

Search and Task Allocation

Swarm Intelligence

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1 Introduction

Search and Task Allocation (STA) problems are considered a general class of problems in Multi-Agent Systems (MAS), and many real-world problems can be formulated as an STA problem [1]. This is a study of reactive agents, where we investigate how the introduction of communication impacts performance.

2 Formalism

We define a search A as an area bound by two points. Over the search area, n_T tasks T are spawned at random positions. The tasks have a task capacity T_c indicating how many agents R are required to solve a task. The task is solved immediately if T_c agents are within the task radius T_r . The agents R move randomly around the search area at a speed R_v . There are n_R agents. When an agent is inside the task radius T_r of a task, the agents will wait for other agents to complete the task. The agents can also call for aid in solving a task. The communication distance R_d determines how far an agent can send a call for aid from another agent.

The position of the agents are updated in a discrete Langevinian manner,

$$r_{R,t+1} = r_{R,t} + N(a_R + b_{R,t}), \quad (1)$$

where $r_{R,t}$ is the position of agent R at time t , a_r is a drift term, $b_{R,t}$ is a stochastic velocity term and N is a normalising operator, ensuring equal velocity of all agents. The drift term is assigned at the start of each simulation and the stochastic velocity term is updated for each time step. The trend is added in order to make sure that the agents will venture away from their origin point, as the expected value of a sum of equally distributed stochastic

variables with mean zero will be zero. That is, even though there is a likelihood for agents to eventually cover the entire area, one would expect them to meander about the point they were initially placed.

In addition to walking randomly across the area, the agents have the possibility of calling other agents in the vicinity, if they are within a communication distance R_d .

3 Implementation

We implement a tool for visualising the problem described above in PyGame [2]. The full implementation is available at github.com/gregwinther/mas, and consists of three classes. Two of these, `Task` and `Agent`, both inherit from PyGame’s `Sprite` class. The last class, `Simulation`, takes care of the game mechanics such as updating states and drawing the area with tasks and agents. Initialising and running a particular game (simulation) can be done with very few lines. For example;

```
simulation = Simulation(1000)
simulation.cycles = 1000
simulation.communicate = True
simulation.write = True
simulation.n_T = 3
simulation.Tr = 50
simulation.n_R = 10
simulation.Tc = 3
simulation.start()
```

A screenshot of this example is shown in Figure 1.

The most important methods of the `Task` and `Agent` classes is the `update()` method, which is called for each iteration of the game. For a `Task`, this method is quite simple. It simply checks if there are enough agents within the task radius T_r to complete the task, if so the task sprite is killed.

The `update()` method for agents is more subtle. Firstly, it has to update the positions of the agents according to Equation 1. This is done by generating a random movement step, or finite difference velocity, which is added to the trend and then normalised to have length equal to R_v .

Since it is possible for an agent to wander outside the area, we take care of the boundaries in the following manner. When a moving agent hits one of the boundaries of the area, the trend unit vector which is perpendicular to the boundary line is reversed. This has the effect of “soft bounce” off the boundary.

