating the expert demonstrations $\tau = \{s_0, a_0, s_1, a_1, \ldots, s_T, a_T\}$, that is,

$$\mathcal{L}(\theta) = \log P_D(\tau).$$

$P_D(\tau)$ in (2) is defined as

$$P_D(\tau) = D(s_0) \left[ \prod_{t=0}^{T} \pi_\theta(a_t|s_t) \right] \left[ \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t) \right].$$

Computing the logarithm of (3) and neglecting the elements not parameterized by $\theta$ we obtain the following maximization problem

$$\max_{\theta} \sum_{t=0}^{T} \log(\pi_\theta(a_t|s_t)).$$

Solving the maximization problem in equation (4) is the main objective of our IL step.

2.5. Reinforcement learning

After defining a model, collecting the data and performing the imitation step, our final goal is to further refine the imitated policies using RL. In RL, the artificial agents are allowed to experience the task themselves and receive a reinforcement according to the reward function $r(s_t, a_t)$. Mathematically, the goal is to find the policy parameters $\theta$ which maximize the expected total discounted reward $J(\theta) = \mathbb{E}_r[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)]$, where, as previously, $\tau = (s_0, a_0, s_1, a_1, \ldots)$ is sampled according to $s_0 \sim D, a_t \sim \pi_\theta(\cdot|s_t)$ and $s_{t+1} \sim P(\cdot|s_t, a_t)$. Our focus is on model-free RL methods in which the artificial agent does not know the transition probability function $P(\cdot|s_t, a_t)$, and it can only explore the environment and experience rewards. Among these types of algorithms, we can distinguish two main groups: (i) algorithms that update the current policy following the agent’s generated trajectories according to this policy, also known as on-policy algorithms, and (ii) algorithms that update the
current policy using experience from multiple policies used previously, known as _off-policy_. We provide a more thorough introduction on this difference in the Supplementary Materials.

State-of-the-art _on-policy_ algorithms include Trust Region Policy Optimization (TRPO) (Schulman et al., 2015), and some robust variants such as Uncertainty Aware TRPO (UATRPO) (Queeney et al., 2021), and Proximal Policy Optimization (PPO) (Schulman et al., 2015). Whereas, _off-policy_ methods include the Soft-Actor Critic (SAC) and Twin Delayed Deep Deterministic Policy Gradient (TD3) (Fujimoto et al., 2018; Haarnoja et al., 2018). All the mentioned algorithms are tested in our experiments and more details about the NNs design are available in the Supplementary Materials. It is worth noting that these algorithms are actor critic-based approaches, comprising both a policy network (the actor) and a critic network. In this context, we exclude value function-based approaches that rely solely on critic networks. This decision is motivated by the fact that the IL step returns only pre-trained policy networks, since the pre-training of critic networks is prevented by the absence of expert rewards (Levine et al., 2020).

3. Results

In this section, we present our results and describe all the steps that lead to our design. All the code and data to replicate the experiments are freely accessible at our GitHub repository. An overview of the NNs used to parameterize \( \pi_\theta \) and all the hyperparameters used for each of the IL and RL algorithms are in the Supplementary Materials.

3.1. Pre-processing

Our first step is to collect and process the 50 trajectories, of 8 minutes each, recorded on the second day of tests. Each 8-minute trajectory consists of 28973 data points, on average, which means we collect a data point every \( 0.17 \) seconds, where the data points are the human agent’s coordinates with respect to the fixed environment frame. Note that it is possible that a human agent does not move for a few seconds, for example, and then makes many rapid decisions about where to explore in the next milliseconds following this stationary period. Therefore, the first “few seconds” could be aggregated in a single data point while the next “milliseconds” would require more than a single point. As a result, we aggregate the data points considering the discretization of the \((x, y)\) coordinates. After that, we go over each of the trajectories and determine the human decisions (i.e., for each aggregated state, the direction of the human’s next movement). We cast each human decision for each trajectory in the pre-determined action space \( \mathcal{A} \) and construct in this way our state-action pairs (i.e., actions \( a \) taken at state \( s \)). This process allows us to reduce the average length of human trajectories from 28973 to 3464 data points without losing key information. Note that this processing is an expensive but necessary step for reducing the computational burden and enabling learning. Future research will focus on how to automate this step and developing methods which can handle learning from raw data.

