Abstract—Agents in decentralized multi-agent navigation lack the world knowledge to make safe and (near-)optimal plans reliably. They base their decisions on their neighbors’ observable states, which hide the neighbors’ navigation intent. We propose augmenting decentralized navigation with inter-agent communication to improve their performance and aid agent in making sound navigation decisions. In this regard, we present a novel reinforcement learning method for multi-agent collision avoidance using selective inter-agent communication. Our network learns to decide ‘when’ and with ‘whom’ to communicate to request additional information in an end-to-end fashion. We pose communication selection as a link prediction problem, where the network predicts if communication is necessary given the observable information. The communicated information augments the observed neighbor information to select a suitable navigation plan. As the number of neighbors for a robot varies, we use a multi-head self-attention mechanism to encode neighbor information and create a fixed-length observation vector. We validate that our proposed approach achieves safe and efficient navigation among multiple robots in challenging simulation benchmarks. Aided by learned communication, our network performs significantly better than existing decentralized methods across various metrics such as time-to-goal and collision frequency. Besides, we showcase that the network effectively learns to communicate when necessary in a situation of high complexity.

I. INTRODUCTION

Safe and efficient navigation is at the core of various robotic applications, such as last-mile delivery, warehouse automation, self-driving cars, and drone surveillance. Due to improved efficiency and throughput, these applications benefit by deploying multiple robots in tandem. Multi-robot navigation has gathered significant attention over the past decade and is complex due to the problem’s large state space associated with the multi-robot system.

Centralized and decentralized methods are two primary classes of multi-robot navigation algorithms. Centralized methods [1], [2] view the robots as a single composite system and thus have global knowledge about all the robots. Centralized path generation has gained widespread application in warehouses due to its relative ease of guaranteeing collision-free paths and their efficiency. However, they have limited scalability owing to the central computation of trajectories and are primarily deployable in controlled environments such as warehouses, labs, etc. In the worst case, their computation time can increase exponentially with the number of agents [3], [4].

In decentralized navigation [5]–[7], robots make independent decisions using local sensing. As agents make independent decisions, the computation cost is limited and enables large-scale deployment. But, decentralized methods lack global knowledge about other agents and can result in less efficient paths, robot freezing behavior, and even collisions.

Recently, deep RL-based methods [8], [9] for multi-agent collision avoidance have showcased improved success rate and time-to-goal compared to model-based methods. RL methods leverage their extensive offline training to learn and map the observation directly into actions. However, they lack explainability and rigorous safety guarantees. Some RL methods [8], [9] use observation vectors containing neighbors’ positions and velocities information as network input, similar to model-based methods. These methods map the state of the robots and their neighbors to actions by using recurrent neural networks (RNNs) to extract invariant features from the input. But, RNNs tend to focus on recent information rather than treating knowledge of all robots equally.

A. Main Contribution

1) We propose a novel method for collision-free navigation in dense multi-robot scenarios

2) Motivated by their success in NLP, we utilize a multi-head attention mechanism to encode the observation vectors from all neighbors to create a fixed-length observation vector. Thus, we do not limit the maximum number of neighbors. Moreover, we do not

3) Our method allows robots to communicate with neighbors to augment their observed neighbor information with the communicated information.

We evaluate our method on multiple simulated benchmarks to compare its navigation performance against prior methods. We consider metrics such as path length, time to goal, collision rate, deadlock, and the overall success rate in reaching the goal.

II. RELATED WORK

A. Model-based Collision Avoidance

Fiorini and Shiller present the velocity obstacle (VO) [10] concept, which computes collision-free velocities for the agents based on their observation of neighbors’ position
and velocity. RVO [6] improves on VO by assuming equal responsibility between agents to avoid a collision. Further, ORCA [5] linearizes the RVO constraints to improve computational efficiency. BVC [7] constructs a Voronoi-based free space for each agent to perform collision-free navigation. BVC shows similar collision-free performance to ORCA but requires only positional information about its neighbors. V-RVO [11] presents a hybrid between RVO and BVC for improved collision avoidance performance.

B. Learning-based Collision Avoidance

CADRL [8] proposed an RL method for multi-agent navigation which showed improved time-to-goal performance compared to ORCA. Semnani et al. [12] presents a hybrid-framework switching between RL and force-based planning based on the scene complexity, resulting in an improved success rate and time-to-goal. Everett et al. [9] further improved CADRL to account for an arbitrary number of neighboring agents by using an LSTM to encode a varying-size observation vector into a fixed length vector. In contrast, our method uses multi-head self-attention [13] to encode the observation to a fixed length vector. Self-attention can be parallelized and is independent of sequence order, unlike LSTM.