More than the mere movement of the agents, it is possible for them to

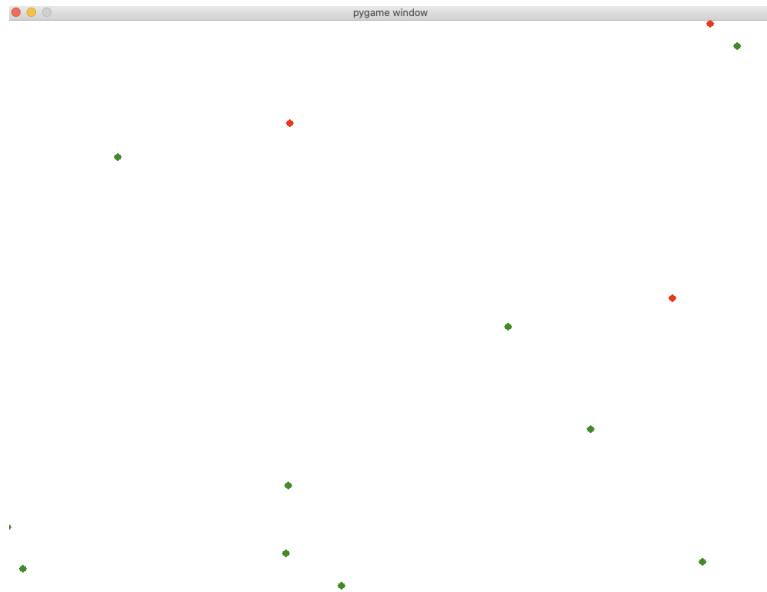


Figure 1: Sample screenshot of a simulation with $n_T = 3$ and $n_R = 10$. The green dots are agents R , and the red dots are tasks T .

be in different states. They may be *searching*, *tasked* or *called*. The default state, *searching*, is what we just described above. Whenever an agent is within the task radius T_r of a task T its state will change to *tasked*. If the task capacity T_c required more agents than the one(s) present, the agent will stay put until enough agents arrive at the task to help. With the mechanic enabled, an agent may also be *called* if it is within the communication distance R_d of another agent. The agent will then move at speed towards the position of the signalling agent. When the task is solved, the call will cease, in effect calling off any approaching agents. All of the transitions between agent states are handled within the main game loop of the `Simulation` class.

4 Results

All the simulations in this study is run five subsequent times in order to get better averaged values, for a total of 1000 time steps. All simulations also has the same task radius $T_r = 50$. Figure 2 shows the results of two arbitrary chosen sets of five simulations. The thin lines represent the individual simulations, while the bold lines are the averages. For both of these sets the number of tasks was $T_n = 1$ with a task capacity $T_c = 1$, while the number of agents n_R are five and 20. The figure is meant to give illustrate the necessity of repeated simulations in order to make results separable.

To benchmark the system we run a number of simulations for various number of tasks T and number of agents R , with task capacity $T_c = 1$. The results of these simulations are shown in Figure 3. The points indicate the average number of completed tasks at the end of a simulation, with standard deviation given by the error bar. As expected, the number of completed tasks increase with the number of agents R and with the number of tasks T .

The results of introducing a higher task capacity is depicted in Figure 4. Here we set $T_c = 3$, meaning that three agents is needed to complete a task T . This figure is comparable to the left-hand subfigure in Figure 3. We see a notably lower number of completed tasks when a task capacity is introduced.

The results of introducing a call signal with reach $R_d = 250$ can be seen in Figure 5. The average performance is markedly and significantly better when agents can call to others for help.

Figure 6 shows the effect of increasing the communication distance of the agents. The cumulative number of completed tasks is plotted against time. In the simulations, only the communication distance is varied, $R \in$

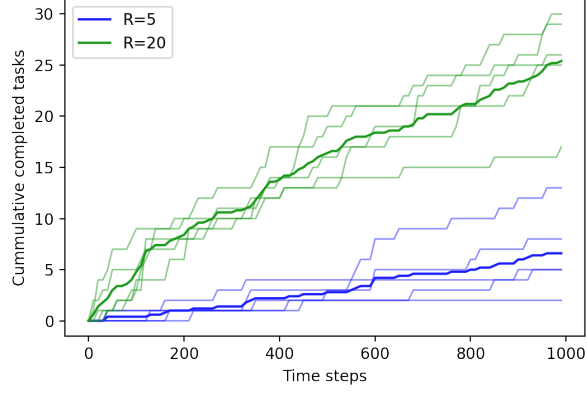


Figure 2: Illustration of arbitrary simulations, with cumulative number of solved tasks is plotted against the number of time steps. The number of tasks T_n is 1 and the number of agents R_n are 5 and 20. The task capacity T_c was set to one. No communication was allowed in these simulations.

