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SYNERGY: Smart System for Home Device Control and User Interaction

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ABSTRACT

Smart home management is becoming increasingly important, requiring high-end systems that seamlessly integrate with users' needs and preferences. We introduce SYNERGY, an intelligent system to optimally support home environment management that can integrate smart home devices through context-aware actions and natural language interactions. By integrating NLP, machine learning, and the AI2-THOR virtual environment, SYNERGY detects users' intentions and emotional signals, enabling adaptive responses. Unlike systems limited by superficial empathy, SYNERGY facilitates deeper and more meaningful interactions. To effectively address task allocation, SYNERGY uses a reward-based mechanism that optimizes device usage and minimizes user effort. Our research demonstrates high accuracy in emotion and intent recognition, along with superior performance in task allocation and real-time adaptability. Evaluation confirms its effectiveness in improving user satisfaction by providing contextually relevant responses and seamless device control. Future work aims to incorporate more user-centric features, advancing SYNERGY as a practical and empathetic smart home solution.

Keywords: Smart Home Automation, Context-Aware Interaction, Natural Language Processing, Emotion Detection, Task Allocation, AI2-THOR, User-Centric Design, Assistive Technology, Machine Learning

1. INTRODUCTION

In recent years, efforts to integrate language understanding with interactive decision making have become central to the development of conversational AI systems for the smart home. Large language models (LLMs), which are state-of-the-art AI systems trained to understand and generate human language, have demonstrated impressive capabilities in tasks such as reasoning about home automation and planning actions such as adjusting thermostats, controlling lights, and managing appliances. These capabilities are often studied in isolation, limiting their effectiveness in creating truly intuitive and useful smart home experiences. Deeper integration of these capabilities is needed to create systems that seamlessly adapt to the nuances of life in the home.

1.1 Beyond Interactions with Smart System.

Using Natural Language Learning in an Educational Context Sajja et al., 2024 presents AIIA to create an interactive platform that reduces the cognitive load on learners, using the contextual environment and learning outcomes to assess the best support. It is evident that education is embracing the benefits of large language models to improve work efficiency. The advent of ChatGPT can be said to be a huge change, the latest research by Naamati-Schneider & Alt, 2024 examines how AI-powered assistants like ChatGPT are reshaping digital literacy skills. This research is based on the empirical premise that such tools can make some digital competencies obsolete by taking over tasks that students previously needed to master. This is the evidence for the integration of LLM into support is being greatly promoted This is evidence that the integration of LLM into support is being strongly promoted.

1.2 User Interactions in Home environment.

In our hyper-connected world, meaningful social interaction is paramount to well-being. Isolation can have devastating consequences, as highlighted by a Shanghai survey “Risk factors for depression among older adults living alone in Shangha” by Y. Chen in which 26.9% of older adults living alone reported feeling bored. This highlights the urgent need

for AI-powered solutions to foster genuine human connection and bridge the gap for socially isolated individuals. Technology, when harnessed responsibly, has the potential to create meaningful connections and significantly improve the quality of life for those most at risk of social isolation.

The future of AI in assisting humans is becoming increasingly clear. Recent research suggests that AI can do more than just perform simple tasks; it can also provide deep emotional support. Research by Chu et al. (2024) demonstrated the potential of AI to understand and respond to human emotional needs, while research by Miksik et al. (2020) opens up new avenues for AI to proactively interact with users. The combination of these research directions promises a future where AI becomes an integral part of our lives, providing support and companionship to humans.

