VOILA: Visual-Observation-Only Imitation Learning for Autonomous Navigation

Haresh Karnan\textsuperscript{1}, Garrett Warnell\textsuperscript{2,3}, Xuesu Xiao\textsuperscript{3} and Peter Stone\textsuperscript{3,4}

\textit{Abstract—} While imitation learning for vision-based autonomous mobile robot navigation has recently received a great deal of attention in the research community, existing approaches typically require state-action demonstrations that were gathered using the deployment platform. However, what if one cannot easily outfit their platform to record these demonstration signals or—worse yet—the demonstrator does not have access to the platform at all? Is imitation learning for vision-based autonomous navigation even possible in such scenarios? In this work, we hypothesize that the answer is yes, and that recent ideas from the Imitation from Observation (ifo) literature can be brought to bear such that a robot can learn to navigate using only ego-centric video collected by a demonstrator, even in the presence of viewpoint mismatch. To this end, we introduce a new algorithm, Visual-Observation-only Imitation Learning for Autonomous navigation (VOILA), that can successfully learn navigation policies from a single video demonstration collected from a physically different agent. We evaluate VOILA in the photorealistic AirSim simulator, and show that VOILA not only successfully imitates the expert, but that it also learns navigation policies that can generalize to novel environments. Further, we demonstrate the effectiveness of VOILA in a real-world setting by showing that it allows a wheeled Jackal robot to successfully imitate a human walking in an environment using a video recorded using a mobile phone camera.

I. INTRODUCTION

Enabling vision-based autonomous robot navigation has recently been a topic of great interest in the robotics community [1]–[3]. Classically, vision-based autonomous navigation has proven to be a challenging problem in that it is difficult to pre-define good visual features that autonomous systems can use for navigation. However, by applying recent ideas from computer vision based on deep learning, researchers have started to have success for tasks such as lane keeping [1]. Imitation learning in particular has emerged as a useful paradigm for learning vision-based navigation controllers, in which the desired navigation behavior is demonstrated by another agent (usually a human), recorded, and then supplied as training data to an artificial learning agent that seeks to find a controller that can mimic the demonstration. To date, most approaches in the navigation domain that adopt this paradigm require demonstration recordings that contain both state observations (e.g., images) and actions (e.g., steering wheel angle or acceleration) gathered onboard the deployment platform [1], [2], [4], [5].

While the approaches outlined above have succeeded as long as their assumptions are met, there are scenarios in which it would be beneficial to relax the requirements they impose on the demonstration data. For example, if we wish to collect a large number of demonstrations from many experts, it may prove too difficult or costly to arrange for each expert to operate particular deployment platforms, which are often expensive or difficult to transport. However, due to the low cost and portability of video cameras, it may still be entirely feasible to have demonstrators record ego-centric video demonstrations of their navigation behaviors while operating a different platform. Demonstrations of this nature would consist of video observations only (i.e., they would not contain control signals), and, because of the difference in platform, the videos would likely exhibit ego-centric viewpoint mismatch compared to those that would be used by the deployment platform. A particular example of such data is the plethora of vehicle dashcam videos available in publicly-accessible databases [6] or on YouTube. Unfortunately, to the best of our knowledge, there exist no current imitation learning techniques for vision-based navigation that can leverage such demonstration data.

Fortunately, recent work in Imitation from Observation (ifo) [7] has shown a great deal of success for several related tasks. Ifo refers to the particular sub-problem in imitation learning of trying to learn imitating policies when demonstrations do not include action information. Approaches that have been proposed for ifo have shown that successful imitation policies can be found using such demonstrations—including video-only demonstrations—for limbed robots both in simulation [8], [9] and in the real-world [10]. However, no literature of which we are aware has considered whether these ifo techniques can be applied to the vision-based autonomous navigation problem we have outlined above.

In this paper, we hypothesize that it is possible to perform imitation learning for vision-based autonomous navigation using video-only demonstrations that have been collected using physically different agents. To this end, we introduce a new ifo technique for vision-based autonomous navigation called Visual-Observation-only Imitation Learning for Autonomous navigation (VOILA). Based on recent ideas in feature extraction and image retrieval in computer vision, VOILA uses a novel reward function specific to vision-based navigation to drive a reinforcement learning procedure that results in navigation policies that can successfully imitate the demonstrations.

