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TRANSFER LEARNING AND LIMITED DATA LEARNING TECHNIQUES APPLIED TO AUTONOMOUS ROBOTICS

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Abstract: *This study reviews recent developments in the field of transferable learning, with direct applicability to autonomous robotics. Through a comparative approach, the paper reviews the conceptual and methodological foundations, highlighting how few-shot and zero-shot learning techniques support the adaptability of robots to novel tasks under data-limited conditions. Relevant applications – ranging from navigation and manipulation to human-robot interaction – are discussed, illustrating the capabilities of these methods. The study also identifies a number of major constraints that prevent the widespread adoption of these techniques and provides recommendations for future research oriented towards transfer scenarios from a simulated environment to reality and between robotic platforms with different kinematics.*

Key words: *Mobile robot*, *Transfer learning (TL)*, *Few-Shot Learning (FSL)*, *Zero-Shot Learning (ZSL)*, *Learning by demonstration (LfD)*, *Artificial neural network (ANN)*, *Reinforcement Learning (RL)*, *Autonomous robotics*, *Collaborative robot*, *Autonomous navigation*.

1. INTRODUCTION

Recent advances in artificial intelligence – including meta-learning systems, artificial neural networks, and generative models – are directly transforming how robotic autonomy is conceptualized, thereby revising and updating the very definition of the autonomous robot. Thus, robotics supported by artificial intelligence is at a contemporary peak where the ideas of knowledge transfer between tasks, contexts and robotic platforms are no longer just theoretical ideas, but algorithmic methodologies applicable to current systems. This significant change signals the emergence of a new innovative method: Machine learning that coherently brings together transferable learning and learning with few or no examples, in a unitary system, clear and analysed through the lens of their integration into real solutions.

In an unknown environment, every choice made by an autonomous robot can determine its success or failure. Whether it is an industrial robot or a robot for special services, the ability to adapt is essential for autonomous operation and technological "survival". This involves the ability to react to new stimuli, the ability to build internal models of the new environment in which it operates, and the ability to learn quickly to make effective decisions in a framework full of uncertainty. The advancement of machine learning in these contexts is accompanied by considerable challenges. Many methods currently used are dependent on extensive data sets and repeated training, which makes their application in unexplored contexts difficult. According to Jaquier et al. (2023) [1], these methods are difficult to transfer between new tasks and environments, thus limiting the practical adaptability of mobile robots. Muratore et al. (2022) [2] also highlight that policies acquired in simulated environments may not be functional in real environments without well-established adaptation mechanisms.

The central aspect of current research is the development of unified frameworks capable of integrating two or even all three methods – TL, FSL and ZSL. The approach is based on treating these methods as complementary mechanisms, with the aim of ensuring a more robust and flexible learning process, capable of handling the complexity of unexplored environments.

A notable example is the work of Mandlekar et al. who propose an innovative framework [3] called GTI (Generalization Through Imitation) that uses a small number of human demonstrations and some structural learning principles that make the robot capable of generalizing to new tasks, leveraging the experience accumulated in similar tasks. The introduction of a common representation between tasks and contexts allows the authors to provide efficiently elements of TL and ZSL in an adaptable architecture for robotic applications.

In addition, Ali Ghadirzadeh et al. [4] explore few-shot learning in the context of cross-platform transfer. By using a Bayesian meta-learning framework, the system is able to adapt pre-existing policies to new robotic configurations and based on a small amount of data, successfully highlighting the correspondence between TL and FSL.

In another direction, Driess et al. propose PaLM-E [5], an integrated perception model that integrates language, vision, and action learning into a unified

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framework designed to address complex robotic tasks. Although the focus of the work is on context-based planning, its architecture facilitates knowledge transfer between tasks and unknown contexts, serving as a basis for combining ZSL and TL learning methods into a unified system. These studies reinforce the belief that the progress of autonomous robotics directly depends on algorithmic and architectural adaptation, and the development of systems capable of generalized learning becomes a fundamental technological requirement.

2. RELEVANT CONTRIBUTIONS IN THE FIELD OF TRANSFER LEARNING

In the field of robotics, machine learning is based on several fundamental models, each with specific characteristics and applications. *Supervised learning* is based on the use of labelled data sets, in which the robot receives input-output examples and learns to correctly reproduce the relationship between them, being one of the most widespread methods in classification and recognition tasks. *Unsupervised learning* aims to identify hidden patterns and structures in unlabelled data, allowing grouping, organization or reduction of the raw information dimension, an essential aspect for the analysis of complex data. *Reinforcement learning* is based on the trial and error process, in which the robot agent maximizes a reward function by accumulating experience. Monika Rybczak et al. [6] have studied this methodological framework in detail. In addition, *Learning from demonstration* involves imitating the behaviour of a human expert, a method that facilitates the direct transfer of knowledge to the robot [7]. Finally yet importantly, online learning represents a continuous process of adaptation to new and dynamic conditions, being essential for functioning in real environments. Serhat Sönmez et al. [8] describe this approach experimentally.

Transfer Learning (TL) is a recent and increasingly important direction in artificial intelligence applied to robotics. This method aims to capitalize and reuse knowledge acquired in a certain context, be it a specific task, a robotic platform or an activity environment, in order to accelerate and improve the learning process in a new but similar context. Through this mechanism, previously accumulated experience is not lost, but becomes a reusable resource, reducing the data requirement, training time and associated costs. In robotics, this principle translates into the ability of a robot to adapt quickly the skills learned in a previous situation to a new task or an unknown environment, thus contributing to increasing the flexibility and autonomy of intelligent systems.

A remarkable aspect highlighted by Jaquier et al. (2023) [1] is the constant increase in interest in transferable learning at the IROS and ICRA conferences (two of the most important international conferences in the field of robotics, recognized for their major contributions to the development of autonomous systems), especially since 2015. The data presented in Fig. 1 show that in the last two decades, this topic has evolved from a marginal to a central concern, reaching the point of being present in approximately 30–40% of all published articles. This trend confirms the increasing relevance of knowledge transfer in the development of autonomous robotics. Regarding the distribution of subtopics, Fig. 2 highlights that learning through imitation, respectively the transfer from the virtual to the real environment, represent the dominant research directions, concentrating the majority of the published works. At the same time, subtopics such as meta-learning, adaptation between domains or transfer of skills and complete tasks outline a diverse and dynamic landscape, reflecting the complexity and progressive maturation of the field of transferable learning.

