Cognitive Science Student Journal
Osnabrück University

Submission template

Great that you submit your scientific paper!

Make sure that you adhere to our **style guide** and fill out our **author form**.

The submission of your scientific paper is divided into three parts within one LaTeX project, for which we provide individual .tex files:

1. Summary
2. Information
3. Text body

1 Summary

Each publication on the Cognitive Science Student Journal website will be introduced with a summary of the publication. The aim of this summary is to give prospective students, students and alumni of the Cognitive Sciences a thematic overview of the publications' content and spark their interest to read the full publication.

We ask you to consider the following guidelines and example to write the summary. The summary consists of the following three subparts: Summarizing statement, spoiler alert, good to know. Insert your summary below as indicated.

Summarizing statement

- Start with a hook
- Central question (aim of the paper)
- State what the paper is about
- In the end shortly state the roadmap that the reader can expect

Spoiler Alert

Summarize the papers conclusion.

Good to know

State what prerequisite knowledge is needed to understand the paper. Consider including helpful links.

Tone/ Language

- Use simple language and avoid specific scientific terms. If you do use it, provide a short explanation.
- If appropriate, address the reader directly using "you".
- Do not use abbreviations but the full term followed by the abbreviation in brackets.

Example Summary

A summary might reads as following.

Summarising statement

Is it possible to control technology with your imagination? The paper at hand discusses four types of neural networks and their applicability to the domain of visual imagery, i.e. whether you can predict what action a user wants a brain-computer interface (BCI) to perform based on a subject's neuronal data, usually electroencephalographic data (EEG). The paper provides a closer look into visual imagery tasks and the use of neural networks. The networks compared are standard artificial neural networks (ANNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), as well as spiking neural networks (SNNs). You will be introduced to the general pros and cons of each network and the specific advantages and disadvantages their architecture poses to the field of visual imagery. In the end you will be given a summary and a general recommendation.

Spoiler Alert

For the specific task of translating mental imagery into a command, CNNs are ill-suited; ANNs, RNNs, and SNNs do well but SNNs will potentially outperform the others in the long run.

Good to know

Ideally, you are familiar with the basics of machine learning, what an artificial neural networks is, what different networks there are. You know about electroencephalography (EEG) measurements, what is being measured and how.

Your Summary

Please insert a summary for your paper here.

Summarising statement

Can agents communicate about physical objects in the simulation while separated by a wall? This paper showcases and discusses the results of experiments we conducted in order to assess whether communication emerges in a sender-receiver scenario that is physically grounded. The paper will give a short overview over reference/signaling games and embodiment in multi-agent systems (MAS) and lay out our theoretical framework, experimental setup and discuss our findings thereafter.

Spoiler Alert

The language that (partially) emerges from reference games can be grounded in the physical environment of a simulation and facilitate effective communication between agents.

Good to know

For reading this paper you should have heard about the concept of language emergence as well as embodiment and have an idea about the basics of reinforcement learning and multi-agent systems. If not, here are some links to catch you up:

Information

Please answer the following questions.

To which Cognitive Science discipline is the paper affiliated to?

The paper is affiliated with the domains of artificial intelligence and computer linguistics. It specifically concerns itself with language emergence in the context of reinforcement learning.

In which seminar did you write that paper?

This paper is a product of a series of papers written by the students of the study project "Emergent Behaviors in Multi-Agent Systems" (EBIMAS) by Julius Mayer in the summer term 2023. The authors are Cornelius Wolff (cowolff@uos.de), Jennifer Kempkens (jkempkens@uos.de), Charlotte Uhlemann (chuhlemann@uos.de), Therese Mayr (tmayr@uos.de), Eunhye Yun (eyun@uos.de), Julius Mayer (julius.mayer@uos.de), and Elia Bruni (elia.bruni@uos.de)

What kind of paper is it? (e.g. original research, summary, meta paper, experimental sketch, explanation of a paradigm, discussion, . . .)

We present the experimental results of our original research from the EBIMAS and put it in a literary context by discussing previous research.

If you wrote your paper within a University course, what was your task?

The task of the language emergence subgroup in the EBIMAS project was to research established methods and experimental set ups in language emergence experiments in multi-agent systems and design an experimental set up that fits our multi-agent scenario.