We experimentally confirm our hypothesis both in simulation and on a physical Jackal robot. In the simulation

\footnote{A preliminary version of this work was presented at the 2021 AAAI Spring Symposium on Machine Learning for Navigation.}
Fig. 1: Policy rollout trajectories of the VOILA agent (green) successfully imitating a demonstration (black) of patrolling a rectangular hallway clockwise. The demonstration consists of a video gathered by a human walking while using a handheld camera that is considerably higher than the robot’s camera. We see that the VOILA agent is able to successfully imitate the expert demonstration even in the presence of this egocentric viewpoint mismatch.

experiment, demonstrations are collected using an Unmanned Aerial Vehicle (UAV), whereas the imitator is an Unmanned Ground Vehicle (UGV). Collecting demonstrations using the UAV introduces egocentric viewpoint mismatch between the expert and the imitator. For the physical experiments, a video collected by a human demonstrator walking around an indoor office space using a handheld camera is used as the demonstration (see attached video to visualize the demonstration data), which induces viewpoint mismatch with the small UGV that we use as the imitator. We compare VOILA against a state-of-the-art IfO algorithm called GAIfO [9], and find that VOILA can learn to imitate an expert’s visual demonstrations better even in the presence of viewpoint mismatch, while also generalizing to unseen environments. Our real-world experimental results also confirm our hypothesis that VOILA enables successful IfO for autonomous navigation in the presence of viewpoint mismatch, as shown in Fig. 1. Additionally, we experimentally demonstrate the flexibility of VOILA by showing that it can also support learning navigation policies over sensing modalities other than vision.

II. BACKGROUND AND RELATED WORK

The proposed approach, VOILA, performs reinforcement learning using a novel reward function based on local image keypoints in order to accomplish imitation from observation for autonomous navigation with viewpoint mismatch. In this section, we review related work in autonomous robot navigation, imitation from observation, and in computer vision techniques for feature extraction.

A. Machine Learning for Autonomous Navigation

The use of machine learning methods in the design of autonomous navigation systems goes back several decades, though recent years have seen a spike in interest from the research community [2], [3], [11], [12]. One of the earliest successes was reported by Pomerleau [13], in which a system called ALVINN used imitation learning to train an artificial neural network that could perform lane keeping based on demonstration data generated in simulation. Since then, several improvements, both in the amount and type of demonstration data and in network architecture and training, have been proposed in the literature. In particular, LeCun et al. proposed the use of a convolutional neural network (CNN) to better process real demonstration images for an off-road driving task [4], and, more recently, Bojarski et al. reported that gathering a large amount of real-world human driving demonstration data and applying data augmentation made it possible to train even more-complex CNN architectures to perform lane keeping [1].

While the aforementioned approaches each use end-to-end imitation learning to find autonomous navigation policies, other machine learning for autonomous navigation work has adopted the alternative training paradigm of reinforcement learning (RL). The work closest to ours is that of Kendall et al. [14], in which the proposed system learns a navigation policy using RL, where the reward function is the total distance travelled by their autonomous vehicle before a human driver intervenes (to, e.g., prevent collisions). However, unlike VOILA, Kendall et al. utilize experience gathered exclusively by the learning platform itself, considering neither imitation from observation nor the particular problem of viewpoint mismatch.

B. Imitation from Observation

Recently, there have been a number of imitation from observation (IfO) techniques introduced in the literature, including the adversarial approach, GAIfO, proposed by Torabi et al. [9], [15] which we use as a comparison point in this paper. In GAIfO, the reward signal is provided by a learned discriminator network which seeks to reward state transitions similar to those present in the demonstration and penalize — if it can tell the difference — state transitions
that come from the imitator. While Gaifo has been shown to be successful in both low- and high-dimensional observation spaces, it has thus far only been applied to continuous control tasks for limbed agents. Moreover, as we will show in our experiments, while Gaifo is able to imitate the expert when the egocentric viewpoints between the expert and the imitator match, it is unable to do so in the presence of viewpoint mismatch.

