

GestureGPT: Zero-shot Interactive Gesture Understanding and Grounding with Large Language Model Agents

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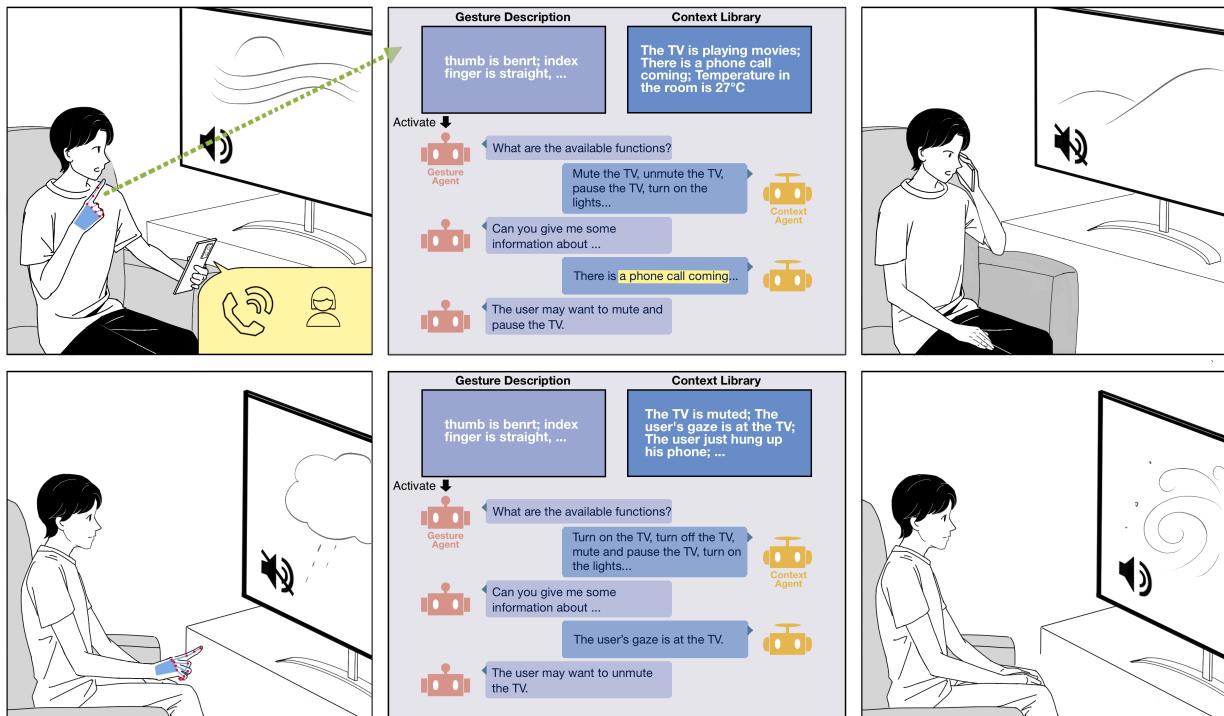


Fig. 1. Example interaction of GestureGPT. a) Tom is watching TV at home and he just receives a phone call from his mom. To create a more silent environment for communication, he performs a ‘mute’ gesture to indicate that he wants to mute the TV. b) The landmarks of the hand are extracted and used to generate rule-based descriptions and consequently activate *Gesture Agent*. Context information includes states of devices, gaze position, interaction history, etc. Then, *Gesture Agent* and *Context Agent* have a multi-turn dialogue to predict the user’s intention of interaction. c) The TV is muted and Tom talks to his mom on the phone. d) After Tom hangs up the phone, he looks at the TV and makes a point gesture to indicate that he wants to continue watching TV. e) The gesture description and context information, including the user history that he muted the TV just now, are sent to *Gesture Agent* and *Context Agent* respectively. They have a multi-turn dialogue to predict the user’s intention of interaction. f) The TV is unmuted.

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Current gesture recognition systems primarily focus on identifying gestures within a predefined set, leaving a gap in connecting these gestures to interactive GUI elements or system functions (e.g., linking a ‘thumb-up’ gesture to a ‘like’ button). We introduce GestureGPT, a novel zero-shot gesture understanding and grounding framework leveraging large language models (LLMs). Gesture descriptions are formulated based on hand landmark coordinates from gesture videos and fed into our dual-agent dialogue system. A gesture agent deciphers these descriptions and queries about the interaction context (e.g., interface, history, gaze data), which a context agent organizes and provides. Following iterative exchanges, the gesture agent discerns user intent, grounding it to an interactive function. We validated the gesture description module using public first-view and third-view gesture datasets and tested the whole system in two real-world settings: video streaming and smart home IoT control. The highest zero-shot Top-5 grounding accuracies are 80.11% for video streaming and 90.78% for smart home tasks, showing potential of the new gesture understanding paradigm.

CCS Concepts: • Human-centered computing → User interface management systems; • Computing methodologies → Natural language processing.

Additional Key Words and Phrases: zero-shot, gesture recognition, interaction context

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1 INTRODUCTION

Gestures offer an intuitive and immediate channel of expression of human intents, which is of vital importance for communication between humans and computers. They enable users to interact with digital systems in a manner that mirrors real-world interactions, reducing cognitive load and enhancing natural user experience. Thus, numerous efforts have gone into the development of gestural interaction interfaces [2, 11, 34]. However, most of the work in this field focuses on gesture recognition tasks; *i.e.*, classifying the gesture performed into a category within a predefined gesture set. On one hand, users need to learn the predefined gestures, which limits spontaneity and expressiveness; on the other hand, digital systems still need to associate the gesture category with an interactive element or function, which is highly context-dependent and not always straightforward. Such constraints of traditional gesture interfaces make them feel less natural and intuitive, which leads to Norman’s famous argument that “Natural Interfaces are Not Natural”[19]. While significant advances have been made in gesture recognition technologies over the years, the naturalness challenge persists: the translation of gestures into actual interaction actions.

As Norman pointed out, gestures are ephemeral and thus highly relevant to the interaction context, including user identity and cultural background, interaction interface, interaction history, and other modalities of concurrent input (*e.g.*, gaze, speech). Recognizing the importance of interaction context for natural gesture interfaces, we propose GestureGPT, a context-aware gesture understanding and grounding framework that enables zero-shot association between gestures and interactive functions. The core idea of GestureGPT is leveraging the prior knowledge of gestures and context information of large language models (LLM) to interpret the interaction intention behind the performed gesture. To that end, we introduce a dual-agent dialogue system that involves both an LLM *Gesture Agent* and an LLM *Context Agent*. There are three key modules in GestureGPT: 1) The gesture description module transfers gestures into natural language for LLM understanding. We designed a set of rules to describe gestures based on hand landmarks detected in visual data. The state of each finger, the closeness of adjacent fingers, and fingers and hand moving directions (if any) are described according to the rules by calculation of angles and distances of finger joints. 2) *Gesture Agent* takes the summarized description as input, inquires *Context Agent* about the context information, and predicts which interactive function the user intents to activate after synthesizing the gesture and context information. 3) *Context Agent* organizes a context knowledge base and answers the questions of *Gesture Agent* accordingly. For each detected gesture, the two agents engage in an iterative conversational exchanges for a holistic understanding of the interaction situation, which finally leads to a dynamic grounding of the gesture with a interactive function.

GestureGPT offers a suite of advantages that address the challenges and limitations of traditional gesture recognition systems. Firstly, its zero-shot gesture understanding capability allows for the recognition of gestures beyond predefined gesture sets,

allowing more natural and intuitive gesture interfaces; Secondly, it goes beyond traditional gesture classification and actually grounds the gesture to an interactive function, bridging the gap between gesture recognition and actionable interface elements; This is achieved by leveraging LLM's prior knowledge of gestures and contexts in a novel way, enabling a holistic understanding of the interaction gesture and context. Thirdly, GestureGPT relies on visual-based hand landmarks for gesture descriptions, making it independent of category and angle views, thus offering a wider range of applications for our system. Rather than a static mapping of gestures, GestureGPT dynamically grounds them to interactive GUI elements, offering flexibility in interactions and addressing the ephemeral challenge of gestures.

We design and evaluate our gesture description module on public datasets with first-view and third-view gesture images and videos. Our description rules have an overall description accuracy of 91.8% on the first-view dataset and 81.0% on the third-view dataset. We conducted two user studies to evaluate the dual-agent dialogue system in two typical interaction scenarios: a first-view smart home IoT device control with AR headset scenario and a third-view video streaming on desktop PC scenario. The highest zero-shot Top-5 gesture grounding accuracies are 90.78% for IoT control tasks and 80.11% for video streaming. This performance is close to human accuracy and even surpasses human benchmarks in one of the context settings. The results show that our gesture description method and dual-agent framework are efficient in gesture-based interfaces and have potential for other natural input modal understanding and grounding.

Our contribution is three-fold:

- (1) We proposed a novel dual-agent gesture understanding framework that grounds gestures to interactive functions in a zero-shot manner by leveraging large language models' prior knowledge of gestures and context, closing the gap between gesture recognition and function grounding.
- (2) We designed a set of gesture description rules based on hand landmarks extracted from images and videos, which are compatible with existing gesture recognition methods and agnostic to angles of view.
- (3) We evaluated the effects of different contexts on the gesture grounding task, providing guidance for future context-aware gesture understanding work.

2 BACKGROUND AND RELATED WORK

2.1 Context-aware Gesture Recognition

Gestures have long been a pivotal component in human-computer interactions, garnering significant attention in associated fields. As early as the previous century, researchers started introducing neural networks for hand gesture recognition [18]. Numerous advanced methodologies have seen substantial evolution over time [13, 17]. However, while these methods yield satisfactory performance, their practical applications are constrained by two factors: Firstly, high-performing algorithms depend on large-scale annotated data and struggle to adapt to diverse scenarios or user groups. Secondly, many gesture recognition methods pre-define a specific set of gesture categories and do not generalize to unseen gestures. This limitation is particularly problematic because many applications demand custom interaction semantics.

Accordingly, the focus has shifted towards recognizing gestures in low-resource or few-shot settings [16, 23]. Rahimian et al. [23] first explored this few-shot learning setting. A more recent contribution by Maslych et al. [16] significantly enhanced performance by effectively integrating multiple data augmentation strategies. However, although the need for large-scale annotation has been alleviated, these improved methods still necessitate the pre-definition of gesture categories. Contrarily, in immersive environments, hand gestures can encapsulate rich and diverse semantics when adapted to different devices or contexts. For instance, [30] demonstrated that even nuanced gestures could be informative within an interactive framework. In an ideal setting, users should be able to spontaneously express fine-grained, adaptive gestures to communicate their interactive intentions. To this end, this paper innovatively leverages the prior knowledge of LLMs to enable adaptive comprehension of spontaneous user gestures in pervasive environments, empowering users to express their interaction intentions both intuitively and naturally.