2. LITERATURE REVIEW

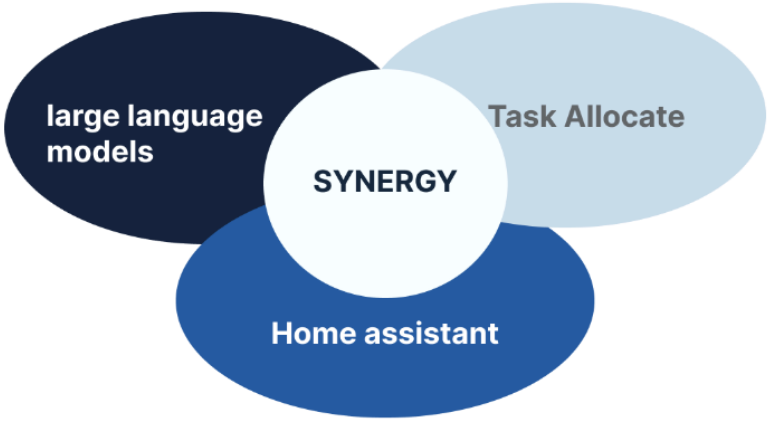


Fig 1: Scope diagram

As illustrated in the Fig. 1, SYNERGY, when combined with the power of large language models (LLMs), promises to revolutionize automation. By simulating the user's "inner speech," LLMs will help SYNERGY gain a deeper understanding of context, make better decisions, and adapt better to changes in the environment. This synergistic combination, which includes large language models, task allocation, and home assistant capabilities, will enable the system to continuously learn and adapt. This opens the door to a wide range of applications, from creating intelligent virtual assistants to optimizing manufacturing processes in factories. SYNERGY, combined with LLMs, will become a powerful tool that will help us automate complex tasks and improve productivity.

To provide context, AI2-THOR (AI2-The House Of Interactions), developed by the Allen Institute for AI (founded by Paul Allen), is a 3D simulation platform for training and testing machine learning algorithms in a virtual home environment. AI2-THOR provides a rich dataset of actions performed by robots on objects, such as picking up a pillow or opening a refrigerator. This approach, popularized by many studies, provides a cost-effective and faster alternative to real-world testing. However, a major limitation is the lack of natural language understanding and task planning in the environment itself. AI2-THOR focuses primarily on low-level object interactions, requiring an external system to process natural language user input and translate it into tasks executable for the AI2-THOR environment.If the paper does not have the margins shown in Table 1, it will not upload properly.

Noah Shinn and colleagues proposed an alternative to traditional reinforcement learning, called Reflexion, which uses reflective linguistic feedback. This approach aims to avoid the need for extensive model retraining by allowing the system to learn from its own internal reflections on past actions. While scientific methods provide reliable data, individual personality and environmental factors can influence intentions and introduce biases. Reflexion attempts to mitigate this by allowing for preprocessing of past tasks, improving decision-making over time and leading to more objective results.

However, Reflexion focuses primarily on improving learning for complex tasks, lacking a complete framework for integrating internal interactions or planning real-world actions.

In a recent study by Anonymous (2023) titled "Comparative Analysis of A3C and PPO Algorithms in Reinforcement Learning: A Survey on General Environments," the effectiveness of A3C and Proximal Policy Optimization (PPO) algorithms was compared two prominent deep reinforcement learning algorithms, A3C and Proximal Policy Optimization (PPO), in the context of the CartPole and Lunar Lander environments. The study evaluates the effectiveness of these algorithms in training agents to navigate and achieve optimal performance in these challenging environments. Han Shen et al. provide a theoretical foundation for the A3C algorithm, establishing its asymptotic convergence guarantees. The authors demonstrate that A3C achieves linear speedup as the number of parallel agents increases, highlighting the benefits of parallelism and asynchrony in agent-critic algorithms.

3. RESEARCH METHODOLODY

SYNERGY addresses the limitations of traditional control systems by providing a flexible and adaptive solution for task allocation. Its multimodal input processing, efficient task retrieval, and real-time adaptability make it suitable for use cases in smart homes, industrial automation, and other complex environments.

3.1 Data Sources and Processing

The system collects data from multiple sources to enhance the system's functionality and responsiveness.

User Inputs: The system relies heavily on user inputs, such as commands or queries related to the smart home environment. These inputs are carefully analyzed to decipher the user's intentions, emotions, and desired actions, allowing the system to provide contextually relevant responses. Activities that promote mental well-being, such as relaxing and unplugging devices, are often included in these commands (Puyat et al., 2020).

