Knowledge Evolution for Lifelong Embodied AI: A Brief Survey

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***Abstract*— In real-world scenarios, biological agents thrive by continuously evolving and adapting throughout their lifetime. However, current research in embodied AI primarily relies on stationary models trained for fixed tasks or environments. Lifelong embodied AI, in contrast, aims to support ongoing adaptation and self-improvement. Achieving this requires agents to autonomously acquire new knowledge, consolidate it into memory, and refine it to accommodate future information. In this article, we propose a knowledge evolution cycle for lifelong embodied AI, inspired by memory mechanisms in neuroscience, and present a brief survey that contextualizes existing research within this framework. We believe this framework will provide a valuable reference for researchers seeking to advance lifelong embodied AI. The collection of papers discussed in this article is available at: https://github.com/zehao-wang/Paper-List-of-Lifelong-Embodied-AI.**

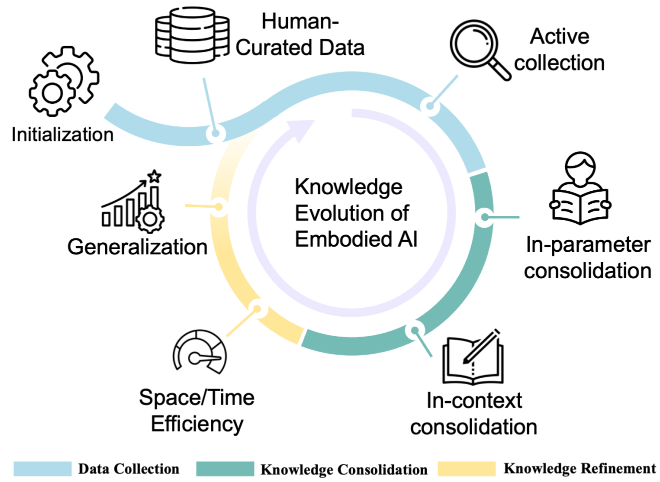

Fig. 1. The knowledge evolution process for lifelong embodied AI. The embodied agent begins with an initialization, providing essential capabilities for active interaction with the environment. It then iterates through a cycle of data collection, knowledge consolidation, and knowledge refinement.

I. Introduction

Current embodied AI research often relies on one or multiple pre-trained models, each specialized for a unique task. This approach is effective when the agent operates in a fixed environment with consistent observations, such as fixed lighting conditions, uniform object arrangement, and other stationary factors. However, it falls short when the environment changes or when the agent needs to update its knowledge or acquire new skills. For instance, a home assistant robot must adapt to modifications in the household environment, learn new recipes, adjust to the owner's preferences, and even develop its own evolving personality. In such dynamic settings, a lifelong learning agent becomes essential.

We explore the challenge of lifelong embodied AI and draw inspiration from neuroscience. In biological systems, the brain filters perceptual information based on previous experiences [1], [2], processes it through short-term memory in the hippocampus, and subsequently transfers it to the cerebral cortex with enhanced efficiency and abstraction [3]–[5]. Similarly, AI knowledge evolution over a lifetime can follow a similar process, progressively refining and consolidating learned representations as experience accumulates. As illustrated in Figure 1, we introduce a knowledge evolution cycle within the lifespan of an embodied AI agent, which is initialized by models pretrained on human-curated data and then iterates through active data collection, knowledge consolidation, and knowledge refinement. **Active data collection** refers to an agent autonomously acquiring data to get familiar with new environments, enhance existing skills or develop new ones. During the **knowledge consolidation phase**, the embodied agent learns from the collected data, encoding knowledge either within its model parameters or organizing it in an external storage as in-context memory for future querying. Finally, in the **knowledge refinement phase**, the model is optimized to improve efficiency in time and storage, preventing resource overgrowth on edge devices, and to enhance generalization, reducing the risk of performance degradation during iterative evolution.