What is the research question of your paper?

How is embodiment affecting the efficiency and effectiveness of reference games?

Abstract

This study explores the potential of language in shaping perception and behavior, even across physical boundaries, within a 3D simulation. Two reinforcement learning agents demonstrate unidirectional human-induced communication, conveying a single token to match a target object, and subsequently receiving shared rewards. This research extends the traditional signaling game by incorporating embodiment, paving the way for the emerging field of embodied language emergence. The unique experimental setup delves into the mechanisms of partially emergent communication between agents, aiming for efficient collaboration in a matching task despite physical separation. The study provides insights into the agents' grounded language rooted in the simulated environment's physical properties and shares experimental outcomes. The modifications to the experimental setup yield meaningful results, demonstrating the efficacy of the language learning process and affirming the integration of the given language structure. Our findings underscore the robustness and efficiency of the language learning process within this experimental framework, shedding light on the potential of embodied language emergence.

Title of the paper: Embodied Minds, Shared Language: An embodied multi-agent reference game using human-induced language.

2 Introduction

The capacity of language to shape perceptions, influence behaviors, reshape experiences, and bridge divides is a fundamental aspect of human cognition and social interaction. This principle also extends into the realm of artificial intelligence, where it is exemplified by the interactions between reinforcement learning agents within a three-dimensional (3D) simulated environment. To date, language emergence experiments using reinforcement learning, both uni-directional and bi-directional, have been primarily limited to gridworld-like environments or image reference/reconstruction game environments (Lewis, 2008; Mordatch and Abbeel, 2018; Rita et al., 2022). However, given that humans exist in a 3D environment and our language and general perception are constantly grounded in this 3D embodied perspective Pfeifer and Bongard, 2006, we believe that expanding language emergence setups to similarly embodied 3D setups is a crucial and necessary step toward developing agents that are humanly interpretable and interactable. Therefore, this paper will introduce an experimental setup, termed an embodied reference game, which aims to observe how agents utilize language grounded in their environment to solve complex tasks. This innovative approach extends the conventional signaling game model, promoting a deeper understanding of the agents' interaction with their simulated world. Consequently, this study explores the impact of embodiment on the precision and efficacy of referential communication within such an artificial context.
Thus, the core contributions of this paper are

1. the extension of the conventional signaling game by the implementation of an embodiment scenario and thereby lay the foundations for further research in the upcoming field of embodied language emergence.

2. the introduction of a novel way of inducing a very simple human-created language understanding.

3. the proof-of-concept that modern reinforcement learning algorithms are able to solve such embodied reference games by using language.

3 Related Work

Originating in philosophical theory, the traditional Lewis signaling game (Lewis, 2008) contains two players with differing roles: a sender with a fixed set of signals and a receiver that can take actions, but not observe the state of the world. Both players share a common interest, namely matching the state of the world with the correct action of the receiver based on the sender's signal. The Lewis game has been discussed and adapted in a lot of accounts (Spike et al., 2017) and has laid the groundwork for referential games (Lazaridou et al., 2016). Physical properties of a continuous environment have not played a role in previous studies utilizing reference games. But when it comes to assessing language emergence in multi-agent reinforcement learning (MARL), incorporating embodiment appears necessary, since researchers use reference games to gain insights on language emergence. Including embodiment in the experimental setup might bring us closer to natural language emergence, which is fundamentally grounded in the physical environment.

Krishnaswamy and Alalyani, 2021 highlight the importance of using embodied agents to demonstrate how actions, words, and interpretations are interconnected. By allowing agents to actively participate in the simulated environments and observe the outcomes of the agent's actions, a deeper understanding of how meaning is grounded can be achieved. They introduce interactive multimodal agents with natural language technology, opening up new possibilities for developing systems that not only process, but also comprehend language.

In the context of emergent communication, Bullard et al., 2020 were the first to explore deep reinforcement learning for communication in embodied agents using articulated motion, which means the agents have to control their joints to signal. Their work focused on the emergence of non-verbal communication in high-dimensional simulated environments, providing insights into the potential of embodied agents in developing effective communication protocols.

