Flipbot: Learning Continuous Paper Flipping via Coarse-to-Fine Exteroceptive-Proprioceptive Exploration

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Abstract— **This paper tackles the task of singulating and grasping paper-like deformable objects. We refer to such tasks as paper-flipping. In contrast to manipulating deformable objects that lack compression strength (such as shirts and ropes), minor variations in the physical properties of the paper-like deformable objects significantly impact the results, making manipulation highly challenging. Here, we present Flipbot, a novel solution for flipping paper-like deformable objects. Flipbot allows the robot to capture object physical properties by integrating exteroceptive and proprioceptive perceptions that are indispensable for manipulating deformable objects. Furthermore, by incorporating a proposed coarse-to-fine exploration process, the system is capable of learning the optimal control parameters for effective paper-flipping through proprioceptive and exteroceptive inputs. We deploy our method on a real-world robot with a soft gripper and learn in a self-supervised manner. The resulting policy demonstrates the effectiveness of Flipbot on paper-flipping tasks with various settings beyond the reach of prior studies, including but not limited to flipping pages throughout a book and emptying paper sheets in a box. The code is available here : https://robotll.github.io/Flipbot/**

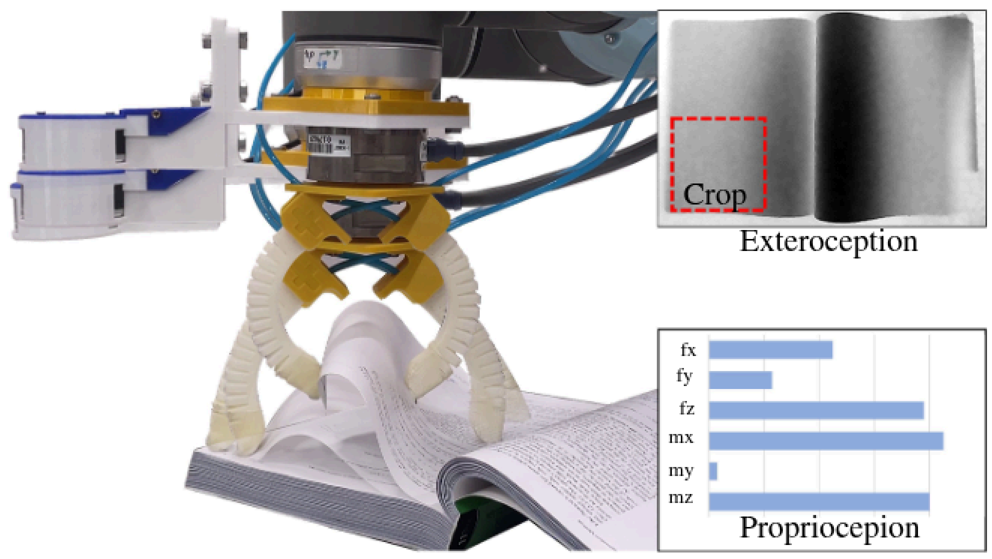

Fig. 1. A soft gripper with the learned policy flips a book. The time-lapse image depicts the operation of the gripper as it interacts with the book to singulate and grasp a piece of paper. The cropped depth image in the red line box located at the upper right corner presents the exteroceptive observation from the depth camera. The readings on the bottom right show the proprioceptive observation from the force-torque sensor.

I. INTRODUCTION

Deformable object manipulation has achieved notable progress in robotics. However, until now, robots could not match the generalization and robustness of humans in manipulating thin and flexible objects. One of these tasks is flipping book pages, as shown in Fig. 1, which requires singulating and grasping paper page by page. Humans can briskly turn pages of a book by watching the target and using the tactile sensations on their fingertips to adjust their actions. In this process, human instinctively combines exteroceptive and proprioceptive perception to accommodate the irregular paper thickness and physical properties, such as slipperiness, stiffness, and friction. Endowing robots to have such capability is a grand challenge in the field of robotics.

One of the foremost challenges in manipulating thin and flexible objects is incomplete and noisy perception [1]. For example, a stack of paper is unstable, and the contact between each layer is not observable. Therefore, the robot may have to perceive physical properties between paper, such as friction, and elasticity, to successfully singulate and grasp a sheet from a stack. Exteroceptive perception obtained from camera sensors is incomplete for such tasks and unreliable in real-world conditions. The depth sensors, which most existing works rely on, cannot distinguish the different layers of stacked paper due to the paper thickness. Depth sensors are also inherently incapable of capturing the surface's physical properties, such as hardness and flexibility [2]. Some works use tactile sensors as proprioception to estimate deformable objects' physical properties. For example, [3] uses a high-precision tactile sensor to measure the geometry of the contact surface and the object's hardness. [4] manipulates cables with a pair of robotic grippers using real-time tactile feedback. Nevertheless, high-precision tactile sensors are often expensive and require specific finger shapes to fit. In addition to the challenge in environment perception, manipulating thin and flexible objects may desire the gripper with the dexterity and compliance of human fingers, which further adds to the difficulty [5].

To address the above challenges, we present Flipbot, a self-supervised method for singulating and grasping paper-like deformable objects at unprecedented robustness, enabling continuous paper flipping. At its core, Flipbot is based on a principled solution integrating exteroceptive and proprioceptive perceptions into policy learning. We obtain proprioception from the Force/Torque (F/T) sensor readings and exteroception from a depth camera. We use a procedural motion, referred to as "Swipe" to actively interact with the environment. When a "Swipe" motion is applied to a piece of paper, the deformation brought about by the interaction between the finger and object reveals imperceptible physical characteristics like mass, flexural rigidity, and friction. Meanwhile, visual observation provides global information on the environment. We design a cross-sensory encoder to integrate exteroceptive and proprioceptive perceptions into an

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Flipbot：通过从粗到细的外感受本体感觉探索学习连续翻纸

赵超、江春丽、蔡俊浩、王宇、俞洪宇和陈启峰

摘要 — 本文解决了分离和抓取纸状可变形物体的任务。我们将此类任务称为翻纸。与纵缺乏抗压强度的可变形对象（例如衬衫和绳索）相比，纸质可变形对象物理属性的微小变化会显著影响结果，这使得纵极具挑战性。在这里，我们介绍了 Flipbot，这是一种用于翻转类似纸张的可变形物体的新型解决方案。Flipbot 允许机器人通过整合外感受和本体感知来捕捉物体的物理特性，这些感知对于纵可变形物体是必不可少的。此外，通过结合提出的粗到精勘探过程，该系统能够通过本体感觉和外感受输入学习最佳控制参数，以实现有效的翻纸。我们将我们的方法部署在带有软夹持器的真实机器人上，并以自我监督的方式学习。由此产生的政策证明了 Flipbot 在翻纸任务上的有效性，其各种设置超出了先前研究的范围，包括但不限于翻阅书籍和清空盒子中的纸张。代码可在此处获得：https://robotll.github.io/ Flipbot/

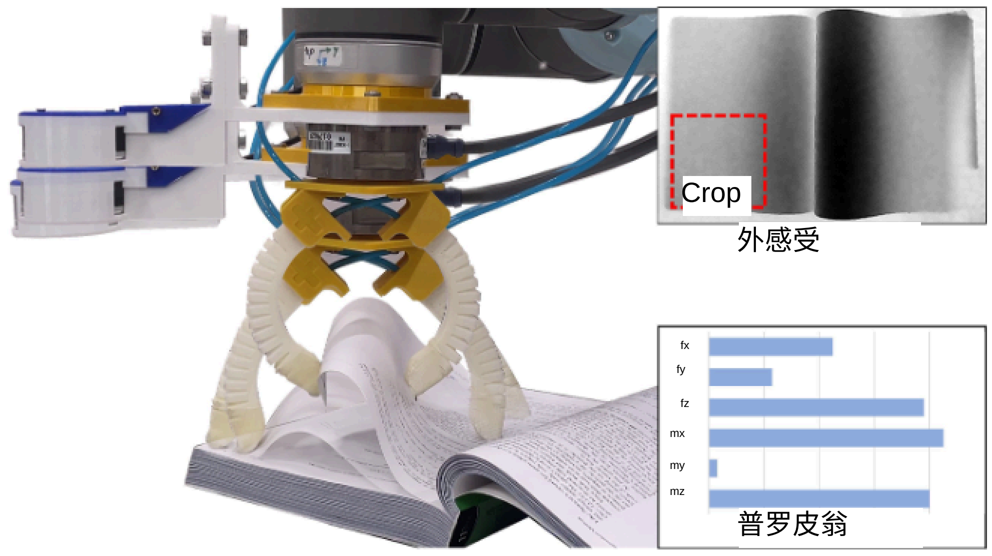

图 1.具有学习策略的软抓手会翻书。延时图像描绘了抓手在与书交互以分离和抓取一张纸时的作。位于右上角的红线框中裁剪的深度图像显示了深度相机的外感观察。右下角的读数显示了力-扭矩传感器的本体感受观察。

I. I 可变形对象作在机器人技术方面取得了显着进展。然而，直到现在，机器人在纵薄而灵活的物体方面还无法与人类的通用性和稳健性相媲美。其中一项任务是翻书页，如图 1 所示，这需要逐页分离和抓取纸张。人类可以通过观察目标并使用指尖的触觉来调整他们的动作，从而轻快地翻开书页。在这个过程中，人类本能地将外感和本体感知结合起来，以适应不规则的纸张厚度和物理特性，如光滑度、刚度和摩擦力。赋予机器人具有这种能力是机器人领域的一项巨大挑战。

纵薄而灵活的物体时，最大的挑战之一是不完整和嘈杂的感知 [1]。例如，一叠纸不稳定，并且无法观察到每一层之间的接触。因此，机器人可能必须感知纸张之间的物理特性（例如摩擦力和弹性），才能成功地从堆栈中分离和抓取纸张。从相机传感器获得的外感受感知对于此类任务来说是不完整的，并且在现实世界条件下不可靠。大多数现有作品所依赖的深度传感器无法区分由于纸张厚度的原因导致堆叠的纸张。深度传感器本身也无法捕捉表面的物理特性，例如硬度和柔韧性 [2]。一些作品使用触觉传感器作为本体感觉来估计可变形物体的物理特性。例如，[3] 使用高精度触觉传感器来测量接触表面的几何形状和物体的硬度。[4] 使用实时触觉反馈，通过一对机器人夹持器纵电缆。然而，高精度接触式传感器通常价格昂贵，并且需要特定的手指形状才能适应。除了环境感知方面的挑战外，纵薄而灵活的物体可能希望抓手具有人类手指的灵巧性和柔顺性，这进一步增加了难度 [5]。

为了应对上述挑战，我们提出了 Flipbot，这是一种自我监督方法，以前所未有的稳健性分离和抓取纸质可变形物体，从而实现连续的纸张翻转。Flipbot 的核心是基于一个原则性的解决方案，将外感受和本体感受感知整合到政策学习中。我们从力/扭矩（F/T）传感器读数中获得本体感觉，从深度相机获得外部感觉。我们使用称为“滑动”的程序运动来主动与环境交互。当对一张纸进行“滑动”运动时，手指与物体之间的相互作用带来的变形会显露出难以察觉的物理特性，如质量、弯曲刚度和摩擦力。同时，目视观察提供有关环境的全局信息。我们设计了一个跨感官编码器，将外感受和本体感知整合到

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implicit state representation. The encoder is trained end-to-end in a self-supervised manner as a part of policy learning. By incorporating exteroceptive-proprioceptive information into policy learning, the robot is able to discover the optimal policy for paper-flipping through continuous exploration. Furthermore, the reward signal for policy learning is derived from visual observation; Flipbot is fully trained by self-exploration without human demonstration or annotation.

