Abstract—Deep reinforcement learning (DRL) has shown great potential in training control agents for map-less robot navigation. However, the trained agents are generally dependent on the employed robot in training or dimension-specific, which cannot be directly reused by robots with different dimensional configurations. To address this issue, a novel DRL-based navigation method is proposed in this paper. The proposed approach trains a meta-robot with DRL and then transfers the meta-skill to a robot with a different dimensional configuration (named dimension-scaled robot) using a method named dimension-variable skill transfer (DVST), referred to as DRL-DVST. During the training phase, the meta-agent learns to perform self-navigation with the meta-robot in a simulation environment. In the skill-transfer phase, the observations of the dimension-scaled robot are transferred to the meta-agent in a scaled manner, and the control policy generated by the meta-agent is scaled back to the dimension-scaled robot. Simulation and real-world experimental results indicate that robots with different sizes and angular velocity bounds can accomplish navigation tasks in unknown and dynamic environments without any retraining. This work greatly extends the application range of DRL-based navigation methods from the fixed dimensional configuration to varied dimensional configurations.

Index Terms—Autonomous navigation, deep reinforcement learning, dimension-variable navigation, mobile robotics.

I. INTRODUCTION

SELF-NAVIGATION, referred to as the capability of automatically reaching a given goal position while avoiding collisions with obstacles, is the core skill required for mobile robots. In the conventional approach, the robot needs to localize itself, estimate the current state, check obstacles, and plan a global path as well as local path [1], which is computation-hungry. Besides, in dynamic, unknown or unstructured environment scenarios like search and rescue tasks, the application of map-based methods become less effective. Recently, deep reinforcement learning (DRL) [2] has been employed to address the map-less navigation problem in an end-to-end manner and achieved notable successes [3-6]. More specifically, DRL-based methods utilize deep neural networks (DNN) [9] to learn a function that directly maps the raw observations into the moving command of the mobile robot. Given a reward function for evaluating the effects of executing an action on a state, the DRL-agent automatically learns to control the robot from scratch via interaction with the training environment. Notably, after training, the commands are generated from the forward propagation of DNNs, which is computationally efficient [10]. Owing to those characteristics, DRL-based methods have attracted extensive attention in robot navigation domain [11].

To alleviate the high cost of real-world training, sim-to-real (simulation-to-real-world) is a commonly adopted approach for learning navigation skills with DRL. Tai et al. [12] trained a robot in simulation with Asynchronous DDPG (Deep Deterministic Policy Gradient) [13] and directly deployed the learned controller to the real robot for performing navigation tasks. In addition, Xie et al. [14] utilized a PID controller to accelerate the training of DRL in simulation and successfully controlled a real robot to navigate in an unknown environment. They further accelerated the training process by introducing a human-engineered obstacle-avoidance reactive controller and extended the 2D Lidar to a depth camera [15]. Moreover, to enhance the navigation ability in maze-like environments, intrinsic rewards were proposed for encouraging exploration during navigation [16]. This reward shaping method encourages the robot to explore unseen areas and aids the robot to reach the goal in unvisited areas.

Currently, most DRL-based robot navigation studies mainly focus on improving the navigation performance of the controller with fixed robot dimensional configuration, such as constant robot radius and velocity bounds [3-6, 9, 12, 14-16]. However, in real-world applications, those dimensional configurations may change. For example, when a robot carries some large and heavy goods, its dimension coverage will increase, and its maximum velocities may decrease. The dimensional change may cause the robot’s false awareness, leading it to fail.

To control the dimension-scaled robot, the simplest way is retraining the DRL-agent from scratch. However, retraining a robot from scratch usually takes near one day [12], which is quite costly for real-world applications. Compared with complete retraining, skill-transfer is a more feasible approach. Specifically, skill transfer means transferring the old navigation skill to the dimension-scaled robot. One commonly used skill-transfer approach is meta learning [17, 18], which can adapt the robot to unexpected situations by online learning. However, these methods need learn several tasks first, still require some time for real-world retraining and have a high requirement for the on-board processor. In addition, transfer learning using domain randomization [19] is another skill-transfer approach. However, it focuses on transferring the skill learned from training environment to the same robot in a new environment. By sharp contrast, our problem is...
transferring the skill to a new robot.