Context provides informative clues for understanding users' interactive intent in a pervasive environment. For example, Schilit et al. [25] from XEROX PARC uses location, distance, and time as context to trigger events. Dey et al. [7] formulates a conceptual framework for context-aware applications, and introduces the Context Toolkit to facilitate the creation of such applications. Dey et al. [8] propose programmable prototyping environment where users can demonstrate adaptive behaviour to enable context-aware application. Gu et al. [10] proposes an ontology-based context architecture to reason about various contexts. In our work, we use a

large language model agent to manage and synthesize context information. Compared to previous work, LLM agent provides fast access to context information through a conversational interface, greatly reduces the complexity of context information extraction. It is even possible for LLM agent to abstract high-level context information from low-level context data like location and time, thanks to the reasoning capability and common sense of LLMs.

2.2 Large Language Model as Autonomous Agent

Large language models have displayed an exceptional ability to understand and execute a broad spectrum of natural language tasks [1, 20]. Numerous recent studies have delved into the feasibility of using LLMs beyond the confines of traditional natural language processing. These studies aim to emulate human-level intelligence, allowing LLMs to accurately perceive generalized environments and act accordingly when faced with diverse situations [27]. Agents based on LLMs show potential in various domains, from web browsing [6, 31] and strategic planning [26, 32] to robotic control [3, 9]. Deng et al. [6] uses LLMs as web agents, establishing benchmarks for a multitude of web tasks spanning hundreds of websites across varied domains, such as booking flights or locating specific information. Yao et al. [32] introduced a prompting strategy in which LLMs reason and act by externalizing their thoughts and assimilating the corresponding observations. Subsequent research discovered that LLMs can self-identify errors, iterating improvements to enhance outcomes [26]. Brohan et al. [3] show that when grounded in visual environments, LLMs can interpret and execute robotic instructions, even with previously unseen objects and tasks. Finally, frameworks like AutoGPT¹ and LangChain² integrate various agents and hold promise as powerful personal assistants. Distinct from the aforementioned studies, this paper focuses on the exploration of LLM-based agents to comprehend free-form user gesture intentions and execute corresponding instructions in pervasive computing environments.

Several recent works further explore the collaboration of multiple agents to accomplish more complex tasks. For instance, Park et al. [21] designed a multi-agent system that simulates human behavior in a virtual environment, where agents can perform daily tasks such as cooking breakfast or initiating conversations. Qian et al. [22] utilize multiple LLM agents for software development, enabling communication and mutual verification, and eventually produce a holistic software solution inclusive of source codes, environment dependencies, and user manuals. Saha et al. [24] demonstrated how an LLM can teach a weaker language model, providing natural language explanations for reasoning skills through a theory of mind. Other applications span reasoning [15], evaluation [5, 35], and a myriad of intricate tasks [36]. In comparison, GestureGPT employs two separate agents: one for interpreting free-form gestures and another for environmental context management. These two agents collaborate seamlessly to achieve accurate gesture comprehension and execution.

3 METHOD

GestureGPT is a context-aware gesture understanding and grounding framework supporting zero-shot association of gestures with interactive functionalities. By synthesizing gesture descriptions and context information, GestureGPT discerns the intended interaction behind each gesture without additional training for the grounding task. The whole framework can be seen in Fig 2.

The core of this framework is a novel dual-agent dialogue system used in understanding interactive gestures. This system comprises a LLM-based **Gesture Agent** and a LLM-based **Context Agent**, as well as a **Gesture Description** utility module. The gesture description module translates images of static gestures and videos of dynamic gestures into natural language, making them comprehensible for LLMs. We carefully crafted a set of rules that characterize gestures with the finger and joint states. These descriptions are extracted from hand landmarks derived from visual data, detailing each finger's status, their relative closeness, and their directional motion. These decisions rely on intricate calculations of angles and distances between finger joints. Further details are provided in Section 4.

Upon receiving the gesture descriptions, *Gesture Agent* consults *Context Agent* to comprehend the current context. After that, it synthesizes the gesture and contextual data to infer the user's intended interactive function. Initially, *Gesture Agent* requests information about the interaction interface and the available target function list. Based on this data, the *Gesture Agent* determines additional context information that can assist with the gesture grounding task and seeks it from the *Context Agent*. The *Context Agent* manages a context library and serves as a conversational interface, allowing the *Gesture Agent* to access various types of context information.

¹<https://github.com/Significant-Gravitas/Auto-GPT>

²<https://github.com/langchain-ai/langchain>

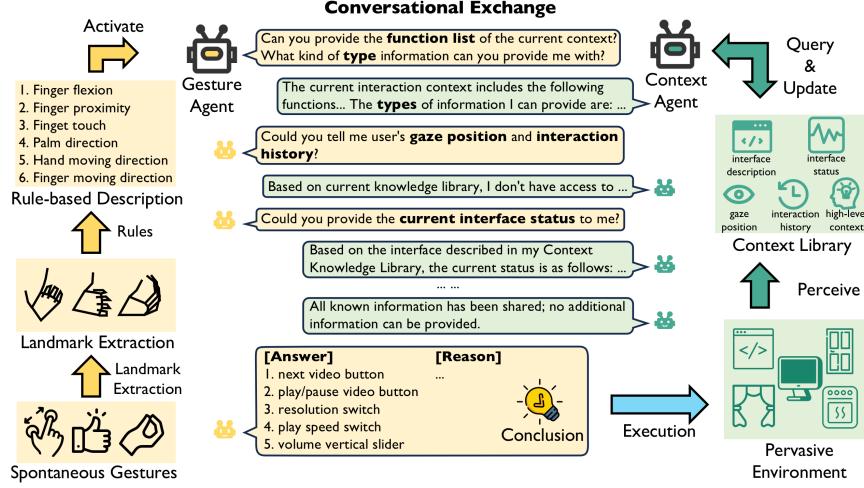


Fig. 2. GestureGPT Workflow: Spontaneous hand gestures are captured and translated into hand landmarks. These gestures are then described using specific rules and sent to the gesture agent. Concurrently, contextual data is gathered, including the user’s interface details, gaze position, and interaction history. The gesture agent collaborates with the context agent to interpret the user’s intended action, relying on both gesture and context data. After each interaction, the context information is updated in the library.

Context Agent manages a context library and acts as a conversational interface for the *Gesture Agent* to access different types of context information. Depending on its knowledge of the context library, *Context Agent* interprets and abstracts the context information, ensuring a fast and reliable response to queries from *Gesture Agent*.

The two agents engage in iterative dialogue for a thorough understanding of the interactive scenario. Their collaboration results in a dynamic association between the gesture and its corresponding interactive function.

4 RULE-BASED GESTURE DESCRIPTION MODULE

The gestures are described based on hand landmarks and a set of rules for finger states. Through hand landmarks, we can transform intricate gesture movements into manageable data by considering finger joint positions, spatial translation distance, and direction. This data allows us to outline the guidelines for gesture description. Moreover, leveraging cutting-edge computer vision techniques ensures that our description method isn’t confined to any specific perspective or gesture type, enhancing its adaptability in the interaction domain. Our system first extracts 24 hand landmarks using mature computer-vision techniques, then calculates features like finger spread status and joint angle. We define a set of rules based on such features to describe gestures in terms of finger state, closeness to each other, etc. The description is later provided to the *Gesture Agent* for further synthesis.

4.1 Hand Landmarks Extraction

We use MediaPipe [33] to extract 3D hand landmarks from images. The 3D hand landmark consists of 21 hand-knuckle points (including hand joints and wrist) as shown in Fig 3. These landmarks represent real-world 3D coordinates in meters with the origin at the hand’s geometric center. They are robust across different angles of view, hand-camera distances, and other factors. This greatly improves the generalizability of our method to different interaction scenarios.

4.2 Gesture Description Rules

We define rules for both static gestures (*i.e.*, poser) and dynamic gestures (*i.e.*, involve fingers or hand movement). Such rules describe flexion of individual fingers, proximity and touch of different fingers, palm orientation, as well as hand and finger moving directions if any. For each rule, a state of ‘unsure’ is added in the prediction, because incorrect descriptions can be greatly misleading to *Gesture Agent*. The rules are summarized in Table 1.

4.2.1 Rules Definition for Static Gestures. For static gestures, we designed a set of rules to describe the state of the hand and each finger, including

Table 1. Rules for Static Hand State Description

Rule Type	Rule Name	Applicable to	Value	Parameters
static	flexion	thumb	straight, bent, (unsure)	<i>straight_threshold</i> , <i>bent_threshold</i>
		index finger, middle finger, ring finger, pinky finger		
	proximity	index-middle finger, middle-ring finger, ring-pinky finger	pressed together, separated, (unsure)	<i>together_threshold</i> , <i>separated_threshold</i>
	touch	thumb-index finger, thumb-middle finger, thumb-ring finger, thumb-pinky finger	contact, not contact, (unsure)	<i>contact_threshold</i> , <i>not_contact_threshold</i>
dynamic	palm orientation	hand	up, down, left, right, inward, outward, (unsure)	<i>angle_threshold</i>
	hand moving direction	hand	static, up, down, left, right, inward, outward, (unsure)	<i>moving_threshold</i>
	finger moving direction	thumb	static, inward, outward, (static)	<i>moving_threshold</i>
		index finger, middle finger, ring finger, pinky finger		

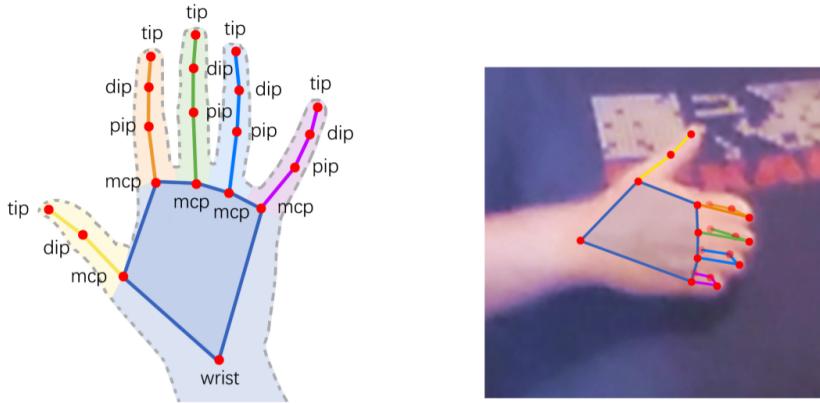


Fig. 3. A typical gesture's landmark and expected descriptions based on the rules: a) An illustration of hand landmarks. b) A picture of 'like' gesture clipped from the HaGRID Dataset, and the landmarks extracted by MediaPipe. Expected descriptions obtained by the rules is: Thumb is straight, index finger / middle finger / ring finger / pinky finger are bent. Index finger, middle finger, ring finger and pinky finger are pressed together. Thumb's fingertip is not in contact with the other four fingers. Palm is facing inward. (Not literally the same as the generated description. For simplicity, we just keep the meaning reserved.)

Flexion Whether the finger is straight or bent (applicable to all fingers).