The primary contribution of the presented work is the proposed new approach, Flipbot, for sigulating and grasping paper-like objects. It achieves substantial improvements over the prior studies while maintaining exceptional robustness. Our extensive experiments show that Flipbot is able to perform page-flipping from the beginning to the end of a book accurately and consistently, and exhibits remarkable zero-shot generalization under conditions never encountered during training: novel paper materials such as coated and plastic paper and tasks such as emptying a box full filled with paper.

II. Related Work

Deformable object manipulation presents a persistent and enduring challenge within the field of robotics. Conventional analytic approaches rely on modeling object dynamics and then using model predictive control [6], or trajectory optimization [7] for manipulation. However, analytic approaches require substantial prior knowledge of geometry, and the physical properties of the object [1]. For example, [8] presents an approach for manipulating a piece of thin deformable object by analyzing the object's internal energy exchange concerning object poses. And [9] proposes a close-loop shape control method utilizing visual markers, which limits the generality. Moreover, the high-dimensional state representation and complex dynamics of the deformable object provide additional challenges to generalizing novel objects and environments.

Recently, learning-based methods have become increasingly popular alternatives to perform deformable object manipulation. Most work [10], [11] learns the object dynamic from visual features rather than explicit modeling physical processes. For example, [12] encodes visual observation into latent space with self-supervision, followed by model-based planning. Another line of approach defines a set of primitives for deformable object manipulation and learns a mapping from image to predefined primitives [13]. Such image-to-primitive formulation has been applied across various tasks including manipulating rope [14], smoothing fabric [15], and blowing bags [16]. However, the physical information of the environment, which necessitates deformable object manipulation, is challenging to be obtained from visual perception. In this regard, [17] estimates the physical properties of fabric materials through a high-resolution tactile sensor, GelSight [18]. Further, [4] proposes an approach to manipulate a cable based on tactile feedback without vision sensory. [19] employs tactile sensors to manually collect data for training a classifier that can differentiate between towels with thicknesses of 1-3 layers. Then a heuristic approach is used to consistently attempt to grasp specific layers of towels based on the classifier's prediction outcomes. Nevertheless, tactile sensors alone are hard to provide global information about the environment, which inevitably restricts the range of manipulation or requires prior knowledge of objects.

More recently, a small number of papers have explored the use of soft grippers in deformable object manipulation, which is known for its ease of grasping objects without high precision control [8], [20]. The authors of [21] demonstrated a soft gripper system that is capable of handling a wide range of food products by reconfiguring fingers into different poses. In addition, [5] quantitatively indicates that the compliance of the soft gripper can facilitate the manipulation of thin deformable objects.

Compared with the above studies, our presented approach, Flipbot, incorporates exteroceptive and proprioceptive feedback in deformable object manipulation rather than relying on a single perception source. Flipbot thus combines the best of both worlds: the global information about the environment afforded by exteroception and the local information about physic property afforded by proprioception. Filpbot also leverages the compliance from a soft pneumatic gripper for performing dexterous behavior. The resulting policy has taken the real robot to various tasks surpassing prior published work in the field of deformable object manipulation.

III. Method

The goal of Flipbot aims to empower robots to effectively singulate and grasp thin and flexible objects through exteroceptive and proprioceptive perception. Our key insight is that global information about positions and shapes on a large scale provided by vision and local information about contact and force provided by proprioceptive perception are indispensable parts of manipulating deformable objects like paper. Also, proprioception and exteroception fusion reveals physical information that helps robots better explore and make decisions. The overview of Flipbot is shown in Fig. 2.

First, we utilize a simple soft gripper for manipulation (see Fig. 4(c)). The natural compliance of the soft gripper provides unique benefits for manipulating thin and flexible objects while avoiding damage to the object. Another advantage is that the soft gripper has a more straightforward actuation strategy in movements such as bending the fingers, compared with fully actuated rigid grippers.

Then, we use a coarse-to-fine exploration process to obtain unobservable physical information about deformable objects. In this process, first, the depth camera provides a rough observation of the object. We then use a procedural motion "Swipe" and an F/T sensor to monitor the object's state. One advantage of using the F/T sensor instead of a tactile sensor is that the force sensor can be assembled seamlessly with soft hands without a specific finger design.

Last, we use a cross-sensory encoder to fuse the proprioception and exteroception and use model-free reinforcement learning (RL) to learn the policy that avoids explicit modeling of diverse and frequent transitions in the contact state between the object and the soft hand.

隐式状态表示形式。作为策略学习的一部分，编码器以自我监督的方式进行端到端训练。通过将外感受-本体感受信息纳入政策学习，机器人能够通过不断探索发现翻阅论文的最佳策略。此外，政策学习的奖励信号来自视觉观察;Flipbot 完全通过自我探索进行训练，无需人工演示或注释。

所介绍的工作的主要贡献是提出的新方法 Flipbot，用于调节和抓取类似纸张的物体。与之前的研究相比，它取得了实质性的改进，同时保持了卓越的稳健性。我们广泛的实验表明，Flipbot 能够准确、一致地从书的开头到结尾进行翻页，并在训练期间从未遇到过的条件下表现出显着的零镜头泛化：铜版纸和塑料纸等新型纸质材料以及清空装满纸张的盒子等任务。

II. RW

可变形物体作在机器人领域提出了一个持久而持久的挑战。传统的分析方法依赖于对对象动力学进行建模，然后使用模型预测控制 [6] 或轨迹优化 [7] 进行作。然而，解析方法需要大量的几何学和物体物理特性的先验知识 [1]。例如，[8] 提出了一种通过分析对象与对象姿势相关的内部能量交换来纵一块薄的可变形对象的方法。并且 [9] 提出了一种利用视觉标记的闭环形状控制方法，这限制了通用性。此外，可变形对象的高维状态表示和复杂动力学为泛化新对象和环境带来了额外的挑战。

最近，基于学习的方法已成为执行可变形对象作的越来越流行的替代方案。大多数工作 [10]， [11] 从视觉特征中学习对象动态，而不是显式建模物理过程。例如，[12] 将视觉观察编码为具有自我监督的潜在空间，然后是基于模型的规划。另一种方法定义了一组用于可变形对象作的基元，并学习从图像到预定义基元的映射 [13]。这种 image-toprimitive 公式已应用于各种任务，包括纵绳索 [14]、平滑织物 [15] 和吹气袋 [16]。然而，环境的物理信息需要可变形的物体作，很难从视觉感知中获得。在这方面，[17] 通过高分辨率触觉传感器 GelSight [18] 估计织物材料的物理特性。此外，[4] 提出了一种基于触觉反馈纵电缆的方法，而无需视觉感应。[19] 使用触觉传感器手动收集数据，以训练可以区分 1-3 层厚度毛巾的分类器

然后，使用启发式方法始终尝试根据分类器的预测结果来掌握毛巾的特定层。然而，仅靠触觉传感器很难提供有关环境的全局信息，这不可避免地限制了作范围或需要事先了解物体。

最近，少数论文探讨了软抓手在可变形物体作中的应用，软抓手以其无需高精度控制即可轻松抓取物体而闻名 [8]， [20]。[21] 的作者展示了一种软夹持系统，该系统能够通过将手指重新配置成不同的姿势来处理各种食品。此外，[5] 定量地表明软夹持器的柔度可以促进对薄的可变形物体的作。

与上述研究相比，我们提出的方法 Flipbot 在可变形物体作中结合了外感受和本体感受反馈，而不是依赖于单一的感知源。因此，Flipbot 结合了两全其美：外感受提供的有关环境的全球信息和本体感觉提供的有关物理特性的局部信息。Filpbot 还利用软气动夹持器的顺应性来执行灵巧的行为。由此产生的策略将真正的机器人带到了各种任务中，超越了以前在可变形物体作领域发表的工作。

三、M

Flipbot 的目标是使机器人能够通过外感受和本体感知有效地分离和抓取薄而灵活的物体。我们的主要见解是，视觉提供的关于大尺度位置和形状的全局信息以及本体感觉感知提供的关于接触和力的局部信息是纵纸张等可变形物体不可或缺的部分。此外，本体感觉和外感受融合揭示了物理信息，可帮助机器人更好地探索和做出决策。Flipbot 的概述如图 2 所示。

首先，我们使用一个简单的软夹持器进行作（见图 4（c））。软抓手的自然柔顺性为纵薄而灵活的物体提供了独特的优势，同时避免了对物体的损坏。另一个优点是，与完全驱动的刚性抓手相比，软抓手在弯曲手指等运动中具有更直接的驱动策略。

然后，我们使用从粗到细的探索过程来获取有关可变形物体的不可观察的物理信息。在此过程中，首先，深度相机提供对物体的粗略观察。然后，我们使用程序化运动“滑动”和 F/T 传感器来监控对象的状态。使用 F/T 传感器代替触觉传感器的一个优点是，力传感器可以用柔软的手无缝组装，而无需特定的手指设计。