Existing surveys on embodied AI contributed to collect and summarize embodied AI tasks and one-off decision-making models [6]–[8], or mainly discuss the embodied AI in the context of large language model agents [9]–[11], vision-language-action agents [12], [13], or the continual learning in the Large Language Models (LLMs) era [14], [15]. Unlike previous surveys that focus on specific models, training strategies, or benchmarks, our work takes a broader perspective by framing embodied AI through the lens of knowledge evolution. The content is organized as follows. In Section II, we review two types of embodied AI foundation models that have gained attention in recent years, forming the basis for lifelong agents. Section III covers data sources and active collection strategies. Knowledge consolidation based on incoming data is covered in Section IV. Finally, Section V discusses strategies for improving model efficiency and enhancing generalization before initiating the next evolution cycle. Building on the key topics outlined above, we aim to provide a brief review of research that advances the long-term goal towards developing self-evolving embodied AI capable of lifelong autonomy and generalization.

Our survey includes papers from peer-reviewed journals, conferences, and preprint archives such as arXiv to capture the latest advancements in this rapidly evolving field.

II. Embodied Agent Initialization

For the lifelong knowledge evolution of embodied agents, a strong initialization provides a solid foundation to kickstart the evolution loop. Two major branches of embodied AI models show great potential in fulfilling this role.

The first branch follows a modular design powered by the strong reasoning ability of LLMs [16]–[19]. Interaction with the environment typically relies on intermediate script-based interfaces or additional policy modules for the execution of natural language instructions [20]–[23]. Althoug the modular design offers flexibility, managing each module separately during lifelong model evolution increases complexity and cost. Additionally, the need for text-based information transfer between different modules introduces inference delays, limiting its practicality in dynamic environments.

The second branch, known as Embodied Foundation Models (EFMs) or Vision-Language-Action models (VLAs), aims to equip embodied agents with capabilities for perception, reasoning, and action in a single framework. While models such as PaLM-E [24] and SayCan [25] follow an end-to-end training approach, their design remains somewhat modular, as they do not directly output robot control parameters. More recent models, including RT-2 [26], RT-X [27], and OpenVLA [28], advance this concept by further enabling direct robot control. This unified modelling approach is one of the core research topics in embodied AI today. Its strong performance and elegant training paradigm make it well-suited for large-scale end-to-end learning. With promising potential for lifelong knowledge evolution, it offers a solid foundation for embodied agent initialization. However, the substantial data requirements remain a notable challenge.

III. Data Collection

Data is the fundamental driver of modern AI models, shaping their learning, adaptation, and decision-making processes. For lifelong embodied AI, data collection is not merely a passive, preprocessing step building on human-curated data (Section III-A) but an active process (Section III-B) that shapes the agent's knowledge evolution over time.

A. Human-Curated Data

Human-curated data refers to data in which humans actively provide annotations and demonstrations, typically to establish essential foundational abilities before the system begins autonomous learning. In this section, we provide a brief summary of some key embodied AI tasks and data collection devices. While these tasks and devices are often introduced during the initialization of embodied models, they also play a crucial role throughout the continuous evolution of lifelong embodied AI. Understanding these foundational tasks is essential for grasping the broader landscape of embodied AI research.

1) Robotic Manipulation: Manipulation tasks have received significant attention in the research community, as they play a central role in embodied AI. These tasks range from fundamental actions such as grasping [29]–[31] and pouring [32], [33] to more complex and compositional tasks such as object rearrangement [34]–[36] and general daily manipulation [27], [37]–[41].

The evolution of teleoperation devices for data collection has progressed significantly. Early methods relied on joysticks [42], [43], followed by VR devices [44]–[46], and twin-arm systems [47]. The latest advancement is the Universal Manipulation Interface (UMI) [48], which is valued for its high flexibility, enabling the execution of long and complex robot arm trajectories.

2) Embodied Navigation: The data collection for embodied navigation still largely relies on simulation environments with human annotators' keyboard or joystick control. The tasks range from object-goal navigation [49] and point-goal navigation [50] to more advanced multimodal tasks such as path-aligned vision-language navigation (VLN) [51]–[54] and goal-oriented VLN [55], [56]. A new trend in this category involves manipulation tasks during navigation, such as OK-Robot [21] and SayPlan [57]. However, the data used in these works is often not publicly available, as it is heavily dependent on the specific scene and the configuration of the mobile device. More recently, benchmarks combining manipulation with embodied navigation on humanoid robots have gained attention, such as Humanoidbench [58].