To our best knowledge, reported DRL-based navigation methods cannot be applied to tasks where the robots need to change their dimensional configurations without retraining. This work, for the first time, proposes a DRL-based method that can be used for mobile robots with varied dimensional configurations. In our approach, a meta-robot is firstly trained in a well-designed simulation environment for the meta-agent to learn robot navigation skills. Once the dimensional configuration changes with a dimension-scaled robot, the meta-robot can adaptively transfer its navigation skill (inside the meta-agent) to the dimension-scaled robot using the proposed dimension-variable skill transfer (DVST) method. Hence, we call our method DRL_DVST. To sum up, the contributions of our paper are as follows:

1) A novel dimension-variable robot navigation method is proposed for extending the application range of DRL-based navigation methods from a fixed dimensional configuration to varied dimensional configurations.
2) The method can directly transfer the DNN controller trained in simulation for meta-robot to a dimension-scaled robot without any retraining.
3) Real-world autonomous navigation of robots with different dimensional configurations is achieved in unknown and dynamic scenarios.

The rest of this paper is organized as follows. A brief introduction of the dimension-variable robot navigation problem and Soft Actor Critic (SAC) algorithm are given in Section II. The proposed dimension-variable DRL-based robot navigation method is described in Section III, followed by simulation and real-world experiments and the corresponding results in Section IV. The discussions based on the results are given in Section V. Last, we draw the conclusions in Section VI.

II. BACKGROUND

In this work, we aim to train a DNN as a real-time navigation controller for a circular robot with various dimensional configurations. Specifically, given the robot radius and velocity bounds, the DNN-based controller can drive the robot to its goal without colliding with obstacles. In this section, the dimension-variable robot navigation problem is firstly outlined followed by the introduction of SAC [20], the platform on which the proposed method is developed.

A. Problem Formulation

The dimension-variable map-less robot navigation problem can be modelled as a sequential decision-making process. As shown in Fig. 1, a circular robot is required to reach its goal position without colliding with any obstacles. The robot is equipped with distance sensors (a 2D Lidar in this paper) on the center for observing its surroundings. Its radius $R$ and the velocity bounds $\{v_{\max}, \omega_{\max}\}$ are known and may vary due to the change of dimensional configurations. At step $t$, the relative position of goal in robot frame $s^0_t = \{a^0_t, q^0_t\}$ is assumed to be obtained by localization sensors such as WIFI or a microphone array. We denote the input of the DNN controller as $s_t = \{s^d_t, s^g_t, v_{t-1}, \omega_{t-1}\}$, where $s^d_t$ is the onboard sensor readings. Besides, the action $a_t = \{v_t, \omega_t\}$ of the robot comprises the linear and angular velocities. Given $s_t$, the robot takes $a_t$ under the current policy $\pi$. It then updates the next input $s_{t+1}$ based on new observations and receives a reward $r_t(s_t, a_t, s_{t+1})$ calculated by the reward function. The objective of this decision-making process is to find an optimal policy $\pi^*$ that maximizes the discounted total rewards $G_t = \sum_{t=0}^{\infty} \gamma^{t} r_t$, where $\gamma \in [0,1]$ is a discounted factor.

B. Soft Actor Critic (SAC)

SAC is an entropy-regularized off-policy DRL algorithm. It aims to maximize the entropy-regularized expected total return as follows:

$$J(\pi) = \mathbb{E}_\pi [G_{t=0} + \sum_{t=0}^{\infty} \gamma^t \alpha H(\pi(\cdot | s_t))]$$

where $H(\pi(\cdot | s_t)) = - \int_{\mathcal{A}} \pi(a | s_t) \log \pi(a | s_t) \, da$ is the entropy of the action distribution on input $s_t$ under policy $\pi$; $\alpha > 0$ serves as a regulation factor that weighs the contributions of the total rewards and the entropy. A large $\alpha$ corresponds to more exploration, while a small $\alpha$ corresponds to more deterministic policy. SAC utilizes entropy to inject the random exploration into the objective functions where the Q-function $Q^\pi(s, a)$ denotes the expected total return from performing action $a$ on input $s$:

$$Q^\pi(s, a) = \mathbb{E}_\pi [G_{t=0} + \sum_{t=0}^{\infty} \gamma^t \alpha H(\pi(\cdot | s_t))] | s_0 = s, a_0 = a].$$