3.2. Imitation learning

We perform IL on each human trajectory individually rather than considering a single dataset with all the trajectories. There are two main factors contributing to this choice. Firstly, as demonstrated in Figure 2, each human trajectory extensively covers the environment, rendering each trajectory inherently informative about the task at hand. Secondly, the policies generating these trajectories exhibit different distributions, leading to high variance in a single aggregated dataset. This variance ultimately undermines the effectiveness of the IL step as the distribution which better fits the aggregated data is close to the uniform distribution. The results of the IL step and all the details on the evaluation are illustrated, for 5 humans’ trajectories, in Figure 3. In summary, we achieve good learning performance for several trajectories but not enough to match the human participants. A figure showing the IL performance for all the 50 trajectories is available in the Supplementary Materials.

3.3. Reinforcement learning

We consider the 50 policies learned from the 50 human trajectories during the IL step. We refine these policies using RL. We design the experiment as follows:

1. First, in order to determine which RL algorithm is more suitable for our goal, we take the same single policy learned during the IL step and use it as initialization of each of the RL algorithms.
2. Given the cardinality of the state-space \((160 \times 160 \times 2 \times 9)\), we consider \( 10^7 \) steps for performing RL. This means that the learning agent can leverage interactions that are on the order of 20 times the number of states.
3. As in the IL step, for each RL algorithm we run the learning process for 8 random seeds.
4. During the learning process, we evaluate the policy learned every 30,000 steps on 10 trials of 3464 steps each. We report averaged results over the 10 trials and 8 seeds. The shaded area in Figure 4 and 5 shows the standard deviation over seeds.
5. After determining the most suitable RL algorithm, we rerun the whole experiment for 50 times in which
each of the 50 policies learned during the IL step is used as initialization of the selected RL algorithm.

Figure 4 compares the various RL algorithms. PPO outperforms all other methods. Broadly speaking, on-policy algorithms, that is, PPO, TRPO, and UATRPO, learn more effectively from a pre-initialized policy with respect to the off-policy algorithms TD3 and SAC. Refer to the Supplementary Materials for more details.

Consequently, we proceed by combining IL together with PPO and compare it with the PPO-only alternative. Figure 5 illustrates the final results for the same trajectories of Figure 3 and a figure showing this final result for all the 50 trajectories is available in the Supplementary Materials. In summary, IL followed by PPO (IL + PPO) outperforms the average human performance and its imitated expert, 39 (78%) and 31 (62%) times, respectively, over the 50 human trajectories. On the other hand, the PPO-only alternative cannot get close to these results in $10^7$ steps. Table 1 summarizes the comparison between humans and IL + PPO policies with respect to the total amount of collectable rewards.

Note that, Figure 5 provides interesting insights on why pre-training with IL makes sense in foraging tasks with sparse rewards. We observe that, in addition to a different initial performance, the IL + PPO and the PPO-only agents show really different exploration strategies which lead to a different reward convergence rate (the difference in rates is clearly visible in Figure 5). The exploration strategy used in PPO-only follows the original approach presented in Schulman et al. (2017), where an entropy regularization term is incorporated in the policy gradient step in order to encourage stochasticity in the decision policy. In this setup,
the human-inspired exploration strategy of IL + PPO represents the main strength of the method and the main source of difference with the PPO-only agents.

3.4. Robustness to reward distribution shift and the importance of egocentric representations

In this section, we test the learned policies for robustness to a reward distribution shift. The motivation is to explore how quickly the artificial agents grasp changes in the environment and adapt to these changes. Throughout this section we consider the new setting described in Figure 6. As in the original experiment, 325 coins are placed across the environment; however, this time according to the new distribution in Figure 1(a) (cf. Figure 6), we include the original coins distribution in Figure 1(b) to facilitate the comparison.

Specifically, 50 coins are distributed according to $\mathcal{N}((-70, 30), 5^2I)$, 75 according to $\mathcal{N}((-60, -20), 11^2I)$, 100 according to $\mathcal{N}((-40, 45), 15^2I)$ and 100 according to $\mathcal{N}((0, 60), 13^2I)$.

We design the experiment similarly to the RL study and the IL + PPO experiments in Figures 4 and 5. Overall, we run, for 8 different random seeds, 100 learning experiments of $2 \times 10^6$ steps each, where in the first 50 we initialize using the policies learned with only IL (Figure 3), while, in the second 50, we initialize using the policies learned by IL + PPO (Figure 5). The results are summarized in Table 2 and show that the policies learned using both IL + PPO generalize well to novel reward distributions. The figures showing the detailed 100 experiments are available in the Supplementary Materials.

In order to produce these results, we conclude that, given the state vector representation as $s = \{x, y, \psi, \chi\}$, the RL agents and their exploration strategies must heavily rely on egocentric information, that is, the variables $\psi$ and $\chi$. This would explain the algorithm performance in the novel reward environment in Figure 1(a), where the previously...
learned allocentric representation is no longer informative. On the other hand, a strategy based on egocentric exploration which facilitates the generation of a new allocentric representation of the environment would explain the results in Table 2. In other words, we suggest that our IL + PPO algorithms exhibit coding of behavioral variables analogous to the observation in animals (Alexander et al., 2020), where electrophysiological recording during foraging strategies indicate neural coding in both egocentric and allocentric coordinate frames.