In the analysis carried out by Noémie Jaquier et al. [1], TL is presented as a direction with major impact in robotics, with the potential to overcome the fundamental limitations of traditional methods. The authors emphasize that classical approaches rely on very large data sets, on task-specific adjustments and on long training periods, which makes them difficult to apply in robotics. Frequent changes in robot configurations, in working environments or in manipulated objects often lead to the need for complete retraining of the systems.

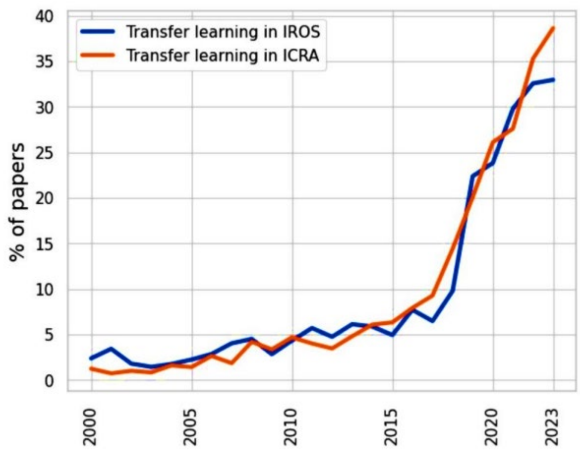

Fig. 1. Evolution of the percentage of papers on transferable learning published at IROS and ICRA conferences during the period 2000-2023 (source: Jaquier et al., 2023 [1]).

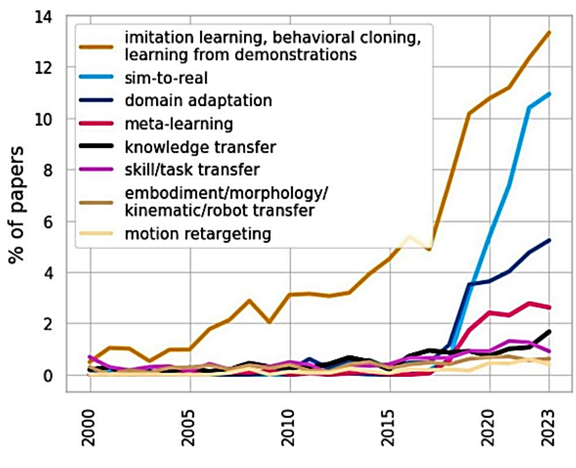

Fig. 2. Distribution of papers on the main sub-themes of transferable learning in robotics (2000-2023) (source: Jaquier et al., 2023 [1]).

Table 1

Classification and analysis of relevant contributions in the field of transferable learning

Article	Main objective	Type of transfer intended	Methodology	Major contributions	Mentioned limitations
Jaquier et al., 2023 [1]	Critical analysis of TL in robotics	Between tasks, robots and environments	Systematic review of ICRA/IROS papers	Trends are identified (30–40% of papers address TL), subthemes are classified (imitation, *sim-to-real*, *meta-learning*)	Lack of consensus in methodologies, partial integration of subfields
Muratore et al., 2022 [2]	Review of simulation learning methods	Simulation-to reality transfer (*sim-to-real*)	RL analysis and various domains	Highlights the effectiveness of environmental variation, discusses various scenarios applied to mobile robots	Results depend on the quality of the simulation, lack of standardization
Mandlekar et al., 2021 [3]	Generalization through imitation (GTI)	Transfer between tasks	Learning from demonstrations	Proposes GTI framework that generalizes with few demonstrations	Requires human demonstrations and complex preprocessing
Ghadirzadeh et al., 2021	Adapting policies across platforms	Transfer between heterogeneous robots	Bayesian meta-learning for FSL	Demonstrates the rapid adaptation of policies between different robots	Limited to controlled environments and reduced data
Driess et al., 2023 [5]	Language-vision-action integration	Transfer between complex tasks	PaLM-E: multimodal language-type model	Demonstrates transfer between tasks through common representations	High computational resources, generalization still limited

In other works with similar themes, Wenshuai Zhao et al. [9] and Mohamed K. Helwa et al. [10] approach transferable learning from complementary perspectives. The work of Mohamed K. Helwa et al. focuses on the transfer between heterogeneous robots (robots differing in structure, functionality, or physical characteristics), viewed from the perspective of a dynamical system, and proposes a framework for identifying and reusing transferable components between robotic models with different characteristics and kinematics. In contrast, Wenshuai Zhao et al. analyses in detail the transfer between environments, with a focus on the transition from simulation to reality in the context of deep reinforcement learning. Both contributions highlight the fact that transferable learning is a key direction for the progress of autonomous robotics, demonstrating its applicability both in transfers between robotic platforms, and in generalization and adaptation to varied and complex environments.

To highlight the perspectives and major contributions from the recent literature, five relevant papers addressing transferable learning in robotics are presented in Table 1 in a comparative manner where they were organized according to common themes. These range from survey papers that examine the evolution and research trends in the field (Jaquier et al., 2023; Muratore et al., 2022), to applied studies that introduce innovative methodological frameworks for knowledge transfer. The latter address the transfer between tasks (Mandlekar et al., 2021), across heterogeneous robots (Ghadirzadeh et al., 2021), or between multimodal approaches integrating multiple data types and modalities of knowledge representation (Driess et al., 2023). This structuring allows not only the comparison of objectives and methodologies, but also the delineation of the limitations and development directions specific to each approach, thus highlighting the complexity and diversity of research in the field of transferable learning applied to robotics.

The rapid development of artificial intelligence algorithms in recent years has favoured the integration of increasingly elaborate learning architectures, among which artificial neural networks stand out for their efficiency in modelling knowledge and decision processes. Applied in robotics, they enhance transferable learning, allowing robots to transfer accumulated experiences between tasks and achieve higher levels of autonomy.