3) Embodied Question Answering: Beyond the aforementioned goal-driven tasks, knowledge-driven tasks require strong reasoning abilities supported by world knowledge. These tasks are typically framed as embodied question-answering challenges. One notable subcategory is episodic-memory question answering, where an agent must develop an understanding of the environment from its episodic memory to answer queries, such as "Where is my smartphone?". Data for these tasks are typically obtained through crowdsourced annotations [59], [60] or generated from predefined templates [61]. Another subcategory, active embodied question answering, requires agents to engage in further exploration and interaction with the environment to retrieve the necessary information [62]–[64]. The datasets for these tasks can originate from abstract text-based game contexts [65] or be collected from more sophisticated simulation platforms [66]–[68].

B. Active data collection

Active Data Collection occurs when the AI agent autonomously interacts with its environment to gather information [69]. By actively selecting and acquiring new data, the agent can identify gaps in its understanding, prioritize informative experiences, and improve the efficiency of subsequent knowledge consolidation. We discuss active data collection strategies in existing embodied AI literature, driven either by low-level perceptual curiosity or the pursuit of high-level skill development. While many traditional strategies rely on additional policy modules, some advanced approaches—particularly those that leverage LLMs—can be adapted directly to the models discussed in Section II.

1) Low-level Perceptual Curiosity: Perceptual curiosity plays a crucial role in motivating an agent to efficiently explore and get familiar with its environment. This involves collecting data to build a spatial memory or obtaining informative samples and labels to further improve visual features.

This objective is typically formulated as a reward function within a reinforcement learning (RL) policy. It can be defined based on criteria such as area of coverage [70], [71], semantic inconsistency [72]–[74], reconstruction error / uncertainty [75], [76], and visual uncertainty [77], [78].

Alternatively, rule-based data collection strategies also provide a viable approach [79], [80]. For example, Pinto *et al.* [79] propose a method where a robotic arm interacts with objects and collects visual data after different predefined interactions. The collected observations can extend the training dataset, leading to more robust visual perception. Lamanna *et al.* [80] leverage symbolic planning to automate data collection for objects with novel properties.

2) Pursuit of High-level Skill Development: Developing novel high-level skills is a more advanced requirement for lifelong embodied AI. This process necessitates the agent's ability to recognize its own skill gaps and proactively seek annotations from either human or environments to address them.

Traditionally, active data collection strategies have been highly specialized for specific tasks and follow human-designed paradigms. In embodied navigation, the agent can rely on rich environment feedback to relabel failed trajectories [81]. Several studies have explored active data collection for robot control by requesting demonstrations based on action uncertainty [82], [83], predictive variance [84], or with the objective of balancing data distributions [85]. Furthermore, self-supervised objectives [86]–[89], encourage models to collect state transition data, specifically pairs of consecutive states, promoting a robust understanding of physical dynamics. Additionally, some approaches employ human-designed and hard-coded questions to enable robots to interact with humans for informative data gathering [90].

For high-level planning tasks, inspired by the success of reinforcement learning from human feedback (RLHF) in natural language processing [91], researchers in embodied AI have increasingly incorporated human feedback as an active data source. Recent studies [92]–[94] treat human feedback as sparse rewards, leveraging it to enhance manipulation skills and improve generalization.

With the emergence of powerful LLMs, model-driven proactive data collection strategies have become a promising alternative, leveraging the world knowledge encoded in LLMs. This approach was initially explored in simulated environments. LLMs propose interaction actions and record environmental responses to generate successful and failed experiences, improving the subsequent reasoning module's learning [95]–[97]. More recently, this method has been extended to robotic manipulation tasks for data collection [98], demonstrating its potential for lifelong learning in real-world scenarios.

C. Discussion

As humans continue to provide annotations for fundamental tasks, the amount of data they can collect will eventually reach a limit. To adapt to dynamic environmental changes and personalized customer requirements, active data collection becomes essential in lifelong embodied AI. However, current research in this area remains limited. Most existing approaches are tailored to specific tasks, such as area exploration, question answering or interaction with a predefined set of objects. These methods typically optimize for task-specific objectives rather than developing a generalizable framework. In addition, some of these strategies require specialized policy module designs, adding complexity to the overall embodied agent architecture. With the advances in LLMs and their integration in embodied agents, the LLM-driven active data collection strategies offer a promising direction. However, a key challenge lies in how the LLMs can effectively identify the agent's current capability gaps and generate informative, context-aware questions based on this understanding. Moreresearch is needed to address this issue.