And $Q^\pi(s, a)$ can be computed by soft Bellman equation:

$$Q^\pi(s, a) = \mathbb{E}_\pi [r + \gamma (Q^\pi(s', a') - \alpha \log \pi(a' | s'))].$$

where $s'$ is the subsequent input of $s$, and $a'$ is the action taken from state $s'$. To address the problem induced by large state space, SAC estimates Q-function $Q_\phi(s, a)$ with a soft critic network parameterized by $\phi$. Besides, to solve the continuous-action problem, it uses a soft actor network $\pi_\theta(a | s)$ to approximate the optimal action distributions. SAC holds a replay buffer $\mathcal{B} = \{B_1, B_2, \cdots, B_N\}$ to store each transition $B = \{s, a, r, s', d\}$, where $d$ is the label of terminal state. If $s'$ is a terminal state, $d = 1$; otherwise $d = 0$. During each training step, SAC samples a minibatch of transitions $\mathcal{M}$ from the replay buffer and uses Bellman equation to train the critic networks:

$$\nabla_\phi L(\phi) = \mathbb{E}_\mathcal{M} [1/|\mathcal{M}|]$$

Fig. 1. Illustration of the robot navigation problem.
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\[
\sum_{(s,a,r,s') \in M} (Q(s,a|\phi) - Q_{\text{target}}(s,a))^2. \tag{4}
\]

where \( \mathcal{L}(\phi) \) is the mean squared error (MSE) loss function for updating \( \phi \); the target Q value is:

\[
Q_{\text{target}}(s, a) = r + \gamma (1 - d)
\]

\[
(Q(s', \tilde{a}|\phi_{\text{target}}) - \alpha \log \pi(\tilde{a}|s', \theta)). \tag{5}
\]

where \( \tilde{a} \) is the action generated by the stochastic policy; \( \phi_{\text{target}} \) is a time-delayed version of \( \phi \) and updated by Polyak averaging:

\[
\phi_{\text{target}} \leftarrow \nu \phi_{\text{target}} + (1 - \nu) \phi. \tag{6}
\]

where \( \nu \in [0,1) \) is the Polyak factor. The actor network is updated by:

\[
\nabla_{\theta} \mathcal{L}(\theta) = \nabla_{\theta} \frac{1}{|M|} \sum_{s \in M} (Q(s, \tilde{a}|\phi) - \alpha \log \pi(\tilde{a}|s, \theta))^2. \tag{7}
\]

where \( \mathcal{L}(\theta) \) denotes the MSE loss function for updating \( \theta \).

III. METHOD

In this section, we propose a novel method named DRL DVST that allows a circular robot to adaptively adjust its control strategies when its dimensional configuration changes. The overall framework of this method is given in Fig. 2, which contains two stages, i.e., meta-skill learning and DVST. In the first stage, a meta-agent is trained using a meta-robot model in a well-designed simulation environment to master the self-navigation skills. The learned meta-skill can be directly deployed to a real robot. In the second stage, the DVST method is utilized for transferring the meta-skill to robots with changed dimensional configurations.

A. Meta-skill Learning

For meta-skill learning, a simulation environment shown in Fig. 3 is built. It is a room of 7×7 m² filled with obstacles of irregular shapes. Compared with the training scenarios in [3, ], [15], this training environment is much more crowded. On the other hand, SAC is adopted as the learning algorithm as it can achieve much better performance in most robot control tasks compared with other model-free DRL methods, such as DDPG [13] and TD3 [21]. Besides, SAC is easy to be implemented and does not need additional exploration methods such as \( \epsilon \)-greedy [2].