Predefined Datasets: To improve intent recognition and action classification, the system uses predefined data sets. These data sets map general user statements to specific actions, such as setting up mindfulness exercises or playing music. This capability is particularly valuable in identifying requests related to mental health activities, including guided imagery and meditation (Radeck et al., 2017).

Emotion Classification: The system incorporates an EmotionDetect layer that uses a pre-trained model to analyze user input and predict their emotional state. This allows the system to respond empathetically by taking appropriate actions, such as playing soothing music, guiding breathing exercises, or suggesting physical activities that help reduce stress (Sarris et al., 2020).

Action Dataset: The system maintains an action dataset that includes a variety of tasks related to smart home devices and wellness activities, such as reminders to stretch or setting up virtual meditation sessions. This dataset empowers the system to predict and perform effective actions based on user commands and the current environment (Quaye et al., 2017).

3.2 Overview Scope

The SYNERGY system aims to address the limitations of traditional control systems by providing a flexible and adaptive solution for task allocation. Leveraging the Large Language Model (LLM) and the AI2-THOR simulation environment, SYNERGY processes user requests to control smart home devices. User inputs are standardized, embedded into vectors, and mapped to a comprehensive "home alone" task database. This database, containing information about devices and their states, facilitates the generation and allocation of appropriate actions. The system dynamically updates the environmental state after each task execution, ensuring real-time consistency and allowing users to interact smoothly with the system.

At the core of SYNERGY lies the Intent Recognition pipeline. A logistic regression model, trained on a large dataset of user inputs labeled with specific intents, forms the foundation of the pipeline. To increase accuracy, the systems incorporate text-based sentiment recognition, which allows the system to identify and interpret the emotional context of user inputs. Building on the work of Bernhard Kratzwald and colleagues, who demonstrated the effectiveness of transfer learning for emotion detection (sent2affect), the system uses a custom deep learning model to outperform established

methods in emotion-based decision support. This sentiment recognition approach allows the classifier to better understand the nuances of user commands, resulting in more accurate and relevant intent predictions. For example, the system can differentiate between urgent and informal requests, resulting in more nuanced and responsive responses.

Action Detection

After identifying the intent, the Action Detector retrieves the corresponding actions using the Support Vector Machine (SVM) method [11]. SVM effectively classifies user intentions by determining the optimal hyperplane that separates different classes in the feature space. By leveraging SVM, the system ensures accurate and timely responses to user commands, improving the overall responsiveness and accuracy of the smart home experience.

Term Frequency-Inverse Document Frequency (TF-IDF)

To further improve the understanding of user commands, the system uses TF-IDF [12] to evaluate the importance of words in a given context. TF-IDF is calculated as follows:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \text{IDF}(t) \quad (1)$$

where:

$$\text{TF}(t,d) = \frac{f_{t,d}}{N_d} \quad (2)$$

$$\text{IDF}(t) = \log\left(\frac{N}{n_t}\right) \quad (3)$$

In these equations:

- $f_{t,d}$: the frequency of term t in document d.
- N_d: the total number of terms in document d.
- N: the total number of documents in the corpus.
- n_t: the number of documents containing term t.

TF-IDF provides a statistical measure reflecting the importance of a term in a document relative to its occurrence in the entire corpus. This analysis helps identify relevant keywords and phrases, which are important for accurately understanding user commands and retrieving relevant information from the knowledge base.

3.3 Task allocation

The main purpose of combining with a virtual environment is to facilitate the navigation of multiple agents to designated objects and perform actions such as turning on, off, opening, and closing objects. This method aims to improve the efficiency of performing tasks in the simulation environment, providing a foundation for practical applications in robotics to paint a complete picture.



Fig. 2. Eco-centric camera.

Each agent starts with a random position in the environment, and the queue system manages its actions to ensure that tasks are performed efficiently. For nonelectric devices that need to move, the distance to approach the object, pick up the object, and then bring it to the userspecified location to place the object down must be calculated. The classical formula for calculating the Euclidean distance is needed to determine the distance of the agent from its target objects. Figure 2 shows a standard camera view from the robot's perspective. This view allows movement in multiple directions, including left, right, forward, and backward, providing a close-up perspective on tasks as they are being executed.