Proximity Whether two fingers are pressed together or separated (only applicable to index-middle finger, middle-ring finger, ring-pinky finger).

Touch Whether thumb's fingertip is in contact with the other four fingers' fingertip.

Palm Orientation The orientation of the palm including upward, downward, left, right, forward, backward.

4.2.2 Additional Rules Definition for Dynamic Gestures. Aside from the above rules, there are two dynamic rules to describe the moving characteristics of the hand and each finger:

Hand Moving State The moving state of the hand including static, upward, downward, left, right, forward, backward.

Finger Moving State If a finger is static, moving inward or outward relative to the palm.

4.2.3 Rules Calculation Method. **Flexion** of a finger is calculated as the total bending angle of each joint. For thumb it is the bending angle of the ip joint, and for other fingers, it is the bending angle of the pip and dip joint. Then, two parameters

straight_threshold and *bent_threshold* are set to determine if the finger is straight, bent, or ‘unsure’ if the result falls between them. Since thumb has a different joint structure compared with other fingers, a new pair of thresholds are specially set for thumb.

Proximity of two fingers A and B is calculated as the average minimal distance from each finger’s joint to the other finger. Two thresholds i.e. *together_threshold* and *separated_threshold* are set to determine if the two fingers are pressed together, separated, or ‘unsure’ if the result falls between them.

Touch of two fingers is computed as the distance between their fingertips. Then, two thresholds, i.e. *contact_threshold* and *not_contact_threshold* are set to determine if the two fingers’ fingertips are in contact or not, or ‘unsure’ if the result falls between them.

Palm orientation is computed as the direction to which the palm is facing, which is obtained from the cross product of two vectors from hand (Fig 4). Then, the direction is compared with six reference vectors representing upward, downward, left, right, inward and outward. If a reference vector has the minimal angle with the palm orientation vector and the angle is below *angle_threshold*, the reference vector would be the palm orientation. Otherwise the orientation of palm is set as ‘unsure’.

For a dynamic gesture with several frames, the static rules is applied to each frame. Then a result is viewed as the description of the whole dynamic gesture if it appears in more than 80% of the frames. Otherwise, the description is set to ‘unsure’.

Hand Moving State of a dynamic gesture is computed as the moving direction and distance of the hand. First, the moving vector is calculated as the moving of the geometrical center of a hand landmark, from the first frame to the last frame. If the vector’s length is smaller than *moving_threshold*, it is recognized as ‘static’. Otherwise, the vector is compared with some reference vectors, and the reference vector which has the minimal angle with the moving vector is recognized as the moving direction.

Finger Moving State of a finger in dynamic gesture is computed as the change of angle formed by wrist, mcp and tip, from the first frame to the last frame. If it is smaller than *moving_threshold*, the finger is recognized as static. Otherwise, whether the finger is moving inward or outward is decided by the changing direction of the angle.

The detailed pseudocode for each rule is shown in Appendix A.

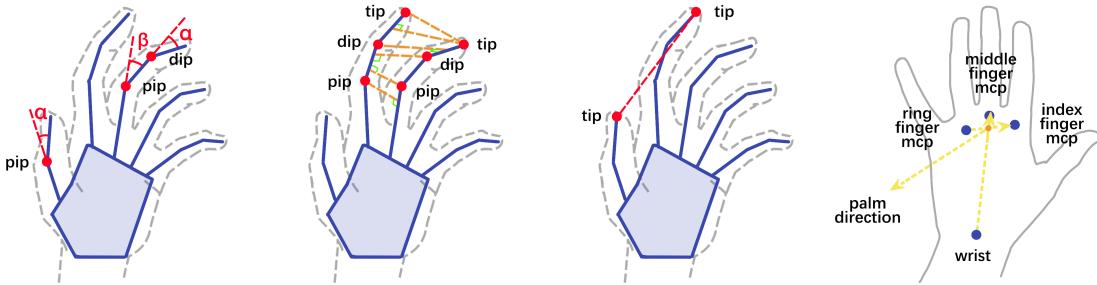


Fig. 4. Calculation of static rules. a) The flexion of a finger is calculated as the sum of bending angle of ip joint (for thumb) or pip and dip joint (for other fingers). b) The proximity of two fingers is calculated as the average distance from each finger’s pip/dip/tip joint to the other finger. c) the touch of thumb and another finger is calculated as the distance of two finger’s fingertips. d) The palm orientation is calculated from the dot product of the two vectors on the hand, pointing towards the reader.

4.3 Parameter Setting and Evaluation Results

For there is no dataset that dynamic gestures are segmented precisely, which makes it difficult to tune an effective result, we only tune the parameters for static gestures. The dynamic rules’ parameters are derived from experience values.

To determine the parameters (i.e. the thresholds) in the static rules mentioned above, we used HaGRID [12] dataset to tune the algorithm. HaGRID contains pictures of people performing 18 kinds of static gestures. For each gesture, we assume that most people perform it in the same way. Thus, when applying the rules to a set of gesture pictures of the same kind, most results would be the same. However, ambient exceptions like ‘whether thumb is straight or bent in the peace gesture’ exist, in which more than

one answers are acceptable. Cases like this are excluded from the parameters setting process. The ground truth of each gesture when applying each rule is initially established by the common knowledge of the gesture. If needed, a gesture can have more than one ground truth label (and it would not engage in the training and testing process).

A subsample of HaGRID is used to tune the thresholds which has 100 pictures for each gesture, and 1800 pictures in total. In our implementation, a small number of samples are filtered out because MediaPipe failed to extract landmarks of the correct hand. Finally we have 1524 pictures, 70 to 96 pictures for each gesture. For most rules except flexion on thumb, we use the whole subsample to tune the parameters. For flexion on thumb, due to the severe imbalance of samples with labels ‘straight’ and ‘bent’ respectively, we specially assign the training set, which is composed of gesture ‘like’ (thumb is straight) and gesture ‘ok’ (thumb is bent, manually filtered to ensure the quality of the training data).

A grid search is conducted to find out the best parameter with minimal loss, which is a variation of accuracy. Because the existence of ‘unsure’ in outputs, we need to treat it differently from the cases when the algorithm outputs an actually incorrect prediction. The test results are divided into three circumstances: 1) Error: incorrect prediction (misleading information); 2) Unsure: no mention of the rule with ‘unsure’ state; 3) Correct: correct prediction (useful information).

The tuning results and performance on the HaGRID test set (38576 images) are shown in Table 2. For most rules, the average error rate among all gestures is below 5% and the overall accuracy is above 88%. One exception is flexion rule for thumb, in which the output ‘unsure’ takes about 45% of all cases. This may be attributed to the unique shape of thumb: the topmost segment of the thumb is curved by nature, so when the thumb is extended, the landmark seems to be slightly bent, which may affect the training and testing. By adding ‘unsure’, we avoid the misleading information that potentially confuses the *Gesture Agent*.

When checking the algorithm’s performance for each gesture, it is shown that the error rates for most gestures are below 5% and none of them are above 16%. The error could be attributed to landmark mistakes made by MediaPipe, the shortcomings of our algorithm, and a small number of people just perform the gesture in a way different from most people (i.e., different from the ground truth we established before). The results show good generalization ability since the parameters are only tuned on a small number of samples.

Table 2. Parameters and Performance of static rules on HaGRID Test Set

Rule	Parameters	Performance on HaGRID Test Set		
		error	unsure	correct
Flexion - thumb	(16, 38)	0.036	0.457	0.507
Flexion - other fingers	(57, 74)	0.019	0.049	0.932
Proximity	(0.024, 0.029)	0.031	0.067	0.902
Touch	(0.046, 0.055)	0.020	0.024	0.956
Direction of the palm	41	0.042	0.075	0.882
Overall	-	0.024 ± 0.023	0.058 ± 0.037	0.918 ± 0.055

To evaluate if the parameters trained on third-view dataset have good performance for first-view images, we tested them on a first-view gesture dataset EgoGesture. We choose 20 static gestures (fist, measure, zero, one, two, three, four, five, six, seven, eight, nine, ok, three2, C, thumb down, thumb right, thumb left, thumb backward, thumb forward) and label the ground truth. For each gesture, we selected around 100 testing samples. The results are shown in Table 3.

Table 3. Performance of static rules on EgoGesture Test Set

Rule	Performance on EgoGesture		
	error	unsure	correct
Flexion - thumb	0.053	0.449	0.499
Flexion - other fingers	0.071	0.104	0.825
Proximity	0.129	0.096	0.775
Touch	0.067	0.050	0.883
Palm Orientation	0.184	0.186	0.631
Overall	0.084 ± 0.059	0.107 ± 0.029	0.810 ± 0.083

More detailed error analysis of our gesture description module’s performance can be found in Appendix B. The performance of the algorithm on the first-view dataset is only slightly decreased, showing that our gesture describing algorithm works across different views.

For dynamic rules, we derive the parameters from experience values. For finger moving direction, the *moving_threshold* is set to 22 for thumb and 17 for the other four fingers. For hand moving direction, the parameter *moving_threshold* is set to 0.1 as an experience value.

5 DUEL-AGENT SYSTEM DESIGN

GestureGPT takes the dual-agent conversational framework where each agent has its own specific roles. The primary challenge lies in guiding two general-purpose LLM models with delicately designed prompting methods to excel in the untrained domain of gesture interaction, particularly when intertwined with environmental context.

LLMs can understand complex instructions and act as designated agents, but only when provided with concrete, structured prompts and augmented with appropriate reasoning logic. Many recent works have made significant progress and efforts along the way [21, 26, 28, 29, 32]. There are generally several important design principles for prompting LLMs, such as writing clear and structured instructions and externalizing the reasoning process. In what follows, we explain our prompting methods for both the gesture and context agents in detail. We demonstrate that this structured thought process can guide the LLM to dissect problems in a manner analogous to human analysis, providing insights into how LLM technology can assist in understanding and grounding gesture input modes.

5.1 Gesture Agent Design and Implementation

Gesture agent first receives the description of any spontaneous gestures from user, it then reasons upon known information and make necessary inquires for context in conversational exchange until it is confident to identify the user interaction intent.

We first define the role of the gesture agent with a specific and detailed description. This identity information is inserted into the *system slot* of the LLM and guides it to behave accordingly. The prompt is composed of four aspects as follows:

(1) **Agent Definition:** We begin by outlining the gesture agent’s purpose, detailing its expected input, output, and conversational style. We specifically emphasize that the agent should organize its reasoning process step by step to emulate human-like cognitive processes. As identified by many existing works [14, 28], such a procedure greatly improves the agent’s performance.

Agent Definition

You are a gesture understanding assistant.
 - Task Introduction
 Your task is to predict the target interactive function from a function list based on a gesture description and interaction context.
 The gesture description will be provided to you directly, while you need to inquiry about the context from a context agent.
 You need to think step by step.
 1. Try to understand the gesture based on the gesture description and have several guesses of what the gesture is. PS: With the new information you have acquired, you can narrow down the candidates based on interactive context information you gathered later.
 2. Ask for the function list from the context agent.
 3. Based on your understanding of the described gesture, ask for more specified context information that you deem will help determine the target function. You can ask multiple times if necessary.
 4. Synthesize the gesture and context information to better understand the interaction scenario.
 5. Based on the available context, reexamine if your understanding of the gesture is accurate.
 Restart from the first step if necessary.
 6. Output the top-5 most possible functions based on your predictions of the gesture candidates and the interactive context.