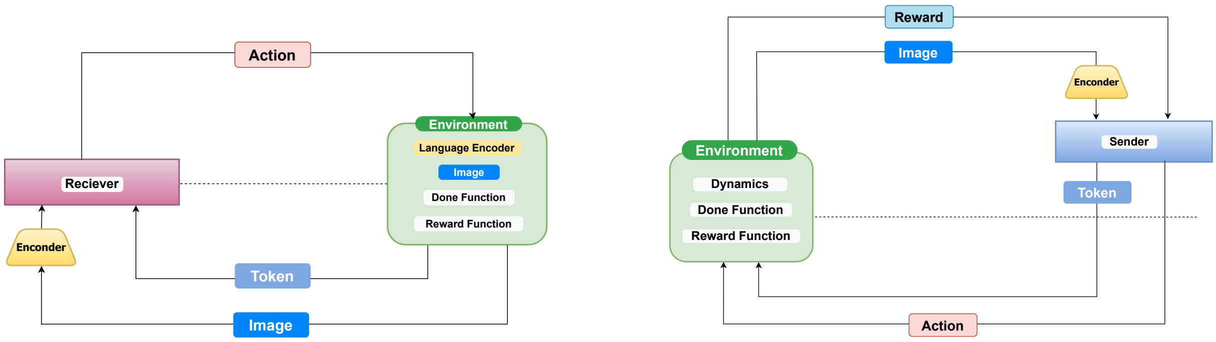
Additionally, Clay et al., 2021 have shown that training neural networks in an embodied framework enables them to learn sparse and meaningful representations of complex sensory input. By interacting with their environment, agents can develop stable and meaningful representations that capture essential features and facilitate effective communication.

4 Methodology

4.1 Environment

General setup: We use the MuJoCo Todorov et al., 2012 physics engine to instantiate two box shaped agents positioned in distinct spatial regions, with a partitioning wall between them. The sender's area contains a solitary target object, while the receiver's area exhibits three distinct objects, including one target and two distractors, which are represented by different colors. Specifically, these objects are cube-shaped and characterized by the colors green, blue, or red. In the training process, we used ten different combinations of color distribution. Training was carried out on a computer with an Intel Core i9-12900KF, 32 GB RAM, and an Nvidia GeForce RTX 3090. As can be seen in Figure 1, both receiver and sender were trained separately on the given language.

Observations and Actions: Both agents are provided with observations encoded as 30 floating-point values, outputted by an encoder that compresses the image data from each agent's respective camera into a meaningful representation within a latent space. This encoding facilitates the agents' interpretation of visual information in a highly abstracted form. Additionally, the receiver agent receives linguistic inputs, which during the training phase are provided by the training algorithm, and during the final evaluation, are provided by the sender agent, which has been trained to generate these inputs.



(a) Training of the receiver (b) Training of the sender

Figure 1: Training Procedures of the sender and receiver

The agents' set of actions in the physical environment comprises two continuous actions, enabling the agents to move forward and backwards, as well as turn left and right. Additionally, the sender agent possesses one extra discrete action for encoding the tokens. These tokens are encoded as one-hot vectors, among which a specific token is designated to indicate the sender's inability to identify the correct target object. This encoding strategy allows the sender agent to communicate both specific object identifications and its own uncertainty, thereby enhancing the depth and reliability of the communication channel between the sender and receiver agents.

Done functions: There are basically two important done functions, governing when one of the agents reach a terminal state: The wall collider function is responsible for overseeing collisions between agents and the boundary walls, ensuring that agents cannot move beyond the designated perimeters of the environment. Concurrently, the target collider function is tasked with managing the interactions between agents and target objects within their allocated spaces. These collider functions are integral to the simulation, as they regulate the agents' movements, maintain the integrity of environmental boundaries, and assess the success of agent-object interactions. In instances where an agent encounters a collision with either a boundary wall or a target object, the current episode is concluded, thereby enforcing the rules of engagement and interaction within the simulated environment.