Euclidean distance is often used in path calculation issues because it provides a simple method for determining the shortest distance between two places in three dimensions. The following formula defines the Euclidean distance d between two points $p_1(x_1,y_1,z_1)$ and $p_2(x_2,y_2,z_2)$, which is commonly used in many positioning and navigation activities:

$$d(p_1,p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$$

In contrast, for electric devices, the agent does not need to physically approach the object. Instead, it can adjust the required control parameters remotely to achieve the desired task.
To enhance the decision-making process of agents in dynamic environments, we integrate the Asynchronous Advantage Actor-Critic (A3C) algorithm. A3C is in learning method that trains multiple agents asynchronously in parallel environments. Each agent learns an optimal policy $\pi(a|s;\theta)$ that maps states s to actions a, while simultaneously learning a value function $V(s;\theta_v)$ to estimate the expected future rewards. The updates for the policy and value function are defined as follows:

a) *Policy Update::*

$$\Delta\theta \propto \nabla_\theta \log\pi(a|s;\theta)A(s,a) \qquad (4)$$

b) *Value Function Update::*

$$\Delta\theta_v \propto A(s,a)\nabla_{\theta_v} V(s;\theta_v) \qquad (5)$$

Where:

- $A(s,a)$ is the advantage function, calculated as $A(s,a) = R - V(s;\theta_v)$,
- R is the cumulative discounted reward.

By leveraging A3C, agents can efficiently learn optimal strategies for navigating complex environments and completing tasks with minimal errors. This approach complements the Euclidean distance metric by enabling agents to dynamically adapt their paths and actions based on real-time feedback from the environment. Combining these methods ensures a robust and flexible framework for efficient task planning and execution.

In contrast, for electric devices, the agent does not need to physically approach the object. Instead, it can adjust the device's mode as long as it is within the robot's frame. For example, the robot can turn off the lights without having to move closer, just by sending a command to the device.



Fig. 3. A camera from the top.

Algorithm 1 Task Assignment and Execution

```
procedure AssignTasks(user_prompt)
    Initialize tasks as an empty list
    {Step 1: Extract relevant objects}
    Determine objects_found based on user_prompt and available_objects
    {Step 2: Analyze action and priority}
    Parse action and priority from user_prompt
    if action is not specified then
        Set action to default (e.g., "turnOn")
    end if
    {Step 3: Create tasks}
    for each object in objects_found do
        Create a task with attributes:
            - Unique Task ID
            - Object
            - Action
            - Priority (e.g., "low", "high")
            - Status (e.g., "to do")
        Add task to tasks
    end for
    {Step 4: Initialize cost matrix}
    Initialize cost_matrix to represent distances between agents and tasks
    {Step 5: Populate cost matrix}
    for each agent do
        if agent is available then
            for each task do
                Calculate distance agent - task location
                Store distance in cost_matrix
            end for
        end if
    end for
    {Step 6: Optimize task assignments}
    Solve assignment problem ( cost matrix minimization algorithm)
    {Step 7: Execute and log assignments}
    for each agent-task pair do
        Assign agent to task
        Output assignment details (e.g., Agent ID, Task ID, Object, Action)
    end for
    {Step 8: Save task details}
    Export tasks to a CSV file
end procedure=0
```

Fig 4. Algorithm for delivery tasking

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1 *Making-decision detection model*

The decision discovery model was evaluated using a diverse set of user inputs, focusing on commands related to smart home environments. The model performed decision-making tasks based

on a combination of intent detection and predefined action categories. The model's robustness in handling multi-step decision processes demonstrated its ability to adapt to complex user commands. The system relied on scientific research standards to respond and perform relevant actions. The response was automatically adjusted to be more appropriate for each request from each user's personality type.

4.2 *Emotional detection model*

The emotion detection model, trained on a pre-labeled dataset, was tested for its ability to classify basic emotions such as happiness, sadness, and frustration based on user input. This emotional adaptability has proven to be crucial in improving user satisfaction, especially in health-related tasks.