(2) **Gesture Description Rule:** We then clarify how the gesture description is formulated to help the agent better comprehend its potential meanings and discern interaction subtleties. We also provide an illustrative example to demonstrate these rules. A vital capability for the gesture agent is navigating ambiguous scenarios, often arising from obscured hand landmarks due to camera issues or finger occlusions. In these situations, the agent should actively make relevant contextual inquiries to summarize the interaction intent.

Gesture Description Rule

- Gesture Description Rule

You will receive a description about the gesture made by the user, including four static features and two dynamic features, and all mentioned direction are from the user's first-person point of view:

1. whether a finger is straight or bent, and the straight finger's direction;
2. whether two fingers are pressed together or separated;
3. whether two fingers' fingertips are contact;
4. the palm's direction;
5. the finger's moving direction;
6. the hand's moving direction;

Not all gestures have the six aspects of description.

If the certain features are not mentioned at all or its features is "unsure", you can guess their states based on your understanding of similar gestures and the current interaction context that you know of.

[Example Gesture Description for 'One' Gesture]

1. index finger is straight, middle finger is bent, ring finger is bent, pinky finger is bent;
2. index finger and middle finger are separated, middle finger and ring finger are pressed together, ring finger and pinky finger are pressed together;
3. thumb and index finger's fingertips are not in contact, thumb and middle finger's fingertips are in contact, thumb and ring finger's fingertips are not in contact, thumb and pinky finger's fingertips are not in contact;
4. the palm is facing outward;

- (3) **In-Context Demonstrations:** To further enhance the agent's capability, we provide a succinct conversation example as in-context demonstrations [4]. This ensures the agent responds appropriately during the conversation without overburdening the response with excessive analysis, which not only disrupts the behavior of the context agent, causing confusion, but also notably increases the conversation token length. This can lead to increased computational costs, especially for commercial APIs, or even cause the conversation to fail.

In-Context Demonstration

- The Example of the Conversation

#You

(You must start with this question)

Can you provide the function list of the current interaction context? What kind of [type] information can you provide me with?

#Context agent

Now interface have function

- expand information
- copy information
- add to cart
- show product 1
- show product 2
- show product 3
- show product 4
- show product 5

#You

(You can ask for whatever information you want, but you must specify the kind of information.) Can you provide XXX information for me?

#Context agent

The user now XXXXXXXX.

#You

(...You can ask questions to request the specific information you need. Please note that your question should only contain the information you need; it should not include your analysis of the gesture or the current interface.)

#Context agent

(... ...)

(... After some time conversing, if you feel you have enough information to make a decision, or the conversation is no longer yielding new information ...)

#You

[Answer]

1. show product 2
2. show product 1
3. show product 3
4. copy information
5. expand information

[End]

[Reason]

(Explain the reasoning behind your answer.)

- (4) **Task Termination And Explanation:** We finally formulate the expected output of the agent. Once it believes it has sufficient information to draw a conclusion, it is instructed to end the conversation, and give its top-5 most possible candidates followed by an explanation for the decisions. We empirically find the explanation aids in result analysis, offering clarity on the importance of context in the ongoing conversation.

Task Termination And Explanation

Please note that your question should only contain the information you need; it should not include your analysis of the gesture or the current interface. All analyses should be reserved for the final conversation under the "[Reason]" tag.

Your final answer should consist of two parts: the answer and the reason. The answer must include exactly 5 options from the interface function list, arranged in descending order according to probability; do not include any options not found on the function list from the context list. The reason part should explain the rationale behind your chosen answer.

Your answer should always contains the tag "[Answer]""[End]" and "[Reason]".

Based on the above instructions, the gesture agent initiates the conversation accordingly upon receiving a new gesture description.

5.2 Context Agent Design and Implementation

The *Context Agent* is responsible for context management and responding to queries from the *Gesture Agent*, which seeks context information. Essentially, the *Context Agent* acts as a supervisor overseeing all sensors and other context sources. Thus, it functions as a manager rather than a sensor.

Similar to the gesture agent, the design of the context agent commences with a role description, which is divided into three main sections:

(1) **Agent Definition:** Beyond specifying the context task, it is vital to inform the context agent about the types of contexts it will encounter during interactions. In the current gestureGPT implementation, we recognize three primary context types:

- **Interface Description and its Status:** This is a JSON structure detailing the interface name (e.g., web of video playing, your home living room, etc.), the subarea of the interface (a categorization of the interface where each subarea encompasses specific functions), the functions within the interface, and their respective positions. It's worth noting that since 'how to summarize the context interface description' is out of our scope, we adopted the Wizard-of-Oz method, asking users to summarize the interface.
- **User Gaze Information (Optional):** This consists of a list of coordinates on the interface, representing the duration and location of the user's gaze during a gesture. Currently, we empirically select the gaze data from 1 second before the gesture starts until its conclusion.
- **Interaction History (Optional):** This captures the user's interaction history over a specific period. At present, we consider the tasks leading up to the current moment as the interaction history.
- **High-Level Interaction Information (Optional):** This isn't tied to a specific context category, meaning it can encompass information beyond the previous three types. As of now, we empirically include contexts such as environmental status (e.g., air quality sensor values, coming ring). The all high-level context used in our evaluation can be seen in Table 4 and Table 8)

Agent Definition

You are an interactive context assistant.

- Task Introduction

You are responsible for managing the current interactive context including interaction interface understanding, interaction history memory, gaze location on the interface, etc.

You need to answer the questions based on your Context Knowledge Library.

Your context information library may contain some or all of the following items:

1. interface description: It contains divisions into subareas, and sub-subareas which having a specified list of functions.

2. interface status.

3. user gaze position. When you providing gaze information, besides the coordinates of the gaze, you need to combine it with the interface description to form a summary. You should tell the gesture agent, the gaze data unavoidably contains certain degree level of inaccuracy.

4. interaction history.

5. other context information.

(2) **In-Context Demonstrations:** For the context agent, a crucial aspect of the example is to emphasize that it should refrain from responding if uncertain. This is to counteract a common issue with LLMs: Hallucination. We mandate that its responses must be grounded in the available context.

In-Context Demonstrations

```

- The Example of the Conversation
The following is an example conversation between you and a gesture understanding agent:
$$$ Current knowledge library:
interface function list;
interface status;
user gaze;
$$$
#Gesture agent
what interaction function list in this interface? what type context you can provide?
#You
Now interface have function
- expand information
- copy information
- add to cart
- show product 1
- show product 2
- show product 3
I can provide the following types of context:
- XXX
- XXX
...
#Gesture agent
I want know the user's now gaze information.
#You
(... Your answers should be based on the knowledge you possess; you should not fabricate facts from thin air or exceed the scope of the question.)
(... When you providing gaze information, besides the coordinates of the gaze, you need to combine it with the interface description to form a summary. You should tell the gesture agent, the gaze data unavoidably contains certain degree level of inaccuracy. Like: Given that the user's gaze is currently located at the coordinates XXX, which is within the xxx Area)
#Gesture agent
...
(After several rounds of conversation.)
#You
(... You can summarize the history of your conversation. If you have already provided all the information you know, then you can respond, 'All known information has been shared; no additional information can be provided.' or other same meaning ...)

```

- (3) **Context Library:** This section houses the entirety of the current accessible context. To simplify implementation, we directly serialize the context into a JSON or list format for the prompt. Given our current use cases, the context library's length is finite, typically ranging between 20 to 1500 tokens.

Upon establishing its role, the context agent awaits queries from the gesture agent and responds based on its context library.

6 EVALUATION

We conducted two typical interaction scenarios: one involving third-view video streaming on a PC and the other involving first-view IoT device control using an AR headset.

Participants were recruited from three local schools, and they were compensated at a rate of \$10 per hour. We informed participants that both video (including facial footage) and eye movement data would be collected during the study, and we assured them of the confidentiality and safety of their data. All participants provided informed consent. The participants in the two user studies were not totally identical.

Each user study consisted of two sessions. The first session, termed the "freedom session," allowed participants to perform any gesture they believed best represented their intent for the given task. The second session, the "assigned session," required participants to perform specific gestures as instructed. In all user studies, we mandated that gestures be performed using only the right hand. Both dynamic and static gestures were permitted in the freedom session. At the end of the study, participants were asked to complete a questionnaire. This questionnaire utilized a 5-point Likert scale to evaluate the assigned gestures, with higher scores indicating an assigned gesture that better aligned with the user's intent.

6.1 User Study 1: Smart Home IoT Control with AR Headset

In this scenario, users simulate cooking in a kitchen equipped with smart home devices that can be controlled through gestures. When users perform specific gestures, the status of the devices changes.

6.1.1 User Study Setting and Procedure. We used the HoloLens 2 headset as our experimental platform. This headset provides an API that allows us to obtain the user's gaze coordinates and hand gesture landmark coordinates directly. Additionally, we



Fig. 5. Experiment setting for IoT device control simulated by Unity.

employed a separate USB camera to record the entire experimental process from a third-person view. Our platform was developed using Unity version 2020.3.24f1, MRTK 2.8.0, and the OpenXR Plugin 1.7.0. To enhance user immersion, we employed 3D models to represent the smart devices. The devices in this scene are a light, a smart cabinet, a smart screen, an oven and an air cleaner. The Experiment setting for IoT device control scenario can be seen in Fig 5. The actual device control is facilitated using the "Wizard of Oz" rather than gesture recognition.

Our user study comprised 6 participants, with ages ranging from 23 to 26 (MEAN = 24.14, SD = 1.45). Among them, 4 were males and 2 were females. Details regarding the tasks and their associated gestures are provided in Table 4.

Table 4. Tasks, Associated Gestures and High Level Context (in ‘Assigned Session’) in Smart Home Environment

Instruction	Assigned Gesture	High Level Context
Unlock the Smart Carbinet.	thumb up	The child lock on this cabinet supports fingerprint unlocking.
Increase the brightness of the light.	pinch and slide up (dynamic)	-
Show the next recipes on the smart screen.	pinch and slide left (dynamic)	-
Open the oven.	zooming in with full hand (dynamic)	Recipe instructions: now you need to open the oven.
Open the air cleaner.	zooming in with full hand (dynamic)	The air purifier’s sensor detected that the current environment has heavy cooking fumes.
Set a timer on the smart screen.	five	Recipe instructions: now you need cook on high heat for five minutes.
Switch input source of the smart screen to the smart bell.	swiping left with full hand	The doorbell rang.
Make a phone call through the smart screen.	call	Just now, it was the deliveryman delivering goods; the owner of the goods is the user’s roommate, Mark.