In this direction, Muhan et al. [11] propose the *Policy Transfer with Online Demonstrations* (PTOD) method, which dynamically selects both the timing and the content of demonstration requests to the subject. This strategy optimizes the transfer of robotic policies in a new environment, even when the pool of examples is limited. Unlike classical approaches based on offline demonstrations, the method reduces the problem of changing the distribution of covariance (covariance shift) (the relationship between the variations of variables) and achieves superior performance, with higher data utilization efficiency, which is confirmed in eight robotic scenarios (Fig. 3).

On the other hand, Sapai et al. [12] introduce the *Domain-adaptable Sequential Variational Bayes* (DSVB) framework, a semi-supervised method that combines domain-adaptable learning with robot state estimation in systems with deformable materials (soft robots). Using a recurrent neural network in a Bayesian model, the method manages to infer missing states (in the absence of labels) and adapt representations between different robotic configurations. In experiments performed on pneumatic robotic fingers and in four transfer scenarios, DSVB provided accurate results even under conditions of partial lack of state labels (Fig. 4).

In another direction, Akbulut et al. [13] present *Adaptive Conditional Neural Movement Primitives* (ACNMP), a framework that integrates demonstration learning with reinforcement learning. By using a common latent space (a learning space), the method improves the efficiency of skill transfer and task extrapolation between robots. Moreover, it manages to preserve the characteristics of the initial demonstrations while adapting to new situations and robotic morphologies, confirming the potential of the combination of neural networks and transferable learning in the development of advanced autonomous robots.

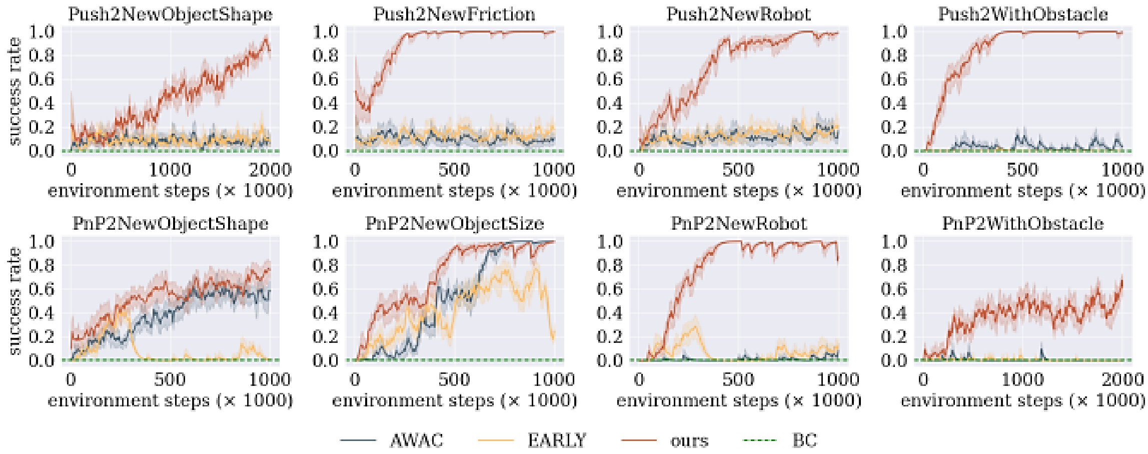

Fig. 3. The results of experimental simulations in the eight scenarios proposed in the PTOD method (Muhan et al. [11]).

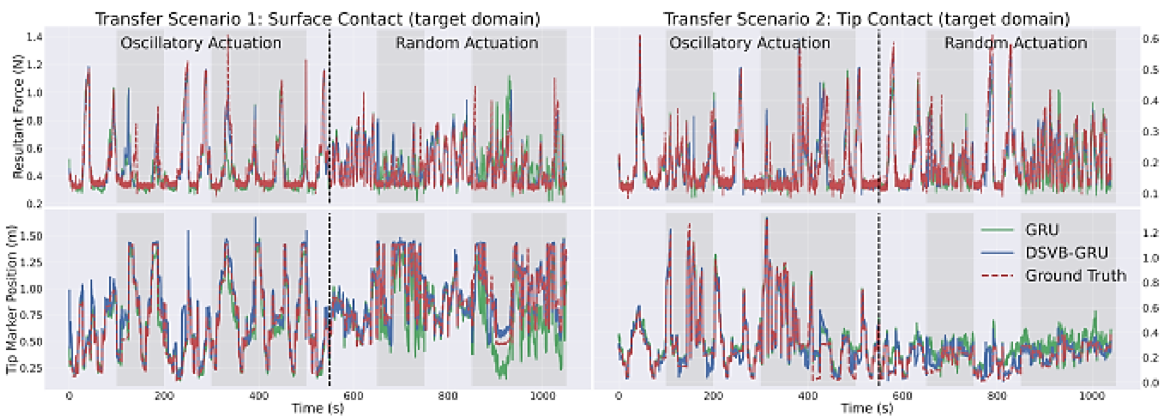

Fig. 4. The results of experimental simulations in the four scenarios proposed in the DSVB method (Sepai et al. [12]).

To illustrate the progress in transferable learning with neural networks, three representative works are summarized in Table 2. Muhan et al. (2025) focuses on policy transfer with online demonstrations, Sapai et al. (2024) analyses transfer between robotic domains using probabilistic models and recurrent networks, and Akbulut et al. (2020) proposes skill transfer between robots and tasks through a common latent space (unified data representation). These approaches highlight the reduction of data dependency, cross-platform adaptation, and transfer fidelity, underlining the central role of neural networks in transferable robotics.

The specialized literature increasingly highlights the trend of integrating artificial neural networks in advanced and varied applications of autonomous robotics. Thus, Yuke Zhu et al. in [14], pre-trained convolutional neural networks are used to allow a robotic model to navigate in dynamic and varied environments, leveraging the ability to recognize and interpret distinct visual objects, with the advantage of transfer to new environments without requiring complete retraining.

Figure 5 illustrates this principle: visual observations obtained by the robot are processed through a deep reinforcement learning (Deep RL) framework, which generates actions such as turning left or right, and navigation is oriented towards predefined goals (target-driven visual navigation), demonstrating the practical applicability of convolutional networks in autonomous visual orientation tasks.