4.3 *Task allocation model*

The task allocation model is responsible for distributing user commands to the right smart device in the simulated environment, learning from Smart Multi-Agent Robot Task Planning by the researcher. Shyam et al (2024). The model's performance is measured by its ability to allocate tasks based on the user's current environment and device availability. However, image generation can be choppy depending on the device's resources, with a rate of 5 frames per second being 1.5 to 2 times slower.

Methods	SR	TCR	GCR	RU	Exe	ER	L
Synergy (GPT-4)	0.62	1.00	1.00	1.00	1.00	0.95	0.90
Synergy (GPT-3.5)	0.62	0.87	0.93	1.00	0.91	0.85	0.88
Synergy (Qwen2)	0.75	0.87	0.93	1.00	1.00	0.97	0.92
Synergy (Llama3)	0.87	1.00	1.00	1.00	1.00	0.97	0.95

TABLE I

EVALUATION METRICS FOR SIMPLE TASKS USING 7 METRICS: SR, TCR, GCR, RU, EXE, ER, AND L.

Methods	SR	TCR	GCR	RU	Exe	ER	L
Synergy (GPT-4)	0.71	0.85	0.92	1.00	0.97	0.95	0.87
Synergy (GPT-3.5)	0.14	0.28	0.35	0.85	0.62	0.75	0.73
Synergy (Qwen2)	0.63	0.71	0.83	0.90	0.89	0.88	0.80
Synergy (Llama3)	0.71	0.71	0.87	0.97	0.92	0.95	0.85

TABLE II

EVALUATION METRICS FOR COMPLEX TASKS USING 7 METRICS: SR, TCR, GCR, RU, EXE, ER, AND L.

4.4 *Implement System*

Deploying SYNERGY in a simulated smart home environment provided a comprehensive evaluation of its end-to-end functionality. Each component, including decision-making models, emotion detection, and task allocation, was integrated into a unified system. Additionally, the system maintained contextual awareness throughout long conversations, improving the ability to provide personalized support.

We employ seven evaluation metrics: Success Rate (SR), Task Completion Rate (TCR), Goal Condition Recall (GCR), Executability (Exe), Efficiency Rate (ER), and Latency (L), following the methodology of [29]. Our evaluations are based on the dataset's final ground truth states, which we compare to the achieved states post-execution to assess task success. These metrics comprehensively capture task success, goal achievement, efficiency, execution quality, and time performance, providing a holistic assessment of the system's effectiveness.

Success Rate (SR): Indicates whether both the Goal Condition Recall (GCR) and Robot Utilization (RU) were met. SR is 1 when GCR = 1 and RU = 1, otherwise 0. The task is considered successful with respect to the goal being achieved and the robot's efficiency.
Task Completion Rate (TCR): Measures the degree of task completion regardless of robot utilization. If GCR = 1, then TCR = 1; otherwise TCR = 0.
Target Condition Recall (GCR): Quantifies the rate at which a specific goal of the task is achieved. This rate is calculated as the difference between the actual final state conditions and the achieved final state, divided by the total number of goals in the dataset.
Executability (Exe): Represents the proportion of actions in the task plan that are successfully executed, regardless of their impact on task completion.
Efficiency Ratio (ER): Measures the degree of adherence to the task plan by calculating the proportion of correctly executed actions relative to the total number of planned actions. Higher ER indicates fewer errors and better execution accuracy.
Latency (L): Measures time efficiency by comparing actual task completion time to planned time. L 1 indicates on-time completion, while L ¿ 1 indicates delay.

5. CONCLUSION

The evaluation of various methods across two task complexities, Simple and Complex, was conducted using seven key metrics: Success Rate (SR), Task Completion Rate (TCR), Goal Condition Recall (GCR), Robot Utilization (RU), Executability (Exe), Efficiency Rate (ER), and Latency (L). The findings reveal distinct performance levels among the tested methods. Synergy (GPT-4) emerged as the most effective across both task complexities, achieving near-perfect scores for Simple tasks in metrics such as TCR, GCR, RU, and Exe (all 1.00), with slightly lower scores for Efficiency Rate (ER = 0.95) and Latency (L = 0.90). For Complex tasks, Synergy (GPT-4) maintained its lead, with the highest results in SR (0.71), TCR (0.85), and GCR (0.92), alongside excellent performance in RU (1.00), ER (0.95), and L (0.87).