6.1.2 Data preprocessing and validation of rules. For each trial, the starting and ending point of the gesture is manually annotated from the video. The starting and ending point are then used to segment the gesture from the recorded data. For the assigned session in which all users performed the same set of gestures, we tested the performance of our static and dynamic rules. The results are shown in Table 5.

Table 5. Performance of static and dynamic rules on smart home scenario

Rule	Performance		
	error	unsure	correct
Flexion - thumb	0.125	0.417	0.458
Flexion - other fingers	0.042	0.062	0.896
Proximity	0	0.130	0.870
Touch	0.007	0.028	0.965
Palm Orientation	0	0.222	0.778
Finger Moving Direction	0.029	0	0.971
Hand Moving Direction	0.048	0	0.952
Overall	0.032 ± 0.047	0.056 ± 0.049	0.913 ± 0.075

For the ‘free session’, we collected data on the number of gestures created by users, specifically gestures that were performed by the users but did not appear in the assigned session. In this experiment, users generated a total of 19 new gestures, with 17 being dynamic gestures and 2 being static gestures.

6.1.3 Main Results Analysis. To assess our system, we employed two of OpenAI’s prominent APIs: *gpt3.5* and *gpt4*. Additionally, we also utilized the renowned open-source chat model, *Vicuna-13B*. The principal results showcased in this section are primarily sourced from *gpt4* due to its demonstrably superior performance. Findings associated with the other models are elaborated upon in Section 7.

Table 6. All results For **Smart Home** with GPT4

	Free gesture				Assigned gesture			
	Top 1	Top 3	Top 5	Negative	Top 1	Top 3	Top 5	Negative
No Additional Context	10.72% \pm 1.74	27.18% \pm 3.93	47.93% \pm 7.81	52.07% \pm 7.81	27.28% \pm 3.41	51.08% \pm 5.20	61.57% \pm 4.02	38.43% \pm 4.02
+Gaze	52.48% \pm 1.00	71.63% \pm 3.62	90.78% \pm 2.65	9.22% \pm 2.65	45.83% \pm 2.95	68.75% \pm 0.00	83.33% \pm 2.95	16.67% \pm 2.95
+History	13.48% \pm 2.65	27.66% \pm 7.96	52.48% \pm 6.58	47.52% \pm 6.58	24.31% \pm 6.87	51.39% \pm 4.28	64.58% \pm 6.13	35.42% \pm 6.13
+History+HLContext	27.27% \pm 6.83	44.56% \pm 7.04	58.94% \pm 5.04	41.06% \pm 5.04	36.11% \pm 6.44	53.47% \pm 2.60	65.28% \pm 5.47	34.03% \pm 5.20
+Gaze+History	46.81% \pm 3.47	67.38% \pm 2.01	87.23% \pm 1.74	12.77% \pm 1.74	41.55% \pm 3.41	64.76% \pm 2.83	84.45% \pm 2.96	15.55% \pm 2.96
+Gaze+History+HLContext	56.03% \pm 4.37	73.76% \pm 3.62	87.94% \pm 4.37	12.06% \pm 4.37	47.16% \pm 5.21	68.39% \pm 4.67	84.54% \pm 2.41	15.46% \pm 2.41

Refer to Table 6 for the primary results and their visualization in Fig 6. Metrics evaluated include the top1 rate, top3 rate, top5 rate (which corresponds to accuracy), and the negative rate (equivalent to 1-accuracy).

GestureGPT showcased a remarkable performance in this context. Peak accuracy, registered during the free gesture session, stood at 90.78%. The designated session displayed an accuracy of 84.54%. These results unveil an intriguing observation: the free gesture sessions outperformed the designated sessions. This was contrary to our initial hypothesis, given that the latter’s gestures were crafted by seasoned HCI researchers and were perceived as intuitive by users, as indicated by an average score of 4.25 (std=0.92) on a 5-point Likert scale from the questionnaire. Upon analysis, we postulate two primary reasons for this observed discrepancy: 1) Participants were required to learn the gestures prior to each trial in the designated sessions. It is plausible that some participants did not fully grasp these gestures and made some wrong gestures, leading to potential inconsistencies in their execution. To ameliorate this, incorporating a warm-up period for each assigned gesture might be beneficial. 2) We observed that during the assigned gesture sessions, participants’ gaze movements were slower and less frequent. We hypothesize that the cognitive load associated with remembering and executing the assigned gestures could have impacted their gaze behavior, suggesting that the designated gestures might have increased their interaction burden.

Furthermore, it became evident that gaze information played a pivotal role in this context as shown in Fig 8. In a smart home environment, multiple devices often possess overlapping functionalities (e.g., power toggling, mode transition). Consequently, a single gesture could potentially correspond to multiple devices which have the same meaning function. Given that each device occupies a unique spatial location, incorporating gaze information enables the system to filter out irrelevant devices. This, in turn, substantially enhances the accuracy of gesture interpretation.

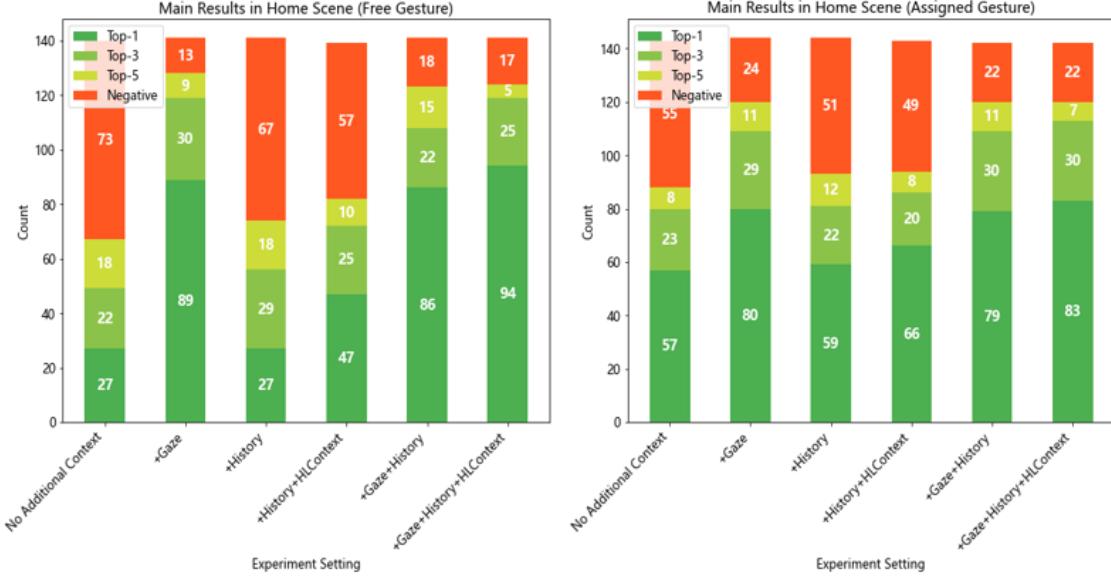


Fig. 6. Comparative analysis of model performance metrics, including Top-1, Top-3, and Top-5 accuracies, as well as the negative rate, for different conditions in a smart home scenario.

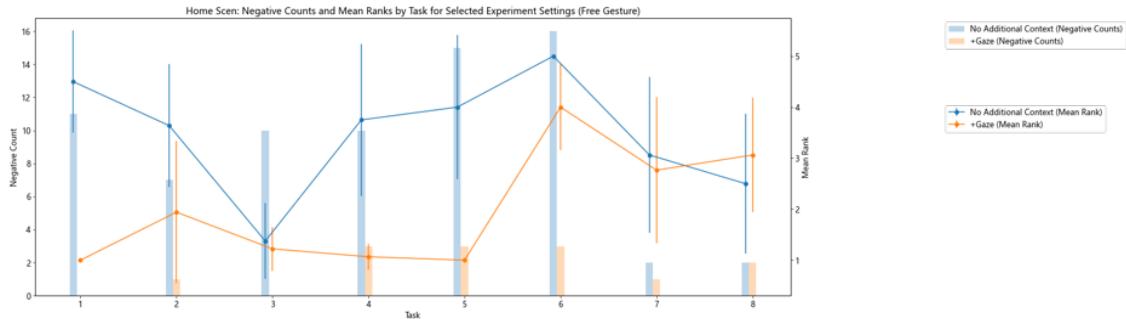


Fig. 7. The impact of adding gaze information on accuracy. Both negative counts and mean rank metrics show a significant improvement for most tasks when **gaze context** is included.

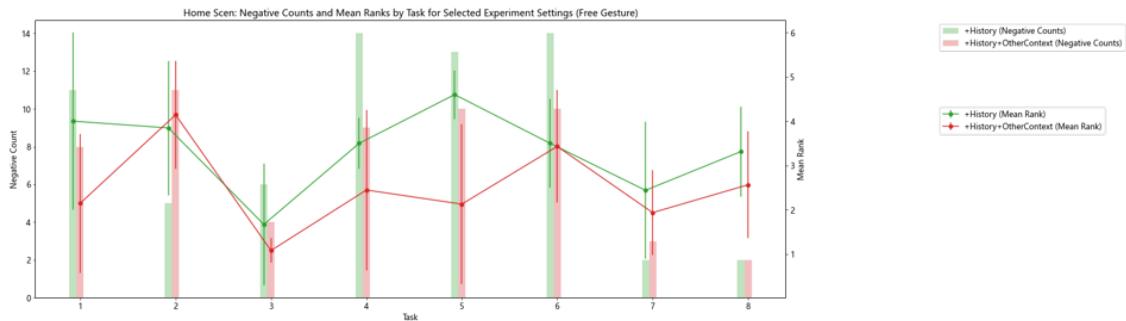


Fig. 8. the difference between tasks with just the history and those augmented with additional context. For tasks 4, 5, 7, and 8, the integration of high-level context notably enhances the results. Specific examples include: Task 4: With the recipe instruction ‘now you need to open the oven,’ the current task is to ‘Open the oven.’ Task 5: Given the context ‘The air purifier’s sensor detected that the current environment has heavy cooking fumes,’ the task is to ‘Open the air cleaner.’ Task 7: With the context ‘Switch input source of the smart screen to the smart bell,’ the task becomes ‘The doorbell rang.’ Task 8: Informed by the context ‘Just now, it was the deliveryman delivering goods; the owner of the goods is the user’s roommate, Mark,’ the task is to ‘Make a phone call through the smart screen.’

From the results presented in Fig 8, the importance of incorporating high-level context into the interpretation process is evident. These findings demonstrate GestureGPT adeptness at handling high-level contextual information. In smart home environments, where user intent and surrounding context heavily influence tasks, mere reliance on history is insufficient. The detailed insights offered by high-level context serve as vital cues, steering the system toward a more precise recognition of the user's goals. For instance, in task 4, the specific instruction to open the oven, as guided by the recipe, is crucial in understanding the intent behind the gesture. Absent this context, the gesture could be misconstrued as a different action. By leveraging high-level contextual information, we can effectively bridge the divide between user intent and system comprehension, setting the stage for more intuitive human-computer interactions. GestureGPT capabilities underscore its potential in managing such intricate information.