Table 2

Progress in transferable learning through artificial neural networks

Article	Main objective	Methodology	Type of transfer intended	Major contributions
Muhan et al., 2025 [11]	Optimizing robotic policy transfer through dynamic demonstration request	Neural Networks for Learning and Adapting Policies Based on Online Demonstrations	Policy transfer between new environments with limited data sets	Reduces mismatches between the source and target environments and improves data efficiency (validated on 8 robotic scenarios)
Sapai et al., 2024 [12]	State estimation and transfer between configurations in robots with deformable materials	Recurrent neural networks integrated in a sequentially varying Bayesian model	*Cross-domain* transfer and different robotic configurations	LfD + RL integration, preserves demonstration fidelity, adapts to new robotic morphologies
Akbulut et al., 2020 [13]	Skill Transfer and Task Extrapolation Between Heterogeneous Robots	Neural networks for common latent representations (*Conditional Neural Process*)	Skill transfer between robots and different tasks	Integration of LfD + RL, preserves demonstration fidelity, adaptable to new robot morphologies

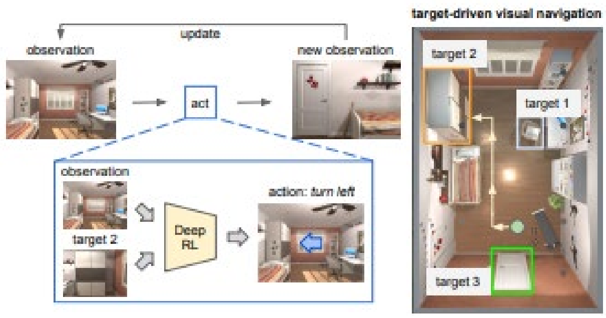

Fig. 5. Autonomous visual navigation based on Deep RL (source: Yuke Zhu et al. [14]).

In a complementary direction, Sadeghi and Levine [15] apply deep reinforcement learning to autonomous flight control, demonstrating that action policies trained exclusively in simulation can be successfully transferred to the physical environment, without additional adjustments. Figure 6 illustrates this process. Figure 6, *a* shows the complete training in simulation, where the agent receives feedback from the environment and learns to avoid collisions with walls or furniture. In Fig. 6, *a* the real-world testing is highlighted, where the learned policies are directly applied to different platforms, demonstrating the generalizability and transferability of the proposed method.

These contributions highlight that artificial neural networks are not limited to elementary tasks, but constitute the foundation of robust solutions to complex problems, reinforcing their central role in the evolution of transferable learning and advanced robotics.

Combining transfer learning with artificial neural networks proves to be a solid and promising direction,

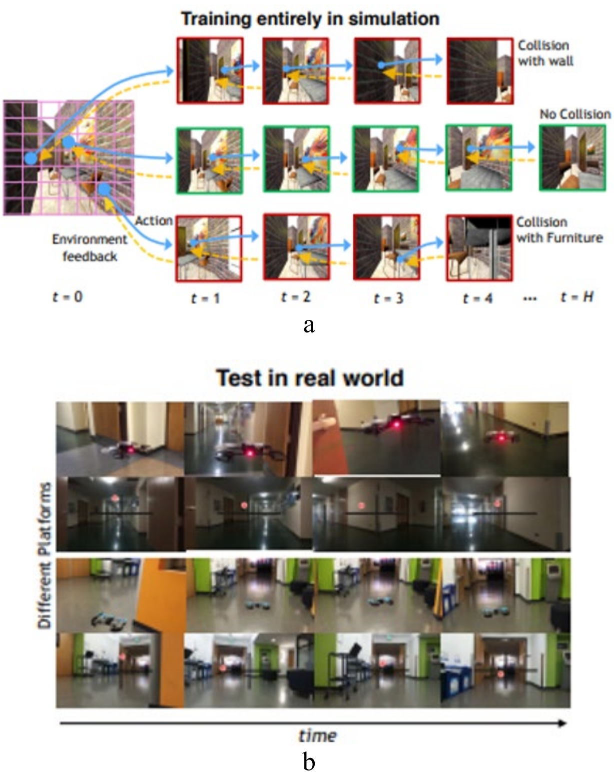

Fig. 6. Transfer of control policies trained in simulation to real environments: *a* – complete training in simulations; *b* – real-world testing (source: Sadeghi and Levine [15]).

supported by experimental results confirming the effectiveness of this unified framework. This combination accelerates the adaptation of robots to new tasks and environments, strengthens the generalization capacity, and marks an important step towards achieving true autonomy in robotics.

3. TRANSFER LEARNING IN ROBOTICS

The analysis of the specialized literature reveals that transfer learning has been subject to sustained efforts of classification, intended to provide a clear structure and to facilitate the understanding of the diversity of existing approaches. A significant example is the structure proposed by Noémie Jaquier et al. [1], which bases the transfer process on three essential components considered as the main axes of the field, Fig. 7. This classification not only organizes the different types of transfer, but also provides an analytical framework to identify what is transferred, between which entities the process takes place and through what mechanisms it is achieved. In this sense, the taxonomy becomes an important methodological landmark, contributing to the consolidation of a unitary vision on how transferable learning can be implemented and evaluated in robotics.

3.1. The basic structure of knowledge transfer

Based on the representation summarized in Fig. 7, the main components on which the transfer learning process in robotics is based can be noted. The method highlights three major axes (called "dimensions") – robot, data/environment and task, which define the nature and direction of knowledge transfer. From the interaction of these components, different types of dual transfer (types I, II and III) are derived, and by their integral combination, the triple transfer is outlined, a form that illustrates the maximum complexity of this conceptual framework. This structuring provides a clear basis for understanding how knowledge can be reused between distinct robots, environments and tasks as follows:

- *Robot transfer*
  R_S = source robot (the robot that initially learns),
  R_T = target robot (the robot to which the learning is transferred),
  D = data (experiments, demonstrations, etc.),
  T = task (the action the robot must take).
  The algorithmic logic is as follows:

$$\{R_S, D, T\} \rightarrow \{R_T, D, T\}. \quad (1)$$

Example: A laboratory robotic arm learns to grasp a cup (T) using cameras and sensors (D). This control policy is transferred to another robotic arm with a different configuration, but which must perform the same task, using the same data. So, the transfer is made to the dimension called "robot" keeping the task and data constant.