Long et al. [14] present a deep RL method that maps raw sensor data to action. The method shows a better success rate, path optimality, agent’s average speed, and time to goal compared to the non-holonomic version of ORCA. Fan et al. [15] further improved the performance by adopting a hybrid framework. Xu et al. [16] use expert human trajectories and knowledge distillation to shape the reward and generate human-like trajectories. Further, the authors show improved energy efficiency and success rate compared to ORCA and RL methods similar to [14]. DRL-VO [17] uses a velocity obstacle (VO) based cost in the rewards to improve the success rate. Han et al. [18] present a DRL method with an RVO-shaped reward for better reciprocal behavior.

Li et al. [19] propose a hybrid method based on RL and ORCA. The RL network computes the desired action for each neighboring agent, weighted to compute a suitable preferred velocity used in the ORCA formulation. Rivièr et al. [20] present a distributed, provably-safe policy generation for multi-agent planning. It uses globally planned trajectories and constructs a local observation action training set, and is used to learn a decentralized policy using deep imitation learning. A differentiable safety module (based on control barrier function (CBF)) trains the network end-to-end to ensure collision-free navigation. The method shows a 20% higher success rate than ORCA in numerical experiments. Cai et al. [21] propose CBF-based shielding for safety-critical MARL tasks.

C. Communication Assisted Multi-agent Navigation

A few works have explored communication in the multi-agent navigation domain. Serra-Gómez [22] learns whom to communicate with and requests the planned trajectories from the chosen neighbor to be used in the MPC planner. Ma et al. [23] present a DRL method for multi-agent pathfinding with broadcast communication. In [24], they reduce the communication overhead by combining the idea of I2C [25] for multi-agent navigation in a grid work domain.

Our proposed network uses a multi-head self-attention module to encode the neighbor information, and we consider a natural navigation domain. Besides, our agents to allowed to communicate with neighbors to improve their decision-making. Our network includes a communication module that communicates with select neighbors at any time. Thus, reducing the neighbors, an agent communicates with, compared to a broadcast type communication.

III. PROBLEM FORMULATION AND OVERVIEW

This section lists our assumptions, summarizes our problem statement, gives an overview of our approach. Table I lists the common symbols and notations used in our paper.

A. Assumption

In this paper, we assume disk-shaped robots with unicycle dynamics. We consider a request-reply type communication between the ego-agent and its neighbors. We assume the request-reply is fast and executed within a single planning cycle.

B. Problem Statement

We consider the problem of cooperative multi-robot navigation between communicating robots. We propose a RL method to navigates individual robots towards their respective goal while avoiding collisions. The robots’ communicates with its neighbors to obtain information to improve their navigation.

Let us consider an environment \( \mathcal{W} \subset \mathbb{R}^2 \) with \( N \) communicating robots \( \{A_1, A_2, \ldots, A_n\} \). Considering a disk shaped robot with 2D position \( p_i \), and radius \( r_i \), the safe-navigation problem can be expressed mathematically as,

\[
\|p_i(t) - p_j(t)\|_2 \geq r_i + r_j \quad \forall i, j \in \{1, 2, ..., N\}, \forall t. \tag{1}
\]

Here, \( p_i(t) \) represents the path of the robots as a function of time \( t \). Following the definition from CADRL [8], the agent’s state \( s_i = [s_i^o, s_i^h] \) includes an observable component and a hidden component. The observable component \( s_i^o \) includes the agents position, velocity, and its radius. While the hidden component \( s_i^h \) include the agent’s goal, preferred speed, and

### Table I: Symbols

| Symbol | Description |
|--------|-------------|
| \( p_i \) | Position of agent \( i \) \((p_x, p_y)\) |
| \( v_i \) | Velocity of agent \( i \) \((v_x, v_y)\) |
| \( \psi_i \) | Heading of agent \( i \) |
| \( r_i \) | Radius of agent \( i \) |
| \( v_{pref,i} \) | Preferred Velocity of agent \( i \) |
| \( g_i \) | Goal of agent \( i \) \((g_x, g_y)\) |
| \( N_i \) | Set of neighbors of agent \( i \) |
| \( C_i \) | Set of selected neighbors for communication |
its current orientation. The agent’s control input include its speed and heading angle, and is given by $u_i = [v_i, \psi_i]$.

$$s^e_i = [p_x, p_y, v_x, v_y, r]$$  
$$s^h_i = [g_x, g_y, v_{pref}, \psi]$$

C. Multi-head Attention

Initially proposed in [13], self-attention has shown immense potential in natural language processing. Self-attention mechanism compares elements of an input sequence with each other to compute a representation of the sequence. For each element in the input sequence, the attention mechanism calculates a self-attention score is computed for each element in the sequence. The score determines the focus awarded to other sequence elements for encoding a particular element.

$$Attention(Q, K, V) = \left( \frac{QK^T}{\sqrt{d_k}} \right) V$$

Here, $\sqrt{d_k}$ is the dimension of K.