6.1.4 Compared With Human Performance. Another aspect of interest in our study pertains to the performance of GestureGPT in comparison to human benchmarks. To gain a holistic understanding, it is instructive to evaluate human performance on the same tasks.

For the human baseline, we recruited 4 participants unfamiliar with our tasks. Data from 4 randomly selected individuals from user study 1 was utilized to assess their ability to identify the top-5 potential functions. Each participant underwent each task twice. In their initial attempt, they were provided with context pertaining to gaze and history. In the subsequent attempt, they were additionally furnished with high-level context. The results can be seen in Table 7.

Table 7. Human Performance Result in **Smart Home** Scene User Study

	Free gesture				Assigned gesture			
	Top 1	Top 3	Top 5	Negative	Top 1	Top 3	Top 5	Negative
without HLContext(Human)	43.8%	62.5%	81.3%	18.7%	50%	75%	81.3%	18.7%
with HLContext(Human)	58.3%	83.3%	91.7%	8.3%	91.7%	91.7%	100%	0%
without HLContext(GPT4)	41.67%	58.33%	79.17%	20.83%	29.17%	60.42%	75.00%	25.00%
with HLContext(GPT4)	47.92%	64.58%	77.08%	22.92%	39.58%	60.42%	70.83%	29.17%

From the results, it is evident that *GestureGPT* performs impressively, closely mirroring human-like intuition, especially in a zero-shot scenario with free gestures. This indicates that *GestureGPT* can effectively harness its background knowledge. However, *GestureGPT*'s performance is somewhat lacking when it comes to utilizing other high-level contexts. One possible explanation is that the abundance of contextual knowledge makes it challenging for the model to discern and prioritize newly introduced contexts. In contrast, human participants displayed a keen sensitivity to the evolving context.

6.2 User Study 2: Online Video Streaming on PC

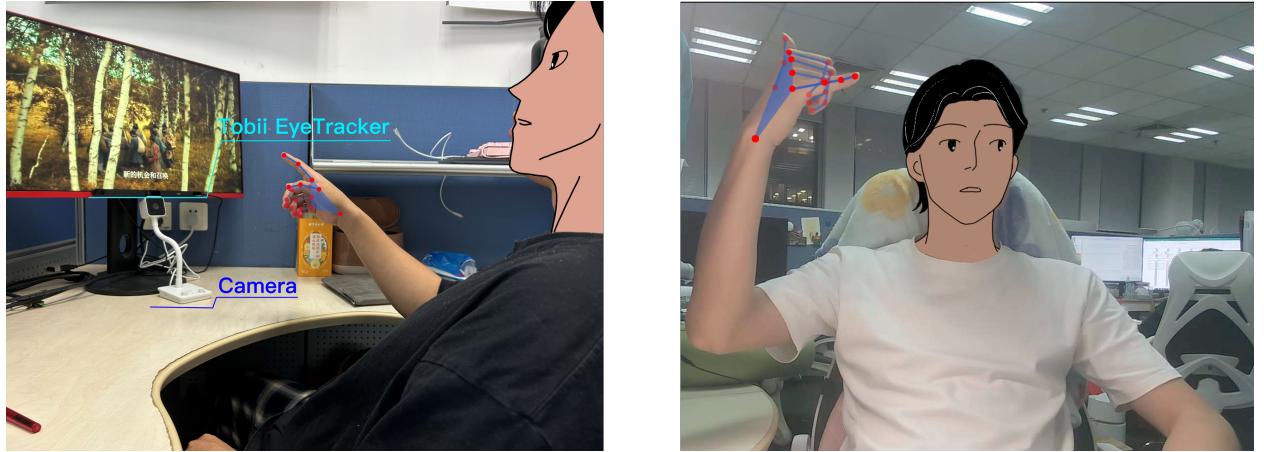


Fig. 9. Experiment setting for video streaming: The user sits at desktop and interact with computers using gestures.

In this scenario, users simulate the experience of Online Video Streaming on a PC. This scenario is more challenging compared to the previous one. The interface here contains a considerably broader range of functions, with numbers varying from 15 to 53. Moreover, many functions have semantically similar meanings, such as the "vlog channel" button and the "anime channel" button or the "recommend video 1/2/3" options, making them difficult to distinguish solely through gestures. Furthermore, the reduced size of the items on the interface compromises the accuracy of the gaze information.

6.2.1 User Study Setting and Procedure. Participants were asked to simulate watching a video on a popular streaming platform, wherein they possessed the ability to control the video and interact with various functions. When participants executed specific gestures, the website reacted in accordance with the given task. However, the actual controls were orchestrated using the Wizard of Oz methodology. Details pertaining to the tasks in this user study can be found in Table 8.

We developed a platform using Python and Selenium to display and control the video streaming interface. For data collection during the experiment, we employed Tobii Eye Tracker 5 to capture user gaze data and a 1080P resolution webcam to record user gestures. The experiment device and process can be seen in Fig 9. Our user study involved 7 participants, aged between 18 and 29 (MEAN = 23.62, SD = 3.43). The gender distribution was 4 males and 3 females.

Table 8. Tasks, Associated Gestures and High Level Context (in ‘Assigned Session’) in Video Streaming Environment

Instruction	Assigned Gesture	High Level Context
Turn up the volume.	pinch and slide up (dynamic)	-
Drag the progress bar forward.	pinch and slide left (dynamic)	The user has watched the earlier part of this video.
Enter full screen mode.	zoom in with full hand (dynamic)	-
Pause the video.	palm	The user’s phone has an incoming call at this moment.
Resume the video.	OK	The user hung up the phone.
Like the video.	thumb up	-
Go to the next episode.	swipe left with two fingers (dynamic)	-

User Study 2 consists of a total of 7 tasks, spreading across 2 sessions, and was initially undertaken with 8 participants. Regrettably, due to issues with camera power, the data from one participant had to be excluded. As a result, the total data collected amounted to 8 participants × 2 sessions × 7 tasks = 98 data points.

6.2.2 Data preprocessing and validation of rules. For each trial, the starting and ending points of the gesture are manually annotated from the webcam video. The starting and ending points are then used to segment the gesture from the recorded data. For the assigned session in which all users performed the same set of gestures, we tested the performance of our static and dynamic rules. The result is shown in Table 9.

Table 9. Performance of static and dynamic rules on video streaming scenario

Rule	Performance		
	error	unsure	correct
Flexion - thumb	0.086	0.429	0.486
Flexion - other fingers	0.045	0.136	0.818
Proximity	0.063	0.262	0.675
Touch	0.020	0.156	0.823
Palm Orientation	0.048	0.286	0.667
Finger Moving Direction	0.294	0	0.706
Hand Moving Direction	0.041	0	0.959
Overall	0.091 ± 0.046	0.142 ± 0.069	0.776 ± 0.095

In the freedom session of user study 2, users generated a total of 16 new gestures, with 13 being dynamic gestures and 3 being static gestures.

6.2.3 Main Results Analysis. Same as user study 1, we analyses the GPT4 results. Refer to Table 10 for the primary results and their visualization in Fig 10.

Table 10. All results For Video Streaming with GPT4

	Free gesture				Assigned gesture			
	Top 1	Top 3	Top 5	Negative	Top 1	Top 3	Top 5	Negative
No Additional Context	16.27% \pm 0.14	48.73% \pm 8.47	60.79% \pm 9.71	39.21% \pm 9.71	16.75% \pm 1.27	52.89% \pm 5.26	64.00% \pm 1.73	36.00% \pm 1.73
+Gaze	22.77% \pm 1.90	53.34% \pm 6.38	65.31% \pm 5.29	34.69% \pm 5.29	36.28% \pm 1.98	66.24% \pm 4.33	80.11% \pm 2.18	19.89% \pm 2.18
+History	36.50% \pm 3.45	55.08% \pm 5.37	64.09% \pm 3.68	35.91% \pm 3.68	34.98% \pm 1.77	52.76% \pm 3.78	66.23% \pm 6.24	33.77% \pm 6.24
+History+HLContext	41.97% \pm 6.49	58.14% \pm 6.46	67.72% \pm 6.16	32.28% \pm 6.16	47.22% \pm 3.46	62.58% \pm 1.61	71.14% \pm 2.52	28.86% \pm 2.52
+Gaze+History	23.64% \pm 3.93	52.73% \pm 1.48	67.27% \pm 2.57	32.73% \pm 2.57	31.43% \pm 5.08	59.26% \pm 3.93	74.11% \pm 5.81	25.89% \pm 5.81
+Gaze+History+HLContext	31.52% \pm 3.74	57.58% \pm 1.71	70.91% \pm 3.93	29.09% \pm 3.93	41.90% \pm 1.42	69.98% \pm 0.70	75.58% \pm 2.09	24.42% \pm 2.09

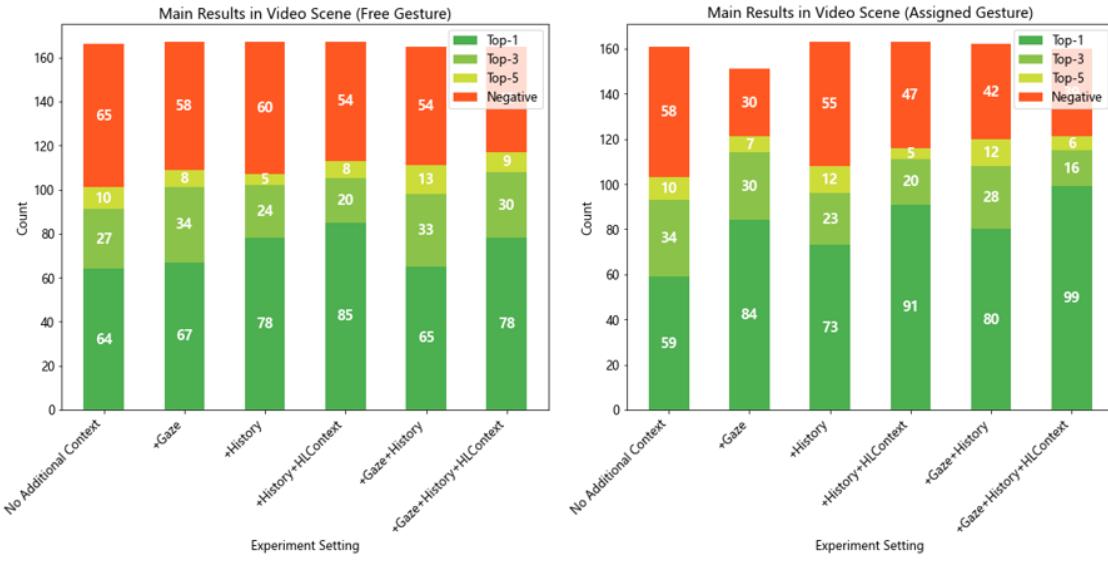


Fig. 10. Comparative analysis of model performance metrics, including Top-1, Top-3, and Top-5 accuracies, as well as the negative rate, for different conditions in a video scenario.