Viewpoint mismatch in IFO has been previously considered in the work by Sermanet et al. [10], which proposes Time Contrastive Networks (TCNs). TCNs use a triplet loss metric to learn a feature space embedding which is then used for rewarding the agent to imitate the expert. While both VOILA and TCNs are robust to viewpoint mismatch, TCNs require demonstration data with multiple viewpoints in order to learn an embedding space that is robust to viewpoint mismatch, whereas VOILA achieves this robustness by leveraging image feature extraction algorithms that are themselves designed to be robust to viewpoint mismatch.

C. Local Feature Detection and Matching

To overcome viewpoint mismatch, VOILA introduces a novel reward function that relies on local image keypoints. Local keypoints have been used for decades to solve challenging tasks such as image verification, matching and retrieval. More recently, deep-learning-based keypoint extractors such as SUPERPOINT [16] have been shown to be more successful than classical approaches. In this work, we use SUPERPOINT to detect keypoints and descriptors, and we determine keypoint matches using the typical method based on the two nearest neighbors in descriptor space [16]. However, in principle VOILA can be used with any local feature detector or feature matching algorithm.

III. VOILA

In this section, we formulate the imitation learning problem for the task of autonomous visual navigation, which we pose as a reinforcement learning problem with a demonstration-dependent reward. The critical contribution of VOILA is the development of this particular reward function, which we describe in detail below.

A. Preliminaries

We treat autonomous visual navigation as a reinforcement learning problem where the environment is a Markov decision process. At every time step $t$, the state of the agent is described by $s_t \in S$, the observation of the agent is described by $O_t \in O$, and an action $a_t \in A$ is sampled from the agent’s policy $\pi(\cdot | O_t)$. A single expert demonstration is represented as a set of $n$ sequential observations $S = \{O_1, O_2, \ldots, O_n\}$. Performing this action in the environment leads to a next state $s_{t+1} \sim T(\cdot | s_t, a_t)$, where $T$ is the unknown transition dynamics of the agent in this environment. For this specific transition, the agent receives a reward, $r_{t+1} \in \mathbb{R}$, which is a function of both the agent’s transition tuple and the demonstration, i.e., $r_{t+1} = R(O_t, a_t, O_{t+1}; \mathcal{D})$.

The relative utility of near-term and long-term reward is controlled using the discount factor $\gamma \in (0, 1]$. The RL objective is to find a policy $\pi$ that maximizes the expected sum of discounted rewards $\mathbb{E}_{t=0}^{\infty} R(O_t, a_t, O_{t+1}; \mathcal{D})$.

B. Reward Formulation for Imitation Learning

For each transition $(O_t, a_t, O_{t+1})$ experienced by the learner, we require a reward $r_{t+1}$ such that the learner, by optimizing the RL objective with this reward, can learn to imitate the demonstration. In particular, because we wish to perform learning in real time, we seek a dense reward function that provides feedback at each timestep without delay. Since the expert demonstrations are from a physically different agent, there can be significant ego-centric viewpoint mismatch between the observation spaces of the learner and the demonstrator as shown in Fig. 1. Such a mismatch poses a challenge to designing a good reward function since it is not immediately clear how to compare images from different viewpoints. Hence, we introduce here a novel reward function based on keypoint feature matches between the expert and the imitator’s ego-centric observations for the task of imitation learning for visual navigation. Keypoint detectors have been extensively used in the computer vision community for several decades to solve challenging tasks like structure-from-motion (SfM), visual SLAM and hierarchical localization. Recent keypoint detection algorithms like SUPERPOINT [16] provide invariance to perspective distortion, scaling, translation, rotation, viewpoint mismatches, and varied lighting conditions between the key and query images. Hence, we use keypoint detectors to help define the reward function to learn visual navigation policies from demonstrations provided by any other agent.