最后，我们使用跨感官编码器来融合本体感觉和外感受，并使用无模型强化学习 （RL） 来学习避免对物体和软手之间接触状态中多样化和频繁过渡的显式建模的策略。

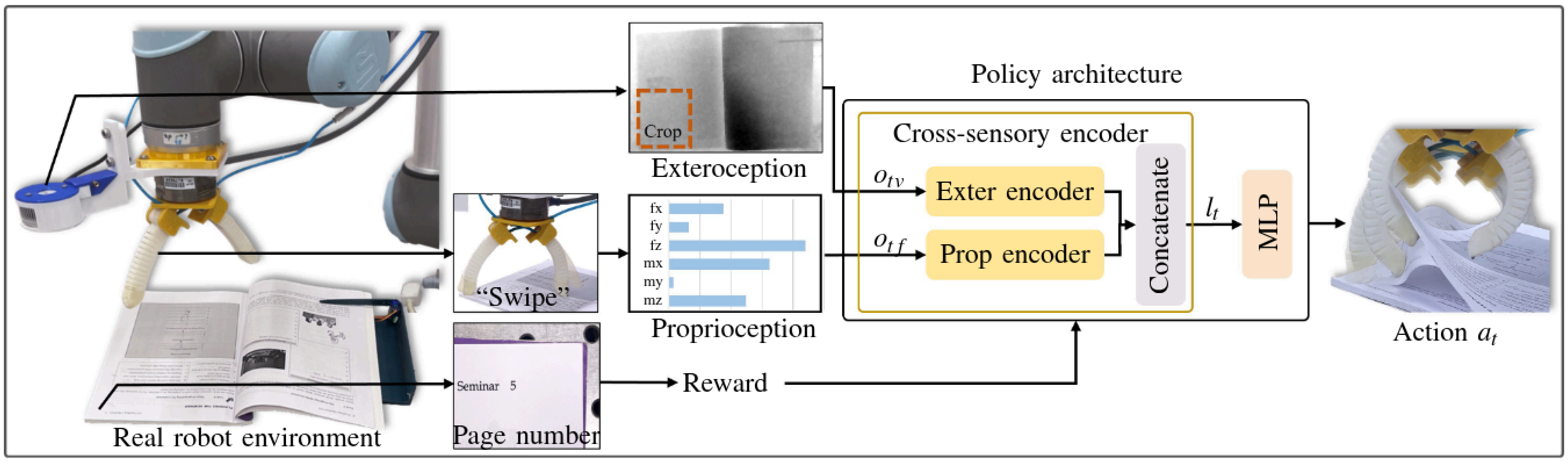


Fig. 2. **System Overview.** We train the policy using SAC in the real world. We follow a coarse-to-fine exploration process to obtain exteroception and proprioception. First, the camera captures the depth image, and the cropped area is used as extrinsic perception. Next, the soft finger "Swipe" on paper captures force (fx, fy, fz) and torque (mx, my, mz) values from force sensors as proprioception. The RL agent receives the observations and predicts the actions to be performed by the robot, and receives the reward based on changes in page numbers.

A. Problem Formulation

We formulate the problem of the paper-flipping as a Markov Decision Process (MDP). An MDP consists of four components: a state space S, an action space A, a reward function $R(s_t, s_{t+1})$, and a transition probability $P(s_{t+1}|s_t, a_t)$. In our framework, an agent uses a policy $\pi(a_t|s_t)$ to select an action a_t for controlling the robot and receives rewards r_t. The goal of the reinforcement learning framework is to obtain the optimal policy π^*, which maximizes the expected discounted sum of rewards over a finite time horizon. To achieve this objective, we utilize the Soft Actor-Critic [22] (SAC) algorithm for training. SAC requires the learning of an actor network that maps observations to actions and a critic network that estimates the expected future rewards based on the input.

B. Observations via Coarse-to-Fine Exploration

The state is defined as $s_t = (o_{tv}, o_{tf})$, where o_{tv} refers to the exteroceptive observation, o_{tf} refers to the proprioceptive observation, shown in Fig. 2. We deploy a coarse-to-fine exploration procedure with two steps for obtaining observations o_{tv} and o_{tf}. First, a wrist-mounted camera takes the environment's point cloud p_t from a height and converts the point cloud to a depth image. We then use a 60 $\times$ 60 resolution window to crop the depth image, as the exteroceptive observation o_{tv}. Next, we perform an exploratory "Swipe" motion, to obtain physical information about the contact surface between the paper and the finger. The robot first descends a certain distance that the finger of a soft hand approaches the surface of the top right corner of the paper diagonally, where the distance is calculated according to the point cloud p_t. Then, we give the soft gripper a positive air pressure so that fingers touch and interact with the paper. After this process, we record readings from the F/T sensor, including forces (fx, fy, fz) in x, y, z axes and three simultaneous torques (mx, my, mz) about the same axes. Thus, the proprioceptive observation o_{tf} is defined as a tuple of (fx, fy, fz, mx, my, mz). Fig. 3 shows forces and torques after "Swipe" on different pages in the book. By incorporating an F/T sensor and exploratory action, o_{tf} latently contains rich information related to contact states between the fingers and the object, such as gripper-object friction.

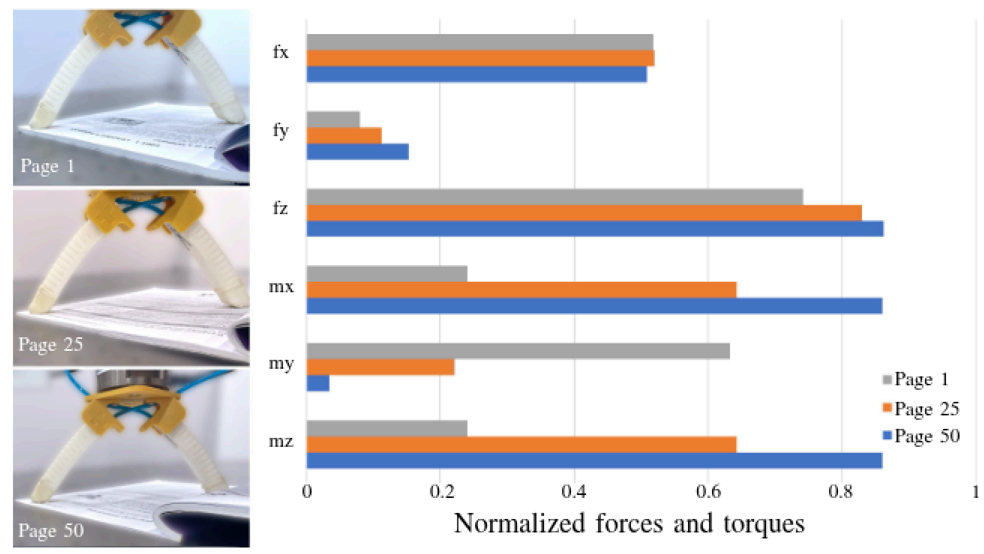


Fig. 3. Visualization of forces and torques after "Swipe" on the different page numbers.

C. Action and Reward

After the coarse-to-fine exploration procedure, the robot predicts the action based on observations to singulate and grasp the paper. The action includes a gripper displacement, denote as (x_t, z_t, θ_t), as shown in Fig. 4(a). The gripper displacement refers to the relative difference between the current pose after the "Swipe" exploration procedure and the desired one. Specifically, $x_t \in [-6mm, 6mm]$ is the relative displacement on the line α connecting the two fingertips, where α belongs to the longitudinal plane A formed by two fingers. $\theta_t \in [0°, 3°]$ is the orientation of the gripper about the normal $\beta \perp A$. $z_t \in [-6mm, 6mm]$ is the the relative displacement on the line γ, where $\gamma \perp (\alpha \times \beta)$. Furthermore, an additional action component Λ is utilized to govern the closing or opening of the gripper. Operationally, we control the gripper aperture by commanding the pressure change. Thus, the action is formally defined as $a_t = (x_t, z_t, \theta_t, \Lambda)$, where each coordinate of the action is discretized based on the characteristics of the workspace.

At the end of an episode, the reward is given, 1 for successfully flipping a single layer of paper and 0 for otherwise. In other words, flipping two or more layers of paper simultaneously is treated as a failure. The reward is

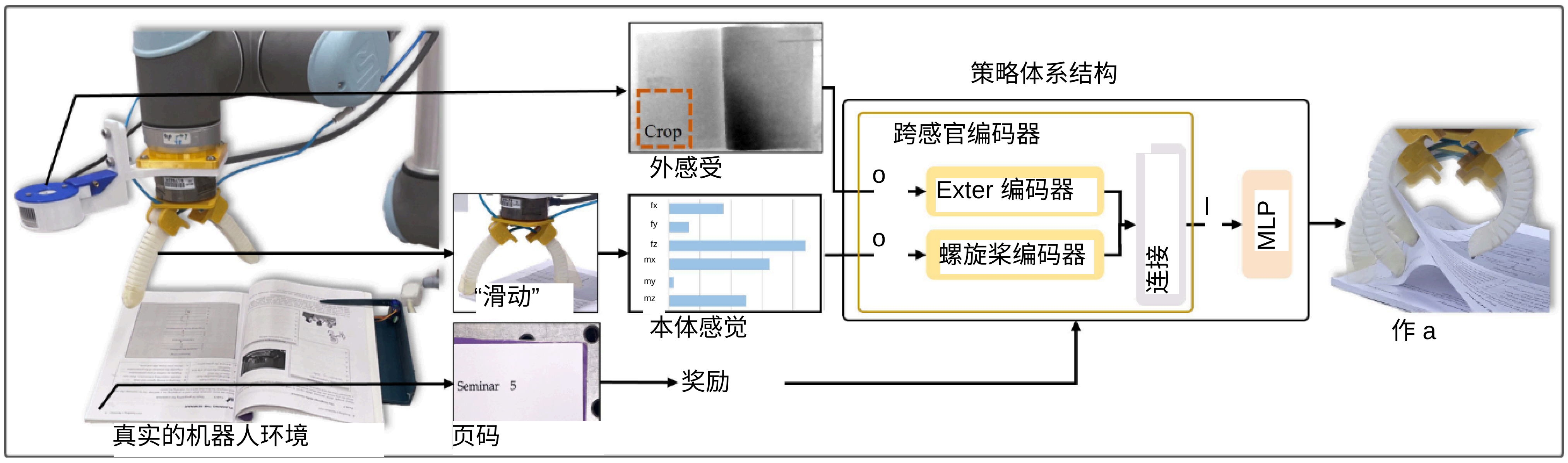


图 2.系统概述。我们在现实世界中使用 SAC 训练策略。我们遵循从粗到细的探索过程来获得外感受和本体感觉。首先，相机捕获深度图像，裁剪区域用作外在感知。接下来，柔软的手指在纸上"滑动"捕获来自力传感器的力 （f x， f y， f z） 和扭矩 （mx， my， mz） 值作为本体感觉。RL 代理接收观察结果并预测机器人将执行的作，并根据页码的变化获得奖励。

A. 问题制定

我们将翻纸问题表述为马尔可夫决策过程 （MDP）。MDP 由四个部分组成：状态空间 S、动作空间 A、奖励函数 R（s， s） 和转换概率 P（s|s， a）。在我们的框架中，代理使用策略 π （a|s） 来选择作 a，用于控制机器人并获得奖励 r。强化学习框架的目标是获得最佳策略π，从而在有限的时间范围内最大化预期的折现奖励总和。为了实现这一目标，我们利用软演员-评论家 [22] （SAC） 算法进行训练。SAC 需要学习一个将观察结果映射到行动的行动者网络，以及一个根据输入估计预期未来回报的批评者网络。