IV. Knowledge Consolidation

Lifelong embodied agents will be exposed to online streams of knowledge due to the open-ended nature of the real world. The key challenge for such an agent will be acquiring new knowledge without forgetting the old one. We have identified works that could potentially overcome this challenge and have categorized them according to whether the new knowledge is stored in the model's parameters through optimization (IV-A) or outside (IV-B), e.g. using external memory, maps, etc.

A. In-parameter knowledge consolidation

When training on new data, neural networks face the challenge of catastrophic forgetting [99], [100], where performance in previously learned tasks is severely degraded after learning a new one. To mitigate catastrophic forgetting, the continual learning community [101] has developed various approaches. Reviewing the embodied AI literature, we categorize the approaches in three groups derived from the continual learning research taxonomy. Each group reflects a distinct trade-off between performance and computational resource requirements.

1) Regularization approaches: Regularization approaches incorporate additional terms to the loss function to preserve previous knowledge. These approaches can be highly efficient with regard to storage and GPU memory, but may require more computational resources for extra forward passes or computations. Despite their memory efficiency, they often do not achieve the best performance relative to other approaches.

A common strategy is functional regularization through knowledge distillation, which helps the model remember what it learned from previous tasks by guiding it to behave similarly to how it did before [102]. This has been applied to sequential grasping [103], adapting agents to novel interactions [104], and lifelong mapping and localization [105].

Another approach is weight protection, where crucial parameters are preserved [106], [107]. For example, Elastic Weight Consolidation (EWC) [106] was used to train LLMs for planning, tracking, and activity recognition [108]. Hybrid methods, such as MAS [109] in combination with distillation, have been used for additional parameter protection [105].

Lastly, regularization can constrain optimization trajectories to prevent interference with previous tasks [110], as seen in [111], which continually refines navigation policies using GEM [110].

2) Architectural approaches: Architectural approaches allocate dedicated parameters to each task, mitigating interference. As new tasks arrive, additional parameters—such as adapters [112], [113]—can be introduced, expanding the neural network. These approaches often yield a high performance, but lead to increased GPU memory usage and computational costs as the number of tasks grows in the iterative evolution cycle. The approach to addressing this issue is further discussed in the Knowledge Refinement Section. Furthermore, some strategies of this approach rely on predefined or inferred task identities to route the data to the corresponding task parameters (e.g. [114]), which may limit their applicability.

Many works in embodied AI adopt this approach in different ways: dynamically adding parameter-efficient adapters for new manipulation [115], [116] or motion control tasks [117], visual prompt tuning for new navigation tasks [118], expanding weight matrices as in progressive networks [119] for Sim2Real adaptation [120], or learning task-specific policies from human demonstrations [121].

3) Replay approaches: Replay-based methods typically maintain a memory buffer containing a subset of previously encountered data or model states to store and replay past experiences during the learning process [122]–[124]. This family of approaches is widely regarded as the most effective approach for mitigating catastrophic forgetting, offering key advantages such as straightforward implementation, high adaptability to various tasks and robust performance.

In embodied AI, replay-based methods enhance learning by leveraging memory during training and inference, enabling agents to adapt to recurring scenarios [125]. [126] proposed retrieving relevant demonstrations from episodic memory using visual and language similarity for rapid skill recovery. Other works explore diverse replay strategies: [127] used a diversity-aware buffer for incremental grasping tasks, while [128] applied adversarial experience replay for incremental dual-arm grasping. LOTUS [129] employs hierarchical imitation learning with experience replay for manipulation, and [130] mitigates forgetting in task and motion planning by replaying all past data.

However, replay-based approaches also face certain challenges such as memory constraints and data privacy issues. To address these limitations, one can use generative models as an alternative [131]. The literature on generative replay for lifelong embodied AI is scarce, but an opportunity. Nonetheless, a pioneering work by [132] uses lightweight hypernetworks to generate neural network parameters for Neural ODE solvers, significantly reducing memory requirements while maintaining performance.