In multi-head attention, multiple heads are created by linearly projecting the Q, K, and V. Each self-attention head focuses on different subspaces, and attention is performed in parallel. The projected queries, keys, and values are fed into attention pooling in parallel. The projected queries, keys, and values are fed into attention pooling in parallel. Next, attention pooling outputs are concatenated and transformed with another learned linear projection to produce the final output.

$$Multi-Head(Q, K, V) = Concat(head_1, head_2, ... head_k)W^0$$

$$head_i = Attention(QW^i, KW^K, VW^V)$$

Where, $W^Q_i, W^K_i, W^V_i$ are parameter matrices for projection.

D. RL

As with prior methods [8], [9], we consider a local coordinate frame with the state composed of information about the ego-agent and its neighbors. The information about the ego-agent includes its distance to the goal, preferred speed, orientation, and radius.

$$s^{ego} = [||g_i - p_i||, v_{pref}, \psi_i, r_i]$$

The world information includes the agent’s neighbors, including its position, velocity w.r.t ego frame, radius, inter-agent distance, and combined radius.

$$s^{obs_j} = [\tilde{p}_{x_j}, \tilde{p}_{y_j}, \tilde{v}_{x_j}, \tilde{v}_{y_j}, r_j, d_a, r_i + r_j]$$

$$s^{obs} = [s^{obs_1}, s^{obs_2}, \ldots, s^{obs_n}] 1, 2, \ldots n \in N_i$$

In addition, our methods allow the agent to request one or more of its neighbors for their hidden state ($s^h_j$) using communication which can augment the network’s input. The communicated information is used to construct a communicated state from each neighbor and includes dist to a neighbor’s goal from the ego-agent, the difference in preferred speed between the ego-agent and its neighbor, and relative orientation/heading. More details are presented in Section [V-B]

Due to the success in [9], this multi-agent RL problem formulation is trained with GA3C. We positively reward the agents on reaching the goal and negatively reward on a collision and communication.

$$R = \begin{cases} 1.0, & p_i = g_i \\ -0.25, & collision \\ -0.0001 \cdot n_i, & n_i: \text{no of comm. links} \\ 0.0, & \text{otherwise} \end{cases}$$ (2)

IV. MULTI-AGENT RL NAVIGATION

This section illustrates our network architecture (Figure 1) and describes its various modules.

Our network consists of 3 components: the observation encoder, communication module, and navigation module.

A. Observation Encoding

The observation encoder takes the observation vector of all neighboring robots ($s^{obs_j}$) as input to create a fixed-length vector for input to the navigation module. Since the number of neighbor around an agent vary at any point in time, our method needs to account for varying agents. Thus, our observation encoder uses multi-head self-attention to encode the neighbors $s^{obs}$ into a fixed-length observation vector.

The input sequence consists of $s^{obs_j}$ for each neighbor, which is represented relative to the ego agent. In addition, we compute $s^{obs_{ego}}$, which is the observed state of the ego agent relative to the ego frame. The ego-agent observed state is necessary as we use the self-attention mechanism. Based on the ego observed state, we identify the attention paid to neighboring observed states combined to produce the encoded vector. The input sequence consists of the ego agent’s observable state followed by its neighbors. Finally, the representation computed for $s^{obs_{ego}}$ is used as the encoded representation.

$$e^o = encode(s^{obs_{ego}}, s^{obs})$$

Our encoder uses 20 heads for our observation encoding module with Key, Query encoding using a dense layer with 128 nodes, and the Value has 256 nodes.

B. Communication Selection

This block performs communication selection using the robot’s local observation. We formulate the communication selection as a link prediction problem between the ego robot and its neighbors. The set of neighbors for a agent $i$ is given by,

$$N^i = \{ j \mid j \neq i, ||P_j - P_i|| < r_{neighbor} \}$$

Where $r_{neighbor}$ represents a radius threshold.

The module takes neighbor’s observable states as input and individually passes them through a series of three fully connected layers layers. Since, the $s^{obs_j}$ is in relative frame
Fig. 1: We illustrate a high-level network architecture of our method. Primarily, the network consists of three modules: the observation encoder, the communication selection, and the navigation block. The observation encoder w.r.t. to the ego agent, we pass the vector through a sequential layer to predict the possibility of a communication link.