The reward function we propose relies on a quantity that we call match density. We define the match density $d(O_1, O_2)$ between two images $O_1$ and $O_2$ as the ratio of the number of keypoint matches between $O_1$ and $O_2$, and the total number of detected keypoints in $O_2$, $d(O_1, O_2) \in [0, 1]$, assuming there is always a non-zero number of keypoints detected in an image. Additionally, instead of imposing a temporal alignment constraint, we define the reward for a particular transition by searching the demonstration for the image which is most visually similar to the learner’s current observation. Here, we define the most visually similar image in the expert demonstration to be the one that has the highest match density with $O_t$, which we denote as $O_{t}^\ast$. For convenience of notation, we denote $O_{t+1}^\ast$ (the next image after $O_t^\ast$ in the demonstration sequence), as $O_{t+1}^\ast$. We also point out here that, while $O_t^\ast$ is the image in the demonstration sequence that follows $O_t^\ast$, it may differ from the image in the demonstration sequence that is most similar to $O_{t+1}$ (i.e., $O_{t+1}^\ast$).

Using the concepts described above, we now define the proposed reward function for VOILA:

\[ R(O_t, a_t, O_{t+1}; \mathcal{D}) = \begin{cases} 
1 & \text{if } d(O_t^\ast, O_{t+1}) > \gamma \\
0 & \text{otherwise} 
\end{cases} \]
where \( F = d(O_{t+1}, O_{e-i}) \) and \( V = \gamma^i d(\hat{O}_{t+1}, \hat{O}_e) - d(O_{t}, \hat{O}_e) \). If the robot is in the done state, i.e., it has crashed (as detected in AirSim, or by the trainer in physical experiments) or the number of matches drop below 10, the agent receives a penalty reward of \(-10\). Otherwise, the agent is in the alive state, and we assign a reward that depends on terms \( F \) and \( V \). The \( F \) term assigns reward value based on the match density encountered at the next observation \( O_{t+1} \) that the agent ends up in the transition. This component encourages the agent to stay on the demonstrated trajectory. The \( V \) term is similar to a potential-based shaping term, and rewards a transition based on the difference in the match densities with the next expert observation \( \hat{O}_e \) and the imitator’s observations. This component encourages the imitator to find a policy that exhibits similar state transitions to those experienced by the expert. We additionally found that adding the action penalty term with a \( \lambda \) of 0.01 penalizes the agent for making large steering changes. The expert image retrieval step is performed in real-time using local feature matching, and is outlined in the implementation section.

IV. IMPLEMENTATION

In this section, we provide specific implementation details of VOILA including those related to representation learning, keypoint feature extraction, and the network architectures.

A. Representation Learning

Representation learning using unsupervised learning is a powerful tool to improve the sample efficiency of deep RL algorithms. In our implementation, we used a Regularized Auto Encoder (RAE) \([17]\) to learn a latent posterior of the visual observations of the imitator. The imitating control policy is then learned using reinforcement learning with the latent code \( z_t = g_{\phi}(O_t) \) as the input to the policy network, where \( g_{\phi} \) is the encoder of the RAE with weights \( \phi \). We used the ResNet-18 encoder-decoder network architecture, and trained the RAE for the task of image reconstruction, with data collected from the imitator using random rollouts. The input images are of size 256 \( \times \) 256 and the size of the latent dimension is 512. We performed random cropping and random affine data augmentation in the image space to regularize the training.

B. Keypoint Feature Extraction

As a preprocessing step, all SUPERPOINT features detected from expert observations are stored in a buffer. At the start of an episode, we retrieve the nearest expert observation \( O_{e-i} \) to \( O_t \) by linearly searching for the closest expert observation in \( D_e \) with the maximum local feature matches. However, as the episode unfolds, instead of exhaustively searching for the closest expert image at every transition, we only search over the 3 next expert observations forward in time from the previous closest expert image in \( D_e \). At each transition, we extract SUPERPOINT features, retrieve the closest expert image and compute the reward according to Equation 1.

![Image](image-url)

Fig. 2: Aerial image of the AirSim simulation environment. Green lines show the tracks used to train the agent and red lines show the tracks unseen by the agent.

C. Navigation Policy Architecture

We model the navigation policy using a 3-layer, fully-connected neural network, with 256 neurons per layer. We perform frame-stacking with two consecutive latent codes of observations in time to alleviate effects of partial observability in the environment. We also additionally include the most recent action performed by the agent as a part of the state. We use Soft Actor-Critic (SAC) \([18]\), an off-policy RL algorithm, to learn the navigation policy \( \pi \).