Reward function:

Receiver: When getting closer to the correct target object, the receiver agent gains a positive reward equally to the difference in distance, reinforcing their ability to discriminate between different objects and supporting successful navigation towards their designated targets. Mathematically, the formula for the reward R_{receiver} is given by:

$$R_{\text{receiver}} = k \times (d_t - d_{t+1})$$

The receiver agent gains a positive reward for successfully approaching the correct target. The reward is scaled by a constant coefficient k, which depends on the difference in distances d_t (initial distance) and d_{t+1} after moving closer to the target.

Sender: The sender in turn is trained using the reward function derived from the mean-squared error, where we used the senders actions prior to the one-hot-encoding as the prediction and the correct utterance as a label. Furthermore, the agent can decide to not utter anything meaningful and simply pick a non-assigned token. That has been done so that the agent can learn not to say anything when it does not see the target object. If the agent decides not to utter anything, it will get neither a reward, nor a penalty. Let $\mathbf{p}$ represent the sender's actions prior to one-hot encoding

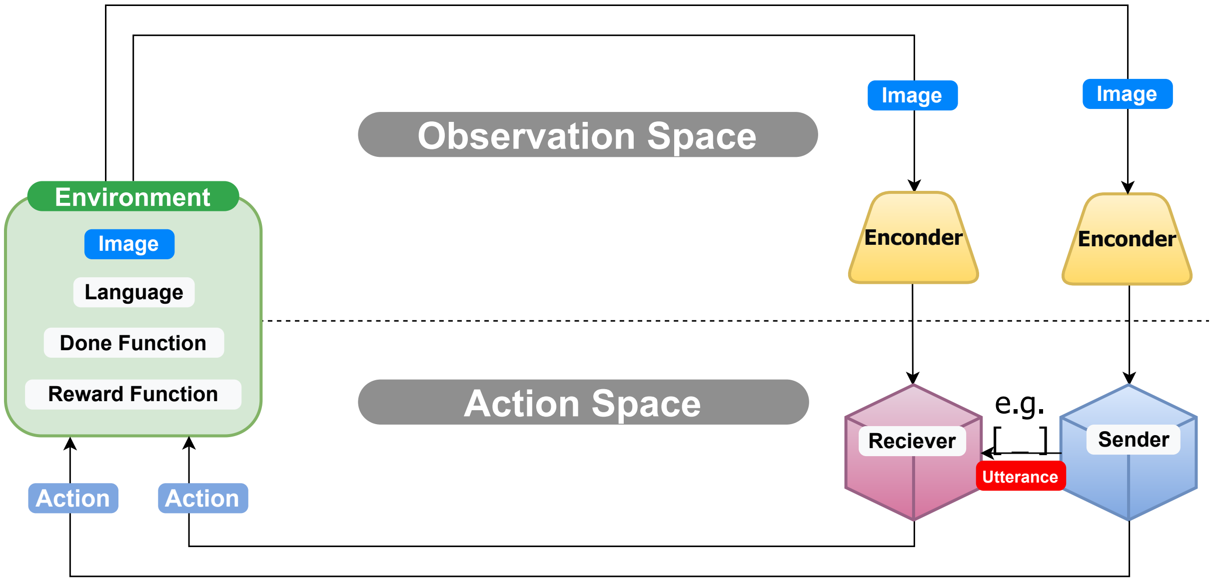


Figure 2: Systematic visualization of the final setup after the successful training. Two agents, sender and receiver, get compressed image input from the environment via the encoder. The environment contains the language channel, done and reward functions and the images. The sender communicates an utterance to the receiver and both agents return actions to the environment according to representations from the observation space and the senders utterance.

and $\mathbf{u}$ be the correct one-hot-encoded utterance. The mean squared error reward function R_{MSE} can be expressed as:

$$R_{\text{Utterance}} = -\frac{1}{N}\sum_{i=1}^{N}(p_i - u_i)^2 \times \text{IsMeaningful}$$