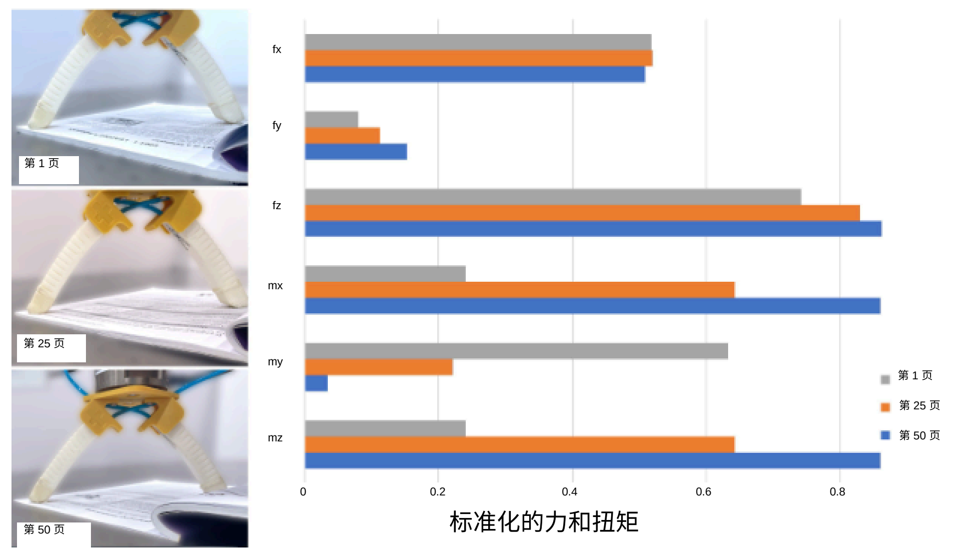


图 3.在不同页码上"滑动"后力和扭矩的可视化。

B. 通过粗略到精勘探进行观察

状态定义为 s= （o， o），其中 o 是指外感受性观察，o 是指本体感受性观察，如图 2 所示。我们部署了一个从粗到精的勘探程序，其中包含两个步骤来获取观测值 o 和 o。首先，腕戴式摄像机从高度获取环境的点云，并将点云转换为深度图像。然后我们使用 60 × 60 分辨率的窗口来裁剪深度图像，作为外感受观察 o。接下来，我们执行一个探索性的 "滑动" 动作，以获得关于纸张和手指之间接触表面的物理信息。机器人首先下降一定距离，柔软的手的手指对角线接近纸张右上角表面，根据点云 p 计算距离。然后，我们给软夹持器一个正气压，使手指能够触摸纸张并与之互动。在此过程之后，我们记录来自 F/T 传感器的读数，包括 x、y、z 轴上的力 （f x、f y、f z） 和关于同一轴的三个同步扭矩 （mx， my， mz）。因此，本体感觉观察 ois 定义为 （f x， f y， f z， mx， my， mz） 的元组。图 3 显示了本书不同页面上 "Swipe" 后的力和扭矩。通过结合 F/T 传感器和探索性作，olatently 包含与接触状态相关的丰富信息

手指与物体之间的摩擦，例如夹持器与物体的摩擦。

C. 行动与奖励

在从粗到精的勘探程序之后，机器人根据观察结果预测动作，以分离和抓取纸张。该动作包括一个夹持器位移，表示为 （x， z， θ），如图 4 （a） 所示。抓手位移是指"滑动"探索程序后的当前姿势与所需姿势之间的相对差异。具体来说，x∈ [−6mm， 6mm] 是连接两个指尖的线 α 上的相对位移，其中 α 属于由两个手指形成的纵向平面 A。θ∈ [0°， 3°] 是机械手绕法线 β ⊥ A 的方向。z∈ [−6mm， 6mm] 是线γ上的相对位移，其中 γ ⊥ （α × β ）。此外，还使用了一个额外的动作组件 Λ 来控制抓手的关闭或打开。在作上，我们通过命令压力变化来控制夹持器孔径。因此，该作被正式定义为 a= （x， z， θ， Λ），其中该作的每个坐标都根据工作区的特性进行离散化。

在一集结束时，会获得奖励，成功翻转单层纸为 1，否则为 0。换句话说，同时翻转两层或多层纸张被视为失败。奖励是

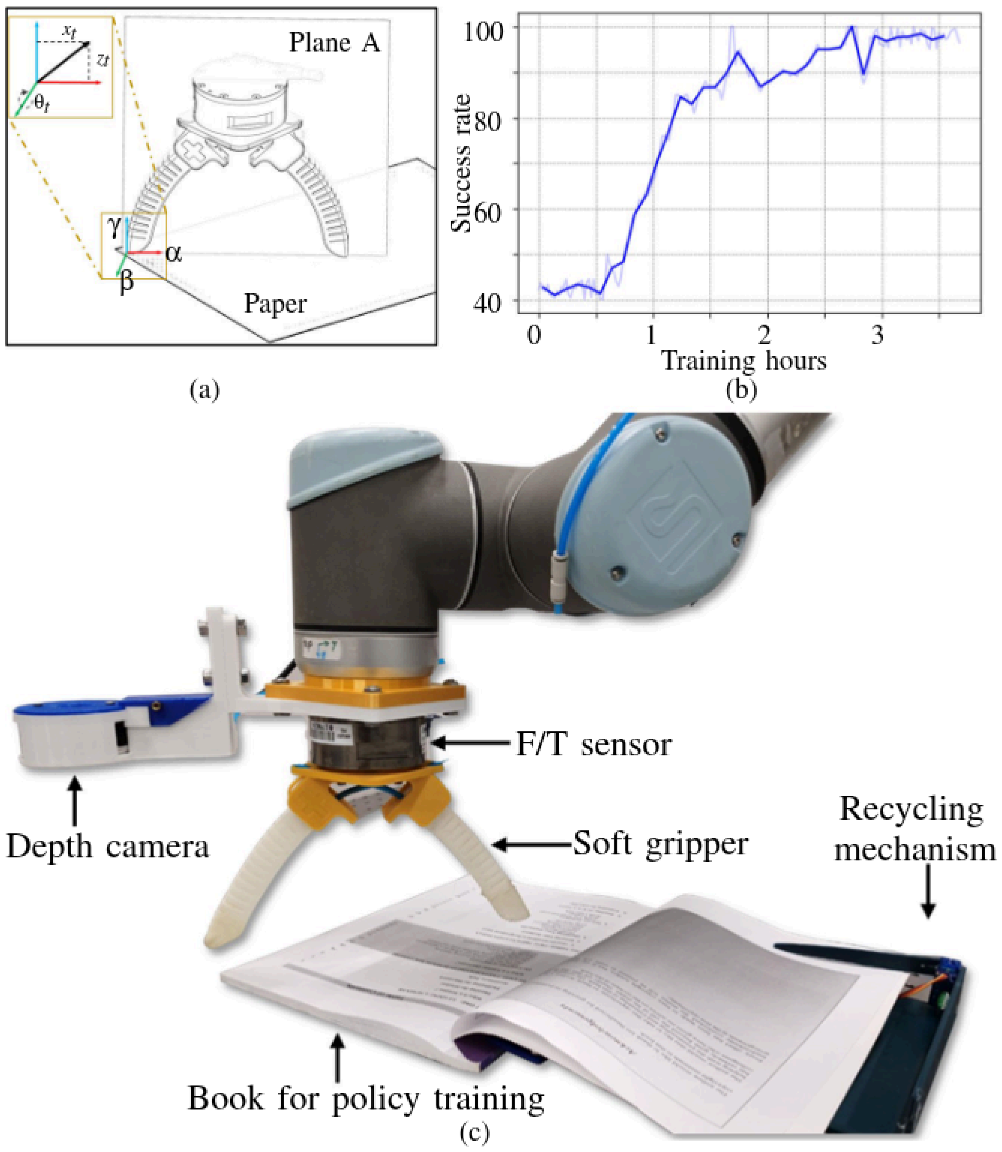


Fig. 4. (a): Visualization of our action coordinate system. (b): Success rate curve of our policy training. (c): Our hardware setting for policy training.

automatically determined by identifying page numbers on the book, which we describe further in Sec. III-E

D. Policy architecture

The policy $\pi(a_t|s_t)$ is modeled with a cross-sensory encoder and a multilayer perceptron (MLP) block, as shown in Fig. 2. The cross-sensory encoder takes the exteroceptive observation o_{tv} and proprioceptive observation o_{tf} as inputs and embeds them into a latent vector, which represents the abstraction of proprioception and exteroception. More specifically, o_{tv} is processed by a global pooling layer and concatenated with o_{tf} to be a vector of size 1x7. Then, the concatenated vector is fed into subsequent an MLP block to compress inputs to a more compact representation l_t. At last, the l_t is fed through the subsequent MLP layer to predict actions.

E. Training via self-supervision

We train the policy in a real robot platform. Fig. 4(c) shows our hardware setting for training, including the following major components: a Universal Robot 10 robot arm equipped with a 3D printed thermoplastic polyurethane soft gripper, an ATI gamma F/T sensor, and an Intel Realsense L515 depth camera, as well as a recycling mechanism. During the whole training, we only use a book assembled with printer paper, as shown in Fig. 4(c). We train our model through trial-and-error with the following procedure:

At each training step, the robot starts to execute coarse-to-fine exploration from an initial pose. In the process of "Swipe", the wrist-mounted camera captures an RGB-D image. The depth channel is used to construct exteroceptive observation o_{tv}, and the page number n_t is recognized from

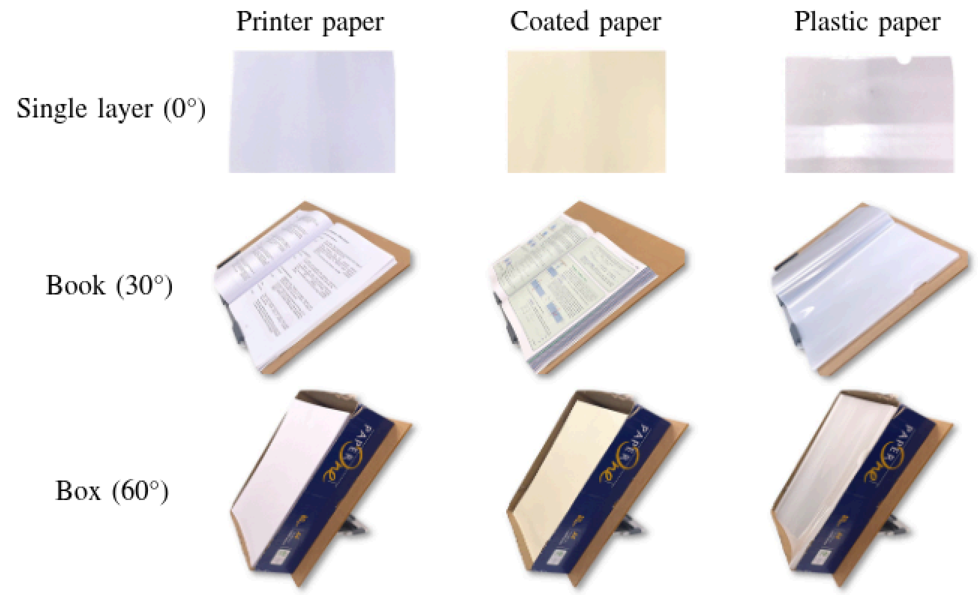


Fig. 5. A subset (9 of 27) of our test scene settings. Columns from left to right show different paper materials: printing paper, coated paper, and plastic paper. Rows from top to bottom show different test scenarios and workspace tilt angles

RGB channels for reward calculation. The robot then descends a certain distance that the finger approaches the paper's surface to perform an exploratory action to obtain the physical observation o_{tf} from the readings of F/T sensors. After this, the robot downloads the latest policy parameters from the optimizer to predict action a_t and executes. We automatically calculate rewards according to the change of page numbers without human intervention, the reward r_t is 1 if $n_{t+1} = n_t + 2$, otherwise 0. The page number identification benefits from Tesseract [23]. At last, the generated episode is added to a replay buffer, and the optimizer sampling from this replay buffer to update the policy. We use the Adam optimizer with a learning rate of 3×10^{-3}. The robot then continuously collects episodes until it reaches the last page of the book, at which point the book is reset to the first page again using the recycling mechanism. In this way, human intervention is kept at a minimum during the training process.