V. EXPERIMENTS

We now describe the experiments that we performed to evaluate VOILA. The experiments are designed to answer the following questions:

(Q1) Is VOILA capable of learning imitative policies from visual-observation-only demonstrations even in the presence of viewpoint mismatch?

(Q2) How well does the policy learned using VOILA generalize to environments unseen during training?

(Q3) Does VOILA work in a real-world setting?

(Q4) Does VOILA work with sensor modalities other than vision?

To answer the questions above, we perform experiments both in simulation and in real-world. To measure similarity of the expert and the imitator policies, we compute the Hausdorff distance metric (lower is better) between trajectories of the expert and the imitator on all tracks.

A. Simulation Experiments in AirSim

In our simulation experiments, we answer questions \( Q_1 \) and \( Q_2 \) using the photorealistic outdoor ‘Neighborhood’ environment in AirSim \([19]\) and learn the task of road following, i.e., driving on a straight road while avoiding collisions with obstacles such as parked cars along the curb. In learning to perform this task, the agent must also contend with varied lightning conditions and the presence of shadows.
and road intersections along its path. To this end, we pick 12 straight road segments (tracks) in the AirSim environment, shown in Fig. 2. Tracks 1 and 2 marked in green are used for training the agent, and the learned policy is deployed on all 12 tracks. The other 10 tracks and their expert demonstrations are not seen by the agent prior to evaluation, and so we use them to test the generalizability of the learned policy to unseen environments. In each episode, the car is spawned at a randomized initial position near the start of the track, so the agent cannot trivially solve the task by learning to drive straight without having to steer. The expert demonstrations consist of a single trajectory (egocentric, front-facing images) for all tracks provided by a human (the first author) controlling the demonstration vehicle with the objective of navigating from start to end of the tracks, driving straight, in the middle of the road, and avoiding collisions with obstacles such as parked cars. We use the latent vector of the RAE as the state representation, and the action space consists of change in steering and throttle values. Note that the expert demonstrations are required only during training to compute the reward. At test time, the agent imitates the expert without requiring access to expert demonstrations.

In these simulation experiments, we compare VOILA against GAIfo, which is a state-of-the-art ifo algorithm that does not explicitly seek to overcome viewpoint mismatch. To ensure a fair comparison, we provide each algorithm the same state representation, i.e., the latent code of the RAE. Further, since GAIfo is an on-policy algorithm whereas VOILA relies on the off-policy SAC algorithm, we allow GAIfo ten times more training timesteps than VOILA (1 million vs. 100,000). Moreover, we report results for GAIfo using the policy that achieved maximum on-policy returns during training.

Fig. 3a compares VOILA and GAIfo without any viewpoint mismatch between the expert and imitator; we see that GAIfo, as expected, is able to imitate the expert demonstration on the training Tracks 1 and 2, but it fails to generalize to most unseen tracks. The policy trained with VOILA performs better than GAIfo at imitating the expert demonstration on the training tracks, and also generalizes to unseen environments. In Fig. 3b, in the presence of viewpoint mismatch, we see that, also as expected, GAIfo is unable to imitate the expert on the training track 2 and does not generalize to other environments. However, confirming our hypothesis, VOILA is able to imitate the expert demonstration even in the presence of viewpoint mismatch on Tracks 1 and 2 and also generalizes to the other 10 unseen tracks. GAIfo performs best on Tracks 6 and 10 as shown in Fig. 3a where there are not many shadows or other distractions like parked cars, but fails to generalize to other unseen tracks.

B. Physical Experiments on the Jackal

To answer all questions Q1–4, we performed experiments using a Clearpath Jackal—a four-wheeled, differential drive ground robot equipped with a front facing camera. The environment we considered is an indoor office space, shown in Fig. 1 which consists of carpeted floors, straight hallways, intersections, and turns. There are also static obstacles such as benches, chairs, whiteboards, pillars along the wall, and trashcans, all of which the robot needs to avoid colliding with.