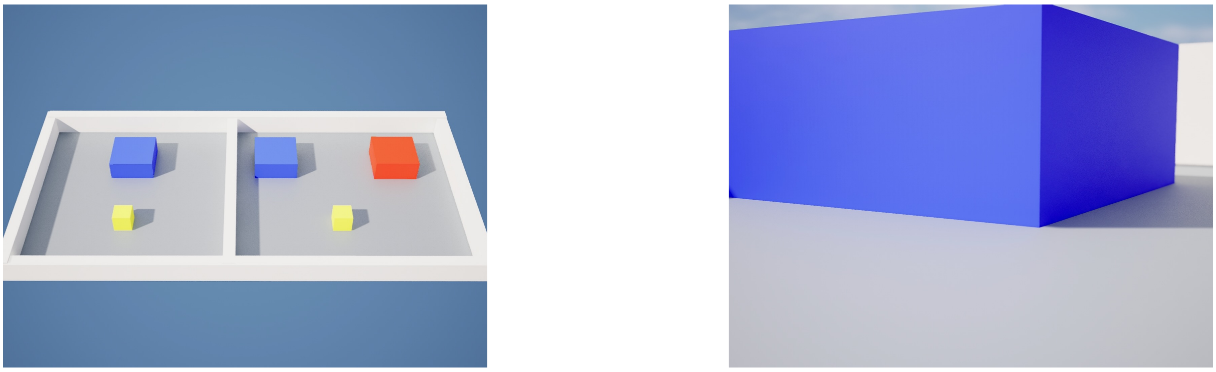
where N is the dimensionality of the action space (i.e., the number of possible utterances) and p_i and u_i are the ith elements of $\mathbf{p}$ and $\mathbf{u}$ respectively and **IsMeaningful** is a binary indicator that is 1 if the agent's action is a meaningful utterance and 0 if the agent's action is picking a non-assigned token (silence):

$$\text{IsMeaningful} = \begin{cases} 1, & \text{if } \mathbf{a} \text{ is a meaningful utterance} \\ 0, & \text{if } \mathbf{a} \text{ is a non-assigned token (silence)} \end{cases}$$

In summary: If the agent generates a meaningful utterance ($\mathbf{a}$ is a meaningful utterance), it receives a reward based on the mean squared error (R_{MSE}) without a penalty (Penalty $= 0$). If the agent chooses not to utter anything ($\mathbf{a}$ is a non-assigned token), it receives a reward of 0.

Furthermore, the sender gets a reward for moving around and exploring the environment. Let (x_t, y_t) denote the coordinates of the agent at timestamp t. (x_{t-i}, y_{t-i}) represent the coordinates of the agent i timestamps ago. The Euclidean distance between the positions at t and $t-i$ is given by $\sqrt{(x_t - x_{t-i})^2 + (y_t - y_{t-i})^2}$. The discount factor d is applied to the reward, scaling down the contribution of past movements as the time difference (i) increases. The reward function for exploration $R_{\text{Exploration}}(t)$ is defined as the summation of rewards considering all previous timestamps:

$$R_{\text{Exploration}}(t) = \sum_{i=1}^{t}\left(\sqrt{(x_t - x_{t-i})^2 + (y_t - y_{t-i})^2} \times d^i\right)$$



(a) Global view on a level of the environment (b) Perspective of the receiver agent

Figure 3: Showing the environment rendered with the Unreal Engine 5 from different perspectives.

This reward function enables a comprehensive evaluation of the agent's movement and exploration efforts, potentially considering the entire trajectory up to the current timestamp t. In our case, we only considered the 20 previous timesteps for this reward function.

4.2 Agent

For the implementation of the agents, we relied on the implementation of Proximal Policy Optimization (PPO) algorithm by Huang et al., 2022, which we adapted for multi-agent use during the final inference setup. In this context, we didn't add additional features to the implementation, besides multi-agent support, as previous research showed that PPO performs quite well in cooperative multi-agent tasks without any additional changes and therefore should also be a good choice for our research questions Yu et al., 2022. In our setup, the agents do not share weights, meaning that both agents have individual neural networks. Shared weights might present a challenge for the agents, as they cannot simply modify their own neural network in isolation to optimize their individual tasks. Instead, having separate neural networks allow the agents to optimize their weights for their own tasks. As the language channel is kept as simple as possible in this setup, the communication will be non-recursive, meaning that it does not incorporate information from past interactions and therefore allows for a direct and immediate exchange of information. In order to handle large image data sets, the visual data is pre-processed by the encoder of a pre-trained auto encoder, while the encoder remains static during the training of the agent and is not updated.