In the context of online video streaming, the performance exhibited by GestureGPT is notably commendable. The highest accuracy was observed during the free gesture session, reaching an impressive 70.91% for Top 5 in the provided results table. Meanwhile, for the assigned gesture, the accuracy peaked at 80.11% for Top 5. Diving deeper into these results reveals an unexpected trend: despite the larger set of functions and the challenges posed by semantically similar buttons, the system demonstrated consistent performance across different context levels. Contrary to our anticipation, given the complexity of the video streaming interface and the proximity of related functions, the system's accuracy remained resilient. Upon reflection, we identify several key factors contributing to these outcomes: 1) The presence of a more intricate interface potentially forced participants to be more deliberate in their gestures, ensuring clarity in their intentions. This heightened clarity might have facilitated the system in correctly interpreting the gestures, even in a cluttered environment. 2) As the interface contained items of reduced size, the accuracy of gaze information was compromised. However, this could have been counterbalanced by the efficiency of the GestureGPT in dealing with high-level context, especially when both gaze and history were combined.

Fig 11 presents an intriguing observation in the context of online video streaming. When we incorporate gaze as an additional context, it seems that the addition of gaze information does not improve the performance as much as in smart home scenario, and even deteriorates the performance in task 8. The blue and orange lines representing "No Additional Context" and "+Gaze", respectively, clearly demonstrate the variance between tasks with and without gaze context. Upon inspection, one can infer that the dense distribution of elements in this video streaming scenario is a contributing factor. In environments with closely

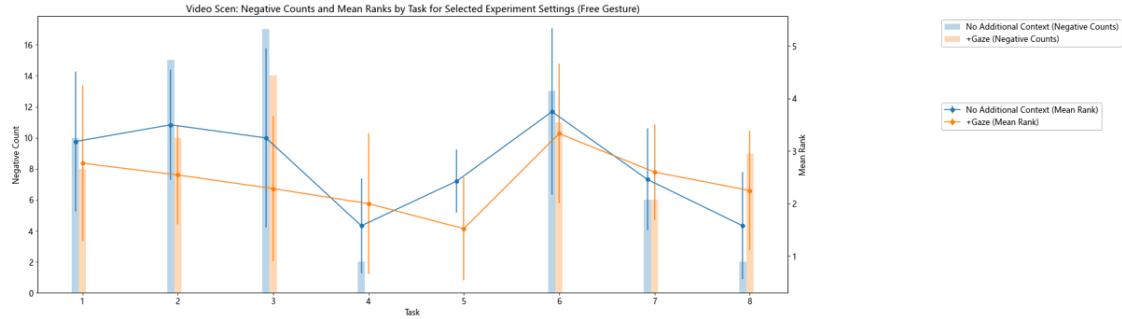


Fig. 11. Comparison of the effect of gaze context in a video streaming scenario, illustrating the ineffectiveness of gaze on most tasks due to the dense distribution of interface elements and the inaccuracy of gaze data.

packed interface elements, the precision of gaze becomes paramount. However, the chart indicates that the gaze data's accuracy might not be sufficiently high, leading to extraneous noise and potentially misinterpreted gestures. Interestingly, the negative counts, represented by the shaded bars, further substantiate the ineffectiveness of gaze information. The increased negative counts for the "+Gaze" context in some tasks suggest that users might often look at unintended interface elements or that the system misinterprets their intention due to imprecise gaze data. This analysis strongly underscores the need for caution when considering gaze as an additional context in scenarios with a dense interface. The potential for misinterpretation, stemming from the imprecise nature of gaze data in such settings, can inadvertently reduce system accuracy and degrade user experience.

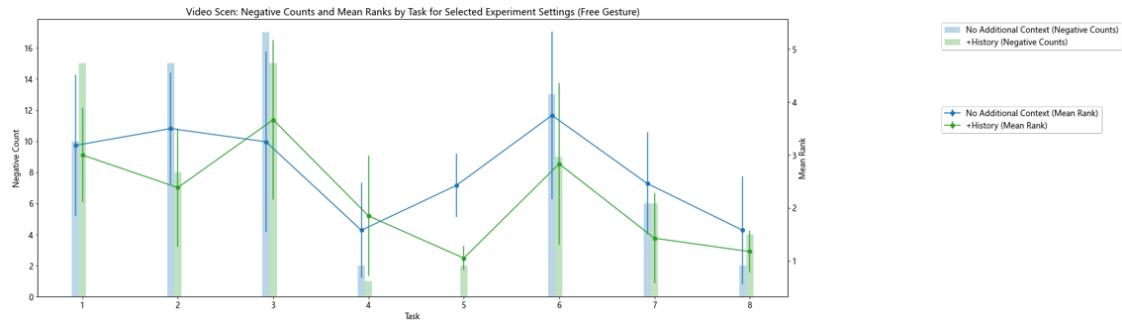


Fig. 12. Comparison of the effects of history context in a video scenario, highlighting distinct performance gains in task 5, 7, and 8 when prior actions are considered.

Fig 12 provides an insightful examination of the influence of history context in a video streaming environment. The blue and green lines, representing "No Additional Context" and "+History" respectively, show the comparative effects on different tasks when the prior actions or "history" of the user is taken into account. There is a noticeable improvement in performance for task 5, 7, and 8 when using the history context. Specifically, task 5 – where the user's previous action was to "Pause the video" and the current task is to "Resume the video," task 7 – where the user previously "Exited full screen" after watching and now wants to "Like the video," and task 8 – where the prior action was to "Like the video" after watching and the current task is to proceed to the "Next video." These findings suggest that the GestureGPT framework, especially its large model component, is proficient at recognizing patterns in human behavior from vast datasets. By discerning these patterns, the model can effectively apply this knowledge to specific tasks, optimizing the response based on prior actions. The evident enhancement in tasks associated with sequential actions, such as pausing then resuming a video or liking a video after watching, underscores the model's ability to align its predictions with natural human behaviors. Consequently, leveraging history context in such situations can substantially enhance user experience and system accuracy.

Fig 13 elucidates the effectiveness of integrating high-level context into video scenarios for the GestureGPT model. Two tasks in particular highlight this efficacy: Task 2 which centers on the context of a user having watched an earlier segment of a video. The task requires the model to drag the progress bar forward. When integrating high-level context, there's a noticeable improvement in the model's performance compared to when this context is absent. Task 4 is set against the backdrop of an incoming call on the

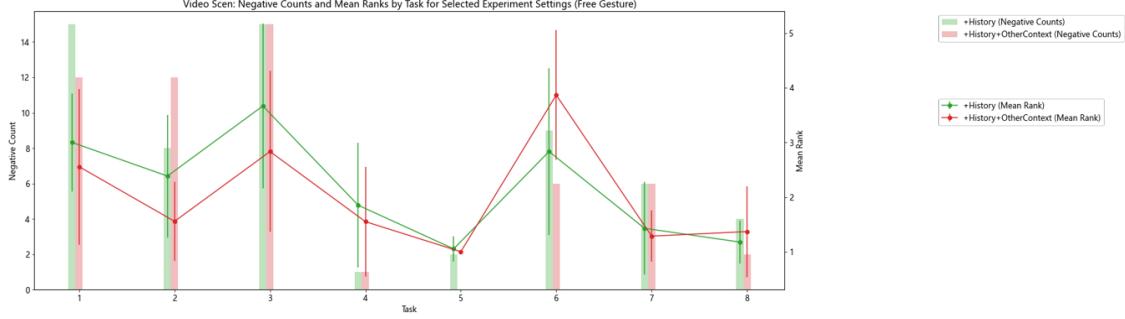


Fig. 13. With and without high-level context in video scenarios..

user's phone, necessitating the video to be paused. Here too, the inclusion of high-level context equips the model to outperform its counterpart that lacks this added context. These findings underscore the capability of GestureGPT in processing and leveraging high-level contextual information. Such integration not only augments the accuracy of the model but also highlights the potential of contextual information in enhancing user experience in real-world applications.

6.2.4 Compared With Human Performance. Just as in the previous study, we also measured the human performance. The result is in Table 11.

Table 11. Human Performance Result in Video Scene

	Free gesture				Assigned gesture			
	Top 1	Top 3	Top 5	Negative	Top 1	Top 3	Top 5	Negative
without HLContext(Human)	18.8%	43.8%	50%	50%	40.9%	47.8%	56.2%	43.8%
with HLContext(Human)	83.3%	83.3%	100%	0%	100%	100%	100%	0%
without HLContext(GPT4)	25.83%	54.17%	65.00%	35.00%	31.25%	56.25%	77.08%	22.92%
with HLContext(GPT4)	36.94%	56.67%	63.33%	36.67%	39.58%	68.75%	75.00%	25.00%

From our observation, *GestureGPT* excels in handling complex tasks, particularly in free-gesture scenarios. This underscores its power in zero-shot gesture-context interaction. However, it appears to struggle when leveraging high-level contexts. One possible reason is that the high-level context given to LLM is mixed in a paragraph of context description, which may be difficult for LLM to recognize; those given to human is in the form of a single sentence, which makes it stand out and shows a strong hint to human.

7 DISCUSSION, LIMITATION AND FUTURE WORK

Gesture Rule. In our current research phase, the system primarily supports right-hand single-hand gesture descriptions and requires accurate gesture cut-off points identification. Dual-handed gestures, while more complex, offer richer communicative potential. Future explorations could expand our rule set or use unsupervised learning from large gesture datasets. Keyframe recognition technologies might address the challenge of pinpointing gesture start and end points, enhancing system accuracy and user experience. Reflecting on our limitations, the system's focus on right-hand gestures may not capture the full spectrum of human expressiveness. These challenges, however, guide our future research direction. A critical objective is developing a real-time context-sensing system, capturing and interpreting interactive scenarios, and generating actionable insights.

Other Model as Agent. We explored the feasibility of using two models, GPT-3.5 and Vicuna-13B, as alternatives to GPT-4 in serving as the agent for GestureGPT. While GPT-3.5 is renowned as one of the most formidable commercial models, second only to GPT-4, and has consistently delivered impressive results across various tasks, Vicuna-13B is recognized within the community as a leading open-source conversational model. However, the results were less than satisfactory. Primarily, both models exhibited disappointingly low accuracy rates: GPT-3.5 at 8.64% and Vicuna-13B, alarmingly, below 1%, indicating almost no successful implementations. Furthermore, they both presented high system failure rates, where a failure is characterized by conversations that extend beyond 20 rounds without yielding any conclusive outcomes, often suggesting a loop without exit. The failure rates

were 54.6% for GPT-3.5 and over 95% for Vicuna-13B. These comparative outcomes underscore the intricacies involved in grasping user intentions in the realm of interaction, demanding models to possess significant cognitive reasoning capabilities. However, one notable disadvantage of GPT-4 is its relatively elevated cost. We are optimistic about future research endeavors, where we aim to collect data and fine-tune dedicated models for specific tasks to uncover more robust solutions.