- *Data/environment transfer*
  D_S = data from the learning source,
  D_T = target scenario data,
  R = robot that takes the action,
  T = task (the action the robot must take).

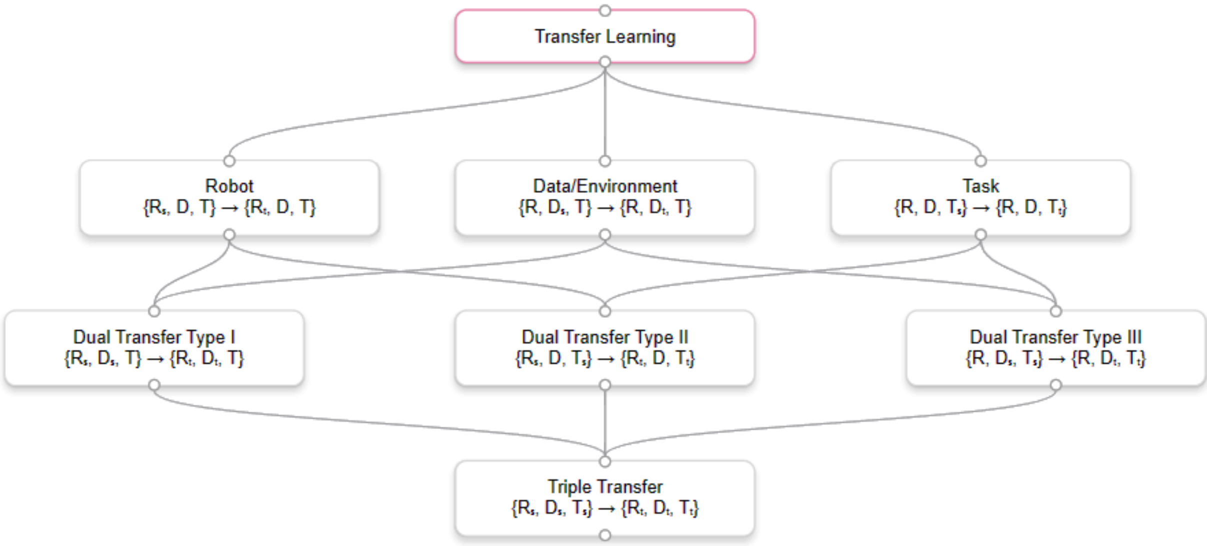

Fig. 7. Transferable learning method in robotics, in graphical format. Image created (diagram created using react flow and the codesandbox simulator based on the conceptual structure in [1]).

The algorithmic logic is as follows:

$$\{R, D_S, T\} \rightarrow \{R, D_T, T\}. \quad (2)$$

Example: A robot is trained in a simulated environment (D_S) to pick up boxes (T). The policy aims to transfer to the real world (D_T) where conditions are different (sensor noise, textures, etc.). So, the goal is to learn and operate in different environments, the same task.

- *Task transfer*

T_S = source task (the robot's initial objective),
T_T = target task (the robot's new task),
R = robot that takes the action,
D = data (experiments, demonstrations, etc.).

The algorithmic logic is as follows:

$$\{R, D, T_S\} \rightarrow \{R, D, T_T\}. \quad (3)$$

Example: A mobile robot is trained to navigate to a point (T_S). That experience is used to teach it to avoid dynamic obstacles (T_T). This is a different task even though it is in the same environment and the robot maintains the same hardware configuration.

- *Dual or triple transfer*

This type of transfer is the most complex, least practiced but most valuable case and occurs when learning is transferred simultaneously to two or all three entities listed previously: robot, task and data/environment. This type of transfer is technically more difficult because it involves multiple variations, increasing uncertainty and reducing the direct applicability of learning knowledge. Algorithmic example:

The following algorithmic examples can be given for:

- *Dual Transfer* in which:

a. the robot and the environment change, but the task is the same

$$\{R_S, D_S, T\} \rightarrow \{R_T, D_T, T\}, \quad (4)$$

b. the task and the environment change, the robot remaining the same

$$\{R, D_S, T_S\} \rightarrow \{R, D_T, T_S\}, \quad (5)$$

- *Triple transfer* in which all three change:

$$\{R_S, D_S, T_S\} \rightarrow \{R_T, D_T, T_T\}. \quad (6)$$

3.3. Development trends in the basic structure of knowledge transfer

Starting from the structure proposed by Noémie Jaquier et al. (2023) [1], where the transferable learning process is structured on three fundamental components – robot, data/environment and task – a unitary conceptual framework is outlined that can be applied in various advanced robotics scenarios. This classification has emerged as a benchmark for subsequent research, serving both to elucidate knowledge transfer across platforms with distinct structures and to characterize rapid adaptation to novel environments and complex tasks. Therefore, understanding these fundamental axes has opened the way to the development of derived methods, oriented towards solving concrete problems of autonomous robotics.

For example, Jian et al. (2023) [16] propose *Policy Stitching*, a modular strategy based on latent neural networks (models that use a hidden representation of data) that allows combining and reusing policies for ZSL and FSL transfer between robots and new tasks with remarkable results (Fig. 8). In a different direction, Yoo et al. (2023) [17] explore the transfer from simulation to reality in the case of robots with deformable elements, through *vision-based proprioception*, demonstrating that robustness can be significantly improved by integrating visual sensors.