The final model training took four hours, with the learning curves for the training presented in Fig. 4(b).

IV. Experiments

We design a set of experiments in real-world settings to evaluate the system's generalization ability to novel object physical parameters and the advantage of using exteroceptive and proprioceptive exploration. For all following experiments, we use the same robot hardware setting and the same model trained with the book assembled from printer paper, described in Sec. III-E. The system's performance is evaluated on its generalization to unseen paper types (i.e., flipping different types of paper when only trained on printer paper) and unseen scenarios(e.g., emptying paper in a box) and its efficiency (i.e., the speed and accuracy of paper-flipping).

Scene setup: We investigate the performance of our system across various object settings and scene configurations. In total, we have 27 different test scenes with the combination of test scenarios, paper types and tilt angles. We test with the following three scenarios:

- Full Book page flipping. It is a similar scenario as in policy training, where the robot needs to flip book pages one by one throughout the book.

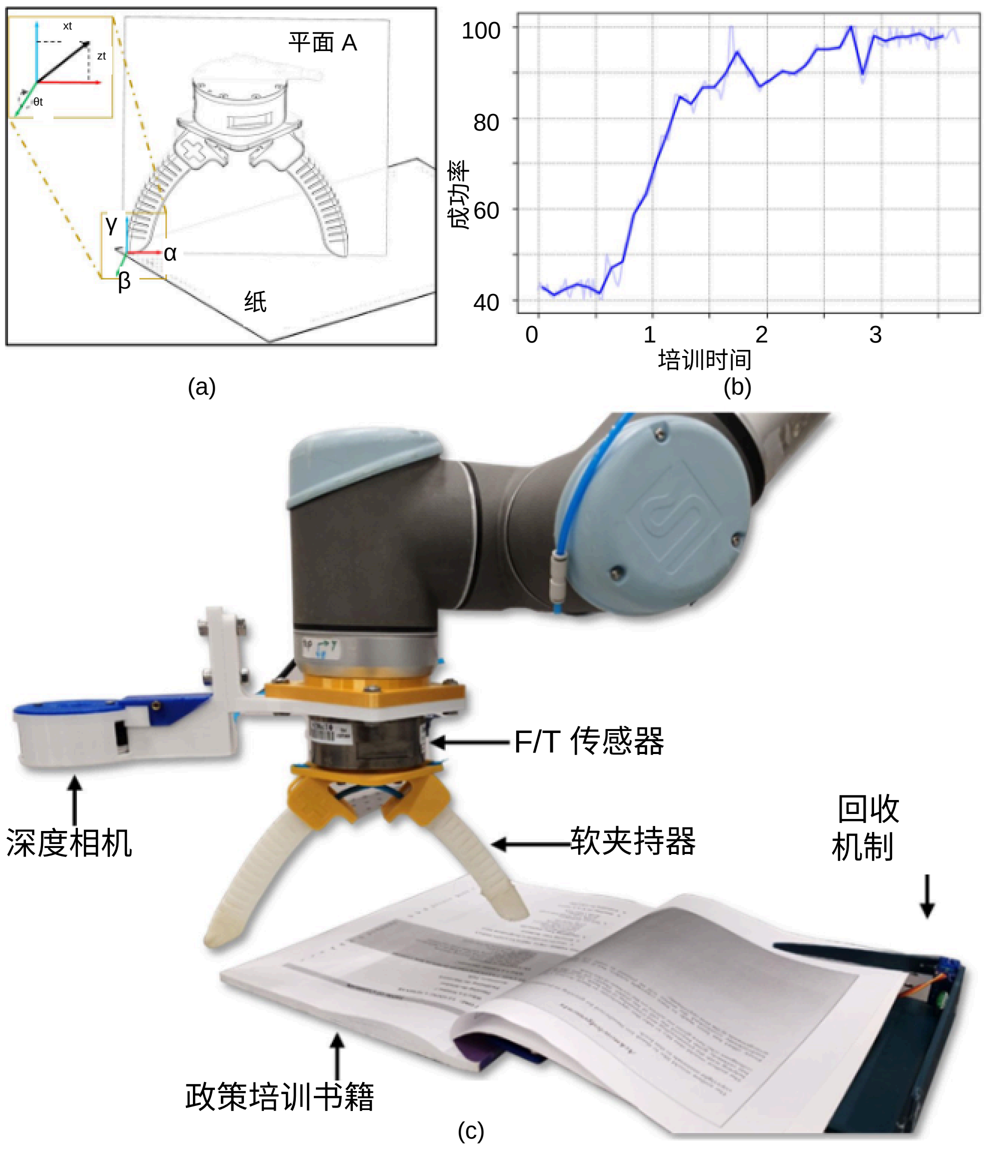


图 4.（a）：我们的动作坐标系的可视化。（b）：我们的政策培训的成功率曲线。（c）：我们用于策略训练的硬件设置。

通过识别书上的页码自动确定，我们将在第 III-E 节中进一步描述

D. 策略体系结构

策略 π（a|s） 使用跨传感器编码器和多层感知器 （MLP） 块建模，如图 2 所示。跨感觉编码器采用外感受观察 o 和本体感觉观察 oas 输入，并将它们嵌入到一个潜在向量中，该向量代表了本体感觉和外感受的抽象。更具体地说，ois 由全局池化层处理并与 oto 连接，是大小为 1x7 的向量。然后，将串联的向量馈送到随后的 MLP 块中，以将输入压缩为更紧凑的表示 l。最后，lis 通过后续的 MLP 层来预测作。

E. 通过自我监督进行培训

我们在真实的机器人平台中训练策略。图 4（c） 显示了我们用于训练的硬件设置，包括以下主要组件：配备 3D 打印热塑性聚氨酯软抓手的优傲机器人 10 机械臂、ATI gamma F/T 传感器和英特尔实感 L515 深度摄像头，以及回收机构。在整个训练过程中，我们只使用一本用打印纸组装的书，如图 4（c） 所示。我们使用以下过程通过试错法训练模型：

在每个训练步骤中，机器人开始从初始姿势执行粗细探索。在 The reward is “Swipe” 的过程中，腕戴式摄像头会捕捉 RGB-D 图像。深度通道用于构建外感受观察 o，页码 nis 从

图 5.测试场景设置的子集（27 个中的 9 个）。从左到右的列显示不同的纸张材料：打印纸、铜版纸和塑料纸。从上到下的行显示不同的测试场景和工作区倾斜角度

用于奖励计算的 RGB 通道。然后机器人下降一定距离，手指接近纸张表面以执行探索性动作，以从 F/T 传感器的读数中获得物理观察。在此之后，机器人从优化器下载最新的策略参数，以预测作并执行。我们根据页码的变化自动计算奖励，无需人工干预，如果 n= n+2，则奖励为 r1，否则为 0。页码识别受益于 Tesseract [23]。最后，生成的 episode 被添加到 replay buffer 中，优化器从这个 replay buffer 中采样以更新策略。我们使用学习率为 3 × 10 的 Adam 优化器。然后，机器人会不断收集剧集，直到到达该书的最后一页，此时使用回收机制将书再次重置到第一页。通过这种方式，在培训过程中将人为干预保持在最低限度。

最终的模型训练耗时 4 小时，训练的学习曲线如图 4（b） 所示。

四、 E

我们在现实世界环境中设计了一组实验，以评估系统对新物体物理参数的泛化能力以及使用外感受和本体感受探索的优势。对于以下所有实验，我们使用相同的机器人硬件设置和相同的模型，该模型使用由打印纸组装的书进行训练，如第 III-E 节所述。该系统的性能是根据其对看不见的纸张类型（即，仅在打印纸上训练时翻转不同类型的纸张）和看不见的场景（例如，清空盒子中的纸张）的泛化及其效率（即翻转纸张的速度和准确性）来评估的。

场景设置：我们调查系统在各种对象设置和场景配置下的性能。我们总共有 27 个不同的测试场景，结合了测试场景、纸张类型和倾斜角度。我们使用以下三种方案进行测试：

- 整本书翻页。这与政策培训中的场景类似，机器人需要在整本书中一页一页地翻阅书页。

TABLE I

RESULTS OF EXPERIMENTS IN THE REAL WORLD.

Method	Tilt angle	Full Book page flipping 						Paper-box emptying 						Single paper grasping 					
		Printer Paper		Coated Paper		Plastic Paper		Printer Paper		Coated Paper		Plastic Paper		Printer Paper		Coated Paper		Plastic Paper	
		SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH
Flex&Flip [8]		72%	223	77%	239	52%	161	69%	214	82%	254	49%	152	83%	260	91%	282	74%	229
Flipbot-w/o prop	0°	85%	264	93%	288	66%	205	81%	251	91%	282	60%	186	95%	295	**98%**	**304**	85%	264
Flipbot		**94%**	**291**	**96%**	**298**	**82%**	**254**	**90%**	**279**	**94%**	**291**	**68%**	**211**	**99%**	**307**	**98%**	**304**	**92%**	**285**
Flex&Flip [8]		76%	236	74%	229	44%	136	62%	192	72%	223	42%	130	80%	248	87%	270	76%	236
Flipbot-w/o prop	30°	88%	273	87%	270	63%	195	84%	260	88%	273	55%	171	85%	264	92%	295	86%	267
Flipbot		**93%**	**288**	**91%**	**282**	**72%**	**223**	**88%**	**273**	**91%**	**282**	**62%**	**192**	**92%**	**285**	**95%**	**295**	**90%**	**279**
Flex&Flip [8]		64%	198	56%	174	47%	192	56%	174	58%	180	38%	118	84%	260	82%	254	83%	257
Flipbot-w/o prop	60°	76%	236	72%	223	62%	192	77%	239	70%	217	58%	179	86%	267	85%	264	91%	282
Flipbot		**84%**	**260**	**82%**	**253**	**70%**	**217**	**82%**	**254**	**80%**	**248**	**66%**	**205**	**96%**	**298**	**92%**	**285**	**94%**	**291**

[*] SR stands for success rate.