Real-time Performance. Our current implementation uses LLM API provided by OpenAI, which has a relatively slow responding time that does not support real-time gesture understanding and grounding. Local models have much less communication latency, but they require expensive computational resources and have a longer inference time. To address this challenge, we envision future agent-based HCI systems to have locally fine-tuned models with a small or moderate size (e.g., with 7B or 13B parameters), which has the potential for real-time HCI applications.

Context Library. Other than the gaze data, the context library is prepared offline. It is important to build an on-line context sensing system that can extract meaningful information from the current interactive scenarios. LLMs has the potential since they have reasoning capabilities and common sense prior knowledge about the interaction and related context information. For future system implementation, we plan to build a real-time context agent that serves beyond only context information extraction, able to manage context sensing and abstract high-level context summaries that are helpful for the interaction scenarios.

8 CONCLUSION

In this paper, we innovatively introduced GestureGPT – a context-aware gesture understanding and grounding framework, which facilitates a zero-shot association between gestures and interactive functionalities. The distinctiveness of our approach lies in its dual-agent dialogue system, composed of an LLM-based Gesture Agent and Context Agent. Through this, GestureGPT seamlessly transforms visual gestures into an understandable natural language format. In terms of empirical validation, our gesture description module showcased robust accuracies of 91.8% for the first-view and 81.0% for the third-view datasets. Through user studies, our framework demonstrated laudable gesture grounding accuracies of 90.78% and 80.11% across diverse scenarios, rivaling, and in instances, surpassing human benchmarks. In essence, GestureGPT has heralded a paradigm shift in gesture understanding. More than mere categorization, it forges a nuanced connection between gesture types and the intended interactive function. With its dual LLM agent system, GestureGPT not only discerns gestures but aligns them with the desired target function. Evidently, GestureGPT marks a pioneering stride, leveraging LLMs to bridge the recognition-action chasm in human-computer interaction landscapes.

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A PSEUDOCODE FOR GESTURE DESCRIPTION RULES

Algorithm 1 Flexion of a finger

```

1: procedure CALCULATEFLEXION(finger)
2:   curlAngle  $\leftarrow 0$ 
3:   if finger is thumb then
4:     curlAngle  $\leftarrow \text{Angle}(\overrightarrow{\text{MCP-IP}}, \overrightarrow{\text{IP-TIP}})$ 
5:   else
6:     curlAngle  $\leftarrow \text{Angle}(\overrightarrow{\text{MCP-PIP}}, \overrightarrow{\text{PIP-DIP}})$ 
7:     curlAngle  $\leftarrow \text{curlAngle} + \text{Angle}(\overrightarrow{\text{PIP-DIP}}, \overrightarrow{\text{DIP-TIP}})$ 
8:   end if
9:   return curlAngle
10: end procedure

```

Algorithm 2 Proximity of two fingers

```

1: procedure CALCULATEPROXIMITY(finger1, finger2, thresholdLow, thresholdHigh)
2:   jointDis  $\leftarrow 0$ 
3:   polylineFinger1  $\leftarrow \text{Polyline}(\text{finger1 PIP}, \text{finger1 DIP}, \text{finger1 TIP})$ 
4:   polylineFinger2  $\leftarrow \text{Polyline}(\text{finger2 PIP}, \text{finger2 DIP}, \text{finger2 TIP})$ 
5:   jointDis  $\leftarrow \text{jointDis} + \min(\text{Distance}(\text{finger1 PIP}, \text{polylineFinger2}), \text{Distance}(\text{finger2 PIP}, \text{polylineFinger1}))$ 
6:   jointDis  $\leftarrow \text{jointDis} + \min(\text{Distance}(\text{finger1 DIP}, \text{polylineFinger2}), \text{Distance}(\text{finger2 DIP}, \text{polylineFinger1}))$ 
7:   jointDis  $\leftarrow \text{jointDis} + \min(\text{Distance}(\text{finger1 TIP}, \text{polylineFinger2}), \text{Distance}(\text{finger2 TIP}, \text{polylineFinger1}))$ 
8:   jointDis  $\leftarrow \text{jointDis}/3$ 
9:   if jointDis is less than thresholdLow then
10:    return adjacent
11:   else if jointDis is greater than thresholdHigh then
12:    return separated
13:   else
14:    return unsure
15:   end if
16: end procedure

```

Algorithm 3 Touch of two fingers

```

1: procedure CALCULATETOUCH(finger1, finger2, thresholdLow, thresholdHigh)
2:   distance  $\leftarrow \text{Distance}(\text{finger1 TIP}, \text{finger2 TIP})$ 
3:   if distance is less than thresholdLow then
4:     return contact
5:   else if distance is greater than thresholdHigh then
6:     return nocontact
7:   else
8:     return unsure
9:   end if
10: end procedure

```

Algorithm 4 Palm orientation

```

1: procedure CALCULATEPALMORIENTATION(hand, threshold)
2:    $\overrightarrow{\text{pinkyFinger MCP}}, \overrightarrow{\text{indexFinger MCP}} \leftarrow \text{Vector}(\text{pinkyFinger MCP}, \text{indexFinger MCP})$ 
3:    $\overrightarrow{\text{wrist}}, \overrightarrow{\text{middleFinger MCP}} \leftarrow \text{Vector}(\text{wrist}, \text{middleFinger MCP})$ 
4:   if hand is left hand then
5:      $\overrightarrow{\text{PalmOrientationVector}} \leftarrow \text{CrossProduct}(\overrightarrow{\text{pinkyFinger MCP}}, \overrightarrow{\text{indexFinger MCP}}, \overrightarrow{\text{wrist}}, \overrightarrow{\text{middleFinger MCP}})$ 
6:   else if hand is right hand then
7:      $\overrightarrow{\text{PalmOrientationVector}} \leftarrow \text{CrossProduct}(\overrightarrow{\text{wrist}}, \overrightarrow{\text{middleFinger MCP}}, \overrightarrow{\text{pinkyFinger MCP}}, \overrightarrow{\text{indexFinger MCP}})$ 
8:   end if
9:   minAngle  $\leftarrow +\infty$ 
10:  PalmOrientation  $\leftarrow \text{None}$ 
11:  for direction in ['right', 'left', 'down', 'up', 'outward', 'inward'] do
12:    angle  $\leftarrow \text{Angle}(\overrightarrow{\text{PalmOrientationVector}}, \text{direction})$ 
13:    if angle is less than minAngle then
14:      minAngle  $\leftarrow \text{angle}$ 
15:      PalmOrientation  $\leftarrow \text{direction}$ 
16:    end if
17:  end for
18:  if minAngle is greater than threshold then
19:    return unsure
20:  else
21:    return PalmOrientation
22:  end if
23: end procedure

```

Algorithm 5 Finger moving direction

```

1: procedure CALCULATEFINGERMOVINGDIRECTION(hand, finger, frame_list, static_threshold)
2:   if len(frame_list)  $\leq 1$  then
3:     return static
4:   end if
5:   start_landmark  $\leftarrow \text{hand}[\text{frame\_list}[0]]$ 
6:   end_landmark  $\leftarrow \text{hand}[\text{frame\_list}[-1]]$ 
7:    $\overrightarrow{\text{start_angle}} \leftarrow \text{Angle}(\text{start\_landmark}'s \text{ MCP}, \text{start\_landmark}'s \text{ TIP}, \overrightarrow{\text{start\_landmark}'s \text{ MCP}}, \overrightarrow{\text{start\_landmark}'s \text{ wrist}})$ 
8:    $\overrightarrow{\text{end_angle}} \leftarrow \text{Angle}(\text{end\_landmark}'s \text{ MCP}, \text{end\_landmark}'s \text{ TIP}, \overrightarrow{\text{end\_landmark}'s \text{ MCP}}, \overrightarrow{\text{end\_landmark}'s \text{ wrist}})$ 
9:   if end_angle – start_angle is less than static_threshold then
10:    return static
11:   else if end_angle is greater than start_angle then
12:     return outward
13:   else
14:     return inward
15:   end if
16: end procedure

```

Algorithm 6 Hand moving direction

```

1: procedure CALCULATEHANDMOVINGDIRECTION(hand, frame_list, static_threshold)
2:   if len(frame_list) ≤ 1 then
3:     return static
4:   end if
5:   start_landmark ← hand[frame_list[0]]
6:   end_landmark ← hand[frame_list[-1]]
7:   move_vector ← end_landmark['wrist'] - start_landmark['wrist']
8:   for joint in ALL_JOINTS do
9:     move_vector ← move_vector + (end_landmark[joint] − start_landmark[joint])
10:  end for
11:  move_vector ← move_vector/joint_num
12:  if len(move_vector) is less than static_threshold then
13:    return static
14:  end if
15:  minAngle ← +∞
16:  HandMovingDirection ← None
17:  for direction in ['right', 'left', 'down', 'up'] do
18:    angle ← Angle(move_vector, direction)
19:    if angle is less than minAngle then
20:      minAngle ← angle
21:      HandMovingDirection ← direction
22:    end if
23:  end for
24:  return HandMovingDirection
25: end procedure

```

B ERROR ANALYSIS OF GESTURE DESCRIPTION RULES ON EGOGESTURE

The detailed error analysis of gesture description rules that are tuned on a third-view dataset and tested on a first-view dataset is shown in Table 12.

Table 12. Analysis of Error Cases on EgoGesture Dataset

Rule	Gesture	Finger	Error Rate	Observed Reasons
Flexion - other fingers	seven	pinky	0.296	Some people perform it differently; MediaPipe's mistake for occluded fingers.
	C	ring	0.611	The finger in this gesture is slightly bent by nature, hard to predict precisely.
		pinky	0.379	Same as above.
	thumb down		0.237	MediaPipe's mistake for occluded fingers.
		index		
		ring	0.376	Same as above.
Proximity	measure	index-middle	0.414	MediaPipe's mistake.
	three	middle-ring	0.320	Same as above.
	four	index-middle	0.245	Landmarks mistake; some people perform it differently; the fingers are slightly separated by nature, hard to predict precisely, but it doesn't influence the recognition of the gesture very much.
		middle-ring	0.736	Same as above.
		ring-pinky	0.368	Same as above.
	five	index-middle	0.400	Same as above.
		middle-ring	0.943	Same as above.
		ring-pinky	0.543	Same as above.
	ok	middle-ring	0.693	Same as above.
		ring-pinky	0.624	Same as above.
	nine	index-middle	0.390	Landmarks mistake.
Touch	seven	thumb-ring	0.276	Some people perform it differently; MediaPipe's mistake for occluded fingers.
		thumb-pinky	0.214	Same as above.
	nine	thumb-pinky	0.550	MediaPipe's mistake for occluded fingers.
	thumb down	thumb-index	0.269	Landmark mistake.
	thumb back-ward	thumb-index	0.421	Same as above.
	thumb for-ward	thumb-index	0.231	Same as above.
	three	-	0.28	Some people perform it differently.
Palm Orientation	four	-	0.264	Same as above.