The employed SAC neural network architecture is given in Fig. 4, consisting of two soft critic networks parameterized by \( \phi_1 \) and \( \phi_2 \) and a soft actor network parameterized by \( \theta \). No weights are shared among the three networks. For each critic network, \( n \) laser beams (\( n = 540 \) in this paper) are fed into 1D CNN layers for feature extraction. The extracted features are flattened and concatenated with robot velocities, the relative position of the goal, and the action output by the soft actor network. The combined features are then fed into fully-connected (FC) layers for computing the Q-value of the input-action pair. The double Q framework can help alleviate overestimate during training [22], and the target Q value used for value updating in (5) is changed to,

\[
Q_{\text{target}}(s, a) = r + \gamma (1 - d)
\]

\[
\left( \min_{i=1,2} Q(s', \tilde{a}^i|\phi_{\text{target}}^i) - \alpha \log \pi(\tilde{a}|s', \theta) \right). \tag{8}
\]

The soft actor network also comprises 1D CNN layers and FC layers. As Gaussian policy is used here, the soft actor network outputs the mean \( \mu(s) \) and the log-standard-deviation \( \log \sigma(s|\theta) \). To alleviate the side effects introduced by large log-standard-deviation at the beginning of training, the same as [17], \( \log \sigma(s|\theta) \) is bounded within \([-20, 2]\). As the actions of the robot are bounded, the policies are squashed into \([-1, 1]\] by tanh function as follows,

\[
\tilde{a}(s|\theta) = \tanh(\mu(s|\theta)). \tag{9}
\]

\[
\tilde{a}(s|\theta) = \tanh(\mu(s|\theta) + \sigma(s|\theta) \odot \zeta). \tag{10}
\]

where \( \zeta \sim \mathcal{N}(0, I) \); \( \tilde{a}(s|\theta) \) and \( \tilde{a}(s|\theta) \) are the deterministic action and stochastic action, respectively. As the output of the actor network is normalized within \([-1, 1]\), the real velocity commands sent to the robot are calculated by de-normalizing.
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The objective of the reward function for learning navigation skills is to drive the robot to safely reach its goal as fast as possible. Similar to [3, 12, 15], the reward function used in this paper contains a large positive sparse part \( r_{\text{reach}} \) for reaching the goal, a large negative sparse part \( r_{\text{crash}} \) for punishing collision, and a small dense part for moving closer to the goal, which is defined as follows,

\[
r_t = \begin{cases} 
    r_{\text{reach}}, & d_t^g \leq D_{\text{reach}} \\
    r_{\text{crash}}, & d_t^{\min} \leq R_{\text{robot}} \\
    c_1(d_t^g - d_{t+1}^g) - c_2, & \text{else}
  \end{cases}
\]

where \( d_t^g \) is the distance between the goal and the robot’s center; \( D_{\text{reach}} \) is the distance threshold for determining goal-reaching; \( d_t^{\min} = \min\{d_1^g, d_2^g, \ldots, d_n^g\} \) is the shortest distance between obstacles and robot; \( R_{\text{robot}} \) is circular robot’s radius; \( c_1 \) is a scale factor; \( c_2 \) is a constant working as a time penalty.

B. Dimension-variable Skill Transfer (DVST)

After training, the meta-agent for the meta-robot is ready for transferring its skill to other dimension-scaled robots. For simplicity, we refer to the meta-robot as \( CR_m \) (with radius of \( R_m \)) and the dimension-scaled robot as \( CR_s \) (with radius of \( R_s \)).

The key idea behind the DVST is: (1) mapping the observations of \( CR_s \) to the observations of \( CR_m \) (observation transfer process) and (2) scaling the DRL policy generated by \( CR_m \) back to \( CR_s \) (policy transfer process). This idea is illustrated with mathematical expressions as follows.