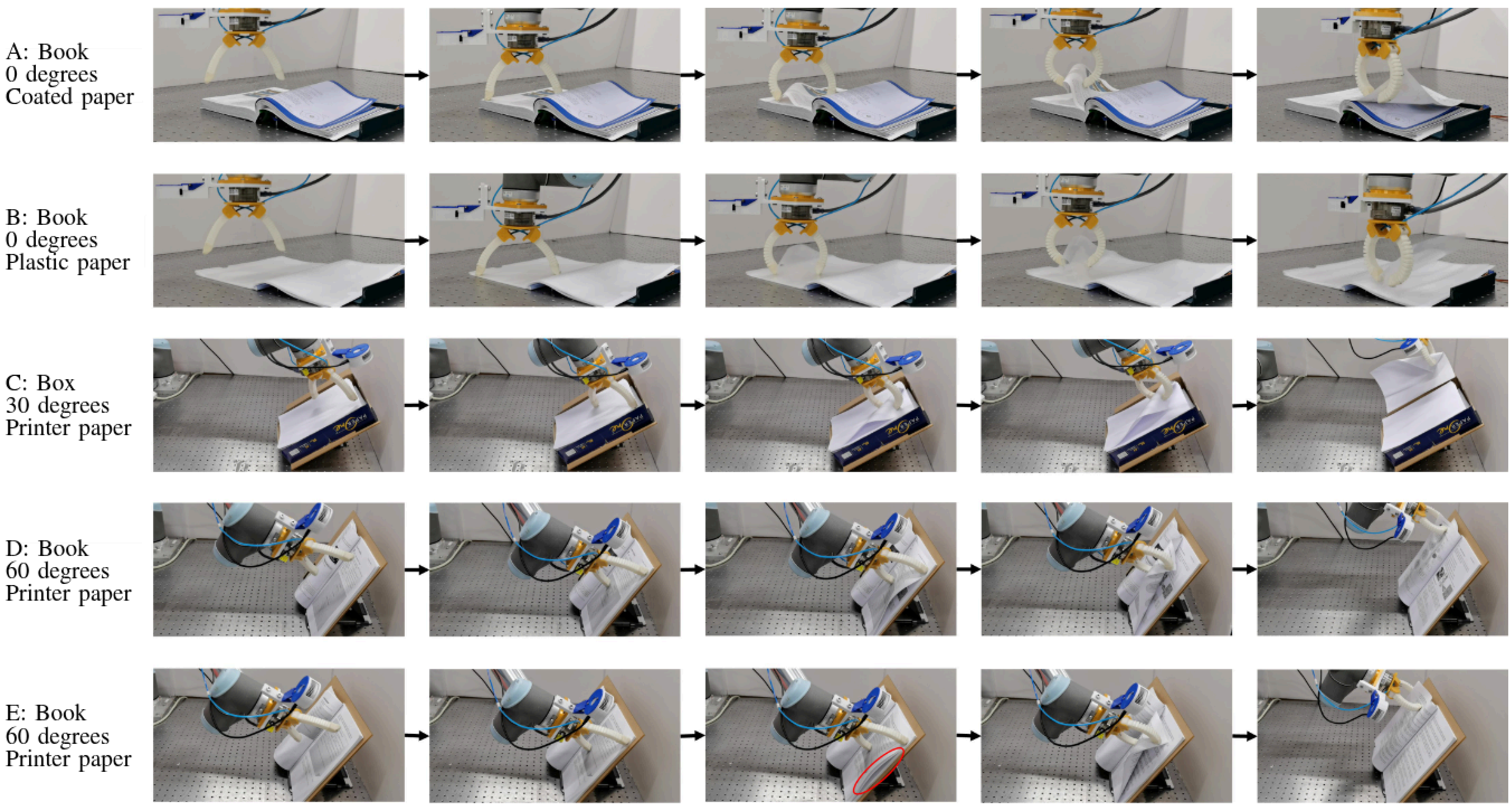


Fig. 6. Flipbot performs paper-flipping in different scenes. A-D: Flipbot successfully singulates and grasps a piece of paper in various settings; E: Flipbot fails to singulate and grasp a piece of printer paper with a 60-degree tilt angle. The circled area in red denotes that two layers of paper were flipped.

- Paper-box emptying. The robot grasps each sheet one by one from a pile of paper dumped into a box until emptying it. This is more challenging than the book setup because the physical interaction between the paper is more complex without the constraints of the spine.
- Single paper grasping. The robot grasps a single piece of paper lying on a flat surface.

In each scenario, we use three types of paper that have different physical properties, including the printer paper, coated paper, and plastic paper. The physical property of printer paper is the same as we have used during training, which has the highest friction coefficient among the three types. The coated paper and plastic paper are unseen paper types. The coated paper has the lowest friction coefficient and the plastic paper has medium friction coefficient. The detailed physical properties of these three paper types are shown in Tab. II. Meanwhile, we also vary tilt angles (0, 30, 60 degrees) for the workspace to test the effect of gravity on paper flipping.

TABLE II

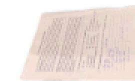
PHYSICAL PROPERTIES OF TEST PAPER

Physical properties	Printer paper (seen type)	Coated paper (unssen type)	Plastic paper (unssen type)
Static Coefficient of Friction	**0.462±0.0087**	0.283±0.0104	0.334±0.0066
Kinetic Coefficient of Friction	**0.417±0.0542**	0.174±0.0229	0.259±0.0263
Young's Modulus in Machine Direction(GPa)	**2.84±0.17**	2.62±0.14	1.54±0.23
Density (g/m^2)	102.5±2.32	59.8±0.93	**385.4±1.74**
Thickness (mm)	0.096±0.006	0.057±0.012	**0.151±0.017**

Metric: We utilize two evaluation metrics for validating algorithm performance: success rates (successful paper

表 I

现实世界中的实验结果。

方法	倾斜角度	整本书翻页 						纸箱清空 						单张纸抓取 					
		打印纸		铜版纸		塑料纸		打印纸		铜版纸		塑料纸		打印纸		铜版纸		塑料纸	
		SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PPH	SR	PP
Flex&Flip [8]	0	72%	223	77%	239	52%	161	69%	214	82%	254	49%	152	83%	260	91%	282	74%	229
Flipbot-w/o prop		85%	264	93%	288	66%	205	81%	251	91%	282	60%	186	95%	295	98%	304	85%	264
翻转机器人		94%	291	96%	298	82%	254	90%	279	94%	291	68%	211	99%	307	98%	304	92%	285
Flex&Flip [8]	30	76%	236	74%	229	44%	136	62%	192	72%	223	42%	130	80%	248	87%	270	76%	236
Flipbot-w/o prop		88%	273	87%	270	63%	195	84%	260	88%	273	55%	171	85%	264	92%	295	86%	267
翻转机器人		93%	288	91%	282	72%	223	88%	273	91%	282	62%	192	92%	285	95%	295	90%	279
Flex&Flip [8]	60	64%	198	56%	174	47%	192	56%	174	58%	180	38%	118	84%	260	82%	254	83%	257
Flipbot-w/o prop		76%	236	72%	223	62%	192	77%	239	70%	217	58%	179	86%	267	85%	264	91%	282
翻转机器人		84%	260	82%	253	70%	217	82%	254	80%	248	66%	205	96%	298	92%	285	94%	291

* SR 代表成功率。

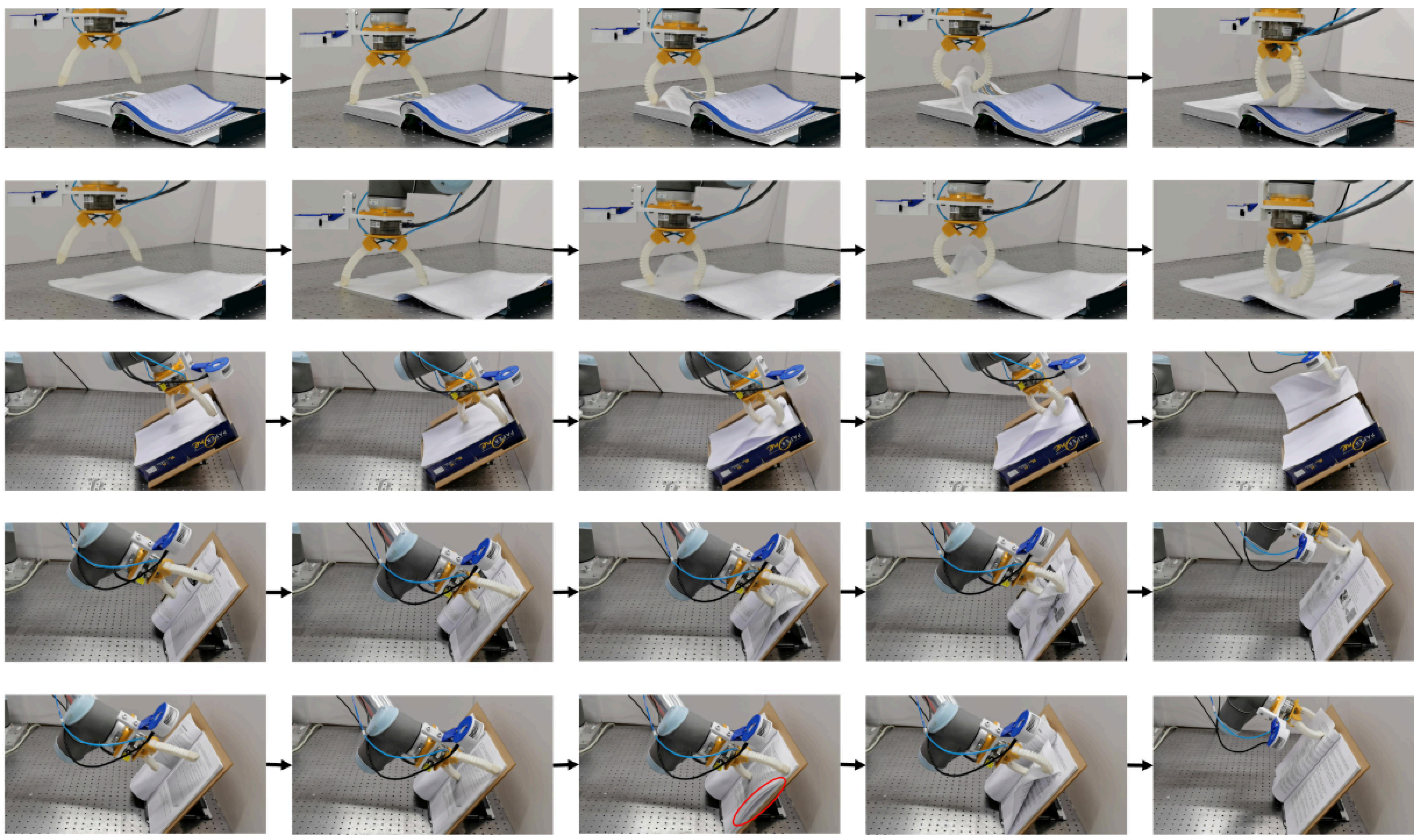


图 6.Flipbot 在不同的场景中进行翻纸。A-D：Flipbot 在各种设置中成功地分离和抓取一张纸;E：Flipbot 无法单独抓取一张倾斜角度为 60 度的打印纸。红色圆圈区域表示翻转了两层纸。