4.2.1 Auto encoder

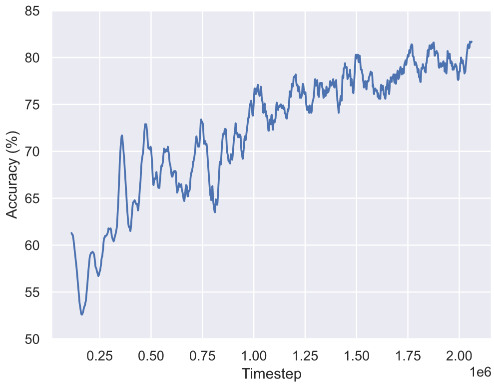
In this paper, we employed a vanilla autoencoder Kingma and Welling, 2022; Rezende et al., 2014; Van Hoof et al., 2016 to pre-process image data for reinforcement learning agents. An autoencoder is a neural network architecture consisting of an encoder and a decoder. The encoder takes an image as input and compresses it into a lower-dimensional latent space representation. The encoder learns to extract the most relevant features and compresses them into a condensed representation. The decoder then attempts to reconstruct the original input data from the latent space representation by minimizing the reconstruction loss.
The autoencoder model was trained on a data set comprising 12,288 images obtained from a single agent. The data collection process involved three episodes of random actions, with each episode consisting of 4,096 time steps.

4.3 Analysis

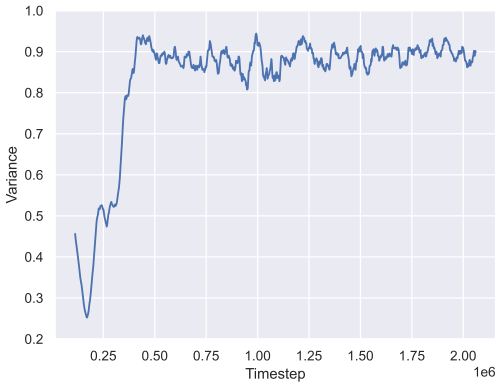
During training, we monitored the progress by tracking four different metrics: Average reward, average length per episode, accuracy, and variance.
Average reward: By tracking the average reward per episode, we can track whether the agent learns to move to the target object of each level. If the reward moves above chance level, it means that the agents are learning.
Average length: In the beginning, we expect longer episodes. Over time, as the receiver learns to move towards the target objects, we expect the average length per episode to go down.
Accuracy: With accuracy, we track the share of the receiver's picks that are correct with respect to the reference object. When the sender is trained on its own, accuracy refers to the correct encoding for the color of the reference object.
Variance: With variance, we monitor how often the receiver touches different target objects. If the agent always picks the same object, the variance will go towards 0. If the agent regularly touches picks both objects, the variance is going towards 1. This is useful, as the agent might learn to only check one target object and decide to terminate the episode by running into a wall, if the color does not match the token.
Once the independent training of the two agents is concluded, both of them are placed in the same environment. Here, we simply check what percentage of levels the agents are able to solve. This will show us, whether the agents were able to gain a common understanding of the previously taught language.

5 Results

Our initial experiment revealed that refraining from imposing a penalty of -1 upon the agent for erroneously targeting the wrong object resulted in a suboptimal behavior where the agent essentially engaged in random navigation towards either of the two target objects without demonstrating any meaningful communication or learning. This outcome can be rationalized by the absence of a genuine incentive for the agent to select the correct target, as there is a 50/50 probability of success in this scenario. Consequently, we decided to modify the experimental setup by introducing a penalty of -1 for both agents in the event that the receiver erroneously selected the wrong target object. Additionally, we introduced a slight negative reward for collisions with the environment's walls. This adjustment was made to ensure that the anticipated reward associated with randomly approaching either of the two potential targets exceeded the expected reward associated with colliding into walls, thereby encouraging the agent to learn more effective navigation and communication strategies.
Our results unveiled several noteworthy findings. First and foremost, the sender agent exhibited a very good level of proficiency, accurately selecting the appropriate word in more than 90 percent of instances after 1.7 million timesteps. Moreover, as anticipated, the sender agent acquired a low language perplexity, aligning with our predictions and affirming the successful integration of the given language structure. Notably, there was no observed symbol redundancy, as the language structure was predefined. On the receiver side, we measured an accuracy rate exceeding 80 percent, further indicating the effectiveness of the learned language. When both sender and receiver agents were combined within the same environment, this cooperative synergy resulted in an receiver accuracy rate of 78 percent, showing the successful utilization of the given language as a communicative tool in this novel context of language emergence. These findings collectively emphasize the robustness and efficacy of the language learning process within our experimental framework.