B. In-context knowledge consolidation

In embodied AI tasks, a common method for integrating external knowledge from multiple modalities is in-context usage. This approach involves dynamically retrieving relevant knowledge and appending it to the model's input. This approach allows knowledge to be stored externally in a sustainable manner for lifelong task executions while maintaining strong interpretability. This section explores knowledge consolidation by examining common external data modalities and their integration in embodied agents, ranging from spatial memory, skill knowledge to temporal facts.

1) Map: The map modality primarily serves as an explicit and updatable spatial memory, traditionally employed in SLAM systems [133]–[135]. With the increasing focus on modularized solutions in Embodied AI research, maps were first adopted in embodied navigation tasks, including path-aligned instruction following [136]–[139], interactive instruction following [140], [141], and goal-oriented embodied navigation [142]–[144]. Initially, these approaches were developed in simulation environments. Since 2022, the rise of vision-language large pretrained models [16], [145]–[147] and semantic neural rendering [148]–[151] has brought attention to relatively implicit spatial memory, valued for its open-vocabulary querying capabilities. Robotics research, exemplified by works such as CLIPField [152], has begun integrating semi-implicit maps into more hybrid embodied AI tasks and deploying them on real-world robots. Additionally, the map modality has gained traction in manipulation tasks and 3D spatial trajectory planning, as demonstrated in works like VoxPoser [23] and novel object pick-and-place [151].

2) Scene Graph: Scene graph [153]–[155] is an abstract modality which supports efficient query, update and encoding. In Embodied AI research, scene graph is designed to capture the abstract layout of the environment, object properties, and object relations. Previously, scene graphs were applied in pure textual environments [156]. With recent advances in LLMs, they have emerged as a widely adopted modality for tackling complex hybrid embodied AI tasks [57], [157]–[159]. Due to their flexible graph structure, external knowledge graphs hold the potential to further enhance planning capabilities [160].

3) Skill library: The skill library serves as a dedicated modality for storing successful experiences in Embodied AI.

This concept was initially referred to as functional tools [161] when LLMs were first integrated into Embodied AI research. Originally, skill libraries were manually designed by human experts to facilitate the reuse of predefined modular robot control functions [20], [22], [162], [163]. However, due to the inherent scalability limitations of human-designed libraries, LLM-driven approaches have taken over. In Voyager [95], researchers introduced a lifelong skill library evolution strategy fully driven by LLMs. This approach was first demonstrated in the Minecraft game environment, where LLMs iteratively proposed new skills through trial-and-error, storing successful experiences as functions in the skill library. More recently, this idea has been extended to robotic manipulation tasks [98], [164], [165].

4) Log data: Temporal event data that do not have a specific structure or use case are usually stored in the log with time stamps for future querying. As illustrated in ReMEmbR [166], the log messages during exploration are sufficient for basic question answering and navigation. For more long-term temporal memory, Bärmann *et al.* [167] propose a hierarchical representation to efficiently store the history.

C. Discussion

The field of lifelong embodied AI is still an emerging area, with limited research specifically focused on in-parameter knowledge consolidation. For example, much of the existing literature lacks rigorous evaluation and analysis of the computational requirements, which are important in the context of embodied AI due to the limited embedded resources. Recent works in the continual learning field [168], [169] suggest caring more about compute constraints, paving the way towards efficient algorithms that enable lifelong learning on embedded devices [170], [171].

Another key question is: where should the knowledge be stored? Similarly to humans, who do not retain all the information they encounter, lifelong embodied agents must balance in-parameter knowledge and in-context knowledge. A truly lifelong agent must intelligently decide which information is worth encoding into its parameters, e.g. for fast and recurrent access, and which should be stored externally for retrieval later on. However, this critical decision-making process is largely absent from current literature.

V. Knowledge Refinement

In the lifelong evolution cycle, the embodied agent continuously accumulates knowledge by increasing its in-context storage or expanding its model size. A critical challenge is how to manage this ever-growing knowledge and data within the constraints of limited edge resources, while maximizing knowledge retention to prevent model degeneration. Achieving this requires a balanced focus on improving both the space/time efficiency and the model's generalization capabilities. Fortunately, for in-parameter knowledge, we have several techniques that can potentially tackle this challenge, including knowledge distillation, model quantization, and network pruning. For in-context knowledge, we can refer to well-studied database compression techniques [172], which have been extensively studied; therefore, we will not elaborate on them further in this section.