In this regard, the output of the sequential layer has 2 nodes, one indicating a probability of a link \( p_{\text{link}} \), while other node indicates \( 1 - p_{\text{link}} \). The first 2 layers have 64 nodes and relu activation with the last layer having 2 output nodes and softmax activation. Gumbel-Softmax layer is used to sample a discrete distribution based on the probability of a link.

\[
\forall j \in N_i \quad [p_{\text{link}_j}, 1 - p_{\text{link}_j}] = \text{Comm. Sel}(s_{\text{obs}_j}) \quad (3)
\]

Thus, for each neighbors, the communication module predicts a communication link. If a link is predicted, the agent sends a communication request to the selected neighbors. The neighbors respond with the hidden states of the agents \( s^h = [g_x, g_y, v_{\text{pref}}, \psi] \).

The received hidden state are combined with the observed state from the neighbors to create a communication state. The communicated state is given by,

\[
s_{\text{comm}^j} = [[|g_j - p|], v_{\text{pref}_j} - v_{\text{pref}_i}, \psi_j - \psi_i] \quad j \in N_i
\]

\[
s_{\text{comm}} = [s_{\text{obs}^1, s_{\text{comm}^1}}, s_{\text{obs}^2, s_{\text{comm}^2}}, \ldots,
\]

\[
[\ldots s_{\text{obs}^n, s_{\text{comm}^n}}] \quad 1, 2, \ldots n \in C_i.
\]

We pass the communication vector through a LSTM to create a encoded vector \( e^c \).

\[
e^c = \text{LSTM}(s_{\text{comm}^j})
\]

C. Augmented Input

The augmented input to the navigation module consists of three important vectors. The first is the host agent state, encoded observation vector, encoded communication vector.

\[
s_{\text{input}} = [s_{\text{ego}}, e^o, e^c]
\]

D. Navigation

Our navigation module consists of a sequential layer with 4 fully connected layers. The first layer has 1024 nodes, followed by two layers with 512, and the last layer with 256 nodes. As in [9], the output from the final layers includes the scalar value function and the distribution over the action space.

V. Evaluation

A. Computational Setup

Our method is implemented on an Intel Xeon 4208 CPU with 32 GB RAM. We use tensorflow and python for the deep learning implementation. We use gym-collision avoidance and GA3C-CADRL package from implementing our method.

We train in a curriculum set up. Initially the robot is trained in a scenario with 4 agents. The training scenario is random with few examples of circle scenarios, random start and stop etc. In phase two the agent number is increased and the training scenarios use corridor type scenarios where the intuitively communication could provide better performance.

B. Baseline

We compare our method against prior model- and learning-based decentralized method. We choose RVO [6], BVC [7], CADRL [8], and GA3C-CADRL [9] as our baseline for comparison.
Fig. 2: We compare the trajectories generated by our proposed method with CADRL and GA3C-CADRL for a circular scenario with 20 agents. We observe the proposed method generates smooth trajectories to the goal, while CADRL results in some collision. In GA3C-CADRL, some agents were deadlocked while others were in a collision, and no agent reached the goal.

### Table II: Collision Rate, Time to Goal, and Success Rate

| Robots | Collision Rate | Time to Goal | Success Rate |
|--------|----------------|--------------|--------------|
|        | PM | RVO | CADRL | GA3-CADRL | PM | RVO | CADRL | GA3-CADRL | PM | RVO | CADRL | GA3-CADRL |
| 4 (5m) | 0 | - | 0 | 0 | 112 | - | 1 | 102 | 104 | 1.00 | 1.00 | 1.00 |
| 6 (5m) | 0 | - | 0 | 6 | 115 | - | 103 | - | - | 1.00 | 1.00 | 0 |
| 10 (5m) | 0 | - | 4 | 10 | 162 | - | - | - | - | 1.00 | 0.6 | 0 |
| 20 (8m) | 0 | - | 2 | 20 | 224 | - | - | - | - | 1.00 | 0.95 | 0 |
| 30 (8m) | 0 | - | 6 | - | 253 | - | - | - | - | 1.00 | 0.6 | 0 |

### VI. Conclusion, Limitation, and Future Work

We proposed a collision avoidance methods for multi-agent navigation with selective communication. Our method uses selective communication to transfer hidden state information between agents so as to improve their navigation performance. The neighbor selection is performed similar to that of link prediction where a link between the agent and its neighbors is predicted based on the local observation. Our method is designed to outperform state-of-the-art model-based and learning-based methods in simulation on multiple complex scenarios.

As a future work, we plan to test the method on a fleet of physical robots. Currently, we try to answer the whom to communicate, problem, and we plan to extend to understand what to communicate.

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