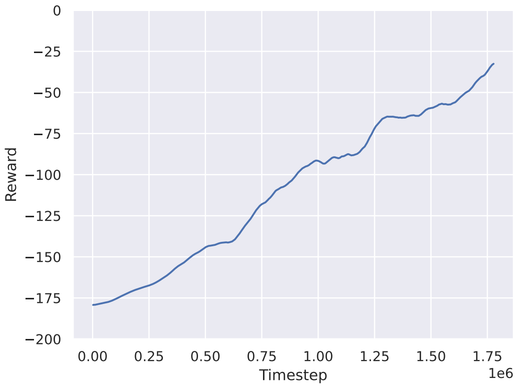


(a) The accuracy of the receiver during training

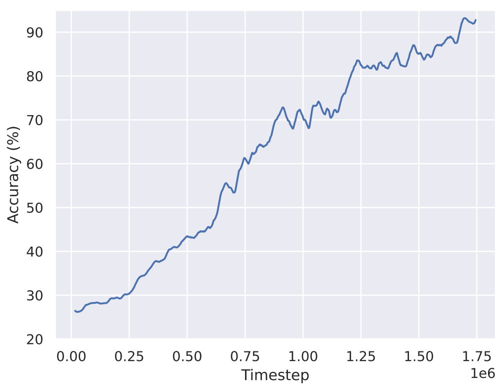


(b) The variance of the receiver during training

Figure 4: The training results of the receiver



(a) The reward of the sender during training



(b) The accuracy of the sender during training

Figure 5: The training results of the sender

6 Discussion

In the frame of this study, we aimed to implement an embodied reference game to show that communication can be learned in an embodied environment. While traditional reference games mainly deal with abstract information transmission and strategic decision-making, embodied reference games incorporate physical, observable signals in communication scenarios. Thus, they offer a more realistic and experiential approach to the examination of communication and interaction between agents. Although the incorporation of embodied signals adds more realism to the communication model, it also raises the complexity of the game leading to increased computational costs.

6.1 Limitations

We acknowledge several limitations that should be taken into account when analyzing our experiment setup and results. The use of a small vocabulary size and deploying only one feature of the element restricted communication between the agents to single words, limiting the expression and comprehension of complex linguistic structures. The absence of sentential context further constrained the agents' comprehension of language, potentially overlooking the influence of contextual information on word meanings. Moreover, the embodiment of the agents was simplified, featuring ant-like shaped entities with multiple joints.

The agents do not have awareness of each other's embodiment. Exploring language learning without relying on pre-existing knowledge of embodiment also means that the agents cannot fully grasp the potential physical affordances of the agents' bodies, which could impact their communication and interaction. Both agents engage in the referential game, wherein they collaboratively aim to establish mutual understanding and refer to specific entities or concepts within their communication process. This simplified representation of embodiment may not fully capture the intricacies and complexities observed in real-world scenarios.

In contrast to common reference games, where training is carried out over several single-time steps, we have pursued a continuous setup that is closer to human-like communication but on the downside brings about more instability and inconsistency. To reduce instabilities between sender and receiver and to speed up the otherwise autonomous communication process, we have manually predefined the vocabulary. Another approach is to alternately freeze the sender and receiver every 20 time steps, so that they learn independently of each other and are finally joined together again.

The most significant drawback of our approach lies in the utilization of a predefined language structure. This design choice restricts the emergence of language to a predefined set of symbols and rules, preventing the development of a fully emergent linguistic system. Consequently, our study lacks the richness and complexity associated with the spontaneous creation and evolution of language, limiting the scope of linguistic analysis that can be conducted. While our results shed light on specific aspects of reinforcement learning and communication, they do not capture the intricate dynamics and nuances of genuinely emergent languages, leaving a potential avenue for future research in this field.