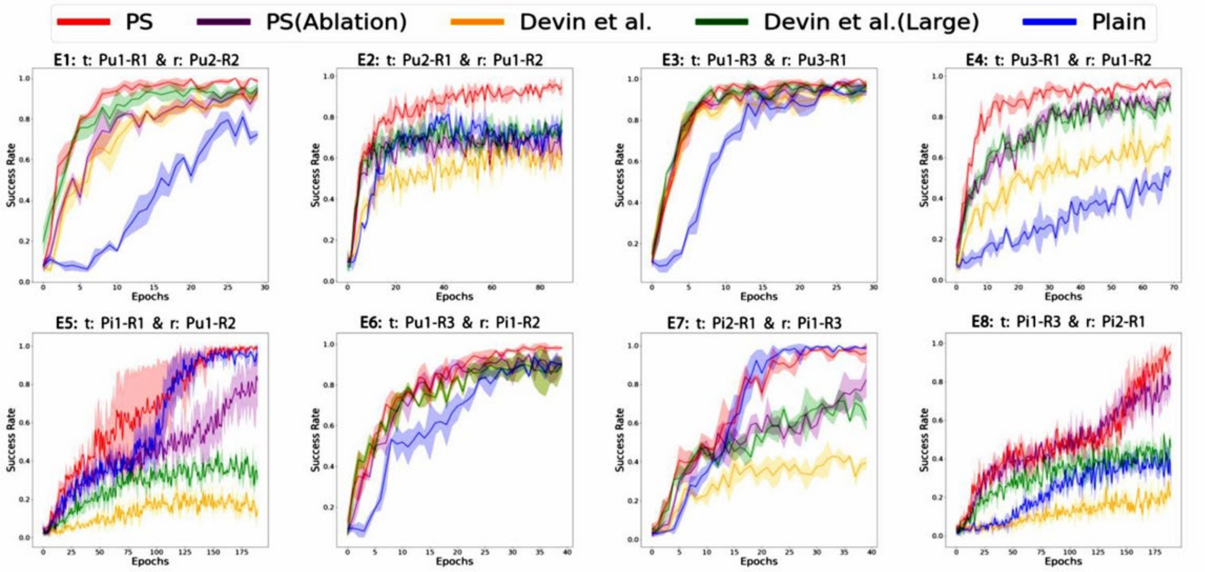

Fig. 8. Success rates of transferable learning algorithms in simulation. Several methods are compared: PS (Policy Stitching, proposed by Jian et al., 2023 [16]), PS (Ablation), Devin et al. [18], Devin et al. (Large) and Plain.

Table 3

Comparative study of methods derived from basic taxonomy

Article	Starting point in relation to [1]	Proposed method	Novelty / Extension brought	Main application
Jian et al. (2023) [16]	It starts from the idea of transfer between robots and tasks (robot-task components from [1])	Modular sequencing and policy combination via neural networks	Allows FSL/ZSL transfer between new combinations of robots and tasks and provides a reusable and flexible policy	Policy transfer between different platforms and tasks
Yoo et al. (2023) [17]	Addresses transfer between environments (data/environment components from [1])	*Vision-based proprioception* for reality simulation	Extends the sim-to-real process to robots, integrating internal visual information for increased robustness	Transfer of policies from sim-to-real for robots with deformable surfaces
Brohan et al. (2023) [19]	It links the task-environment components of [1] through multimodal integration (language, vision, action)	*Vision-Language-Action* (VLM) pre-trained model	Extends TL by integrating large linguistic and visual models into robotics, facilitating knowledge transfer to actions	Multimodal generalization for complex tasks in advanced robotics

Brohan et al. (2023) [19] introduce RT-2, a vision-language-action model capable of transferring knowledge acquired from web sources to complex tasks, marking an important step towards multi-platform generalization. In this paper, the authors demonstrate that representations obtained from large-scale visual-linguistic models can be reused directly for robotic control, transforming abstract instructions into concrete actions. The motivation for including this study in our analysis derives from the fact that RT-2 addresses not only the experimental component, but also the theoretical and programmability dimension of transfer algorithms, by defining clear mapping mechanisms between language, visual perception and action. Thus, the article [19] represents a good example of how recent research extends the logic of the taxonomy proposed by Jaquier through innovative tools, adapted to the increasingly varied requirements of autonomous robotics.

Table 3 illustrates, in a comparative manner, how the taxonomy proposed by Jaquier et al. (2023), based on the three fundamental components – robot, data/environment and task – has been extended and applied in subsequent research. The presented comparative study highlights the continuation of these directions, demonstrating how each work takes the fundamental logic of Jaquier's classification and develops it into innovative methods, adapted to the specific challenges of autonomous robotics.

3.4. Possible correspondences of transferable learning with methods such as FSL and ZSL

Methods such as FSL and ZSL are presented frequently as independent methods. In the context of advanced robotics, however, these methodologies can also be regarded as natural extensions of transferable learning. The essence of transferable learning lies in the reuse of knowledge between tasks, robots or environments, and FSL and ZSL methods do exactly this, but with much more severe constraints in terms of the volume of data received or even the complete lack of training data in the target task. Thus, FSL can be considered as a specialized form of transfer between related tasks, where the model taking the action is exposed to a limited number of examples, using prior knowledge for rapid adaptation. ZSL also involves a semantic transfer that is based on shared representations (conceptual spaces) that allow generalization without direct and specific training.

In robotics, these concepts are encountered frequently in common applications of manipulation, navigation or recognition of objects in unknown environments, where it is almost impossible to cover all combinations of conditions and tasks through prior simulations. More and more research studies propose integrated architectures, where TL provides structural support and the transfer components are activated context-dependently depending on the availability of data or the novelty of the task. A recent direction explores the direct integration of FSL and ZSL strategies, especially in guided transfer or meta-learning architectures. These approaches allow models to be adjusted initially with a small number of examples, then to generalize in the complete absence of initial data to unknown classes or contexts.

Relevant examples are found in the work of Junhyuk Oh et al. [20], where it is demonstrated that an agent can learn a set of tasks through RL and then generalize new tasks using a task-oriented representation space. The work explores a combination of multi-task training and structural learning, thus facilitating the path to ZSL transfer guided by previously accumulated FSL experience. Figure 9 highlights the performances obtained by this approach, comparing flat models with hierarchical architectures according to the number of instructions processed. The results show that hierarchical models, especially those with dynamic structure, achieve significantly superior performances on both *seen* (already met) and *unseen* (new) tasks, demonstrating the generalization capacity and the efficiency of transferring multi-task learning to unknown contexts. These findings highlight the role of hierarchical architectures in bridging the gap between limited-example learning and ZSL generalization.