1) Observation Transfer Process

The observation \( s_t = \{s_t^d, s_t^{di}\} \) received by \( CR_s \) consists of distance-dependent observations \( s_t^d \) (the Lidar readings, the relative distance between the goal and robot, and current linear velocity) and distance-independent observations \( s_t^{di} \) (relative angle between the goal and current angular velocity). During the observation transfer process, as shown in Fig. 5, the distance-dependent observations of \( CR_m \) are scaled to that of \( CR_s \) based on the ratio of \( R_m/R_s \), while the distance-independent observations remain the same. The corresponding observation representation of \( s_t \) in \( CR_m \) after observation transfer is:

\[
s_m = \left\{ \frac{R_m}{R_s} s_t^d, s_t^{di} \right\}.
\]

2) Policy transfer process

Fig. 5. Illustration of the observation transfer process.

\[
\begin{align*}
\text{Definition 4.1:} & \quad \text{For two trajectories} \ L_k \text{ and } L_j, \text{ if point} \ P_k \in L_j \text{ holds for} \ \forall \ P_k \in L_k, \text{ then we define} \ L_k \subseteq L_j. \\
\text{With} \ s_m \text{ as input, the control policy (i.e., the velocities) of the meta robot} \ CR_m \text{ generated the DNN-based controller can be represented as} \ v_m(\frac{R_m}{R_s} s_t^d, s_t^{di}) \text{ and} \ \omega_m(\frac{R_m}{R_s} s_t^d, s_t^{di}).\\
\text{Same as the widely used dynamic window approach [23], the robot is assumed to move with constant velocities within one control cycle. Hence, the corresponding expected trajectory} \ l_m \text{ generated by the velocities within one control cycle is a circular arc (see Fig. 6). It can be represented by its length} |l_m| = v_m \Delta T \text{ and its radius} \ r_m = \frac{v_m}{\omega_m} (\omega_m \text{ is negative if} \ \omega_m \text{ is negative}, \text{ where} \ \Delta T \text{ is one control cycle (the start point is the center of the robot, i.e. the original point). To transfer the policy back to the robot} \ CR_s, \text{ the ideal trajectory} \ l_{s, \text{ideal}} \text{ of} \ CR_s \text{ should be similar to} \ l_m, \text{ and the similarity ratio is} \ R_s/R_m. \text{ Based on this idea, the ideal velocities and trajectory for} \ CR_s \text{ are as follows,}}\\
& v_{s, \text{ideal}} = \frac{R_s}{R_m} v_m(\frac{R_m}{R_s} s_t^d, s_t^{di}), \\
& \omega_{s, \text{ideal}} = \omega_m\left(\frac{R_m}{R_s} s_t^d, s_t^{di}\right), \\
& |l_{s, \text{ideal}}| = v_{s, \text{ideal}} \Delta T, \\
& \rho_{s, \text{ideal}} = \frac{v_{s, \text{ideal}}}{\omega_{s, \text{ideal}}}.
\end{align*}
\]

However, the ideal velocities of \( CR_s \) may exceed the velocity bounds. Constrained by velocity bounds, to make the real trajectory \( l_s \) cover the ideal trajectory as much as possible (i.e., maximize \( |l_s| \)), the objective of the skill transfer problem can be formulated as,

\[
\begin{align*}
\arg \max_{v_s, \omega_s} & \quad |l_s| \\
\text{subject to} & \quad v_s \leq v_s^{\max}, \\
& \quad |\omega_s| \leq \omega_s^{\max}, \\
& \quad l_s \leq |l_{s, \text{ideal}}|, \\
& \quad v_s = \rho_{s, \text{ideal}} \omega_s
\end{align*}
\]

where \( l_s \leq |l_{s, \text{ideal}}| \) is equivalent to \( \rho_s = \rho_{s, \text{ideal}} \) and \( |l_s| < |l_{s, \text{ideal}}| \) (\( l_s \) and \( l_{s, \text{ideal}} \) share the same start point, i.e. the original point). Hence, the above optimization problem can be rewritten as:

\[
\begin{align*}
\arg \max_{v_s, \omega_s} & \quad v_s \Delta T \\
\text{subject to} & \quad v_s \leq \min\{v_s^{\max}, \rho_{s, \text{ideal}}\}, \\
& \quad |\omega_s| \leq \omega_s^{\max}, \\
& \quad v_s = \rho_{s, \text{ideal}} \omega_s.
\end{align*}
\]
The solution to the above problem is piecewise conditioned on whether the ideal radius of curvature $\rho_s^{ideal}$ can be achieved with the maximum linear velocity $v_s^{max}$ or not. If $\frac{v_s^{max}}{\omega_s^{max}} \leq |\rho_s^{ideal}|$, the ideal radius of curvature $\rho_s^{ideal}$ can be achieved with maximum linear velocity $v_s^{max}$ by adjusting the angular velocity $\omega_s$. In other words, given any linear velocity $v_s$ within the velocity bound, we can always find an angular velocity $\omega_s$ within the velocity bound that can ensure $v_s = \rho_s^{ideal}$. Therefore, under this condition, we need to calculate $v_s$ first. To maximize $v_s$, constrained by $v_s \leq \min\{v_s^{max}, \rho_s^{ideal}\}$, $v_s$ should be the smaller value of $v_s^{max}$ and $\rho_s^{ideal}$. Hence, the velocities of robot $\mathcal{R}_s$ are as follows,

$$v_s = \min\{v_s^{ideal}, v_s^{max}\},$$

$$\omega_s = \frac{v_s}{\rho_s^{ideal}}.$$  \hspace{1cm} (16)

Else (i.e., $\frac{v_s^{max}}{\omega_s^{max}} > |\rho_s^{ideal}|$), the ideal radius of curvature $\rho_s^{ideal}$ cannot be achieved with maximum linear velocity $v_s^{max}$. In other words, given an angular velocity $\omega_s$ within the velocity bound, we can always find a linear velocity $v_s$ within the velocity bound that can ensure $v_s = \rho_s^{ideal}$. Therefore, under this condition, we need to calculate $\omega_s$ first. As $v_s$ is proportional to $|\omega_s|$, maximizing $v_s$ is equivalent to maximizing $|\omega_s|$. To maximize $|\omega_s|$, constrained by $|\omega_s| \leq \min\{\omega_s^{max}, |\omega_s^{ideal}|\}$, $|\omega_s|$ should be the smaller value of $\omega_s^{max}$ and $|\omega_s^{ideal}|$. Hence, the velocities of robot $\mathcal{R}_s$ are as follows,

$$\omega_s = \sgn(\omega_s^{ideal})\min\{\omega_s^{max}, |\omega_s^{ideal}|\},$$

$$v_s = \omega_s \rho_s^{ideal}.$$  \hspace{1cm} (17)

Based on (16) and (17), the meta-skill can be transferred to any circular robots with different robot radii and velocity bounds.

### IV. IMPLEMENTATION AND EXPERIMENTS

#### A. Meta Skill Training

The training process is run in ROS Stage [24], a light-weight robot simulator. In the beginning, the meta-agent (blue block in Fig. 7a with a radius of 0.2m) starts at the original point, and the target points (not rendered) are randomly chosen from the obstacle-free area. Each episode terminates when the robot reaches the goal, crashes into obstacles, or the number of total steps exceeds the pre-set maximum value. At the end of an episode, if the goal is reached, the robot starts at the terminal point for the next episode. Otherwise, it will be respawned at the original point. In the first 100 episodes, the meta-agent takes random actions with uniform distribution over valid actions. After that, it returns to the stochastic policy with Gaussian distribution. The training process lasts 400k steps, and the trained agent is tested every 5k steps. In testing, the robot navigates with the deterministic policy and is required to reach four goal-points (see Fig. 7a) from the original point successively. The training process is repeated five times using different random seeds for evaluating the stability of the learning method.

The performance of the trained agent is evaluated based on the total rewards received per episode (Fig. 7b), success rate (Fig. 7c) and the decision steps spent per episode (Fig. 7d) when performing the testing tasks, in which the solid lines indicate the averaged performance curves, and translucent areas represent the variance of the performance curves. As shown in Fig. 7b, the total rewards increase quickly during the first 50k steps and stabilize after 150k steps. Besides, according to Fig. 7c, all four navigation tasks can be accomplished after 150k training steps. In addition, as shown in Fig. 7d, with the increase of training steps, the decision steps taken by the robot firstly rise, and then decrease to a stationary value. This result reveals the robot first learns to survive in the scenario and then learns to take fewer steps to reach its target.