7 Conclusion and Outlook

This research extends the traditional reference game through the incorporation of embodiment. Hereby, we provide a basis for the research field of embodied language emergence. Even though our scenario was constrained by having fixed the agent's vocabularies, it did lay the groundwork for a fully emergent setup. To achieve further up-scaling in this context, different strategies can be considered. For one, the incorporation of longer sequences, along with recursion hold promise for expanding the multi-agent system's capabilities. Additionally, increasing the complexity of the objects used for communication, beyond mere color attributes, would enable more realistic conversation. Consequently, environmental factors play a crucial role in shaping the communicative demands of the simulation. This may entail adopting a shared world space instead of a separated setting, and employing a bidirectional setup wherein both agents assume the roles of senders and receivers. Upscaling the scope of referential games by embodiment holds immense potential for the fields of advancing AI and robotics, but also for linguistics and cognitive science. Future research could first and foremost take an approach in which language is emerging a priori and fully independently. Considering the difficulty of simulating natural language, the successful implementation of an embodied reference using predefined language marks one step towards an embodied fully emergent language setup. We have made an attempt to understand language emergence in the context of physical bodies, which in the future could be extended to exploring topics such as the interaction of language and environment, referential communication and theory of mind.

References

Bullard, K., Meier, F., Kiela, D., Pineau, J., & Foerster, J. (2020). Exploring zero-shot emergent communication in embodied multi-agent populations.

Clay, V., König, P., Kühnberger, K.-U., & Pipa, G. (2021). Learning sparse and meaningful representations through embodiment. *Neural Networks*, *134*, 23–41. https://doi.org/https://doi.org/10.1016/j.neunet.2020.11.004

Huang, S., Dossa, R. F. J., Ye, C., Braga, J., Chakraborty, D., Mehta, K., & Araújo, J. G. (2022). Cleanrl: High-quality single-file implementations of deep reinforcement learning algorithms. *Journal of Machine Learning Research*, *23*(274), 1–18. http://jmlr.org/papers/v23/21-1342.html

Kingma, D. P., & Welling, M. (2022). Auto-encoding variational bayes.

Krishnaswamy, N., & Alalyani, N. (2021). Embodied multimodal agents to bridge the understanding gap, 41–46. https://aclanthology.org/2021.hcinlp-1.7

Lazaridou, A., Peysakhovich, A., & Baroni, M. (2016). Multi-agent cooperation and the emergence of (natural) language. *arXiv preprint arXiv:1612.07182*.

Lewis, D. (2008). *Convention: A philosophical study*. John Wiley & Sons.

Mordatch, I., & Abbeel, P. (2018). Emergence of grounded compositional language in multi-agent populations. *Proceedings of the AAAI conference on artificial intelligence*, *32*(1).

Pfeifer, R., & Bongard, J. C. (2006). How the body shapes the way we think - a new view on intelligence.

Rezende, D. J., Mohamed, S., & Wierstra, D. (2014). Stochastic backpropagation and approximate inference in deep generative models.

Rita, M., Tallec, C., Michel, P., Grill, J.-B., Pietquin, O., Dupoux, E., & Strub, F. (2022). Emergent communication: Generalization and overfitting in lewis games. *Advances in neural information processing systems*, *35*, 1389–1404.

Spike, M., Stadler, K., Kirby, S., & Smith, K. (2017). Minimal requirements for the emergence of learned signaling. *Cognitive science*, *41*(3), 623–658.

Todorov, E., Erez, T., & Tassa, Y. (2012). Mujoco: A physics engine for model-based control. *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 5026–5033. https://doi.org/10.1109/IROS.2012.6386109

Van Hoof, H., Chen, N., Karl, M., van der Smagt, P., & Peters, J. (2016). Stable reinforcement learning with autoencoders for tactile and visual data. *2016 IEEE/RSJ international conference on intelligent robots and systems (IROS)*, 3928–3934.

Yu, C., Velu, A., Vinitsky, E., Gao, J., Wang, Y., Bayen, A., & Wu, Y. (2022). The surprising effectiveness of ppo in cooperative multi-agent games. *Advances in Neural Information Processing Systems*, *35*, 24611–24624.