In the work proposed by Mengye Ren et al. [21], a framework is discussed that starts from learning on a limited support of examples, later appearing an extension to unseen classes through semantic interpolation, thus achieving a hybrid approach between the two methods. The experimental results presented in Fig. 10 confirm the efficiency of this hybrid approach, highlighting a constant increase in accuracy with the integration of unlabelled data. The 5-*shot* scenarios are particularly noteworthy, where the proposed methods significantly exceed the performance of supervised models, demonstrating the ability of semi-supervised frameworks to generalize better to unseen classes.

The PaLM-E linguistic model proposed by Driess et al. [5], which integrates language, vision and action learning in a unified framework, intended to address complex robotic tasks (Fig. 11), shows remarkable results in robotic application. Although the paper focuses on semantic planning (a prior planning), it approaches the study of knowledge transfer between unknown tasks and contexts, which serves as a good example for combining TL and ZSL methods.

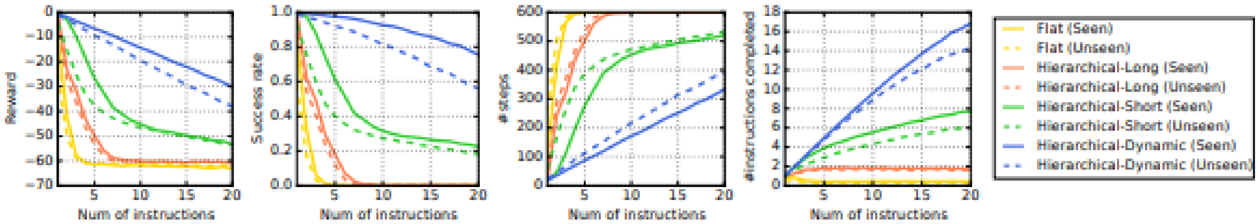

Fig. 9. Success rates of the algorithms in multi-task scenarios (source: Junhyuk Oh et al.[20]).

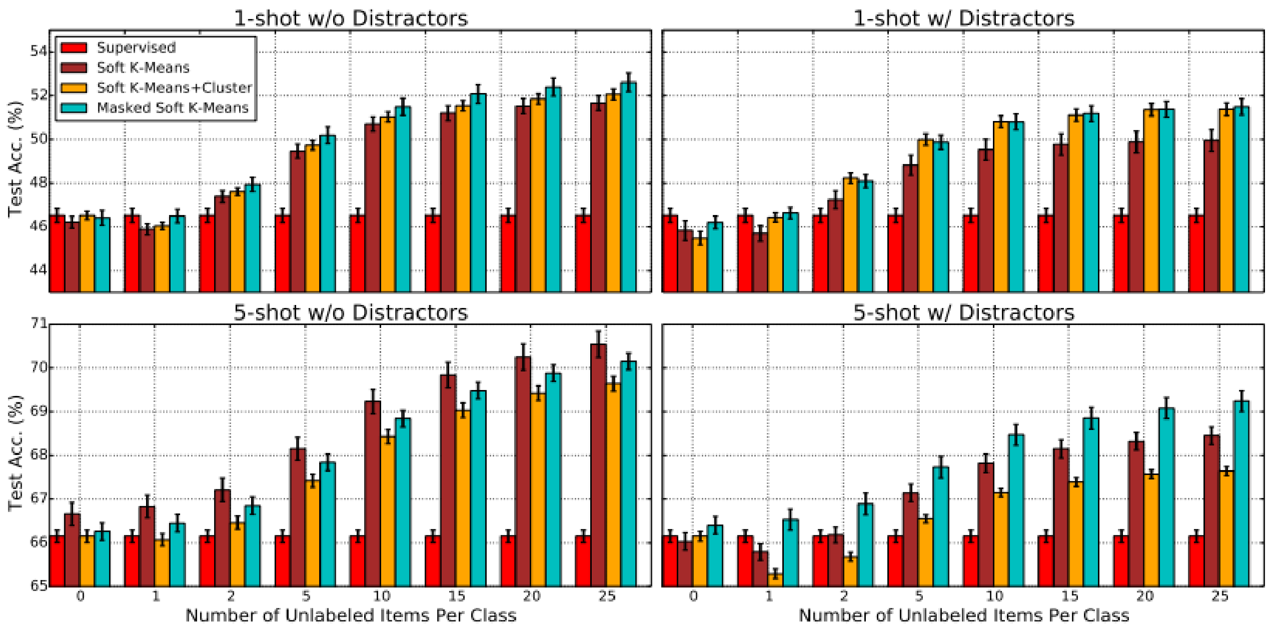

Fig. 10. Experimental results of the proposed method (source: Mengye Ren et al. [21]).

Fig. 11. The PaLM-E robot performs a complete chip fetching task, adapting to unexpected disturbances (source: Driess et al., 2023 [5]).

4. CURRENT CHALLENGES AND LIMITATIONS

Although transferable learning methods have demonstrated notable performance in simulated environments, their implementation on physical robotic systems continues to present significant challenges, mainly driven by discrepancies between simulations and reality, such as sensor noise, variations in motor frequencies, or differences in mechanical dynamics. In addition, knowledge transfer between distinct robotic platforms implies the need to adapt to the specific morphologies and mechanical characteristics of each system.

A key challenge for the effective application of transferable learning in robotics lies in the discrepancy between the data distributions used during training and those encountered in real-world environments. These discrepancies manifest themselves, for example, between simulated and physical environments, where variations in parameters and conditions can lead to inconsistent performance of the models. Added to these are the inherent complexity of the dynamics of robots and the environments in which they operate, the structural and morphological differences between platforms, and the absence of common representations of essential information for different tasks. In the absence of a unified representation framework, the way in which the robot perceives and interprets objectives may be incompatible with the requirements of a new application context. All these aspects create challenges for ensuring proper functionality, defined as the correlation and compatibility between how a robot has learned to perform a task and how that knowledge must be transferred to a different environment or platform – issues analyzed in detail by Noémie Jaquier et al. [1] and Lingfeng Sun et al. [22].