#### B. Performance Evaluation Of DRL_DVST In Simulation

To investigate the navigation performance of the dimension-variable controller, a simulation scenario is built as shown in Fig. 8. During testing, the robot starts at point (0, -1.5) and faces its goal at point (0, 1.3). A wall is placed between the start point and the target with a gate of 0.78m in width. A total of nine experiments, where the radius $R$ increases from 0.2m to 0.6m with an interval of 0.05m, are conducted. In each experiment, the test is repeated 20 times to investigate the stability of the dimension-scaled controller.

![Fig. 7. Testing environment and performance curves of the learning process: (a) Goal locations used for testing; (b) Total rewards per episode; (c) Success rate per episode; (d) Total decision steps per episode. (Clear Figures can be viewed by zooming in)](image_url)

![Fig. 8. The simulation scenario for performance evaluation.](image_url)
The corresponding trajectories of the robot are given in Fig. 9. As shown, with relatively small radii, i.e., 0.2m to 0.3m, the robot passes the gate to its target in a near-optimal way (near a straight line). When \( R \) reaches 0.35m and beyond, the robot is aware that it cannot pass the gate without collision and turns to the left gate instead. Testing results show that correct action policies have been generated and the robot can choose suitable gates according to its size. The testing results reveal that the dimension-scaled robot is capable of performing navigation tasks using the DRL_DVST method without any retraining.

C. Comparison Study

A more straightforward approach to tackle the dimension variable problem is to directly train a robot to navigate with its radius as an additional input (RI) of the DNN controller, referred to as DRL_RI. In this section, we implement this idea by training a DRL-agent in simulation to compare this agent’s performance with the DRL_DVST method. The simulation-based training environment is shown in Fig. 10, in which the distances between obstacles are meticulously designed for robots with different radii to pass. The DNN structure is similar to the neural network structure shown in Fig. 4 except that the robot radius is added to the input. During training, at the beginning of each episode, the robot radius is randomly sampled from the uniform distribution \( U [0.2m, 0.6m] \).

After the success rate during training stabilizes around 100%, the trained DRL-agent is then tested to perform the same tasks described in Section V-B. The corresponding trajectories of the robot are shown in Fig. 11. As shown, when \( R < 0.35m \), most of the time, the dimension-scaled robot firstly moves towards the front gate and then turns to the left gate, which generates unsmooth and non-optimal paths. Moreover, when the \( R \) reaches 0.55m or above, the robot always crashes into obstacles, suggesting that this approach is not able to handle scenarios where the robot radius is relatively large.

We further compare the performance of the two methods in terms of the average completion time, average linear velocity and success rate. For each method, we test additional four DNN-controllers trained with different random seeds. For each robot radius, each controller is tested 20 times as well (100 tests altogether per robot radius). The completion time and linear velocity data will not be used for computing the average value if the task is not completed. The testing results are given in Fig. 12. As shown, with the DRL_DVST method, the robot spends less completion time and achieves higher linear velocity than using the DRL_RI method for all robot radii within \([0.2m, 0.6m]\). Moreover, with the increase of robot radius, the DRL_DVST method can stabilize its success rate around 100%, while the DRL_RI method has a dramatic decrease in success rate (only 20% when \( R = 0.55m \)). To sum up, the results indicate that:

![Fig. 9. Trajectories generated for robots with different radii using the DRL_DVST method.](image)

![Fig. 11. Trajectories generated for robots with different radii using the DRL_RI method.](image)

![Fig. 10. The simulation scenario for performance evaluation.](image)

![Fig. 12. Performance curves of the two methods: (a) Average completion time; (b) Average linear velocity; (c) Success rate.](image)
When the robot radius is small, most of the time, the DRL_DVST approach can generate more optimal paths than the DRL_RI approach. When the robot radius is large, DRL_DVST approach can achieve a much higher success rate than DRL_RI approach. DRL_DVST approach can enable the dimension-scaled robot to perform the navigation task with a higher velocity and less completion time than DRL_RI approach.