Synergy (Qwen2) demonstrated comparable effectiveness, especially for Simple tasks, where it surpassed GPT-4 in SR (0.87) while matching its perfect scores in TCR, GCR, RU, and Exe. For Complex tasks, Claude3 continued to perform robustly, recording high scores in SR (0.71), GCR (0.87), and RU (0.97), confirming its adaptability to increased task complexity. Meanwhile, Synergy (Llama3) displayed consistent performance across both task types, excelling in Exe (1.00) and ER (0.97) for Simple tasks and maintaining strong results in GCR (0.83) and RU (0.90) for Complex tasks. In contrast, Synergy (GPT-3.5) showed moderate performance for Simple tasks, achieving decent results in GCR (0.93) and RU (1.00), but struggled with more complex scenarios, where its scores in SR (0.14), TCR (0.28), and GCR (0.35) highlighted its limitations in handling increased task difficulty.
Overall, the results underscore the superior reasoning and planning capabilities of Synergy (GPT-4o) and Synergy (Qwen2), which consistently outperformed the other methods across both task complexities. While Synergy (Llama3) delivered reliable performance, it remained slightly behind the top performers. Meanwhile, Synergy (GPT-3.5), though effective for simpler tasks, showed significant weaknesses when faced with more complex challenges. These findings emphasize the importance of advanced models in ensuring reliability, efficiency, and adaptability in diverse task execution scenarios. Videos showing all experiments can be accessed via YouTube Video.

TABLE III
COMPARISON OF SYNERGY, REFLECTION, AND SMART-LLM

Feature	SYNERGY	Reflection	SMART-LLM
Sentence Embeddings	✓	✓	
Making-Decision	✓	✓	
Emotional Detection	✓		
Retrieve Tasks	✓	✓	
Function Direction	✓		✓
Performance Action	✓		✓
Task Allocation	✓		✓

Table III provides a detailed comparison of the features in SYNERGY, Reflection, and SMART-LLM. SYNERGY surpasses the other systems by integrating all features of both Reflection and SMART-LLM, in addition to offering Web implementation. Performance evaluation focused on the accuracy and time to perform actions in the AI2-THOR environment. The system could perform tasks such as turning lights on or off, adjusting thermostats, and controlling communication devices with high precision. Performance was further measured by task completion time, with most actions performed in less than 3 seconds. The ability of the system to perform multiple tasks simultaneously without delay is a significant achievement.

The flexibility of system in controlling a wide range of devices was tested using a variety of AI2-THOR [4] smart objects. From kitchen appliances to entertainment systems, the system successfully identified and executed commands on different types of devices. For visualization, for non-electrical objects that require a grasping action, it is possible to move close to the object to directly physically impact it, while for electrical devices, it is only necessary to determine the location of the object, which can be easily done without having to move close. This flexibility is important in validating the system's potential for real-world applications where users can interact with a variety of connected devices in their homes.

6. CONCLUSION

In summary, the SYNERGY system is a powerful AI-driven solution for smart home automation, integrating natural language processing and machine learning with real-time task allocation in the AI2-THOR environment. The system effectively addresses the task allocation challenge by enabling dynamic and context-aware task management. By classifying user intent, detecting emotions, and efficiently allocating tasks, SYNERGY ensures personalized, context-aware responses to deliver a seamless user experience. The system's versatility across multiple smart devices highlights its high performance and potential for real-world applications. Future developments will focus on fine-tuning the task allocation algorithms to further enhance the system's efficiency and adaptability. Incorporating user-centric features, including personal history and lifestyle data, will enable SYNERGY to make tailored recommendations based on habits, moods, and activity patterns. At the

same time, enhanced privacy protection mechanisms will be critical to building user trust and ensuring responsible use of AI. These advancements will make the system more flexible and adaptive, significantly increasing efficiency and user satisfaction for a more intuitive and personalized smart home experience.

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