- 纸箱清空。机器人从倒入盒子的一堆纸中逐一抓取每张纸，直到清空。这比书籍设置更具挑战性，因为没有书脊的限制，纸张之间的物理交互更加复杂。
- 单张纸抓取。机器人抓取一张躺在平坦表面上的纸。

在每种情况下，我们使用三种具有不同物理特性的纸张，包括打印纸、铜版纸和塑料纸。打印纸的物理特性与我们训练时使用的相同，在三种类型中具有最高的摩擦系数。铜版纸和塑料纸是看不见的纸张类型。铜版纸的摩擦系数最低，塑料纸的摩擦系数中等。这三种纸张的详细物理特性是

表 II

试纸的物理特性

物理性质	打印纸	铜版纸（unssen 型）	塑料纸（可见型）（unssen 型）
静态系数 摩擦之	0.462±0.0087	0.283±0.0104	0.334±0.0066
动力学系数 摩擦之	0.417±0.0542	0.174±0.0229	0.259±0.0263
机器方向的杨氏模量（GPa）	2.84±0.17	2.62±0.14	1.54±0.23
密度（克/米）	102.5±2.32	59.8±0.93	385.4±1.74
厚度 (mm)	0.096±0.006	0.057±0.012	0.151±0.017

如表 II 所示。同时，我们还改变了工作区的倾斜角度（0、30、60 度），以测试重力对纸张翻转的影响。

指标：我们使用两个评估指标来验证算法性能：成功率（成功的论文

flips/total attempts) and PPH (successful paper flips per hour). The success of paper flipping for each attempt is measured by whether the gripper detaches and flips strictly one piece of paper. For example, in the book page flipping task, the robot detaches and flips two pieces of paper simultaneously is considered a failure. PPH is the product of the speed of flipping in an hour and the success rate, which includes the time of perception, network inference, and robot execution in enabling paper-flipping manipulation. It is important to note that our Flipbot implementation is not optimized for high-speed execution; thus, the reported PPH is solely used to compare relative performance.

Algorithm comparisons: We compare with the following methods:

- **Flex&Flip [8]:** it simplifies a piece of paper as a linear object and uses a physical model to analyze the motion. Its original version could only grasp a single piece of paper lying on a flat surface. We adapt and extend the physical model provided by the authors and hardcode the thickness of different paper types to allow for multi-layered paper flipping.
- **Flipbot-w/o prop:** policy learns from only exteroceptive sensory (i.e., depth camera), which directly maps the visual observation to action.
- **Flipbot:** policy learns with coarse-to-fine exteroceptive-proprioceptive exploration, which is the full non-ablated method we propose in this article.

A. *Experimental Results*

Comparison to prior work. We first compare the performance of our approach with Flex&Flip [8] with different paper types and scenarios (row 1 vs. row 3 in Tab. I). Note that Flex&Flip [8] is the state-of-the-art method for single-layer paper grasping, and we extend it to multi-layered paper scenarios (i.e., paper-box emptying and full book page flipping). In the single paper grasping case, Flipbot performs better (+16%) than Flex&Flip [8] on printer paper. The advantage is much more pronounced in multi-layered paper cases, with Flipbot outperforming Flex&Flip [8] around 20%. In all three test scenarios, quantitative results in Tab. I suggest that our method (Flipbot) maintains comparable success rates on unseen paper types (i.e., coated and plastic paper) with respect to the seen paper type (i.e., printer paper). In contrast, the performance of Flex&Flip [8] on the plastic paper type degrades significantly (up to -20%) on unseen paper types.

Effectiveness of exteroceptive-proprioceptive exploration. We conduct controlled experiments to evaluate the contribution of exteroceptive-proprioceptive exploration quantitatively. The proprioceptive perception provides information on the unobservable physical features, facilitating policy learning effectiveness. As a result, compared with Flipbot-w/o prop that does not use proprioceptive, Flipbot achieved a higher success rate. Quantitative results in Tab. I indicate that compared to Flipbot-w/o prop, the success rate of Flipbot increases at most 24% and at least 4% across test cases.

Generalization to novel tilt angles of workspace. In this experiment, we investigate the generalization ability of these methods to gravity changes by varying tilt angles (0, 30, 60 degrees) of the workspace (see Fig. 6C-D). In different tilt angle setups, detaching a single sheet of paper becomes more challenging as the physical properties between the different layers of the paper change with the direction of gravity. Quantitative results in Tab. I show that the performance of our learned policy degrades slightly as the tilt angle increases. We hypothesize this happened since the physics in these test scenes differ from the training, increasing the difficulty of generalization. Nevertheless, Flipbot still outperforms other methods in terms of success rate and PPH in all test cases.

Overall, our experimental evaluation demonstrates that Flipbot is an efficient approach for paper-flipping tasks. We find the exteroceptive and proprioceptive perceptions are essential for paper-flipping, particularly for sigulating and detaching a sheet from a pile of paper. The learned policy has been demonstrated to outperform state-of-the-art methods and is also applicable to tasks beyond the reach of prior studies, such as turning pages throughout a book. Our work is not without limitations. First, when the working area is at a larger inclination angle, the friction between the paper tends to be smaller. Hence, multiple layers of paper are easy to be grasped simultaneously (see Fig. 6E). Also, two layers of paper sometimes stick together. We assume it happens because of Van der Waals forces. A dual-arm system may be essential to address this issue, suggesting exciting opportunities for future study.

V. Conclusion

We have presented a novel solution for singulating and grasping thin and flexible deformable objects that utilize the cross-sensory encoding of exteroceptive and proprioceptive perceptions, which we term Flipbot. Meanwhile, the system takes advantage of the under actuation and compliance of the soft pneumatic actuator to control contact forces precisely for the singulation of a thin layer of deformable objects. We deploy the algorithm on a real-robot system and show that integrating exteroceptive and proprioceptive inputs can effectively facilitate deformable object manipulation. Extensive controlled experiments demonstrated the robustness and effectiveness of Flipbot. Beyond the experiment results, our work extends frontiers in deformable object manipulation, and the methodology presented in this work can have broad applications. A future direction is to extend the proposed approach to long-horizon deformable object manipulation tasks, such as origami folding, cleaning messy desktops, collecting mail and letters, etc.

References

[1] J. Zhu, A. Cherubini, C. Dune, D. Navarro-Alarcon, F. Alambeigi, D. Berenson, F. Ficuciello, K. Harada, J. Kober, X. LI, J. Pan, W. Yuan, and M. Gienger, "Challenges and outlook in robotic manipulation of deformable objects," *IEEE Robotics & Automation Magazine*, pp. 2–12, 2022.

[2] T. Miki, J. Lee, J. Hwangbo, L. Wellhausen, V. Koltun, and M. Hutter, "Learning robust perceptive locomotion for quadrupedal robots in the wild," *Science Robotics*, vol. 7, no. 62, p. eabk2822, 2022.

翻转次数/总尝试次数）和 PPH（每小时成功翻纸次数）。每次尝试翻纸的成功取决于夹持器是否严格分离并翻转一张纸。例如，在翻页任务中，机器人同时分离和翻转两张纸被认为是失败的。PPH 是一小时内翻转速度和成功率的乘积，成功率包括感知时间、网络推理和机器人执行以实现翻纸作的时间。需要注意的是，我们的 Flipbot 实现并未针对高速执行进行优化;因此，报告的 PPH 仅用于比较相对性能。

算法比较：我们与以下方法进行比较：

- Flex&Flip [8]：它将一张纸简化为线性对象，并使用物理模型来分析运动。它的原始版本只能抓住一张躺在平坦表面上的纸。我们调整并扩展了作者提供的物理模型，并对不同纸张类型的厚度进行硬编码，以允许多层纸张翻转。

- Flipbot-w/o prop：策略仅从外部感觉（即深度相机）中学习，它直接将视觉观察映射到行动。

- Flipbot：策略通过粗到细的外感受本体感受探索来学习，这是我们在本文中提出的完全非消融方法。

A. 实验结果

与之前工作的比较。首先，我们将我们的方法与 Flex&Flip [8] 在不同纸张类型和场景下的性能进行比较（表 I 中的第 1 行与第 3 行）。请注意，Flex&Flip [8] 是最先进的单层纸张抓取方法，我们将其扩展到多层纸张场景（即纸盒清空和整本书翻页）。在单张抓纸的情况下，Flipbot 在打印纸上的表现优于 Flex&Flip [16] [8]。这种优势在多层纸盒中更为明显，Flipbot 的性能比 Flex&Flip [8] 高出约 20%。在所有三个测试场景中，定量结果都显示在 Tab 中。我建议我们的方法 （Flipbot） 在看不见的纸张类型（即涂布纸和塑料纸）上与看得见的纸张类型（即打印纸）保持相当的成功率。相比之下，Flex&Flip [8] 在塑料纸类型上的性能在看不见的纸张类型上显着下降（高达 -20%）。

外感受-本体感觉探索的有效性。我们进行对照实验以定量评估外感受-本体感受探索的贡献。本体感觉感知提供有关不可观察的物理特征的信息，促进政策学习的有效性。因此，与不使用本体感受的 Flipbotw/o prop 相比，Flipbot 取得了更高的成功率。表中的定量结果。我指出，与 Flipbot-w/o prop 相比，Flipbot 的成功率最多增加 24%，在测试用例中至少增加 4%。

泛化到工作区的新倾斜角度。在这个实验中，我们研究了这些

通过改变工作区的倾斜角度（0、30、60 度）来改变重力的方法（见图 6C-D）。在不同的倾斜角度设置中，分离一张纸变得更具挑战性，因为纸张不同层之间的物理特性会随着重力方向的变化而变化。表中的定量结果。我表明，随着倾斜角度的增加，我们学习的策略的性能会略有下降。我们假设发生这种情况是因为这些测试场景中的物理特性与训练不同，增加了泛化的难度。尽管如此，Flipbot 在所有测试用例中的成功率和 PPH 方面仍然优于其他方法。

总体而言，我们的实验评估表明 Flipbot 是翻纸任务的有效方法。我们发现外感受和本体感知对于翻纸至关重要，特别是对于从一堆纸中模拟和分离一张纸。事实证明，学习到的策略优于最先进的方法，也适用于先前研究无法完成的任务，例如翻阅整本书。我们的工作并非没有限制。首先，当工作区域处于较大的倾斜角度时，纸张之间的摩擦力往往较小。因此，很容易同时抓取多层纸张（见图 6E）。此外，两层纸有时会粘在一起。我们假设这是由于 Van der Waals 力而发生的。双臂系统对于解决这个问题可能是必不可少的，这为未来的研究提供了令人兴奋的机会。