To demonstrate the veracity of this claim we rerun the entire set of experiments, which includes IL as in Figure 3 and IL + PPO as in Figure 5, but this time only providing allocentric information to the artificial agents. In other words, we reduce the state vector from \( s = \{x, y, \psi, \chi\} \) to \( s = \{x, y\} \). The results for a selected number of human trajectories are summarized in Figure 7. For the entire set of trajectories refer to the Supplementary Materials. The final results show that agents trained with the full state \( s = \{x, y, \psi, \chi\} \) outperform agents trained with the allocentric only state \( s = \{x, y\} \) 74% of the times for IL (37 out of 50) and 100% of the times for IL + PPO. We conclude that our learned policies heavily rely on egocentric data and that the absence of such information compromises to a large extent the learning performance as illustrated in Figure 7.

4. Discussion

In this paper, 50 human navigation trajectories were collected in a virtual open-field environment. We extracted a navigation control policy from each of these trajectories and introduced an MDP setting to capture the navigational human decision-making. We learned policies consistent with the experimental data using imitation learning based on log-likelihood maximization for each of the trajectories.

| Performance lower bound | > 70% | > 80% | > 90% | > 95% |
|--------------------------|-------|-------|-------|-------|
| IL-only initialization   | 28%   | 18%   | 0%    | 0%    |
| IL + PPO initialization  | 98%   | 92%   | 18%   | 0%    |

Table 2. A Summary of the Results for the Rewards Distribution Shift Experiment. The Table Shows the Fraction out of 50 Policies, for each Initialization Method, Where After Learning for \( 2 \times 10^6 \) Steps, the Agent is Able to Collect at Least a Certain Percentage of Rewards. As an Example, the Table is Showing that, for the IL + PPO Initialization, 46 Policies (92%) can Collect at Least 270 Coins (> 80%) in this new Scenario After Learning for Only \( 2 \times 10^6 \) Steps.

Figure 7. Performance comparison, for selected trajectories, among agents trained with full state including both egocentric and allocentric information \( s = \{x, y, \psi, \chi\} \) versus an allocentric only state \( s = \{x, y\} \). The comparison is done for both IL (upper figure) and IL + PPO (lower figure). For completeness, we also show the PPO agent without IL initialization performance (PPO allocentric and egocentric Agent).
After obtaining a control policy for each trajectory, we used all of them as a starting point for RL, seeking to find policies that can efficiently outperform the human participants in the same experimental setting. We tested state-of-art on-policy (PPO, TRPO, UATRPO) and off-policy (TD3, SAC) algorithms. We explained more extensively how these two categories differ in the Supplementary Materials. Briefly, the main element of difference lies in the data used to update the policy network $\pi_\theta$ and in how we compute and approximate the critic network. Off-policy algorithms are usually faster to converge but introduce a large bias in the critic estimate, which results in more oscillatory learning which often jeopardizes the IL initialization. On the other hand, the tested on-policy algorithms are more conservative, and the optimization step is constrained so not to diverge too much from the current policy $\pi_\theta$. This results in a slower but more steady improvement of performance. Our preference towards PPO with respect to the other on-policy algorithms is the result of experimental which corroborates other well-known empirical studies on the matter (Andrychowicz et al., 2020; Engstrom et al., 2020).

Finally, we examined the sensitivity of the IL + PPO and IL-only policies to a different reward distribution and investigated to what extent our artificial agents rely on egocentric information. The final results showed that learning only from data is not enough to match human performance and does not lead to robustness over the reward distribution (Figure 3 and Table 1). On the other hand, IL followed by PPO (IL + PPO) showed impressive results in the original experiment and it led to good generalization of the task (Figure 5 and Table 2). Further, we showed that such results are associated with the use of egocentric information, which are crucial in enhancing learning performance both in the IL and the IL + RL setting when compared with the use of allocentric information alone.

In summary, we have developed a method to learn bio-inspired policies from human navigation data, which can be further refined to achieve human-level performance. This approach to modeling human navigational policies can be of great utility for aerial and ground unmanned navigation tasks including scientific exploration and search and rescue operations.

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**Supplemental Material**

Supplemental material for this article is available online.

**Note**

1. https://github.com/VittorioGiammarino/Learning-from-humans-combining-imitation-and-deep-on-policy-reinforcement-learning-to-accomplish-sufoot

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