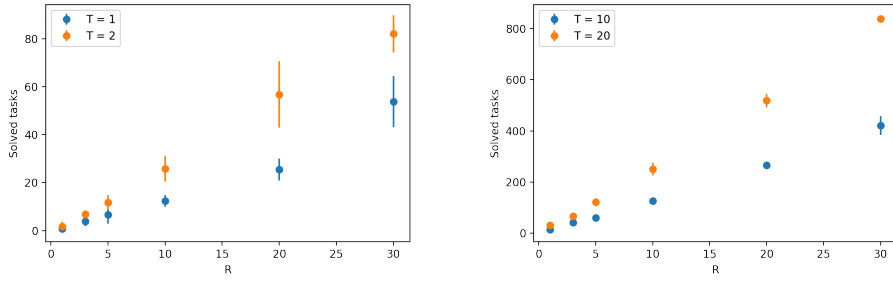


Figure 3: Completed tasks as a function of number of agents after 1000 time steps. The number of agents and tasks are varied, while every other variable is held constant; $T_c = 1$, $T_r = 50$, no communication.

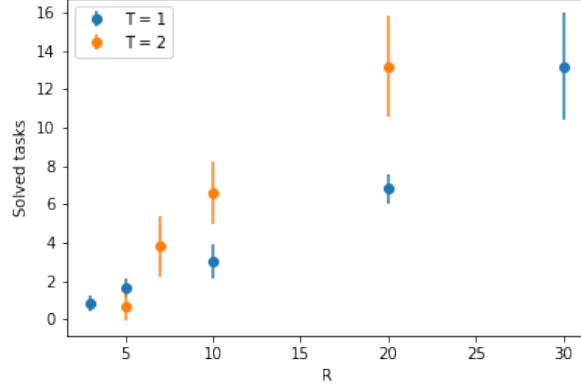


Figure 4: Completed tasks vs number of agents with $T_c = 3$, for two different task numbers $n_T \in \{1, 2\}$.

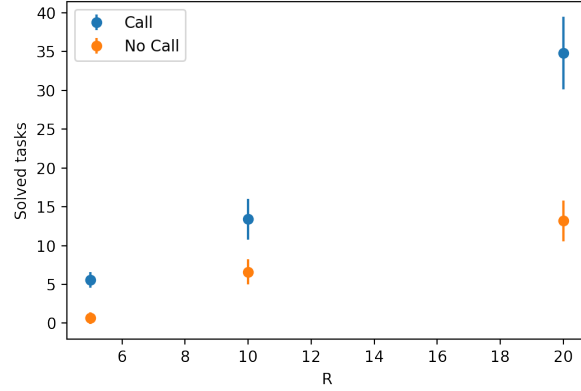


Figure 5: The effect of introducing a calling signal with $R_d = 250$ when an agent finds a task. The number of tasks are $n_T = 2$ with capacity $T_c = 3$.

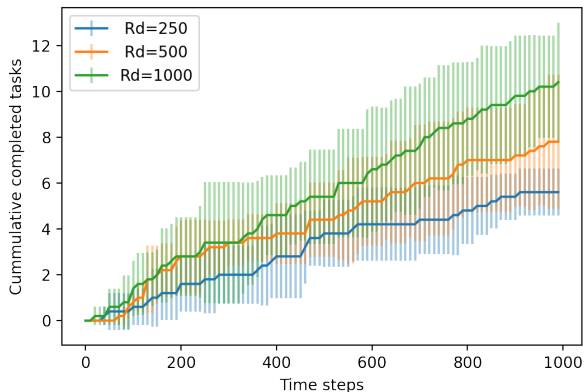


Figure 6: Averages of three sets of five simulations for different communication distances $R_d \in \{250, 500, 1000\}$, with $T_c = 3$, $n_T = 2$ and $n_R = 5$.

$\{250, 500, 1000\}$, all else equal ($T_c = 3$, $n_T = 2$ and $n_R = 5$).

5 Discussion

In order to improve upon the stability of the initial searching of the agents, an improved pattern of movement could likely be devised. There are several improvements one could make when introducing communications, for instance to make the agents keep a distance to each other. There were several simulations where many agents bunched up together. Another improvement with regards to communication is to make sure that only the needed agents are called when a task is found. However, this would be a somewhat complicated alteration. A simpler improvement, would be to alter the drift term of the agents over time in some clever way. As it is now, it stays the same, except for when a boundary is reached. That said, it could be that a more deterministic movement pattern is better at finding tasks than the random movement employed herein.