V. C

我们提出了一种新颖的解决方案，用于分离和抓取薄而灵活的可变形物体，它利用外感受和本体感知的交叉感觉编码，我们称之为 Flipbot。同时，该系统利用软气动执行器的欠驱动和柔顺性来精确控制接触力，以分离一层薄薄的可变形物体。我们将算法部署在真实的机器人系统上，并表明集成外感受和本体感受输入可以有效地促进可变形物体的作。广泛的对照实验证明了 Flipbot 的稳健性和有效性。除了实验结果之外，我们的工作还扩展了可变形物体作的前沿，这项工作中提出的方法可以具有广泛的应用。未来的方向是将所提出的方法扩展到长视距可变形对象作任务，例如折纸折叠、清理凌乱的桌面、收集邮件和信件等。

R

[1] J. Zhu， A. Cherubini， C. Dune， D. Navarro-Alarcon， F. Alambeigi， D. Berenson， F. Ficuciello， K. Harada， J. Kober， X. LI， J. Pan， W. Yuan， and M. Gienger， “机器人作的挑战和前景可变形的物体“，IEEE 机器人与自动化杂志，第 2-12 页，2022 年。

[2] T. Miki、J. Lee、J. Hwangbo、L. Wellhausen、V. Koltun 和 M. Hutter，“在野外学习四足机器人的稳健感知运动”，科学机器人学，第 7 卷，第 62 期，第 eabk2822 页，2022 年。

[3] W. Yuan, M. A. Srinivasan, and E. H. Adelson, "Estimating object hardness with a gelsight touch sensor," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2016, pp. 208–215.
[4] Y. She, S. Wang, S. Dong, N. Sunil, A. Rodriguez, and E. Adelson, "Cable manipulation with a tactile-reactive gripper," *The International Journal of Robotics Research*, vol. 40, no. 12-14, pp. 1385–1401, 2021.
[5] C. B. Teeple, J. Werfel, and R. J. Wood, "Multi-dimensional compliance of soft grippers enables gentle interaction with thin, flexible objects," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 728–734.
[6] F. Allgöwer and A. Zheng, *Nonlinear model predictive control*. Birkhäuser, 2012, vol. 26.
[7] S. Zimmermann, R. Poranne, and S. Coros, "Dynamic manipulation of deformable objects with implicit integration," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 4209–4216, 2021.
[8] C. Jiang, A. Nazir, G. Abbasnejad, and J. Seo, "Dynamic flex-and-flip manipulation of deformable linear objects," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019, pp. 3158–3163.
[9] Y. Guo, X. Jiang, and Y. Liu, "Deformation control of a deformable object based on visual and tactile feedback," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2021, pp. 675–681.
[10] H. Shi, H. Xu, Z. Huang, Y. Li, and J. Wu, "Robocraft: Learning to see, simulate, and shape elasto-plastic objects with graph networks," *Robotics: Science and Systems (RSS)*, 2022.
[11] B. Shen, Z. Jiang, C. Choy, L. J. Guibas, S. Savarese, A. Anandkumar, and Y. Zhu, "Acid: Action-conditional implicit visual dynamics for deformable object manipulation," *Robotics: Science and Systems (RSS)*, 2022.
[12] W. Yan, A. Vangipuram, P. Abbeel, and L. Pinto, "Learning predictive representations for deformable objects using contrastive estimation," in *Conference on Robot Learning*. PMLR, 2022.
[13] H. Ha and S. Song, "Flingbot: The unreasonable effectiveness of dynamic manipulation for cloth unfolding," in *Conference on Robot Learning*. PMLR, 2022, pp. 24–33.
[14] P. Sundaresan, J. Grannen, B. Thananjeyan, A. Balakrishna, M. Laskey, K. Stone, J. E. Gonzalez, and K. Goldberg, "Learning rope manipulation policies using dense object descriptors trained on synthetic depth data," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 9411–9418.
[15] Y. Avigal, L. Berscheid, T. Asfour, T. Kröger, and K. Goldberg, "Speedfolding: Learning efficient bimanual folding of garments," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 1–8.
[16] Z. Xu, C. Chi, B. Burchfiel, E. Cousineau, S. Feng, and S. Song, "Dextairity: Deformable manipulation can be a breeze," in *Proceedings of Robotics: Science and Systems (RSS)*, 2022.
[17] W. Yuan, Y. Mo, S. Wang, and E. H. Adelson, "Active clothing material perception using tactile sensing and deep learning," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2018, pp. 4842–4849.
[18] W. Yuan, S. Dong, and E. H. Adelson, "Gelsight: High-resolution robot tactile sensors for estimating geometry and force," *Sensors*, vol. 17, no. 12, p. 2762, 2017.
[19] S. Tirumala, T. Weng, D. Seita, O. Kroemer, Z. Temel, and D. Held, "Learning to singulate layers of cloth using tactile feedback," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 7773–7780.
[20] J. Hughes, U. Culha, F. Giardina, F. Guenther, A. Rosendo, and F. Iida, "Soft manipulators and grippers: a review," *Frontiers in Robotics and AI*, vol. 3, p. 69, 2016.
[21] J. H. Low, P. M. Khin, Q. Q. Han, H. Yao, Y. S. Teoh, Y. Zeng, S. Li, J. Liu, Z. Liu, P. V. y Alvarado, *et al.*, "Sensorized reconfigurable soft robotic gripper system for automated food handling," *IEEE/ASME Transactions On Mechatronics*, 2021.
[22] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor," in *International conference on machine learning*. PMLR, 2018, pp. 1861–1870.
[23] R. Smith, "An overview of the tesseract ocr engine," in *Ninth international conference on document analysis and recognition (ICDAR 2007)*, vol. 2. IEEE, 2007, pp. 629–633.

[3] W. Yuan、M. A. Srinivasan 和 E. H. Adelson，“使用 gelsight 触摸传感器估计物体硬度”，2016 年 IEEE/RSJ 国际
智能机器人与系统会议 （IROS)。IEEE，2016 年，第 208-215 页。

[4] Y. She、S. Wang、S. Dong、N. Sunil、A. Rodriguez 和 E. Adelson，“使用触觉反应夹持器进行电缆作”，国际机器人研究杂志，第 40 卷，第 12-14 期，第 1385-1401 页，2021 年。[5] C. B. Teeple、J. Werfel 和 R. J. Wood，“软抓手的多维柔顺性使与薄而灵活的物体能够轻柔地交互，”

在 2022 年机器人与自动化国际会议 （ICRA） 上。
IEEE，2022 年，第 728-734 页。
[6] F. Allgöwer 和 A. Zheng，非线性模型预测控制。
Birkhäuser，2012 年，第 26 卷。
[7] S. Zimmermann、R. Poranne 和 S. Coros，“具有隐式集成的可变形对象的动态作”，IEEE 机器人与自动化快报，第 6 卷，第 2 期，第 4209-4216 页，2021 年。[8] C. 江、A. Nazir、G. Abbasnejad 和 J. Seo，“可变形线性对象的动态弯曲和翻转作”，2019 年 IEEE/RSJ

智能机器人与系统国际会议 （IROS)，2019 年，第 3158-3163 页。

[9] Y. Guo， X. 江， and Y. Liu， “Deformation control of a deformable object based on visual and tactile feedback”，2021 IEEE/RSJ
智能机器人与系统国际会议 （IROS)。
IEEE，2021 年，第 675-681 页。
[10] H. Shi， H. Xu， Z. Huang， Y. Li， and J. Wu， “Robocraft： Learning to 使用图形网络查看、模拟和塑造弹塑性对象“，机器人技术：科学与系统 （RSS)，2022 年。[11] B. Shen， Z. 江， C. Choy， L. J. Guibas， S. Savarese， A. Anandkumar，
和 Y. Zhu，“Acid：动作条件内隐视觉动力学
可变形对象作“，机器人学：科学与系统 （RSS)，2022 年。

[12] W. Yan、A. Vangipuram、P. Abbeel 和 L. Pinto，“学习预测
使用对比估计表示可变形物体“，在机器人学习会议上。PMLR，2022 年。

[13] H. Ha 和 S. Song，“Flingbot：不合理的有效性
布料展开的动态作“，机器人学习会议。PMLR，2022 年，第 24-33 页。

[14] P. Sundaresan， J. Grannen， B. Thananjeyan， A. Balakrishna， M. Laskey，
K. Stone、J. E. Gonzalez 和 K. Goldberg，“使用在合成深度数据上训练的密集对象描述符学习绳索作策略，”
在 2020 年 IEEE 机器人与自动化国际会议 （ICRA） 中。IEEE，2020 年，
第 9411-9418 页。
[15] Y. Avigal、L. Berscheid、T. Asfour、T. Kröger 和 K. Goldberg，
“Speedfolding： Learning efficient bimanual folding of garments”(快速折叠：学习高效的双手服装折叠)，载于
2022 IEEE/RSJ 智能机器人与系统 （IROS） 国际会议。IEEE，2022 年，
第 1-8 页。
[16] Z. Xu， C. Chi， B. Burchfiel， E. Cousineau， S. Feng， 和 S. Song，
“Dextairity：可变形作可以轻而易举”，载于《机器人学报：科学与系统
（RSS)》，2022 年。
[17] W. Yuan， Y. Mo， S. Wang， and E. H. Adelson， “活性服装材料”
使用触觉传感和深度学习进行感知“，2018 年 IEEE
机器人与自动化国际会议 （ICRA)。IEEE，2018 年，第 4842-4849 页。

[18] W. Yuan、S. Dong 和 E. H. Adelson，“Gelsight：高分辨率机器人
用于估计几何形状和力的触觉传感器“，传感器，第 17 卷，第 12 期，第
2762 页，2017 年。
[19] S. Tirumala， T. Weng， D. Seita， O. Kroemer， Z. Temel， 和 D. Held，
“学习使用触觉反馈分离布料层”，2022 年
IEEE/RSJ 智能机器人与系统 （IROS） 国际会议。IEEE，2022 年，第
7773-7780 页。
[20] J. Hughes， U. Culha， F. Giardina， F. Guenther， A. Rosendo， 和 F. Iida，
“软机械手和抓手：回顾”，机器人和人工智能前沿，第 3 卷，第 69 页，
2016 年。
[21] J. H. Low， P. M. Khin， Q. Q. Han， H. Yao， Y. S. Teoh， Y. Zeng， S. Li，
J. Liu， Z. Liu， P. V. y Alvarado， et al.， “用于自动化食品处理的传感器化可重构软机器人抓手系统”，IEEE/ASME 机电一体化汇刊，2021 年。

[22] T. Haarnoja， A. 周， P. Abbeel， and S. Levine， “软演员-评论家：Off-
策略最大熵深度强化学习与随机指标
actor“，参加机器学习国际会议。PMLR，2018 年，第 1861-1870 页。

[23] R. Smith，“tesseract ocr 引擎概述”，第 9
文件分析和识别国际会议 （ICDAR 2007)，第 2 卷。IEEE，2007 年，第
629-633 页。