A. Space and Time Efficiency

Model compression techniques effectively enhance both space and time efficiency for in-parameter knowledge. By reducing model size, these techniques enable faster computation and response while alleviating the computational and storage constraints commonly faced when deploying models on resource-limited devices.

1) Distillation: Knowledge distillation [173] reduces computational and memory overhead by transferring knowledge from a larger, complex teacher model to a smaller and more efficient student model. The student model is trained to mimic the teacher's behaviour, supervised by teacher's soft labels [174], intermediate features [175], and more. In Embodied AI, research has focused on distilling perceptual knowledge [176] and decision-making strategies [177]–[181] into multitask embodied agents. With the increasing role of LLMs, strategies for distilling embodied reasoning abilities from large models into small models have gained attention. The recent work, DEDER [177], exploits the generative and self-verification capabilities of LLMs to distill embodied-relevant knowledge into compact models for interactive embodied navigation task.

2) Quantization: Network quantization can also refine knowledge and make models more compact. By reducing numerical precision, it lowers storage requirements and computational costs [182]–[185]. Some hardware is also designed for quantized networks to enhance computational efficiency [186]–[188], which can benefit embodied agents. Recent studies have demonstrated the effectiveness of quantization-aware training [183], [189], [190]. It is used in fine-tuning neural network-based robotic control policies, enabling efficient deployment on hardware with limited computational capacity while maintaining task performance [191]. Despite its advantages, quantization remains relatively underexplored in embodied AI.

3) Pruning: Model pruning reduces model complexity by selectively removing parameters that contribute minimally to performance. Structured pruning eliminates entire convolutional filters or layers, leading to a more compact architecture, while unstructured pruning removes individual weights, enabling finer control over sparsity. Both techniques aim to balance accuracy and computational efficiency. There is a lack of studies on network pruning for embodied AI. However, since LLMs are widely regarded as a mainstream foundation for new methods, advances in both structured [192], [193] and unstructured [194] pruning techniques for LLMs are also worth referencing.

B. Generalization

Keeping or even improving generalization is crucial for embodied AI systems, enabling them to adapt to novel environments and unseen scenarios while preventing model degeneration during lifelong iterative evolution. Unlike training-time generalization which enhances a model's ability to adapt to unseen data through model design [195], or data augmentation [196], refinement-stage generalization focuses on preserving performance when reducing model complexity as first discussed in 1989 [197]. This principle remains applicable and is evident in advanced model compression techniques [177], [198], [199]. As models become more lightweight, their test performance initially improves but eventually declines. In embodied AI research, knowledge distillation on decision-making policies [178] has been shown to significantly enhance data efficiency for further learning. In the study of distilling embodied-relevant knowledge from larger models [177], [181], and quantization work [191], the student model can achieve comparable or superior performance to their larger counterparts. However, the impact of model compression techniques on refining generalization remains largely unexplored in Embodied AI research, especially lack of studies in real-world embodied tasks.

C. Discussion

Research on knowledge refinement in embodied AI is still in its early stages, particularly regarding iterative evolution cycles. While some recent efforts have explored optimizing space and time efficiency for embodied agents, such studies remain scarce. Notably, there has been little to no work specifically studying generalization and model degeneration for embodied agents. However, for lifelong embodied agents, effective knowledge refinement is essential to ensure sustainable operation on resource-constrained edge devices. Model refinement and optimization techniques, such as distillation and quantization, have gained significant attention in the context of LLMs — as highlighted in recent DeepSeek reports [19], [200]. Whether these methods can be seamlessly adapted to embodied AI models or if there are unique challenges that remain difficult to address is an open question. This uncertainty highlights exciting opportunities for future research and exploration.

VI. Conclusion

In this article, we propose a framework for the knowledge evolution of lifelong embodied AI, positioning existing research within this context and identifying potential gaps. Taking a deeper perspective, this framework addresses lifelong from two aspects: first, an outer loop that defines high-level lifelong evolution processes throughout the agent's lifespan, and second, the inner lifelong learning mechanism that consolidates incoming knowledge into the model's parameters. We hope the insights presented in this article will inspire valuable directions for future research.

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