We evaluated VOILA on a patrol task, in which the Jackal robot begins at a start state (shown in Fig. 1) and patrols around the building clockwise by taking the first right at intersections and driving straight in the hallways. To obtain expert demonstrations without viewpoint mismatch, we used the ROS move_base navigation stack with a map of the environment and provided waypoints to patrol the environment while recording the egocentric visual observations from the front facing camera. For the demonstration from a physically different agent, a human (the first author) walked the patrol trajectory once while recording video using a mobile phone camera held approximately 4 feet above the ground (the robot’s camera is at approximately 0.8 feet from the ground).

A VOILA training episode consists of the robot starting at approximately the same start state (as shown in Fig. 1) and
exploring in the training environment until the agent reaches the done state. After each training episode, the robot was manually reset back to the start state by a human operator, and a new training episode began. Training the navigation policy happened onboard the robot on a GTX 1050Ti GPU.

The VOILA agent trained using demonstrations with and without viewpoint mismatch learned to imitate the expert within 60 minutes (100 episodes) and 90 minutes (120 episodes), respectively, of experiment time (including time taken to reset the robot at the end of an episode). In Fig. 4, the trajectory in green shows the performance of the policy trained to imitate the move_base expert without any egocentric viewpoint mismatch. We see that VOILA is able to successfully patrol the indoor environment in a real-world setting, as demonstrated by the expert. Fig. 1 shows the trajectory rollout (in blue) of the policy learned using VOILA, imitating the expert demonstration in the presence of viewpoint mismatch.

To evaluate the generalizability of policies learned using VOILA to unseen real-world conditions ($Q_2$), we deploy VOILA in two new environments to identify environmental changes that do and do not break it. First, we test generalizability of the learned policy in a ‘Perturbed Environment,’ in which positions of movable objects such as trashcans, doors, whiteboards, chairs, and benches in the training environment on the same floor are perturbed as shown in Fig. 5. We see that with such environmental changes, VOILA is able to successfully patrol the hallway without any collisions.

Second, we deploy VOILA on a different floor within the same building, with major visual and structural changes from the training environment as shown in Fig. 6. While the robot succeeds for much of the trajectory, this experiment demonstrates the limitations of the current approach, as the robot collides with the walls in two places where there are large visual differences with the training environment. Trajectories for policy rollouts in Figures 1, 4, 5 and 6 were generated using ROS amcl and for human demonstration in Fig. 1 using the SfM package COLMAP.

Finally, to further demonstrate that VOILA supports sensing modalities other than vision in the navigation policy’s observation space ($Q_4$), we train VOILA with LIDAR range scan as the policy’s input, and observed that the agent learns to imitate the expert within 30 minutes of experiment time. As shown in Fig. 4 in red, VOILA-lidar shows the rollout trajectory of the policy learned using VOILA with LIDAR range scans. The Hausdorff distance between trajectories of the corresponding expert demonstration and the different policies learned using VOILA are shown in Table I. To provide context for the Hausdorff distance metric, we also show results for suboptimal and random trajectories. The suboptimal trajectory was collected by navigating along the hallway in a zig-zag route using move_base, and the random trajectory was collected using a randomly initialized policy $\pi$, which fails quickly. We see that both VOILA policies perform well, and that the LIDAR-based policy provides better performance, which is consistent with findings by Torabi et al. using GAIFO [15].

VI. CONCLUSION AND FUTURE WORK

In this paper, we introduced Visual-Observation-only Imitation Learning for Autonomous navigation (VOILA), a new approach that enables imitation learning for autonomous robot navigation using a single, egocentric, video-only demonstration. Furthermore, unlike prior methods, VOILA is robust to egocentric viewpoint mismatch. VOILA formulates the imitation problem as one of reinforcement learning using

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<th>Expert</th>
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TABLE I: Hausdorff distance between the expert trajectory and the policy rollout trajectory of VOILA. VOILA-lidar performs the best, followed by VOILA-vision.

Fig. 4: Policy rollouts of a VOILA agent trained to imitate demonstrations without egocentric viewpoint mismatch. VOILA is able to successfully imitate the expert demonstration and solve the task of rectangular hallway patrol.
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