Another significant obstacle to the application of transferable learning occurs when the transfer process simultaneously involves multiple elements, such as the robot, task, and work environment. In such situations, complexity is amplified by the overlapping of morphological differences, dynamic variations, and changes in data distribution, which reduces the generalization capacity of the models. Jaquier et al. (2023) [1] and Haoran Geng et al. [23], emphasize that the lack of a common representation framework for these three entities leads to incompatibilities between the way a task is learned and the way it can be applied in another context. In the same sense, Muratore et al. (2022) [2] show that policies obtained in simulation can fail when transferred to real environments, precisely because of the multiple variations and the lack of robust adaptation mechanisms.

Overcoming these difficulties requires the integration of advanced techniques, such as meta-learning, fine-tuning or multi-task learning, designed to facilitate the identification and transfer of reusable components. Ghadirzadeh et al. (2021) [4] propose a Bayesian meta-learning framework that allows for rapid policy adaptation between robots, demonstrating that this approach can significantly reduce retraining costs.

In a complementary direction, Brohan et al. (2023) [19] present RT-2, a vision-language-action model that leverages multimodal representations and fine-tuning for knowledge transfer from web sources to complex robotic tasks. At the same time, Finn et al. (2017) [24] introduce MAML, an architecture-agnostic meta-learning method that provides rapid adaptation to new tasks starting from a minimum number of examples, thus strengthening the potential of transferable learning in robotics.

A critical aspect of transfer learning remains the reliance on very large volumes of data for training, which limits its applicability in practical contexts where data collection and labelling is expensive and often impossible. Furthermore, integrating these methods with existing robotic systems is proving difficult, as major manufacturers of advanced platforms maintain closed ecosystems with proprietary infrastructures and standards. This fragmentation makes it impossible, at least for now, to achieve a unified framework that allows for full transfer and interoperability between different types of robots. Consequently, while theoretical and experimental progress is remarkable, large-scale implementation is still blocked by industrial constraints and the lack of common standards.

5. FUTURE RESEARCH DIRECTIONS

A first aspect insufficiently explored in the current literature concerns the lack of unitary standards that facilitate the transfer between different robotic platforms. Currently, each manufacturer of advanced robots develops proprietary infrastructures, which makes it difficult to integrate and reuse knowledge in a common framework. Future research could aim at defining universal protocols and task representations, capable of supporting a transfer process independent of the hardware or software architecture of the platforms. This direction is essential to overcome the current fragmentation and to create the premises of a unified robotic system.

Another important area is the difficulty of ensuring generalization across complex, dynamic, and unpredictable environments. Most research has focused on transfer in relatively controlled contexts, while real-world scenarios involve multiple unpredictable factors – lighting variations, interference from unforeseen people or objects, sudden task changes. Future research directions should explore methods that allow rapid adaptation in real time, through robust online learning mechanisms and by integrating multimodal information sources, thus ensuring true autonomy.

Despite the obvious progress, the reliance on very large amounts of data for training remains a central problem. There are still few studies demonstrating how to achieve efficient transfer from a minimal number of examples without compromising accuracy and stability. Future research should investigate more data-efficient training strategies, including realistic augmentation techniques, adaptive simulations, and self-supervised learning mechanisms, which reduce the pressure on collecting and labelling massive data.

An area that is still underexplored is the application of transferable learning in multi-robot systems and human-robot collaboration scenarios. Most current studies deal with transfer at the individual level, without considering collaboration between agents with different morphologies or between humans and robots. Future research may aim at developing transfer models that allow knowledge sharing between multiple robots and their adaptation to collective tasks, opening up new possibilities for industrial robotics, public services, and critical applications in safety and health.

Overall, these research directions highlight the significant potential of transferable learning for the advancement of autonomous robotics, but reaching real maturity depends on resolving current gaps regarding generalization, reducing data dependency, and interoperability between platforms. In this context, the creation of a complete unified framework remains, for now, at a theoretical level, but constitutes the major objective towards which future efforts of the scientific community formed in this new field converge.

6. CONCLUSIONS

In recent years, the rapid development of transferable learning methods, together with advances in neural network training and the use of realistic simulations, have led to significant improvements in the design and adaptation of autonomous robotic systems. In particular, the ability to reuse learned knowledge in different contexts allows the creation of more flexible architectures that can be adapted to new tasks and conditions without requiring complete retraining. The application of these methods in advanced robotics offers concrete solutions to problems such as navigation in unfamiliar environments, manipulation of objects of different shapes, or adaptation to environmental variations. Beyond functional efficiency, these directions open clear perspectives for the design of robust, scalable, and easier-to-implement autonomous systems in real applications. The main ideas learned are:

- Transfer learning is an essential tool in the development of autonomous robots, as it allows the reuse of knowledge in new contexts without training from scratch.
- Robots using TL can be adapted more quickly to different tasks or environments, especially if their architecture is modular and allows for clear separation between perception and decision.
- In the context of practical applications, the analysed models demonstrate that TL can be used successfully for manipulation, navigation or control, including under variable or unknown environmental conditions.
- FSL and ZSL can function as extensions of TL, especially in scenarios where there is insufficient data or where new tasks arise that were not previously foreseen.
- Artificial neural networks are core components in these approaches, providing support for both feature extraction and adaptive policy learning.
- Architectures that include TL contribute to increased robustness and safety in critical applications, such as emergency interventions or healthcare.
- In addition to the direct benefits of adaptability and reduced training time, transferable learning opens up new opportunities for the development of collaborative ecosystems between robots and humans. Thus, robots can learn from demonstrations carried out by human operators or other expert robots, facilitating rapid integration into industrial, logistics or personal assistance processes. Furthermore, this ability to transfer knowledge between individuals and different platforms contributes to the creation of learning “networks”, in which experiences gained in one context can accelerate the evolution of other systems, promoting a collective and evolutionary approach to robotic intelligence.

Based on the combination of TL, FSL and ZSL, solid prospects are emerging for the development of mobile robots with a high degree of autonomy. These approaches can facilitate the transition from simple repetitive executions (industrial cases) to complex and adaptive behaviours, supporting the integration of robots in real environments and in direct interactions with users.

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