D. Real-world experiment

To further evaluate the performance of DRL_DVST method, real-world experiments are conducted. As shown in Fig. 13a, a Turtlebot2 robot serves as the meta-robot (R = 0.2m) mounted with a Hokuyo UTM-30LX Lidar. The robot radius is increased to 0.35m by adding a foam slab (see Fig. 13b) for testing the dimension-variable controller. The real-world scenario is a small indoor space with obstacles meticulously placed to ensure that there exists a path allowing the large-sized robot to pass (see Fig. 13c). To obtain the target position in the robot frame, the AMCL ROS package [25] is used to localize the robot in a pre-built map. Notably, the map is not rendered to the robot during testing.

Four experiment scenarios are conducted to test the navigation performance of robots with different radii (0.2m and 0.35m) and maximum angular velocities (π/2 rad/s and π/6 rad/s). The maximum linear velocity keeps 0.5 m/s for all four scenarios. In each experiment scenario, the mission of robot is to start from Goal “0” and successively reach three goals (Goal “1”, “2” and “0”) as shown in Fig. 14. This process is repeated three times to verify performance stability. The robot trajectories (in black) and the average completion time \( T_{task} \) are recorded and shown in Fig. 14. The corresponding videos can be found in https://youtu.be/MBpuCRwSh5U.

For each of the four scenarios, the mission is accomplished successfully. When radius is small (R = 0.2m), the robot chooses short paths to reach the target. When R = 0.35m, the robot is aware that it cannot pass the narrow passages (highlighted with translucent yellow rectangles in Fig. 14c) and adaptively switches to paths with wider passages. In addition, for robots with the same radius, similar trajectories are generated, but the completion time increases with the decrease of maximum angular velocity. This observation can be explained by (17), where a small \( \omega_L^{max} \) restricts the robot to reach its ideal linear velocity \( v_L^{ideal} \), thus leading to longer completion time. Moreover, experiments comprising dynamic obstacles are conducted in the same space with a different layout. The corresponding video can be found in https://youtu.be/oBdCVaywGP8. As shown in this video, the dimension-scaled robot can avoid dynamic obstacles and reach its destinations efficiently.

V. DISCUSSIONS

In the section, we discuss the application limits of the proposed approach from two aspects, i.e., robot shape and sensor type. Firstly, the dimension-scaled robot is assumed to be circular in this paper. To apply DVST on a rectangular robot, we can use a circular robot to replace the rectangular robot. The radius of the circular robot should be the circumscribed circle of the rectangular robot, which ensures the rectangular robot is completely covered. With this approach, for example, we can transfer the learned meta-skill to a large-size rectangular mobile robot (the same size as the Pioneer 3-AT robot [26]), and the corresponding video can be found in https://youtu.be/o44Z4px5XI (the testing scenario comes from [14]). Although the robot behaves well, the approach may be limited to rectangular robots with small aspect ratios. With a large aspect ratio, a robot may fail to pass some narrow passages because the radius of the circumscribed circle is much greater than the robot width. Secondly, as 2D Lidar can only detect obstacles at the same level of its scanning height, the obstacles below or above the scanning height may be missed. To enhance the obstacle avoidance capability of the meta-agent, 3D sensors such as 3D Lidar or depth camera are feasible choices. To use the 3D sensing information in the proposed approach, the 1D CNNs shown in Fig. 4 need to be changed into 2D CNNs.

VI. CONCLUSIONS

In this paper, we present a novel dimension-variable DRL-based robot navigation method. This method significantly
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extends the application range of DRL-based navigation methods from a fixed dimensional configuration to varied dimensional configurations. We train a meta-robot in a crowded simulation environment to learn navigation skills. After training, the meta-skill can be transferred to a dimension-scaled robot through the proposed dimension-variable skill transfer approach. A large number of experiments have been conducted in simulation to assess the DVST method. The simulation results reveal that the skill-transferred robot can accomplish tasks with near 100% success rate even the dimension-enlarged-ratio reaches 3.0. In real-world scenarios, the learned skill can be directly deployed to a real dimension-scaled robot without any retraining. The dimension-scaled robot can efficiently accomplish navigation tasks in unknown and dynamic scenarios. At the current stage, our dimension-variable skill transfer method is only applicable for transferring the meta-skill to circular robots or rectangular robots with small aspect ratio. In the future, we plan to extend the application range of our method to transfer the meta-skill to a robot with various shapes.

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