Looking more closely at Figure 2, we see larger error bars when there are fewer tasks. Because of the reduced probability of encountering a task with lower n_R/n_T ratio, the relative uncertainty of these simulations are higher. A further study into the necessity of either longer simulations or more simulations for a low number of agents, is therefore warranted.

After the introduction of a task capacity, we encounter some “sticky” situations, especially as $n_T T_c \rightarrow n_R$, or more extremely when $n_T T_c \geq n_R$.

In these situations, agents may find themselves waiting at a task until the end of the simulation, because every other agent is also waiting at a task. This leads to the interesting observation in Figure 4 for $n_R = 5$, where the performance is better for a lower number of tasks, which reduces the risk of agents getting “stuck”. This could likely be improved with a limited waiting time or the ability of an call-out from an agent to override a task-solving agent.

References

1. Ijspeert, A. J., Martinoli, A., Billard, A. & Gambardella, L. M. Collaboration through the exploitation of local interactions in autonomous collective robotics: The stick pulling experiment. *Autonomous Robots* **11**, 149–171 (2001).
2. Shinnars, P. *et al.* *PyGame* <http://pygame.org/>. 2020.

A Code listing

```
import pygame, sys
import numpy as np
import math

BLACK = (0, 0, 0)
WHITE = (255, 255, 255)
GREY = (200, 200, 200)
PASTEL_RED = (245, 130, 120)
MINT = (160, 250, 160)
FOREST_GREEN = (30, 140, 30)
RED = (255, 0, 0)

BACKGROUND = WHITE

FRAME_RATE = 12

class Task(pygame.sprite.Sprite):
    def __init__(self, x, y, Tc=1, Tr=50):
        super().__init__()
        radius = 5 # Size of task
        self.image = pygame.Surface([radius * 2] * 2)
        self.image.fill(BACKGROUND)
        pygame.draw.circle(self.image, RED, (radius, radius), radius)

        self.pos = np.array([x, y])
        self.rect = self.image.get_rect()
        self.rect.centerx, self.rect.centery = x, y

        # Task capacity
        self.Tc = Tc
        self.tasked_agents = pygame.sprite.Group()

        # Task radius
        self.Tr = Tr

    def update(self):

        # Task completion
        if len(self.tasked_agents) >= self.Tc:
            self.kill()

class Agent(pygame.sprite.Sprite):
    def __init__(self, x, y, Rv=25, boundary=1000, Rd=250):
        super().__init__()
```

```

radius = 5
self.image = pygame.Surface([radius * 2] * 2)
self.image.fill(BACKGROUND)
pygame.draw.circle(
    self.image, FOREST_GREEN, (radius, radius), radius
)

self.pos = np.array([x, y], dtype=np.float64)
self.rect = self.image.get_rect()
self.rect.x, self.rect.y = x, y

self.Rv = Rv # / FRAME_RATE
self.Rd = Rd

self.vel = np.random.rand(2) * 2 - 1
self.trend = (np.random.rand(2) * 2 - 1) / 2

self.boundary = boundary

self.tasked = False
self.called = False
self.call_dir = np.array([0, 0])

def update(self):
    if self.tasked:
        # Stand still
        return

    if self.called:
        # print(self.call_dir)
        self.pos += self.call_dir
        self.rect.centerx, self.rect.centery = self.pos
        return

    self.pos += self.normalize(self.vel + self.trend, self.Rv)
    self.rect.centerx, self.rect.centery = self.pos

    # Boundary conditions
    if self.pos[0] > self.boundary or self.pos[0] < 0:
        self.vel[0] = -self.vel[0]
        self.trend[0] = -self.trend[0]
        if self.pos[0] > self.boundary:
            self.pos[0] -= 20
        if self.pos[0] < 0:
            self.pos[0] += 20
    elif self.pos[1] > self.boundary or self.pos[1] < 0:
        self.vel[1] = -self.vel[1]
        self.trend[1] = -self.trend[1]
        if self.pos[1] > self.boundary:

```

```

        self.pos[1] -= 20
        if self.pos[1] > self.boundary:
            self.pos[1] += 20
    else:
        self.vel = np.random.rand(2) * 2 - 1

def dist_to_sprite(self, other_sprite):
    return math.hypot(
        self.pos[0] - other_sprite.pos[0],
        self.pos[1] - other_sprite.pos[1],
    )

def direction_to_sprite(self, other_sprite):
    direction = other_sprite.pos - self.pos
    return self.normalize(direction, self.Rv)

def normalize(self, vector, renorm=1):
    vector /= np.linalg.norm(vector)
    return vector * renorm

class Simulation:
    def __init__(self, width=1000):
        self.WIDTH = width # Square

        self.tasks = pygame.sprite.Group()
        self.agents = pygame.sprite.Group()
        self.tasked_agents = pygame.sprite.Group()

        self.cycles = 1000

        self.n_T = 5
        self.Tc = 1
        self.Tr = 50
        self.n_R = 1
        self.Rd = 250

        self.replace_tasks = True
        self.communicate = False

        self.write = False
        self.save_interval = 10

        self.total_tasks_solved = 0

    def start(self):
        if self.write == True:
            f = open(

```

```

        f"sta_T{self.n_T}_Tc{self.Tc}_Tr{self.Tr}_R{self.n_R}.txt",
        "w",
    )

pygame.init()

area = pygame.display.set_mode([self.WIDTH, self.WIDTH])

# Assigning initial Tasks
# Random positions of initial tasks (n, dim)
T_pos = np.random.randint(0, self.WIDTH, size=(self.n_T, 2))

for x, y in T_pos:

    T = Task(x, y, Tc=self.Tc, Tr=self.Tr)
    self.tasks.add(T)

# Assigning initial Agents
R_pos = np.random.randint(0, self.WIDTH, size=(self.n_R, 2))

for x, y in R_pos:

    R = Agent(x, y, Rd=self.Rd)
    self.agents.add(R)

clock = pygame.time.Clock()

# Game loop
for i in range(self.cycles):
    for event in pygame.event.get():
        if event.type == pygame.QUIT:
            if self.write:
                f.close()
            sys.exit()

    if (self.write == True) and (i % self.save_interval == 0):
        f.write(f"{i:3}_#{self.total_tasks_solved:3}\n")

    self.tasks.update()
    self.agents.update()

    # Any tasks completed? Create new tasks.
    n_new_tasks = self.n_T - len(self.tasks)
    self.total_tasks_solved += n_new_tasks
    if n_new_tasks > 0:
        print("Solved!")
        R_pos = np.random.randint(
            0, self.WIDTH, size=(n_new_tasks, 2)
        )

```

```

        for x, y in R_pos:
            T = Task(x, y, Tc=self.Tc, Tr=50)
            self.tasks.add(T)
        for agent in self.agents:
            agent.tasked = False
            agent.called = False
        self.tasked_agents.empty()

# Checking if a task is found
        for agent in self.agents:
            for task in self.tasks:
                distance = agent.dist_to_sprite(task)
                if abs(distance) < task.Tr and not agent.tasked:
                    print(f"Aha! A task at {task.pos}")
                    agent.tasked = True
                    task.tasked_agents.add(agent)
                    self.tasked_agents.add(agent)

# Call out (and off)
        if self.communicate:
            for agent in self.tasked_agents:
                # Make sure to not call oneself.
                other_sprites = self.agents.copy()
                other_sprites.remove(agent)
                for agent2 in other_sprites:
                    distance = agent.dist_to_sprite(agent2)
                    if abs(distance) < agent2.Rd:
                        agent2.called = True
                        agent2.call_dir = agent2.direction_to_sprite(
                            agent
                        )

        area.fill(BACKGROUND)
        self.tasks.draw(area)
        self.agents.draw(area)
        pygame.display.flip()

        clock.tick(FRAME_RATE)

    if self.write:
        f.close()
    pygame.quit()

```